THE ROLE OF FOREST CARBON MODELS TO INFORM POLICY AND PLANNING IN SUPPORT OF NET-ZERO GREENHOUSE GAS EMISSION REDUCTIONS

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ABSTRACT

Forests are increasingly seen as cost-effective mechanisms to mitigate and adapt to climate change. However, significant uncertainties remain for how climate change may affect future forest carbon sink or source strength. This challenge is compounded by the fact that most forest policy and planning decisions made today will not manifest for years, decades, or centuries. To improve the outcomes of regional greenhouse gas emission reduction efforts, salient and robust forest carbon science and data are required. Few studies have assessed gaps and barriers to integrating forest carbon data and models into policy and planning. Furthermore, there is an increasing need to quantify the impacts of enacting specific policies and management strategies to inform decision-making across scales, as well as advancements of associated tools to provide robust quantification and characterization of disturbance impacts on future forest carbon dynamics. Given these challenges, the first chapter of this dissertation provides a brief overview of forests and global climate change and the role of forest carbon data and models to inform forest decision-making. The second chapter focuses on assessing barriers and gaps to integrating forest carbon data and tools into regional policy and planning initiatives. Our results provide a roadmap for more effective science-based communication and education to improve forest carbon outcomes. The third chapter explores a suite of alternative forest management and wood utilization scenarios, compared to a business-as-usual scenario, to quantify the impacts of specific forest policies in the mid-Atlantic region in support of net-zero greenhouse gas emissions targets. These results suggest that key climate-smart forestry practices can increase both the short-term and long-term forest carbon sink strength without hindering timber supplies or reducing forest resilience. The fourth analysis uses a Monte Carlo simulation approach and a random forest model to quantify and characterize model variability and sensitivity to future

disturbance regimes. These findings suggest that disturbance, including land-use change, harvesting, and disease outbreaks, play an important role in driving net ecosystem carbon balances in Maryland's forests. Together, these results exhibit the value of forest carbon models to inform forest policy and planning in support of decision-making to address the climate crisis. Future work should continue to address future barriers to enhancing forest carbon decision-making by further integrating climate considerations and leveraging data and tools to inform forest policy and planning.

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LIST OF ABBREVIATIONS

BAU	Business-as-usual
C	Carbon
CBM-CFS3	Carbon Budget Model of the Canadian Forest Sector version 3
CCRF	Climate change response framework
CI	Confidence interval
DOM	Dead organic matter
GHG	Greenhouse gas
ED	Ecosystem demography
FIA	Forest Inventory and Analysis
FIADB	Forest Inventory and Analysis Database
FVS	Forest vegetation simulator
HWP	Harvested wood products
IPCC	Intergovernmental Panel on Climate Change
LUC	Land-use change
MDNR	Maryland Department of Natural Resources
MMT	Million metric tons
NBP	Net biome productivity
NEP	Net ecosystem productivity
NbCS	Nature-based climate solutions
NCS	Natural climate solutions
NLCD	National Land Cover Database
NSVB	National scale volume and biomass estimators

PCNR	Pennsylvania Department of Conservation and Natural Resources
RF	Random Forest
US	United States
USDA	United States Department of Agriculture
USFS	United State Department of Agriculture Forest Service

CHAPTER 1

INTRODUCTION

1.1 Forests and global change

Forests and society are facing unprecedented challenges due to human-induced climate change (Raupach and Canadell, 2010). Forests are increasingly poised to play an outsized role in combatting climate change in at least two ways. First, it is well documented that forests are primary drivers of global biogeochemical cycling including Earth's carbon cycle, hydrologic cycle, and energy budget (Canadell et al, 2007, Bonan, 2008, Cox et al, 2000, IPCC, 2014, Mitchard, 2018, Pugh et al, 2019). Second, forests and forest products provide increasing potential to enhance the global forest carbon sinks (Canadell and Raupach, 2008, Griscom et al, 2017, Fargione et al, 2018, Nunes et al, 2020) in addition to the continued supply of other cultural, economic, and ecological services (Diaz et al, 2018). Future contributions of forests to mitigating and adapting to climate change are predicated on the successful stewardship and management of forests globally.

The sustainable provisioning of ecosystem services and co-benefits provided by forests requires a greater understanding and forecasting of complex forest dynamics to inform decision-making with imperfect information where decisions made today will not manifest for years, decades, or centuries (Clark et al, 2001, Lindenmayer and Likens, 2009, McDowell et al, 2020). Forest example, significant research gaps remain in determining the effect of natural- and anthropogenic- stressors, climate change impacts, and disturbance effects on forest characteristics and how forests in turn, respond to these drivers (Walker et al, 2020, Anderson-Teixeira et al, 2021, Hogan et al, 2023). Additionally, significant barriers exist to addressing the capacity and technical needs of natural resource managers, landowners, and other forestry professionals to address threats and vulnerabilities due to climate change (Engle, 2011, Nicotra et al, 2015, vonHedemann and Schultz, 2021). The sustainable management of forests, to meet the needs of today and tomorrow, inherently requires the assessment of trade-offs and the identification of opportunities in decision-making to advance the health, resiliency, and productivity of our forests and forested lands (Littlefield and D'Amato, 2022). To do so, requires increasingly integrated approaches to forest policy and planning where iterative processes between science, management, and policy inform and influence each other (Littell et al, 2012, Lamb et al, 2021, Peterson St-Laurent et al, 2021).

1.1.1 Legacies of forest management and climate change considerations

Forests in the United States (US) approximate 68% of terrestrial carbon (C) stocks (Liu et al, 2014) and 90% of the land sector sequestration potential (EPA, 2016) offsetting nearly 11% of total GHG emissions annually (Domke et al, 2020). Increasing mitigation efforts while boosting climate resiliency through land restoration and improved management interventions can enhance both the sequestration and storage potential of forests in the US (Fargione et al, 2018). Working forestlands, which refers to forestlands that are managed to sustainably supply timber, energy, paper, and other forest products, provide potential low-cost solutions to abating greenhouse gas (GHG) emissions (Griscom et al, 2017). Forests are increasingly seen as natural climate solutions (i.e., deliberate human actions that protect, restore, and improve management of ecosystems for climate mitigation) which are viable pathways to sustain biodiversity and other critical ecosystem services in addition to boosting mitigation potential (Ellis et al, 2024).

The eastern US, which comprises of states throughout the lake states region, the lower Midwest, the mid-Atlantic region, and the New England region, is home to 65.67 million hectares of forestlands (USDA Forest Service, 2024). These diverse forests had been managed sustainably for millennia by indigenous tribes and First Nations (Baumflek et al, 2021, Bulkan, 2017, Waller et al, 2018). However, throughout the 18th and 19th century, western settlers shifted management of forests to prioritize extensive logging and clearcutting of forests to meet the energy and building demands of growing urban populations throughout the Atlantic seaboard and Midwest (Otto, 1989). Ultimately fears over deforestation, increasing wildfires, and dwindling timber supplies shifted management approaches in the late 19th and early 20th century to focus on the sustainability of management practices (Millers et al, 1989). The results of these shifts in management priorities yielded the current heterogeneous landscape influenced by both human-induced and natural activities.

This new era, with a greater focus on forest conservation and resilience, led to substantial increases in the complex understanding of forest dynamics. However, unabated GHG emissions have led to increasing threats and vulnerabilities to eastern forests that are expected to alter fundamental ecosystem processes (Joyce et al, 2011, Vose et al, 2016). Vulnerability can be conceptualized as the outcome of the combination of multiple stressors and exposures and the sensitivity to those stressors (Fussel, 2007, Yoshikawa et al., 2023). Adaptive capacity, or the ability of an ecosystem to cope with change due to exposure, can mitigate vulnerability and risk (Engle, 2011). For example, forests in the mid-Atlantic regions are projected to face increased risk of drought during the growing season, pest pressures, and heavier precipitation events (Butler-Leopold et al., 2018, Swanston et al, 2018) which can lead to decreased tree vigor and increased mortality, in turn changing their compositional and structural characteristics (Peters et al. 2013, Vose et al. 2016). These new and novel forest ecosystems perturbed by climate change impacts may be at greater risk of collapse or decreasing biodiversity and forest function (Lindenmayer et al, 2016). Where, proactive and adaptive management to address climate change induced threats and vulnerabilities can have substantial implications for future forest adaptive capacity.

Incorporating climate change considerations in forest planning will always be challenging due to uncertainties of longer time horizons and the complexities of forest ecosystems. Increasingly terms such as forest carbon management (Ontl et al, 2020), carbon stewardship (Failey and Dilling, 2010, Rockstrom et al, 2021), adaptive management (Yousefpour et al, 2012), adaptive silviculture (Nagel et al, 2017), or climate-smart forestry (Nabuurs et al, 2017, Cooper and MacFarlane, 2023) are being adopted to explicitly link climate change considerations with forest planning and management. However, to properly address climate vulnerabilities through adaptive and mitigative actions requires a framework to facilitate successful implementation. One example, the Climate Change Response Framework (CCRF), serves as a guide to i) identify locations, time frames, and goals; ii) assess forest threats and vulnerabilities; iii) identify strategies and approaches; iv) plan and implement actions are appropriate scales; v) monitoring and evaluation effectively (Swanston et al, 2016).

Successful forest carbon stewardship is predicated on bridging science-practice gaps (Kirchhoff et al, 2013) in which a framework such as the CCRF can provide a useful roadmap. This task requires deeper understandings of broad-scale scientific information, potential climate change impacts on forests, and the integration of this knowledge into forest planning and management activities (Ontl et al, 2018, 2020). However, crucial gaps still exist between the assessment of vulnerabilities, identification of appropriate strategies and approaches, and the implementation of management activities on-the-ground including landowner perceptions and barriers to adoption (McGann et al, 2023a, McGann et al, 2023b). Necessitating, in part, research on not just socio-economic barriers of forest carbon management, but improved quantification and monitoring of the implementation of forest climate action (Keith et al, 2021, Novick et al, 2022a).

Policymakers from national to local scales are advancing forest and climate specific policies. Increasingly these policies recognize the ability of forests to reduce GHG emissions but also provide a suite of climate adaptation, economic, and social justice benefits (Bennet et al, 2019, Erbaugh et al, 2020). However, to enact these policies requires interdisciplinary and cross sector coordination between state regulators and public land managers, private industry, smallholder landowners, and local municipalities. Significant challenges remain in translating science into measurable evidence-based targets and policy decisions (Ananda and Herath, 2009). Despite these challenges, state and local forestry stakeholders are positioned in a way to further implement climate action through incentivizing action (Guerry et al., 2015, Kumar et al, 2020). Although action cannot wait, there is still a strong need for continual refinement of frameworks and methodologies to responsibly downscale carbon management approaches while addressing barriers to implementation (Seddon et al, 2020b).

While the study of the global carbon cycle is not new, optimum mitigation and adaptation actions are only as good as the tools and information used to support such decision-making. In response, the number of tools aimed at assessing the fate of atmospheric CO_2 has grown significantly across the past decade. The uncertainty of future forest statuses relies upon the adoption and integration of innovative data, tools, and models to inform policy and planning continually and iteratively (Novick et al, 2022a). Operationalizing forest carbon management requires cross-sector and trans-disciplinary collaborations (Kumar et al, 2020). The impetus is to act now to curb the worst effects of climate change. There is increasing importance of forest management and policy in tackling climate change from a forest carbon perspective, focusing on the implementation and promotion of robust and interdisciplinary understandings of forests.

1.1.2 Systems-based forest carbon budget

Forest carbon budgets primarily consist of the storage and flows of carbon through a forest ecosystem driven by photosynthesis, biomass turnover, and decay processes. The rate of carbon uptake is determined by many factors including solar radiation, air temperature, atmospheric chemistry, the availability of water and nutrients, and various ecological processes influenced by disturbance, succession, and competition (Odum, 1969, Chapin et al, 2011, Stephenson et al, 2014, Curtis and Gough, 2018). The Intergovernmental Panel on Climate Change (IPCC) outlines five major pools of carbon: aboveground biomass, belowground biomass, aboveground dead organic matter (DOM), belowground DOM, and soil C. Carbon moves through the system through a variety of ecosystem processes including forest productivity, senescence, mortality, biomass turnover, and decay (Turner et al, 1995, Canham et al, 2024). Other anthropogenic actions such as deforestation or tree plantings are also major drivers to current forest C sink or source strength (Houghton 1995, Guo and Gifford, 2002, Thom et al, 2018).

System-based approaches provide more holistic ways to evaluate and account for the monitoring and measuring the forest carbon budget (Nabuurs et al, 2007, Evans et al, 2012). There is a growing consensus that the role of carbon leaving the ecosystem via harvest and the storage of that carbon in long-lived wood products is essential to further understand potential contributions of forests for both mitigation and adaptation activities (Malmsheimer et al, 2008, Verkerk et al, 2020). Utilizing a system-based approach enables the assessment of interdependent systems and potential feedbacks between forest ecosystems and forest products, concurrently (Evans et al, 2012). Providing deeper insights into the trade-offs of specific forest management practices and linkages to other sectors (e.g., energy and construction) that are influential to regional and global carbon dynamics.

1.1.3 Forests as nature-based climate solutions

Nature-based climate solutions (NbCS) are concerted actions to manage ecosystems to increase C sequestration or reduce GHG emissions (Griscom et al, 2017, Seddon et al, 2020a) including the moving of systems beyond their original structure, function, or composition (Buma et al, 2024). NbCS encompass a wide range of activities across different types of ecosystems and agricultural systems grounded in sound scientific principles including conservation, restoration, and improved land management such that healthy and resilient natural and working lands provide a myriad of societal benefits (Watson et al, 2018, Ontl et al, 2020, Buma et al, 2024). However, critical misunderstandings about what constitute NbCS, broader nature-based solutions (NbS, Nesshover et al, 2017), and the related natural climate solutions (NCS) – a nearly identical term to NbCS but narrower in focus – have garnered considerable controversy and confusion (Ellis et al, 2024). While all these concepts are built upon a long history of sound ecosystem principles from different disciplines, there has been a significant focus specifically on mitigation activities (Nolan et al, 2021) and at times, can be exclusionary of other forest co-benefits (Cohen-Shacham et al, 2016).

Recent criticisms of potential pitfalls of forest specific NbCS such as greenwashing (Nygaard, 2023) or over crediting of carbon offsets (Badgley et al, 2021), has led to a call-to-action to improve the climate outcomes through using the best available science (Anderson-Teixeria and Belair, 2021) and improved methodologies (Novick et al, 2022a). A recent study, Ellis et al, (2024), outlines five foundational principles for the narrower term, natural climate solutions, including nature-based, sustainable, climate-additional, measurable, and equitable. However, recent observed shifts in forested ecosystems and new novel growing conditions (McDowell et al, 2022, Yoshikawa et al, 2023, Liu et al, 2024, Trew et al, 2024), increases the need to further improve methods to not only measure and monitor current trends (Novick et al, 2022b), but also forecast future potential states (De Frenne et al, 2021).

Going-forward, there is a strong need to test emerging trends in forest dynamics (McDowell et al, 2020) as well as improve the ability to simulate forward looking forest dynamics. Rapidly changing ecosystems have strong implications for future forest function and resilience (Hobbs et al, 2009) where in part, proper management and stewardship may assist in guiding forest ecosystems away from catastrophic collapse (Sato and Lindenmayer, 2017). The sustainable management of working forestlands will only increase in importance as widespread mismatches are observed between vegetative communities and climate (Song et al, 2021, Hill et al, 2023). Ultimately, revisions to how humans view conservation and restoration way from more traditional approaches or historical forest assemblages may be required (Hobbs et al, 2009, Backstrom et al, 2018, Messier et al, 2019) exacerbating the urgency of enacting climate action now (van Kooten et al, 2021).

1.2 Overview of forest carbon models

Models, simplified representations of reality that focus on key factors and relationships of a phenomenon, are useful tools that provide a structured way to investigate and quantify forest carbon dynamics including the influence of various biophysical, socioeconomic, and/or geographic factors that drive historical and future changes in carbon stocks (Lambin et al, 2001, Rindfuss et al, 2008, Anderson-Teixeira et al, 2021). However, models have also been developed specifically to inform decision-making across scales from individual smallholder landowners to industrial actors to local or national governments. Increasingly there is a growing need to not only monitor, report, and verify historical changes to carbon stocks in forests but quantify future potential contributions of forest NbCS to mitigate climate change (Prasad et al, 2024). This need is exacerbated by critical mismatch between the most common scales at which forest carbon data is collected and the ecosystem to landscape scale at which many relevant planning and policy decisions are made (Novick et al, 2022a).

Forest carbon models, which are a subset of broader ecosystem models, are models that describe the interactions between at least two components of forest carbon cycle but oftentimes incorporate other factors that influence forest carbon (Daigneault et al, 2022). The variety of types of models and the temporal and spatial scales at which they capture forest carbon dynamics can be overwhelming. However, the increasing number of models should be considered a strength such that the novel nature in which a particular model might inform forest policy and planning is an imperative to increase the predictive power across broad areas helping to reduce challenges with the scale at which data is collected and analyzed (Bugmann and Seidl, 2022). Models can be categorized in a variety of ways such as methodological approaches to estimate or project carbon stock and stock changes. Briefly outlined below, are some major differences between empirical, process-based, and hybrid models which all can be used to varying degrees to understand the current status of or future impacts to forest carbon dynamics from a specific management or policy actions.

Process-based ecosystem models, designed to represent underlying biogeochemical processes, lend certain strengths to modeling the forest C cycle such as preventing unrealistic outcomes through model and variable constraint or explicit coupling of various ecosystem processes but remain sensitive to bias inherent to model structure (Renard et al., 2010). Further, these models are built on explicitly stated assumptions about how a system works providing transparency grounded in ecological theory making for easier interpretation of results (Cuddington et al, 2013). Process-based models generally use “top-down” approaches (atmosphere-based) to estimate forest carbon budgets. These models oftentimes are built on eddy-covariance flux observations (Medlyn et al, 2005) and atmospheric inversion models (Bousquet et al, 1999). These approaches rely on direct measurements of spatial and temporal patterns of CO_2 and estimate productivity through modeling physiological processes such as photosynthesis and autotrophic respiration (Jung et al, 2009, Xiao et al, 2012).

Process-based models often lack direct methods and estimates of model uncertainty, sensitivity, and validation whereas empirical models inherently provide error and uncertainty metrics (Adams et al., 2013; Bonan and Doney, 2018). Generally, forest C models that include process-based elements generate uncertainty and biases from i) data uncertainty from methodologies, field measurement errors, or instrument imprecisions; ii) sensitivity to initial conditions; iii) lack of understanding of underlying processes leading to poor representation in model structure; iv) inaccurate assumptions about parameter estimates and distributions; v) unknown or poorly constrained drivers; and vi) amplitude of natural variation associated with biological systems (Larocque et al., 2008). However, the lack of defined methodologies to account for uncertainty creates challenges that should be considered (Geary et al., 2020).

Empirical models derive results from extrapolating correlative relationships between observed variables. Forest inventorying models and carbon budget models, two examples of empirical forest C models, can directly scale-up carbon estimates by utilizing spatio-temporal interpolation (Kurz et al., 2013; McGlynn et al., 2022). These direct measurements frequently serve as the basis for evaluating or parameterizing process-based models and assessing trends in ecosystem production. One advantage of biometric measurements of ecosystem C pools is the availability and distribution of forest inventory plots and data (Tinkham et al., 2018). However, challenges remain with remeasurement periods, forecasting predictions, and addressing uncertainties and model validity (McGlynn et al., 2022).

Hybrid methods that combine process-based elements and empirical elements such as "gain-loss" approaches use field-based measurements to estimate inventories, forest productivity, and disturbance data and process-based elements to simulate dynamics into the future (Kurz et al., 2009). These approaches estimate forest carbon stocks and fluxes by tracking total ecosystem carbon (or "carbon budget") and explicitly tracking the fluxes or transfers of carbon between pools over time using process-based equations for biomass turnover and decay. These types of approaches use age related metrics of forest growth, volume-to-biomass expansion factors to convert stem wood in carbon pools, and process-based elements to simulate biomass turnover, decay, and heterotrophic respiration.

1.2.1 Examples of Forest Carbon Accounting Models

Daigneault et al, (2022) provides a qualitative analysis and summary of relevant forest carbon models and frameworks. Additionally, the report creates a framework for model selection criteria to aid in assessing the accessibility, usability, spatial and temporal extents and utility of scenario predictions to inform future planning and action. The remainder of this section will briefly highlight the diversity, application, and limitation of some key models that been employed in the eastern US including the Forest Vegetation Simulator (FVS), LANDIS-II, the Carbon Budget Model of the Canadian Forest Sector (CBM-CFS3), and the ecosystem demography model (ED v3.0) to understand past and present forest carbon dynamics.

FVS (Anderson et al, 2020) is a widely used tool developed and maintained by the USDA Forest Service that simulates forest stand-level models to assess how forest vegetation changes from management, disturbances, or succession. The model uses annual timesteps and forest inventory data from the USDA Forest Service Forest Inventory and Analysis Database (FIADB) to model growth and yield at the individual tree to stand-level. A sub-carbon extension was created to explicitly track the effects of user-defined dynamics on forest carbon and explore how current or alternative management actions could affect carbon by projecting tree-level growth and mortality of the provided inventory including site-level attributes. The model includes all 5 IPCC carbon pools plus harvested wood products and generally, provides moderate high utility (Daigneault et al, 2022) in exploring management and policy questions related to forest carbon. However, spatio-temporal statistics are required to extrapolate results across larger spatial scales.

LANDIS-II (Scheller et al, 2007) is a forest landscape model designed to model growth, disturbance, and succession at larger landscapes. Entirely open-source, the model has numerous extensions used to examine processes such as seed dispersal, carbon dynamics, forest management, and climate change effects. The model is quite flexible with regards to both temporal and spatial resolutions. The biomass extension can model aboveground mortality, net primary productivity, and the decay of dead organic matter using static variables designated by species and ecoregion. Currently, the biomass extension only simulates aboveground dynamics and HWP. LANDIS-II has high utility for assessing the impacts of forest management and policy on forest carbon dynamics (Daigneault et al, 2022).

The CBM-CFS3 (Kurz et al, 2013) is an empirically derived, processed-based model that simulates stand and landscape-level C dynamics of above- and belowground biomass, litter, deadwood, and mineral soils. The model uses a detailed forest inventory and empirical growth-yield relationships to simulate productivity with process-based equations to simulate biomass turnover and decay processes. The CBM-CFS3 serves as a core component of the Canadian national forest carbon monitoring accounting, and reporting system developed within a spatially referenced tier 3 approach based on the IPCC gain-loss methods. The model incorporates user defined activity data to capture human activities and natural disturbances on annual timesteps. The model has had broad applicability within North America and elsewhere globally with high utility (Daigneault et al, 2022) for assessing the impacts of management and policy on forest carbon with a separate associated framework that is used to track the fate of biomass transferred through harvest and land-use change (LUC) to the forest products sector.

ED v3.0 (Ma et al, 2022) is a cohort-level, dynamic vegetation model designed to run as a stand-alone land surface model that couples with RAMS, the Regional Atmospheric Modeling System, providing strengths to modeling future climate states and biophysical feedbacks between the atmosphere and biosphere. ED v3.0 provides a temporal resolution on hour timescales and a spatial resolution of 90m pixels where the land surface is separated into spatially-contiguous tiles of polygons designed to match the regional atmospheric grid cells of RAMS. ED differs from other terrestrial models by scaling up physiological processes through individual-based vegetation dynamics where cohorts of plants compete mechanistically under varying conditions for light, water, and nutrients. The model simultaneously applies natural disturbances, land use, and regeneration of lands from disturbance only for aboveground biomass. The utility of ED for assessing forest management and policies is moderate as the model does not track all carbon pools, timber harvest, or HWP.

1.2.2 Decision-support applications and limitations of models

Decision-support applications of models for policy and management are not new (Bagstad et al, 2013, Geary et al, 2020). However, the tools developed for quantifying or evaluating forest benefits or trade-offs of forest carbon are oftentimes neither comprehensive nor systematic (Noble and Paveglio, 2020, Wong-Parodi et al, 2020) necessitating increased integration of these tools into holistic frameworks that better assist decision-making that accounts for differences among stakeholders and multi-dimensional aspects of management (Xu and Peng, 2022). Enhancing the practical applications of tools to assist in a decision-making process provides additional strengths to managing ecosystems under a changing climate (Watkiss et al, 2015, Zulian et al, 2018). Further, understanding the limitations and biases of models and their results provides added strength within applications (Fischer et al, 2016, Bonan and Doney, 2018).

Ideally accounting for interactions, feedbacks, and other complex aspects of ecosystems is fundamental to develop appropriate management measures (Evans et al, 2017). When managing in the face of uncertain climate futures, forecast models or making predictions should be a key goal of a modeling exercise providing additional insights during future decision-making processes (Bode et al, 2017). Evaluating alternative management approaches or understanding the effect of specific policy-levers on ecosystem components is useful in identifying potential pathways forward to meet desired goals (Baker et al, 2016). The impetus is for scientists, forest managers, and policymakers to make the most informed decisions now despite the challenges and social and ecological constraints highlighting the importance of the fundamental uncertainty of managing complex forest systems (Milner-Gulland and Shea, 2017).

1.3 Overview of chapters

The goal of this dissertation is to first address barriers and gaps to implementation of forest planning and management for climate change. Second, to develop a process to collaboratively engage with forest resource managers and decision-makers to identify priorities and quantify C impacts of those decisions through modeling alternate forest management and wood-use pathways in support of net-zero GHG emission targets. Third, advance methodologies to quantify model uncertainties and sensitivities to further the potential of forest carbon models and forecasting to inform policy and planning. This dissertation relies on mixed-methods research, forest inventory data, remotely-sensed metrics of land-use change and forest disturbance, and hybrid process-based models to potentially inform future forest management and planning. Finally, this dissertation summarizes both policy and management implications of the findings.

In Chapter 2 (Science-based communication and education needed to improve forest carbon science, policy, and management outcomes), this dissertation addresses science-practice gaps in forest carbon science, policy, and management by first, assessing gaps and barriers to further integrating forest carbon models and science into policy and planning and second, developing a framework to bridge the divide. This analysis developed a mixed-method study focusing on state forest agencies in the eastern US to assess "where do gaps persist?" and "what opportunities exist to improve forest carbon outcomes?" Utilizing survey and semi-structured interview devices, the results identified barriers to integrating forest carbon science more explicitly into policy and management. Drawing from both the focus groups and survey results, I developed a framework with three key areas to improve forest carbon outcomes. Together, this research can enhance decision-making through both the identification of barriers and by providing a roadmap to emphasize forest climate action.

In Chapter 3 (Modeling climate-smart forest management and wood use for climate mitigation potential in Maryland and Pennsylvania), I helped lead a multi-institutional participatory research project where I worked directly with state regulators in the mid-Atlantic region of the US to: 1) identify priorities and issues for forest management; 2) develop a business-as-usual (BAU) simulation to forecast forest carbon and harvest wood product dynamics using the CBM-CFS3 modeling framework parameterized with USDA Forest Service FIADB and other remotely-sensed metrics of land-use change and forest disturbance; 3) identify and model a suite of climate-smart forest management practices and wood utilization scenarios to quantify contributions to net-zero GHG targets; and 4) develop outreach materials for managers and policymakers. This analysis can help future decision-making by providing robust quantification of potential alternative management and wood utilizations strategies in support of regional GHG targets.

In Chapter 4 (characterizing the sensitivity of carbon stocks and fluxes to disturbance variation in Maryland's forests using the CBM-CFS3 modeling framework), I sought to develop and test methodologies to assess confidence intervals and sensitivities of the modeled results from chapter 3. This chapter applies a Monte Carlo simulation approach to estimate confidence intervals and assess the contribution of disturbance to key model results by introducing variation in the disturbance input data. Further, I use a random forest model to assess the sensitivity of the results to the individual contribution of carbon fluxes and disturbance. Lastly, I validate the model results by comparing them to other published estimates of forest carbon fluxes. By doing so, I further understanding of how forest carbon models can inform policy and planning and assessing trade-offs between methodological approaches.

Chapter 5 (Outcomes and implications for forest policy and planning) summarizes the overarching findings of this dissertation. I explore my results as well as lessons learned throughout the participatory approach to modeling forest carbon dynamics in light of management and policy implications for climate change mitigation and adaptation. I will address challenges and future directions of research to continue to inform both forest management and policy directly related to forest carbon.

CHAPTER 2

SCIENCE-BASED COMMUNICATION AND EDUCATION NEEDED TO IMPROVE FOREST CARBON SCIENCE, POLICY, AND MANAGEMENT OUTCOMES

2.1 Abstract

Climate change is one of the most pressing issues facing humanity and forests are increasingly seen as a key pathway to mitigating and adapting to the climate crisis. Because forests stand to play a significant role in reaching net-zero emission targets, politicians and policymakers must act decisively to engineer a rapid paradigm shift that maintains forests' resilience and adaptive capacity. While there has been significant investment and advancement in forest carbon science to inform policy and planning, there remains a persistent science-practice gap to further integrate scientific information into forest carbon policy and management. Here, we use a survey, semi-structured interviews, and a review of relevant policy literature to assess the nature and extent of, as well as possibilities to bridge, the science-practice gap with regards to forest carbon science, management, and policy. Our results identified barriers to the science-practice gap and provide potential pathways to bridge the divide. We identified three key areas to improve forest carbon outcomes 1) improved data, tools, and models to assess trends and statuses of forests; 2) enhanced carbon science training among state forest practitioners and decision-makers; and 3) effective science-based communication for decision-makers and general audiences. Engagement with forestry stakeholders and iterative and participatory approaches, including targeted education and communication of complex scientific topics, can inform both policy and on-the-ground management. Overcoming such barriers to communication highlights important linkages between forest managers, policymakers, and scientists to address challenges of reaching a net-zero emission.

2.2 Introduction

Global climate change poses an existential threat to ecosystems and society at large. Forests play a pivotal role in climate change through regulating the Earth's carbon, hydrologic, and energy cycles (Bonan, 2008) while providing provisioning services such as fiber and food (Diaz et al, 2018). Forests are seen as a key pathway to combatting the climate crisis due to their potential for carbon sequestration, storage, and substitution benefits from wood products and bioenergy (Skog, 2008, Smith et al, 2014, Myllyviita et al, 2021, Petersson et al, 2022) and their roles regulating the hydrological cycle including substantial climate cooling benefit (Bonan, 2008).

The impetus is for practitioners, scientists, and policymakers to act now to curb the worst effects of climate warming (Cox et al, 2000, Sitch et al, 2008, IPCC, 2014, Allen et al, 2015). Forests are not a panacea for climate change mitigation, with the maximum carbon contributions limited by tree size and age, forested area, and other aspects of forest dynamics (Clark et al, 2014, Griscom et al, 2017, Anderson-Teixeira et al, 2019) and may contribute to global GHG emissions through maladaptation (Jandl et al, 2015, Gougherty et al, 2021). However, forests still provide crucial, low-cost mitigation and adaptation opportunities to meet net-zero emissions targets (Swanston et al, 2016, Fargione et al, 2018). Forests provide additional co-benefits including improved air and water quality, rural livelihood derivation, and poverty alleviation (Locatelli et al, 2008, Diaz et al, 2018, Ontl et al, 2018, Petersson et al, 2022). But to sustain the critical co-benefits of forests, the ongoing biodiversity crises must be addressed concurrently (Portner et al, 2023).

Long-term and short-term forest management objectives increasingly consider trade-offs between interdependent goals and co-benefits of carbon-specific management and other traditional management goals, including timber production (Wollenberg et al, 2001, Carpenter et al, Hellegers et al, 2008, Hirsch et al, 2010). Understanding the priorities and perceptions of forest stakeholders is necessary to fully assess trade-offs and opportunities between management, policies, and other goals (Lawler et al, 2008, Williams and Isaac, 2013) to ultimately balance mitigation and adaptation goals through more integrated management approaches (Littell et al, 2012). **Figure 1** provides a complementary perspective of interactions between scientists, practitioners, and policymakers that engage in forest carbon science, policy, and management. However, significant gaps and barriers exist to further integrate forest carbon science into planning and policy (von Winterfeldt, 2013, Clifford et al, 2020). Identifying where gaps arise and addressing them allows for targeted efforts to increase the capacity of managers and policymakers to properly assess, evaluate, and communicate climate management and policy implications to all stakeholders resulting in more effective outcomes addressing complex climate issues (Janowiak et al, 2014). This emphasizes the need to downscale policy and management decision making from the state or sub-regional level to address localized or site-specific climate change threats and vulnerabilities to forests (Halofsky et al, 2018).

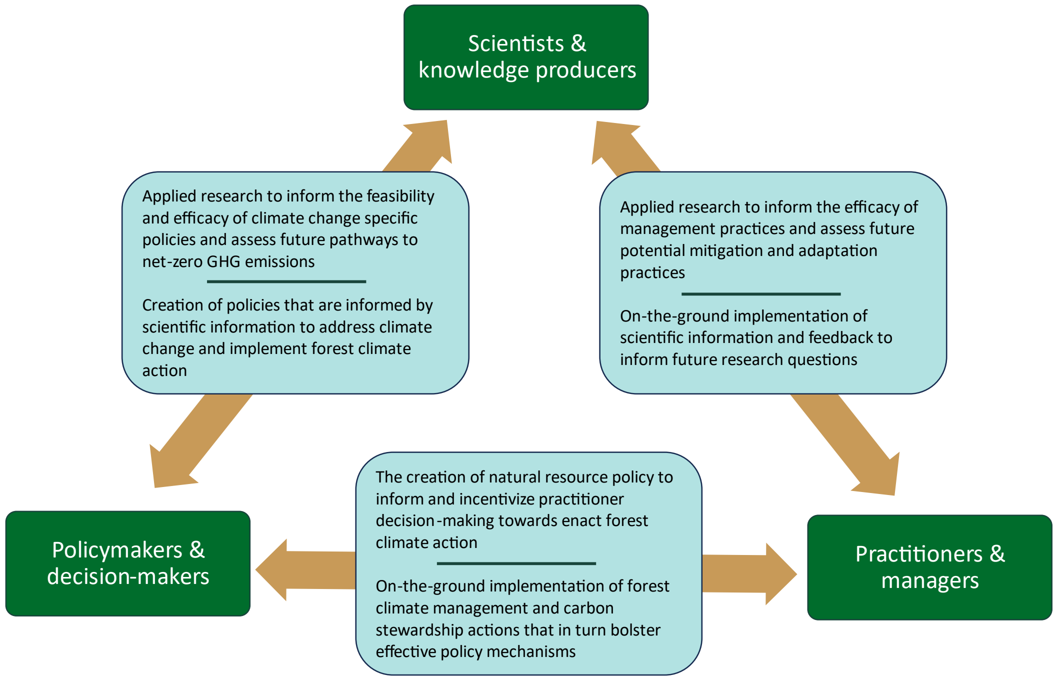


Figure 1. Complementary perspective on the interactions between scientists – practitioners – policymakers to address the climate crisis through forest carbon science, management, and policy

This persistent gap between science production, forest management activities, and policy creation is well documented (Kirchhoff et al, 2013), oftentimes referred to as a "climate information usability gap" (Lemos et al, 2012), "knowledge-practice gap" (von Winterfeldt, 2013), "knowledge-action boundary" (Cook et al, 2013), or "science-practice gap" (Cooper and Macfarlane, 2023). Previous studies show a variety of barriers to implement adaptation and mitigation actions in forest management and planning, including knowledge deficits (Nelson et al, 2016, Dietze et al, 2018), landowner and manager perceptions (Sousa-Silva et al, 2018), lack of mandates or coordination between policy and adaptation and mitigation management activities (Keenan, 2015), limited resources for adaptation and mitigation activities (Williams and Nelson, 2017), institutional barriers (Bierbaum et al, 2013), uncertainty within policy mechanisms (Olander et al, 2018), and inadequate information on specific tactics or approaches to address vulnerabilities (Williamson et al, 2012). Importantly, climate change impacts on forests are oftentimes site-specific or local in nature requiring more place-based or localized information to inform subsequent science-practices gaps and leverage local expertise to better contextualize the often fuzzy science-practice boundaries that vary across disciplines, institutions, and decision-makers (Bertuol-Garcia et al, 2018).

This paper seeks to do two things: first, measure the scope and scale of the science-practice gap informed by sub-regional and localized considerations, and second, propose potential paths forward to inform mitigation efforts through improved science communication and education. We utilized interviews, survey results, a review of relevant policy documents, and our own experiences conducting forest carbon outreach efforts to identify barriers and gaps with state agency managers and regulators within the eastern United States to more clearly understand how forest carbon science can influence on-the-ground planning and management action as well as inform policy creation and enaction at the state-level.

2.2.1 The challenge of merging science with policy and practice

The dominant role that forests have in determining the fate of atmospheric CO_2 has been well studied, resulting in the development of diverse methodologies for monitoring and quantifying ecosystem dynamics (Novick et al, 2022a) as well as forecasting carbon dynamics (Clark et al, 2001; Luo et al, 2011). Approaches should assess the efficacy of management and policy as well as inform future forest planning and the influence of socioeconomic systems on forest carbon dynamics (Dietze et al, 2018; Garcia-Gonzalo and Borges, 2019). The most common method to assess forest carbon—forest inventorying—can directly scale-up carbon estimates with spatial and temporal interpolation (Kurz et al, 2013, Shaw et al, 2014). While this serves as a basis for most fundamental forest carbon research, inventory methods may not capture sufficient historical and ecological information to address fundamental questions such as "how are ecosystems going to change?" and "how does society affect those trajectories?" (Dietze et al, 2018).

Forest policy and management decisions focused on climate goals require both accurate knowledge of current carbon stocks and future changes in these stocks; nevertheless, state-of-the-art carbon modeling tools addressing these needs have yet to be widely adopted in the US (Lamb et al, 2021, Weiner et al, 2021) instead, oftentimes relying on decades-old empirical models (Novick et al, 2024). Additional complexities arise in decision-making around the proper selection of methodologies to inform the desired question or outcomes (Daigneault et al, 2022). For example, choosing between which spatial scale at which to forecast carbon dynamics such as the stand-level, landscape-scale, or earth system. Despite recent emphasis at the federal level to improve carbon data and tools (GHG IWG, 2023, Westfall et al, 2024), substantial deviations remain between the scientific literature and on-the-ground practice implementation (Haya et al, 2023). This problem is compounded with additional methodological trade-offs between accessibility (i.e., financial accessibility and the ease at which data can be obtained) and the robustness in which complex ecosystem dynamics (i.e., temporal resolution, spatial scales, and biophysical processes modeled) are captured (Novick et al, 2022a).

Natural resource policies strongly influence the role forests play in mitigating climate change (Howells et al, 2013) through incentivizing better forest management and disincentivizing practices that may harm future forest resiliency (Nabuurs et al, 2017). Ideally, scientific data and tools, such as quantitative ecological forecasting (Luo et al, 2011), would inform management activities and policies to optimize decision-making (Keenan et al, 2019). In turn, management and policies would imbue future research trends (Lemos et al, 2012).

However, significant communication gaps remain between scientific information, creation of climate policy mechanisms, and implementation of climate-focused management activities with considerations for the localized effects and vulnerabilities of climate change (von Winterfeldt, 2013, Bertuol-Garcia et al, 2018, Novick et al, 2022a, Cooper and Macfarlane, 2023). Identifying where and how to address communication and educational gaps arise within the scientist-practitioner-policymaker paradigm (**Figure 1**) remains of key importance with a specific focus on how managers can address regional- to local- challenges.

Despite these barriers, states and local governments have increasingly been promoting legislation, executive orders, or regulatory changes to proactively address climate change and reduce GHG emissions through forest climate action (Canadell and Raupach, 2008, Grassi et al, 2017). Subnational and localized actors, such as state agency natural resource managers and state or local policymakers, are uniquely suited to bridge any knowledge-practice gaps and do so in potentially a more impactful way than national level policies and mechanisms (Lemos and Morehouse 2005) through their strong influence on publicly managed forests, relationships with landowners, and direct interactions with scientists or other knowledge producers (Wellstead et al, 2003, Lowrey et al, 2009, Halofsky et al, 2018).

2.2.2 Improving forest carbon science, management, and policy outcomes

Science-policy models that serve to utilize science for society through policy are not new (Kirchoff et al, 2013, Wall et al, 2017). However, forest carbon policies provide emerging opportunities where low-cost climate mitigation can be achieved (Griscom et al, 2017) through active dialogues and the exchange of information with policymakers (Djenontin and Meadow, 2018). Both legislative and executive branches can inform future planning through laws and executive actions, establishing carbon task forces, or other value setting documents along with allocation of funds to assess current state-wide statuses and trends in forest carbon. In forest management, these challenges involve applying scientific principles in ecology (e.g., species interactions, growth, mortality) and climate (e.g., forest-climate interactions and feedbacks) to forestry practices (Cooper and Macfarlane, 2023). This dynamic is also crucial in policy spaces, where understanding actors' perceptions, adoption feasibility, and outcome assessments is necessary (Keenan et al, 2019, Jewell and Cherp, 2023).

How science influences management and policies is inherently political and has high stakes: in the case that important science is ignored or incorporated in an incomplete or incorrect manner, consequences can include climate maladaptation, which refers to cases when management fails to identify or address vulnerabilities to climate change (Pannell and Gibson, 2015, Sun and Yang, 2016, Hill et al, 2023). As the science of climate adaptation and mitigation continuously advances to address new climate and environmental conditions, education and communication must continue apace and serve as a conduit for the cross-communication between scientists and managers that produces management actionable science; ultimately this is critical for effective adaptation and mitigation (Meadow et al, 2015, Howarth and Robinson, 2024). **Figure 2** provides a logical diagram for how effective change to produce robust climate solutions by advancing knowledge production, management, and policy together.

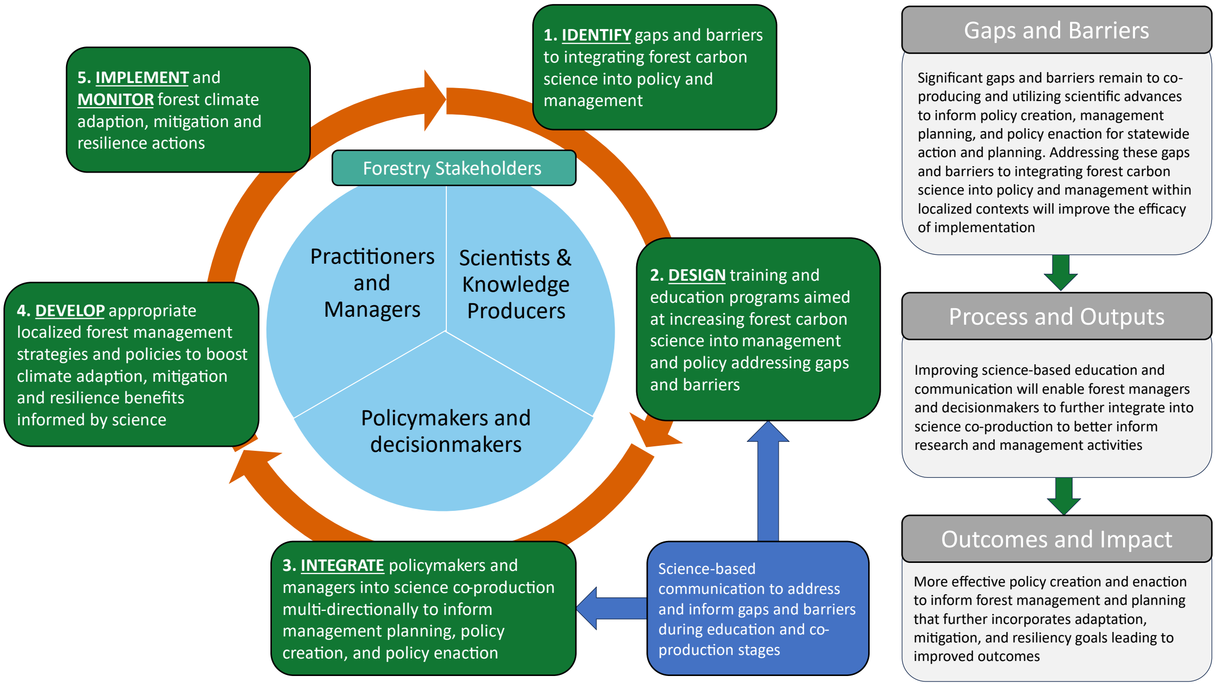


Figure 2. Logical framework diagram outlining a five-step process to inform forest carbon outcomes by identifying gaps and barriers and then address those gaps through education and science-based communication

Science-based communication and education training ideally empowers scientists and resource professionals to improve understanding and ability to make informed decisions (Buine de Bruin and Bostrom, 2013) and engage in bidirectional dialogues (Roux et al, 2006). The increased engagement of researchers with scientific education in the management and policy communities, enhances the communications management and policy needs, allowing for studies to be designed and conducted addressing these needs through knowledge co-production (Littell *e* et al, 2012). While forestry professionals may be comfortable advising landowners in more traditional topics such as managing for timber, their expertise is limited when landowners seek advice on managing their land for carbon climate benefits or participation in carbon payment programs (Brand et al, 2020). Communication alone is not enough to craft policy; here, it is critical that scientists and managers work together with policymakers to develop specific policies (Bremer and Meisch, 2017, Bertuol-Garcia et al, 2018). Furthermore, policy must be amended to reflect recent science, particularly in light of rapidly occurring climate changes (Cooper and MacFarlane, 2023, Frohlich et al, 2018, Abram et al, 2021).

Therefore, the goal of effective science-based communication should focus on enabling capacity building through the development of appropriate skills, allowing practitioners to work effectively across sectors and disciplines to combat climate change through improved management and policy outcomes (Cvitanovic et al, 2015). Addressing formative changes in policy requires knowledge transfer from researchers and practitioners including landowners. Research informed by management further enhances capacity to respond to climate change through providing practical knowledge (Fazey et al, 2016). While significant challenges remain in the design and implementation of co-produced science, improving the efficacy of relevant parties to transfer information through improved communication helps guide decision-makers (Djenontin and Meadow, 2018).

2.3 Methods

2.3.1 Assessing barriers to utilizing forest carbon science and models for planning and management in the Eastern US

To highlight current gaps and opportunities to address forest carbon science-practice gaps, we conducted an analysis of state-level experiences, barriers, and motivations regarding the use of forest carbon science, data, and tools to inform policy and management within the eastern region of the USDA Forest Service (USFS). The eastern region is comprised of 20 US states with varying forest priorities, forest product industries, and policy initiatives providing a wealth of differential experiences with how scientists, practitioners, and policymakers interact within forest carbon science, policy, and management. Currently, forests in the eastern region largely drive forest carbon sinks nationally (Hogan et al, 2024), provide substantial economic contributions (White et al, 2010), and are comprised of a mosaic of natural and working across private (both family forest and industrial), state, tribal, and federal ownerships (Markowski-Lindsay et al, 2024). Furthermore, eastern forests represent a diversity of forest communities and subsequent differences in how climate change will affect system drivers, stressors, and adaptive capacity (Brandt et al, 2017). This study built off previous experience developing different types of education and capacity building materials for forest carbon science, management, and policy (FCCP, 2024a, 2024b) as well as conducting pathway analyses to assess carbon trade-offs with forest management and wood utilization strategies in the mid-Atlantic region of the US and elsewhere (Dugan et al, 2018, Papa et al, 2023).

2.3.2 Data collection and analysis

We developed a survey (n = 21, response rate 13%) and semi-structured interview (n = 30) instruments, to target state-level forest agency employees as well as experts from government, academia, and non-governmental organizations (NGO) within the eastern region. The survey design was not random such that participants were specifically selected for their expertise in their state's forest planning, inventorying, and modeling efforts. The total number of professionals working in forests carbon management and planning at state agencies is not large despite recent growth. Interviewees were also selected for their expertise in forest carbon science, management, and policy. Both the surveys and interview protocols were developed in direct coordination with USDA forest service researchers along with subsequent detailed review of key publicly available climate-focused policy documents and previous expert inputs. The instruments aimed to explore current activities and assess technical capacity at the "team" or "division" level to understand how forest carbon data and tools are used in policy and management planning along with assessing motivations for forest climate action. We sought to identify how state agencies were currently utilizing forest carbon data and tools to address climate adaptation and mitigation practices, state climate goals, and internal policies related to forest carbon and climate change. Additionally, we sought to identify current initiatives and characterize motivations to inform why communication gaps persist. Lastly, we quantified interest towards implementing specific policies in forest carbon management to further highlight the complexities driving science-practice, education, and communication gaps. We used descriptive statistics to summarize the results from the surveys and a deductive approach to assess themes and trends within the interviews. Survey and interview protocols along with longer descriptions of respondents can be found in **Appendix A** and **Appendix B**.

2.4 Results

2.4.1 Knowledge gaps and barriers

We found that gaps in five key areas of expertise created barriers to integrating forest carbon science into policy and management. Those five areas are: 1) forest carbon science: inventorying and carbon estimation, 2) forest management behavior, 3) harvested wood products (HWPs), wood utilization, and carbon storage, 4) forecasting: forest carbon simulations and future pathway assessments, and 5) communication of results to inform public and private decision-making. We broadly found alignment and agreement across the interviews and surveys without a lot of dispersion across professionals and their roles in being able to identify key topics and gaps. Despite differences across the state contexts such as differences in public lands and statewide policies on forests and climate, respondents articulating the same higher-level gaps and barriers. However, the ways gaps and barriers were characterized were largely informed by localized considerations for climate change threats and vulnerabilities.

We found that most respondents reported high levels of team familiarity with traditional forest inventory measurements (**Figure 3**, 79% reported expert team knowledge)**.** However, knowledge diverged when considering carbon estimation and integrating remote sensing or other ancillary data into assessments (**Figure 3**, 74% reported limited or moderate team knowledge). We found a lack of information on current forest management practices, especially on municipal, federal, and tribal forestlands (**Figure 3**). Notable barriers existed in understanding the role HWPs and wood utilization play in carbon storage (60% reported limited or no team knowledge in communicating these topics), especially regarding information about product end-uses, product half-lives, product retirement, biomass derived energy, substitution effects, and leakage which are all critical components of HWP carbon analyses which were strongly echoed in the interviews.

We found little technical capacity (52.5% reported limited or no team knowledge) to comprehensively analyze sector-wide GHG emission (including both forests and HWPs) despite increasing needs and interest (75% reported strong interest in learning more about forest carbon datasets and source, 45% reported strong interest in learning more about best practices, and 65% reported strong interested in learning more about life-cycle analyses). Interview responses strongly expressed that readiness and robustness of analyses increased with direct collaboration and support from academia and outside experts. We identified needs for more robust resources to assist in the identification of appropriate methodologies to account and forecast carbon (85% reported limited or no team knowledge), including the assessment of trade-offs between approaches (**Figure 3**). We generally found low knowledge, or comfort, communicating the links between forest carbon and related environment and policy dimensions (50% reported limited or no team knowledge) to all relevant stakeholders (**Figure 4**). Interviews reinforced assessing potential management options, informed by scientific expertise and data, including carbon estimation and projections, need to be considered to optimize decision-making and balance trade-offs.

Our results suggest addressing critical gaps and communications needs require the use of scientific information (**Figure 4**), to provide insights and clarify decision-support applications. Survey results point to a strong knowledge transfer need within agencies (50% reported strong interest in learning about other state's approaches, and 55% reported strong interest in learning about current policies within their own state) to support their role in effectively communicating with landowners and policymakers (**Figure 4**). Whereas interviews largely provided additional clarity on specific situations in which the gaps manifest. Two areas of particular relevance were the communication of potential climate benefits of HWPs (65% reported strong interest in learning more about these topics) and the role of prescribed fire and cuttings for adaptive management which came through during interviews.

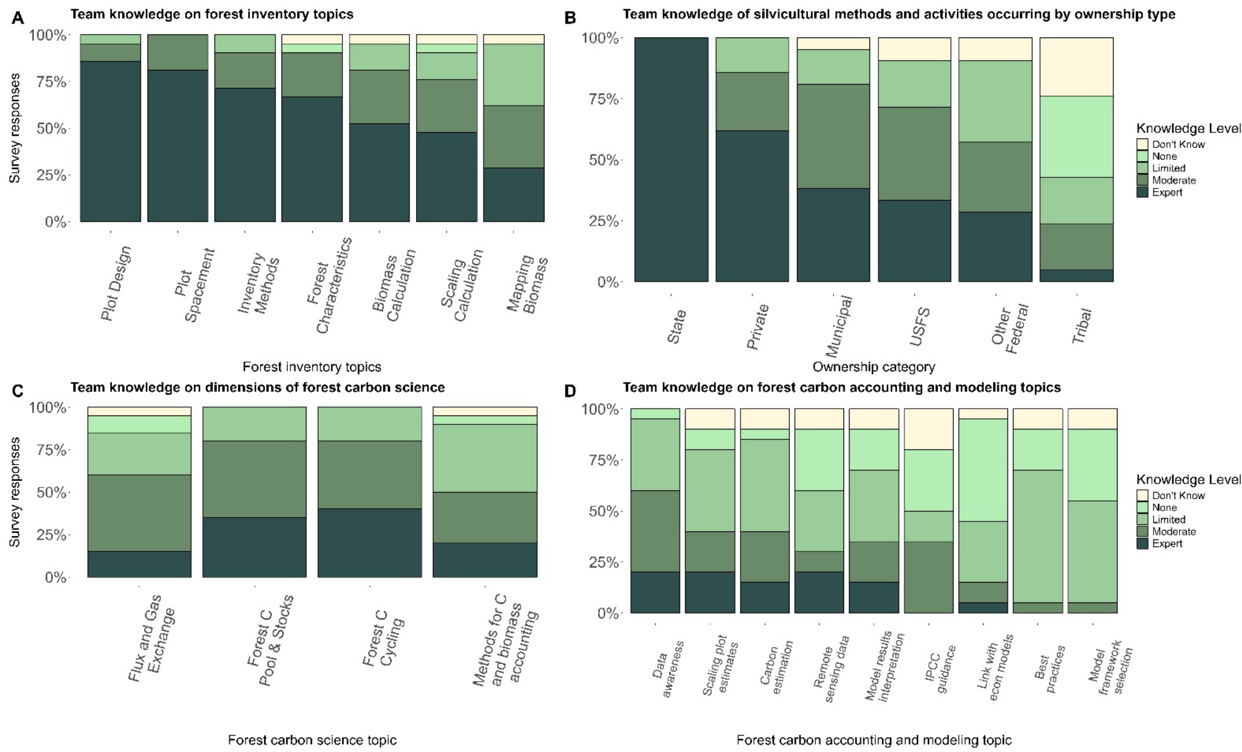


Figure 3. (**A**) Reported team knowledge on various forest inventory topics including i) forest plot designs and how to establish forest plot; ii) plot placement and spatial randomization of inventory plots; iii) determining appropriate inventory methods and sampling designs; iv) identifying forest characteristics to be measured and why; v) scaling plot and subplot level measurements to either the stand, landscape, or regional level; vi) calculating forest biomass, carbon, basal area, or volume using plot measurements; vii) mapping forest biomass, basal area, or volume estimates and uncertainty using remote sensing; (**B**) state silviculture methods and activities by diverse ownership types throughout the state; (**C**) dimension of forest carbon science including i) forest carbon cycling and dynamics; ii) forest carbon or biomass stock and pools; iii) forest carbon fluxes and gas exchange; iv) forest carbon and biomass measurements and accounting; (**D**) forest carbon accounting and modeling topics including i) knowledge about what datasets and sources exist that can be used in forest carbon accounting; ii) how to estimate forest carbon from plot-level measurements; iii) how to scale plot-level measurements to the landscape or regional level; iv) how to use remote-sensing data to map or calculate forest carbon; v) ability to process and interpret primary results and data outputs from carbon assessments; vi) IPCC guidance and best practices regarding carbon accounting and monitoring with the forest sector; vii) how to link carbon modeling with economic analysis and modeling; viii) other states' approaches to carbon accounting and modeling; ix) which forest carbon modeling frameworks would best suit state or agency goals and needs. See survey questions 5, 11, 18, and 20 in **Appendix A** for survey language and response categories

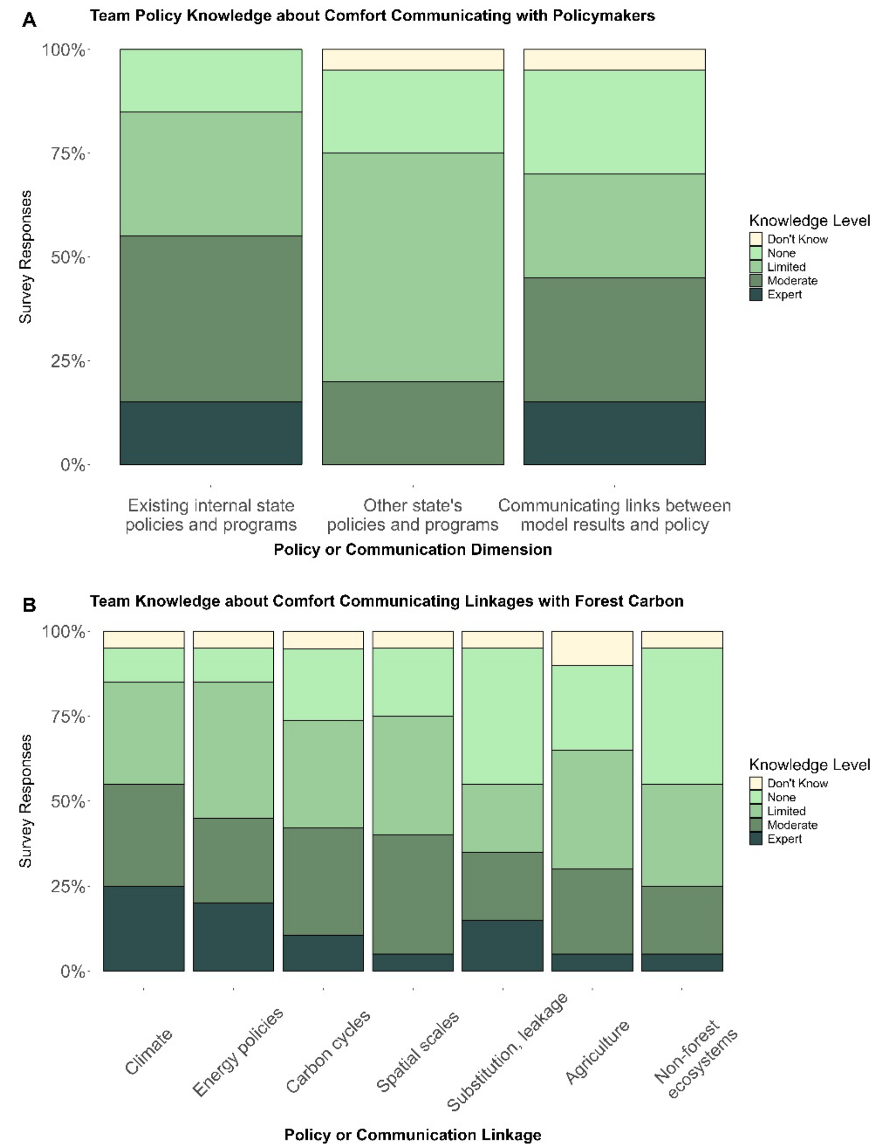
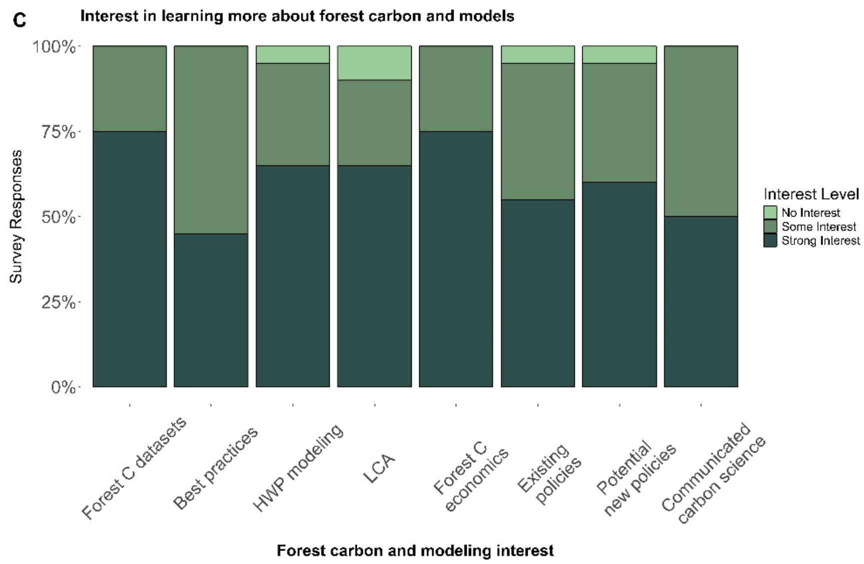


Figure 4. (**A**) Reported team awareness of policy linkages and comfort communicating forest carbon science and results with policymakers include i) existing state or sub-state policies and programs that incentivize or discourage particular forest management practices (e.g., incentivizing harvest, incentivizing delayed harvest) *within your state*; ii) communicating links between carbon assessment and modeling results and policy *for policymakers*; and iii) state-based policies, programs, and levers in use in other states or countries. (**B**) reported team comfort communication linkages between forest carbon and related environmental and policy topics including: i) forest carbon and climate; ii) forest carbon and/or energy policies; iii) links between short- and long-term carbon cycles add their importance in climate mitigation; iv) forest carbon assessments and modeling results across spatial scales including smaller spatial extents (i.e., parcel or county) to larger spatial extents (i.e., state, region, or subregion); v) harvested wood products storage, fossil fuel substitution, and carbon leakage; vi) forest carbon assessments and modeling results in relation to other working lands (agriculture) assessments and modeling results and policies); vii) links between forest carbon assessments and modeling results with

Figure 4. (cont'd)
other non-forested ecosystems. (**C**) reported interest in learning more including: i) datasets and sources that can be used in forest carbon accounting; ii) IPCC guidance and best practices regarding carbon accounting and monitoring; iii) modeling carbon in harvest wood products; iv) life-cycle assessments including substitution and leakage concepts; v) links between carbon and economic modeling; vi) Existing policies that impact forest management practices; vii) potential new policies or programs for forest management; viii) how to communicate linkages between carbon modeling results and policy. See survey questions 20 & 21 in **Appendix A** for survey language and response categories



2.4.2 Regional forest carbon initiatives, motivations, and policy interest

Understanding the priorities and motivations of why forestry stakeholders undertake specific initiatives or allocate funding can be an important step to addressing potential barriers and opportunities. **Table 1** highlights forest carbon accounting and modeling and capacity building initiatives currently undertaken in the Eastern region identified during interviews and reviews of publicly available documents. These examples provide insights into motivations and initiatives which may help us understand and circumvent barriers preventing integration of scientific knowledge and forest policy and management planning. Interviews provided additional insights that factors that vary from place to place such as the role and size of the forest products sector, voter concern, specific climate change impacts such as sea-level rise or wildfire also play an important role in understanding motivation towards forest climate action. Highlighting the need for flexible and locally informed efforts to bridge communication or education gaps that are effective in the context of individual states.

Table 1. Examples of key forest carbon accounting, modeling, capacity building initiatives and educational trainings undertaken by states in the USDA forest service eastern region. See **Appendix B** for a complete list of examples identified in review of relevant literature

	Project Overview	**Funding and Motivation**
State Examples		
Maine	Maine has assessed forest carbon mitigation potential using forest inventory and analysis (FIA) data, remote sensing, Forest Vegetation Simulator (FVS), and the LANDIS-II forest landscape model. Results published in Saffeir et al, (2021).	Funded through the Governor's Forest Carbon Task Force established by Executive Order on Jan 13, 2021 charged with developing incentives to encourage forestland management practices that increase carbon storage while maintaining harvest levels.
Maryland and Pennsylvania	These states conducted a project to assess alternate GHG pathways in the forestry and forest products sectors using the CBM-CFS3 modeling framework, parameterized by FIA data and other remotely sensed metrics of disturbance and land-use change. Includes forest product sector analyzes a subsequent process-based model to track harvested wood product (HWP) carbon dynamics. Results are published in Papa et al, (2023). -- Includes subsequent economic trade-off analysis to assess the viability of voluntary forest carbon offsets by assessing the sensitivity of additional carbon benefits across a range of carbon prices. Results in Pokharel et al, (2024a; 2024b)	Funded through the United States Climate Alliance (USCA) and carried out by a partnership between American Forests, Michigan State University Forest Carbon and Climate Program, and Northern Institute of Applied Climate Science (NIACS). The goal is to continually build capacity within state policymaking to understand the role of forest management and policy under climate change and assess implications for forest mitigation activities.
Regional Example		
Securing Northeast Forest Carbon Program	Cooperative effort of the State Foresters of Connecticut, Maines, Massachusetts, New Hampshire, New York, Rhode Island, and Vermont focused on securing private forest carbon on working lands through targeted trainings and through the sales of voluntary and compliance markets, conservation easements, and management practices.	Funded through the USDA Forest Service's Landscape Scale Restoration grant program with a goal to increase capacity of consulting foresters and landowners to increase carbon benefits on working forestlands through voluntary and compliance markets, management practices, and conservation easements.

Assessing the interest and feasibility of specific forest carbon policies or programs provides additional insights into where science-practice gaps may occur. **Table 2** provides our survey findings on interest and disinterest of specific policy assessments or implementation related to forest carbon and the forest sector highlighting important variation across states and complications with state needs and interests. We found strong interest in keeping forests as forests, either through avoiding permanent forest loss or through reforestation and afforestation practices. Results show broad interest in carbon offsets on both public and private lands, increasing the intensity of management of adaptation, and support for not disrupting timber supplies. We found that perceptions were broadly disinterested or mixed for regulatory frameworks such as carbon taxes and cap and trade programs in addition to reducing or delaying harvest. Results suggest the need for stronger emphasis on both science and policy towards forest conservation and the efficacy of carbon offset mechanisms.

Table 2. Respondent's perceived agency interest in assessing or implementing various policies or programs at the state-level (% of respondents). See survey question 27 in **Appendix A** for survey wording and response categories

Policy/ Program	Disinterest	Mixed For and Against	Interest
Keep forests as forests	0.0%	0.0%	94.7%
Carbon projects, public lands	0.0%	26.3%	73.7%
Encourage carbon projects, private lands	5.3%	15.8%	73.7%
Emission reduction targets	10.5%	15.8%	57.9%
Minimize disturbance impact, public lands	0.0%	36.8%	52.6%
Encourage harvest, private lands	5.3%	31.6%	52.6%
Intensify management	5.3%	21.1%	52.6%
Green growth/ sprawl limits	10.5%	15.8%	52.6%
Delay/ reduce harvest, private lands	10.5%	42.1%	36.9%
State-level clean fuel standard	15.8%	21.1%	36.9%
Encourage use of biomass energy	15.8%	42.1%	36.8%
Offsetting of public sector emissions	15.8%	21.1%	31.6%
Cap and trade program	15.8%	31.6%	26.3%
Carbon tax	36.9%	15.8%	21.1%
Delayed/ reduced harvest, public lands	38.9%	38.9%	16.7%

LEGEND:

Negative	<10
	>10
	>30
	>50
Mixed	<10
	>10
	>30
	>50
Positive	<10
	>10
	>30
	>50

2.5 Discussion

2.5.1 Closing gaps and ways forward: how education and communication can better inform climate change mitigation outcomes

In the past decade, there has been considerable growth in carbon science, policy, and management. To meet current and future demands, there is a need for more trained professionals with proper communication tools (Wynes and Nicholas, 2017). By first assessing barriers and gaps, and then identifying regional motivations and policy interests, novel strategies to enhance decision-making can be framed to further translate science into action. Drawing from both the results and expertise in forest carbon education and outreach, we propose three areas to reduce gaps and barriers by advancing scientific methods, accessible and effective tailored scientific training, and science-based communication of complex forest carbon science.

2.5.1.1 Improved data, tools, and models

Effective policies and management strategies necessitate robust and accurate science production (Fahey et al, 2009, Cook et al, 2013). Carbon accounting serves as a basis for understanding the role of forests in GHG emissions reductions. However, there is a need for refined data and tools, specifically fine scale heterogeneous data and more accessible tools, to improve not just general needs but inform site-specific prescriptions of management and needs (Novick et al, 2022a). Increased information about management activities on privately managed lands is critical to, first, reveal the consequences of current policy across landscapes and, second, to craft effective policy (Peterson St-Laurent et al, 2021, Poudel et al, 2024). The task of downscaling broader recommendations and guidance into specific management tactics is difficult, but the streamlining of tools and models that continually incorporate information and data in real time will continue to improve decision-making (Klug and Kmoch et al, 2015).

At present, the amount of forest land managed with cutting edge and continually updated forest management models like forest vegetation simulator (FVS, Dixon et al, 2002), LANDIS-II (Scheller et al, 2007), CBM-CFS3 (Kurz et al, 2009, Kull et al, 2019), and Ecosystem Demography model (ED v3.0, Ma et al, 2022) remains modest (Lamb et al, 2021, Daigneault et al, 2022). A deeper understanding of databases, methods, and models used to derive conclusions about specific management and policy decisions on forest outcomes only serves to improve future decision-making. In addition to the creation of more accessible tools, we identified three specific data needs to improve forest carbon outcomes: i) better integration of data in continuous assessments (Lister et al, 2020), ii) improved small area estimation to move beyond the general recommendation paradigm (Lister and Leites, 2021), and iii) better quantification of forest disturbance data to constrain forest dynamics more accurately (Kurz et al, 2018, Decuyper et al, 2022). The use of modeling tools and data likely serves to improve the policy process, which ultimately creates better outcomes for forest management and society (Sutherland et al, 2011).

2.5.1.2 Enhanced trainings and learning modalities

Our results demonstrate that practitioners and decision-makers would benefit from additional training to gain knowledge in forest carbon science. Such training would better inform their own management work and improve their ability to accurately advise landowners on potential tradeoffs of more traditional forest management, prioritizing carbon stewardship, or enrolling in carbon payment programs. Forestry professionals need training on a variety of methodological approaches to understanding the current state of forest carbon, tracking past and future trends, and performing scenario analyses of management practices to meet future goals (Knight et al, 2008). Specific training focus areas include gaining familiarity with current forest carbon modeling frameworks, assessing trade-offs between modeling results, and the development of statistical and coding skills.

We found a disconnect between the current workforce knowledge and what is needed and desired. Improving training would better inform management activities and help stakeholders balance potential trade-offs between objectives such as timber production and carbon storage. Drawing from our experience developing education and training materials for forest carbon practitioners, we have found that increasing access to information targeting key topics in state-level forest carbon inventorying and modeling (including annotated bibliographies) helped make this connection. Training targeting fundamental forest carbon concepts and advanced understanding of how to model harvest wood product yields, and associated statistical uncertainties, enabled participants to be more confident and effective decision-makers (FCCP, 2022).

Traditional academic education in forestry has been slow to incorporate forest carbon accounting, ecosystem modeling, and life-cycle analyses of HWPs. Hybrid learning models utilizing both remote learning and in-person learning targeted at professions, landowners, and policymakers provide ideal situations fostering peer-to-peer learning environments, a form of social learning, that begins to increase the efficacy of communication. Reducing the barriers of education through cost-effective training available online through broad collaborations and partnerships such as the Forests + Climate Learning Exchange Series (LES, 2024) can foster thoughtful exchange between audiences. Hybrid and remote learning may remove language and locality barriers for governments, non-governmental organizations, and practitioners should not hinder educational and training availability (Amano et al, 2016).

Lastly, we highlight a cutting-edge virtual reality visualization, the Forest + Climate Visualization Partnership, that uses a science-aligned, data-driven approach to communicate the complex relationships between forests, carbon, and climate (Ackerman et al, 2022). While landscape visualization techniques have long been recognized as an effective communication tool to bridge communication gaps and public perceptions (Lange, 2001), advances in visualization techniques serve as a new frontier in connecting stakeholders with sustainable forest management, forest carbon dynamics, and other forest benefits.

2.5.1.3 Effective science-based communication

Our results show that communication of forest science concepts and results to inform public and private decision-making remains lacking. To properly communicate with diverse forest stakeholders requires a diversity of knowledge and communications strategies (Anderson, 2013). Linking forest carbon to policy and social-economic systems is of bidirectional importance (Garcia-Gonzalo and Borges, 2019). Properly communicating findings to policymakers supports achieving improved impacts on the ground (O'Connell and McKinnon, 2021). Improved awareness from planners and managers can serve to help shape assessments to further target and improve management decisions (Littell et al, 2012).

Social learning and processes for robust decision-making are supported by a body of science (Dietz, 2013). Interview discussions point towards the need for adaptable methods of communication linking scientific analysis and public deliberation enhance awareness and the development of new value systems regarding forest management improving decision-making and in turn forest carbon outcomes. Sound decisions are subject to preferences and values of the decision-makers; thus, it is imperative that managers understand the science regarding outcomes—particularly negative outcomes—associated with inactions in the face of climate change impacts, as well as the benefits of management practices that help adapt and mitigate these impacts. Interviews reinforced the notion that collaboration across government, academia, and industry may encourage more open and transparent processes that can be easily and continuously improved through effective science-based communication (Yohe and Oppenheimer, 2011).

Our results found that audiences that are diverse in backgrounds, knowledge sets, and levels of education in relevant areas necessitate the creation of new and novel communication techniques (Bowers et al, 2016). Communication and training strategies should be crafted directly towards the desired audiences; there is no one size fits all method to creating effective scienced-based communication (Monroe et al, 2019). Developments in technology such as virtual reality environments (Ackerman et al, *2022*) and hybrid-learning models should serve as starting points to increase the ability to effectively translate complex scientific topics into understandable segments for a variety of audiences and stakeholders.

2.6 Conclusion

The results of this study of state forest agencies represent concepts that are directly applicable across disciplines and audiences. Bridging the science-practice gap through communication and education serves to improve climate outcomes through the development of multifaceted priorities and opportunities. Addressing climate change requires scalable solutions sensitive to on-the-ground contexts. Further integration of carbon accounting, ecological models, life-cycle analyses, and policy assessments is necessary to improve future climate outcomes while balancing the economic benefits of forests accomplished through the robust training of future forest carbon professionals and leaders who possess the proper tools.

Forest managers are uniquely suited to advance the ever-evolving demands of research in relation to climate and forests through their unique localized expertise. The co-production of knowledge driven by the scientist-manager knowledge flow then provides critical information to crafting more effective and salient policy devices. While the idea of science-policy models is not new, forest carbon science, policy, and management has emerged as another discipline in which significant climate impacts may be achieved through policy creation.

Forestry and forest sciences are critical to achieving the policies and management strategies required to act on information about natural and natural-managed forest systems to prevent the collapse of forest ecosystems and the exacerbation of climate change. Improved science-based communication serves to help align interests from across sectors reducing the likelihood of adopting biased policies and management strategies that may ultimately lead to goal failures. The cross-disciplinary nature of forest carbon science necessitates the importance of further integrating research and tools, education, and policy opportunities through robust communication techniques to effectively leverage prior and ongoing efforts to address climate change to ensure better outcomes.

2.7 Ethical statement

The Michigan State University Institutional Review Board determined this study (MSU Study ID: STUDY00007550) had been exempt under 45 CFR 46.104(d) 2ii. All participants provided written informed consent prior to interview or survey.

CHAPTER 3

MODELING CLIMATE-SMART FOREST MANAGEMENT AND WOOD USE FOR CLIMATE MITIGATION POTENTIAL IN MARYLAND AND PENNSYLVANIA

3.1 Abstract

State and local governments are increasingly interested in understanding the role forests and harvested wood products play in regional carbon sinks and storage, their potential contributions to state-level greenhouse gas (GHG) reductions, and the interactions between GHG reduction goals and potential economic opportunities. We used empirically driven process-based forest carbon dynamics and harvested wood product models in a systems-based approach to project the carbon impacts of various forest management and wood utilization activities in Maryland and Pennsylvania from 2007 to 2100. To quantify state-wide forest carbon dynamics, we integrated forest inventory data, harvest and management activity data, and remotely-sensed metrics of land-use change and natural forest disturbances within a participatory modeling approach. We accounted for net GHG emissions across (1) forest ecosystems (2) harvested wood products, (3) substitution benefits from wood product utilization, and (4) leakage associated with reduced in-state harvesting activities. Based on state agency partner input, a total of 15 management scenarios were modeled for Maryland and 13 for Pennsylvania, along with two climate change impact scenarios and two bioenergy scenarios for each state. Our findings show that both strategic forest management and wood utilization can provide substantial climate change mitigation potential relative to business-as-usual practices, increasing the forest C sink by 29% in Maryland and 38% in Pennsylvania by 2030 without disrupting timber supplies. Key climate-smart forest management activities include maintaining and increasing forest extent, fostering forest resiliency and natural regeneration, encouraging sustainable harvest practices, balancing timber supply and wood

utilization with tree growth, and preparing for future climate impacts. This study adds to a growing body of work that quantifies the relationships between forest growth, forest disturbance, and harvested wood product utilization, along with their collective influence on carbon stocks and fluxes, to identify pathways to enhance forest carbon sinks in support of state-level net-zero emission targets.

Material from: Papa, C. C., DeLyser, K., Clay, K., Gadoth-Goodman, D., Cooper, L., Kurz, W.A., Magnan, M., Ontl, T. (2023). Modeling climate-smart forest management and wood use for climate mitigation potential in Maryland and Pennsylvania. *Front. For. Glob. Change,* 6, 1259010.

For full text of this work, please go to: https://doi.org/10.3389/ffgc.2023.1259010

CHAPTER 4

CHARACTERIZING THE SENSITIVITY OF CARBON STOCKS AND FLUXES TO DISTURBANCE VARIATION IN MARYLAND'S FORESTS USING THE CBM-CFS3 MODELING FRAMEWORK

4.1 Abstract

Forests play a key role in climate mitigation while simultaneously providing additional co-benefits, including wildlife habitat, air and water purification, and cultural values. Forecasting forest carbon dynamics is essential to policy and planning in support of net-zero greenhouse gas emission targets. However, complex environmental issues require advancements in methodologies and models to support decision-making for climate policies. In this study, we simulated carbon dynamics in Maryland forests from 2007-2050 under a range of varying disturbance regimes utilizing the CBM-CFS3 modeling framework. We leveraged nationally consistent datasets, including inventory data from the USDA Forest Service's Forest Inventory and Analysis program, empirical growth-yield relationships, and remotely-sensed data on land-use change and natural disturbances. We applied a Monte Carlo simulation approach to estimate confidence intervals for carbon stocks and fluxes by taking into account the nature and distribution of disturbance input data. Additionally, we applied a random forest model to assess ecosystem flux, biomass turnover, and decay rates sensitivity to variation in disturbance inputs in terms of relative importance. We then validated model results against other estimates of carbon stocks and fluxes for the region. Under varying disturbance regimes, net biome productivity sequestered on average -0.41 MMT CO_2e yr^{-1} with an averaged 95% confidence interval width of 0.26 MMT CO_2e yr^{-1} (-0.54 and -0.29 MMT CO_2e yr^{-1}, or ±31.7%) from 2007-2050. Net ecosystem emissions were most sensitive to land-use change, harvest allotments, and disease

outbreaks. Our study advances methodological approaches to characterize the variability and sensitivity of an empirically-derived processed-based model to inform future forest management and planning actions in direct support of increasing the substantial mitigation benefits of forests.

4.2 Introduction

Forests are an increasingly valued pathway for achieving carbon neutrality via their role in sequestering carbon through photosynthesis and storing carbon in woody biomass and soils (Griscom et al, 2017). Not only are forests influential in global biogeochemical cycling (Bonan, 2008, Pan et al, 2011), they provide many co-benefits to society (Diaz et al, 2018). To understand the current and future potential of forests to mitigate climate change, regional- and national-scale forest carbon accounting, monitoring, and forecasting are essential (Nabuurs et al, 2007). In order to assess the applicability of models under increasingly and rapidly changing climatic and disturbance regimes, advances in forest carbon modeling methodologies must be accompanied by thorough assessments of model variability, uncertainty, and sensitivity (Magnussen et al, 2014). This will improve the effectiveness of decision-support applications of models for future policy and management actions by allowing for more accurate assessments of potential trade-offs between goals (Bruno Soares et al, 2018, Geary et al, 2020, Littlefield and D'Amato, 2022).

Modeling the flows of carbon (C) stocks is a complex undertaking with multiple and interacting processes, including vegetative growth and mortality, biomass turnover rates, litterfall, heterotrophic respiration, and natural and anthropogenic disturbances (White et al, 2008, Sturtevant and Fortin, 2021). Climate change complicates ecosystem dynamics and adds novel complexities in a rapidly changing world including natural and anthropogenic disturbances influencing and interacting with tree recruitment, growth, death, and turnover (McDowell et al, 2020). Alongside climate change, past and future changes to land use, forest management, and natural disturbance regimes add additional challenges to predicting how forests will respond to stressors (Sturtevant and Fortin, 2021). Disturbance and management furthermore influence key ecosystem processes such as biomass turnover and decay rates, in turn influencing future C dynamics (Pugh et al, 2019, Yuan et al, 2019, Wijas et al, 2024).

The intersection of these drivers is particularly relevant in the eastern US, where tree cuttings – including the conversion of forestland to non-forests – are some of the most impactful forest drivers of net ecosystem C fluxes at local to regional scales (Williams et al, 2016, Brown et al, 2018, Oswalt et al, 2019). Recent studies have shown that the scale of harvest and biomass removals (Brown et al, 2024), forest regrowth (Pugh et al, 2019), forest successional dynamics of carbon sequestration (Birdsey et al, 2023, Canham et al, 2024), harvested wood product dynamics (McKinley et al, 2011, Birdsey et al, 2023, Brown et al, 2024) and carbon leakage, a shift in carbon emissions to another area caused by shifts in timber supply and market conditions (Nepal et al, 2013, Pan et al, 2020), are poised to play an outsized role in the future mitigation potential of forests in the eastern US. Thus, ongoing forest management decisions will greatly impact the future strength of regional forest C sink or source.

To quantify and incentivize the capacity of forests to offset anthropogenic GHG emissions driving climate change, regional and global forest C budgets must capture complex drivers, including forestry activities (Kurz et al, 2009, Klug and Kmoch, 2015, Wang et al, 2016). Models must accurately characterize the influence of future disturbance regimes (both natural and anthropogenic), interacting with uncertain growing conditions and decay rates, and capture robust estimates of uncertainty and sensitivity to better inform decision-making about forest management and policy (Beier et al, 2016, Kautz et al, 2016, Hartmann et al, 2018, Hudiburg et al, 2019, Sturtevant and Fortin, 2021, Novick et al, 2022a).

To meet these challenges, forest ecosystem models have rapidly evolved over the past few decades (Clark et al, 2001, Luo et al, 2011, Bugmann and Seidl, 2022, Novick et al, 2022a) with a greater emphasis on operationalizing the indicators modeled (Klug and Kmoch, 2015). These models address complex environmental issues, providing decision support for forest policy and management in direct contribution to net-zero greenhouse gas (GHG) emission targets from national to regional scales (Larocque et al, 2011, Dugan et al, 2017, Bodner et al, 2021, Novick et al, 2022a, Sleeter et al, 2022). Increasingly, operational or landscape scale models that incorporate ecological, socioeconomic, or political perspectives at larger spatial and temporal scales have greater utility for informing forest management and planning and the potential use of forests to offset GHG emissions (Kurz et al, 2002, Novick et al, 2022b).

Methods and criteria for characterizing model behaviors, uncertainty, and sensitivity are commonly developed for other types of models such as hydrological models (Haghnegahdar et al, 2017) and earth and environmental system models (Razavi and Gupta, 2015, Pianosi et al 2016, Haghnegahdar and Razavi, 2017, Razavi et al, 2021). However, empirically-based simulation models for forest carbon dynamics generally lack defined methods or criteria (Yanai et al, 2010, Xiao et al, 2014) especially related to GHG inventories and emissions reporting for forests (Raczka et al, 2013, Yanai et al, 2020, Yanai et al, 2023). There are several areas of opportunity for forest carbon model improvement and expansion. First, many forest C models focus on near-term simulations (Dietze et al, 2017), in part due to modeling limitations as well as variability about future climate and disturbance regimes oftentimes limiting decision-making applications. Second, identifying the scale and complexity at which to model ecosystem dynamics remains challenging (Green et al, 2005, Van Nes and Scheffer, 2005). Third, rigorous assessments of models and systematic methods are needed to improve forward looking analyses of forest policy and management (White et al, 2008, Yanai et al, 2020, Bugmann and Seidl, 2022, McGlynn et al, 2022). Fourth, inter-model comparisons provide additional insights on model performance and relevant ways to significantly improve model performance (Wang et al, 2011, Raczka et al, 2023). Refining methodological approaches will further reduce variability and uncertainty in forest C dynamics caused by natural variability in forest ecosystems (Niu et al, 2017, Piao et al, 2019). These refinements enhance the application of models to inform decision-making under the context of climate change, providing resource managers and policymakers with robust information to tackle increasingly complex issues (Keenan, 2015, Boisvenue et al, 2016, Larocque et al, 2016, Geary et al, 2019).

In this study, we build off previous modeled results published in Papa et al, (2023) to characterize and assess both model variability and sensitivity to disturbance inputs, a topic with regional policy implications for achieving net zero GHG emission targets utilizing a 'Gain-Loss' approach within the CBM-CFS3 modeling framework. Papa et al, (2023) used a system-based approach accounting for GHG emissions across the forest ecosystem, harvest wood products, substitution benefits from wood utilization, and carbon leakage associated with reducing in-state harvesting activities, showing that enacting key forest management practices can increase the forest C sink strength by 29% in Maryland by 2030 without disrupting timber supplies as compared to a business-as-usual simulation. Here, we build upon those results to characterize the variability and sensitivity of the CBM-CFS3 model to the key forest disturbances and variation in those disturbances – including regeneration and management processes that comprise it – revealing how fluctuations in both the extent and severity of these drivers underlies our certainty in model predictions. Assessing these drivers offers important inferences for how future changes in forest disturbance regimes may alter key ecosystem processes. Specifically, we estimated confidence intervals for key forest ecosystem C stocks and C fluxes for the business-as-usual (BAU) simulation from Papa et al, (2023) using a Monte Carlo approach to investigate the range of potential net C ecosystem balances by simulating future potential forest disturbance regimes. We then assessed model sensitivity to variation in disturbance regimes for key model outputs including biomass turnover, heterotrophic respiration, and other disturbance related emissions and fluxes to better understand how model structure and disturbance inputs may affect net C balances. Finally, we validated the model results by comparing and benchmarking estimated projections with other estimates of regional net forest C balances to evaluate model reliability and reasonability of the estimates. This study informs future policy and planning by refining our understanding of how changes in future potential disturbance regimes may affect the regional potential of forests to be a C sink or source.

4.3 Methods

4.3.1 Study Area

Maryland forests have a substantial portion of aging forests (i.e., reaching their commercial rotational age) with almost half of the forest area being over 80 years old (**Figure 5**). The current age distribution of forests in Maryland has resulted from a legacy of land management since the 19th century which involved widespread clearing of forested landscapes for agriculture and growing populations. The subsequent rate of forest regrowth of depleted agricultural lands was influenced by alterations of forest management regimes, legacy effects of unsustainable harvests, and disruptions to historic natural disturbance regimes specifically the exclusion of fire (Millers et al, 1989; Otto, 1989). Therefore, Maryland provides a unique case study to explore the role of future harvest and other disturbances on driving regional C balances. The structure of Maryland's forests is indicative of forests within the mid-Atlantic region more broadly, making the results widely applicable.

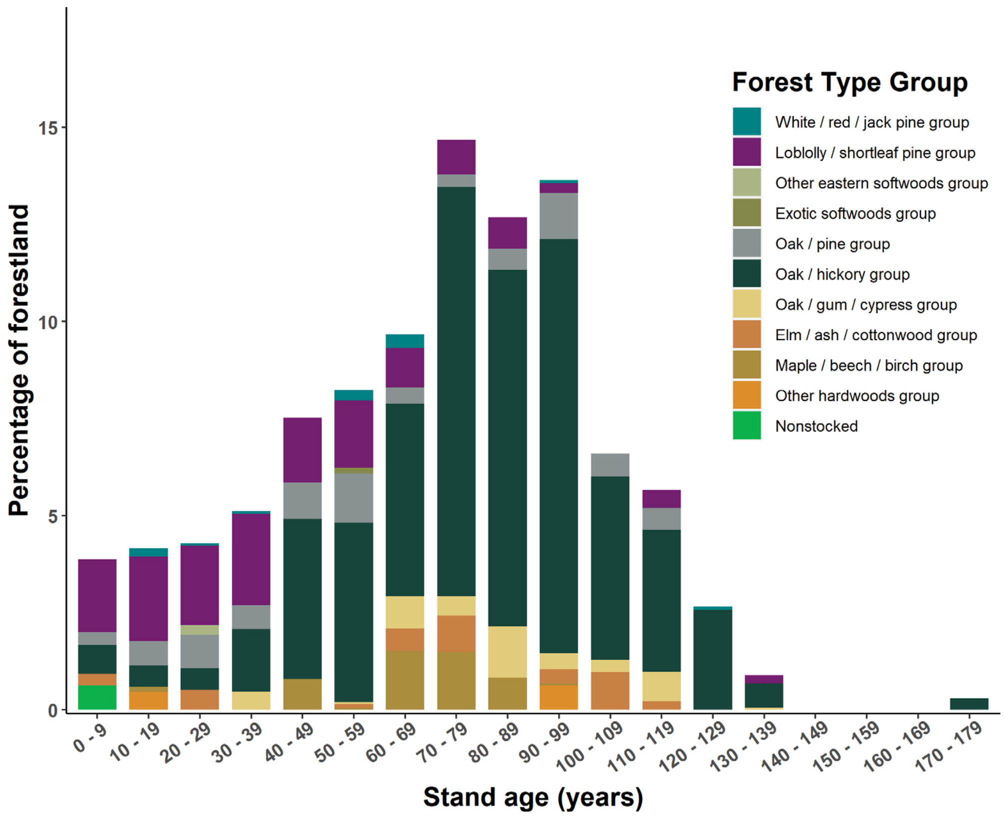


Figure 5. Forest age demographics by forest type group in 2019. Data: USDA Forest Service, 2024

Maryland has 37% forest cover (0.99 million hectares) dominated by hardwood forests (*Quercus spp*., *Carya spp*., *Fagus grandifolia*, *Acer rubrum*, *Liquidambar styraciflua*, and *Liriodendron tulipifera*) but with a sizable area of forest communities dominated by loblolly and shortleaf pine (*Pinus taeda*, *P. virginiana*, and *P. echinata*) along the coastal areas (**Table 3**). Privately managed forestlands comprise about 73% of the forested area while state and municipal managed forestlands account for another 24.3% with the remaining 2.7% of forestland being under federal jurisdiction (**Figure 6**).

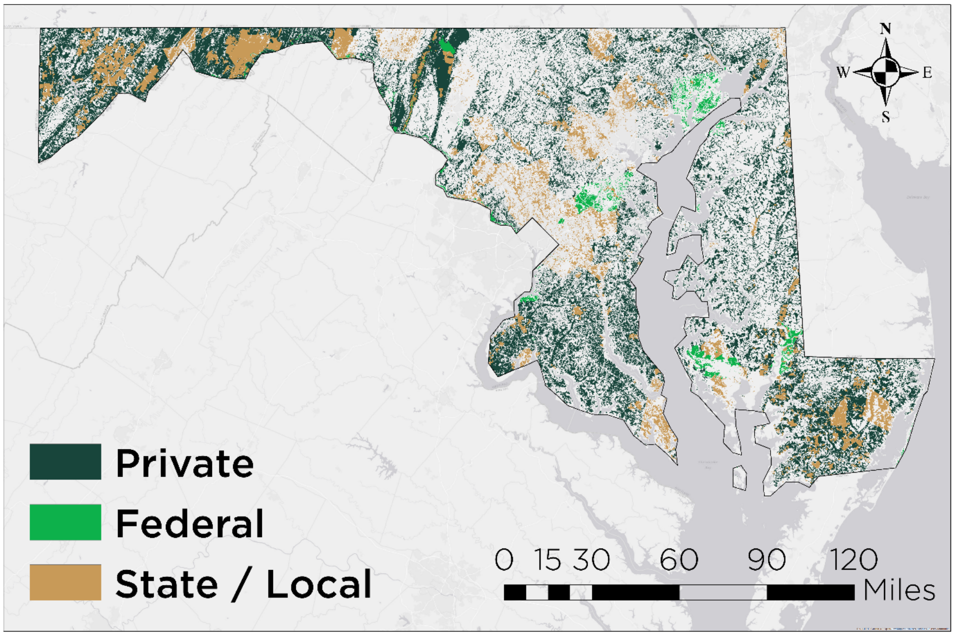


Figure 6. Map of forest distribution and forest ownership in Maryland. Data: Sass et al, 2020

Table 3. Percentage of forestland by forest type group in Maryland. Data: USDA Forest Service, 2024

Forest Type Group	Percentage (%)
Oak / hickory group	59.81
Loblolly / shortleaf pine group	16.26
Oak / pine group	7.82
Oak / gum / cypress group	4.70
Elm / ash / cottonwood group	3.91
Maple / beech / birch group	3.75
White / red / jack pine group	1.42
Other hardwoods group	1.22
Nonstocked	0.66
Other softwoods group	0.58

4.3.2 CBM-CFS3 Modeling framework

The Carbon Budget Model of the Canadian Forest Sector version 3 (CBM-CFS3) is an empirically derived processed-based model used to simulate forest carbon dynamics (Kurz et al, 2009; Kull et al, 2019). The model incorporates both human activities and natural disturbances to simulate forest C dynamics on annual timesteps. Although this model was originally developed as a core component of Canada's national GHG monitoring system (Kurz et al, 2018), it has been widely utilized internationally and domestically in the United States to explore questions regarding forest carbon cycle science and forest management and policy (Kurz et al, 2013, Pilli et al, 2013, 2017, 2022, Dugan et al, 2017, 2018a, 2018b, 2021, Oguin et al, 2018, Sleeter et al, 2022, Papa et al, 2023) and has been validated against national forest inventory data (Smyth et al, 2010, Shaw et al, 2014, Pilli et al, 2013, Pilli et al, 2016). It also complies with the Intergovernmental Panel on Climate Change (IPCC) systems-based modeling framework (Kurz and Apps, 2006).

The CBM-CFS3 utilizes empirically derived growth-yield curves to simulate forest growth and productivity along with user-defined disturbance and activity data, including harvests, cuttings, land-use change (LUC), and disease and insect outbreaks. The model estimates ecosystem carbon stocks using a detailed forest inventory defined by forest attributes such as ownership, forest type, or site productivity, and volume-to-biomass equations. Process-based equations are used to simulate annual C turnover and decay. Further, the model uses disturbance matrices to capture the flows of carbon between biomass and dead organic matter (DOM) pools caused from both natural and anthropogenic actions (Kurz et al, 1992). Disturbance matrices are at their core a set of assumptions about the transfer and fate of carbon following a disturbance event. Matrices define the proportion of each biomass or DOM pool that is transferred to another terrestrial carbon pool, the atmosphere, or the forest products sector (Kull et al, 2019).

The CBM-CFS3 framework allows for seamless transitions between previously modeled outcomes and future forecasted estimates where carbon removed via harvest, cuttings, or LUC can be directly inputted into an associated process-based harvested wood products (HWP) modeling framework, critical for sector-wide accounting and life-cycle analyses. Important to note, the CBM-CFS3 modeling framework does not include assumptions around changes to albedo, hydraulic regimes, or other climate change effects on growing conditions. The current framework can only support spatially referenced data and is not spatially explicit, meaning that users can define spatial areas by defining them in the forest inventory, but the model does not take a pixel-based approach to modeling forest carbon dynamics. The model is not stochastic in the sense that activity data are entirely user-defined, and the model applies a rule-based approach to implementing and sequencing individual disturbance events. Further, post disturbance dynamics are use-defined and must be informed by literature-based or expert assumptions as processes such as forest regrowth are not assumed (i.e., will forest stands naturally regenerate, regenerate due to human actions, or remain treeless). Lastly, despite temperature, precipitation, and soil type dictating rates of decomposition and soil respiration, the model lacks within simulation climate sensitivity to ecosystem process controlled by process-based equations.

4.3.3 Model Inputs

Papa et al, (2023) describes in detail model inputs and parameterization which we briefly summarize here. Model inputs came from several key sources. We estimated growth-yield relationships with the USDA Forest Service Forest Inventory and Analysis Database (FIADB, USDA Forest Service 2024) using a Gompertz growth curve which assumes non-asymptotic symmetry (Fekedulegn et al, 1999). We also estimated a detailed forest inventory and annual harvest removals from the FIADB. Additionally, we used the FIADB to calibrate allometric volume-to-biomass equations and other necessary stand attributes. We used remotely-sensed data to describe the frequency and extent of both natural disturbances and LUC including utilizing the national Insect and Disease Detection survey (USDA Forest Service, 2020) to estimate and characterize defoliating and mortality events. We used the LANDFIRE Historic Disturbance dataset to estimate the extent and severity of wind and wildfire disturbances (USGS, 2016); we further validated wildfire estimates through tabular data provided by the Maryland Department of Natural Resources (MDNR). Lastly, we estimated annual rates of deforestation and afforestation overlaying the National Land Cover Database (NLCD, Wickham et al, 2021) with a forestland ownership dataset (Sass et al, 2020) and a national geodatabase of protected areas (USGS, 2018) to conduct a from-to change assessment. We validated disturbance and post-disturbance dynamics heuristically with direct input from experts within the Maryland Department Natural Resources. Again, additional details are available in Papa et al, (2023).

4.3.4 Conceptual description of uncertainty and sensitivity

For this analysis, we define "uncertainty" (U) as a confidence interval (CI: typically 95% CI) for model output indicators by introducing variation within model disturbance data that reflects the uncertainty in these inputs as determined by a normal distribution. Total uncertainty contains multiple sources of uncertainties (U_1, U_2, U_3, …, U_n) such as parameter inputs for forest areas, biomass increments determined by growth-yield curves, disturbances targets, DOM C stock initialization, or parameters for controlling rates of biomass turnover and DOM decay. Uncertainty may also arise from the model structure and random selection of forest stands for disturbance. However, in this study, we only consider uncertainty defined as a confidence interval estimated from varying the extent and severity of annual disturbance regimes randomly (e.g., annual fluctuating the amount of biomass removed from harvest).

Sensitivity is defined as the degree to which model results are influenced by changes to process-based equations, input parameters, or model structure. It is a valuable tool to assess the significance of complex interactions (Holling, 1973) and is increasingly popular with ecosystem models (Cariboni et al, 2007, Seddon et al, 2016). Other forms of model performance such as "accuracy" which refers to the difference between estimates and a true value or "precision" which considers the distribution of estimates relative to each other, irrespective of the true value, may also contribute to uncertainty and sensitivity. However, formally assessing accuracy or precision was out of the scope of work for this study. We benchmarked estimates against other published datasets. Here, we assessed sensitivity by applying a random forest model to the model outputs to determine the degree of importance variation in disturbance input data had on model results.

4.3.5 Summary of analysis, sensitivity, and model validation

In the previous analysis published in Papa et al, (2023), a business-as-usual (BAU) simulation was developed for all forestlands in Maryland that projected longer-termed data of forest disturbance and management activities from 2007 to 2100. The BAU outcome (i.e., the counterfactual) was compared to 15 alternative scenarios exploring forest management, climate change impacts, and bioenergy to compare the net difference in mitigation potential. However, the original study (Papa et al, 2023) did not report any estimation of confidence intervals or uncertainty and merely reported the outcomes of each individual simulation. Therefore, we reran the BAU simulation from 2007-2050 utilizing a Monte Carlo approach while introducing variation to annual disturbance regimes randomly by generating new disturbance tables for each simulation drawn from the data distribution of the underlying disturbance data used to parameterize the model inputs. This allowed us to estimate confidence intervals for key model outputs to assess and characterize shifting disturbance regimes effects on ecosystem processes. We then compare the median estimates against the BAU simulation in part to validate the BAU simulation projected estimates. We also conducted a sensitivity analysis – using a random forest model – to assess each disturbance's contribution to the confidence intervals as well as the range of variation for each model output. Lastly, we benchmarked our results against different regional estimates of C stock density and fluxes to further assess and validate our results.

Ecosystem processes related to biomass turnover, decay, and other ecosystem emissions are important determinants of net C ecosystem balances thus assessing the importance of and the range of values caused variation introduced from model inputs informs understanding of structural model assumptions (Razavi et al, 2021). Doing so can highlight processes and parameters that cause the highest variability in model outputs (Haghnegahdar and Razavi, 2017). Further, assessing the sensitivity of key model parameters caused by variation in disturbance inputs allows for the examination of potential model limitations, particularly regarding long-term applications (Pappas et al, 2013). Given the outsized role disturbance and forest recovery from disturbance play in determining forest carbon sink or source strength in the eastern region (Brown et al 2018, Canham et al, 2024), we focused our analysis on characterizing the effects of varying model disturbance data as determined by the distribution of said data. Therefore, we did not vary process-based equations for turnover and decay, climate parameters, model allometry, inventory, growth-yield curves, or individual disturbance matrices. Parameter values for disturbance data were varied independently and randomly because the correlation structure among parameters or their contribution to the overall uncertainty is not known.

For each simulation, 2007-2019 encompasses what is referred to as the rollback period and 2020-2050 is referred to as the simulation projection, 2020 is the model projection point. The rollback period was parameterized with historical data whereas the simulation project was parameterized projecting longer-termed data informed by the data distribution. To provide seamless transition between past disturbances and future projects, we started with a forest inventory estimated from 2020 data and ‘rollbacked’ (i.e., a procedure that uses multiple iterations and historical information related to stand-replacing disturbance events to retroactively estimate an earlier forest inventory) the inventory using the probability distribution of stand-replacing disturbances to estimate a new inventory for the year 2007. This was done to ensure the forest inventory matched year 2020 all while providing better constrained and initialized DOM C and Soil C stocks, improving model projections (Smyth et al, 2017). The rollback period has been shown to better stabilized belowground dynamics in addition to the model’s own internal spin-up procedure for stabilizing DOM pools (Morken et al, 2022, Metsaranta et al, 2023).

4.3.5.1 Monte Carlo modeling approach to estimate confidence intervals

Building upon the results in Papa et al, (2023) in which scenarios were simulated a single time (including the BAU), a Monte Carlo simulation approach was used to estimate confidence intervals for key model outputs which represents the uncertainty of future C trajectories under varying disturbance regimes. Spanning 2007-2050, we conducted 100 simulations to estimate and construct 95% CIs from the 2.5th and 97.5th percentiles for expected values. Additional runs become prohibitive due to computational and data storage limitations. Variation for each simulation was introduced by altering annual disturbance input data randomly (**Table 4**) which represent and characterize the amount, extent, and severity of each individual disturbance and post-disturbance dynamics. We generated disturbance event tables – tabular tables used to characterize and define disturbance events by dictating the flows of carbon proportionally – for each individual simulation by taking a random draw determined by the probability distribution of each individual disturbance type (**Table 4**) using a normal distribution. Disturbance events are inputted on an annual basis in terms of area or weight of carbon disturbed using a rule-based approach constraining the type of forest, ownership, age, or other characteristics that are then chosen by the model to be disturbed. In addition to summarizing the data inputs and distributions, **Table 4** briefly summarizes the model output and distributions of disturbance events. These outputs inform model reliability in disturbance representation within the model framework and serve as a check on model reliability of data input representation within the modeling framework (Pianosi et al, 2016). Longer descriptions of each individual disturbance type can be found in **Appendix C**.

Our analysis focuses on estimating confidence intervals for key model outputs including Net Biome Productivity (NBP), Net Ecosystem Productivity (NEP), biomass turnover, and heterotrophic respiration or decay as well as forest C stock densities and individual components of forest C pools; other ecosystem indicators are briefly reported. We chose these indicators due to the outsized role they play in determining net ecosystem C balance. Additionally, we estimated confidence intervals for carbon transferred to harvest wood products, but we do not address variation in emissions from the forest products sector. Fluxes are presented in terms of MMT CO_2e, and C stocks and densities are presented in terms of Tg C and Mg C ha^{-1}, respectively. **Appendix C** provides longer descriptions of disturbances, ecosystem fluxes, transfers, and carbon pools used in this study.

Table 4. Summary of disturbance inputs, disturbance outputs, and data distributions used in Monte Carlo approach expressed in rates per year. Business-as-usual (BAU) results originally reported in Papa et al, (2023) are reported here to show variation in results from the Monte Carlo approach compared to median results

	2.5th	**50th**	**97.5th**	**se**	**BAU median default value**	**Relative difference (%)**	**Absolute difference**
Disturbance Inputs							
Harvest (MMT C yr^{-1})	0.217	0.229	0.241	0.006	0.228	0.17	393.29
Deforestation (ha yr^{-1})	2926	3000.1	3067.7	36.2	2988.99	0.37	11.15
Afforestation (ha yr^{-1})	2658.4	2789.5	2931.6	69.7	2796.12	0.24	6.58
Fire (ha yr^{-1})	326.1	330.3	334.6	2.2	330.57	0.08	0.25
Abiotic (ha yr^{-1})	2591.5	2653.4	2717.5	32.1	2655.67	0.09	2.31
Disease (ha yr^{-1})	10879.6	11323.5	11765.1	225.9	11367.53	0.39	44.00
Insect – Defoliation (ha yr^{-1})	3525.5	3666.7	3825.2	76.5	3678.18	0.31	11.48
Insect – Mortality (ha yr^{-1})	145.6	150.5	155.4	2.5	150.68	0.14	0.20
Disturbance Outputs							
Harvest (ha yr^{-1}**)**	6841.62	7134.35	7506.41	207.2	7302.05	2.30	167.7
Deforestation (ha yr^{-1}**)**	2653.75	2722.92	2807.53	35.31	2810.16	3.10	87.25
Afforestation (ha yr^{-1}**)**	2658.43	2789.54	2931.64	69.70	2796.12	0.24	6.58
Fire (ha yr^{-1}**)**	326.10	330.33	334.64	2.18	354.07	6.71	23.74
Abiotic (ha yr^{-1}**)**	2573.57	2635.74	2699.41	32.10	2571.17	2.51	64.57
Disease (ha yr^{-1}**)**	10826.32	11271.9	11711.68	225.82	10805.2	4.32	466.7
Insect – Defoliation (ha yr^{-1}**)**	3516.5	3657.63	3816.12	76.44	3602.4	1.53	55.23
Insect – Mortality (ha yr^{-1}**)**	143.98	148.85	153.74	2.49	147.18	1.14	1.67

For each disturbance iteration, a value in terms of area or weight of carbon was randomly drawn from its assumed distribution, and an estimate for annual disturbance rate was calculated. To estimate annual harvest allotments, we used a random draw and a normal distribution with the estimated standard error (se) and variance derived from FIA population estimates in Bechtold and Patterson (2005) utilizing the same forest attributes outlined in **Appendix C**. Population estimates (and associated sampling errors) are standardized equations and procedures used to estimate sampled-based population estimates for forest attributes of interest such as forest area, number of trees, and merchantable volume typically from state-wide inventories conducted across a specific set of years. In FIA estimation, samples are a set of plots selected for the attributes of interest in which plots are assigned to a stratum (non-overlapping areas of a known or estimated size) that in aggregate define the population of interest (Pugh et al, 2018). FIA assumes normality of the distribution of estimates and can be used to compute appropriate confidence intervals from the stratum mean.

Uncertainty within LUC estimates derived from remotely-sense metrics can arise from error associated with wrongful classification of forest versus nonforest as well as mischaracterization of harvest and deforestation. Additionally, imprecise boundaries, satellite artifacts, and multiple statuses occurring within an individual pixel (Lechner et al, 2012, Povey and Grainger 2015, Persson and Stahl, 2020) can also contribute to uncertainties. Currently, no precise estimates of error exist for these data or other similar types of remotely-sensed data products. Estimates of LUC uncertainty vary widely from ±10-30% (Wickham et al, 2017, Wickham et al, 2023). We chose an error of ±15% after discussion with forestry experts in the region as projecting LUC remains difficult due to predicting future driving factors such as population growth, populations concentrated in urban areas, and economics.

Similarly, we applied the same ±15% using a normal distribution to estimate variation in remotely-sensed derived estimates for fire, abiotic, disease, and insect disturbances assuming similarly derived data have similar uncertainty. We then compared the results of the Monte Carlo approach to median values estimated from the results in Papa et al, (2023), which applied the median target values for disturbance inputs (**Table 4**) again serving as a check on model assumptions previously made.

4.3.5.2 Random forest model to assess variable importance and sensitivity

In order to understand the importance of key model parameters and the range of values caused by varying disturbance input data, we conducted a sensitivity analysis to assess each disturbance type contribution to the total estimated confidence interval (u) in terms of variable importance and parameter ranges. Variables of higher importance and larger parameter ranges represent model inputs that have a greater influence on model outputs relative to the distribution of the input variable. The randomization of disturbance input data lends greater strength to characterizing variable contributions to estimating the confidence intervals and assessing model sensitivities through detecting influential interactions (Razavi et al, 2021). We assessed sensitivity within two key parts of the modeling framework due to their outsized influence on net C ecosystem balances. First, we assessed the sensitivity of biomass turnover and decay rates (i.e., ecosystem transfers) by their component parts to variation in disturbances. Second, we assessed sensitivity to ecosystem indicators and emissions including biomass lost from disturbance, total emissions from all DOM pools, total emissions from all biomass components, and NBP which estimates total biome emissions including harvest removals and disturbance.

To assess model sensitivity, we used a random forest (RF) model (Breiman, 2001) from the 'caret' package (Kuhn, 2008) in the R coding environment (R Core Team, 2020) to calculate relative importance, parameter range, and overall contribution to the model parameter results. RF models offer advantages over other parametric approaches (such as generalized linear models), including handling residual noise for predictions and probably estimates for multicategory depend variables (Gromping, 2012, Ziegler and Konig, 2014). RF models minimize overfitting and provide straight-forward checks of model results to limit bias and increase validity including for high-dimensional problems involving many features (Ziegler and Konig, 2014, Fox et al, 2017, Antoniadis et al, 2021). Furthermore, RF models have been shown to provide unbiased variable selection and importance measures can be used reliably for variable selection even when predictor variables vary in scale and number (Strobl et al, 2007, Gromping, 2012, Probst et al, 2019)

The RF method is a machine learning algorithm developed as an extension of bootstrap aggregation which is a method to reduce variance within noisy data and improve accuracy in comparison to other regression or supervised classification methods (Breiman, 2001). Random forest regressions consist of a collection of regression trees which can be used to assess the prediction accuracy of the out-of-bag observations (i.e., observations in the dataset that were not used in training the regression model) allowing for an estimation of an unbiased error rate. The algorithm draws *n* bootstrap samples from the original data and grows regression trees where at each node it chooses the best split among variables (Breiman, 2001, Liaw and Wiener, 2002). Prediction accuracy can then be estimated for each predictor variable permutation. This approach then takes the averaged difference between the two accuracies and normalizes by the standard error over all trees. Further, the mean squared error (MSE) is calculated on the out-of-bag data and variable permutation (Liaw and Wiener, 2002). These differences are then averaged and normalized by the standard error (Bylander, 2002). Sensitivity results are measured with regards to variable importance measures model improvement when splits are made on an individual predictor (Wei et al, 2015). Relative importance is defined as a percentage of model improvement with respect to the top predictor. Predictor variables are then scored relative to other variables (Archer and Kimes, 2007). We then constructed variable importance plots in descending order. Lastly, we constructed tornado diagrams which depict graphically how much of the variation in data inputs (i.e., RF model predictor variables) affect each subsequent model result, conditional to the mean. Larger widths indicating variation in the inputs had the greatest effect on the modeled results.

4.3.5.3 Model validation

The benchmarking of model results against other estimates provides validity and confidence to reasonable estimates as well as upper and lower limits of C stocks and stock changes. Although models may vary methodologically, we compared forest C stock densities and fluxes against both FIADB derived biomass estimates and other remotely-sensed derived regional estimates to assess agreement or disagreement in other approaches as this had yet to be regarding the results published in Papa et al, (2023). To validate our model results against similar estimates, we compared historical baselines of C densities and C stocks to model outputs with estimates of two other inventory-based estimates aggregated at the state level of Maryland from 2010-2019 as well as a variety of published remotely-sensed estimates.

First, we estimated biomass using the component ratio method (FIAcrm) which provides nationally consistent biomass estimates by using tree attributes to estimate tree volume which is converted to biomass using compiled sets of species-specific specific gravities and proportions of tops, limbs, and stumps (Jenkins et al, 2003, Heath et al, 2009, Woodall et al, 2011). For this method, we used the FIADB which we accessed through the FIA DataMart (USDA Forest Service, 2024) using the rFIA package (Stanke et al, 2020) to estimate C density. Second, we compared our modeled estimates of C stock density against both the FIAcrm method and revised FIA estimates published in Walters et al, (2023) which utilize the new National Scale Volume and Biomass Estimators (NSVB) providing improvements in consistency and accuracy of accounting of structured components of trees, biomass, and carbon (Westfall et al, 2024). Importantly, definitions of soil and litter pools varied between the methodologies, but the CBM results were redefined to better match FIA definitions. In addition to inventory-based comparisons, we compared model estimates of C stock densities and total statewide C stocks against remotely-sensed derived estimates (Wang et al, 2018, Huang et al, 2019, Hurtt et al, 2019, MDE, 2023). When possible, we compared both mean values and confidence intervals, if reported. Lastly, we directly compared a temporal trend in total ecosystem stock density change against those previously published in Walters et al, (2023).

4.4 Results

4.4.1 Carbon fluxes

While the net C sink is predicted to decline (**Figure 7**), it remains a net sink for the entirety of the simulation with only minimal drops in the timber supply (**Figure 7**) consistent with Papa et al, (2023). Additionally, our results show a minimal decrease in C transferred to HWP primarily driven by a lack of eligible forest records that met the criteria to be harvested. Average 95% CI width was 0.26 MMT CO2e and 0.22 MMT CO2e for NBP and HWP respectively. The average annual flux for NBP was -0.41 MMT CO2e. Whereas, C transferred to HWP products had an average annual flux of 1.30 MMT CO2e noting this is not an instantaneous emission and a transfer of C.

The largest relative difference between simulation and BAU medians was NEP (2.37%) followed by NBP (2.16%). Disturbance release, net growth, and NPP had the next largest difference, albeit relatively smaller differences. NBP had the largest CI width (0.26 MMT CO_2e yr^{-1}, or ±31.7%) and standard error (0.067) suggesting that disturbance remains an important driver of C dynamics (**Table 5**). NEP and decay showed the two smallest average CI widths of 0.124 MMT CO_2e yr^{-1} and 0.111 MMT CO_2e yr^{-1} (**Figure 8**). Turnover had the largest average

CI width of 0.237 MMT CO_2e yr^{-1}. Finally, CI width for NPP increased the largest amount as compared to other ecosystem indicators.

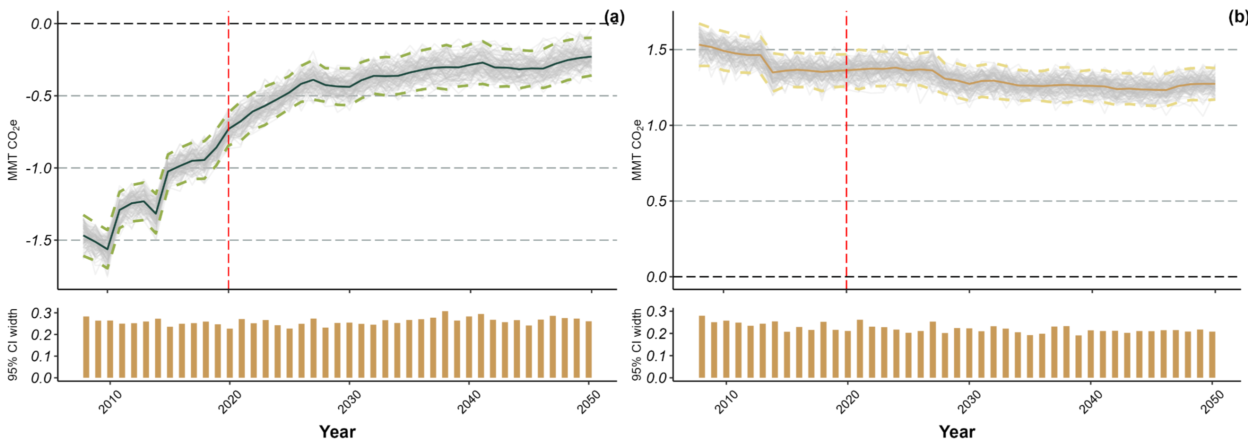


Figure 7. Estimates for annual flux rates of (a) Net Biome Productivity and (b) C transferred to HWPs with associated uncertainty for all forestland in Maryland (2007-2050) in MMT CO2e. The solid lines represent the 50th percentile (median) and the dashed lines represent the 2.5th and 97.5th percentiles of 100 bootstrapped totals. NBP represents total ecosystem productivity minus carbon transferred to harvest wood products sector and other disturbance related emissions; negative values denote net sequestration. Positive values for carbon transferred to harvested wood products represent a removal of carbon from the ecosystem. The bottom panels represent the CI width (97.5th - 2.5th percentiles). Red dashed lines show simulation projection point

Table 5. Median values (2007–2050) for ecosystem carbon flux components in the simulations (97.5th, 50th, and 2.5th percentiles) and for default parameter values, as well as the percentile at which the default value lies in the simulations and the difference between the simulation median and the default estimate, in both relative (%) and absolute (MMT CO_2e yr^{-1}) terms

Carbon flux component	2.5^{th}	50^{th}	97.5^{th}	se	BAU median default value	Relative difference (%)	Absolute difference
Net primary productivity	-21.768	-21.696	-21.624	0.037	-21.65	0.213	-0.046
Litterfall	18.816	18.870	18.924	0.027	18.849	0.109	0.021
Net growth	2.770	2.825	2.881	0.030	2.818	0.222	0.006
Heterotrophic respiration	19.901	19.956	20.009	0.028	19.945	0.057	0.011
Net ecosystem productivity	-1.800	-1.747	-1.687	0.032	-1.707	2.372	0.040
Disturbance releases	1.203	1.316	1.423	0.055	1.324	0.611	0.008
Net biome productivity	-0.542	-0.406	-0.293	0.067	-0.398	2.155	0.009
Disturbance transfers	1.189	1.300	1.408	0.055	1.309	0.658	0.009

Amount individual turnover parameters, other C to soil which includes non-merchantable biomass pools such as stumps, tops, and branches had the largest standard error (**Table 6**). The two largest turnover fluxes, in terms of absolute values, were foliage C (9.044 MMT CO_2e yr^{-1}) and Fine root C (4.699 MMT CO_2e yr^{-1}). Foliage C had an average annual flux of 9.044 MMT CO_2e and a CI width of 0.072 MMT CO_2e. Inversely, fine root C to soil saw an annual average flux of 4.699 MMT CO_2e and an average CI width of 0.013. Very fast aboveground decay and slow aboveground decay had the largest standard errors of decay parameters. These two decay parameters also had the largest median values of 9.236 MMT CO_2e and 3.066 MMT CO_2e yr^{-1}. The fast belowground and fast aboveground pools had the next largest annual flux of 2.095 MMT CO_2e and 1.945 MMT CO_2e, respectively.

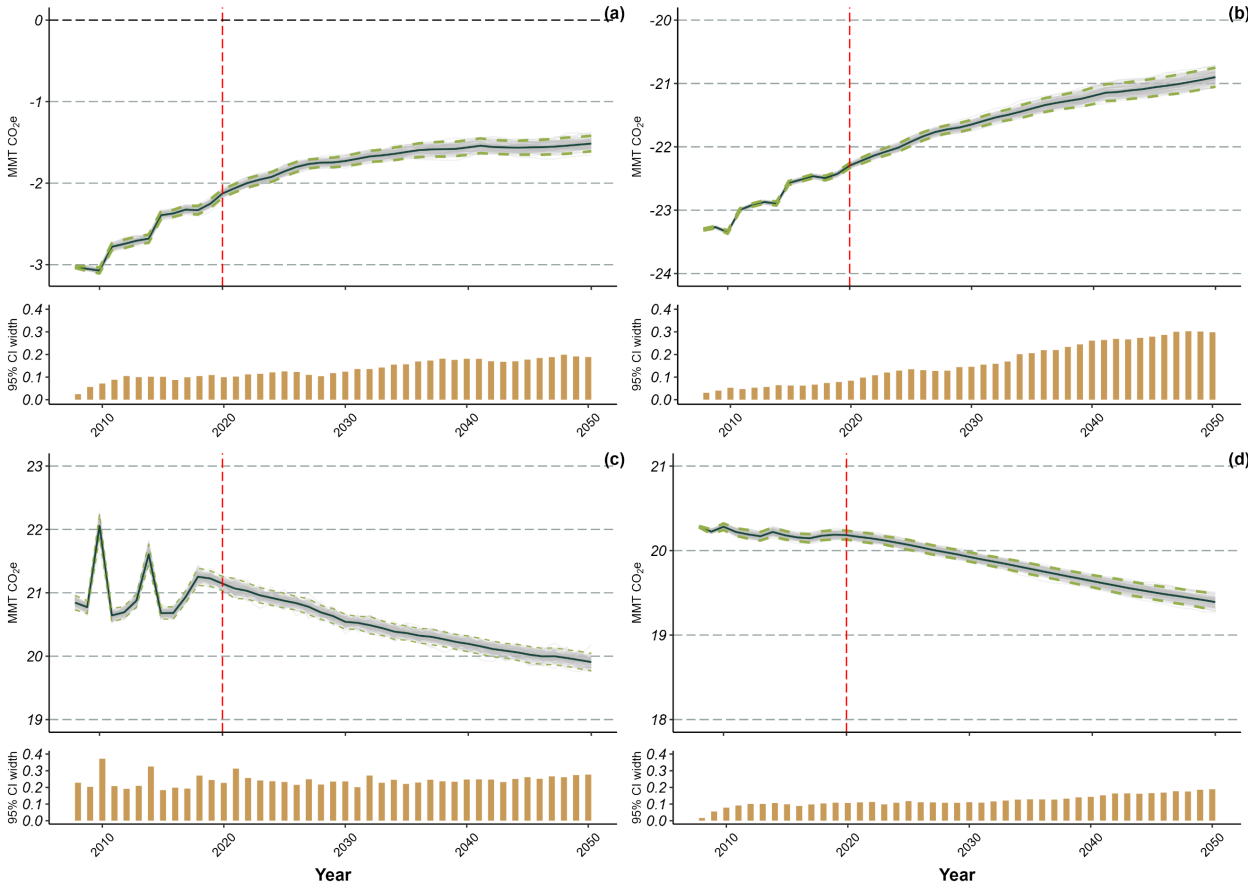


Figure 8. Estimates for (**a**) net ecosystem productivity; (**b**) net primary productivity; (**c**) turnover; and (**d**) decay rates with associated uncertainty for all forestland in Maryland (2007-2050) in MMT CO_2e. The solid lines represent the 50th percentile (median) and the dashed lines represent the 2.5th and 97.5th percentiles of 100 bootstrapped totals. Negative values for growth denote a net sequestration whereas positive values for decay rates denotes a positive emission to the atmosphere. Positive values for turnover rates denotes the amount of carbon transferred from living biomass C pools to DOM pools. The bottom panels represent the CI width (97.5th - 2.5th percentiles). Red dashed lines show simulation projection point

Table 6. Median values (2007-2050) for turnover and decay parameters by component for the Monte Carlo simulation results (97.5th, 50th, and 2.5th percentiles) and for BAU default parameters, as well as the percentile at which the default value lies in the simulations and the difference between the simulation median and the default estimate, in both relative (%) and absolute (MMT CO_2e yr^{-1}) terms

Carbon flux component	2.5th	50th	97.5th	se	BAU median default value	Relative difference (%)	Absolute difference
Turnover Parameters							
Total biomass to soil	20.515	20.63	20.747	0.237	20.563	0.327	0.067
Merchantable C to soil	1.786	1.813	1.84	0.056	1.815	0.133	0.002
Foliage C to soil	9.008	9.044	9.081	0.072	9.024	0.225	0.020
Other C to soil	3.289	3.342	3.391	0.109	3.332	0.295	0.010
Coarse root C to soil	1.613	1.641	1.669	0.056	1.646	0.290	0.005
Fine root C to soil	4.69	4.699	4.71	0.013	4.699	0.003	0.001
Decay Parameters							
Total heterotrophic respiration	19.896	19.951	20.003	0.028	19.945	0.032	0.006
Very fast aboveground	9.207	9.236	9.266	0.015	9.224	0.134	0.012
Fast aboveground	1.938	1.945	1.953	0.004	1.945	0.015	0.001
Slow aboveground	3.033	3.066	3.095	0.015	3.068	0.074	0.002
Medium	0.618	0.623	0.629	0.002	0.623	0.078	0.001
Very fast belowground	0.871	0.879	0.887	0.004	0.877	0.208	0.002
Fast belowground	2.090	2.095	2.100	0.003	2.092	0.109	0.002
Slow belowground	1.362	1.366	1.369	0.002	1.367	0.063	0.001
Stem Snag	0.428	0.43	0.432	0.001	0.430	0.172	0.001
Branch Snag	0.255	0.257	0.258	0.001	0.257	0.184	0.001

4.4.2 Carbon stocks

All carbon pools and total ecosystem C stock density CI width increased over time, implying that disturbance has a large impact of C stock density following model initialization of C pools (**Figure 9**). Increases in soil C and deadwood pools are consistent with the results showing larger annual biomass turnover than decay throughout the simulation. Even though C stock density varied across pools, total C stocks statewide increased as the forests remain a net sink throughout the simulation. Fluctuations in C stock density was largely driven by changes in the forest area, where forest area initially decreases but eventually begins to increase in 2028. Total ecosystem C density had an average of 281.14 Mg C ha^{-1} across the simulation and the highest average CI width of 0.959 Mg C ha^{-1} (**Figure 9**).

For individual C pools, aboveground biomass had the largest simulation CI width of 0.511 Mg C ha^{-1}. Soil C has the largest overall stock density of 116.12 Mg C ha^{-1} with an average CI width of 0.46 Mg C ha^{-1}. Total ecosystem C and slow C belowground had the two largest standard errors of 0.258 and 0.125 respectively (**Table 7**). Merchantable C had the largest average CI width of 0.343 Mg C ha^{-1} (**Table 7**). Branch snag C and stem snag C had the two largest median differences of 0.393% and 0.167% suggesting that variation in disturbances has an important effect on dead wood dynamics.

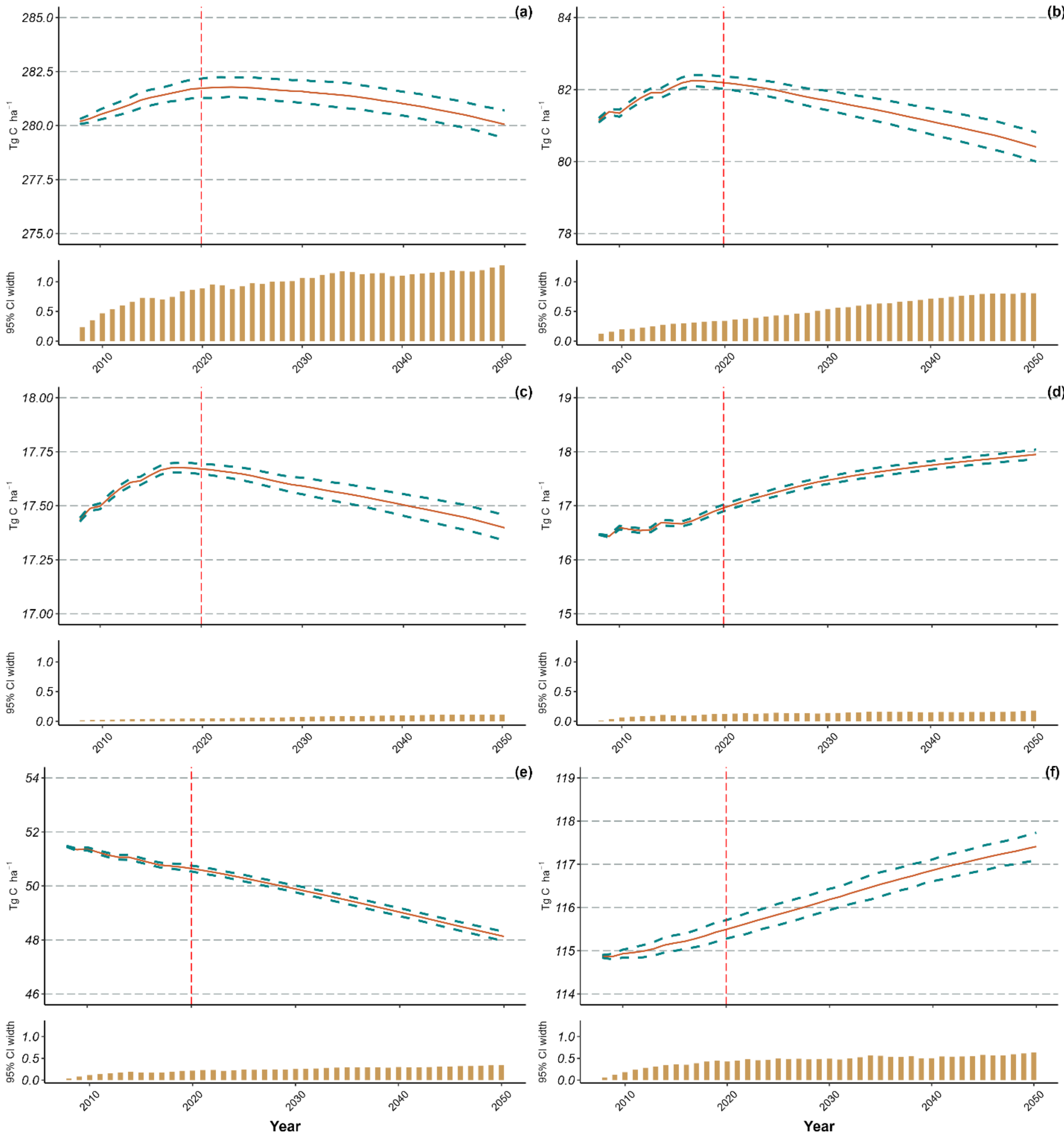


Figure 9. Estimates of carbon density (Mg C ha^{-1}) for total ecosystem C (**a**), aboveground biomass (**b**), belowground biomass C (**c**), deadwood (**d**), litter (**e**), and soil (**g**) with associated uncertainty for all Maryland forestlands (2007-2050) in Tg C ha^{-1}. Solid line represents the 50th percentile (median) where dashed lines represent the 2.5th and 97.5th percentiles from 100 bootstrapped totals. The bottom panels represent that CI width (97.5th – 2.5th percentiles). Red dashed lines show simulation projection point

Table 7. Median values (2007-2050) for carbon stock density (Mg C ha^{-1}) by pool component for the Monte Carlo simulation results (97.5th, 50th, and 2.5th percentiles) and for BAU default parameters, as well as the percentile at which the default value lies in the simulations and the difference between the simulation median and the default estimate, in both relative (%) and absolute terms (Tg C ha^{-1})

Carbon stock density by component	2.5th	50th	97.5th	se	BAU median default value	Relative difference (%)	Absolute difference
Total Ecosystem C	280.774	281.278	281.746	0.258	281.026	0.09	0.252
Merchantable C	59.064	59.265	59.479	0.087	59.232	0.055	0.033
Foliage C	3.396	3.408	3.42	0.006	3.408	0.003	0.001
Other C	18.876	18.963	19.044	0.043	18.961	0.010	0.002
Coarse Root C	15.528	15.56	15.596	0.018	15.547	0.081	0.013
Fine Root C	2.003	2.005	2.006	0.001	2.004	0.025	0.001
Stem Snag C	7.515	7.549	7.585	0.018	7.519	0.393	0.030
Branch Snag C	1.104	1.109	1.117	0.003	1.111	0.167	0.002
Very Fast C Aboveground	5.722	5.74	5.757	0.009	5.739	0.024	0.001
Very Fast C Belowground	0.651	0.652	0.655	0.001	0.652	0.068	0.001
Fast C Aboveground	6.052	6.103	6.163	0.028	6.115	0.194	0.012
Fast C Belowground	1.232	1.242	1.252	0.004	1.242	0.007	0.001
Medium C	7.486	7.554	7.617	0.032	7.55	0.053	0.004
Slow C Aboveground	37.919	38.008	38.101	0.046	37.996	0.031	0.012
Slow C Belowground	113.958	114.205	114.442	0.125	114.257	0.045	0.052

4.4.3 Model sensitivity to disturbance

4.4.3.1 Turnover and decay sensitivity by component

Belowground very fast DOM emissions (i.e., labile root materials) and aboveground slow DOM emissions (i.e., coarser woody debris, **Figure 10**) were the most important variables in determining total decay sensitivity. Both aboveground very fast DOM and belowground very fast DOM emissions have stronger negative influences on decay rates whereas aboveground slow DOM and belowground slow DOM have stronger positive influence on decay rates (**Figure 10**). Total biomass turnover was most sensitive to foliage turnover rates (**Figure 10**). The total turnover remained significantly less sensitive to other biomass turnover rates. Both the upper and lower limits for foliage turnover have the largest overall range of sensitivity (**Figure 10**).

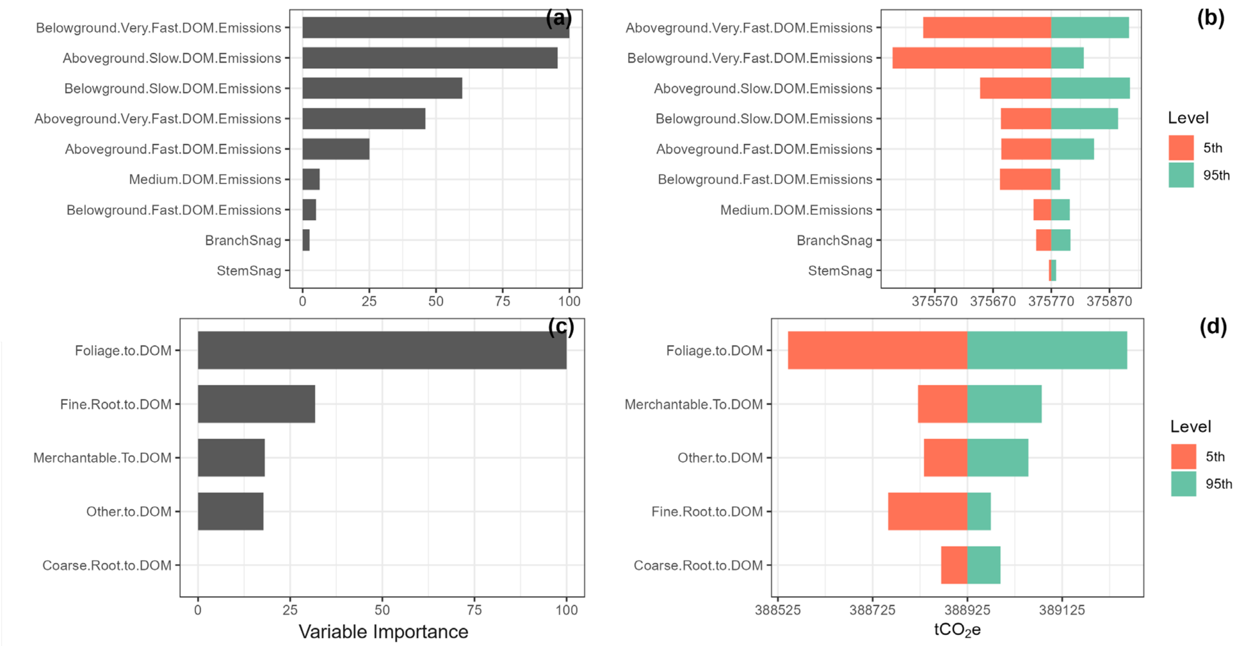


Figure 10. Relative importance and sensitivity of decay rates (**a**, **b**) and biomass turnover (**c**, **d**) by individual component to variation in disturbance amount from the random forest model. Variable importance (panels **a** and **c**) is determined by mean change in accuracy scaled by its standard deviation. Panels **b** and **d** show the 90% confidence interval in tCO_2e for each component part for biomass turnover and decay rates

4.4.3.2 Ecosystem indicator sensitivity by disturbance

Biomass turnover to soil caused directly by disturbances (i.e., not annual ecosystem processes such as litterfall) was highly sensitive to harvest rates (**Figure 11**). Total DOM emission rates remained most sensitive to rates of disease disturbances; however, harvest, LUC, and defoliator events were also influential (**Figure 11**). While LUC and harvest were ranked higher in variable importance, the tornado plots suggest fire and harvest have important

Figure 11. Sensitivity and relative importance of biomass to soil from disturbance (**a**, **b**), total DOM emissions (**c**, **d**), total biomass emissions (**e**, **f**), and net biome productivity (**g**, **h**) to variation in disturbance amount by disturbance type from the random forest model. Variable importance (panels **a**, **c**, **e**, and **g**) is determined by mean change in accuracy scaled by its standard deviation. Panels **b**, **d**, **f**, and **h** show the 90% confidence interval in tCO_2e for each disturbance type for each major ecosystem flux or emission

implications to the overall range of sensitivity values, showing the largest range in values from the mean (**Figure 11**). Total biomass emissions and net biome productivity suggest that LUC and harvest disturbances are the most important to determining model sensitivity (**Figure 11** and **Figure 11**).

4.4.4 Model comparison and validation

Our model estimates of carbon stock densities are comparable to other inventory-based and remotely-sensed estimates averaged across 2010-2019. For inventory-based assessments (**Table 8**), total ecosystem C stock densities from our results varied by -7% to +9% when compared to FIAcrm and revised FIA estimates from Walters et al, (2023). The largest differences occurred in aboveground, deadwood, and soil C densities. Compared to remotely-sensed estimates of C stocks, our aboveground C density estimates fell within ranges reported by Huang et al, (2019) of 49.8-93.8 Mg C ha^{-1}. However, Hurtt et al, (2019) estimated an average aboveground C density 51.85 Mg C ha^{-1} which was substantially lower (-40%) than our results. Wang et al, (2018) estimated ranges for aboveground C density of 0-200 Mg C ha^{-1}, but does not provide any averaged values, making it difficult to draw direct comparisons other than that our estimates fall well within that range. The averaged remotely-sensed estimates of C density vary -40% to +14% as compared to our results.

Table 8. Comparison of C density to other modeled estimates of C density (Mg C ha^{-1}) for Maryland forests from average across 2010-2019. The definition of litter was changed from the definition in the CBM-CFS3 framework which includes a portion of organic soil to reflect definitions used more closely in the other studies. Definitions for carbon pools do not always remain consistent across studies, but CBM results were redefined to match FIA definitions. FIAcrm method is only estimated from 2014-2019 which comprises of the most recent complete inventory window

Carbon Pool	CBM-CFS3	se	FIAcrm	se	Walters	se
AGB	81.86	0.066	92.08	0.711	88.64	-
BGB	17.60	0.009	16.18	0.122	16.92	-
Deadwood	16.66	0.023	20.00	0.147	6.18	-
Litter	11.92	0.027	13.35	0.045	13.34	-
Soil C	115.13	0.078	113.57	0.211	101.43	-
Total ecosystem C	243.08	0.194	256.18	0.985	226.51	-

When comparing estimates to remotely-sensed estimates of total statewide C stocks, our results estimated an average total C stock of 81.1 Tg C for aboveground biomass and 98.5 Tg C for total biomass for all forestlands from 2010-2019. The Maryland 2020 GHG inventory (MDE, 2023) estimated 115 Tg C for aboveground biomass for the same time period, which is approximately 41% larger than our estimate. Hurtt et al, (2019) reported statewide aboveground C stocks of 110.8 Tg C (100.3-125.9 Tg C), which corresponds to a 36.6% increase over our results. Huang et al, (2015) report a range of values for both aboveground biomass, 97.2 – 146.6 Tg C, and total biomass, 125.5 – 175.8 Tg C, which are both larger than our estimates. These remotely-sensed estimates of statewide biomass consistently estimated larger aboveground biomass stocks of 20-80%, whereas total biomass C varied 27-78% larger than our results.

Lastly, we compared temporal trends in C stock density from 2010-2019 against Walters et al, (2023). Both estimates increase in C density across the simulation (**Figure 12**). However, estimates from Walters et al, (2023) increased at a substantially higher rate when compared to our estimates. This is consistent with Walters et al, (2023) larger annual net C flux of -3.32

MMT CO_2e yr^{-1} estimate as compared to -0.61 MMT CO_2e yr^{-1} for our model results suggesting significant differences in productivity and emissions.

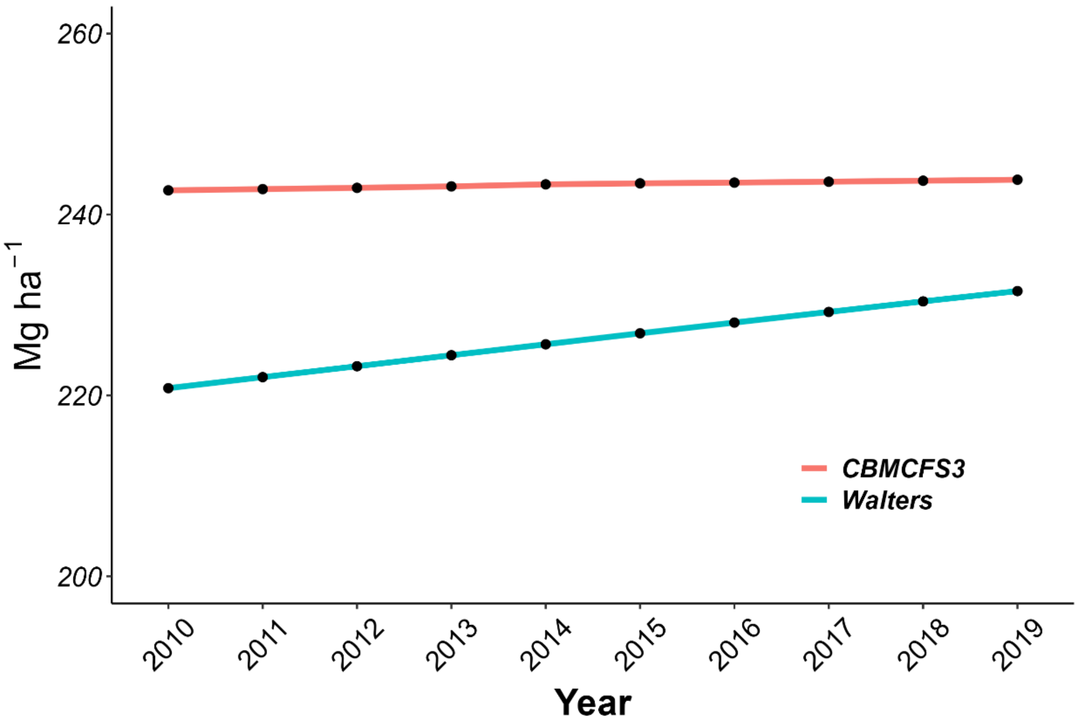


Figure 12. Trend in ecosystem C stock density (Mg C ha^{-1}) for CBM-CFS3 results and estimates published in Walters et al, (2023)

4.5 Discussion

There has been increasing emphasis on developing and advancing methods for ecosystem models that contain process-based elements to more holistically understand uncertainty, model calibration, model diagnostics with the aim to improve robust decision-making (Pianosi et al, 2016, Razavi et al, 2021). Analyzing the effects of and sensitivity to input parameter variation provides more detailed insights into the subjectivity of a model and the influence of data distributions of the inputs (Haghnegahdar and Razavi, 2017, Haghnegahdar et al, 2017). To date, few studies have attempted to systematically assess forest C models that employ a "gain-loss" approach such as the CBM-CFS3 modeling framework. Furthermore, diagnosing possible model deficiencies allows for future improvements and enhancements of decision-making applications for similar approaches (Pappas et al, 2013, Razavi and Gupta, 2015). This further emphasizes the importance of our study to advance methods of model characterization and diagnostics in support of forest planning and policy creation.

Improving both management activities and policy requires refined projections of forest carbon dynamics and the interaction with human management and natural disturbances, which requires reducing uncertainty in forecasting forest C dynamics. Improved models allow policymakers and planners to lower the risk of ecosystem failure under global climate change (Tulloch et al, 2020). This study quantified model variability and sensitivity by constructing confidence intervals and characterizing model sensitivities to variation in disturbance input data, and then, validating model results against other estimates of forest carbon for Maryland's forests. Our results suggest that even with variation in disturbances, Maryland's forests are projected to remain a net sink until 2050, albeit with significant weakening of the sink strength over time. In addition to, providing increased understanding in how shifting disturbance regimes may impact an empirically-derived process-based model with direct decision-support applications for forest management.

4.5.1 Opportunities to improve forest carbon assessments

Comparing results across analyses remains challenging due to differences in model configurations and uncertainty profiles. Stinson et al, (2010), which used the CBM-CFS3, suggests annual emissions are highly sensitive to widespread and severe disturbances in Canadian forests. However, Metsaranta et al, (2017) suggests that growth and soil C dynamics are more impactful than disturbance in determining CBM-CFS3 uncertainty. This result partially contradicts results in Smyth and Kurz, (2013) which suggests that dead organic matter C stocks were insensitive to variations in model parameters. Our results do suggest that variation in disturbances have larger effects on live aboveground biomass and labile dead organic matter pools whereas recalcitrant dead organic matter pools have lower variation except for soil C (**Table 6**). These results reflect recent findings suggesting that labile root inputs are approximately five times more likely to be stabilized as soil organic matter than aboveground litter (Jackson et al, 2017).

Our specific approach allows for comparison to a similar analysis conducted by Metsaranta et al, (2017) which suggested that biomass increments, and decay parameters are the largest sources of uncertainty within the CBM-CFS3. Results are consistent with other ecosystem model approaches including across regional (Richardson et al, 2010, Xiao et al, 2014), national (Peltoniemi et al, 2006), and global (Todd-Brown et al, 2013) scales where the largest contributors to uncertainty are model parameters (Xiao et al, 2014). Our results suggest that changes to productivity and decay – which are driven in part by disturbance dynamics – influence net C balances aligning with recent evidence across the US with uncertainty towards future C sink strength (Hogan et al, 2024). Other studies suggest that insufficient sample sizes of inventory data can limit Monte Carlo approaches to estimating net C balances (Magnussen et al, 2014). However, this is somewhat ameliorated in this study by leveraging a nationally-consistent inventory database (Yanai et al, 2023).

Directly comparing results of our analysis with other assessments of forest C estimation remains challenging due to different model purposes, unique model configurations, legacies of model code, and the processes they represent (Metsaranta et al, 2017, Bugmann and Seidl, 2022). For example, we found it challenging to compare our modeled results to other estimates of C stocks and fluxes as definitions of forestlands varied, which treed systems were included (i.e., all treed systems included woodlands and urban canopies versus FIA definitions of forestlands), core assumptions around methodological approaches, model structure differences, and varying degrees of opacity with regards to detailed peer-reviewed methodologies. Other studies suggest that omissions of certain land use classifications can contribute significantly to model uncertainties (McGlynn et al, 2022). However, we still found it beneficial to benchmark our estimates (**Table 8** and **Figure 12**) against previously published estimates to better compare the benefits and biases of different approaches. There is a growing need to understand differences across modeling approaches and the ramifications of model assumptions with a specific focus on improving the usability of models for planning and policy applications (Pretzsch et al, 2008).

Multiple paths exist for future emphasis on analyses seeking to characterize the effects of and sensitivity to forest disturbance including 1) emphasis on the process and implementation of approaches or 2) improving representation of ecological processes in models including further integrating climate change impacts and inclusion of inherent methods to quantify sources of uncertainty (Klug and Kmoch, 2015, Dietze et al, 2017, McGlynn et al, 2022). Additional emphasis can be placed on understanding the interpretation of results across spatial scales and implications of those results to inform decision-making (Beier et al, 2016, Bodner et al, 2021). For example, statewide forest planning versus management planning of a specific forest has very different implications for decision-making that reflect selecting appropriate methods to quantify both C accounting and associated uncertainties.

4.5.2 Impacts of forest management on carbon trajectories

Our results suggest that harvest, LUC, and disease play an important role in determining biomass turnover and decay rates as well as dictating future forest productivity. This finding agrees with other system level studies that included temperate mixed forests (Metsaranta et al, 2010, Yuan et al, 2019) and national scale studies (Williams et al, 2016). Additionally, our study suggests long-term management can balance timber supply with ecosystem productivity to sustain a net C sink in working forests (**Figures 7**). Where, timber production has the potential to provide additional carbon storage as a long-lived durable wood product and economically sustain a forest products sector which often provides a substantial portion of the financing for forest management (Mckinley et al, 2011; Petersson et al, 2022; Skog, 2008). While this area deserves more attention, long-lived HWP may provide additional substitution benefits through the replacement of fossil-based materials, products, and energy with sustainable source forest fiber and biomass (Geng et al, 2017; Howard et al, 2021) further boosting the climate mitigation potential of forest products (Sharma and Malaviya, 2023).

One of the single largest threats to both forest health and forest C stocks and future sequestration potential is human-caused global climate change and the subsequent future risk of disturbance (Allen et al, 2015, Seidl et al, 2017, McDowell et al, 2020) and could potentially offset future net positive changes in forest C stocks national (Williams et al, 2016). Uncertainty around the future risk driven of tree mortality driven by the confluence of drought and disease pressures should be an area of increased focused going forward (Teshome et al, 2020, Hartmann et al, 2022, McDowell et al, 2022)   Our results corroborate that future disturbance regimes – including both anthropogenic and natural disturbances – can have substantial impacts on forest C trajectories. Climate change induced risk necessitates further evaluation of intensifying disturbance regimes caused by climate change due to varying effects of the type and severity of disturbance on net ecosystem C balances (Thom and Seidl, 2015).

Prioritizing forest resilience and adaptive capacity in management provides a suite of opportunities to ensure the needs of society are met without compromising future benefits of forests (Seidl and Lexer, 2013; Falk et al, 2022). Future priorities of forest management should consider the increasing importance of new and novel pests and diseases (Roberts et al, 2020), alterations to habitat distributions (Iverson et al, 2008), increasing frequency in drought and fire (Allen et al, 2015). Doing so allows for the prioritization of multiple benefits and goals in addition to carbon specific goals (Littlefield and D'Amato, 2022). This could potentially serve as a key mechanism to optimize C balances over multiple spatial scales and time horizons without minimizing other integral forest co-benefits.

4.5.3 Knowledge gaps and future research

This study only seeks to assess and characterize model variation and sensitivity with regards to specific disturbance parameters derived from the input data distributions and estimates. While we identify other areas that variation may arise (**Appendix C**), we did not attempt to estimate or characterize variation related to these sources including random stand selection, biomass increments, DOM C pool initialization, model parameters for turnover and decay, tree allometry and C fraction, error associated with inventory estimates, and other uncertainty that may arise from model structure. It is likely that these factors may significantly influence results from the CBM-CFS3 modeling framework. Furthermore, issues such as climate change – including changes to tree mortality and productivity – as well as uncertainty around future LUC most likely increases the range of variation in future C stocks and fluxes.

Our results suggest that the net C balance of Maryland's forests is dominated by net primary productivity, decay, and harvest removals. Changes to environmental conditions such as CO_2 fertilizations, nitrogen depositions, changes to moisture regimes, and other climate forcings including shifts in albedo will continue to have large impacts on ecosystem fluxes but were largely outside the purview of this study. Future operational-scale models need to incorporate more process-based elements such as these to continue to reduce forecasting uncertainties. Finding synergies across model approaches and leveraging different advantages across methodologies serves as one example where the diversity in approaches can be seen as a strength (Bugmann and Seidl, 2022, Sleeter et al, 2022). Efforts should continue to focus on addressing discrepancies between areas where approaches disagree and focus on how to further integrate remote sensing data and improve ecophysiological representation into empirically derived models used in forecasting. Furthermore, improved benchmarking of forest C estimates requires continued advancements in measuring and monitoring of forest carbon to both improve model assumptions and validate model results (Novick et al, 2022b).

Community dynamics such as interactions between forest demographics, site conditions, impacts of natural disturbances, regeneration, and species competition play an outsized role in determining forest C balance (Ekhold et al, 2023). By necessity, models such as the CBM-CFS3 implicitly capture some of these dynamics within the growth-yield relationships to estimate forest productivity. Increased understanding of how species life history strategies interact with disturbance, competition, and growth conditions serve to further inform forest planning and decision-making. As of now, these factors are not explicitly captured but future analytical refinements should consider further integrating new and novel scientific information across disciplines and data to refine forecasting ability. Our study does not incorporate information about future states of ecosystem and growing conditions such as shifts to habitat suitability, species migration, biodiversity, and changes to the adaptive capacity or resilience of forests.

Lastly, our study only considered carbon dynamics within the forest ecosystem and did not track C that left the forest for the forest products sector. Future research should focus on furthering methods to incorporate and quantify uncertainty related to the storage of C in short- and long-lived HWP (Jasinevivius et al, 2015). Substitution benefits from durable long-lived wood products and bioenergy are poorly understood (Birdsey et al, 2023). Quantification of displacement factors of substituting wood for other carbon intensive materials is an additional area that necessitates future focus (Myllyviita et al, 2021). Additional methodological approaches should focus on further refining, improving, and reducing uncertainty estimates for forest C models. Increasing both the precision and accuracy of model predictions further facilitates forest management and policy decision-making in support of reducing climate change impacts. Forecasting of future carbon dynamics provides a wealth of information to managers and policymakers to assist decision support in achieving those goals (Bodner et al, 2021). For example, quantification of the magnitude of future C sink or source strength can inform management activities to improve both climate benefits and forest resilience. Where, continuing to leverage operational or landscape scale models serve to provide strengths for forest policy and planning at the subregional level (Kurz et al, 2009).

4.6 Conclusion

Utilizing a Monte Carlo simulation approach, we estimated and characterized variation in net C balances in Maryland's forests contributed from shifting disturbance regimes. Our results suggest that Maryland forestland will remain a net C sink through 2050 without substantially reducing future timber supplies even with increases in the extent and severity of forest disturbances. Additionally, we quantified CBM-CFS3 model sensitivity to natural and anthropogenic disturbance with regards to turnover and decay components and major ecosystem fluxes. Our results suggest major ecosystem components were most sensitive to rates LUC, harvest, and disease outbreaks increasing understanding of the magnitude in which these factors may affect future forest C balances. Lastly, we validated and compared estimates of C density and stocks against both inventory-based and remotely-sensed estimates for Maryland. Our results demonstrate an advancement in assessing both model potential and reducing uncertainty in forest C budgets within an empirically derived processed-based modeling approach.

While our results suggest that Maryland's forests are projected to remain a net C sink, the strength of the forest C sink is projected to weaken through the middle of the century. Carbon densities by ecosystem component varied over the simulation but remained relatively stable at the ecosystem level. Our results also suggested certain disturbance regimes may lead to larger C stocks in soil and dead organic material and lower C stocks in living biomass. Further management and policy actions that focus on boosting forest health and resilience in addition to conserving forestland can be enacted now to increase the relative strength of the net C sink without hampering future adaptive capacity and resilience of Maryland's forests.

A variety of methods exist to estimate C balance in managed forests in Maryland, but few methods provide uncertainty with estimates or assessments of how model parameters are affected by disturbance. Continued refinement and advancement of uncertainty and sensitivity methods is required to address gaps in the monitoring, observation, and quantification of forest C dynamics in particular managed forests in the eastern US. Addressing the climate crisis necessitates multi-sector actions, but improving quantification of forest C balances significantly contributes to meeting cross-sector collaborations to meet net-zero emission targets.

CHAPTER 5

OUTCOMES AND IMPLICATIONS FOR FOREST POLICY AND PLANNING

5.1 Research Synthesis

The preceding chapters explored various aspects of forest carbon and the use of forest carbon models to inform policy and planning by improving both the understanding of barriers to utilization and furthering methodological approaches to quantify forest contributions to net-zero GHG emission targets. Chapter 2 identified gaps and barriers to further integrating forest carbon models and science into policy and planning along with developing a framework to bridge the divide. Chapter 3 developed a business-as-usual simulation for Maryland and Pennsylvania forestlands and a suite of climate-smart forest management and wood utilization scenarios to quantify contributions of forests to net-zero GHG targets informing future management and policy planning. Chapter 4 further advanced methodological approaches and understanding of CBM-CFS3 model sensitivities to disturbance, a major driver of forest carbon dynamics, using a tier 3 IPCC compliant modeling framework improving projections of future management actions. These results have critical implications for future forest planning and policy as implementation and planning around natural climate solutions continues from local to national levels.

Analysis of gaps and barriers to further integrating forest carbon science and data into policy and planning (chapter 2) identified five areas where significant gaps occur including: 1) forest carbon science: inventorying and carbon estimation, 2) forest management behavior, 3) harvested wood products (HWPs), wood utilization, and carbon storage, 4) forecasting: forest carbon simulations and future pathway assessments, and 5) communication of results to inform public and private decision-making. Additionally, chapter 2 identified regional forest carbon initiatives, motivations, and policy interests to better inform ways to circumvent barriers preventing integration of scientific knowledge into forest policy and planning. With these results, a framework was developed to bridge the science-practice gap in forest carbon science through: 1) improved data, tools, and models to assess trends and statuses of forests; 2) enhanced carbon science training among state forest practitioners and decision-makers; and 3) effective science-based communication for decision-makers and general audiences. The science-practice gap is not new (Kirchhoff et al, 2013, Cooper and Macfarlane, 2023), but through participatory engagement and targeted education and communication, these efforts can inform policy and on-the-ground management (Hedelin et al, 2021). Ideally leading to sound decision-making through providing more effective guidance to improve forest carbon science, policy, and management outcomes through science-based communication and education (Anderson, 2013, O'Connell and McKinnon 2021).

Chapter 3 developed a suite of participatory model simulations to analyze potential trade-offs between climate-smart forestry, wood utilization strategies, and a continuation of business-as-usual practices. Results showed that implementing a variety of climate-smart forestry practices can provide substantial climate change mitigation potential, increasing the forest C sink by 29% in Maryland and 38% in Pennsylvania by 2030 as compared to the business-as-usual simulation without disrupting timber supplies. Informed by state-wide priorities and concerns for forest management, the modeled scenarios examined various forest management activities including maintaining and increasing forest extent, fostering forest resiliency and natural regeneration, encouraging sustainable harvest practices, balancing timber supply and wood utilization with tree growth and preparing for potential future impacts of climate change. The results of this study furthers a growing body of literature examining and quantifying future potential relationships between forest growth, forest disturbance, and harvest wood product utilization. Results such as these may provide valuable information to forest managers and planners when designing and implementing management activities for climate benefits while properly balancing trade-offs, risks, and uncertainties associated with the complex interactions of managing forests and the forest product sectors (McKinley et al, 2011, Yuan et al, 2019, Littlefield and D'Amato, 2022).

Chapter 4 used a Monte Carlo approach and random forest model to assess and characterize variation and sensitivity of Maryland's project forest carbon sink until 2050 in response to changes in disturbance frequency and severity. Anthropogenic activities, such as harvest, and other natural disturbances remain an important driver to forest carbon dynamics in the eastern United States. However, significant uncertainties remain in quantifying the potential contribution of forests to net-zero GHG emission targets (Cook-Patton et al, 2020, Pugh et al, 2020, Mo et al, 2023, Wu et al, 2023, Lamb et al, 2024). The results of this study suggest that both human and natural disturbances including land-use change remain important drivers to the strength of forest carbon sinks. Additionally, the results suggest that major ecosystem fluxes within the CBM-CFS3 modeling framework remain sensitive to variation in disturbance. However, potentially to a lesser degree than other model parameters such as process-based equations to model biomass and turnover, modeling initialization, and estimates of forest productivity (Smyth et al, 2013, Metsaranta et al, 2017). This study supports a growing need to develop and implement robust and accessible tools for forest managers and practitioners to make better informed decisions regarding the trade-offs between management strategies (Bradford and D'Amato, 2012, Creutzburg et al, 2017, Schwaiger et al, 2019). Improving the efficacy of forecasting models to inform forest policy and planning empowers forest stakeholders by better informing the decision-making process (Yousefpour et al, 2017, Klapwijk et al, 2018).

Together, these results suggest that concerted efforts now to reduce barriers of utilization of forest carbon models to inform forest policy and planning can provide valuable insights to decision-making for natural and working forestlands. The importance of forests in both climate change mitigation and adaptation will only increase in the coming years as recent studies suggest that current proposed mitigation activities globally, do not align with current temperature targets (Lamb et al, 2024). However, trade-offs between interdependent goals and co-benefits across both spatial and temporal scale will also increase in importance. The sustainable management of forests depends upon thoughtful stewardship practices and the balancing of multiple goals to foster resilient and healthy forests continue to provide the benefits in which human society relies upon.

5.2 Future Research

The previous analyses represented methodological improvements for quantifying future potential contributions of forests to net-zero GHG emission reduction goals as well as improving the integration of forest carbon science and data into forest policy and planning by identifying gaps and barriers and conducting a pathway analysis of potential mitigation strategies. However, areas of future work remain in terms of both methodological advancements and applications of those methods to inform important questions around future forest carbon dynamics and improving the efficacy of mitigation and adaptation outcomes through informed decision-making. Future work will continue to build on the concepts to inform forest stewardship in direct contribution to increasing the resiliency and health of forests globally in an effort to limit the negative effects of unabated GHG emissions and subsequent climate warming. Presented below are a few specific areas of future research.

5.2.1 *Further integrating models into policy and planning*

As more US states and local governments begin to adopt legislation and executive actions with the goal of reducing GHG emission, there is a growing need to understand how those policy levers will affect both forest ecosystems (Markkanen and Anger-Kraavi, 2019, Morecroft et al, 2019) as well as socioeconomics (Chazdon et al, 2015). The needs across states and governance levels differ widely depending on region specific climate change threats and vulnerabilities, current capacities, and political will. Forest carbon models can be useful in helping to identify effective and politically feasible policy strategies (Jewel and Cherp, 2020) in addition to quantifying the potential impacts of enacting such policies (Hoppe et al, 2023). Increasing the transparency and verifiability of methodologies used to estimate potential carbon fluxes can shed new insights on the efficacy of voluntary offset mechanisms or other future mitigation actions specific to forests and the forest sector at large (Badgley et al, 2021, Jones and Lewis, 2023).

In addition to increasing the understanding of forest climate specific forest management through empirical studies (Torresan et al, 2021), there is a growing need to also identify gaps and barriers to landowner adoption of climate-smart forestry practices or adaptive silviculture (Mason et al, 2021). This is even more important in places such as the eastern US where forestlands are predominately private smallholder managed. The development of decision-support tools to help in planning and management is critical to the success of proper forest stewardship in the face of climate change (Menzel et al, 2012, Acosta and Corral, 2017). Managers and landowners need to navigate an unprecedented time where the culmination of decisions now may not be realized for decades to come necessitating that the best available data, predictions, and decision-support tools be utilized to manage forested landscapes for a multitude of benefits.

Continued refinements to methodologies used to account, monitor, and forecast forest dynamics is necessary to inform planning and management efforts (Novick et al, 2022a). Additional emphasis is needed on just assessing the impacts of specific management practices or policies on forest dynamics but the subsequent impacts on the forest products sector (Keith et al, 2015). Alterations to harvest rotations and silvicultural regimes can have profound impacts on the socioeconomics of the forest products sectors and landowner incomes (Roberge et al, 2016) in turn potentially impacting management practices through perturbing the flow of finance from forest products to landowners (Favero et al, 2017). The creation of datasets that continue to represent diverse site conditions across forests can be used to benchmark modeling efforts used to assess impacts across policy-relevant scales (Coulston et al, 2014).

Improved implementation of modeling frameworks used in scenario or pathway assessments to understand potential trade-offs will only become more important as managers are asked to make decisions with large uncertainties and the impacts of those decisions that may not be observable over longer time periods (Maxwell et al, 2022, Cantarello et al, 2024). Lastly, significant knowledge gaps remain regarding the climate mitigation potential for the forest products sector and more specifically the substitution effects or wood utilization and the monitoring of leakage from forest carbon offset projects (Howard et al, 2021, Hurmekoski et al, 2021). The current emphasis on carbon capture and storage from wood-based bioenergy and emissions from the wood product manufacturing process will also continue to increase as policymakers seek new and novel ways to boost the climate benefits of forest products in the near term (Petersson et al, 2022, Cantarello et al, 2024).

5.3 Concluding Remarks

Addressing the climate crisis requires substantial reductions in global GHG emissions. However, forests will continue to provide a myriad of mitigative and adaptive benefits to help society cope with the negative effects of sustained climate warming. Near term climate mitigation from natural and working forestlands should not supplant the other crucial benefits forest provide such as fuel, fiber, and timber in addition to other regulating and supporting ecosystem services. The management of our global forests will require new and novel approaches to foster resilient and healthy forests in the face of a changing planet. While there is large disagreement on the best path forward with regards to forest management and planning, all relevant stakeholders need to continue an active dialogue informed by the best available scientific knowledge to continue to work together to advance the importance of forest conservation and management in combatting global climate change.

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APPENDIX A: DETAILS ON SURVEY PROTOCOL

Online survey introduction

This survey has been designed to assess state-level forest carbon and harvested wood product inventory and modeling needs, including for data interpretation, results communication, and linkages with state policy and goals.

The survey is part of the Forest Carbon Data and Modeling Integration and Evaluation Project, made possible with a grant from the U.S. Department of Agriculture, Forest Service Eastern Region. The project's aims are to assess interest in and build capacity for forest carbon modeling among USFS Region 9 states. You are being asked to complete this survey as your skills, experiences, and perceptions will be helpful in identifying state-level capacities, motivations, and knowledge gaps. Please know that all responses are anonymous.

A couple of clarification notes as you complete this survey:

1) By 'forest carbon', we are referring to any of the five major carbon pools in terrestrial ecosystems (i.e., aboveground live, belowground live, aboveground dead, dead organic matter, and soil carbon), carbon fluxes between terrestrial carbon pools and carbon fluxes between forest carbon pools and the atmospheric carbon pool.

2) Some questions ask about your "team's" level of knowledge or experience, rather than solely your individual knowledge or experience. For the purposes of this survey, a "team" is defined as a group of people who perform interdependent tasks to

accomplish a common mission or specific objective, in this case forest carbon modeling and forest inventory and analysis. Depending on your position and role within your agency, your "team" could be large (e.g., the entire department, agency, or division), or small (e.g., your immediate workgroup). Question 4 will ask you to briefly describe your "team" for the purposes of this survey.

We anticipate 30-40 minutes for survey completion and are extremely grateful for your participation.

Online survey questions and possible answers

#	Survey Question	Possible Responses
1	For which state do you work?	Drop-down: all states and DC
2	For which organization or agency do you work?	Open-ended
3	What is your position title?	Open-ended
4	As noted in the introduction to this survey, some of the following questions will ask about your team's level of knowledge or experience. By "team", we are referring to a group of people who perform interdependent tasks to accomplish a common mission or specific objective, in this case forest carbon modeling and inventorying. In a few words, please describe the "team" you work with on matters related to forest carbon modeling and/or forest inventory and analysis.	Open-ended
5	How would you categorize your team's knowledge on the following forest inventorying topics? [rank 1-6]: A. Forest plot designs and how to establish forest plots B. Plot placement and spatial randomization of inventory plots C. Determining appropriate inventory methods and sampling design D. Identifying forest characteristics to be measured and why E. Scaling plot and subplot level measurements to either the stand, landscape, or regional level	1) No knowledge; 2) Limited knowledge; 3) Moderate knowledge; 4) Expert knowledge; 5) Don't know; 6) Don't know what this refers to

	F. Calculating forest biomass, carbon, basal area, or volume using plot measurements G. Mapping forest biomass, basal area, or volume estimates and uncertainty using remote sensing (e.g., LiDAR, satellite imagery)	
6	In which ways has your team used Forest Inventory and Analysis (FIA) and other forest inventory data? [1-5 – check all that apply]: A. Use of annual FIA produced reports and statistics B. Analysis/ estimation of summary statistics and forest characteristics using FIA online tools C. Analysis of forest inventory and measurement data collected outside of FIA (e.g., collected by state, academic, or other organizations) D. Further analysis using FIA data but also incorporating other sources or types of inventory data (i.e., supplemental inventory data, geospatial data, survey data, etc.) E. More robust estimation of forest attributes using FIA or non-FIA data, including but not limited to: *Estimation of forest recruitment, growth rates, annual productivity, age-structures, size classes, species diversity/abundance, or canopy dynamics* F. Economic analyses to complement forest inventory analysis	1) completed internally; 2) completed by other state teams/ agencies; 3) done by external (e.g., consultants or academic partners); 4) Don't know; 5) Not applicable
7	What is your team's level of familiarity about aspects of the FIA database [rank 1-6]: A. FIA database content B. Accessing FIA data C. FIA data interpretation D. FIA sampling and stratification methodology E. FIA database structure, nomenclature, and data attributes F. FIA population estimates procedures G. FIA Quality Assurance and Quality Control (QA/QC) and accuracy standards H. Forest carbon/biomass calculations using FIA data	1) No knowledge; 2) Limited knowledge; 3) Moderate knowledge; 4) Expert knowledge; 5) Don't know; 6) Don't know what this refers to
8	Regarding the FIA program and database: Which of the following would you be interested in learning more about? [choose 1-4]: A. FIA database contents B. Accessing FIA data C. FIA data interpretation D. FIA sampling and stratification methodology E. FIA database structure, nomenclature, and data attributes F. FIA population estimates procedures G. FIA Quality Assurance and Quality Control (QA/QC) and accuracy standards	1) No interest; 2) Some interest; 3) Strong interest; 4) Don't know what this refers to

	H. Forest carbon/biomass calculation using FIA data	
9	Which of following methods have you used to access FIA Inventory data? [choose 1-5]: A. EVALIDator B. DATIM (Design and analysis toolkit for inventory and monitoring) C. FIA DataMart D. FIADB/EVALIDator Application Programming Interface (API) E. SQL F. rFIA G. Other coding language or environment	1) Do not use; 2) Used 1-2 times; 3) Used 3-10 times; 4) Used more than 10 times; 5) Unsure what this is
10	[If 'other', above] What other coding language or environment have you used to access FIA inventory data and with what regularity?	Open-ended
11	How would you classify your team's knowledge of silvicultural methods and activities across the following ownership categories in your state? [rank 1-5]: A. Private B. State C. USFS D. Other Federal E. Local/Municipality F. Tribal Lands	1) no knowledge; 2) limited knowledge; 3) moderate knowledge; 4) expert knowledge; 5) don't know
12	What information, resources or training do you need to improve your ability to access, process, and understand FIA Inventory Data for state level forest carbon inventory and modeling needs?	Open-ended
13	Does FIA meet your data needs to measure or monitor state or program goals? Please explain.	Open-ended
14	How would you classify your team's knowledge about the following items relating to Timber Product Output (TPO) assessments and data [rank 1-6]: A. What TPO surveys measure B. Sampling and stratification methodology C. Database structure, nomenclature, and data attributes D. Where and how to access primary data E. How to interpret data	1) No knowledge; 2) Limited knowledge; 3) Moderate knowledge; 4) Expert knowledge; 5) Don't know; 6) Don't know what this refers to; 7) Don't Use/Not Available

15	In which ways has your team used mill and timber product data? Check all that are appropriate and leave blank if none apply or are not applicable to your team. [1-5]: A. Use of TPO/ RPA reports or summary estimates provided (e.g., fact sheets) B. Primary analysis using TPO data C. Primary analysis using TPO data in combination with supplemental state-level mill or wood products data D. Use of state-collected mill data reports or summary estimates E. Primary analysis of state-collected mill data F. Analysis of harvested wood product export and import data G. Analysis of harvested wood product carbon storage H. Analysis of product end-uses I. Analysis of product half-lives J. Analysis of product retirement (e.g., recycling, landfills, burning for energy capture) K. Economic analyses regarding mills or harvested wood products L. Mill or economic analysis to determine existing or potential product feasibility M. Analysis of harvested wood products energy use N. Analysis of harvested wood product fossil fuel emissions offsetting	1) completed internally; 2) completed by other state teams/ agencies; 3) completed by external (e.g., consultants or academic partners); 4) don't know; 5) Don't know what this refers to
16	How would you rank the available mill data in your state (either from TPO or state assessments) for state carbon and harvested wood product modeling needs along the following dimensions? [rank 1-4]: A. Updated with sufficient regularity B. Sufficient representation of existing mills C. Product categories are appropriately and sufficiently categorized or binned	1) Inadequate; 2) Adequate; 3) More than necessary; 4) Don't know
17	What information, resources or training do you need to improve your ability to access, process, and understand mill and harvested wood product data for state level forest carbon inventory and modeling needs?	[open-ended]
18	How would you rank your team's knowledge around carbon cycle science and forest carbon and/or biomass [rank 1-5]: A. Forest carbon cycling and dynamics B. Forest carbon or biomass pools/stocks C. Forest carbon fluxes and gas exchange	1) No knowledge; 2) Limited knowledge; 3) Moderate knowledge; 4) Expert knowledge;

	D. Forest carbon and biomass measurements and accounting	5) Don't know; 6) Don't know what this refers to
19	How much of your job involves policy or management analysis or decision making related to the following forest carbon topics? [rank 1-3]: A. Forest carbon cycling and dynamics B. Forest carbon or biomass pools/stocks C. Forest carbon fluxes and gas exchange D. Forest carbon and biomass measurements and accounting	1) none; 2) some; 3) a significant amount
20	How would you rank your team's knowledge regarding forest carbon *accounting, modeling, and linkages with policy* [rank 1-6]: A. Knowledge about what datasets/sources exist that can be used in forest carbon accounting B. How to estimate forest carbon from plot-level measurements C. How to scale plot-level measurements to the landscape or regional level D. How to use remote sensing data to map or calculate forest carbon E. IPCC guidance and best practices regarding carbon accounting and monitoring within the forest sector F. Which forest carbon modeling frameworks would best suit state or agency goals/ needs G. Other states' approaches to carbon accounting and modeling H. Ability to process and interpret primary results/ data outputs from carbon assessments I. How to link carbon modeling with economic analysis/ modeling J. Awareness of existing state or sub-state policies/ programs that incentivize or discourage particular forest management practices (e.g., incentivizing harvest, incentivizing delayed harvest) *within your state* K. Awareness of state-based policies/ programs/ levers *in use in other states or countries* L. Comfort using the appropriate language to communicate about forest carbon and climate M. Comfort using the appropriate language to communicate about forest carbon and/or energy policies N. Comfort communicating links between carbon assessment and modeling results and policy *for policymakers* O. Comfort communicating links between carbon assessment and modeling results and policy *for general audiences (e.g., including landowner, constituents, business interests)*	1) No knowledge; 2) Limited knowledge; 3) Moderate knowledge; 4) Expert knowledge; 5) Don't know; 6) Don't know what this refers to

	P. Comfort communicating links between forest carbon assessments and modeling results in relation to other working lands (agriculture) assessments and modeling results and policies. Q. Comfort communicating links between forest carbon, harvested wood products storage, fossil fuel substitution and carbon leakage. R. Comfort communicating links between short term and long-term carbon cycles and their importance in climate mitigation. S. Comfort communicating links between forest carbon assessments and modeling results with other non-forested ecosystems including but not limited to, grasslands, prairies, wetlands, shrublands, savannas, peatlands, high altitude montane systems, coastal systems T. Comfort in understanding and communicating forest carbon assessments and modeling results across spatial scales including smaller spatial extents (i.e., parcel or county) to larger spatial extents (i.e., state, region, or subregion)	
21	Regarding forest carbon modeling, which of the following would you be interested in learning more about? [1-3]: A. Datasets/sources that can be used in forest carbon accounting B. How to estimate forest carbon from plot level measurements on site carbon C. How to scale plot-level measurements to landscape or regional level D. Forest sector IPCC guidance and best practices regarding carbon accounting and monitoring E. How to model carbon in harvested wood products F. Lifecycle assessment of wood products versus fossil fuel-based products incorporating substitution and leakage concepts G. Other states' approaches to forest carbon accounting and modeling H. Differences between existing modeling frameworks and tools for scenarios and projections I. Links between carbon and economic modeling J. Existing state or sub-state policies/ programs that impact forest management practices *within your state* K. Potential state-based policies/ programs for forest management (e.g., those used in other states or countries) L. How to communicate linkages between carbon modeling results and policy	1) No interest; 2) Some interest; 3) Strong interest
22	To what degree are the following barriers to your engagement with forest carbon modeling? [rank 1-4]:	1) not at all; 2) slight barrier; 3)

	A. Insufficient data B. Lack of *access* to data C. Insufficient funding D. Lack of trained personnel E. Insufficient personnel time F. No interest G. Political barriers H. Other	significant barrier; 4) don't know
23	What other barriers to carbon modeling do you encounter?	[If 'Other', above]
24	Do you expect your agency would prefer to build in-agency capacity for carbon modeling or hire outside consultants? A. Building in-agency capacity B. Hiring outside consultants C. Both D. Neither E. Don't know	[Choose one]
25	How would you rank the interest in raising awareness of activities leading to *increased carbon storage* among the following groups within your state? [rank 1-5]: A. Your personal interest B. Executive-level interest (i.e., governor and governor's office/ administration) C. Department or Agency-level interest D. State legislature interest E. Industrial forest sector interest F. Industrial/investor landowner interest G. Family forest landowner interest H. General population interest	1) No interest; 2) Little Interest; 3) Moderate Interest; 4) High Interest; 5) Unsure
26	How would you rank the interest in raising awareness of activities leading to *reduced GHG emissions* among the following groups within your state? [rank 1-5]: A. Your personal interest B. Executive-level interest (i.e., governor and governor's office/ administration) C. Department or Agency-level interest D. State legislature interest E. Industrial forest sector interest F. Industrial/investor landowner interest	1) No interest; 2) Little Interest; 3) Moderate Interest; 4) High Interest; 5) Unsure

	G. Family forest landowner interest H. General population interest	
27	How would you characterize the current interest (for either assessment or implementation) in the following policies and programs *within your agency?* [rank 1-8]: A. Policies for delayed or reduced harvest on public lands B. Policies to keep forests as forests C. Programs to minimize the impact of forest disturbances on public lands D. Incentive programs delayed or reduced harvest on private lands (e.g., via property tax incentives) E. Incentive programs encouraging harvest on private lands (e.g., via property tax incentives) F. Carbon projects on public/ state lands G. Programs to encourage/ support carbon projects on private lands H. Green growth/ sprawl limits I. Emissions reduction targets (including determined at the agency level, legislatively determined, or through an Executive Order) J. Cap and trade program K. Carbon tax L. Offsetting of public sector emissions M. State level clean fuel standard N. Programs to intensify management O. Programs to encourage use of biomass energy P. Other	1) Strong disinterest; 2) Some disinterest; 3) Mixed interest for and against; 4) Somewhat interested; 5) Strong interest; 6) Not discussed; 7) Don't know; 8) Unsure what this means
28	If 'other', what other policies or programs does your agency have an interest (positive or negative) in assessing or implementing?	[If 'Other', above] [open-ended]
29	Has your agency identified any potential issues or barriers to implementing carbon projects on state lands?	[open-ended]
30	To what degree are the following forest disturbances of concern in your state? [rank 1-5]: A. Climate change B. Wildfire C. Insect D. Disease E. Storm/ wind throw F. Harvesting G. Drought H. Flooding I. Conversion to non-forest uses	1) No concern; 2) Minimal concern; 3) Some concern; 4) Strong concern; 5) Unsure

	J. Fragmentation	
31	Are there any other forest disturbances of particular interest or concern in your state? If so, please list briefly here.	[open-ended]
32	Which forest management scenarios would you have the greatest interest in assessing with a carbon model (that is, deviations from current forest management practices on either public or private lands)? [rank 1-6]: A. Deferred harvest B. Pre-commercial thinning C. Commercial thinning D. Reforestation following harvest E. Afforestation F. Prescribed burning	1) No interest; 2) Little interest; 3) Moderate interest; 4) High interest; 5) Unsure; 6) Don't know what this refers to
33	Are there any other forest management scenarios you have an interest in assessing with a carbon model?	[open-ended]
34	Regarding harvested wood products, which of the following would you have the greatest interest in assessing with a carbon model? [rank 1-6]: A. Increased wood reuse/ recycling B. Development of new wood products or wood product industries (e.g., mass timber, biochar) C. Shifting use of lower value wood (e.g., toward different products) D. Increased use of post-harvest forest residues E. Leaving low-grade wood and residues on-site (cut and leave) F. Increases in sawmill lumber volume recovery G. Increased use of sawmill residues H. Decreased use of wood products I. Increasing the use of wood fuel for heat only J. Increasing the use of wood fuel for electricity generation only K. Increasing the use of wood fuel for combined heat and power	1) No interest; 2) Little interest; 3) Moderate interest; 4) High Interest; 5) Unsure; 6) Don't know what this refers to
35	Are there any other harvested wood product scenario you have an interest in assessing with a carbon model?	[open-ended]

APPENDIX B: DETAILS ON REVIEW OF RELEVEANT LITERATURE AND SEMI-STRUCTURED INTERVIEWS

Table B.1. Examples of key forest carbon accounting, modeling, capacity building initiatives and educational trainings undertaken by states in the USDA forest service eastern region

	Project Overviews	Funding and Motivation
State Examples		
Maine	Maine has assessed forest carbon mitigation potential using forest inventory and analysis (FIA) data, remote sensing, Forest Vegetation Simulator (FVS), and the LANDIS-II forest landscape model. Results published in Saffeir et al, (2021).	Funded through the Governor's Forest Carbon Task Force established by Executive Order on Jan 13, 2021 charged with developing incentives to encourage forestland management practices that increase carbon storage while maintaining harvest levels.
Maryland and Pennsylvania	These states conducted a project to assess alternate GHG pathways in the forestry and forest products sectors using the CBM-CFS3 modeling framework, parameterized by FIA data and other remotely sensed metrics of disturbance and land-use change. Includes forest product sector analyzes a subsequent process-based model to track harvested wood product (HWP) carbon dynamics. Results are published in Papa et al, (2023). -- Includes subsequent economic trade-off analysis to assess the viability of voluntary forest carbon offsets by assessing the sensitivity of additional carbon benefits across a range of carbon prices. Results in Pokharel et al, (2024a; 2024b)	Funded through the United States Climate Alliance (USCA) and carried out by a partnership between American Forests, Michigan State University Forest Carbon and Climate Program, and Northern Institute of Applied Climate Science (NIACS). The goal is to continually build capacity within state policymaking to understand the role of forest management and policy under climate change and assess implications for forest mitigation activities.
Michigan, Minnesota, and Wisconsin	These states are currently conducting a project to assess alternate GHG pathways in the forestry and forest products sectors using the CBM-CFS3 modeling framework, parameterized by FIA data and other remotely sensed metrics of disturbance and land-use change. Includes forest product sector analyses a subsequent process-based model to track harvested wood product (HWP) carbon dynamics.	Funded through the United States Climate Alliance (USCA) and carried out by a partnership between American Forests, Michigan State University Forest Carbon and Climate Program, and Northern Institute of Applied Climate Science (NIACS). The goal is to continually build capacity within state policy-making to understand the role of forest management and policy under climate change and assess implications for forest mitigation activities.
Massachusetts	Massachusetts has utilized FIA inventory data and FVS to model forest characteristics through space and time to assess the response of forest dynamics to management decisions.	Primarily focused on more traditional forest planning but includes a carbon component and is intended for internal agency planning, motivated by Massachusetts legislature and regional initiatives

Table B.1. (cont'd)

New Jersey	New Jersey developed the Forest Management Optimization Model (ForMOM), a set of tools designed to optimize forest management for carbon and simulated using FIA data and the FVS. ForMOM applies linear optimization to FVS outputs to assess optimal management.	Motivated by internal planning for forest management and stewardship with the goal to simulate different management scenarios to constrain and optimize to find optimal management activities.
New York	The Climate & Applied Forest Research Institute (CAFRI) based at SUNY ESF is a multi-disciplinary team that developed a summary report utilizing high-resolution forest mapping, change detection, and hierarchical forecasting for carbon accounting and future landscape change. Results published in Beier et al, (2023).	Funded by the New York State Department of Environmental Conservation and the New York State Environmental Protection Fund, state funding with the goal of applying emerging technologies to study and translate the role New York's Forest ecosystems play in climate adaptation and mitigation to guide and support statewide adaptive management efforts.
Vermont	Vermont developed a framework to continually monitor forest carbon dynamics following IPCC guidelines (IPCC 2006) using FIA data on forest cover, carbon, and land-use change. Results published in Kosiba, (2021).	Motivated in part by the passage of legislation and by the Governor's office. Results are one part of a larger statewide carbon budget including all sectors (Galford et al, 2021) with the goal to decision making and planning by informing on the current GHG balance, emissions, and carbon stocks as well as serve as a foundation to improve tracking and accounting of GHG emissions going forward.
New York Connects: Climate Smart Farms & Forests	The NY Department of Environmental Conservation partnered with New York State Agriculture and Markets, Cornell University, SUNY ESF, and Syracuse University to expand cost share grant programs focused on enhancing carbon uptake on private-lands and fund efforts to improve MRV, research forest management practices and identify barriers of implementation.	USDA Partnerships for Climate-Smart Commodities Grant program funded partnership between DEC, AGM, Cornell University, SUNY ESF, and Syracuse University with a state goal to increase implementation of climate smart agriculture and forestry practices in an effort towards reducing GHG emissions through the Climate Leadership and Community Protection Act.
Regional Examples		
Securing Northeast Forest Carbon Program	Cooperative effort of the State Foresters of Connecticut, Maines, Massachusetts, New Hampshire, New York, Rhode Island, and Vermont focused on securing private forest carbon on working lands through targeted trainings and through the sales of voluntary and compliance markets, conservation easements, and management practices.	Funded through the USDA Forest Service's Landscape Scale Restoration grant program with a goal to increase capacity of consulting foresters and landowners to increase carbon benefits on working forestlands through voluntary and compliance markets, management practices, and conservation easements.

Table B.1. (cont'd)

State and Tribal Capacity Building on Forest Carbon Webinar and Workshop Series	Cooperative partnerships between Michigan State University Forest Carbon and Climate Program, Penn Soil Resource Conservation and Development Council, USDA Forest Service, and the Northern Institute of Applied Climate Science (NIACS) conducting a webinar and workshop series targeted at state and tribal forest agency staff to increase capacity towards forest carbon science, management and policy with a specific focus on carbon models, accounting, and science communication.	Funded through Penn Soil Resource Conservation and Development Council under a cooperative agreement with the USDA forest Service, and with other support from the USDA Forest Service, and NIACS with a goal to increase the capacity of state and tribal employees in forest carbon science, adaptation and mitigation as an effort to inform forest policy and planning at the state or tribal level.

Overview of semi-structured interviews

Table B.2. Descriptions of key personnel who participated in semi-structured interviews

Group	Description of duties
State agency personnel	
Forestry division leaders	Oversee implementation of agency level mission including the implementation of legislative and/or executive directives. Development and implementation of forest management goals and climate action plans. Provide direction for forest restoration, forestry assistance and landowner engagement programs.
Forest resource specialists, biometricians, and forest planning specialists	Oversee statewide forest planning, inventorying, and analyses of forests and forest resources. Provide technical assistance related to commercial and small holder forest landowners. Development management strategies for state managed lands. Coordinate with planning and implementation of climate action plans.
Climate and adaptation policy specialists	Analyze legislative and regulatory proposals, develop climate policy strategies, and lead strategic thinking related to climate policies. Prepare strategic briefs and documentations about emerging trends to provide technical assistance for both internal agencies and legislative climate policy.
Wood utilization and marketing specialists	Maintains working relationships with forest products industry providing technical assistance. Aids in coordination of timber harvest and production surveys.
Urban forest specialists	Provide technical assistance for the development of urban forest planning. Development of outreach materials and programs about urban forests. Fostering urban wood reuse initiatives.
Non-state agency personnel	
Climate scientists (academia, federal agencies)	Conduct applied research related to forest carbon science, forest health, silviculture, carbon accounting, and various ecosystem processes. Develop of forest carbon tools, models, and guidelines to aid in the quantification of forest carbon stocks, fluxes, and other GHG emissions. Development and implementation of forest inventories for GHG emission reporting.
NGO personnel	Third party verification of forest carbon offset projects, development of forest carbon offset projects and accounting protocols. Third party auditing of forest certification and provision other forestry related consulting services.
Forestry consultants	Provides technical assistance and consulting services to private landowners, Develop individual forest management plans.

Forest agency personnel – Interview protocol:

1. Could you briefly introduce yourself by stating name, title, and roles/responsibilities within your organization?

2. Could you please describe any timber allocation models or timber supply models utilized by your state in planning?

3. Has your agency or state ever conducted any type of forest carbon accounting exercise, either in-agency or with external partners?

4. Has your agency or state done any type of data collection on or analysis of harvested wood products outside of TPO surveys and reports, either in-agency or with external partners?

5. Has your agency or state ever conducted any type of forest carbon modeling exercise to simulate or project future forest sector emissions including any type of scenario assessment of future management practices on forest sector emissions, either in-agency or with external partners?

6. Within your agency, can you briefly describe current capacity and constraints to conducting both forest carbon accounting and forest carbon modeling exercises?

7. In our experience, we have found that some prefer to hire consultants to conduct carbon modeling exercises for a variety of reasons including expertise and agency constraints as well as science communication and credibility. Do you have (or do you expect your agency would have) a preference to conduct such exercises in-house or hire out to consultants? Why?

8. What type of modeling exercise would be most beneficial to your state's and/or agency's goals? What type of results would be most useful? Why?

9. Regarding carbon modeling, what are some of the most important knowledge sets that current and/or future staff will need in the future? Is there a want and/or desire for

trainings/materials around these knowledge sets? If so, what is the preferred way to increase agency capacity?

10. Is there or has there ever been a task force, working group, committee etc. at the state level exploring carbon (may include those related to economic, social, political analyses; emissions targets; other carbon)? What motivated that?

11. What policies, programs, or incentive structures (if any) exist that include goals for increasing forest carbon (and for what ownerships or geographies might those cover)?

12. Does your state have an interest in bolstering participation with carbon markets on public or private lands?

13. Does your state have interest in developing or incentivizing new forest commodities?

14. Is there anything else that you would like to share or discuss?

15. Do you have any questions for me?

APPENDIX C: DETAILS ON MODELING APPROACH AND PARAMETERS

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

The CBM-CFS3 is a landscape-level model for forest ecosystem carbon dynamics to assess the carbon stocks and changes in carbon stocks. Developed for operational scale, the model can also be used down to the stand level to assess both past changes and evaluate future changes seamlessly. The CBM-CFS3 accounts for carbon stocks and stock changes in tree biomass and dead organic matter (DOM) represented in **Figure C.1**. The CBM-CFS is a growth and yield based ecosystem C model that predicts C stocks and stock changes in 10 biomass pools using user provided volume to age relationships and volume to biomass conversions. In additional to the 10 biomass pools, the model also estimates 11 DOM pools (including woody litter, soil organic horizon, and mineral soils) as well as carbon dioxide (CO_2), methane (CH_4), carbon monoxide (CO), and nitrous oxide (N_2O) from combustion process caused by wildfires or prescribed burns. Emissions can be easily reported in terms of CO_2 equivalent (CO_2e). **Table C.1** provides an overview of biomass and DOM pools represented by the CBM-CFS3 while **Table C.2** provides an overview of fluxes and ecosystem transfers estimated by the CBM-CFS3.

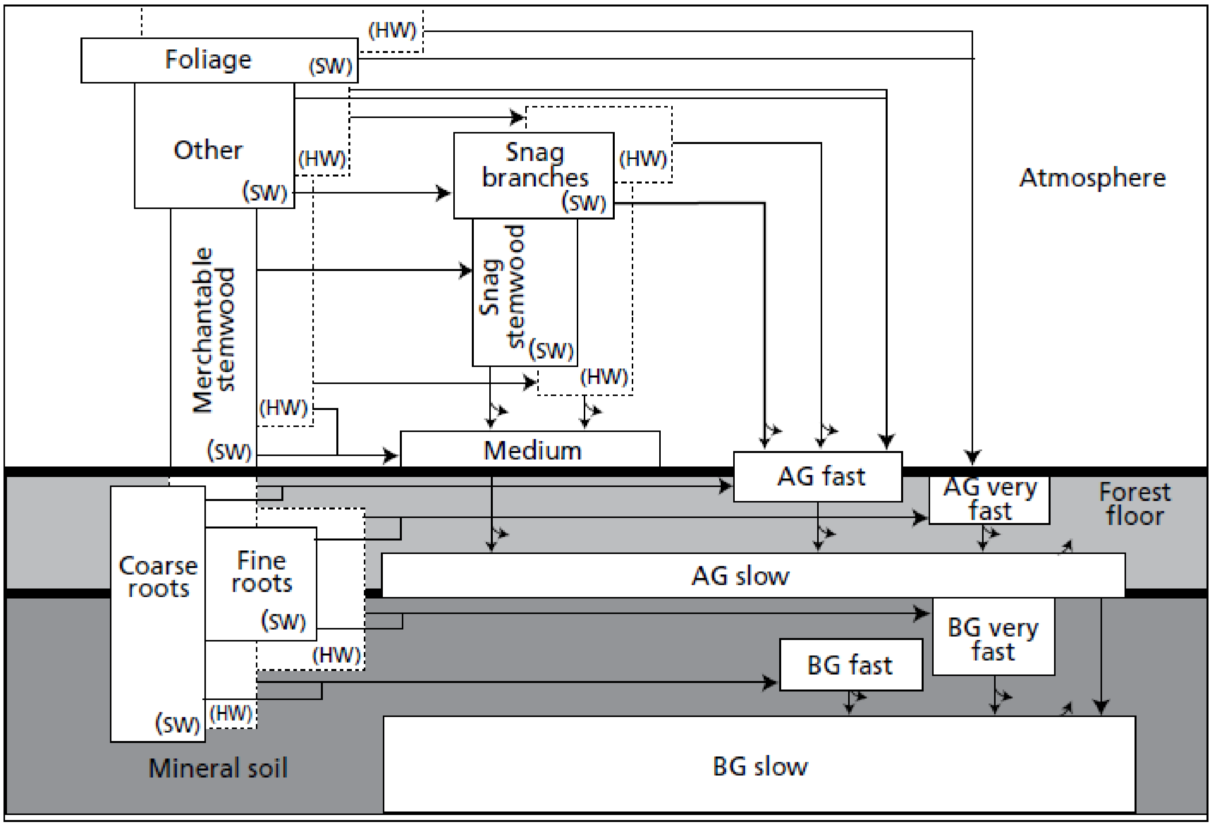

Figure C.1. The Carbon pool structure of the CBM-CFS3. “Very fast,” “fast,” “medium,” and “slow” refer to the relative decay rates for the pools. Curved arrows represent transfers of carbon to the atmosphere, and straight arrows represent transfers from one pool to another. SW = softwood, HW = hardwood, AG = aboveground, BG = belowground. Used with permission from Kull et al, (2019)

Table C.1. Ecosystem carbon pools represented by the Carbon Budget Model of the Canadian Forest Sector (CBM-CFS3) and brief descriptions of the biomass, dead organic matter (DOM) and soil C contained in these pools

CBM-CFS3 pool	Description
Total Ecosystem	Carbon in biomass and DOM pools
Aboveground Biomass	Carbon in all aboveground biomass pools
Belowground Biomass	Carbon in all belowground biomass pools (coarse plus fine roots)
Aboveground DOM	Carbon in DOM pools above the mineral soil
Belowground DOM	Carbon in DOM pools in the mineral soil
Deadwood	Carbon in belowground fast, medium, softwood, and hardwood stem snag, and soft and hardwood branch snag DOM pools
Litter	Carbon in very fast aboveground, fast aboveground, and slow aboveground DOM pools
Soil C	Carbon in very fast belowground, slow belowground, and black carbon DOM pools
Merchantable C	Carbon in the merchantable portion of softwood and hardwood stem wood and stem bark (excluding tops and stumps)
Foliage C	Carbon in softwood and hardwood live foliage
Other C	Carbon in softwood and hardwood nonmerchantable stem wood and bark, and both merchantable and nonmerchantable branches, tops, stumps, and their bark
Coarse Root C	Carbon in softwood and hardwood coarse live roots (≥5 mm in diameter)
Fine Root C	Carbon in softwood and hardwood fine live roots (<5 mm in diameter)
Stem Snag C	Carbon in DOM with input from the Merchantable biomass pool includes dead standing stemwood of merchantable size including bark; default decay rate is half the default decay rate for the medium pool to the stem snag pool
Branch Snag C	Carbon in DOM with input from the Other biomass pool includes dead stand branches, dead tops and stumps of merchantable size trees, and dead non-merchantable size trees, including bark; default decay rate is half the default decay rate for the fast pool to the branch snag pool
Very Fast C Aboveground	Carbon in DOM with input from foliage biomass and fine roots in the forest floor (the L horizon[1], consisting of foliar litter and dead fine roots <5 mm in diameter); very fast turnover rate
Very Fast C Belowground	Carbon in DOM with input from fine root biomass in the mineral soil (Dead fine roots in the mineral soil, <5 mm in diameter); very fast turnover rate
Fast C Aboveground	Carbon in DOM with input from branches, tops, stumps, and sub-merchantable trees (Fine and small woody debris and dead coarse roots in the forest floor, approximately ≥5 and <75 mm diameter); fast turnover rate
Fast C Belowground	Carbon in DOM with input from coarse roots (Dead coarse roots in the mineral soil, ≥5 mm in diameter); fast turnover rate
Medium C	Carbon in DOM with input from merchantable stemwood and/or stem snags (Coarse woody debris on the ground; medium turnover rate
Slow C Aboveground	Carbon in DOM with input from Aboveground Very Fast, Fast, and Medium DOM pools (The F, H, and O horizons[1]); slow turnover rate
Slow C Belowground	Carbon in DOM with input from Belowground Very Fast and Fast DOM pools (Humified organic matter in the mineral soil); slow turnover rate

[1]Soil Classification Working Group (1998)

Table C.2. Ecosystem carbon fluxes represented by the Carbon Budget Model of the Canadian Forest Sector (CBM-CFS3)

Category	CBM-CFS3 flux or ecosystem transfer	Descriptions
Ecosystem Transfers	Net primary production (NPP)	Sum of all bomas carbon production during a year
	Litterfall	Total litterfall minus loss of litter carbon due to decomposition
	Net growth	Net biomass increment before losses from disturbances
	Net ecosystem production (NEP)	NPP minus all losses of carbon due to decomposition
	Disturbance releases	Sum of all carbon released to the atmosphere due to decomposition and excluding direct losses from disturbance
	Net biome production (NBP)	NEP minus losses of carbon due to harvesting and disturbance
	Disturbance transfers	Carbon transferred to the forest product sector from disturbances such as LUC, harvests, or cuttings
	Biomass to soil from disturbance	Total transfer of carbon from all biomass pools to all DOM pools due disturbance
	Delta total DOM	Change in DOM carbon stocks
	Delta total biomass	Change in Biomass carbon stocks
Biomass turnover	Total biomass to soil	Sum of all Biomass turnover processes
	Merchantable C to soil	Transfer of carbon from Merchantable pools to DOM pools
	Foliage C to soil	Transfer of carbon from Foliage pools to DOM pools
	Other C to soil	Transfer of carbon from Other pools to DOM pools
	Coarse root C to soil	Transfer of carbon from Coarse root pools to DOM pools
	Fine root C to soil	Transfer of carbon from Fine root pools to DOMpools
Heterotrophic respiration (decay)	Heterotrophic respiration (decay)	Sum of all decay processes
	Very fast aboveground	Transfer of carbon from the Aboveground Very Fast DOM pool to the atmosphere
	Fast aboveground	Transfer of carbon from the Aboveground Fast DOM pool to the atmosphere
	Slow aboveground	Transfer of carbon from the Aboveground Slow DOM pool to the atmosphere
	Medium	Transfer of carbon from the Medium DOM pool to the atmosphere
	Very fast belowground	Transfer of carbon from the Belowground Very Fast DOM pool to the atmosphere
	Fast belowground	Transfer of carbon from the Belowground Fast DOM pool to the atmosphere
	Slow belowground	Transfer of carbon from the Belowground Slow DOM pool to the atmosphere
	Stem Snag	Transfer of carbon from the Stem pool to the atmosphere
	Branch Snag	Transfer of carbon from the Branch pool to the atmosphere

CBM-CFS3 Parameterization, activity data, and data inputs

We employed a spatially-referenced IPCC compliant approach to simulate past and future forest carbon dynamics with the CBM-CFS3 modeling framework. The modeling framework represents forested landscape spatially by assigning each stand a series of forest attributes, called classifiers, derived from the forest inventory (**Table C.3**). The CBM-CFS3 is an empirically driven growth-yield ecosystem C model where forest growth is predicted using mean annual increment (MAI) of tree volume determined by stand age and forest attributes. As the simulations progress, carbon is transferred from biomass pools to dead organic matter pools by both annual forest processes such as litterfall and user defined disturbance data. Disturbance even schedules including harvest, land-use change, and natural disturbances are user defined where users create transitions rules to define post-disturbance dynamics. **Figure C.2** provides a conceptual diagram of the causal-flow of the modeling process showing data inputs and model parameterization, the monte carlo simulations, post simulation error propagation, and random forest model.

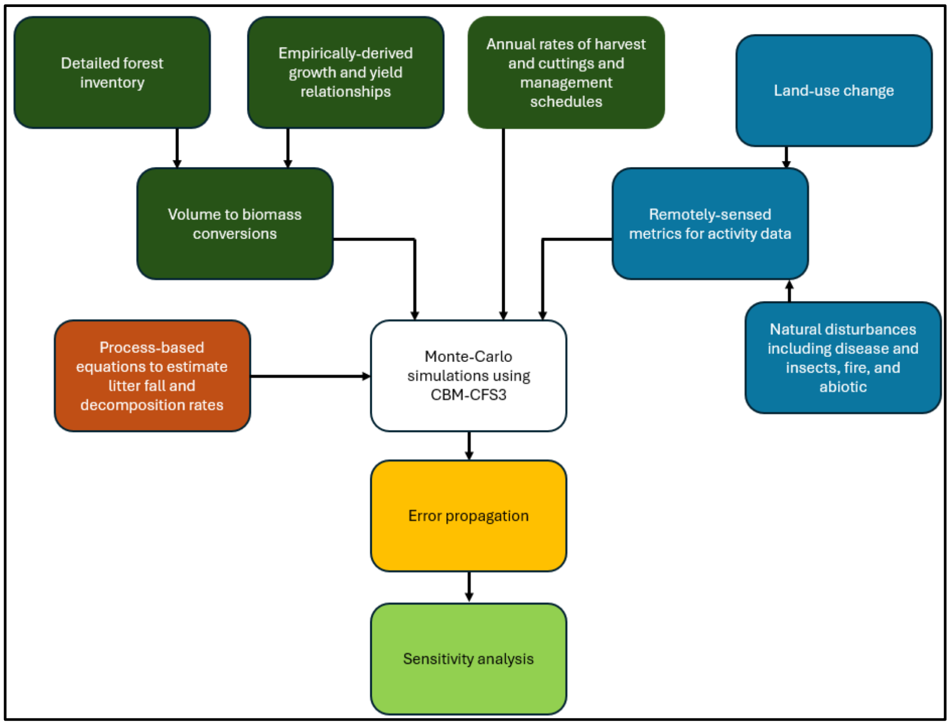

Figure C.2. Causal-loop diagram showing modeling flow outlining steps for data acquisition and modeling processes

Table C.3. List and descriptions of classifiers for the forest inventory

Classifier	Description	Values
STATE_UNIT	FIA condition code to identify FIA survey unit (groupings of counties within each state)	24_2 Maryland: North Central 24_3 Maryland Southern 24_4 Maryland: Lower Eastern Shore 25_5 Maryland: Western
OWNGRPCD	FIA condition code to delineate stand ownership	10 USFS 20 Other Federal 30 State and Local Government 40 Private and Native American
RESERVCD	FIA condition code to denote reserves tatus for public lands, where reserved land is permanently prohibited from being managed for wood products; however, logging may occur to meet other management objectives.	0 Not reserved 1 Reserved
TYPGRPCD	FIA reference code indicating forest type group	0 Nonforest 100 White / red / jack pine group 120 Spruce / fir group 160 Loblolly / shortleaf pine group 170 Other eastern softwoods group 200 Douglas-fir group 260 Fir / spruce / mountain hemlock group 380 Exotic softwoods group 390 Other softwoods group 400 Oak / pine group 500 Oak / hickory group 600 Oak / gum / cypress group 700 Elm / ash / cottonwood group 800 Maple / beech / birch group 900 Aspen / birch group 960 Other hardwoods group 990 Exotic hardwoods group 900 Nonstocked
ALSTKCD	FIA condition code indicating stocking code for all live trees including seedlings	1 Overstocked (100+%) 2 Fully stocked (60-99%) 3 Medium stocked (35-59%) 4 Poorly stocked (10-34%) 5 Non-stocked (0-9%)
THINCD	Binary code to denote whether a stand has undergone a thinning treatment to signal transition to post-thinning yield curve	0 Stand has not been previously thinned 1 Stand has been previously thinned

Activity data

To parameterize the CBM-CFS3 framework, we utilized longer-term averaged activity data from 2007-2019 to quantify harvest removals, LUC, and other natural disturbances including wildfire, prescribed fire, disease and insect outbreaks, and other abiotic disturbances that affect forest C cycling. Model simulations were run from 2007-2050 where the years 2007-2019 were parameterized with historical activity data and longer-term averages were utilized to forecast model simulations until the year 2050. To provide seamless transition between past disturbances and future projects, we started with a forest inventory estimated in 2020 and 'rollbacked' the inventory utilizing the probability distribution of stand-replacing disturbances to estimate a new inventory for year 2007. This rollback period was utilized to better constrain and initialize DOM C and Soil C dynamics and stocks for model projections (Smyth et al, 2017). Estimates of merchantable volume and corresponding biomass from FIADB were used to calibrate model allometric volume-to-biomass assumptions to better reflect forest and growth conditions in Maryland.

The first primary input of the CBM-CFS3 modeling framework is a detailed forest inventory derived from the US Forest Service's Forest Inventory and Analysis Database (FIADB) which was access through the FIA DataMart (USDA Forest Service, 2019) using the rFIA package (Stanke et al, 2020) in the R programming environment (R Core Team, 2020). Methods from Bechtold and Patterson (2005) and Pugh et al, (2018) were used to estimate the inventory that delineates forest stands by attributes such as forest type, stocking class, ownership, age, and region. The second key input is volume-age curves used to predict merchantable volume which are then converted to biomass utilizing allometric equations (Boudewyn et al, 2007). These growth-yield curves are linked explicitly to the aforementioned forest inventory allowing for landscape scale C stock estimation for each unique combination of forest type and stocking class represented in the forest inventory. Growth-yield relationships were estimated using a Gompertz growth curve (eq. 1) which assumes non-asymptotic symmetry (Fekedulegn et al, 1999).

$$y(t) = \alpha \exp\left(-\beta \exp(-k^{t}\right) \qquad \text{(C1)}$$

Where, α is the upper asymptote, β is the growth displacement, and k is the growth rate or slope at time t.

Data used to describe the location and quantity of forest harvest or cuttings, LUC, fire, and other natural disturbances are the final key inputs. Longer term averages from 2007-2020 were utilized to forecast the model until 2050 from the projection point of 2020. Historical harvest allotments for the model rollback period were estimated using FIADB data from 2007-2019 and methods from Bechtold and Patterson (2005) and described in more detail in Papa et al, 2023. Removals were estimated in merchantable volume and were converted to carbon using methodologies and specific gravities reported by Smith et al, (2006).

The national Insect and Disease Detection survey (USDA Forest Service, 2020) was used to estimate defoliating and mortality events. Wind disturbance was estimated using the LANDIFRE Historic Disturbance dataset (USGS, 2016). Wildfires were also derived from the LANDFIRE Historic dataset and validated through tabular data provided by the Maryland Department of Natural Resources (MDNR). Annual rates of deforestation and afforestation were estimated by overlaying the National Land Cover Database (NLCD, Wickham et al, 2021) with a forestland ownership dataset (Sass et al, 2020) and a national geodatabase of protected areas (USGS, 2018) Individual disturbance matrices were developed for both defoliating and mortality events by wood type (i.e., hardwood versus softwood) caused by disease and insects outbreaks based off an extensive literature review to assess the impacts of and more accurately capture post disturbance dynamics understanding that in temperate mid-Atlantic forests, disease and insect pathogens are primarily host specific. Disturbance and post-disturbance dynamics were validated heuristically with direct input from experts within the Maryland Department Natural Resources.

Volume to biomass conversions

To convert the growth-yield curves represented as a volume to biomass, the CBM-CFS3 utilizes allometric equations to predict wood volume-to-biomass (Boudewyn et al., 2007). Additionally, volume-to-biomass relationships account for the non-merchantable portions of trees (tops and limbs, stumps, bark, and foliage). The allometric equations utilized are specific to forest type group and environmental conditions. To account for differences in growth form and volume-to-biomass relationships, we augmented existing default allometric equations to better represent these relations for Eastern US growing conditions. To do so, we estimated volume and biomass values estimated from the FIADB (USDA Forest Service 2019) and related them to model coefficients for the following equation:

$$b_m = a\ x\ volume^b \tag{C2}$$

where b_m is total biomass in metric tons per hectare, *volume* is merchantable volume (defined as stems with at least 5-inch DBH and one 8-foot log) in cubic meters per hectare, and *a* and b are non-linear model parameters fit separately to ecozone and leading tree species. Using FIA derived inputs by forest type group for b_m and *volume*, we recalibrated the allometric equation above using new coefficients for each forest type group in Maryland.

Description of forest disturbances

Disturbance name, intensity and description for disturbance matrix events utilized and parameterized in the CBM-CFS3 modeling framework (**Table C.4**). When default disturbances matrices were insufficient to capture dynamics, new disturbance matrices and transition rules were created with consultation with state partners.

Table C.4. Definition and description of disturbances

Disturbance Category	Disturbance Name	Intensity (averaged)	Description
Harvest	Clearcut	90% volumetric removal	A silvicultural method used to regenerate a stand by the removal of most or all woody vegetation during harvest creating a completely open area leading to the establishment of an even-aged stand. Regeneration can be from natural seeding from adjacent stands or from trees cut in the harvest operation. Regeneration is established during or following stand removal.
	Seed tree cut	70% volumetric removal	A silvicultural method designed to bring about reproduction by leaving enough large mature trees, singly or in groups, to naturally seed the area with adequate stocking of desired species. Varies from shelterwood cuts such that the residual stocking is not sufficient to protect, modify, or shelter the site in a significant way. Mature trees can be later removed in an overstory removal cut or retained indefinitely.
	Shelterwood cut	50% volumetric removal	A silvicultural method used to regenerate a stand by manipulating the overstory and understory to create conditions favorable for the establishment and survival of desirable tree species. The method is designed to regenerate an even-aged stand and normally involves removal of most of the overstory, in two or more cuttings, after the new stand is established. The overstory serves to modify understory conditions, create a favorable environment for reproduction, and provide a seed source. A secondary function of the overstory is to allow further development of quality overstory stems during seedling establishment to increase the efficient use of growing stock. The system is characterized by a preparatory cut (optional), seeding cut(s), and overstory removal. The most vigorous trees are normally retained and less vigorous trees removed.
	Group selection / overstory removal	30% volumetric removal	Silvicultural methods in which the stand overstory is removed in one cut to provide release of established seedlings and saplings. Group selection refers to a silvicultural method designed to regenerate and maintain uneven-aged stands by removing some trees at regular intervals. Overstory removal results in an even-aged stand structure as opposed to uneven-aged. It differs from the clearcut and the coppice regeneration methods in that seedling and sapling regeneration is established prior to overstory removal. It differs from the shelterwood and seed tree methods in that no manipulation of the overstory is needed to establish regeneration.
	Diameter-limit-cut	70% volumetric removal	An unsustainable cutting method that selectively removes or cuts the most valuable and highest quality trees leaving behind lower value and lower quality trees. Landowners in the past have been economically incentivize to conduct unsustainable diameter-limit-cuts, also known as high-grading, to maximize short term economic yields, but reducing overall structure and vigor of the remnant stand.

Table C.4. (cont'd)

	Thinning	30% volumetric removal	Thinning is a cultural treatment conducted in stands past the sapling stage to reduce stand density, primarily to improve tree growth, enhance tree health, or recover potential mortality. It entails the removal of trees to temporarily reduce stocking to concentrate growth on the more desirable trees. Normal thinning does not significantly alter the gross production of wood volume. Thinning does impact stand growth, development, and structure. It provides the main method, implemented between regeneration and final harvest, to increase the economic productivity of stands. Individual thinnings can be commercial or non-commercial (TSI), depending on landowner objectives and local markets for materials cut in the thinning operation. Regeneration is not an objective of thinning; overstory gaps are small and should close rapidly
Land-use change (LUC)	Afforestation		Planting of trees on non-forest lands converting to a forest land-use designation
	Deforestation		The permanent conversion of forest lands to non-forest categories including agriculture or settlements
Defoliator	Insect - Defoliation (SW)		Low severity defoliation event affecting conifer species (~10 defoliation)
	Insect - Defoliation (HW)		Low severity defoliation event affecting broadleaf species (~10 defoliation)
Mortality	Insect - Mortality (SW)		Low severity mortality event affecting conifer species (~10% mortality)
	Insect - Mortality (HW)		Low severity mortality event affecting broadleaf species (~10% mortality)
Disease	Disease		Moderate severity mortality and defoliation event affecting both conifer and broadleaf species (~10% mortality and ~10% defoliation)
Abiotic	Abiotic		Low severity mortality and defoliation even caused by windthrow or other abiotic disturbances (~10% mortality and ~10% defoliation)
Fire	Prescribed fire		Low severity fire that consumes ~60% of litter, ~36% of small deadwood and ~12% of coarser deadwood materials. Also consumes ~40% of nonmerchantable stemwood, branches, foliage, and roots.
	Low-intensity wildfire		Low severity fire that consumes deadwood and litter pools with minimal mortality

Default model parameters

Default parameters for proportions of stumps, tops, and merchantable stems for softwood and hardwood species (**Table C.5**) and default DOM turnover parameters and values (**Table C.6**).

Table C.5. Merchantable softwood and hardwood proportions used in the CBM-CFS3

			Softwood			Hardwood		
Stump height (cm)	Top Diameter (cm)	Minimum DBH (cm)	% tops	% stumps	% merchantable stem	% tops	% stumps	% merchantable stem
30	7	9	2.132	5.390	92.478	3.477	5.52	91.003

Table C.6. CBM-CFS3 default dead organic matter (DOM) turnover parameters and values

Average; Slow DOM Pool	**0**
Average; Decay Multiplier	1
Average; Stand-Replacing Disturbance Interval (years)	125
Turnover Rate; Softwood Branch	0.04
Turnover Rate; Hardwood Branch	0.04
Turnover Rate; Stem Annual	0.0067
Snag Fall Rate; Softwood Stem	0.032
Snag Fall Rate; Softwood Branch	0.1
Snag Fall Rate; Hardwood Stem	0.032
Snag Fall Rate; Hardwood Branch	0.1
Foliage Fall Rate; Softwood	0.15
Foliage Fall Rate; Hardwood	0.95

Sources of model uncertainty

There is additional uncertainty associated with the modeling framework attributable to the selection of stands for disturbance across geographies and spatial boundaries. However, the specific stands affected are not known. The CBM-CFS3 framework utilizes and applies rule-based decision-making used to select specific forest records to be affected by an individual disturbance per year (Kurz et al, 2009). For disturbances such as harvest, disease and insect outbreaks, and LUC, forest type specific information was used to inform targeted records, but spatial boundaries were not. Fire and abiotic disturbances, however, were targeted completely at random to capture the stochastic nature of such events more thoroughly. This resulting approach increases the uncertainty around the effects of disturbance on model results as each execution per simulation differs in the records affected caused by the random selection of stands. The disturbance data formatted as model inputs and are entirely user-defined.

Growth-yield curves, volume-to-biomass equations, and the forest inventory primarily influence model estimates of net growth portion of Net Primary Productivity (NPP, i.e., growth minus autotrophic respiration). The CMB-CFS3 estimate NPP as the sum of net biomass increment and replacement of biomass turnover (Kurz et al, 2013). While uncertainty estimates can be estimated for both the forest inventory and yield curves, we chose not to introduce this uncertainty within our analysis to isolate the effects of disturbance inputs on model parameters and minimize the uncertainty within the modeled results. **Table C.8.** provides a list of factors, parameters, and model structures that affect model uncertainty in the CBM-CFS3 framework.

Table C.7. Summary of model parameters affecting uncertainty (U_i). This study focuses solely on disturbance targets as a source of uncertainty for carbon stocks and fluxes. Summarized from Metsaranta et al, (2017), Kull et al, (2019), Kurz et al, (2009), Kurz et al, (2013), and Kurz et al, (2018)

Disturbances	Description	Additional methodological detail
Random stand selection	The random seed value for sorting records prior to selection stands for disturbance	Disturbance events specified by the user periodically affect certain eligible stands, but eligible stands are compiled and sorted according to user-specified rules. Eligible forest records can only be affected by one disturbance event per simulation timestep (Kull et al, 2019)
DOM C stock initialization	Historic and last disturbance severity and frequency during model initialization to populate soil and DOM carbon pools	Default parameters based on initial nonforest soil type (Janzen et al, 1997) to initialize soil carbon pools during model spin-up period (Kurz and Apps, 1996, Kurz et al, 2009, and Li et al, 2003)
Biomass increments	Mean annual increment of merchantable volume predicted by stand age	Empirical growth-yield models inherently provide uncertainty metrics. However, the CBM-CFS3 does not stochastically model stand dynamics. Additionally, stand age can be an inaccurate predictor of volume (Stokland, 2021, Brunner, 2021) especially in stands with multiple age cohorts

Table C.7. (cont'd)

Allometric equations / wood type / bark fractions	Models used to predict tree volume-to-biomass relationships. Equations used to convert aboveground biomass to belowground biomass by components. Wood densities used to describe hardwood and softwood forests, and the ratio used to estimate bark fraction of tree bole and branches	Utilized generalized equations for forest type groups and standard bark fractions found in Boudewyn et al, 2007 and Li et al, 2003. Where, wood density (Pretzsch, 2019) and bark fraction (Jenkins et al, 2003) have been shown to significantly affect allometry in mixed stands
Biomass turnover / DOM C modelling parameters	Parameters used to simulate biomass turnover and DOM C dynamics dependent on ecological parameters determined by local conditions.	Ecological parameters including soil type, precipitation, and temperature control and impact of turnover, decay, and initialization throughout the model (Kull et al, 2019)
C fraction	Model assumes a 0.5 ratio of biomass to carbon	0.5 is commonly deployed to convert dry biomass to carbon. However, recent estimates imply that C concentrations of woody tissues vary from 18-75% dependent upon tissue type, growing conditions, wood density, and species (Doraisami et al, 2022, Martin et al, 2021)
Inventory	The area, age distribution, and productivity class for forest records used to classify forestlands	Materials and methods describes inventory estimation. Longer description of methods can be found in Papa et al, 2023
Disturbance targets*	The amount, severity, and frequency of the targets used to simulate forest management activities and natural disturbances including harvests, cuttings, land-use change, wildfire, prescribe fires, defoliating events, mortality events, and windthrow	Materials and methods describe uncertainty of disturbance targets. **Table 3** gives probability distribution of harvest removals and areas disturbed. Papa et al, 2023 provides longer detailed methodologies of disturbance estimation and definitions. Longer descriptions of disturbances can also be found in **Additional materials 1**.
Post-disturbance assumptions	Assumptions regarding regeneration, stand growth, and recovery following disturbance	User defined transition rules for post-disturbance dynamics of stands affected by disturbance events (Kull et al, 2019)

*Only source of uncertainty considered in this study

APPENDIX D: DETAILS ON RANDOM FOREST MODEL

Hyperparameter and tuning for random forest model

Table D.1. Hyperparameter tuning for turnover. Defined as the number of randomly drawn candidate variables out of which eat split is selected when growing a tree. For each model tuning the model with the lowest RMSE and MAE is bolded

mtry	*RMSE*	*R-squared*	*MAE*
2	173.0727	0.891	134.428
5	**168.9187**	**0.875**	**129.724**
9	178.4722	0.850	137.852

Table D.2. Hyperparameter tuning for decay. Defined as the number of randomly drawn candidate variables out of which eat split is selected when growing a tree. For each model tuning the model with the lowest RMSE and MAE is bolded

mtry	*RMSE*	*R-squared*	*MAE*
2	141.959	0.911	102.243
3	**133.527**	**0.917**	**96.132**
5	133.537	0.908	97.338

Table D.3. Hyperparameter tuning for biomass to soil from disturbance. Defined as the number of randomly drawn candidate variables out of which eat split is selected when growing a tree. For each model tuning the model with the lowest RMSE and MAE is bolded

mtry	*RMSE*	*R-squared*	*MAE*
2	212.490	0.786	157.424
4	179.514	0.806	134.149
7	**173.834**	**0.785**	**133.136**

Table D.4. Hyperparameter tuning for total DOM emissions. Defined as the number of randomly drawn candidate variables out of which eat split is selected when growing a tree. For each model tuning the model with the lowest RMSE and MAE is bolded

mtry	*RMSE*	*R-squared*	*MAE*
2	307.283	0.155	239.300
4	**305.635**	**0.169**	**237.763**
7	308.796	0.165	241.008

Table D.5. Hyperparameter tuning for total biomass emissions. Defined as the number of randomly drawn candidate variables out of which eat split is selected when growing a tree. For each model tuning the model with the lowest RMSE and MAE is bolded

mtry	*RMSE*	*R-squared*	*MAE*
2	368.524	0.351	284.432
4	**353.616**	**0.386**	**276.449**
7	355.418	0.378	279.559

Table D.6. Hyperparameter tuning for net biome productivity. Defined as the number of randomly drawn candidate variables out of which eat split is selected when growing a tree. For each model tuning the model with the lowest RMSE and MAE is bolded

mtry	*RMSE*	*R-squared*	*MAE*
2	386.119	0.278	315.216
4	**372.186**	**0.317**	**306.121**
7	373.240	0.327	304.779