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Specifying Forest Sector Models for Forest Carbon Projections

David N. Wear[1] and John W. Coulston[2]

[1] *USDA Forest Service, Southern Research Station, Research Triangle Park, NC, USA; dwear@usda.gov*
[2] *USDA Forest Service, Southern Research Station, Blacksburg, VA, USA; jcoulston@usda.gov*

ABSTRACT

Forest sector models merge models of timber inputs and final wood products markets with biophysical models of forest dynamics to project forest futures. Comprehensive treatment of biophysical dynamics is required to address the product detail of timber markets and to track changes in forest carbon. We examine assumptions for existing Forest Inventory Projection Models and empirically examine the implications for forest carbon projections. We compare model results with observations from remeasured forest inventories in the eastern United States. Results show forest carbon projections are sensitive to non-harvest disturbances, ownership, and stand-origin. Additionally, bias can arise when forest carbon stocks are estimated using correlations between average stock density and biomass aggregates. Current forest inventories provide a dataset of consistently remeasured forest plot records that will increasingly support a strong empirical foundation for Forest Inventory Projection Models.

Keywords: Forest production, Age transitions, Greenhouse gas (GHG), Carbon sequestration, Forest Inventory and Analysis (FIA)

1 Introduction

Forest sector models combine descriptions of economic behavior including timber demand with a biological/management model of forest inventory dynamics to specify intertemporal timber supply relationships. Forest inventory models

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account for biological growth, land use changes, timber harvesting and other forms of mortality to project change in a region's forest biomass to define timber supply in future periods. Because forest carbon stocks are correlated with forest biomass, forest sector models have been modified to project forest carbon (C) stocks and to study policy options for enhancing C sequestration to mitigate climate change (Alig *et al.*, 2010; Nepal *et al.*, 2012; Tian *et al.*, 2018). Shifting the focus from wood product and timber market projections to forest C projections implies a different approach to model validation/verification. Carbon projections are directly linked to the level of detail and specification of forest dynamics. For long-term projections, misspecification can lead to compounding errors. Minimizing misspecification in the forest dynamics components of C projection models prior to incorporating modeled climate change and market mechanisms is imperative for avoiding biased projections. The objectives of this paper are to (1) explore the common assumptions of forest inventory models used for forest sector analysis and their potential to introduce bias into C projections and (2) identify specifications for these models that might produce the most accurate biomass and forest C projections.

The modern forest sector model derives from the work of McKillop (1967). Ten years later, Adams (1977) developed the intertemporal logic for modern forest sector models by linking endogenous timber harvests to a forest growth framework to support long term policy analysis and projections of market activity. Adams adopted a stand-table projection method (TRAS, Larson and Goforth, 1974) to link forest growth and harvests to changes in biomass inventory. The subsequent Timber Assessment Market Model (TAMM, Adams and Haynes, 1980) adopted a spatial optimization approach (Haynes, 1975) and replaced the forest inventory model with a variant of the Timber Resource Inventory Model (TRIM, Tedder *et al.*, 1987) which was later modified to define the Aggregate Timberland Assessment System (ATLAS, Mills and Haynes, 2007). For TAMM and many subsequent forest sector models (e.g., FASOM, Adams *et al.*, 1996; Guo and Gong, 2017; Latta *et al.*, 2018; Pohjola *et al.*, 2018), the logic of using a forest inventory projection model broadly organized by the age structure and growth dynamics of forests has been a constant.

Forest inventory projection models (FIPMs) describe the dynamics of forest biomass, generally in terms of the growing stock biomass, to provide a means to position timber supply curves in future periods. Since Adams (1977), timber supply has been defined as a statistical relationship between timber output, timber price, and growing stock inventory level. The economic rationale for the use of the stock variable varies over management contexts (e.g., declining inventories imply increasing scarcity or higher costs in an old-growth mining context, stock levels are positively correlated with production capacity in a renewable forestry context) but expanding inventories are expected to shift supply outward.

Some forest sector models, while adopting the broad logic of biological growth to project stocks, compress the inventory model into a highly aggregate form where exogenous growth rates are applied to total forest biomass at regional or country levels without consideration of the age or other constituent structures of the forest inventory. Most international trade models necessarily adopt this approach because a majority of countries lack the inventory data needed to support detailed constituent analysis (e.g., IIASA GTM: Kallio *et al.*, 1987; GFPM: Buongiorno *et al.*, 2003). An exception among trade models is Sohngen and Mendelsohn (2003) where trade modeling is coupled with inventory projections based on age/forest type dynamics applied to inventory aggregates. Our focus is on understanding the specification of forest inventory models that can account for the changes in forest structure that are essential for linking inventory futures to forest C outcomes.

FIPMs were developed during a period when forest inventory data were scarce and largely inconsistent across regions of the U.S. Early models used information from various and disparate sources including growth and yield models for managed forest stands and incomplete and regionally variable forest inventories. Forest inventory methods and their deployment in the United States have improved substantially over the last two decades and now provide data with enough temporal breath to test the implications of previous modeling assumptions. This paper proceeds with a general description of FIPMs and a set of their common assumptions. We simulate the implications of alternative assumptions for predicting change in forest C taken from re-measured forest inventories in the eastern United States (representing approximately 78% of the U.S. C sink; Wear and Coulston, 2015), examine projections for signs of bias over the re-measurement period, and for out-year projections. An exploration of these alternative assumptions supports recommendations for specifying forest sector models when assessing forest C futures.

2 Generalized Model

FIPMs have been derived from combinations of empirical and mechanistic (logic or rule based) approaches. However, most models follow the general approach described below with modifications to address data gaps or novel conditions. An existing forest inventory can be described in terms of its areal extent as follows:

$$I(Age\ class,\ Forest\ type,\ origin,\ owner\ class,\ slope,\ harvest \ldots) \quad (1)$$

Where I is a multidimensional array of forest area with dimensions defined by the number of categorizing variables or strata. Stratifying variables differ by implementation but all models include age class, which provides a means to simulate intertemporal change. For ease of exposition, combine all categorical variables except age in (1) into a vector X that defines a set of n discrete conditions, so $I(a, X)$ describes the inventory as an $m \times n$ matrix where a represents age class and m is the number of age classes. We can further decompose this inventory into a set of n vectors: $\boldsymbol{a}_k$ defining the age class distribution for each of the n relevant forest conditions defined by the permutations of stratifying variables (indexed by k). Average values for inventory attributes from a measured inventory can be applied to the inventory age class structure defined by I to estimate stock values:

$$\mathbf{B}_t = I_t(a, X) \circ \mathbf{b}(a, X) \tag{2}$$

where $\mathbf{b}$ is the $m \times n$ matrix of areal averages for the variable of interest (e.g., growing stock density or C density), $\circ$ is the Hadamard product obtained by element-wise multiplication, and $\mathbf{B}$ is a matrix of stock values. The total value for the inventory (e.g., growing stock volume or C stock) is defined by summing across all elements of $\mathbf{B}$.

The fundamental elements of an FIPM are (1) an age transition mechanism that changes age distributions through time, (2) a stratification of the inventory through the selection of the X variables, (3) a mechanism for transitioning into and out of strata, for example by land use changes, and (4) assigning inventory values to strata (the $\mathbf{b}(a, X)$ matrices). We examine each element below.

2.1 Age Transitions

Simulating the future state of the inventory involves moving each of the age class vectors through time by applying transitions defined endogenously (aging, harvests, and sometimes investment) or exogenously (fire or other disturbance). Define $\mathbf{T}$ as an $m \times m$ age transition matrix where each element $\mathrm{T_{ij}}$ defines the proportion of forest area in age class i transitioning to age class j and t defines the time increment of the projection so: $\boldsymbol{a}_{j,t+1} = \boldsymbol{a}_{j,t} \cdot \boldsymbol{T}$. The values of the elements of $\mathbf{T}$ depend on a number of factors, including forest disturbances such as harvests, fire, storms, and others, and the value of t, especially relative to the span of the age classes. For example, consider a case where we hold area fixed, allow for no mortality, define the time step t equivalent to the span of age classes, and assign four age classes. $\mathbf{T}$ would be:

$$\mathbf{T} = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 \end{bmatrix} \tag{3}$$

At every time step all forest area progresses to the next age class and forests within the terminal age class are retained forever. With this version of $\mathbf{T}$, after three time steps all forests would be in the terminal age class. Relaxing assumptions changes the structure of $\mathbf{T}$. If we allow for disturbances including harvesting and fire that result in stand regeneration and allow for stochastic elements in forest aging:

$$\mathbf{T} = \begin{bmatrix} 1-t_1 & d_2 & d_3 & d_4 \\ t_1 & 1-t_2-d_2 & 0 & 0 \\ 0 & t_2 & 1-t_3-d_3 & 0 \\ 0 & 0 & t_3 & 1-d_4 \end{bmatrix} \tag{4}$$

where t_i is the proportion of forest of age class i transitioning to age class $i+1$, d_i is the proportion of age class i that experiences a stand-replacing disturbance, and $(1-t_i-d_i)$ is the proportion retained within age class i which could be the result of a non-stand-replacing disturbance. These assumptions are still highly restrictive since observed disturbances shift forest ages in a variety of ways – even increasing average forest age when a suppressed cohort of older trees is released due to disturbance/mortality focused on younger trees that comprise the overstory.

The transition matrix also depends on the treatment of harvest activity and the age allocation of forest area following a harvest. Timber can be harvested using intermediate treatments (i.e., thinning), partial harvests, or clear felling. Clear felling is the simplest treatment to model, but in the eastern U.S. a large majority of harvests (65%) is derived from partial harvests (partial harvest defined as <80% above ground live tree biomass removed). Clearcuts remove all timber and reset the forest age to the first age class (consistent with d_i in Equation 4). FIPMs have adopted a variety of mechanisms for simulating partial harvesting and defining post-harvest ages. For example, the ATLAS system uses a set of rules based on expert opinion to remove a portion of volume from the inventory for partial harvests and reset the age of the treated area to a younger age class (i.e., defines age transitions that are not a part of the first row or the diagonal of $\mathbf{T}$). These kinds of harvest rules can be described using equations to approximate the distribution of partial harvests hp and clearcut harvests hc across age classes. For example consider separate harvest distribution for partial harvests and clearcuts:

$$hp = \begin{bmatrix} 0 & hp_2 & hp_3 & hp_4 \end{bmatrix} \tag{5a}$$

$$hc = \begin{bmatrix} 0 & hc_2 & hc_3 & hc_4 \end{bmatrix} \tag{5b}$$

Where the elements of hp and hc are the proportion of the age class harvested by partial and clearcut approaches respectively. This defines the following transition matrix:

$$\mathbf{T} = \begin{bmatrix} 0 & hc_2 & hc_3 & hc_4 \\ t_1 & hp_2 & hp_3 & 0 \\ 0 & t_2 & 0 & hp_4 \\ 0 & 0 & t_3 & t_4 \end{bmatrix} \tag{6}$$

that assumes that clearcut forests (h_c) are returned to the first age class while partial cuts (h_p) reduce the age by one age class. Here all entries must be non-negative and all columns must sum to one ($t_i = 1 - hc_i - hp_i$) i.e., harvesting cannot remove more than the total area in each age class. The definitions of the hp and hc arrays can be based on empirical measures from a remeasured inventory or based on regional silvicultural prescriptions or expert opinions.

2.2 Inventory Stratification

The transition matrix ($\mathbf{T}$) summarizes the intertemporal dynamics of the forest inventory including aging, harvesting (or other management choices), other disturbances, and noise associated with measurement error. The transition logic is developed to match the information structure defined by the stratified inventory (*I[a,X]*) recalling that a is age and X is a set of stratifying variables. Ideally, X variables define strata with minimal variance for variables of interest (i.e., $b\,(a, X)$ in Equation 2) and with homogenous management approaches (i.e., described by harvest propensities or intensities). Stratification choices generally focus on minimizing within-strata variance of biomass measured as growing stock volume, and consistent harvest intensities (Equation 5). The structure of projection scenarios may define the need for additional stratifying variables, for example analysis of climate change may require stratifying the inventory by climate variables. Stratification decisions are therefore driven by multiple and potentially competing objectives.

Modelers face the challenge of defining strata that are statistically discernable and can support analysis of relevant scenarios. Stratification based on biomass volume suggests using variables that influence forest productivity including site class, forest type group, and soil category. Additionally, the product structure of the model may require separating forests into, for example, hardwood and softwood types. Stratification based on management homogeneity suggests including variables that describe owner objectives or cost structures. Ownership category – for example, public *versus* commercial *versus* family owners – may capture differences in objectives while slope and distance from road can proxy for some operating costs. These variables, taken directly from inventory records, can be augmented with variables from ancillary sources to support scenario analysis, for example, using climate variables assigned to plot locations that can then be linked to alternative climate projections. Management propensities have been shown to vary by socioeconomic context suggesting that inventory be stratified by variables such as population density or personal income. The potential scope of the model can be enhanced by increasing the number of strata (adding stratification variables), but over-stratification can weaken the analysis. As the number of strata increases, the sample size of each stratum declines and the potential for unpopulated (novel) stratum increases.

Early FIPMs were organized by the logic of growth and yield tables that describe merchantable forest biomass as a function of stand age, site productivity, and stand structure. As an example, ATLAS uses this type of logic and variables describing management or silvicultural prescriptions (management intensity class) to stratify the inventory (Mills and Haynes, 2007). Biomass volume densities were estimated using both growth and yield models (e.g., TAUYIELD and DFSIM) and empirical volume estimates from some measured inventories. The choice of strata reflected the questions of the 1980s and 1990s when forest production was shifting from old growth removals to an agricultural approach and timber scarcity was a strong focus. At the time, detailed inventory data were limited and inconsistent across regions (e.g., not covering public lands) and new management approaches (intensive pine plantations) had not been fully deployed so were essentially "novel." Given the paucity of data, simulation models provided the only practical means of providing estimates of future production.

More recent models have started to rely more on empirical estimates from measured inventories. Latta *et al.* (2018) for example, modeled biomass growth rates using FIA plot estimates stratified by ecoprovince, site class, forest type and age. In constructing the USFAS, Wear *et al.*, 2013 use empirical approaches to define strata that produce statistically discernable distributions of volumes across strata. Potential stratifying variables taken from within the inventory (e.g., site class, slope, etc.. . .) and from ancillary variables describing climate conditions, were evaluated using multi-variate regression trees to identify significant stratifying variables and the breakpoints for stratification (i.e., defined the stratifying variables and the number of classes within these variables). Forest age was also used as a stratifying variable within the regression trees and defined breakpoints for age at irregular age intervals, and a transition logic with age steps smaller than most age classes. USFAS's exclusive use of empirical estimates from inventories to stratify and transition the inventory was allowed by the enhanced consistency and intensity of US forest inventories since 2000. The empirical approach generally leads to fewer strata than approaches based on yield tables (Wear *et al.*, 2013).

2.3 Strata Transitions and Land Use

The transition matrix ($\mathbf{T}$) coupled with a stratified inventory ($I(a, X)$) defines intertemporal projections within each inventory stratum. Changes among strata can occur, especially following a disturbance, and need to be addressed within the modeling framework. For example, insect outbreaks may lead to a change in forest type, harvesting of an upland hardwood forest may be followed by a transition to a planted pine forest type, and climate change may lead to a shift in climate "class." These dynamics can be incorporated within the model's transition logic using either rule-based or empirical approaches.

A special case of strata transitions is land use change which defines how land enters or exits the inventory matrix. Rates of land use change are typically defined by exogenous estimates or models (e.g., land use based on National Resource Inventory data, Lubowski *et al.*, 2008) and the treatment of these changes strongly influence estimated changes in forest C (Wear and Coulston, 2015). Since 1982, net changes in forest area in the United States have been small in relative terms but reflect much more substantial gross changes – that is, largely offsetting shifts into and out of forest use. The distribution of these changes across strata determines the amount of biomass and C entering or leaving the forest inventory implying a large range of potential effects. For example, no net change in forest area may involve the conversion of old forests to other uses but offset by the planting of forests on agricultural lands. In this case, no net loss of forests could be consistent with a large reduction in biomass and C stocks in the forest sector and considerable C transfers to and from other land sectors.

2.4 Constructing Inventory Values

Within a forest sector model, FIPMs serve to provide projections of forest biomass which are used to specify future timber supply relationships. In recent applications, they have also provided a mechanism for projecting change in forest C stocks based on the correlation between biomass volume and C stock (e.g., FASOM-GHG, Adams *et al.*, 2009). In this role, the objective is to extend historical C stock estimates derived from a forest inventory in a way that captures the full suite of relevant dynamics. That is, projections of C need to account for more than changes driven by timber market/harvest dynamics to include all relevant disturbances as well as land use changes.

Inventory level estimates of biomass or carbon require a set of stock densities consistent with the inventory stratification. The construction of biomass estimates ($b(a, X)$, Equation 2) from a full forest inventory simply involves defining areal averages of biomass values within each strata of ($I(a, X)$) (e.g., Wear and Coulston, 2015). Early FIPMs defined $I(a, X)$ using inventories but used both growth and yield models and inventory records to estimate $b(a, X)$ (e.g., ATLAS, FASOM-GHG). Alternatively some implementation of FIPMs have defined $b(a, X)$ with estimates of growth from either inventory records or growth and yield models and used growth to increment a separate volume matrix (e.g., Mills, 1989; Latta *et al.*, 2018). Because measured inventory changes are rarely consistent with estimates from growth and yield models parameterized independently (Clutter, 1963; Moser and Hall, 1969), adjustment factors are utilized to force consistency with historical levels of inventory (Mills and Haynes, 2007) and this raises concerns regarding the ability to mirror historical dynamics in projections. However, there should be a logical compatibility between growth and standing inventory (yield) and this compatibility has not been examined within the context of FIPM projections of C.

C stock estimates for an existing forest inventory are constructed by applying predictive models for several C pools to measured inventory variables at the plot level (e.g., forest type, and age) and using ancillary data (e.g., precipitation and temperature). C stock density estimates ($c(a, X)$) can be estimated from a forest inventory by averaging plot values for the total of all C pools within each stratum (which includes age class). This approach provides a direct match between projections and the historical levels of C estimated from the forest inventory. Where forest biomass has been derived from growth and yield models, a simple correlation approach has been applied to estimate forest C stocks from projected forest biomass and forest age. FASOM-GHG, for example, uses a set of conversion factors to translate merchantable volume (output from the growth and yield framework) into total biomass volume and then into live and dead tree C. Understory C and forest floor C are modeled as a fixed proportion of live tree volume and forest age, and soil C as a regression function of forest age using regional equations (Adams *et al.*, 2009). Adjustments to C stocks are driven by harvest activities. The work presented here considers the generalized model and examines the sensitivity of C outcomes given alternative modeling choices.

3 Methods

Our analysis explores modeling choices in four areas: stratification, age transitions, density estimates, and growth and yield compatibility. In particular, we examine four questions:

1. How do varying levels of aggregation defined by stratification strategies (i.e., selection of X variables) affect the accuracy of forest C projections?

2. How do common assumptions about the transition matrix ($\mathbf{T}$) affect the accuracy of forest C projections?

3. Are forest C ($c(a, X)$) and forest biomass ($b(a, X)$) projections highly correlated and what are implications of estimating forest C based on correlative methods?

4. Do growth-based and yield-based approaches provide compatible projections of forest C?

We used the USDA Forest Inventory and Analysis data for the eastern United States to examine these four questions based on 73,937 repeated inventory plot observations that define forest C stocks for beginning (time 1) and ending (time 2) periods (data available at https://apps.fs.usda.gov/fia/

datamart/CSV/datamart_csv.html). These plots were classified as forest land use at both time 1 and time 2 (i.e., land use change is not considered). We compare observed change in the forest C stocks with alternative projections based on (1) eleven alternative stratifications of the inventory, (2) three alternative age transition approaches defined by Equations 3–4, 6, and (3) two alternative models for forest C estimation to address questions 1–3 respectively (Table 1). To address question 4 we develop an alternative model based on observed growth in C stocks from time 1 to time 2 rather than time 1 C stocks.

The accuracy of each stratification was determined by predicting a time 2 forest C stock based on the time 1 inventory using each stratification of the inventory plots (Question 1). The stratification with the smallest time 2 forest C prediction error was then used to compare alternative age transition models (Question 2). To address the third question we applied two approaches to estimating forest C stocks applied to the alternative age transition modeling approaches. In addition to examining the short-term (5-years) error we further examine the variability among approaches in the long-run (50 years).

Alternative stratifications were based on five descriptive variables: Region (1 eastern United States region), forest type group (9 groups), site class (7 classes denoting potential site productivity), owner class (4 ownership classes), and stand origin (planted *vs.* natural regeneration, Table 1). We then constructed six two-variable combinations for the latter four variables.

We used the estimators given by Bechtold and Patterson (2005) to estimate the requisite parameters (**a**, **c**, **dc**, and **T**) where **a** is the forest area by age vector, **c** is the C density by age vector, C stock density change by age vector (**dc**), and $\boldsymbol{\lambda}$ is an age transition matrix with transition probabilities **T**. The total Ŷ for each k age class was estimated by:

$$\hat{Y}_k = A \sum_F W_f \sum_{nf} y_{if} I / n_f \tag{7}$$

where A is the total land area of the population, W_f is the inventory group (f) weight, y_{ih} is the observation for each i plot in each f inventory group, I is an indicator value where $I = 1$ if the observation was in k and zero otherwise, n_f is the number of inventory plots in group f. For forest area, y_{if} is the plot-level percent forest land use and each k element of a is estimated directly from Equation 7. Likewise each element of $\boldsymbol{\lambda}$ is estimated from Equation 7 for each time 1 to time 2 age transition and is the forest area of each transition. To calculate **T** from $\boldsymbol{\lambda}$ each element of $\boldsymbol{\lambda}$ was divided its corresponding column total. For more details on the estimation of $\boldsymbol{\lambda}$ and **T**, we point the interested reader to Coulston *et al.* (2015). For C, y_{if} is the plot-level C stock per unit area of land and each k element of **C** (total C stock by age) was estimated based on Equation 7. The **c** vector is ratio estimate **C**/**a**. In the case of plot-level C stock change $y_{if} = y_{if\ time\ 2} - y_{if\ time\ 1}$ and **dC** was the total stock change for each age class. The **dc** vector was the ratio **dC**/**a**.

Table 1: Description of grouping, age transition approaches, and C expansion ratios examined.

Question 1: Stratification variables for Stock models	**Question 2**: Transition models	**Question 3**: Forest carbon estimators	**Question 4:** growth and yield compatibility
Region: one broad region	Empirical: transition frequencies observed for each age/strata	Empirical: Total forest C based on averages of all plots within strata	Yield: empirical model based on stock density and Equation 8.
Forest Type Group: 9 groups based on dominant species	Mechanical: deterministic aging logic (Equation 3)	Ratio: Total forest C estimated by expanding live above ground tree C to total using strata based ratios	Growth: empirical model based on change in stock density and Equation 9.
Site productivity class: 7 classes	Cutting: Mechanical for unharvested forest; empirical for harvested forest (Equation 6)		
Ownership class: 4 classes	Disturbance: Mechanical for unharvested forest; empirical for all disturbed forests (including harvests – Equation 4)		
Stand origin: planted *versus* non-planted forests			

We used the projection model offered by Wear and Coulston (2015) to project future C stocks which is generally consistent with Equations 1–6. The forest area by age distribution is projected to the next time step by $\mathbf{a} \cdot \mathbf{T}$ where $\mathbf{a}$ is a $k \times 1$ vector and $\mathbf{T}$ is a $k \times k$ matrix. The total C stock is then $\mathbf{a} \cdot \mathbf{T} \cdot c$ where $\mathbf{c}$ is a $k \times 1$ vector of C density by age class. Formally,

$$C_{t+s} = \boldsymbol{a}_t' \boldsymbol{T} \boldsymbol{c} \tag{8}$$

where C_{t+s} is the total C stock at time step s. Alternatively, when stock change density is used

$$C_{t+s} = C_t + \boldsymbol{a}_t' \boldsymbol{T} \boldsymbol{dc} \tag{9}$$

To compare the efficacy of alternative stratification approaches, we estimate empirical transition matrices ($\mathbf{T}$ and $\boldsymbol{\lambda}$ elements) for each stratum which are defined by observed transitions between time 1 and time 2.

After defining the stratification with the least error, we compare projections using four alternative age transition models (question 2). One is the "*empirical*" model based on observed age changes between time 1 and 2 described above. The other three models define forecasts based on various rules applied to time 1 observations alone. The first, labeled "*mechanical*," uses the simple aging approach described in Equation 3 where all forests age to the next period without accounting for disturbance. Another transition approach, labeled "*disturbance*," augments the aging logic with the inferred rates of disturbance based on time 1 inventory plots coupled with aging rules (all disturbances including cutting were included with this approach). The final transition approach, labeled "*cutting*," similarly augments the aging logic with inferred age transitions for plots that are cut (only cutting disturbance was considered to influence age transition). The "*disturbance*" transition matrix was estimated from the time 1 inventory as follows:

$\boldsymbol{\delta} = 1 \times k$ vector of disturbance area by age class

$\mathbf{u} = 1 \times k$ vector of non-disturbed area by age class

$\mathbf{a} = 1 \times k$ vector of total area by age class

Note the age class from the single inventory is "post-disturbance." Assuming that the area of disturbance in age class 0 was the result of stand replacing disturbance, the area of stand replacing disturbance (including cutting) by age class was modeled as:

$$\mathbf{r} = \delta_1 \delta_1 (\textstyle\sum \delta)^{-1} \quad \delta_1 \delta_2 (\textstyle\sum \delta)^{-1} \quad \cdot \quad \cdot \quad \delta_1 \delta_k (\textstyle\sum \delta)^{-1}. \tag{10}$$

Where the $\sum \delta$ is total disturbance area. The area of non-stand replacing disturbance by age class was:

$$\boldsymbol{\rho} = 0 \quad \delta_2 - \mathrm{r}_2 \quad \cdot \quad \cdot \quad \delta_k - \mathrm{r}_k. \tag{11}$$

The probabilities of stand replacing disturbance were $\mathbf{d} = \mathbf{r}/\mathbf{a}$, non-stand-replacing disturbance $\mathbf{p} = \boldsymbol{\rho}/\mathbf{a}$, and undisturbed probabilities were $\mathbf{t} = \mathbf{u}/\mathbf{a}$. Imposing the logic from Equation 4, where undisturbed forests progress to the next age class (until reaching the terminal age class) and non-stand replacing disturbance are set back one period, defines the following transition matrix:

The transition matrix corresponding to Equation 4 was

$$\mathbf{T}_{\boldsymbol{disturbance}} = \begin{bmatrix} d_1 & d_2 & d_3 & d_4 & \cdots & d_k \\ 1-d_1 & p_2 & 0 & 0 & & 0 \\ 0 & t_2 & p_3 & 0 & & 0 \\ 0 & 0 & t_3 & p_4 & & 0 \\ \vdots & & & & \ddots & \\ 0 & 0 & 0 & 0 & & 1-d_k \end{bmatrix} \tag{12}$$

The *cutting* transition matrix was estimated in a similar fashion except that only cutting disturbances were used to infer transitions—cutting yields both stand-replacing and non-stand replacing forest conditions:

$\mathbf{h} = 1 \times k$ vector of cutting area by age class

$\mathbf{uh} = 1 \times k$ vector of non-cut area by age class

$\mathbf{a} = 1 \times k$ vector of total area by age class

Assuming that the area of cutting in age class 0 was the result of clear-cut harvest practices, the area of clear-cut harvest by age class was modeled as:

$$\mathbf{Hc} = 0 \quad h_1 h_2 \Big(\sum_{i=2}^{k} h\Big)^{-1} \quad \cdot \quad \cdot \quad h_1 h_k \Big(\sum_{i=2}^{k} h\Big)^{-1} . \tag{13}$$

The area of non-stand replacing disturbance by age class was:

$$\mathbf{Hp} = 0 \quad h_2 - Hc_2 \quad \cdot \quad \cdot \quad h_k - Hc_k . \tag{14}$$

The probabilities of stand replacing disturbance were $\mathbf{hc} = \mathbf{Hc}/\mathbf{a}$, non-stand-replacing disturbance $\mathbf{hp} = \mathbf{Hp}/\mathbf{a}$, and undisturbed probabilities were

$$\mathbf{t} = uh_1(a_1 - h_1)^{-1} \quad uh_2 a_2^{-1} \quad \cdot \quad \cdot \quad uh_k a_k^{-1} . \tag{15}$$

The transition matrix corresponding to Equation 6 was

$$\mathbf{T}_{\boldsymbol{cutting}} = \begin{bmatrix} 0 & hc_2 & hc_3 & hc_4 & \cdots & hc_k \\ t_1 & hp_2 & hp_3 & 0 & & 0 \\ 0 & t_2 & 0 & hp_4 & & 0 \\ 0 & 0 & t_3 & 0 & & 0 \\ \vdots & & & & \ddots & \\ 0 & 0 & 0 & 0 & & hp_k \\ 0 & 0 & 0 & 0 & & 0 \\ 0 & 0 & 0 & 0 & & t_k \end{bmatrix} \tag{16}$$

To examine question 3, we compare our empirical estimates of forest C based on the recorded C quantities for the seven forest C pools (above and below ground live tree, above and below ground dead tree, litter, under story, and soil organic matter) with an approach that uses above ground biomass C as a correlate for total forest C. Here we construct ratios of total forest C to the above ground live tree C pool for strata and use this ratio to estimate forest C in time 2. This is comparable to ratio methods used in many FIPMs. We also examine the stability of the C ratios across age classes to assess the assumption that a ratio can be used to expand above ground live tree C to total C in all pools.

To examine question 4, we develop an alternative model using observed C changes between time 1 and 2 (Equation 9) and apply it using the best-performing stratification and transition model.

4 Results

The total C stock in the eastern United States was 27544 TgC at time 1 and 28060 TgC at time 2 (approximately 5.3 year time step based on the average remeasurement period for all plots) with an average annual stock change of 97 Tg C yr^{-1}. For the eleven alternative stratifications, errors in time 2 forest C stock predictions ranged from -76 Tg C to $+2$ Tg C. These errors from a C stock perspective were small (-0.27% to $+0.01\%$). Errors in stock change predictions ranged from $+0.61$ to -14.0 Tg C yr^{-1} (percent error ranged -14.39% to $+0.63\%$). The *stand origin * owner* yielded the smallest error (panel 1 in Figure 1). The results for single factor stratification indicate predictive strength of variables in descending order as: *stand origin, owner group, region, site class, and forest type.* Among the two-variable combinations, those that included *stand origin* persistently outperformed other groupings.

Evaluation of alternative transition models (question 2) were based on the *stand origin * owner* stratification and the empirical transition model is the base of comparison ($+0.61$ Tg C yr^{-1} error in stock change; panel 2 in Figure 1). The estimated empirical transition model (Figure 2) is consistent with substantial partial harvests and non-harvest disturbances. Among alternative transition models, the disturbance model produces the smallest error (-2.3 Tg C yr^{-1} error in stock change). The mechanical transition model produces the greatest error ($+105$ Tg C yr^{-1}) and the cutting transition model produces error of intermediate value ($+7$ Tg C yr^{-1}). These results suggest that the predictive strength of age transition models increases as accounting for disturbances in modeling age transitions increases.

To examine question 3, we compared the empirical forest C estimates from the four transition models with an alternative approach based on tracking only the live tree biomass and applying strata based ratios to estimate total forest

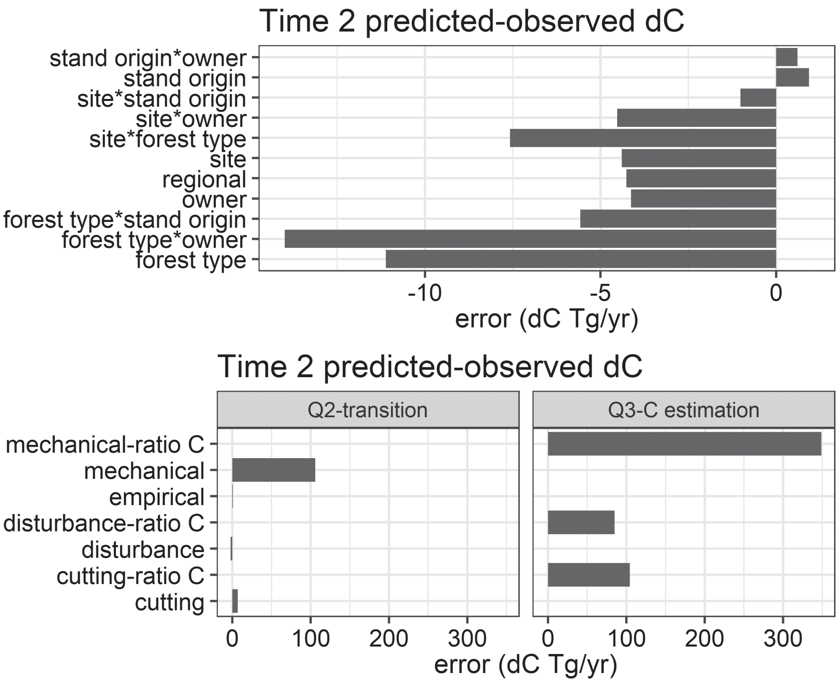

Figure 1: Error in predict annual C stock change based on different stratification approaches, different assumptions about age transitions, and different estimation techniques.

C. Based on the time 1 data the average C expansion ratio was 3.5. In all cases the ratio approach greatly increased the error of the period 2 prediction (panel 3 in Figure 1). For the *disturbance* transition model, error increased from -2.3 Tg C yr^{-1} to 84.9 Tg C yr^{-1}; from 7.2 to 116.1 Tg C yr^{-1} for the *cutting* transition model, and from 105.9 to 349.0 Tg C yr^{-1} for the *mechanical* transition model. We further examined the stability of the total C to live tree C ratio across age classes. The ratio ranged from 21 at age zero to 3 at age 100 (Figure 3). This results was logical because young forests may have little above ground tree C yet retain a significant amount of soil organic C (Figure 3).

The results presented above reflect a broad range of errors for the five year time step of the remeasured inventory that depend on assumptions regarding stratification and transitions. To explore the implications for longer run projections, we also constructed 50 year projections based on the alternative transition models (Figure 4). By construction, the long run projections are hypothetical from the perspective of harvesting and climate conditions – that is, harvests are not directly derived from timber market dynamics and climate-induced shifts in productivity are not incorporated – but they further illustrate the potential implications of various specification choices. For this analysis,

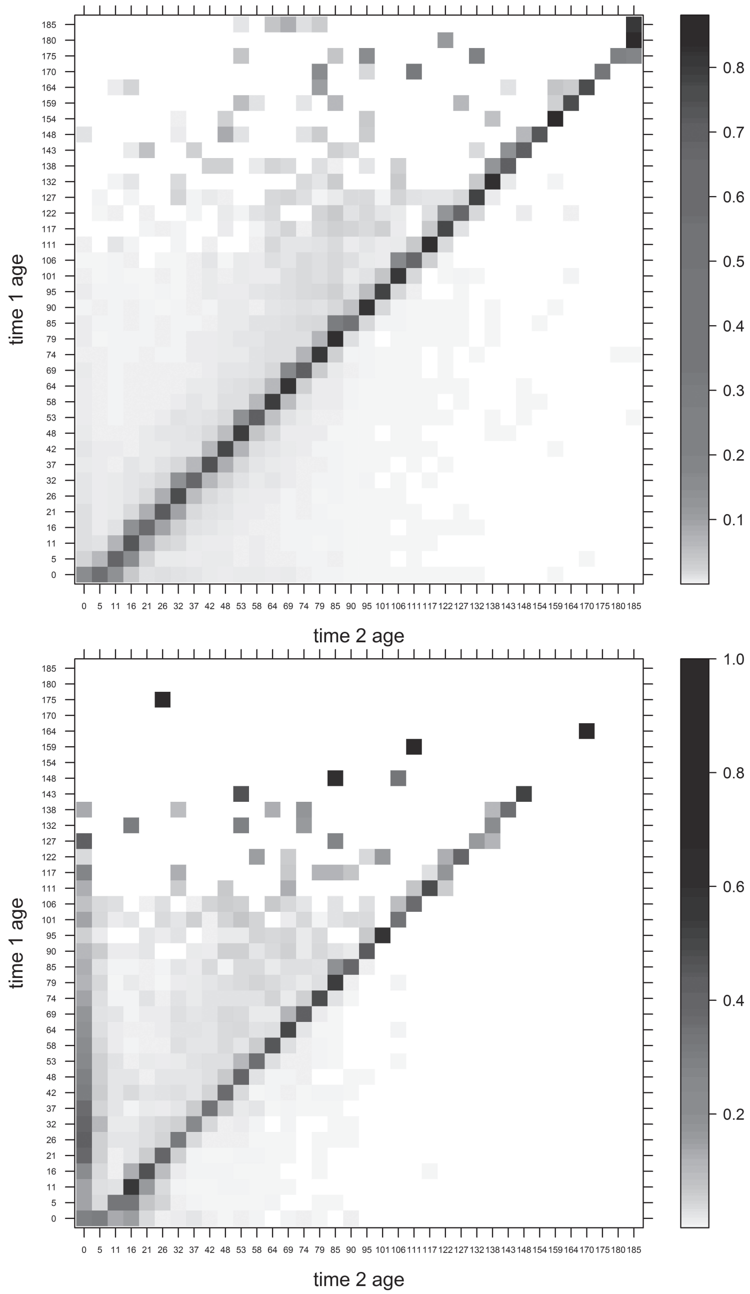

Figure 2: (a) Transition probabilities for non-harvest plots.(b) Transition probabilities for harvested plots.

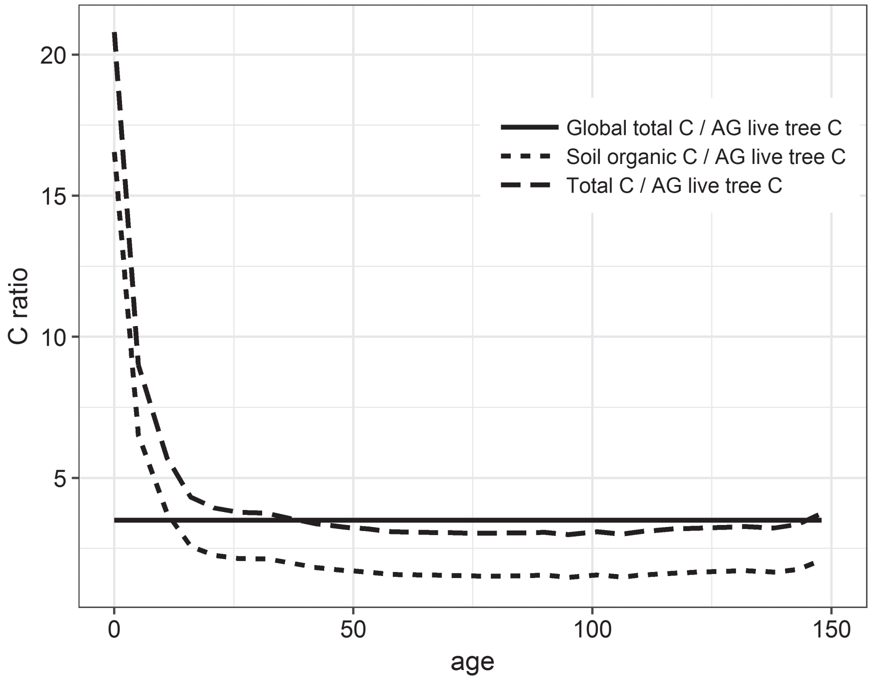

Figure 3: Carbon expansion ratios by age class.

the amount of harvesting (both clear-cut and partial) was held constant by age class over the projection period (this amount was equal to the harvest recorded in the time 2 inventory). The *cutting* transition model predicts greater values of C stock and C stock change than both the *disturbance* and *empirical* models. Over a 15-year projection period the percent difference between the empirical model and the disturbance, and cutting models were 0.5%, and 1% respectively for C stock and 27%, and 34% for C stock change. These percent differences increased with time where for a 30-year projection period the percent difference between the empirical model and the disturbance and cutting models were 40% and 45% for C stock change, respectively. Over the full 50-year projection period these different assumptions suggested that an additional 684Tg C was sequestered under the *disturbance* transition model, and additional 938 Tg C were sequestered under the *cutting* model.

To examine Question 4, we used the projections described above. We further constructed projections of C stocks and C stock change based on Equation 9. The *stand origin * owner* stratification was used for these projections. We denote the use of Equation 9 with the *stand origin * owner* stratification as the *growth* approach. The error at time-step 1 for the *growth* approach was 0 for both C stock and stock change (by definition because plot-level stock

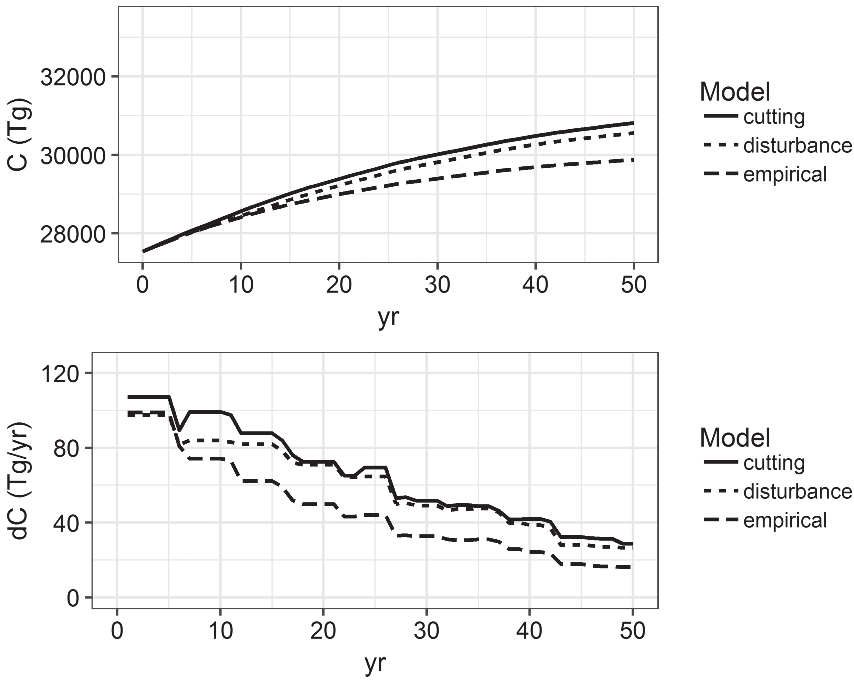

Figure 4: Projected C stocks and projected annual C stock change based on three age transition assumptions.

change was used directly). We compared the projections to the *empirical* projection based on the *stand origin * owner* stratification. Percent difference between C stock estimates for the *growth* approach and the *empirical* approach was less than 1% for a 30 year projection period. The percent difference for C stock change projections was less than 13% for a 16 year projection period. Differences in C stock and C stock change projections increased for projection periods longer than 16 years suggesting overall compatibility between approaches for short to mid-term but not long-term projections.

5 Discussion

Stratification (Question 1) results indicate that the most important distinctions in forest C stock distributions and especially dynamics are related to stand origin and ownership class. There are several reasons for this finding. Planted stands are clearly different than natural stands. The typical planted stand is planted with genetically improved seedlings (see e.g., (McKeand *et al.*, 2003)) resulting in enhanced survivorship, greater growth rates, and better tree-form.

Intensive management associated with planted stands includes fertilization: Fox *et al.* (2007) suggests that 0.5 million ha of plantation forests in the Southern United States were fertilized in 2004. Given the fertilizer application may occur once or twice over a rotation and that there are approximately 14 million ha in the eastern United States, this suggests fertilization is a common practice to increase growth and yield. Forests under different ownerships have different management regimes. The most obvious distinction is that 90% of the planted forests were on private lands and further 77% of the harvest occurred on private lands. Less obvious is the age class distribution of public lands. Forests on public lands tend to be older than on private land. For example the average age of non-plantation forests on public land was 64 years as compared to 51 years on private land.

Transition (Question 2) results indicate that incorporation of disturbance driven age dynamics is critical for simulating the evolution of forest C. This indicates that accounting for disturbances through the estimation of forest C densities with representative portions of disturbed stands within each age class is insufficient for capturing their full effects. Rather, resetting the age triggers out year dynamics that would not be included otherwise. Among transition models, the empirical parameterization of **T** minimized error in predicting time 2 C stock. Alternative models of **T** generally failed to capture the observed age transitions. Both the *cutting* and *disturbance* matrix models either assume stand replacement (age reset to zero) or assume a limited de-aging associated with partial cutting or disturbance. These models did not capture a consequential component of the aging process (Figure 2). Applying the *disturbance* transition models generated an additional 684 Tg C of sequestration over a 50-year projection while the *cutting* transition model generated an additional 939 Tg C compared to the *empirical* approach. Part of the challenge of specifying age transitions arises because most forests in the eastern United States are uneven-aged. The definition of age and change in age in uneven-aged stands is unintuitive and forest growth and yield modeling in these types of forest has shifted to other approaches that are less dependent on age alone such as imputation (Wear *et al.*, 2013; Van Deusen, 2006; Van Deusen and Roesch, 2013), diameter distribution models, and mechanistic models (see Peng, 2000 for example).

Forest C estimates using the ratio method (Question 3) led to strong overstatement of forest C stocks and stock change indicating that methods that proxy change in forest C based on change in standing biomass may be mispecified. The seven constituent pools of forest C follow different trajectories associated with age and location and the correlation between standing live biomass and total forest C is variable by age (Figure 3). Based on our analysis the average ratio between above ground live tree C and total forest C was 3.5. This ratio may be substantially larger than ratios used by others because we incorporated the latest US Forest Service soil C model (Domke *et al.*,

2017) in our estimates. This forest soil C model accounts for a deeper soil layer with a 75% increase in forest soil C than previously used forest Soil C models. Regardless, the seven forest C pools do vary by stand development, disturbance, and forest type and relying on a single conversion factor has been demonstrated to be error prone.

Question 4 focused on the compatibility between stock (yield-based) and stock change (growth-based) methods. Much of the focus on forest C is on stock changes because it reflects the amount of atmospheric CO_2 being removed through forest growth. However, projection methodologies have focused on stock-based approaches and assumed that the difference in stock at two-points in time is compatible with stock change. As Clutter (1963) and Moser and Hall (1969) first identified for timber volumes, many yield-based approaches parameterized independently from growth can have poor predictive power for estimating stock change, even on the same dataset. This issue is further exacerbated within an uneven-aged forest modeling context. Our results suggest that the *empirical* approach and the *growth* approach were relatively compatible in terms of estimate forest C stock change for the eastern United States over a 16-year projection period but with substantial inconsistencies over the long run. However, the compatibility of stock and stock change approaches for forest C projection is an area of research that has been under-investigated.

While this research focused on the dynamics of persistent forest land, land use changes impact forest age structures and forest C stocks in various ways and treatments of land use change vary across FIPMs. Based on the data from this analysis, forest area expanded by 1.5 million ha between time 1 and 2, with 0.62 million ha of the net increase occurring in forests with ages <10 years consistent with a conversion of agricultural land to forest use, but with 0.69 million ha of the net increase occurring in forests with ages of 10–50 years. This counterintuitive result reflects the conversion of land with forest cover from a non-forest use to a forest use. If a FIPM assumes that all 1.5 million ha had arisen from afforestation then forest C dynamics would be biased upward for several time periods. Furthermore, net forest area change obscures a much larger gross land use dynamic where the age and C content for land moving out of a forest use may be substantially different than for the land moving into a forest land use with unanticipated C dynamics. For example, no net change in forest land could result in declining forest C stocks. While beyond the scope of this study, it is clear that the mechanisms of gross land use change are an important component of forest C inventories that need consideration within FIPMs.

6 Conclusions

The FIPMs developed for Forest Sector Models from the work of Adams (1977) forward evolved through a unique policy context and in a period of scarce and inconsistent forest inventory data. Comprehensive modeling of inventory change during the transition from harvesting old growth to agricultural forest production systems required ingenuity to draw together a description of existing forests and their dynamics from disparate sources and a view of the future that would be characterized by essentially novel planted pine technologies. The resulting combination of growth and yield, field inventories, and expert opinions that comprised FIPMs was the only viable approach at the time but these models could not be verified against actual forest changes. The current spatially and temporally consistent national forest inventory in the U.S. allows for verification/validation of these models against observed forest dynamics and also allows for development of fully empirical FIPMs.

All alternative models examined here are based on empirical estimates from measured forest inventories organized by different assumptions regarding forest stratification, age transition, and C density estimates. They do not represent alternative FIPMs from the literature, but construct the best cases for each of the alternatives – for example, they are based on estimates derived from consistent measures of the inventory and not from the coupling of inventory and exogenous growth models. Model comparisons are intended to inform future model development efforts and not to specifically address alternative FIPMs developed from disparate information sources. Blending information from growth and yield models, developed in a controlled experimental setting, with inventories based on random samples would, by definition, suggest strong upward bias in biomass or C stock estimates.

Our evaluation of forest stratification strategies indicates that stratifying by stand origin (planted *vs.* natural) and forest ownership (public *vs.* private) lead to the least error in predicting time 2 forest C stocks and dynamics when compared with forest type, region, or site class. These two variables that characterize management intent dominate the evaluated biophysical variables in reducing error, indicating the importance of ownership and institutional factors in determining future forest C sequestration. Ownership clearly influences the age distributions of forests (public forests are generally older), but because we separately account for forest age, this indicates a qualitative difference in forest management and conditions across ownerships that warrants additional investigation. Ignoring (i.e., averaging across) these variables could lead to substantial bias in biomass/C projections. Their importance suggests further investigation of detailed ownership categories (e.g., commercial *vs.* family) or other socioeconomic variables in characterizing and projecting forest inventories.

The differences in C projections arising from alternative transition models highlights the importance of addressing the age dynamics associated with forest disturbances. FIPMs generally do not include an accounting of forest disturbances beyond harvests, but rely on the averages of C densities across age classes to represent the effects of any extant disturbance regime. This may be an important misspecification. Forest age transitions are not generally consistent with an even-aged management logic and are highly complex in remeasured forest inventories indicating a need for a different approach that accounts for all sources of transitions. Accuracy of age transition models will likely be enhanced with additional cycles of remeasurement for forest inventory plots. We also find that ratio approaches to converting aboveground timber biomass to forest C are unlikely to accurately capture forest C dynamics within a forest due mainly to the variable age dynamics of individual C pools among strata of the forest inventory.

This study addresses the question of whether a forest projection model focused on predicting future timber inventories can be modified to adequately address a different type of ecosystem service: C sequestration. As forest policy questions have shifted away from exclusive concerns about timber availability and federal timber policies and toward the provision of multiple ecosystem services, FIPMs need to project forests at finer levels of detail. For example, the influence of forest cover on water production is largely influenced by tree species as well as tree cover and density (Martin *et al.*, 2017). In general other ecosystem services such as biodiversity and recreation also depend on, not only the amount of forest, but the location and configuration of various forest conditions. Forest C sequestration may therefore be the most direct analog to the timber market questions for which forest sector models were originally designed. Given the importance of timber harvesting on future forest conditions demonstrated here, it seems clear that forest sector activity remains a critical component of projecting future forest C services. However, our findings indicate the need to also address the mechanisms of non-harvest disturbances to avoid bias in projection of C stocks and sequestration. The accuracy and usefulness of these projections will depend on capturing the dynamics of forests essential for defining ecosystem services and therefore on the design of their associated FIPMs. Developing C projections that are fully consistent with historical C inventory changes requires a full accounting for biological, physical and management dynamics in addition to the market processes that influence them.

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