Forest Carbon Modeling Resource Guide

Topic 2: Understanding the Landscape of Modeling Approaches and Best Practices for Addressing and Interpreting Uncertainty

Table of Contents

Types of Modeling Approaches and Frameworks: A General Overview

Forest ecosystems are a major component of the terrestrial biosphere, which plays an outsized role in determining the fate of atmospheric carbon dioxide (CO_2) in addition to exerting strong biophysical controls over carbon, water, and energy budgets (Bonan 2008). Accordingly, efforts to quantify terrestrial carbon cycling within forest ecosystems have been made to not only understand and monitor carbon dynamics within forests, but also to assess potential mitigation and adaptation strategies to combat climate change (Novick et al. 2022). The need to answer the fundamental question of "how are ecosystems changing?", and the direct impacts of these changes on human lives, furthers the urgency to utilize and develop approaches to answer this foundational question (Dietze et al. 2018). With a diversity of methodologies in use, it may be useful to take a step back and examine the landscape of dominant modeling approaches used to assess ecosystem change.

Modeling approaches to understand and quantify the forest carbon cycle can be categorized along two sides of the same continuum, empirical models and processed-based models. Empirical models derive results from extrapolating correlative relationships between observed variables (i.e., statistical models that rely on observations to predict an outcome using a function). Process-based models apply a more mechanistic approach to explicitly represent relationships within the model mathematically using sets of equations based on theoretical principles and laws selected heuristically (Korzukhin et al. 1996; Novick et al. 2022). In practice, these modeling approaches are not exclusive of one another, as *most* process-based models incorporate empirical information, either from data inputs derived from empirical models, or through validation using empirical models. On the other side of the spectrum, the correlative relationship assessed in empirical models are assumed to be linked to observed or unobserved processes or causal mechanisms (Makela et al. 2000).

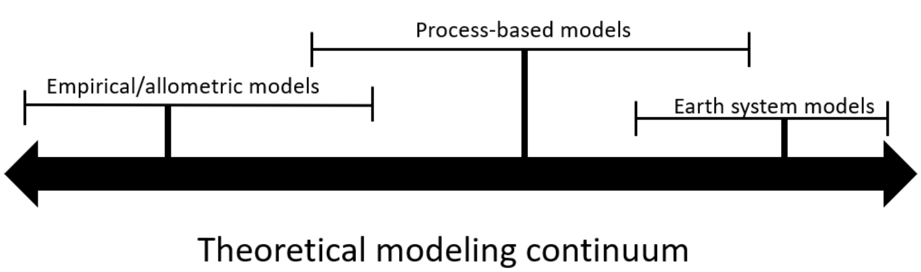

Figure 1: *Theoretical modeling continuum for modeling approaches and frameworks to understand forest carbon stocks and fluxes*

An important category of process-based models that inform, but do not explicitly model forest carbon are Earth System Models (ESMs). ESMs couple General Circulation Models (GCMs), climate models for atmospheric flows and processes, with Terrestrial Biosphere Models (TBMs) which represent land surface processes such as ocean circulation and biogeochemical processes. ESMs are used to predict future climate states through climate-ecosystem feedbacks by estimating physical and biogeochemical impacts (i.e., how changes to albedo caused by deforestation impacts atmospheric forcings). In doing so, they 'close' the carbon budget between the atmosphere, oceans, and land surface; that is, they connect the atmospheric carbon cycle with the terrestrial carbon cycle into a closed-loop global system. TBMs represent the terrestrial biosphere, of which forests are just one component, through highly mechanistic relationships to track the flow of carbon, water, and other elements through ecosystems with coupled-climate feedbacks informed by a variety of data and ground observations. While ESMs, TBMs, and GCMs have broad informative applications, forest carbon generally is not the focus of these models. The remainder of this resource guide will focus only on models used explicitly for estimation and assessment of forest carbon.

Both empirical and process-based modeling approaches for estimating forest carbon dynamics have varying advantages and disadvantages. For example, empirical models rely on variables that are easily measured, but can be sensitive to bias linked to spatial heterogeneity, leading to unrealistic estimation (Novick et al. 2022). Alternatively, process-based models are constrained to prevent unrealistic outcomes but remain sensitive to bias inherent to the model structure. Establishing a set of criteria for model selection is critical when selecting a model or an approach to estimating forest carbon stocks and fluxes. Among other factors, modeling frameworks should be available, peer-reviewed, validated, and verified. However, other factors may be important to satisfy specific modeling needs, e.g., important considerations for how a model assesses error, uncertainty, and biases.

Approaches to Modeling Forest Carbon Dynamics

Estimating Forest Growth

Models that focus specifically on forest carbon dynamics approach forest growth in two distinct ways, where growth is either: 1) driven by empirical yield curves or 2) driven by simulating photosynthesis. Both approaches can model forest dynamics at the individual level (i.e., individual stems or trees) (Ma et al. 2017) or at the cohort or stand level (i.e., groupings of trees or communities). Further, regardless of approach, models are either spatial or aspatial and spatially referenced in representation of forests. Models that are inherently spatial in nature can model at different scales, from global, to kilometers, to meters to individual trees. Spatial models represent the forest or trees in space or a specific location on the Earth's surface using pixels or vectors. Whereas aspatial models ignore the representation of forest dynamics in space (or with spatially referenced frameworks), they may use a categorical spatial unit to characterize a forest stand such as county, management unit, or ecoregion.

Empirical Yield Curve-Driven Growth Models

Models that use growth-yield relationships estimate forest productivity through the relationship between stand age, volume, height, biomass, specific gravity, and other forest characteristics or information collected by operational foresters used in forest planning and inventorying (Kurz et al. 2009). Growth-yield-based models generally capture stand dynamics, such as growth, mortality, regeneration, and competition, inherently through correlative relationships (i.e., predicting a response variable from observations such as using tree age to predict tree volume).

Photosynthesis-Driven Growth Models

Models that use photosynthesis-driven growth require similar datasets to TBMs, such as leaf-area index, climate variables, and soil variables to estimate productivity over time. Unlike growth-yield-based models, photosynthesis-based models stratify the forest canopy into vegetation types to explicitly model productivity by simulating interactions between different components of the ecosystem such as biophysical variables, light and competition.

Estimating Forest Carbon Dynamics

Modeling frameworks, or the theoretical description of a model that accounts for forest carbon (i.e., carbon stocks, transfers between pools, and emissions) have two broad methodological approaches to estimate forest carbon dynamics that fall within tier 3, or most advanced, approaches outlined by the Intergovernmental Panel on Climate Change (IPCC) (Kurz et al. 2009):

Method 1: Inventory change

"Inventory change" methods involve calculating the difference between inventory remeasurement periods (i.e., net change in carbon = C in t_2 – C in t_1). This method is highly accurate and built upon robust empirical allometric models to convert measurements of forest characteristics to carbon but can be costly in time and funding. Additionally, this method requires a robust sampling design to ensure unbiased estimates of forest characteristics across the desired study area. Depending on the repeat interval between remeasurements, this method may not provide information on inter-annual variation within the observation period (Kurz et al. 2009). Furthermore, while this method inherently integrates all relevant drivers of carbon (i.e., natural disturbance, management, land-use change), it may not necessarily incorporate non-CO_2 emissions.

Method 2: One inventory plus change

"One inventory plus change" methods still require a detailed forest inventory as well as detailed information around land-use change (LUC), management practices, and natural disturbances. These methods also require empirical models for estimating growth (through growth-yield relationships or simulating photosynthesis) and processed-based equations for turnover rates applied within a process-based modeling framework. Applications of this method require a high level of complexity, computational expense, and analyst training, but lend strength to future predictions if model parameters are properly constrained and validated.

Uncertainty and Quality Assurance in Forest Carbon Measurements

Understanding and evaluating model uncertainty is important for assessing the robustness of inferences being drawn, with strong ramifications for decision-making and planning. In purely empirical models, uncertainty is both inherent and quantified, constituting error associated with sampling design, observations (e.g., natural variation in space and time), and statistical methods. On the other hand, process-based model outputs often lack uncertainty estimates from deterministic simulations (Larocque et al. 2008). Lack of uncertainty *estimation* does not mean there is a lack of uncertainly; this can lead to poor model performance and unsound decision-making regarding environmental issues (Rowe 2004). Within process-based models, uncertainty can arise from error propagation resulting from variability in model inputs, uncertainty associated with the model structure itself, as well as uncertainty toward scenario forecasting (Adams et al. 2013; Bonan and Doney 2018).

In both modeling approaches, uncertainty may arise from a host of inputs and dimensions. Larocque et al. 2008 summarizes the different sources of uncertainty as:

1. Data uncertainty resulting from statistical errors associated with sampling methodology, field measurement errors, instrument imprecision, or differences in spatial or temporal scales;
2. Sensitivity to initial conditions;
3. Lack of understanding of the underlying processes, resulting in the derivation of inaccurate or inadequate mathematical representation in model structure;
4. Parameter estimates, which may be associated with the use of parameter estimation methods or inaccurate assumptions about the parameter distribution;
5. Unknown or poorly constrained drivers; and
6. The amplitude of natural variation associated with the biological system under study.

Simulation Uncertainty and Assumptions

While major advances in both data models and tools for estimating forest carbon dynamics have been made, large research gaps remain, serving as additional sources of model uncertainty for predictions and forecasting. Empirical models have strong predictive power; however, the mechanistic underpinnings of process-based models often lend higher predictive power when attempting to forecast future forest dynamics and climate scenarios. These forecasts or simulations create unique challenges when trying to predict future states of forests. Specific care must be taken in stating and deciding on assumptions for model representation of forest dynamics to obtain improved modeled results and reduced uncertainty (Bonan and Doney 2018).

Ecosystem models are, broadly, an abstraction of complex systems. Increasing accuracy in representation of forest dynamics across scales within both deterministic (i.e., process-based) and empirical models will increase confidence in forest carbon modeling results. However, more complexity does not always lead to reduced uncertainty and, in turn, better predictions. The predictability of a forecast is impacted by initial conditions, imperfections in the understanding of underlying biophysical dynamics, stochasticity and natural variability, randomness inherent to discrete and especially rare events (e.g., severe drought events or landslides), and model uncertainty (both structural and parameterizations).

Table 1 provides a non-exhaustive list of examples of forest dynamics, their influence on modeled forest carbon dynamics, and specific knowledge gaps and how those gaps can weaken modeling results. The forest dynamics listed influence unique aspects of the forest carbon cycle at disproportionate scales. Furthermore, some of the knowledge gaps related to forest dynamics become problematic and exacerbated when implemented in longer simulations across heterogeneous landscapes. For example, uncertainty surrounding regeneration and post-disturbance recovery dynamics may have little effect on shorter simulation lengths (i.e., < 20 years), but will become increasingly pronounced as the simulation period is extended (i.e., until the end of the century).

Table 1. Examples of forest dynamics that impact forest carbon model results, knowledge gaps, and future research needs

Forest Dynamic	Effects on forest carbon	Knowledge gap and research needs
Regeneration and mortality	Strongly influences carbon future behavior in forest ecosystems. These dynamics interact with both human management and growth conditions, leading to changes in future carbon stocks and fluxes	Growth and yield models generally exclude regeneration and mortality; greater understanding of how both human induced change and climate-driven change impact regeneration and morality is needed to appropriately account future carbon accumulation
Disturbance	Biotic disturbances (i.e., pest and disease outbreaks) and abiotic disturbances (i.e., fire and wind) influence forest productivity and mortality through a variety of mechanisms ultimately leading to perturbations in forest carbon cycling by changing carbon pool quantities and turnover	Accurately being able to predict future biotic and abiotic disturbances in extent, frequency, and severity is necessary to capture future disturbance dynamics to better model forest carbon; more accurate representation of post-disturbance dynamics is also necessary across longer timescales to increase accuracy future predictions
Succession and senescence	Late-stage successional dynamics and age-dependent senescence are poorly understood with regards to tree carbon balance, growth, and mortality which strongly effects carbon storage and turnover	Current growth models do not adequately capture late-stage stand dynamics and the interaction with biomass productivity and storage contributing to a strong need for better models to understand late-stage forest dynamics and associated uncertainty with generalized allometric models
Competition and site quality	Carbon allocation dynamics change in response to competition for light, space, and nutrients, affecting growth and mortality. Furthermore, poorly understood interactions with site quality (i.e., soil fertility, slope, and hydrology) impacts growth characteristics influencing carbon stock change over time	Need for strong understanding of the future effects on growth and tree development in response to changes to competition caused by anthropogenic and climate factors as well as the interaction with soil fertility and soil water content. Increasing accuracy across heterogeneous landscapes allows for improved model-driven decision making
Climate	Future growth conditions will impact the tree growth, survival strategies, and physiological responses to stress. For example, changes to atmospheric CO_2 concentrations and water supply will strongly impact future trends in growths	Need for better understanding of tree physiological responses to future climatic states such as carbon allocation in growth versus reproduction to understand future trends in carbon stock change and turnover rates

Simulation *assumptions* chosen to represent forest dynamics can have important impacts on *projected* sinks and sources of carbon in forested landscapes. For example, the model form chosen to predict stand volume using basal area or age strongly influences net annual increments of carbon. Similarly, the function chosen to estimate the amount of biomass and carbon from tree volume also influences estimation of forest carbon by influencing growth over time. This reality, that assumptions impact results, is even more important to consider and acknowledge when forecasting future carbon dynamics to inform decision-making and planning. Increasing the length of forecasting (i.e., how far into the future one's model projects) inherently introduces more uncertainty from a lack of ability to predict (i.e., make accurate assumptions about) future states.

Broad thematic areas of focus to continually improve model framework and model predictions include:

Improved integration of inventory data to align with modeling frameworks – continual development of better data models to support the ingestion of forest inventory data with existing modeling frameworks.

Improved representation of biophysical feedbacks with forest dynamics – continued advancement of empirical studies to support and constrain process-based models with the specific focus on understanding climate-forest feedbacks.

Continued validation of modeled results with empirical observations – ensuring model validation and accuracy, modeling frameworks should continually be refined and updated with newer innovated data tools, in an iterative process to cross-validate results with ground observations and measurements.

Continued advancement of model tools and data – to refine methodologies for better representation of forest dynamics. Ideally bridging the gap between theory of forest dynamics with real-world observations.

Methods to Address Uncertainty in Forest Carbon Models

While error and uncertainty are inherent to empirical modeling approaches, the most common methods to address uncertainty within process-based models are sensitivity analyses, differential equation optimization and analytical solutions, and Monte Carlo methods. Other non-probabilistic methods exist but are not as commonly used (Larocque et al. 2008).

Sensitivity analyses can provide parameter evaluation without quantifying actual estimation of error, as might be done with uncertainty analysis (Zhao et al. 2022).

Model parameters are systematically assessed while holding other model parameters constant; inference can be drawn from identifying which parameters influence model outputs and to what degree (Kremer 1983).

Approaches that apply differential equation and analytical solutions of equations estimate uncertainty by analyzes model output response from the partial derivative with respect to input parameters by increasing the order of derivatives to estimate error propagation (Hammonds et al. 1994). However, the approach Is generally not appropriate for forest carbon models due to the complex nonlinear relationships within the model structure.

Monte Carlo methods are the most used method to estimate error propagation and evaluate parameter influence on model uncertainty. Monte Carlo methods consist of running a model multiple times sampling the probability distribution function of model inputs with increasing statistical validity with subsequent increases in the sampling intensity (Smith and Heath, 2001). The relatively simple assumption for Monte Carlo methods represents an advantage in estimation uncertainty by allowing the computation of frequency distributions, means, or standard deviations of both state variables of interest and modeled results.

Guidance on Uncertainty and Quality Assurance

Robust estimation of carbon stocks and carbon change requires adequate measures of quality control and assurance, with the understanding that there is no such thing as a “perfect” forecast or prediction (Dietze et al. 2018). Quality control and assurance are assessed via routine and consistent checks to verify the integrity, correctness, and completeness of estimated of data inputs and modeled results. Determining best practices for assuring the validity of modeled results is a difficult task; there are strengths and weaknesses to various approaches. However, some underlying principles may be applied to promote better estimation of both data inputs, model outputs, and uncertainty associated with model structure and predictive simulations:

Utilizing best possible data inputs and data tools collected using robust methodologies. Ensuring high quality data and data tools for model input and parameterization increases confidence in predictive results. Peer-reviewed and openly available data are generally considered to be higher quality. Additionally, applying simplified methods, such as representing data as “averaged” values for data inputs, lends strength to future prediction due to the high complexity in predicting future stochasticity and randomness.

Utilizing models, modeling frameworks, and methods that have been published and verified throughout the literature. There is a long history of models and data tools developed to capture forest carbon dynamics. Relying on commonly used and peer-reviewed models lends strength to any results or inferences being made. Furthermore, open-source modeling tools provide additional credibility to the modeled results and allows for reproducibility.

Identifying potential sources of uncertainty such as data inputs, model structure, model calibration, methodological approach, and simulation assumptions. Articulating all assumptions made during the modeling process is important to inform the decision-making process and assess the robustness of results. Acknowledging information or data gaps can help inform modeling results as well as explain model behavior so that correct conclusions can be drawn.

Comparing modeled results to previously published model results in the literature for quality assurance and verification. Model and verify past trends within the chosen approach before simulating future projections (i.e., Trend Analyses). Properly assessing model outputs with regards to other literature findings to ensure proper constraints of estimates or to identify sources of model disagreement.

Conduct an analysis to understand degrees of uncertainty, including regarding limitations of mechanisms, model simulation processes, data observation, and robustness of results. Methods for error-propagation may include: 1) sensitivity analysis; 2) analytical solution of differential equations; 3) Monte Carlo analysis; 4) fuzzy sets; 5) first-order analysis; 6) Bayesian approaches.

Shifting the paradigm for carbon estimation from assessing statuses to estimating trends (e.g., periodic estimation to continuous monitoring). Individual assessments and studies provide multitudes of information. Yet, improving confidence in future projections requires an increase in the frequency of analyses, to both assess past decisions and reevaluate future planning and decision making. Currently, the paradigm in ecosystem modeling is shifting from assessing the status of the ecosystem on a periodic basis, to continual monitoring of ecological states and trends. Utilizing modeling frameworks that allow for increased frequency of results as new information becomes available create an iterative process of quantitative assessment. This continuous refinement of methods as new models and data tools become available from trusted sources, ensures greater result latency for model driven decision-making.

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Fisher, R.A. & Koven, C.D. (2021). Perspectives on the future of land surface models and the challenges of representing complex terrestrial systems. *Journal of Advances in Modeling Earth Systems,* 12, e2018MS001453.

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Smith, J.E., Heath, L.S., (2001). Identifying influences on model uncertainty: an application using a forest carbon budget model. *Environ. Manage.* 27, 253–267.

Zhao, J., Liu, D., Zhu, Y., Peng, H., Xie, H. (2022). A review of forest carbon cycle models on spatiotemporal scales. *Journal of Cleaner Production.* 399:120692.

Additional Resources

Webinars/videos

Bullock, E. (2017, June 23). *Module 2.7 Estimation of uncertainties* [Lecture presentation]. REDD+ MRV training module series, GOFC-GOLD Land Cover Office, World Bank.

- *Training presentation highlighting how to identify sources of uncertainty in the estimates of area change and carbon stocks change, how to implement the correct steps to calculate these uncertainties, and discusses the possible treatment of uncertainties in a conservative way*

Dietze, M. (2020, April 23). *Propagating Uncertainty* [Lecture presentation]. Ecological Forecasting lecture series, National Science Foundation's National Ecological Observatory Network (NEON).

- *Presentation introducing the key concepts involved in propagating and analyzing uncertainty: sensitivity analysis, uncertainty propagation, uncertainty analysis, and optimal design*

LaDeau, S. (2020, April 23). *Characterizing Uncertainty* [Lecture presentation]. Ecological Forecasting lecture series, National Science Foundation's National Ecological Observatory Network (NEON).

- *Presentation discussing classic assumptions in traditional statistical models and approaches to model uncertainties in models versus observations, with information on accounting for model error, observation error, and error within frameworks, modeling missing data, and the use of latent variables*

Lombardozzi, D. (2014, October 22). *Uncertainty in Projections of Future Terrestrial Carbon Cycling* [Seminar presentation]. Montana Institute on Ecosystems' Rough Cut Science Series.

- *Presentation discussing causes of uncertainty in modeling, effects of natural variability on the carbon cycle, and when climate change driven effects on the carbon cycle become apparent*

Peer-Reviewed Resources

Adams, H. D., Williams, A. P., Xu, C., Rauscher, S. A., Jiang, X., & McDowell, N. G. (2013). Empirical and process-based approaches to climate-induced forest mortality models. *Frontiers in plant science*, 4, 438.

- *This paper's intro lays out quite systematically differences between empirical and processed-based approaches and uncertainty associated with both with a focus on forest mortality. A table of relative differences between modeling approaches is provided and bridging representation across forest scales*

Campbell, John L.; Green, Mark B.; Yanai, Ruth D.; Woodall, Christopher W.; Fraver, Shawn; Harmon, Mark E.; Hatfield, Mark A.; Barnett, Charles J.; See, Craig R.; Domke, Grant M. 2019. Estimating uncertainty in the volume and carbon storage of downed coarse woody debris. Ecological Applications. 29(2): e01844-.

- *Article provides methods to address shortcomings in quantifying uncertainty of forest properties that are not directly measures such as wood density and carbon concentration and its relationship with downed coarse woody debris. Paper provides confidence estimation of downed coarse woody debris and identifies where resources can be applied to improve monitoring designs*

Clough, Brian J.; Russell, Matthew B.; Domke, Grant M.; Woodall, Christopher W. 2016. Quantifying allometric model uncertainty for plot-level live tree biomass stocks

with a data-driven, hierarchical framework. Forest Ecology and Management. 372: 175-188.

- *Provides data-driven hierarchical modeling approach to predict aboveground and foliage biomass with relative uncertainties compared against generalized biomass models utilized in North America. However, results remained biased in model fitting for woodland and conifer species suggesting poor representation of individual tree model error while improving overall accuracy and precisions of annual regional GHG inventories*

Dietze, M. C., Fox, A., Beck-Johnson, L. M., Betancourt, J. L., Hooten, M. B., Jarnevich, C. S., ... & White, E. P. (2018). Iterative near-term ecological forecasting: Needs, opportunities, and challenges. *Proceedings of the National Academy of Sciences*, 115(7), 1424-1432.

- *Articles discusses the advantages and disadvantages of near-term ecological forecasting and decision-making as well as suggestions to improve interoperability, latency, and uncertainty quantification in ecological forecasting to push predictive ecological modeling forward*

Domke, G. M., Woodall, C. W., & Smith, J. E. (2011). Accounting for density reduction and structural loss in standing dead trees: Implications for forest biomass and carbon stock estimates in the United States. *Carbon Balance and Management,* 6(1), 1-11.

- *Traditionally, standing dead trees were estimated as a function of live growing-stock trees. This study incorporates standing dead tree adjustments to supplant purely modeled estimation to assess biomass and C stocks across spatial scales with improved error estimation.*

Fisher, R. A., & Koven, C. D. (2020). Perspectives on the future of land surface models and the challenges of representing complex terrestrial systems. *Journal of Advances in Modeling Earth Systems*, 12(4), e2018MS001453.

- *Paper identifies three "grand challenges" in the development of Land Surface Models based around complexity, representation of land surface heterogeneity, and parametric dynamics across a broad set of problems. Authors discuss previous progress and future directions of research for each challenge*

Gormanson, Dale D.; Pugh, Scott A.; Barnett, Charles J.; Miles, Patrick D.; Morin, Randall S.; Sowers, Paul A.; Westfall, James A. 2018. Statistics and quality assurance for the Northern Research Station Forest Inventory and Analysis Program. Gen. Tech. Rep. NRS-178. Newtown Square, PA: U.S. Department of Agriculture, Forest Service, Northern Research Station. 25 p. https://doi.org/10.2737/NRS-GTR-178.

- *Report outlines inventory methodologies, the multi-phase inventory process, and other FIA surveys. The report provides stratification and precision methods, integration of newer data models with previous inventories and detailed* *information on sources and types of error within the USFS FIA database. Furthermore, it provides documentation on data collection and quality assurance of data measured in the field*

Harmon, M. E., Fasth, B., Halpern, C. B., & Lutz, J. A. (2015). Uncertainty analysis: an evaluation metric for synthesis science. *Ecosphere,* 6(4), 1-12.

- *Devises four general classes of uncertainty estimation (1) measurement uncertainty (2) sampling uncertainty (3) model prediction uncertainty (4) model selection uncertainty. Examine sources of uncertainty to improve future biomass estimation outlines future opportunities and challenges.*

Larocque, G. R., Bhatti, J. S., Boutin, R., & Chertov, O. (2008). Uncertainty analysis in carbon cycle models of forest ecosystems: research needs and development of a theoretical framework to estimate error propagation. *Ecological Modelling*, 219(3-4), 400-412.

- *Article discusses development of process-based models for forest ecosystems and knowledge gaps in error propagation of forest C models. Discusses commonly used methods to facilitate uncertainty to further facilitate model development and model-driven decisions systems to derive optimum pathways*

Link, J.S., Ihde, T.F., Gaichas, S.K., Field, J.C., Brodziak, J.K.T., Townsend, H.M., Peterman, R.M. (2012). Dealing with uncertainty in ecosystem models: The paradox of use for living marine resource management. *Progress in Oceanography,* 102, 102-114.

- *Article characterizes uncertainty as applied to ecosystem models into six major factors, including: natural variability; observation error; inadequate communication among scientists, decision-makers and stakeholders; the structural complexity of the model(s) used; outcome uncertainty; and unclear management objectives*

Makela, A., Landsberg, J., Ek, A.R., Burk, T.E., Ter-Mikaelian, M., Agren, G.I., Oliver, C.D., Puttonen, P. (2000). Process-based models for forest ecosystem management: current state of the art and challenges for practical implementation. Tree Physiology, 20, 289-298.

- *Article discusses the operational implementation of process-based models to practical forest management, reviewing several carbon balance models for estimating stand productivity and individual tree growth and competition, and reviewing model calibration and validation methods that take account of the hybrid character of models*

McRoberts, R. E., Chen, Q., Domke, G. M., Ståhl, G., Saarela, S., & Westfall, J. A. (2016). Hybrid estimators for mean aboveground carbon per unit area. *Forest Ecology and Management*, 378, 44-56.

- *IPCC outlines two criteria for satisfactory guidance: 1) minimizing bias and 2) minimizing uncertainty. McRoberts introduces a novel hybrid inferential framework to estimate error propagation for tree-level allometric models, a source of bias and uncertainty previously ignored in carbon estimation to meet IPCC guidance. This study considers 6 sources of uncertainty and determines that allometric model variance is negligible when using species-specific models and model assisted regression estimators.*

Penman, J., Kruger, D., Galbally, I., Hiraishi, T., Nyenzi, B., Emmanul, S., Buendia, L., Hoppaus, R., Martinsen, T., Meijer, J., Miwa, K., & Tanabe, K. (Eds) (2000). *Intergovernmental Panel on Climate Change Good Practice Guidance and Uncertainty Management in National Greenhouse Gas Inventories, Chapter 6: Quantifying Uncertainties in Practice*. IPCC National Greenhouse Gas Inventories Programme.

- *Describes good practice in estimating and reporting uncertainties associated with both annual estimates of emissions and emission trends over time, and identifies types of uncertainty from the viewpoint of the inventory practitioner, and shows how to obtain expert judgements in a consistent manner*

Penman, J., Kruger, D., Galbally, I., Hiraishi, T., Nyenzi, B., Emmanul, S., Buendia, L., Hoppaus, R., Martinsen, T., Meijer, J., Miwa, K., & Tanabe, K. (Eds) (2000). *Intergovernmental Panel on Climate Change Good Practice Guidance and Uncertainty Management in National Greenhouse Gas Inventories, Chapter 8: Quality Assurance and Quality Control*. IPCC National Greenhouse Gas Inventories Programme.

- *This guidance establishes good practice consistent with the Revised 1996 IPCC Guidelines for National Greenhouse Gas Inventories (IPCC Guidelines), and reflects practicality, acceptability, cost-effectiveness, existing experience, and the potential for application on a worldwide basis, to improve transparency, consistency, comparability, completeness, and confidence in national inventories of emissions estimates.*

Penman, J., Kruger, D., Galbally, I., Hiraishi, T., Nyenzi, B., Emmanul, S., Buendia, L., Hoppaus, R., Martinsen, T., Meijer, J., Miwa, K., & Tanabe, K. (Eds) (2000). *Intergovernmental Panel on Climate Change Good Practice Guidance and Uncertainty Management in National Greenhouse Gas Inventories, Annex 1: Conceptual Basis for Uncertainty Analysis*. IPCC National Greenhouse Gas Inventories Programme.

- *This annex document for IPCC good practice guidance is concerned with the basis for concepts used to discuss uncertainties in greenhouse gas inventories*

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