Fusion of Tree Ring Data and Forest Inventory Data to Improve Estimates of Tree Growth, C Sequestration Variability, and Climate Sensitivity

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1950 — U.S. Periodic Forest Inventories — GHG LULUC baseline –1971 — 1985 — Periodic-annual data gap — GHG Baseline—1990 — 1999 — U.S. Annual Design Forest Inventory and Analysis (FIA) — 2022 — 2050

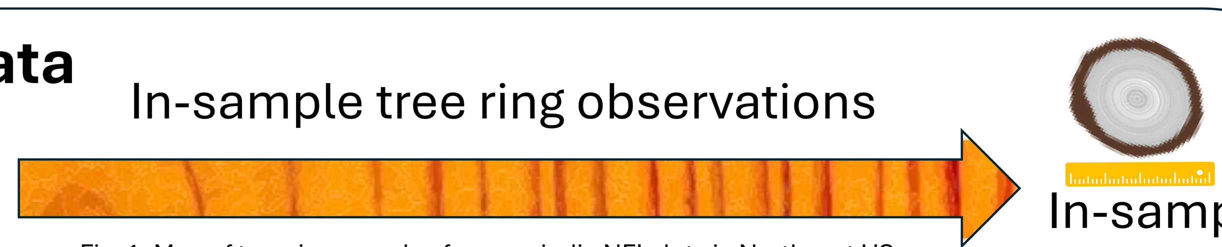
Introduction & objectives

- National Forest Inventory (NFI) data support greenhouse gas (GHG) estimation for UNFCCC reporting (USGHG Inventory)
- The USGHG Inventory includes estimates for the period 1990-two years before present & ideally including data back to 1971
- Attribution of interannual variability in forest GHG estimates is important for assessing progress and informing mitigation strategies
- The US forest C sink is declining & this work advances understanding of drivers of this change

Data

Site Tree Data from Periodic Inventories

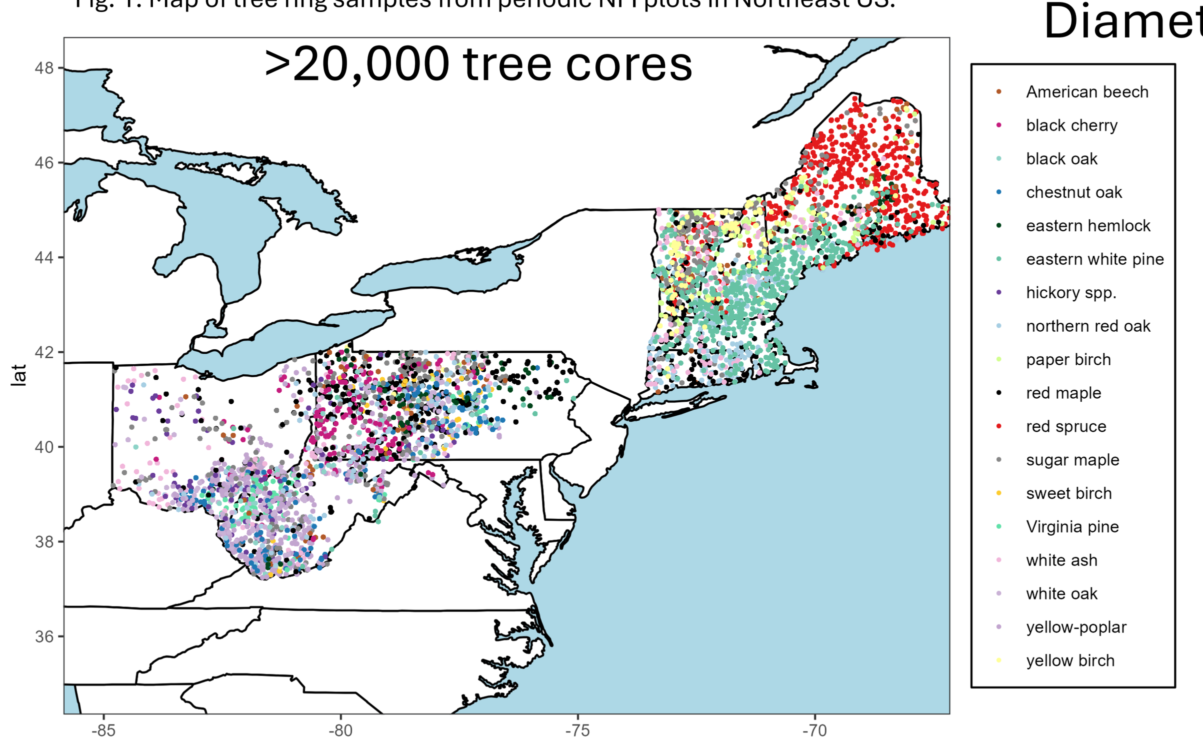
In-sample tree ring observations



In-sample Diameters

Fig. 1. Map of tree ring samples from periodic NFI plots in Northeast US.

>20,000 tree cores



Data previously analyzed in: Smith, R. B . *et al.* (1990). *Res. Pap. NE-637;* Canham, C. D. *et al* (2018) *Ecosphere*

Interannual estimates of growth & diameter

(historic forest inventories)

Model Assisted Estimation:

1. Prediction & Validation
2. Data Assimilation of second diameter
3. Tree-level hindcast

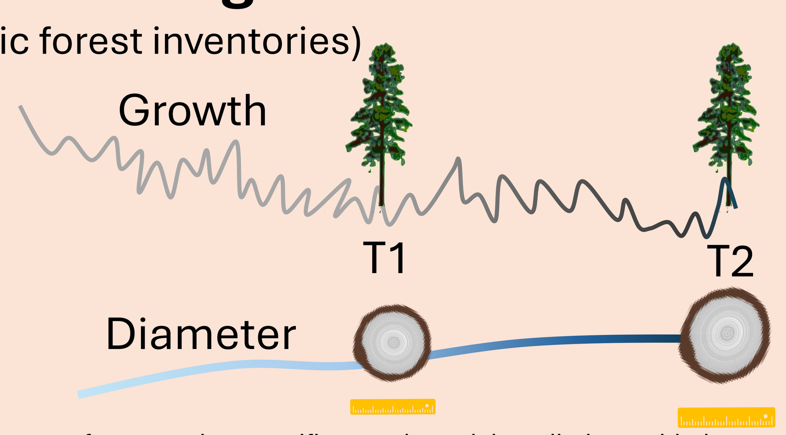
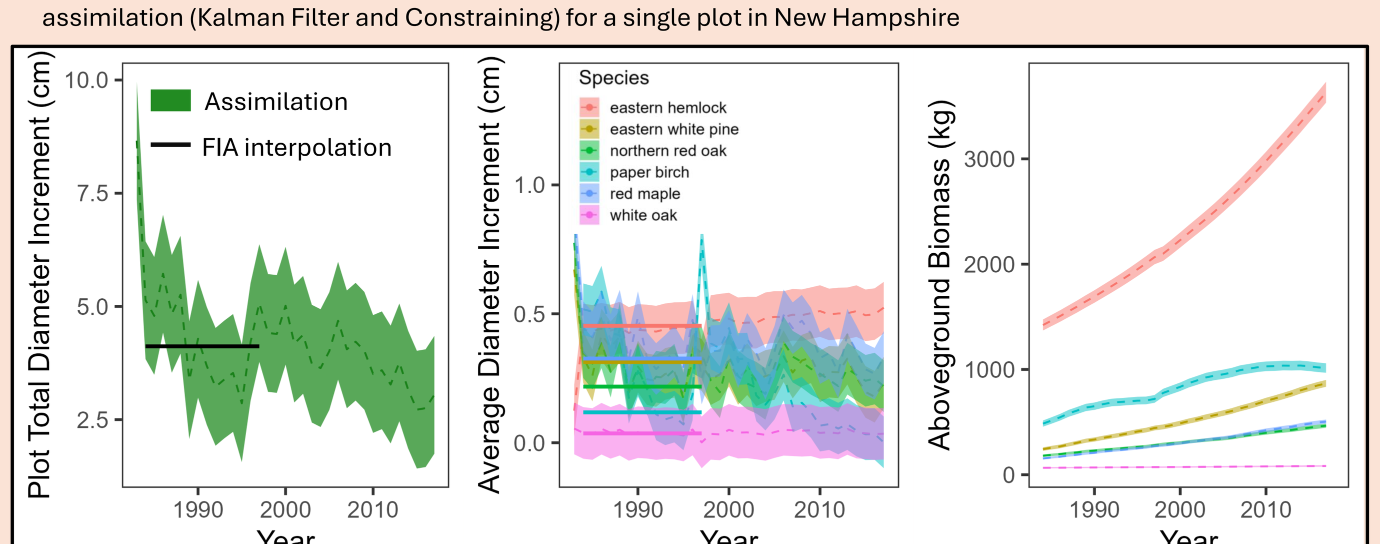


Fig. 3. Interannual variation in growth and diameter from species-specific growth model predictions with data assimilation (Kalman Filter and Constraining) for a single plot in New Hampshire



Bayesian State-Space Model of Tree Growth

Process model

$$Diameter_{i,t} = Diameter_{i,t-1} + increment_{i,t}$$
$$increment_{i,t} = lognormal(\mu_{i,t}, \sigma_{additive})$$

$$\mu_{i,t} = \alpha_{plot} + \beta_1 * diameter_{i,t-1} + \beta_2 * climate_{i,t} + \beta_6 * pollution_{i,t} + \beta_6 * disturb. + \beta_4 * competition + \beta_7 * site\ variables)$$

(annual seasonal variables selected using Climwin)

N deposition (annual)

Annual acres defoliated % damage (FIA)

BAL
BA non-focal
Species density

Slope aspect elevation MAP & MAT

Data models

$$y_{i,t} \sim normal(inc_{i,t}, \sigma_{inc})T(0,)$$
$$z_{i,t} \sim normal(x_{i,t}, \sigma_{dbh})$$

Priors for covariate effects

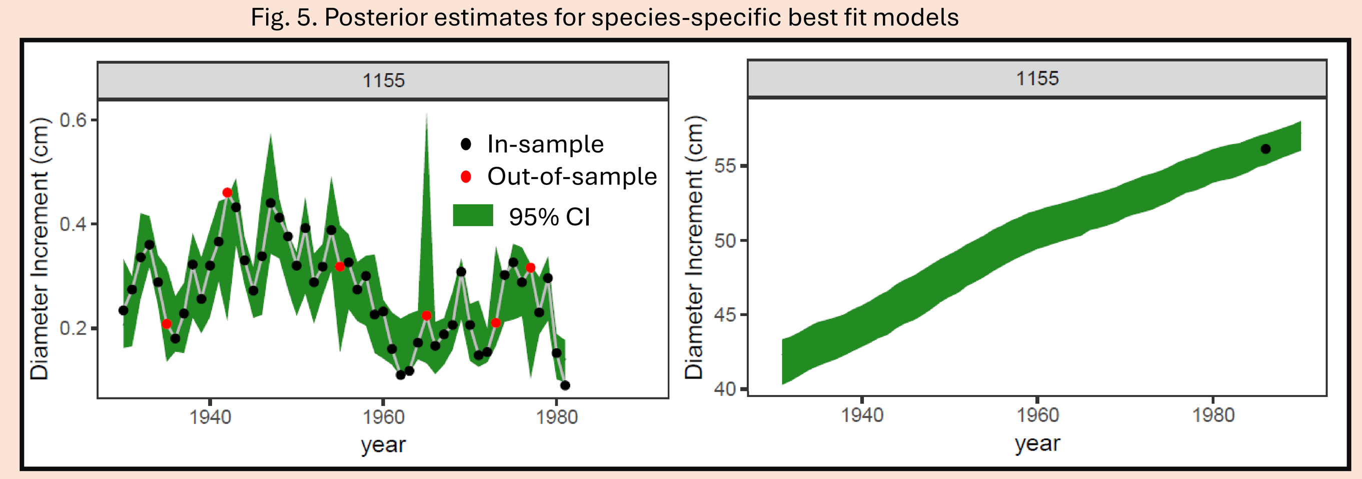
$$\beta_i \sim normal(0, 10)$$

Software

STAN via rstan
Cyverse DE

Tree-level annual growth and diameter predictions

Fig. 5. Posterior estimates for species-specific best fit models



Model Validation with Site Tree Data

Table 1. Fit statistics for species-specific growth models

			R-squared		
Species	SPCD	model	In-Sample Diameter	In-Sample Increment	Held-Out Increment
Virginia pine	132	model.7	1.0000	0.9974	0.6481
bigtooth aspen	743	model.5	1.0000	0.9980	0.5734
paper birch	375	model.7	1.0000	0.9890	0.5245
black cherry	762	model.6	1.0000	0.9971	0.4265
white ash	541	model.5	0.9999	0.9898	0.3527
red maple	316	model.3	1.0000	0.9948	0.3505
northern red oak	833	model.3	0.9999	0.9835	0.3456
yellow birch	371	model.6	1.0000	0.9894	0.3451
American beech	531	model.7	1.0000	0.9890	0.2322
hickory spp.	400	model.7	0.9999	0.9716	0.1018
chestnut oak	832	model.7	0.9995	0.9419	0.0562
eastern hemlock	261	model.5	0.9999	0.9762	0.0247
yellow-poplar	621	model.5	0.9999	0.9934	0.0185
sugar maple	318	model.3	0.9996	0.9783	0.0153
white oak	802	model.5	0.9998	0.9637	0.0128
red spruce	97	model.6	0.9999	0.9702	0.0109

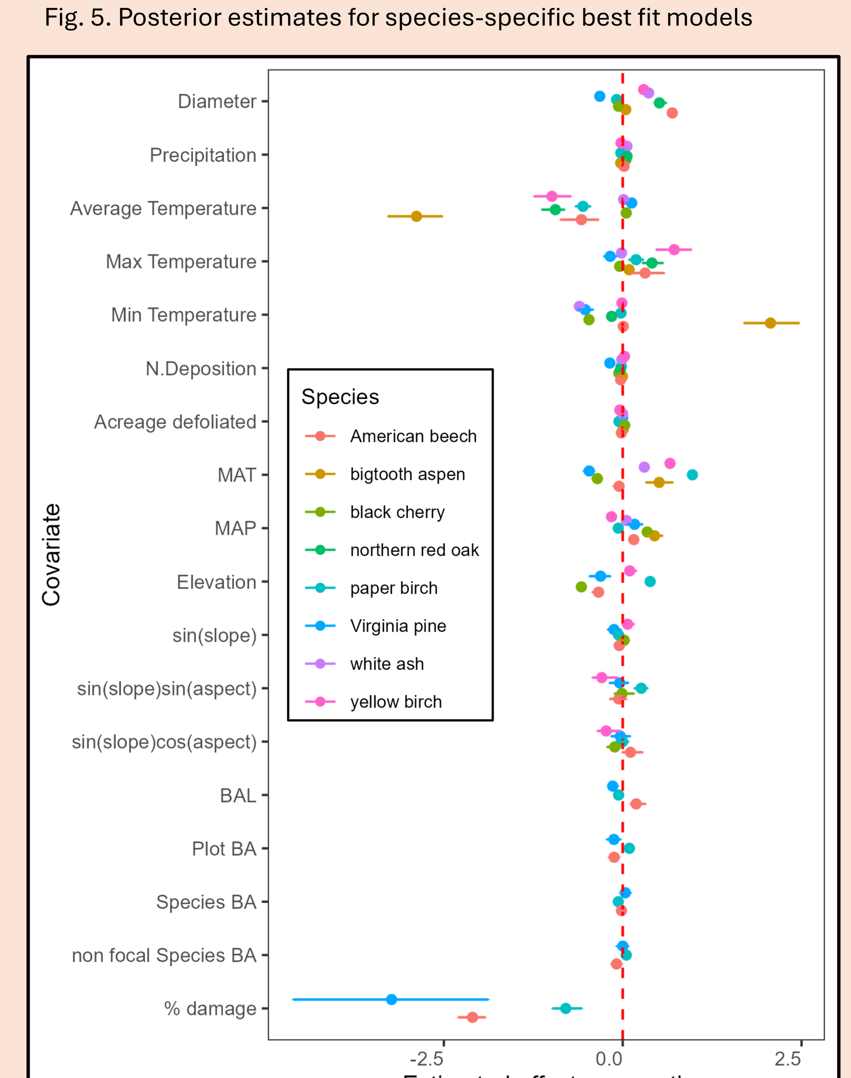
Solutions to improved predictive ability for some species:

1. QA/QC
- revisit original crossdating

2. Model improvement
- spatially varying responses
- better disturbance representation

Species-specific growth responses

Fig. 5. Posterior estimates for species-specific best fit models



Results

- Continuous tree ring data associated with inventories allow us to estimate interannual variation in growth & parse important drivers:
  1. interannual variation in climate
  2. spatial variation in temperature across species ranges
  3. % damage information from inventory records is important for some species

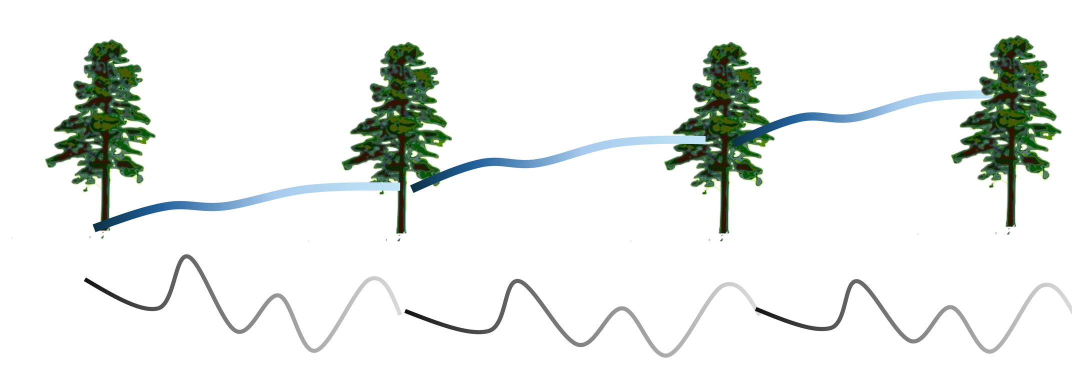
Future work will extend this work to the nationally consistent inventory, which has remeasurements that inform growth, damage, and mortality

Future work: Interannual variation in FIA tree tables

Step 1: Link tree level FIA measurements with **ForestTIME**

Incorporate growth predictions with a tool to create longitudinal dataset, linking trees through time from FIAdb

Step 2: Prediction & validation with climate-sensitive growth models, then assimilating with repeat observations



Step 3. Using predictions with assimilated remeasurements, generate Annualized tree tables

Example Assimilation of second diameter with Kalman Filter to improve estimation