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

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Motivation

- The US forest C sink has been declining since at least 1990
- Estimation of interannual variability and attribution of drivers in the forest C sink strength is important for assessing progress and informing mitigation strategies
- Historic National Forest Inventories (NFIs) provide a long-term perspective on drivers of change

Objective: Combine tree remeasurements from early US NFIs with tree ring data to forecast tree size over time, building "enhanced NFI" estimates with interannual variability.

Data from historic NFIs: a long-term perspective on drivers of change

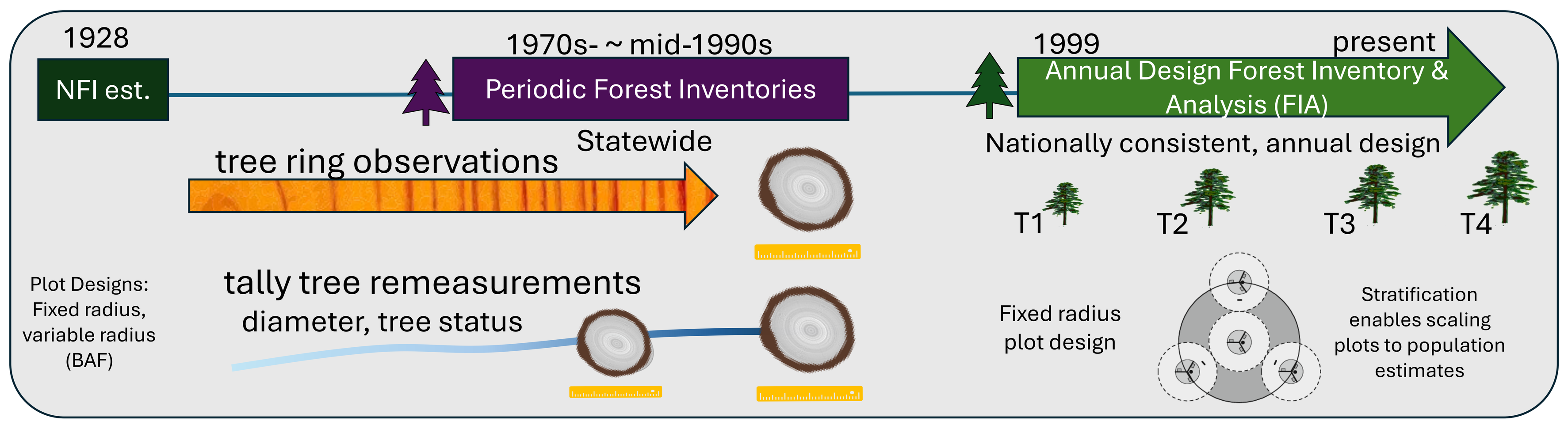
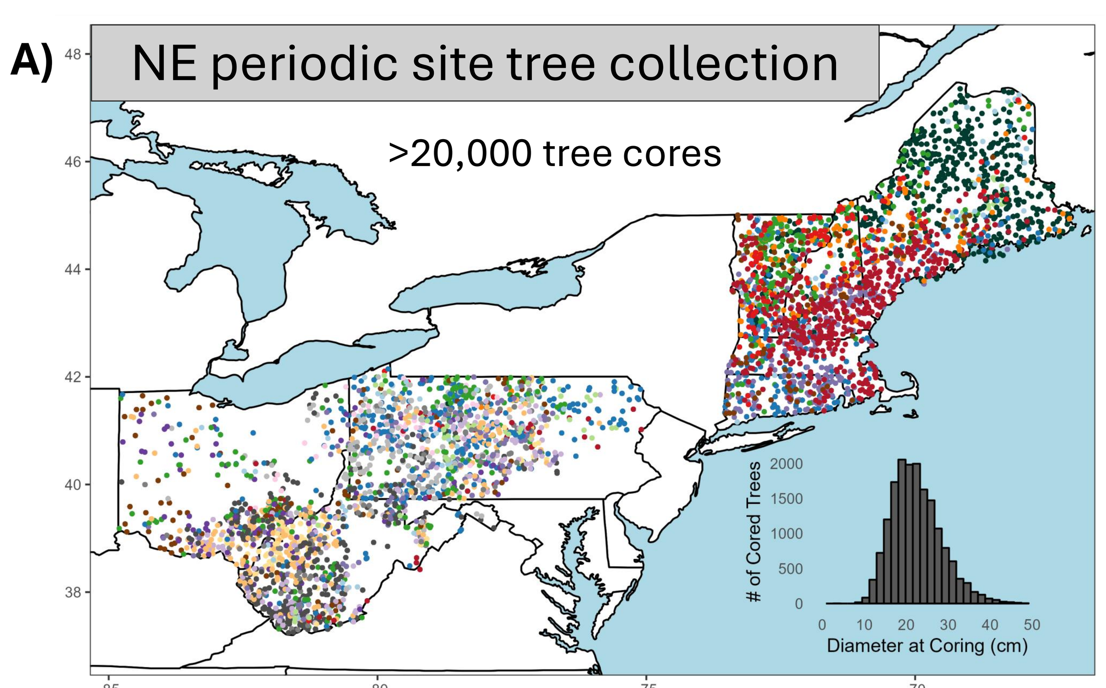
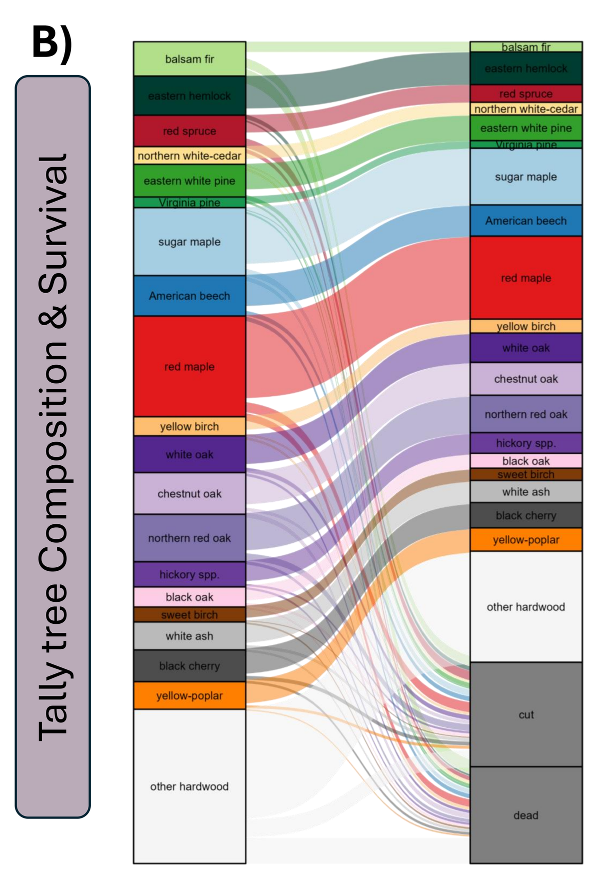


Fig. 1. A) Map of tree ring samples from periodic NFI plots in Northeast US and B) observations of status code change from periodic tally trees. The periodic inventory era overlaps with the onset of changes in drivers of growth, including climate C), N deposition D), and three disturbance agents E) in this region.

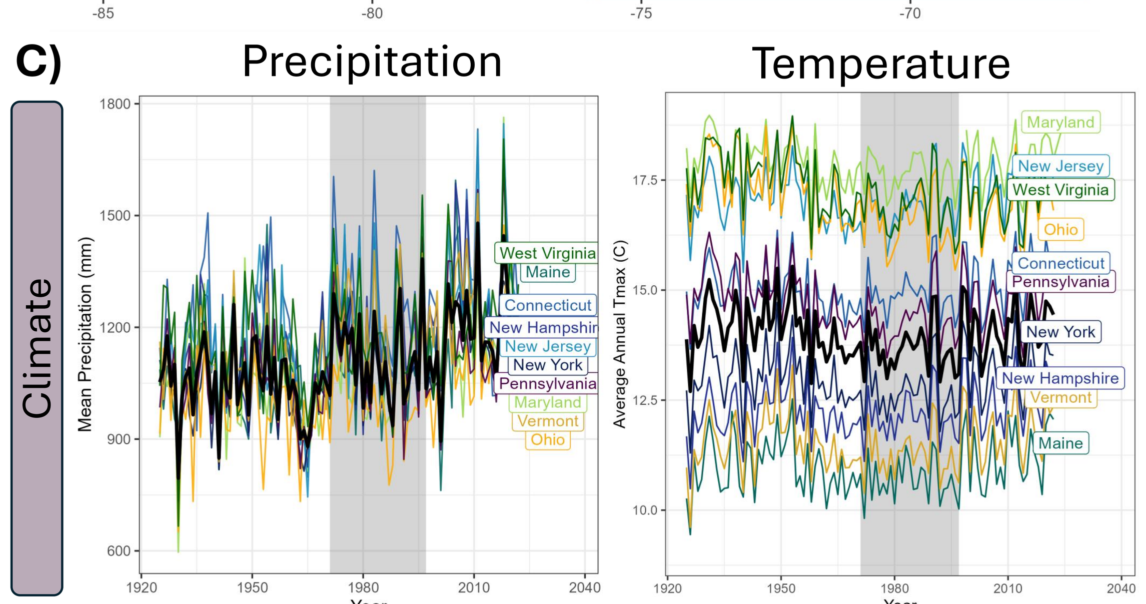
A)



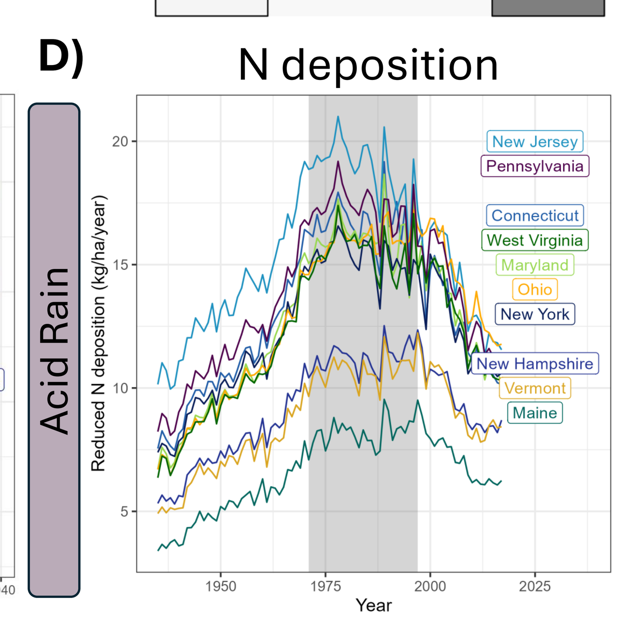
B)



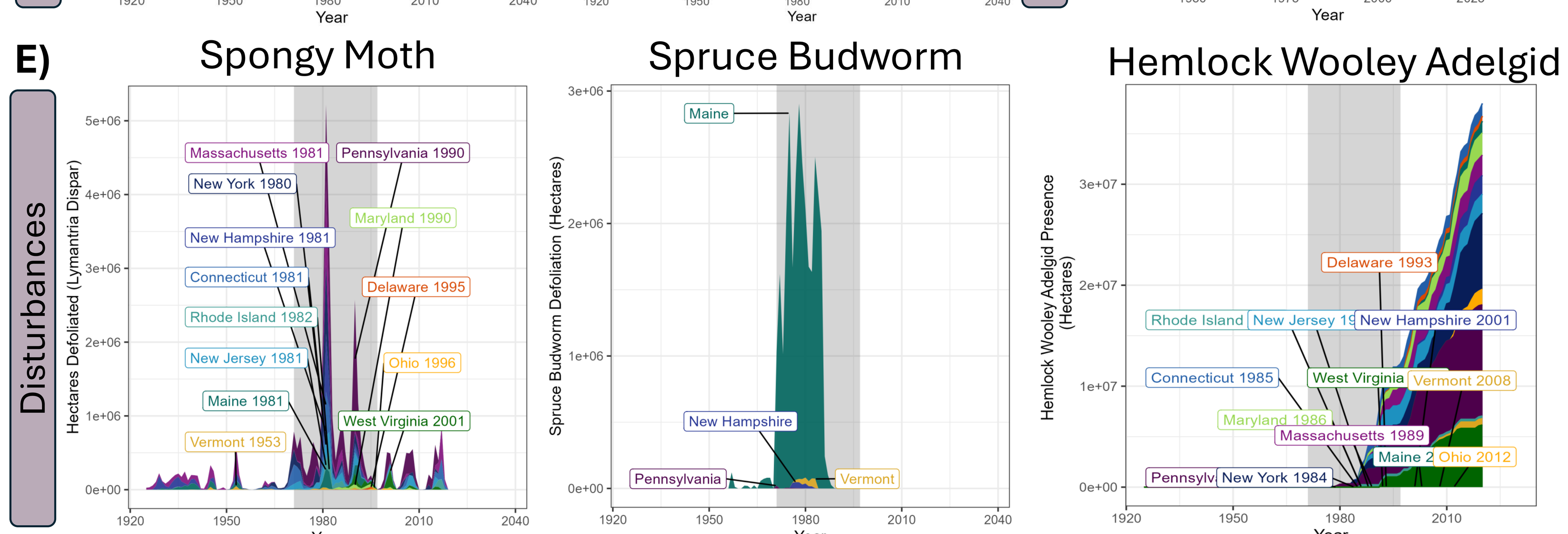
C)



D)



E)



Bayesian State-Space Model of Tree Growth

Process model

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

$$\mu_{i,t} = \alpha_t + \boldsymbol{\beta}_{1\ldots a} * \textbf{annually varying}_{t,a} + \boldsymbol{\beta}_{1..s} * \textbf{spatially varying}_{s}$$

Predictors of growth included in current version

seasonal climate (selected for each species using Climwin) — *Nitrogen deposition* — *Spongy moth acres defoliated % damage (FIA)* — *BAL, BA non-focal, Species density* — *slope, aspect, elevation, MAP & MAT*

Data models

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

Priors

$$\boldsymbol{\beta} \sim N(0,5)$$
$$\boldsymbol{\alpha}_t \sim N(0, \sigma_{TREE})$$
$$\sigma_{TREE} \sim cauchy(0,1)$$
$$\sigma_{inc} \sim cauchy(0,1)$$
$$\sigma_{add} \sim cauchy(0,1)$$
$$\sigma_{dbh} = 0.5$$

Software: STAN via rstan in Cyverse DE

Growth Model Validation with Site Tree Data

			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

Table 1. Fit statistics for species-specific growth models

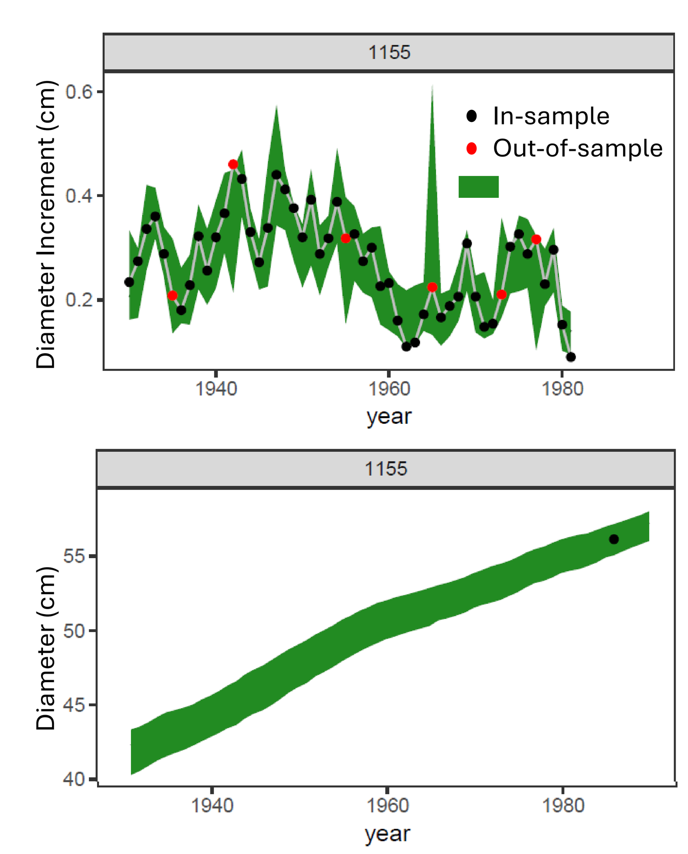


Fig. 2. Posterior estimates of diameter growth (top), and diameter (bottom) with 95% Credible Intervals for a red oak tree.

Further state-space model development

1. Improvements to QA/QC of our dataset (i.e., crossdating, filtering)
2. Exploration and inclusion of additional drivers, especially disturbance agent data
3. Exploration of interaction effects and/or different function forms
4. Validation and simulation exercises
   - Hold out full tree ring time-series?

References:

Tree core data
1, Smith, R. B . *et al.* (1990). *Res. Pap. NE-6372*
2, Canham, C. D. *et al* (2018) *Ecosphere*

Nitrogen deposition data
3, Byrnes, D. K., Meter, K. J. V., & Basu, N. B. (2020). *Global Biogeochemical Cycles*, *34*(9).

Disturbance data
4. *USDA Forest Service Lymantria dispar Digest 2.1.01 released on 1/12/2022.* *https://apps.fs.usda.gov/nicportal/lddigest/cfm/dsp/dsplddigesthome.cfm*
5. *HWA National Initiative. Distribution Maps*. Retrieved May 16, 2025, from https://hemlock-woolly-adelgid-national-initiative-gmsts.hub.arcgis.com/pages/distribution-maps
6. Spruce Budworm records compiled from regional USFS Forest Health annual reports.
7. Cale and Morin. "County-level detection dates for beech scale in Canada and the United States", http://dx.doi.org/10.7939/DVN/10835 V1

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Interannual estimates of growth and diameter

1. **Prediction & Validation** with model posteriors
2. **Data Assimilation (DA)** of tally trees with ssm model posteriors (STAN, not updating parameters)
3. **Full Data Assimilation** with re-estimation of parameters

Posterior prediction of tally tree diameter may lead to biases in tree diameter and increment estimates for non-cored, tally trees

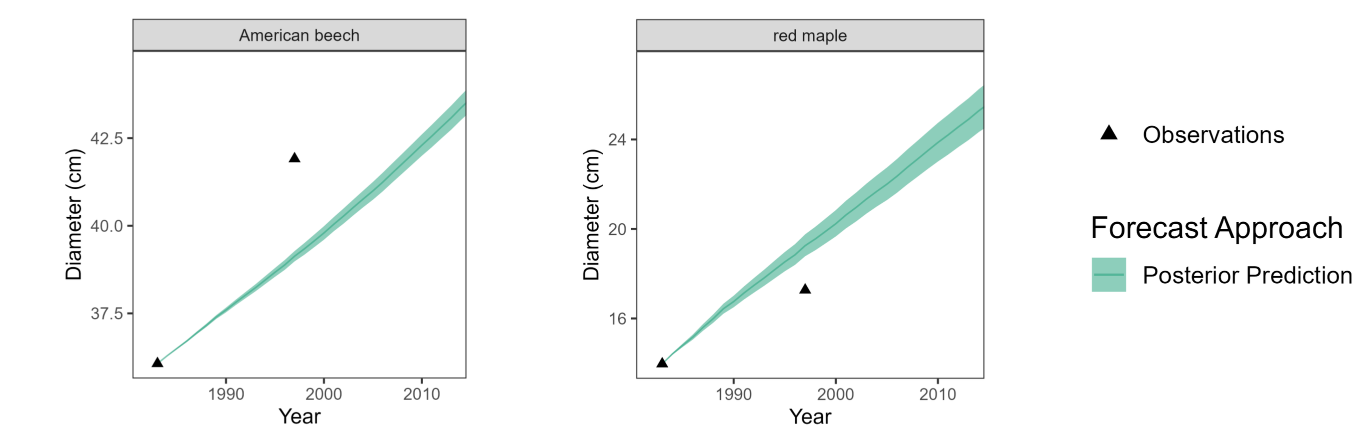

Fig. 3. Single tree examples of how posterior predictions from the first tally tree measurement may strongly underestimate (left) or overestimate (right) the tally tree remeasurement.

Data Assimilation and prediction within STAN reduces bias in estimates & preserves interannual variability

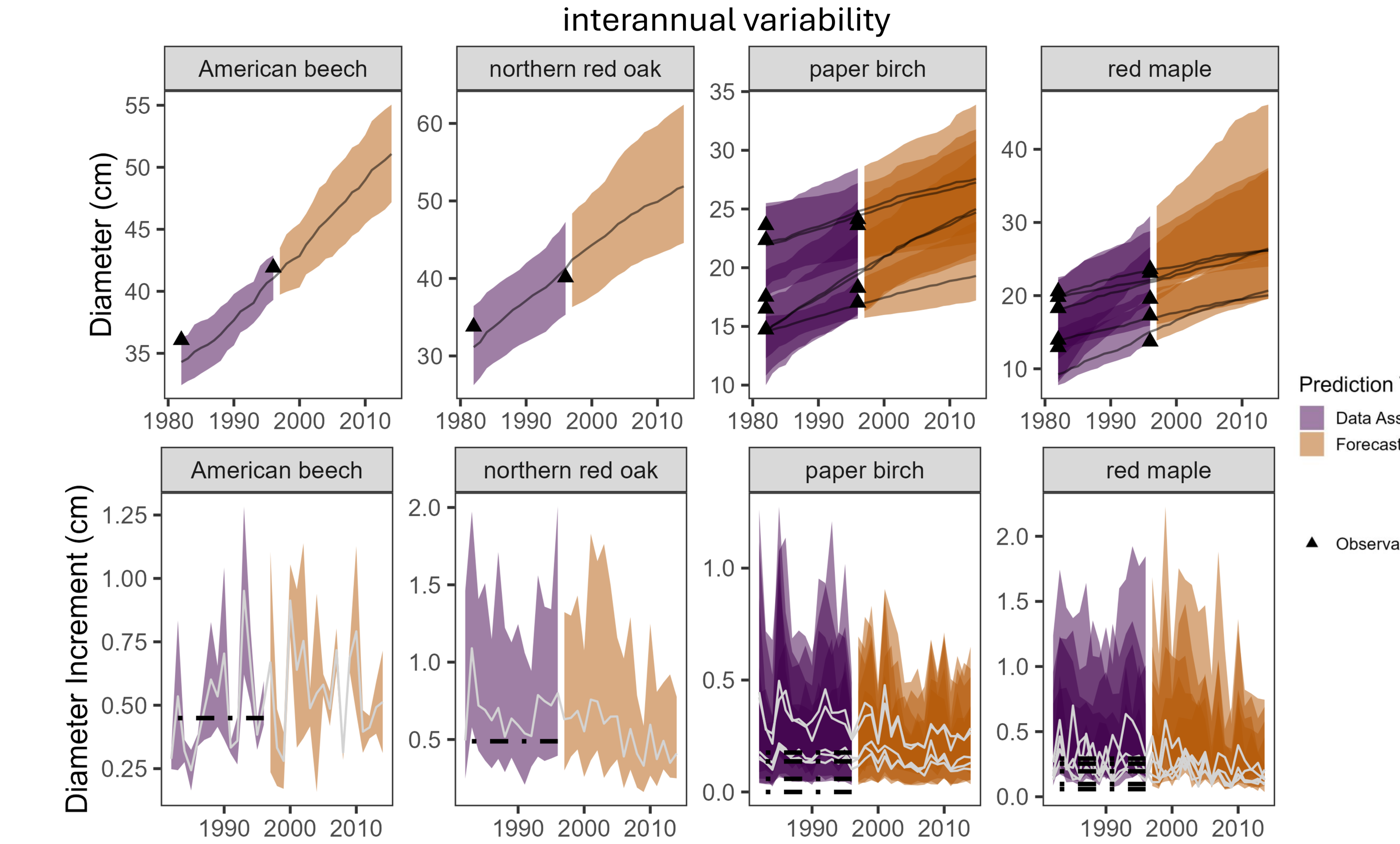

Fig. 4. Estimated diameter (top) and (bottom) diameter increments for all tally trees on an example NFI plot in New Hampshire using DA within STAN modelling framework

From tree to plot to population

Towards the "enhanced NFI"

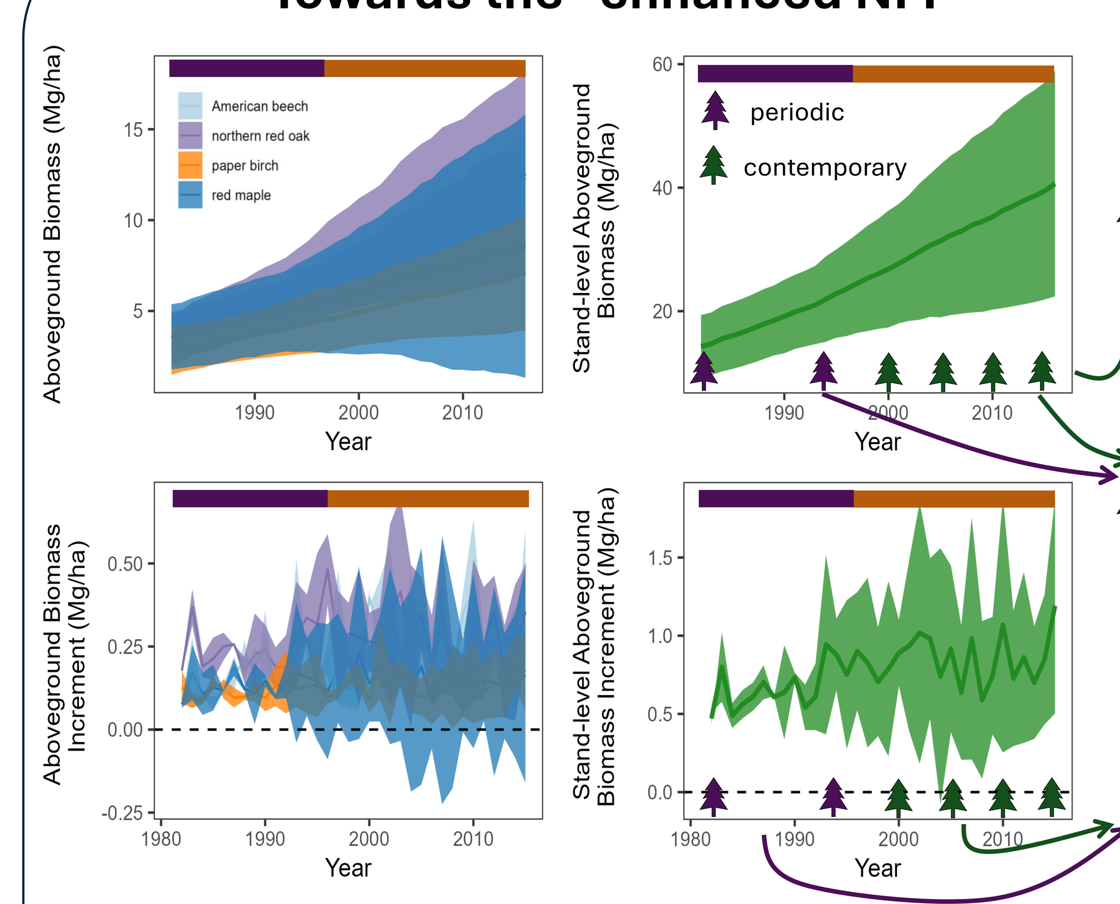

Fig. 5. Estimated AGB (top) and AGB increment (bottom) by species (left), and total stand (right) for an example NFI plot in New Hampshire using DA within STAN modelling framework

Future work

Contemporary NFI data are and opportunity for validation (at plot and/or tree scale), and assimilation

What do we learn about the ecology from updating parameters in a full DA in both time periods?

Parsing dominant ecological drivers of species and stand-scale AGB & AGBI trends