Remote Sensing and Growth Modeling Garbage In, Garbage Out

Don’t Forget The Inventory

Aaron R. Weiskittel, Greg Johnson, David Marshall

OLI/GMUG Joint Meeting

Vancouver, WA

April 21, 2026

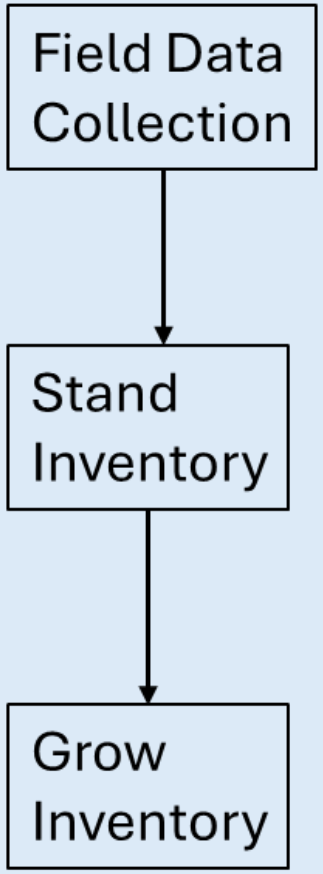
Garbage In, Garbage Out

- **The idea that bad (incorrect or biased) input data results in poor outcomes has been around since the early days of computing : Charles Babbage (1860s), William D, Mellin (1950s) and George Fueschsel (1950s).**

- **Stensom, R. 2016. Is this the first time anyone printed, ‘Garbage In, Garbage Out’? Atlas Obscura**
- https://www.atlasobscura.com/articles/is-this-the-first-time-anyone-printed-garbage-in-garbage-out

Stand-Level (In-place) Inventory

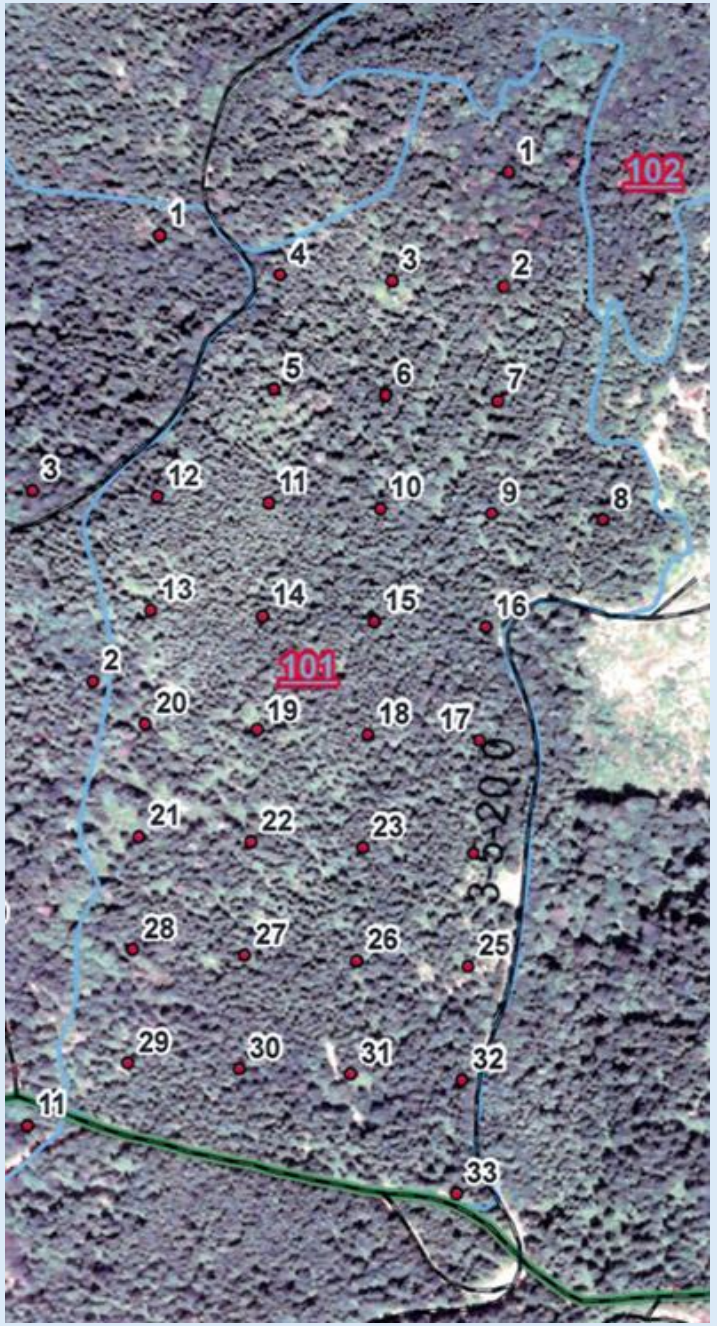
- Since the 1960s and 1970s most forest management has relied on stand-level (in-place) inventories.
- Basis for reporting, tactical and strategic planning
  - What is there?
  - Where is it?
- Cruise a stand (desired precision)
- Compile the inventory
  - Stand Variables
  - Diameter Classes
  - Tree-Lists
- Grow with appropriate model
  - Yield tables or whole stand models
  - DBH distribution models
  - Tree-list Models



Example Stand Exam

- 60.9 acres
- 32 plots random grid
  - 93º random azimuth
  - 275 feet between plots
- 30 BAF for tree counts (DBH)
- Walk-Through on edge plots
- Check borderline trees
- Slope correction
- Tree measurements

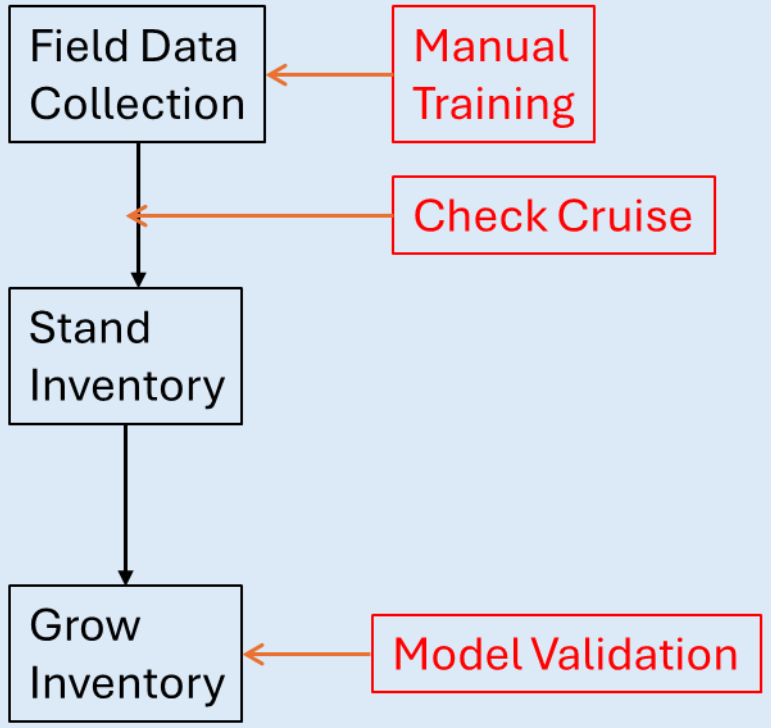
25.6 MBF/acre	SE=7.4%



Stand-Level (Inplace) Inventory

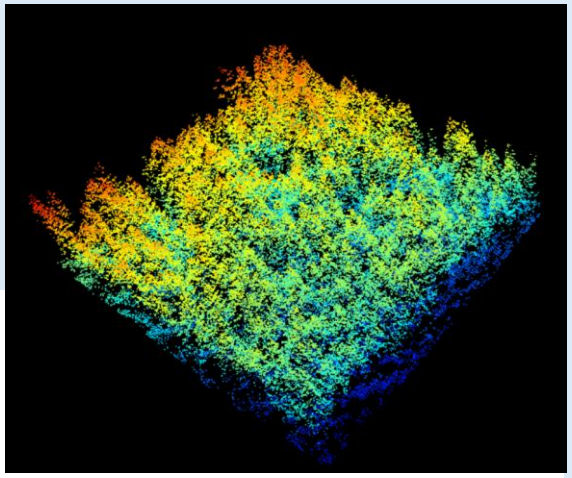
- The Good
  - Unbiased estimate for the stand.
    - if everything is done correctly (not necessarily a given).
    - QA (procedures and training) / QC (check-cruises) – for confidence.
  - Sampling precision (SE) is easily computed.
  - Plots give variation within stand.
- The Not So Good
  - Plots are expensive.
  - Getting harder to find qualified people.
  - Does not tell where things are within the stand.
  - Operations may “split” the stand.
  - Safety exposure.

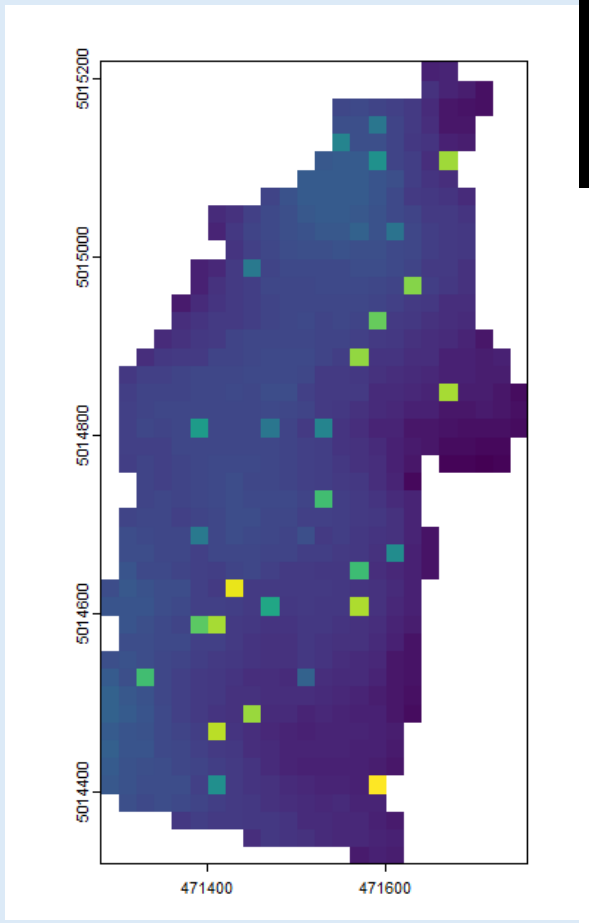
Garbage In, Garbage Out

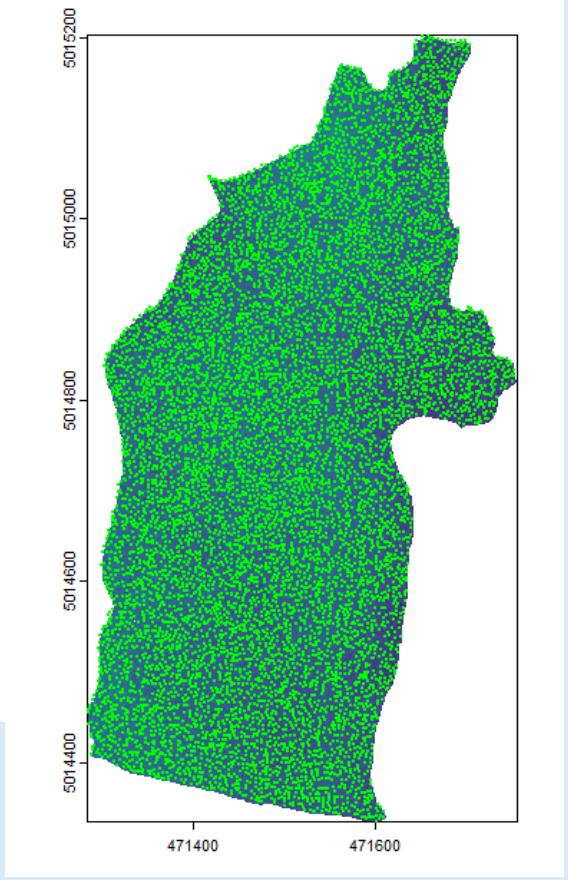


Remotely Sensed Inventory

- Field Data
  - Plots
- Remote Sensed Data
  - Pixels or tree objects
- Modeling
  - Field + Remote Sensed Data
  - Evaluation of fits
- Predict Inventory
  - Aggregate to Stand(?)
- Grow With Appropriate Model







Remotely Sensed Inventory

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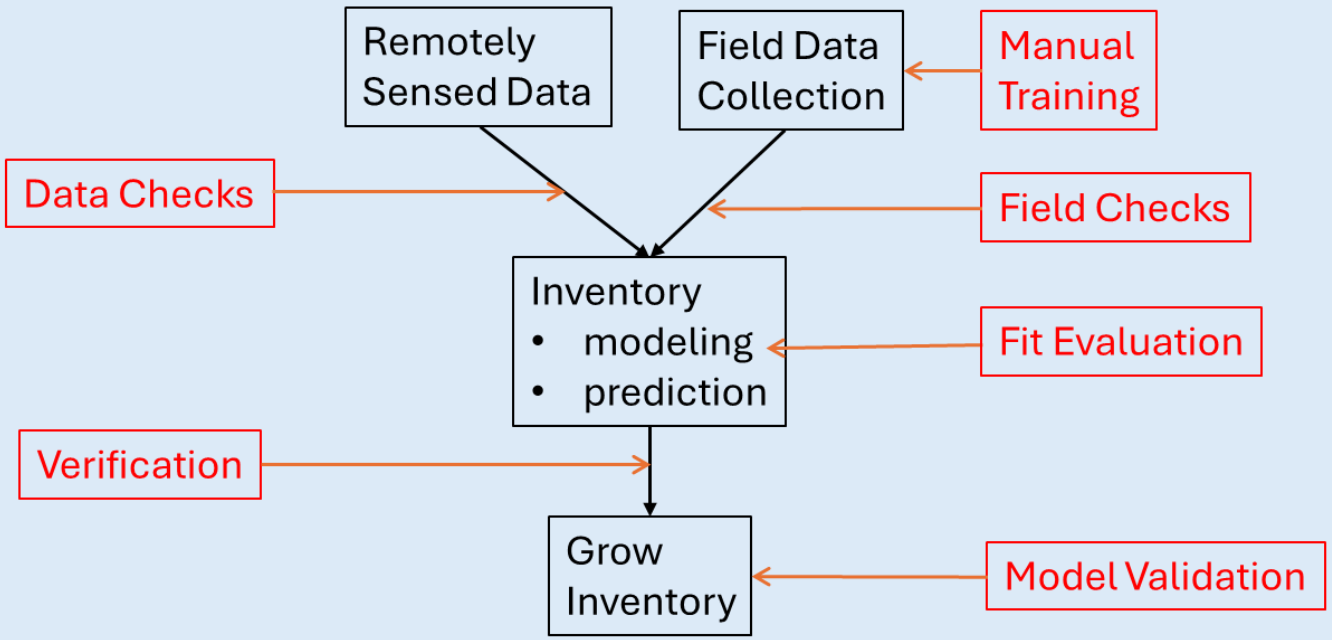
Remotely Sensed Inventory

- The Good
  - Less field work
  - Consistency coverage across large area
  - Within stand scale
  - Cost per unit area (?)
  - Remotely Sensed data value beyond inventory
- Challenges
  - Greater technical requirements (cost)
    - Contracts
    - Modeling
  - Understand Bias and Precision (how good?)
  - Weather (rain, smoke, etc.)
  - Species (if important)
  - Fitting within current management systems

Remotely Sensed Inventory

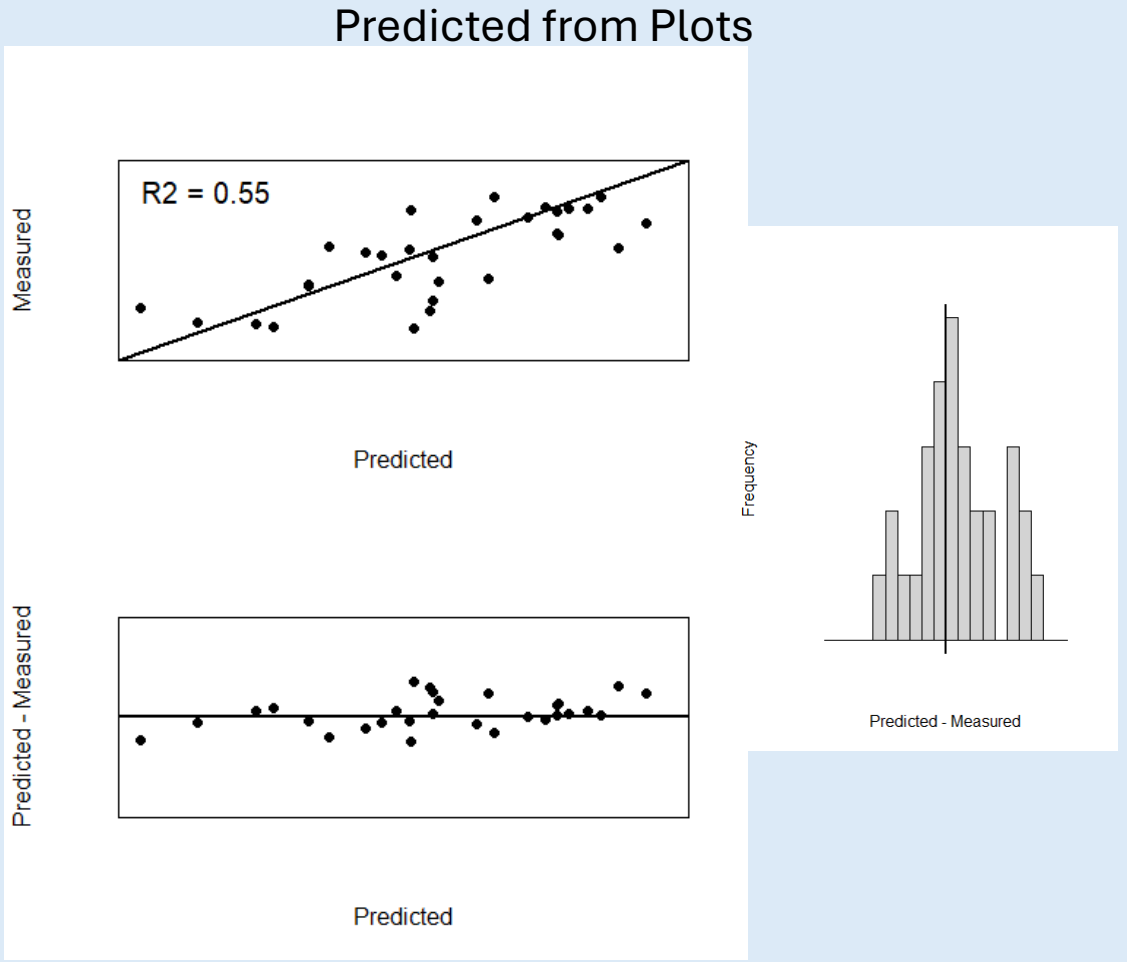
- Field Data
  - Training
  - Field Checks
- Remote Sensed Data
  - Data (contract) Checks
    - Return Density
    - Gaps
    - Ground hits
- Model
  - Field + Remote Sensed Data
  - Fit statistics
- Inventory
  - Verification?
  - At what scale?

Garbage In, Garbage Out



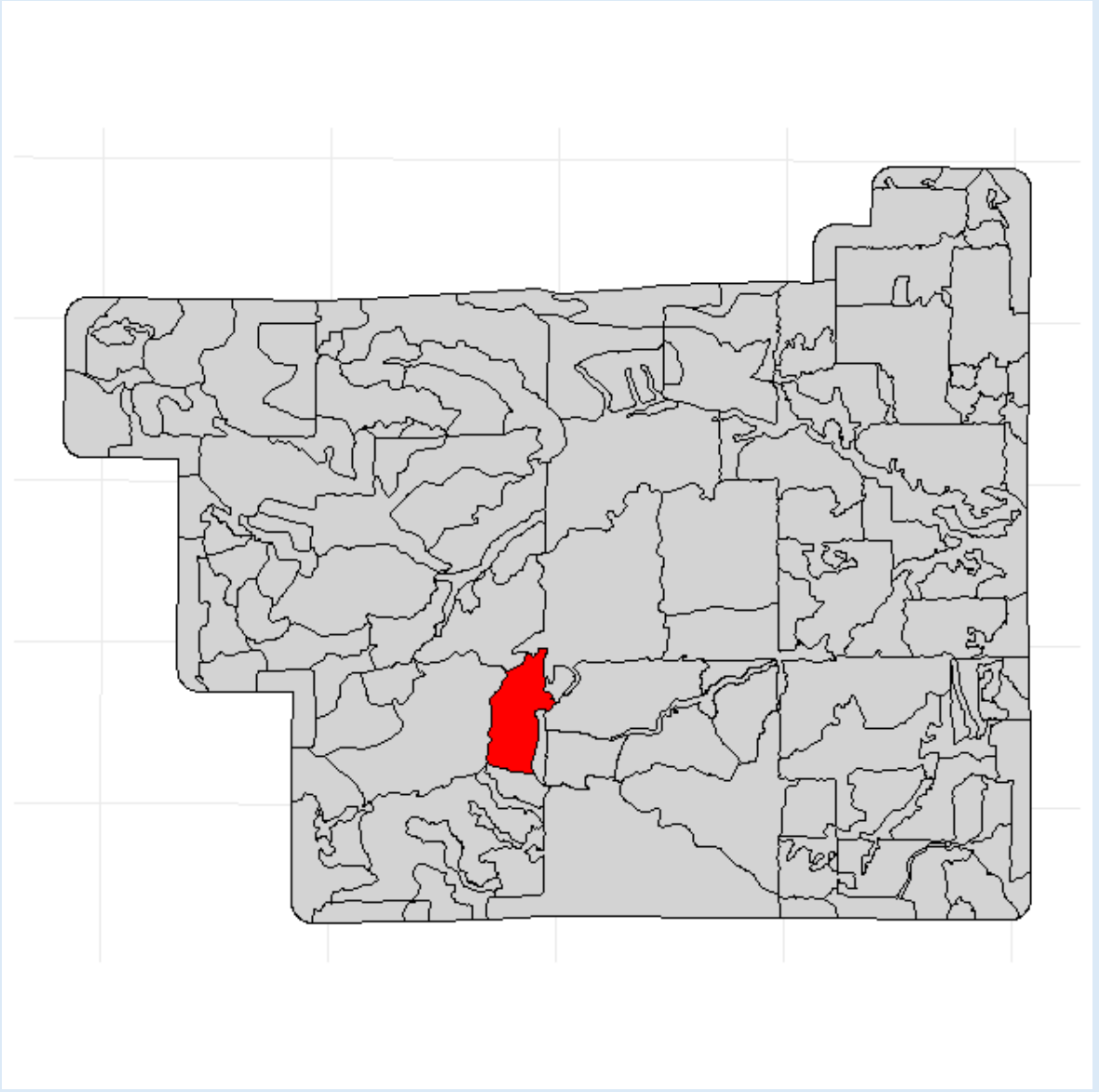
Remote Sensing Forest Inventory

- Different from sampling
- Bias (estimation)
  - Modeling using pixel or tree objects data.
  - Unbiased not ensured
    - Model data “representative”
    - Model specification
- Precision (estimation)
  - The R^2 of fits is not the system’s measure of performance.
    - Fitting Pixels/Tree Objects vs population of Stands
  - Variation between Stands
- How do we independent verify predictions and at what scale?



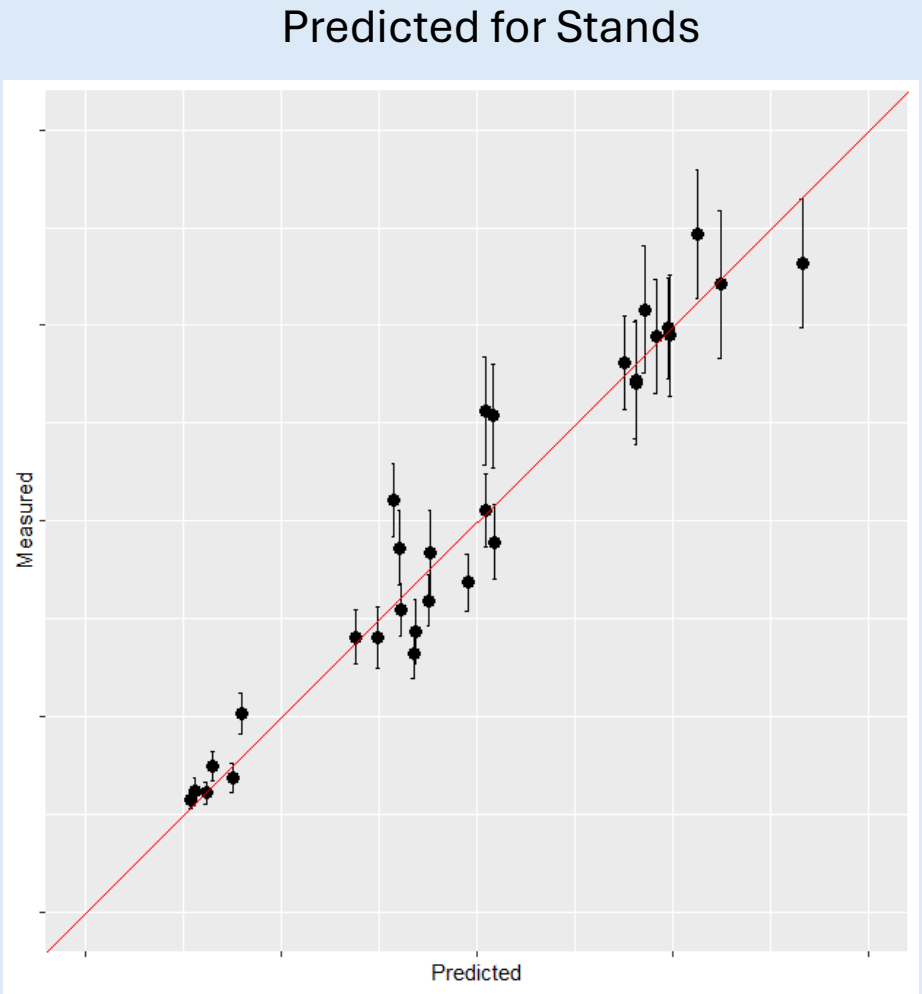
Implementation

- As long as the paradigm for management is the stand:
  - harvest scheduling
  - harvesting units
  - management units
- Managers will still ask how good is the estimate for the stand?



Implementation

- Inventory foresters and inventory users understand a sampled stand level inventory.
- However, they may not understand pixels or tree objects or predictions.
- Some of this is statistics and some of it is psychology!
  - Stand exams vs. predictions.
  - What is (hopefully) unbiasness?
  - Sampling variation vs Prediction variation?
  - What is the full cost comparison.
- One way to gain comfort is with high quality verification cruises
  - Are we doing at least as well (or adequate) for cost?



Verify Growth Estimations

- Project plots
  - Ground-truth inventory (plot)
  - Remotely sensed inventory (plot)
  - Project both with growth model
  - Compare projections … are they of any practical difference?
- Have an “end-of-period” estimate of the ground-truth and remotely sensed inventory can provide important insights.
- Examples
  - Li, Y.; Johnson, G.; Marshall, D. 2021. A case study on forest inventory consistency between multi-temporal forest measurements and LiDAR. Western Mensurationists Meeting.
  - Londo, H.A. 2010. The suitability of LiDar-derived forest attributes for use in The suitability of LiDar-derived forest attributes for use in individual-tree distance-dependent growth-and-yield modeling. Ph.D. Thesis. Mississippi State University, Department of Forestry. 135p.

Caveat Emptor
Doveryay, no Proveryay

The End

Remote Sensing and Growth Modeling – Hope is not a Strategy

OLI/GMUG Joint Meeting

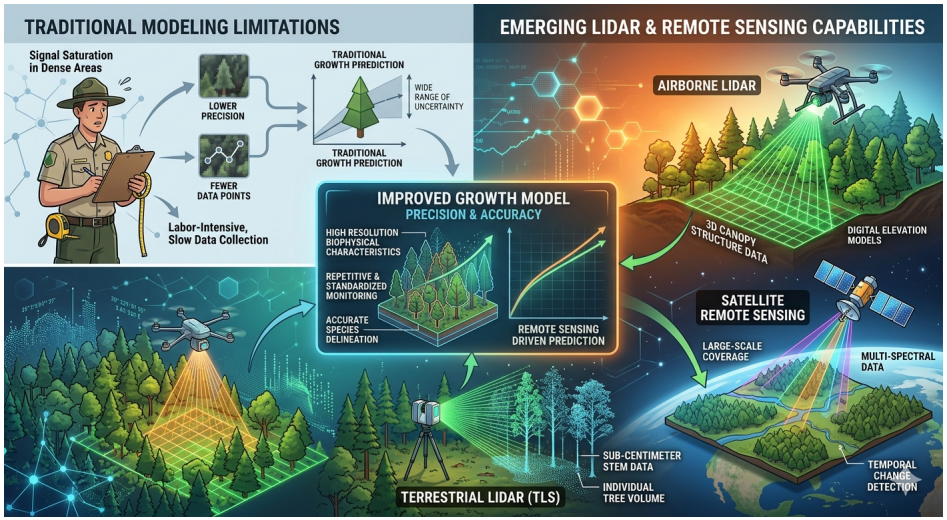
Aaron R. Weiskittel, Greg Johnson, David Marshall

Vancouver, WA

2026-04-21

Hope

- Remotely sensed data (e.g., lidar, Sentinel, Landsat) provide new and comprehensive "measurements" of the forest (or trees?).
- Surely these new metrics can be used to improve growth model precision and accuracy.



See for example:

"Remote sensing, particularly LiDAR, enhances forest growth modeling by providing detailed, multi-scale observations of forest structure that were previously difficult to capture"[1].

[1] He, J., Li, W., Zhao, Z., Zhu, L., Du, X., Xu, Y., Sun, M., Zhou, J., Ciais, P., Wigneron, J.-P., Liu, R., Lin, G., & Fan, L. (2024). Recent advances and challenges in monitoring and modeling of disturbances in tropical moist forests. Frontiers in Remote Sensing, 5. https://doi.org/10.3389/frsen.2024.1332728

Reality

- Lidar metrics have not provided gains in growth model increment equation prediction performance, despite some claims to the contrary[2].
- Successes with lidar metrics have been in the ability to estimate structural changes over time (lidar provides data on forest structure — such as canopy height, density, and vertical profile) and in forest disturbance (wildfire, storm damage, harvests).
- But, can we just predict diameter and height growth better with something remotely sensed???

[2] Štefan Kohek, Borut Žalik, Damjan Strnad, Simon Kolmanič, Niko Lukač, Simulation-driven 3D forest growth forecasting based on airborne topographic LiDAR data and shading, International Journal of Applied Earth Observation and Geoinformation, Volume 111, 2022, 102844, ISSN 1569-8432, https://doi.org/10.1016/j.jag.2022.102844.

Well ...

Maybe we should not expect anything miraculous. In 1995:

"The distance-independent relative size competition indices CC_p, CV_p, and CSA_p, performed as well as or slightly better than the best distance-dependent competition indices based on their reduction in MSE.

This result is counterintuitive. We had expected that explicit knowledge of tree spatial location would prove superior to other indices which do not take location into account. It is not possible with the data at hand to explore the exact causes of this result. Certainly it is possible that the zone in which competition takes place is greater than was examined in this and other research work on competition."[3]

[3] Biging, G.S and M. Dobbertin. Evaluation of Competition Indices in Individual Tree Growth Models. Forest Science, Volume 41, Issue 2, May 1995, Pages 360–377, https://doi.org/10.1093/forestscience/41.2.360

Well ...

In 1985, or 1980, or 1978:

"In general, competition indices by themselves explain a disappointingly small proportion of variation in tree growth, even in stands occupying uniform sites (e.g., Alemdag 1978; Noone & Bell 1980). Invariably, the most important predictor of how a tree is growing is its own size, independent of its neighbours."[4] [5] [6]

[4] Perry, D.A. 1985. The Competition Process In Forest Stands. IN: Attributes of Trees as Crop Plants. 1985. M.G.R. Cannell and J.E. Jackson, eds. Institute of Terrestrial Ecology, Abbots Ripton, Hunts, England.

[5] Noone, C. S. & Bell, J. F. (1980). An evaluation of eight inter-tree competition indices. (Research note no. 66). Corvallis, OR: Oregon State University, Forest Research Laboratory.

[6] Alemdag,I.S. 1978. Evaluation of some competition indexes for the prediction of diameter increment in planted white spruce.For. Manage.Inst. Inf. Rep. FMR-X-108. 39 p.

Oh, and about that growth data set

- It is only recently that we have the ability to pair on-the-ground, tree measurements with contemporaneous remote sensing data.
- The vast majority of our growth and yield data base does not have remotely sensed metrics.

Inventory Anyone?

Perhaps our biggest gains will be in improving inventory estimates taking David's admonitions into account.

Hey AI, create an image of someone giving up on using LiDAR to estimate tree growth and falling back to use it for inventory estimates only

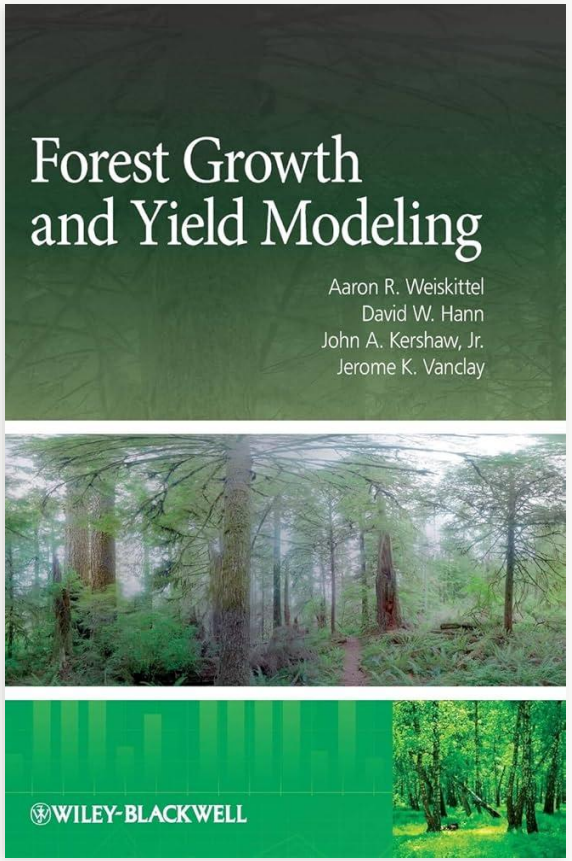
Considerations for Remote Sensing Integration with Growth & Yield Models

Aaron Weiskittel, Greg Johnson, David Marshall

University of Maine | Center for Research on Sustainable Forests

OLI / GMUG Joint Meeting | Vancouver, WA | April 21, 2026

Have We Progressed in 15 Years?



Weiskittel, Hann, Kershaw & Vanclay (2011)

Chapter 17: Future Directions

"LiDAR technology will likely be the most effective remote sensing tool for improving predictions of forest growth..."

p. 459

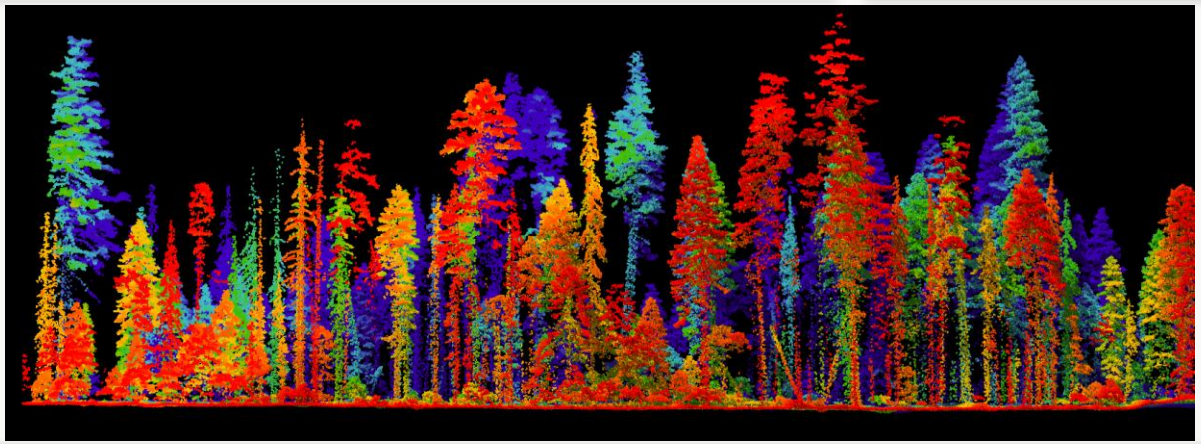
"Growth models need to be capable of handling large amounts of data..."

p. 460

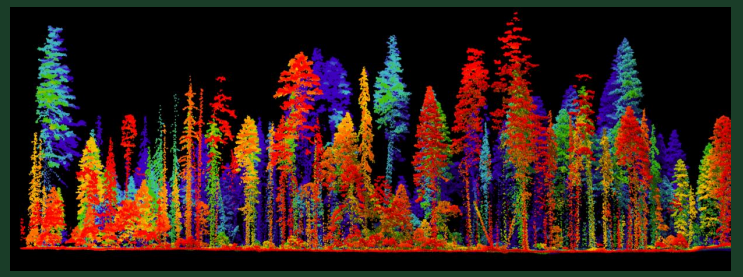
In 2011, the vision was:

same models, better data from LiDAR

Greg's challenge: LiDAR metrics have NOT improved growth model increment equations. Competition indices disappointing since 1978 (my birth year!!!).



Today, the data landscape has changed so dramatically that it calls for different models entirely.



"How do we get RS data into GY models?"

▼

"What GY models does RS data actually enable?"

This reframing changes everything.

David showed us what goes wrong when we force RS into field inventory frameworks.

Greg showed us that LiDAR does not improve tree-level growth predictions.

So stop forcing new data into old frameworks!

The ITC to FVS Pipeline

Error rates from Howland Research Forest validation (Weiskittel et al., in review)

LiDAR Point Cloud
ALS Point density; geolocation error
→
Tree Detection
25-40% miss
→
Species ID
30-50% error
→
DBH Prediction
15% RMSE
→
FVS Tree List
35%+ total

ITC Pipeline: $0.75-1.25+/ac

Large potential compound error at every step.

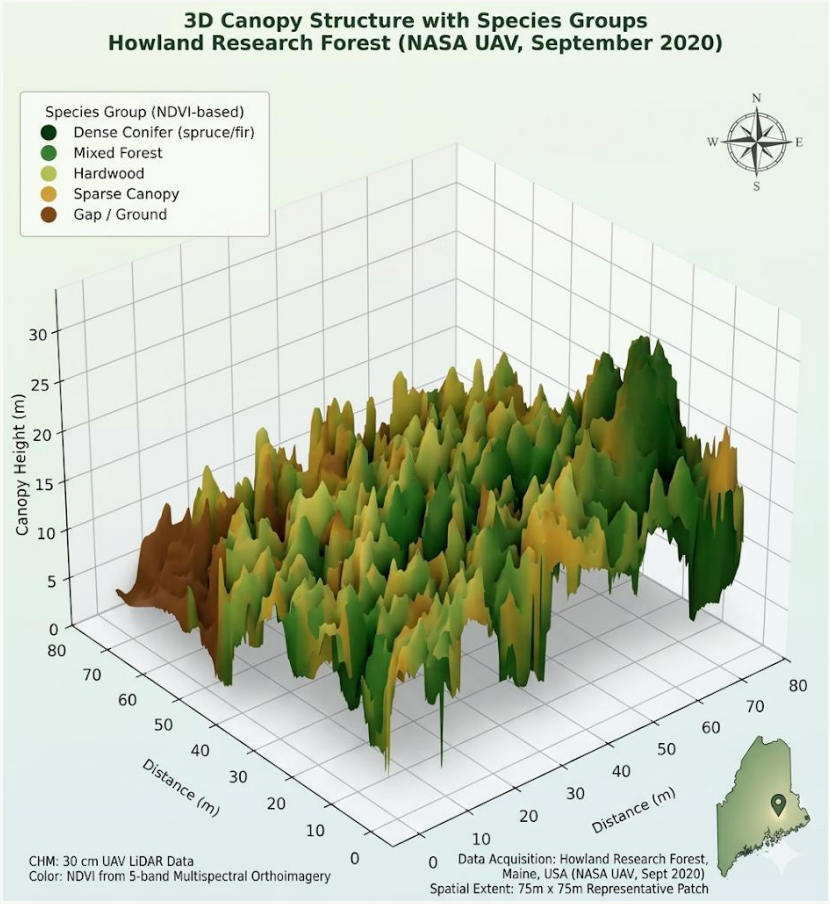
David's point: "Garbage in, garbage out"

Area-Based: $0.25-0.55/ac

No individual tree reconstruction.

Simpler pipeline, lower compound error.

Directly produces stand-level metrics.



What matters more: resolution or accuracy/precision?

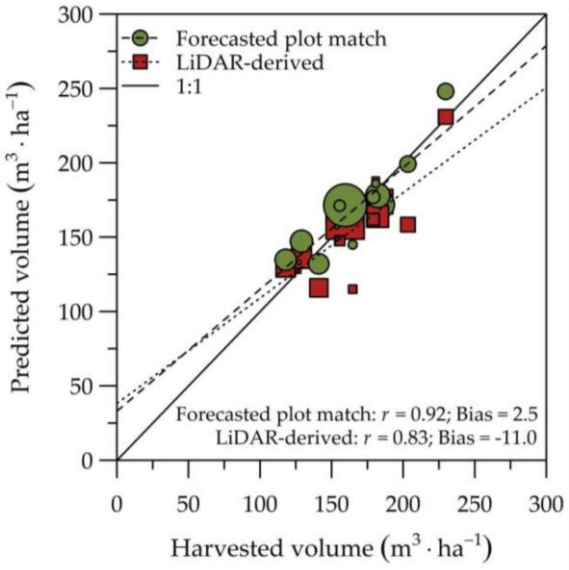
Stand-Level GY from LiDAR Grid Cells

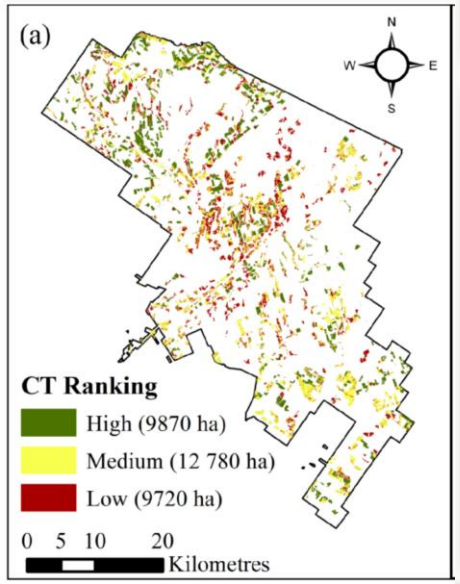
The Lamb et al. (2018) kNN imputation approach

1. **LiDAR Inventory**
   6 stand-level variables per 20x20m cell
2. **kNN Plot Matching**
   Match each cell to library of 5,630 plots
3. **Tree List Imputation**
   Assign measured tree list from best match
4. **Growth Model Forecast & Update**
   Run FVS tree-list model for 10 years

forests MDPI
Article
Forecasting Forest Inventory Using Imputed Tree Lists for LiDAR Grid Cells and a Tree-List Growth Model
Sean M. Lamb [1,*], David A. MacLean [1], Chris R. Hennigar [1] and Douglas G. Pitt [2]

IRVING WOODLANDS SINCE 1882





Key Results

- 2.1M 20 x 20 m cells across 205,000 ac
- r = 0.75-0.86 across 6 plot variables
- RMSE 13-37% (49% for merchantable BA)
- 15 harvested blocks: volume within 1.5%

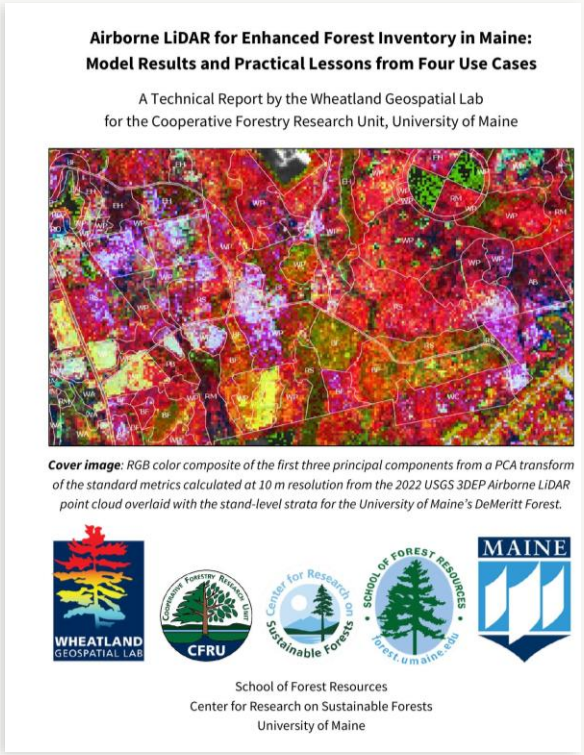
Limitations

- Extensive plot network necessary
- Locally calibrated growth model required
- Tested only on even-aged spruce plantations
- Howland extension: mixed conifer, 27.6% RMSE
- (middle of Lamb et al. 2018 range)

A promising framework, but can we bypass tree-list models entirely with area-based approaches?

EFI Case Studies in Complex Stands of Maine

CFRU / Wheatland Geospatial Lab

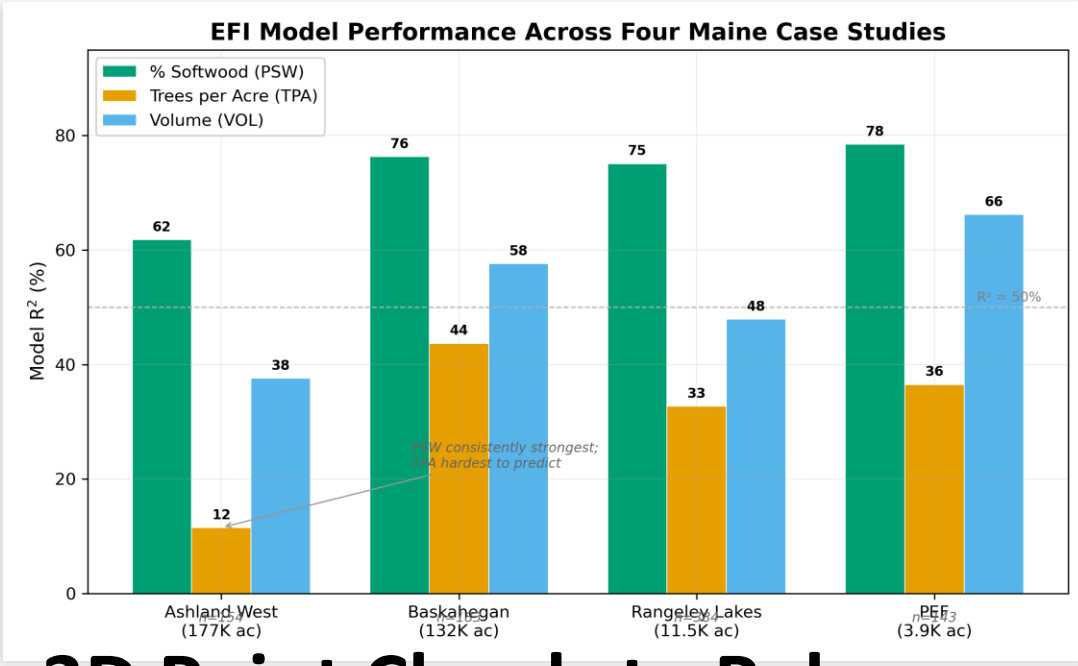


Ashland West — 177K ac | 154-1,233 plots — **R^2=62%**

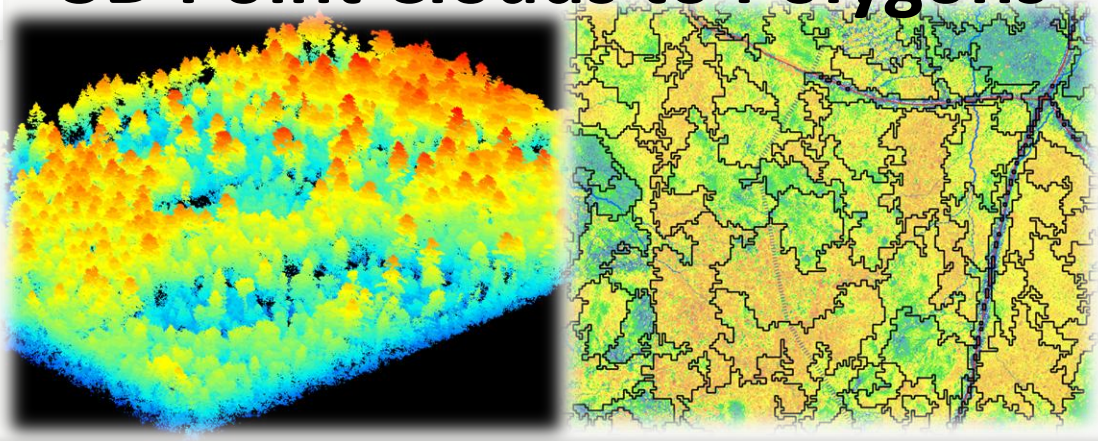
Baskahegan — 132K ac | 183 plots — **R^2=76%**

Rangeley Lakes — 11.5K ac | 384 plots — **R^2=75%**

Penobscot (PEF) — 3.9K ac | 143 plots — **R^2=79%**



3D Point Clouds to Polygons



PSW (% Softwood) R^2 shown. VOL consistently lower. Free 3DEP matched research-grade G-LiHT at PEF.

GPS accuracy matters most, not LiDAR density or sensor

A Better Path Forward?

Observe yield directly from repeated 3D point clouds (e.g., LiDAR), not reconstruct individual trees

Every 10m pixel = virtual permanent plot

No individual tree reconstruction or GY models needed

Directly produces tons/ac, BA/ac, VOL/ac

Calibrated with field plots, validated with holdout data

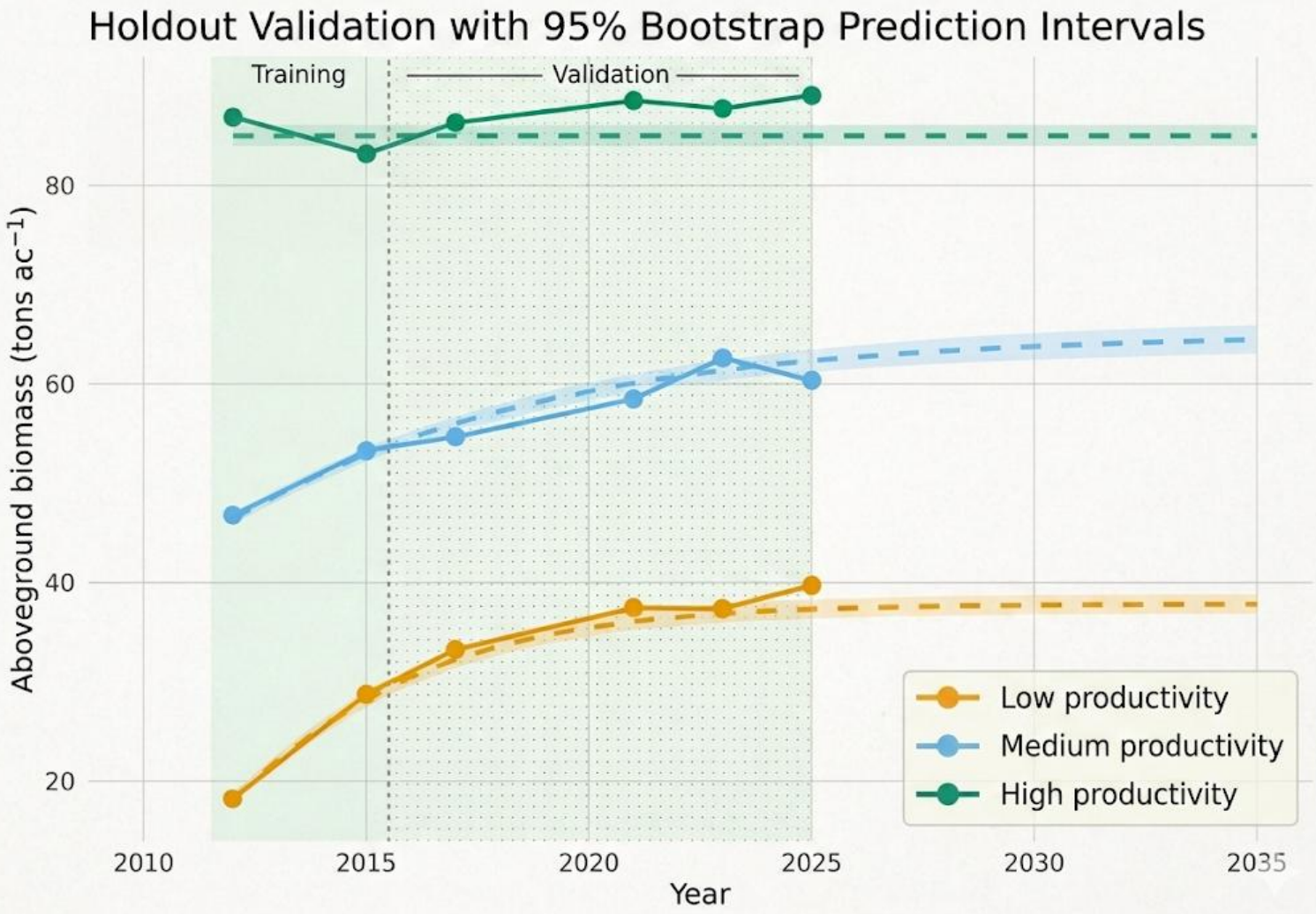
Area-based Chapman-Richards yield curves:

-2.4% error at 10-year holdout validation

FVS: +24.2->50% overestimation

Compounds with time and other inventory issues

Greg agrees: "Our biggest gains will be in improving inventory estimates."

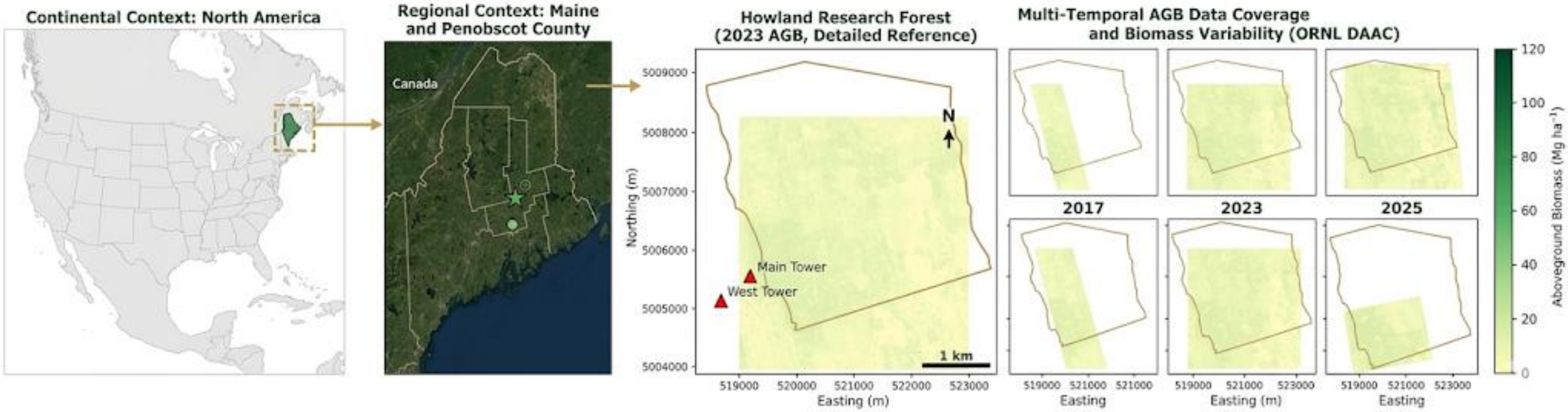


Area-based yield curves: -2-5% error vs. FVS >50% overestimation

Howland Research Forest

Penobscot County, Central Maine | Study Site Overview

Refined Multi-Scale and Multi-Temporal Aboveground Biomass (AGB) Characterization of Howland Research Forest (Penobscot County, Maine)



~4,000 acres

153 field plots

3,591 trees measured

6 LiDAR campaigns

13 year time series

Data: NASA G-LiHT (2012, 2017, 2021), USGS 3DEP (2015, 2023), Phoenix/MELiTE (2025), Purdue TLS (2025), NAIP (4 epochs), AmeriFlux, USFS

Unique yet representative and well-studied mixed conifer research site

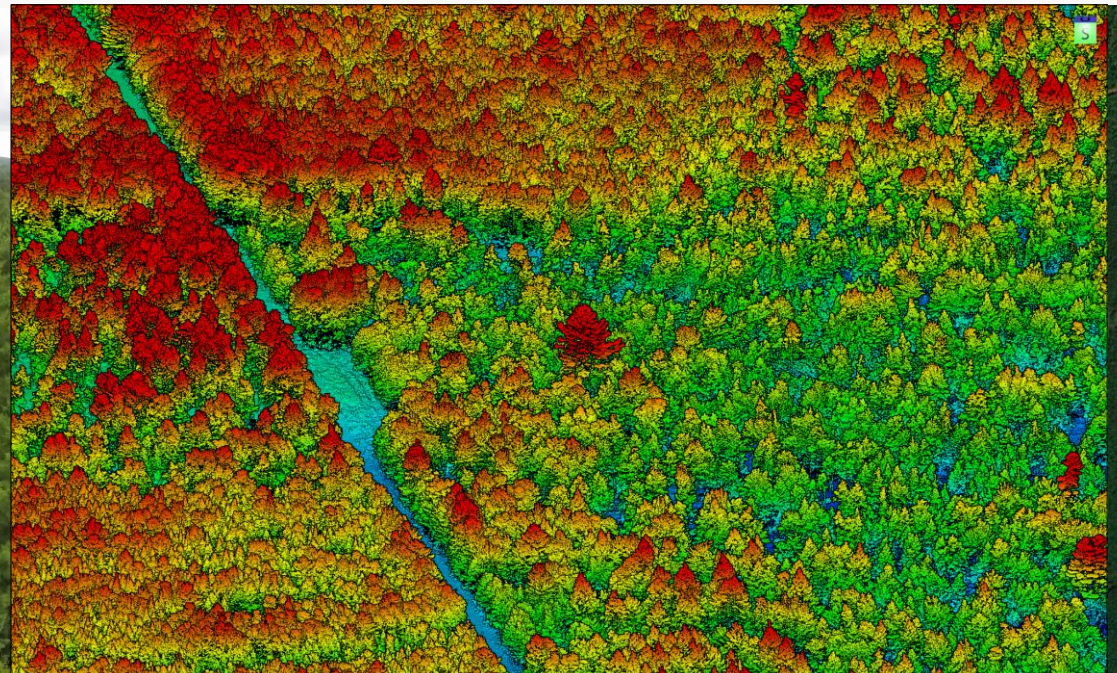
A Comprehensive Data Ecosystem

Howland Research Forest: multi-sensor, multi-temporal coverage

Year	T+	Source	Density	Season
2012	0	G-LiHT	~15 pts/m²	Leaf on
2015	3	USGS 3DEP	~5 pts/m²	Leaf off
2017	5	G-LiHT	~20 pts/m²	Leaf on
2021	9	G-LiHT	~35 pts/m²	Leaf on
2023	11	USGS 3DEP	~8 pts/m²	Leaf off
2025	13	Phoenix/MELiTE	~100 pts/m²	Leaf on
2025	13	TLS	-	Leaf on

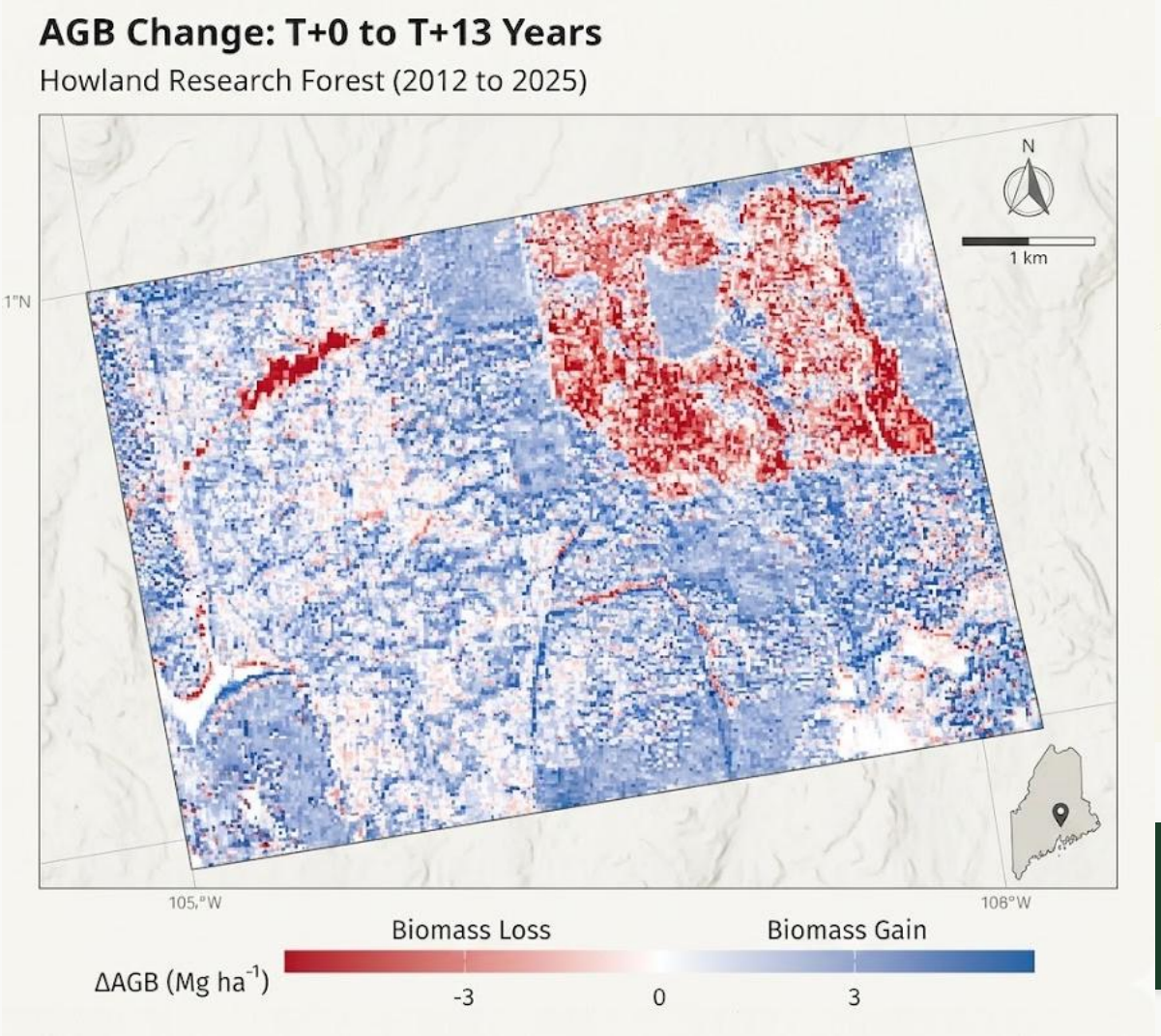
Additional Data Sources

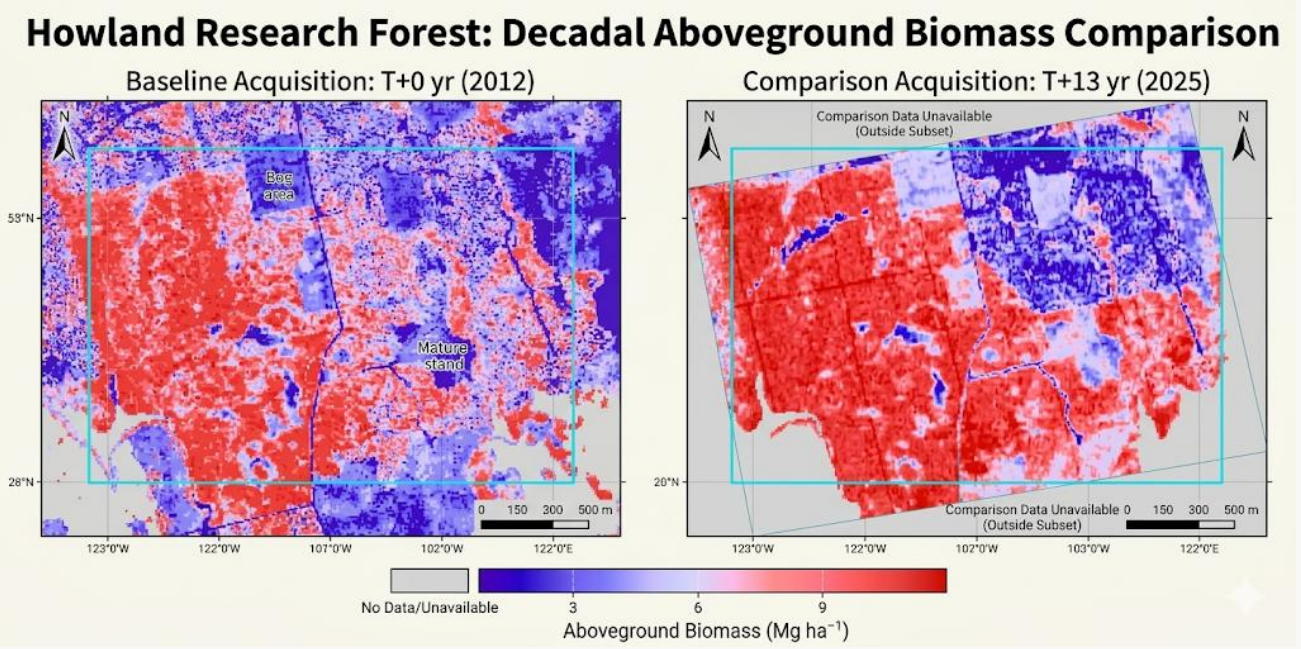
- 4,271 TLS trees (Purdue/PERSEUS, 2025)
- NAIP imagery (4 epochs, 2011-2021)
- Eddy covariance flux tower (continuous)
- NEON AOP overflights
- Fixed area periodic remeasurements
- Species composition from field inventory



13 Years of Aboveground Biomass Change

Howland Research Forest | T+0 to T+13 years | 67,275 pixels at 10 m



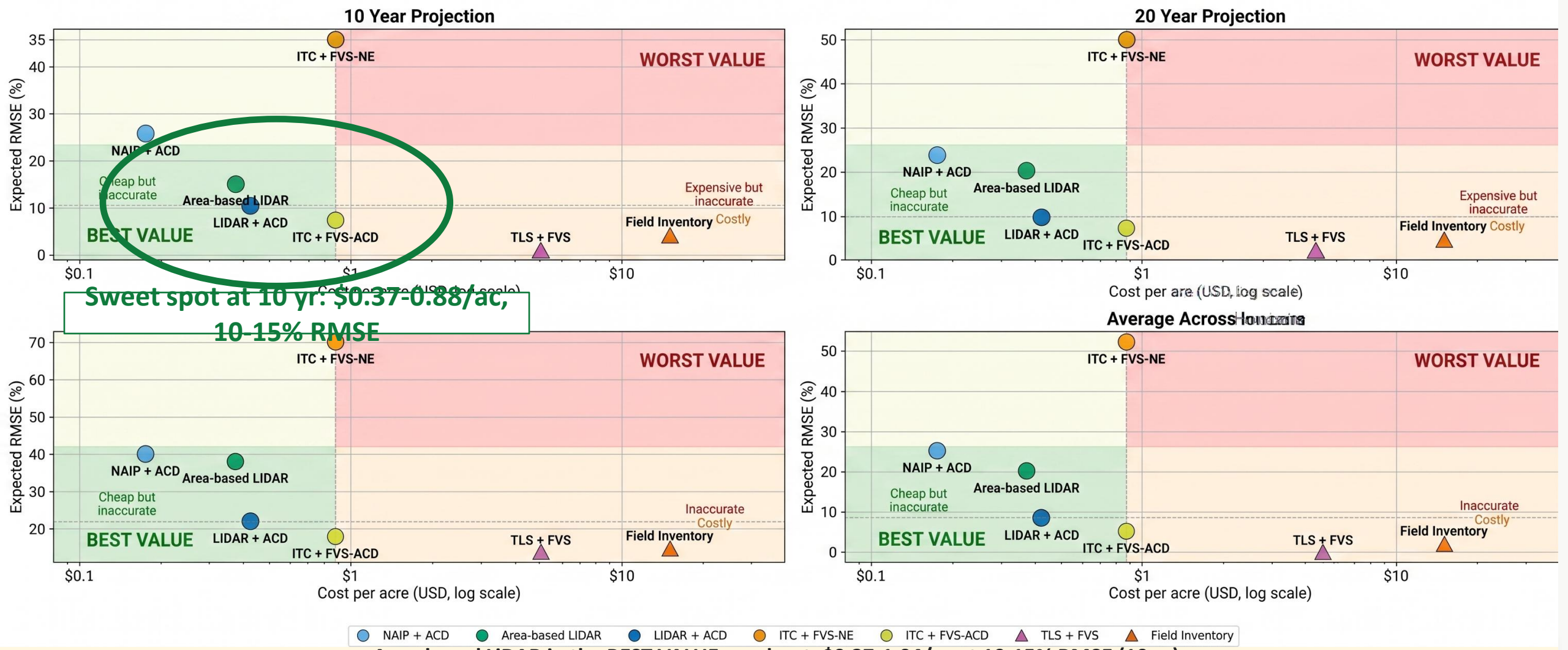


No growth model can produce this spatial detail or data

Wall-to-wall biomass change at 10m resolution. Blue = growth, red = loss.

Cost vs. Accuracy: 8 Methods Compared

Quadrant analysis: low cost + low RMSE = best value for operational forestry in complex stands



Area-based LiDAR in the BEST VALUE quadrant: $0.37-1.04/ac at 10-15% RMSE (10 yr).

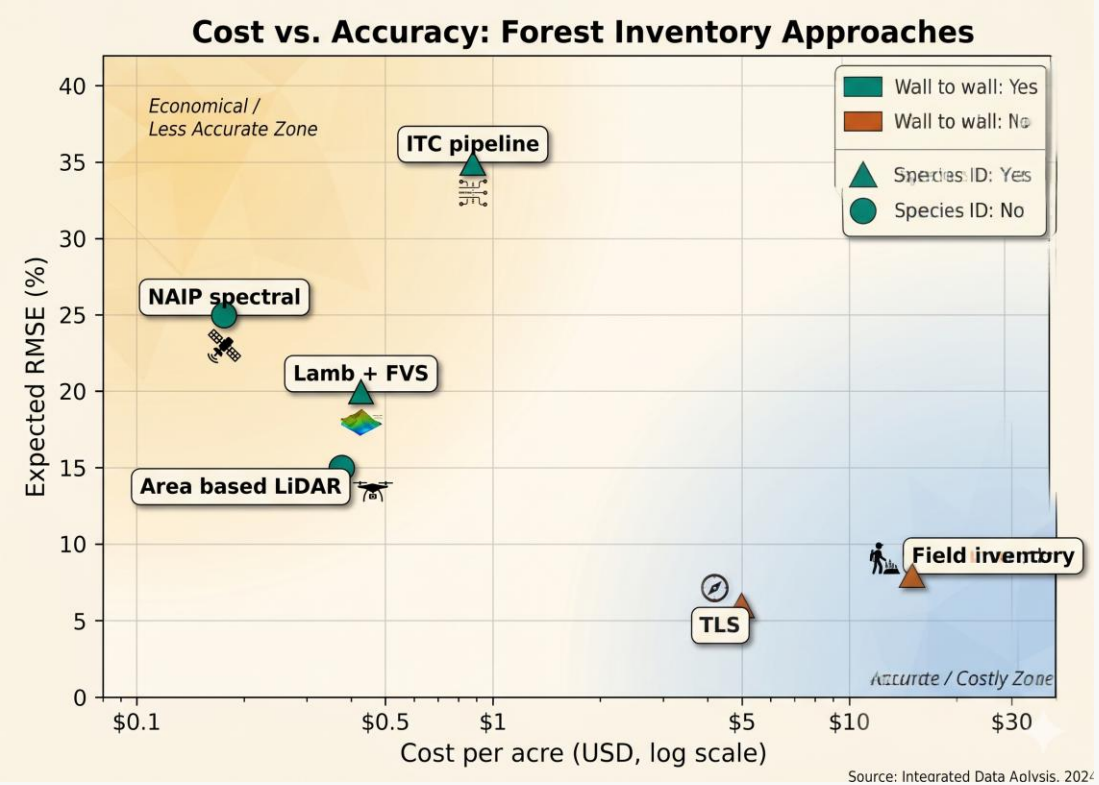
ITC + FVS-NE: worst value at $0.87/ac, 35% RMSE (+50% overestimation at 50 yr).

FVS-ACD: +6-8% overestimation. TLS: high precision but 10x the cost.

Weiskittel et al. v4.2 (in review, Forestry) | Monte Carlo n = 24,000 | TLS anchored ITC RMSE 27.6%, TLS direct 1.9% | Fig 6 quadrant framing (costs in $/ac)

Practical Recommendations

Which method for which scenario?



Scenario	Recommended Method
Budget < $0.25/ac, screening	NAIP + yield curves
Budget $0.25-1/ac, carbon monitoring	Area-based LiDAR-derived yield curves
Budget > $1-2/ac, species-level detail	TLS + FVS
Initial ALS/NAIP Calibration	TLS
Projection < 20 years	Area-based kNN-imputation (Lamb et al.)
Projection > 20 years	ALS + yield curves + periodic recal
Wall-to-wall map required	LiDAR-based methods
Disturbance expected	LiDAR + FVS

From Weiskittel et al. v4.2, Forestry | Howland 8-method comparison anchored on 2025 TLS campaign + 4-point LiDAR recalibration

Area-based approaches deliver the best value. TLS fills the calibration niche. Field plots at 10-50x the cost.

Questions for This Community

If area-based RS gives you tons/ac at 10m resolution, do you still need individual tree data?

1. **What growth model inputs ACTUALLY require field-measured DBH?**
   Stand-level metrics via LiDAR, not trees

2. **Could repeated LiDAR replace permanent plot networks for yield estimation?**
   Howland: area-based curves outperformed ITC + FVS (67K+ pixels vs. ~7M tree records)

3. **What role do GY models play when RS can observe outcomes directly?**
   Greg: process understanding still matters for extrapolation

4. **What does the next G&Y textbook look like when the primary data source is RS?**
   2011 primary-supplemental assumption has flipped

5. **How does uncertainty quantification align with precision/accuracy needs?**
   Accuracy and precision scale nonlinearly

Greg, David, and I present Unshackling FVS tomorrow over lunch

Thank You

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Don't ask how to fit RS into old models.

Ask what new models RS makes possible

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Modernizing FVS

Bayesian Calibration and the Path to a Unified CONUS Growth Engine

Aaron Weiskittel | Greg Johnson | David Marshall

Center for Research on Sustainable Forests | University of Maine

Growth Model Users Group | April 2026

Why Modernize FVS?

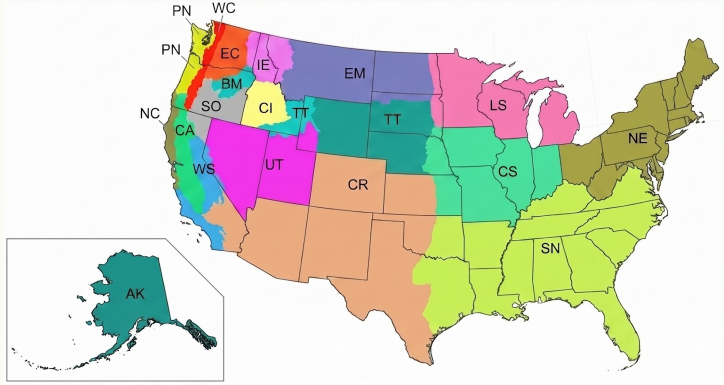
25 geographic variants
each with different equation forms, species tables, and site handling

40+ years of legacy code
many equations have not been updated with contemporary data

0 uncertainty estimates
no built-in mechanism for propagating parameter or model uncertainty

The Result

- The same species behaves differently depending on which variant you use
- Some variants validate poorly against independent FIA remeasurements
- Site productivity is handled inconsistently across variant boundaries
- No systematic way to quantify prediction confidence for planning decisions



FVS-Modern: Bayesian Recalibration

1

FIA Data

16.2M trees
435K condition pairs across CONUS

2

Bayesian Fitting

Stan/ADVI posteriors for 6 components per variant

3

25 Variants Calibrated

DG, HG, H-D, mortality, CR, SDI equations refitted

4

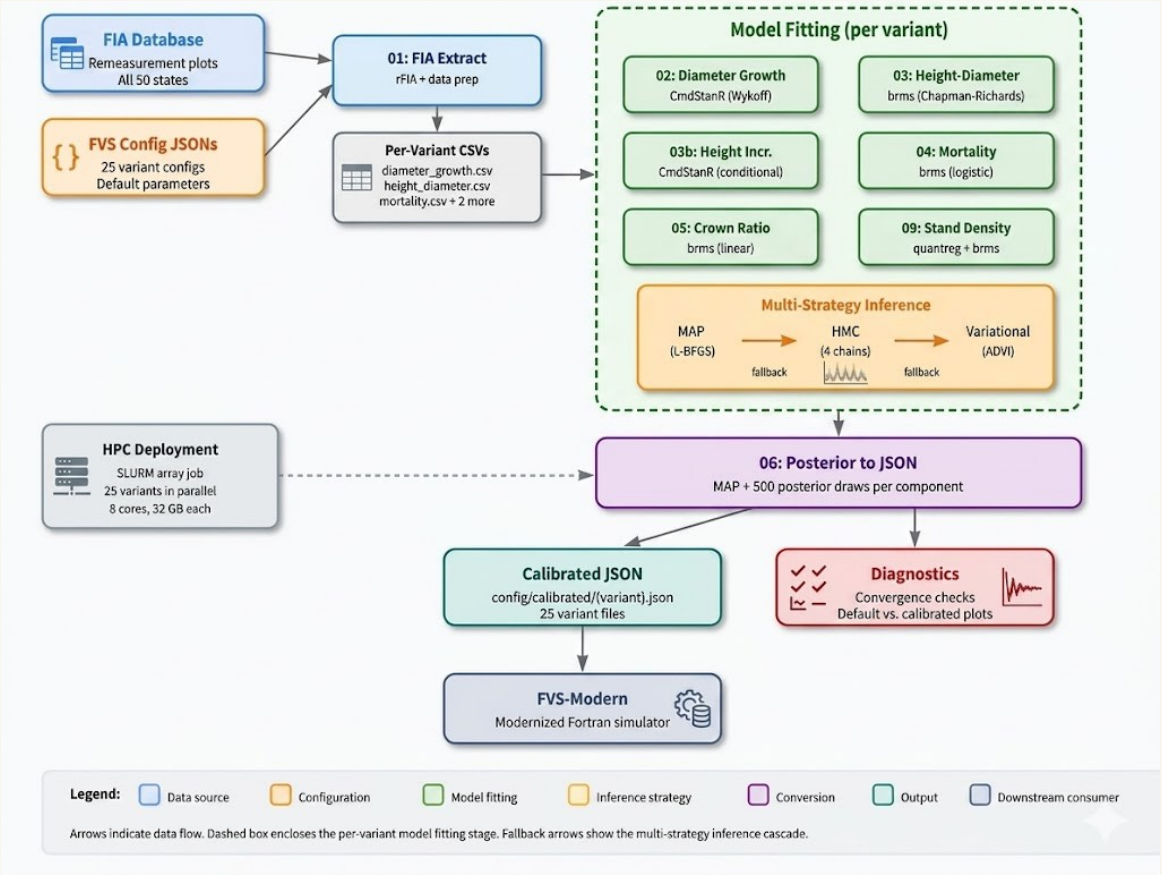
Uncertainty Propagation

500 posterior draws per variant for credible intervals

0.75 – 0.90	0.30 – 0.69	0.66 – 0.93	6
HT-DBH R^2	CR/DG/HG R^2	Mortality AUC	Components Calibrated

Bayesian Calibration Pipeline Architecture

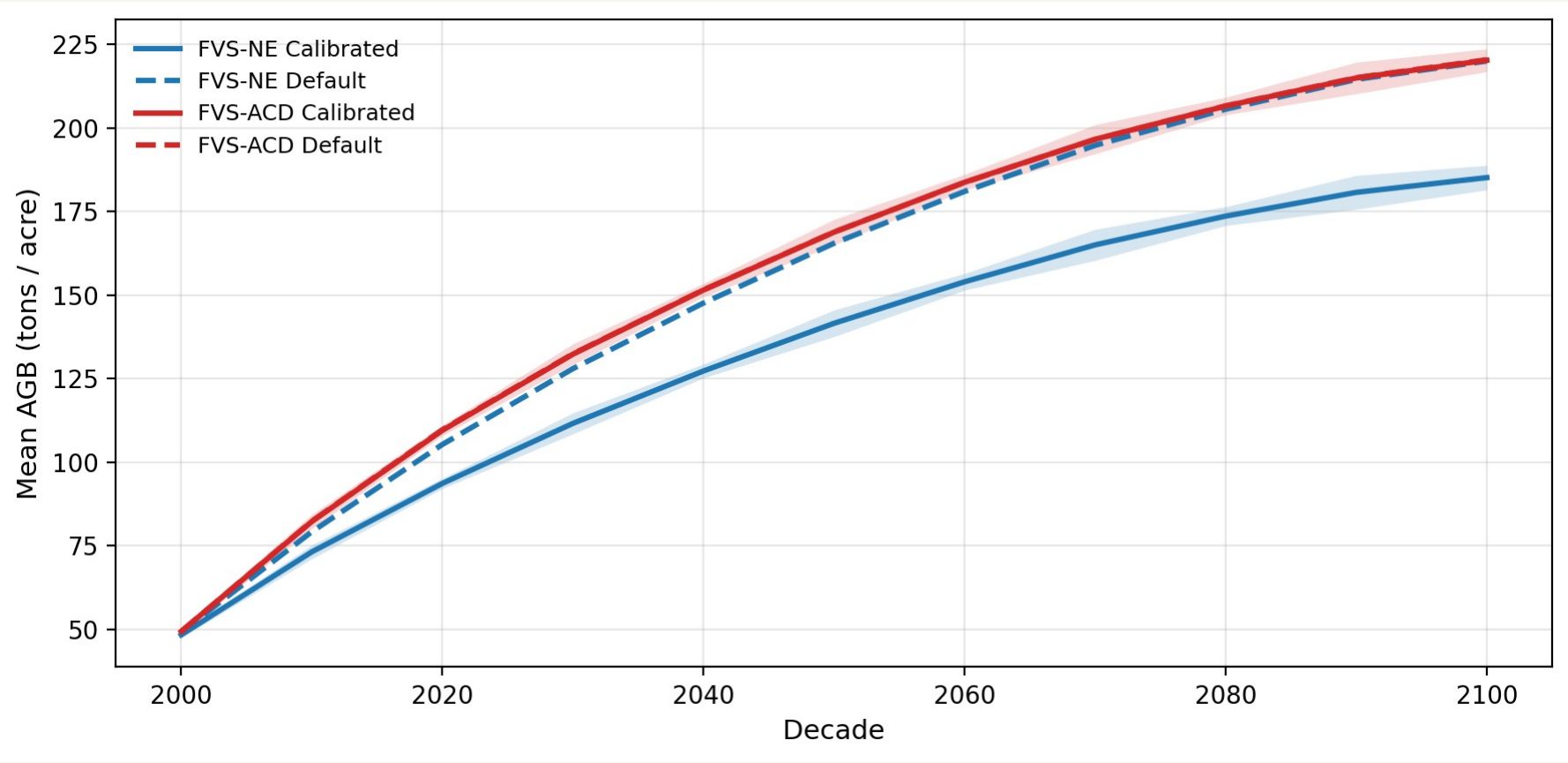
FIA → ADVI/HMC posteriors → calibrated JSON → FVS-Modern engine



Six component models per variant: DG, HD, HG, mortality, crown ratio, stand density index

FIA Validation: Calibrated FVS with Confidence Bands

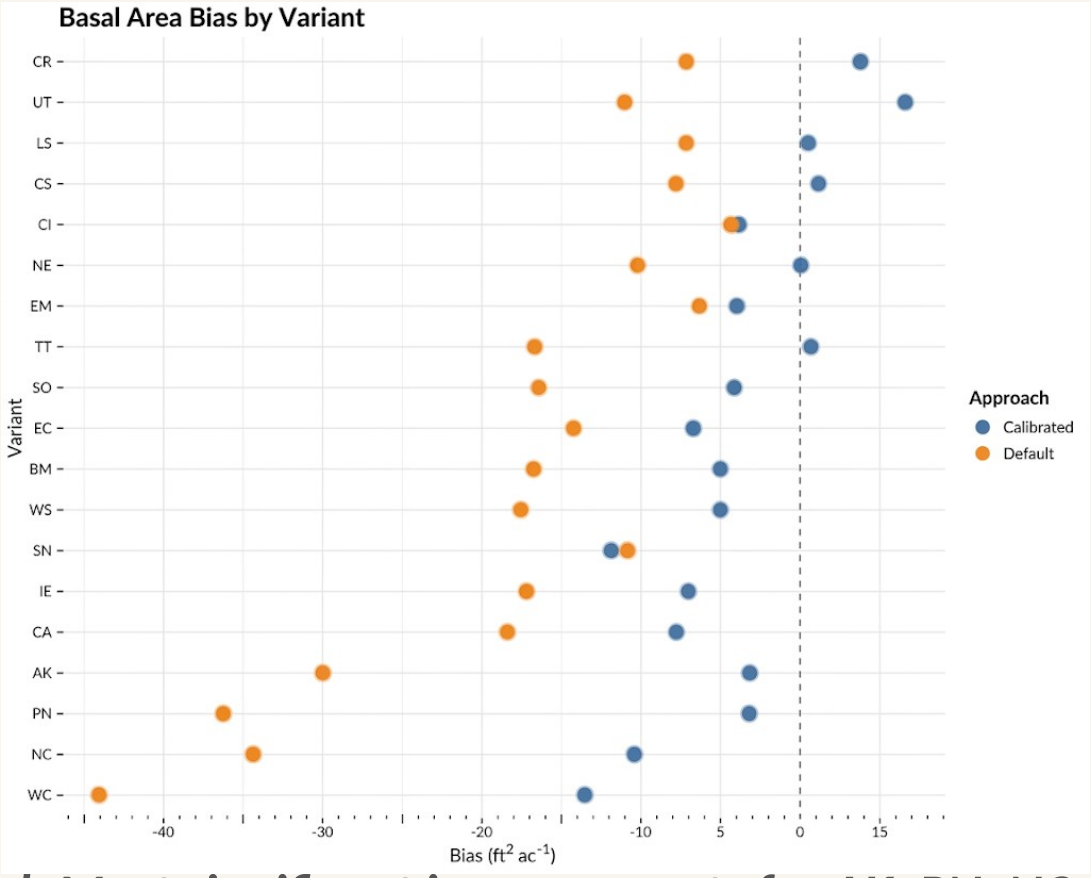
USFS FIA untreated plots, Maine — 95% CI ribbons from posterior + plot-level SE



n = 3,060–3,188 USFS FIA plots | ribbons = 95% CI from plot-level SE | Bayesian posterior CIs (500 draws)

Basal Area Bias: Calibrated vs Default, All 25 Variants

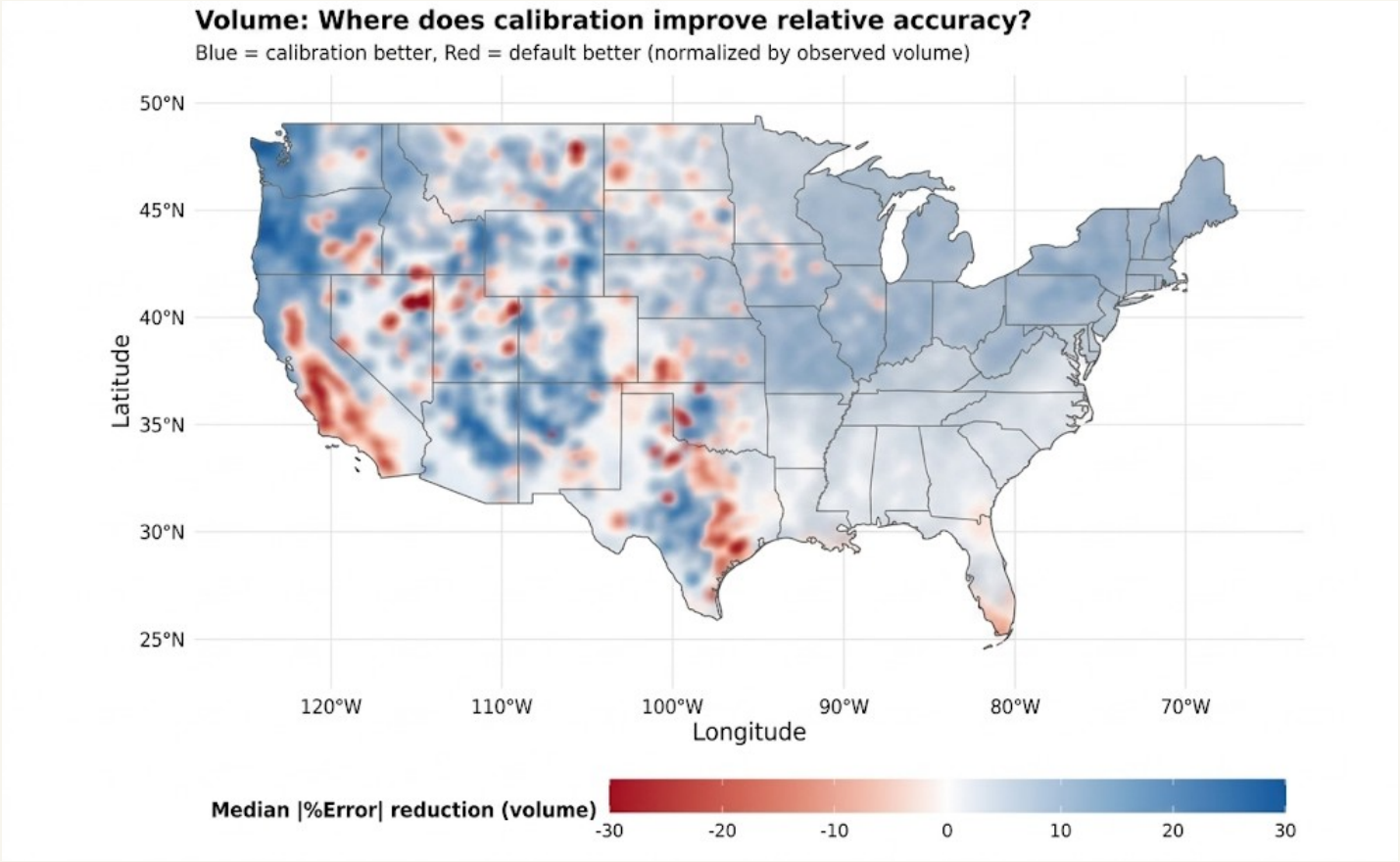
Most variants pulled toward zero; calibration recovers ~10–35 ft²/ac in the West



Observed – Predicted; Most significant improvements for AK, PN, NC, and WC Variants

Where Calibration Improves Volume Predictions

Median |%Error| reduction by hex bin — blue = calibration wins, red = default wins



Largest improvements in PNW and portions of PSW, but CA and TX need refinement

Release: fvs-modern v2026.04.5 | Now Public

First Public Tag Shipped 2026-04-13

Repository public on GitHub with all 25 calibrated variants, Docker image, and rFVS bindings. 66 of 67 regression tests passing (98.5%).

Upstream synchronization

Tracks the USFS GitHub repositories and provides automated tooling for integration

What Ships in v2026.04.5

Fortran 90 free-form source for all 25 variants, posterior medians as the calibrated parameter set, and 500 posterior draws per component for ensemble projections via fvs2py and microfvs.

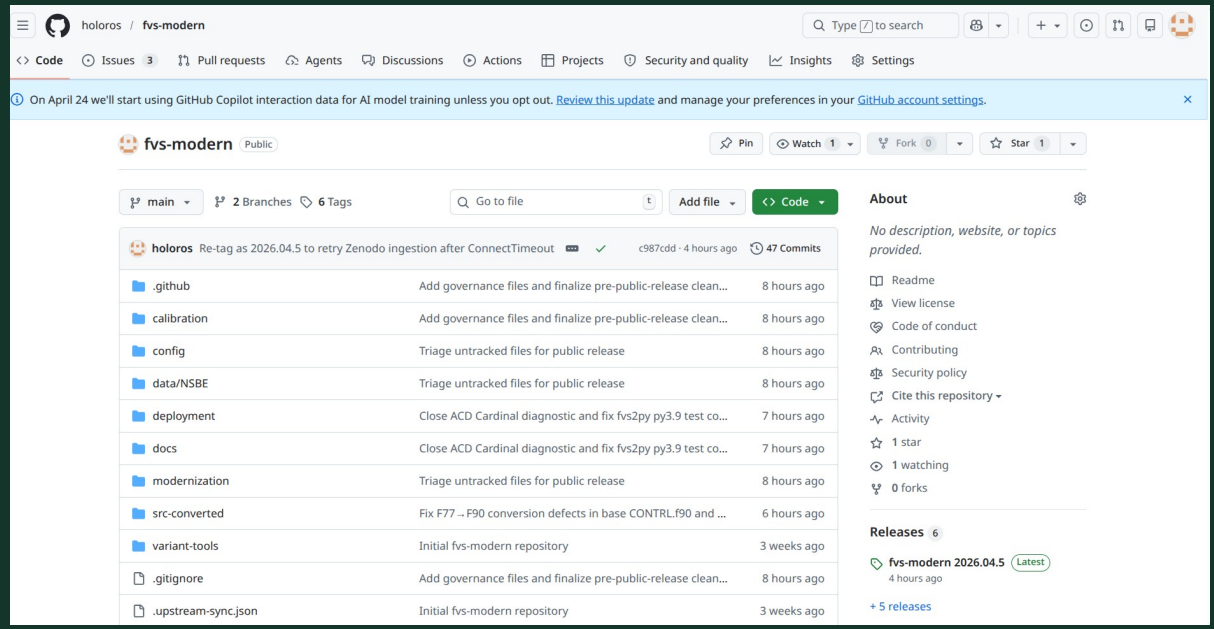
See David Diaz's MicroFVS talk

Get the Code | github.com/holoros/fvs-modern

v2026.04.5 | shipped 2026-04-13

Public repo, Apache-2.0

25 calibrated variants | Docker image | rFVS bindings



https://github.com/holoros/fvs-modern

The Case for a Unified CONUS GY Engine

Variant Boundaries Are Arbitrary

The same species should not predict differently just because it crosses a state line. Our calibration shows that equation form, not ecology, drives inter-variant divergence.

ORGANON Equations Scale to CONUS

Biologically consistent, parsimonious growth forms (ORGANON DG & HG equations) fit well across 84+ species using FIA remeasurement data from all 48 states.

Bayesian Framework Enables Uncertainty & Future Calibration

A single hierarchical model provides both point predictions and credible intervals. Posterior draws propagate directly into FVS projections.

Next: unified CONUS variant with Greg Johnson — hierarchical fits across all 48 states