

Workflow for estimating above ground biomass from satellite imagery with non-geolocated ground validation data

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Peer review status: This is a non-peer-reviewed preprint submitted to EarthArXiv.

Abstract

Satellite-based aboveground biomass mapping typically relies on validation data from field-based inventory plots or other high resolution ground truthing, but acquiring validation data is challenging. In the United States, the Forest Inventory and Analysis (FIA) program is a common source of field validation data for biomass mapping, but currently the US Forest Service is not processing Material Transfer Agreements (MTA) that share exact plot coordinates due to reductions in the federal workforce. We developed a workflow that circumvents this limitation, by using individual tree-level data and stand density information from the FIA database to model “hypothetical plots” of uniform canopy structure that can be downscaled to 10 m Sentinel pixels to approximate aboveground biomass given a pixel’s canopy height and vegetation class, predicted from a separate canopy and vegetation modeling workflow. This approach is readily transferable to other regions globally where precise geolocation of validation data is not available.

1. Introduction

1.1 Relevance of pixel-scale biomass

Spatially explicit aboveground biomass (AGB) mapping is critical for quantifying terrestrial carbon stocks and informing forest management (He et al., 2026). Sentinel-2 supports operational pixel-scale (10 m) biomass mapping; recent such work produces 10 m canopy-height and AGB maps from Sentinel-1/2 + lidar validated against national inventory plots (Su et al., 2025). Workflows that leverage satellite data for predicting biomass are useful for carbon accounting, restoration monitoring, temporal change detection, and wall-to-wall coverage without the need for extensive airborne acquisitions.

1.2 The conventional approach and its data dependency

Standard plot-to-pixel AGB modeling trains on ground plots matched to their exact pixel locations, requiring precise plot coordinates. The Forest Inventory and Analysis (FIA) program of the USDA Forest Service Research and Development Branch is constrained by law from disclosing exact locations and reports plot coordinates that are deliberately perturbed ("fuzzed and swapped"): most plots relocated within 0.5 mile, some up to 1 mile, masking true location within ~500 acres, with swapping of some private plots (*Spatial Data Services | US Forest Service Research and Development*, 2023). True coordinates are released only under a formal, legally binding Material Transfer Agreement (MTA), requiring a study plan, data-security plan, and a sponsoring FIA scientist. More broadly, any pixel-level training approach presumes spatially precise ground reference data.

True coordinate FIA access is currently suspended due to the recent reduction of the federal workforce, and there is no announced timeline for future resumption (*Spatial Data Services | US Forest Service Research and Development*, 2023). Even absent policy disruption, high resolution ground truthing is often unavailable. Many regions and tree species have inventory data but no way to tie it to pixels, hindering mapping efforts.

1.3 The proposed alternative

Pixel-based allometric functions can be built at the species level from publicly available, non-geolocated inventory attributes: individual-tree height, tree biomass, and stand density. Neither individual tree allometry nor stand density require plot coordinates, yet together they reconstruct pixel-scale biomass from a per-pixel height + class label. Height-based allometry is well established; tree biomass relates nonlinearly to height (Lu et al., 2016). Additionally, the

limitations of remote-sensing-only and a 10 m spatial resolution prevented the use of a species-level allometric model that includes DBH or a common proxy, crown diameter. However, models derived solely from the relationship between height and biomass have been shown to exhibit only slightly reduced performance (Liu et al., 2024). Height alone is considered a weak biomass predictor unless conditioned on species/taxa, although among ecologically similar classes this conditioning turned out to matter less than expected in our study (see Section 3.3) (Brolly et al., 2012). The method presented here applies wherever some applicable tree-level data (paired height-biomass observations for the relevant species/region exists: FIA is one such source, but not the only one. Others include Canada's National Forest Inventory and the harmonized tree-level data of the European National Forest Inventory Network (Guindon et al., 2024; Miettinen et al., 2025). Training data is filtered to ecological contexts comparable to the application area, substituting for precise georeferencing. This paper is focused on the allometric function methodology: a reproducible, species-level, coordinate-free framework converting per-pixel canopy height and vegetation class into AGB.

1.4 Riparian areas of the American West as a study system

Riparian ecosystems within the sagebrush biome of the United States exemplify a heterogeneous ecosystem undergoing consequential gradual changes. In the sagebrush biome, wet habitats comprise 1-2% of the landscape, yet 80% of wildlife species depend on them (J. D. Maestas et al., 2023). They are believed to store disproportionately high carbon per unit area, but estimates vary widely, and the exact magnitude of this relative carbon storage has not been investigated at broad scales in the American West. These Western-US-riparian ecosystems are “emerald islands in a sagebrush sea” (J. Maestas et al., 2018), and support a mosaic of distinct vegetation types that potentially store high amounts of aboveground carbon packed into narrow, discontinuous corridors. Four vegetation functional groups broadly represent the assemblages found in the valley bottoms and mesic ecosystems of the sagebrush steppe: deciduous trees, shrubs, herbaceous vegetation, and evergreen trees. These functional groups are subject to growth and decline that affects the AGB and thus carbon stored within them. The workflow presented here is paired with predictive models for canopy height and vegetation class at a 10 m spatial resolution.

2. Methods

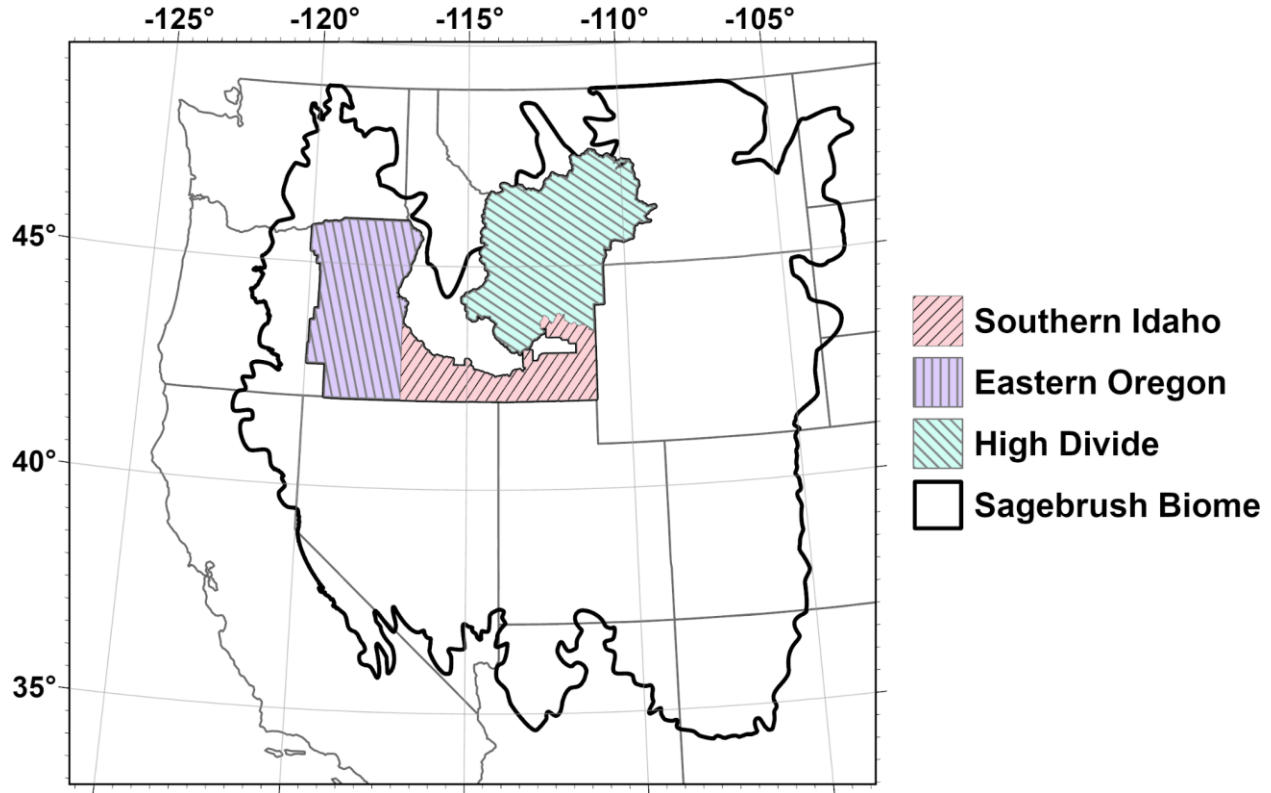


Figure 1. Study area in the western United States.

2.1 Forest inventory data acquisition

We accessed all FIA data through *rFIA*, an R package that facilitates interaction with the complex FIA database (Stanke et al., 2020). We constrained analysis to states found within the sagebrush biome (ID, OR, MT, WA, WY, CO, UT, NV, CA). From the non-geolocated TREE/COND/PLOT tables, we used tree height, dry biomass, and trees-per-acre (TPA), converting lb to kg and ft to m. FIA plots within the sagebrush biome were filtered to retain cottonwood-dominated plots (*P. trichocarpa*, SPCD 747) and ponderosa pine plots (*Pinus ponderosa*, SPCD 122). Tree-level attributes used include height, diameter at breast height (DBH), total dry aboveground biomass, and trees per acre expansion factors. For ponderosa pine, FIA data were further filtered to valley bottom conditions to ensure the sample represents trees found in the study system rather than upland stands. Filtering criteria included: physiographic class codes 21-25, 29, 31-32, 34, 39 (bottomland, floodplain, valley floor, drainageway, and related classes); slope < 15%; and further spatial constraint to the 3-region study area shown in Figure 1 (unlike cottonwood observations, which were limited in number, warranting the use of the entire sagebrush biome) (*The Forest Inventory and Analysis Database User Guide (NFI) | US Forest Service Research and Development*, 2023). We used individual tree data from 249 cottonwoods from 50 plots, and 15,055 ponderosa trees from 1370 plots in the FIA database for modeling. FIA data contained insufficient willow (*Salix*) observations ($n = 4$) within our study area for developing species-specific allometric models. We therefore adopted a height-to-age chronosequence approach using data from Pacaldo et al., 2014.

2.2 General approach for aboveground biomass estimation

Aboveground biomass (AGB) was estimated for each 10-meter pixel by applying class-specific allometric models that translate canopy height into biomass density (Figure 2). At the time of writing, confidential FIA plot locations could not be requested with a Material Transfer Agreement, so we did not directly link plot data with other geospatial data as in Kennedy et al., 2018 and others. Rather, we used tree-level data, along with stand density information, to construct hypothetical plots representing uniform stands of equally-tall trees and with height-dependent stand densities, which are then readily downscaled to 10-meter pixels. Inputs to the estimation pipeline included the pixel's predicted canopy height, vegetation class assignment, and associated uncertainties from both the CHM and classification models. The general form of the estimation differs by vegetation class. For tree classes (deciduous, evergreen), a Bayesian Gamma GLM with log link and a quadratic height term predicts individual tree biomass from height, which was then scaled by a height-dependent trees per acre (TPA) function to produce a stand-level biomass for a “theoretical stand” of uniform height. For shrubs, a height-to-age-to-biomass chronosequence yields stand-level biomass directly. For herbaceous vegetation, a constant biomass density is applied. The general form of the estimation for trees is:

$$\text{Pixel AGB (Mg)} = f(\text{height}) \times \text{TPA} \times \text{pixel_area} \quad (1)$$

Where $f(\text{height})$ is a species-specific height-to-biomass function, TPA is the trees per acre value scaled to the pixel area (0.01 ha per 10m $\times$ 10m pixel), and the function form and parameters differ by vegetation class. The choice of allometric model is perhaps the most important source of error in remote sensing estimates of aboveground biomass (Chave et al., 2004; Clark & Kellner, 2012; Borsah et al., 2023). To our knowledge, there are no published allometric models for *Populus trichocarpa* (black cottonwood) that rely solely on height, which necessitated our creation of one using FIA data. Models derived solely from the relationship between height and biomass have been shown to exhibit only slightly reduced performance (Liu et al., 2024).

2.3 Stand density and the TPA scaling problem

Converting per-tree allometry to a per-pixel biomass estimate requires an estimate of how many trees occupy a 10 m pixel: the trees-per-acre (TPA) term, downscaled to pixel area. We drew TPA directly from the function built in to *rFIA*, which computes plot-level TPA using the FIA program's expansion factors and design-based estimators. This is worth emphasizing for anyone reproducing the approach: TPA_UNADJ in the FIA database is not an analysis-ready metric, and TPA cannot be simply derived by counting records in the TREE table. Attempting to derive TPA manually by joining tables invites error, because the correct calculation depends on the subplot design, tree-level expansion factors, and condition proportions that *rFIA* already handles correctly. There is no reason to reconstruct these table relationships manually.

There are two opposing relationships that require careful consideration when translating individual-tree biomass to pixel-level biomass. Individual-tree biomass scales steeply with height, but stand density generally declines with height, because tall stands are older and self-thinned while short stands are dense with regeneration. If TPA is applied carelessly, total pixel biomass may decline with increasing height, an erroneous output that is an artifact of the tallest inventory trees coming from sparse plots that downscale to a small fraction of a tree per pixel. We resolved this with a three-step procedure applied to both tree classes encapsulated in a shared

scaling function so cottonwood and ponderosa are processed the same way. First, a split-weight blend combines a local, bin-level TPA median with a global TPA median.

$$\text{TPA}(h) = w(h) \cdot \text{global_median} + (1 - w(h)) \cdot \text{local_median}$$

Where the blend weight $w(h)$ is height-dependent: $w = W_LOW$ below a height threshold and $w = W_HIGH$ above it. This lets local density variation come through at short heights, where the inventory is data-rich, while anchoring tall-tree TPA to the more stable global median where bin-level estimates are noisy. For both tree classes we used $W_LOW = 0.5$, $W_HIGH = 0.7$, with a threshold of 20 m.

Second, a monotonicity constraint enforces that total pixel biomass never decreases with height. Walking up the height axis, if the biomass product (per-tree biomass * TPA) at height h would fall below its value for $h-1$, TPA at h is adjusted upward until monotonicity is restored. This guarantees that taller pixels hold at least as much biomass as shorter ones without imposing a specific functional form. Third, for implementation in Google Earth Engine (GEE), the constrained TPA values were smoothed with a parametric exponential-decay function:

$$\text{TPA}(h) = \text{tpa_floor} + (\text{tpa_max} - \text{tpa_floor}) \cdot \exp(-k \cdot h)$$

Which reduces the constrained step function to a small set of coefficients GEE can apply per pixel. This TPA-scaling procedure is generalizable to any height-driven, density-scaled biomass estimate, although data-specific adjustments may be needed.

2.4 Cottonwood (*Deciduous Class*)

For cottonwood-dominated pixels, a Bayesian Gamma generalized linear model (GLM) with a log link and a quadratic height term was fit to FIA tree-level data using the *brms* package in R version 4.4.2 (Bürkner et al., 2025; R Core Team, 2025):

$$\text{biomass_kg} \sim \text{Gamma}(\mu, \text{shape}), \log(\mu) = \beta_0 + \beta_1 \cdot h + \beta_2 \cdot h^2 \quad (2)$$

The quadratic term was added based on LOO model comparisons, which showed improved fit over the linear Gamma GLM, which tended to over-predict biomass for the tallest trees. The log link ensures predictions are always positive regardless of height, eliminating the need to floor at zero (Caughlin et al., 2016). Individual tree dry aboveground biomass was modeled as a function of tree height (converted from feet to meters).

2.5 Ponderosa Pine (*Evergreen Class*)

An analogous Bayesian Gamma GLM with log link and quadratic height, with height-dependent TPA scaling, was fitted to ponderosa pine (SPCD 122) FIA data, using equation 2.

2.6 Willow (*Shrub Class*)

FIA data contains insufficient willow (*Salix*) observations ($n = 4$) within the study area for developing species-specific allometric models. We therefore adopted a height-to-age chronosequence mapping approach, applying a published age-biomass relationship from Pacaldo et al., 2014:

$$\text{Biomass (Mg/ha)} = 13.40 \times \ln(\text{age}) - 7.020 \quad (5)$$

We mapped pixel height to stand age using linear interpolation (0.5m → 2 years, 10.0m → 19 years), calibrating the height range to observed distributions of shrub-classified pixels (mean 4.12 m, SD = 2.47). The equation was extrapolated to age 2 years (below the paper's minimum of 5 years) to accommodate young/short shrubs and avoid an artificial biomass floor. Heights > 10 m were capped at the maximum value, and heights < 0.5 were floored to prevent negative biomass predictions. This method yields an AGB range of 2.3-31.6 Mg/ha across the observed shrub height distribution. Unlike the tree classes, the shrub model outputs Mg/ha directly (stand level) rather than individual biomass x TPA. Therefore, no TPA scaling is needed.

2.7 Herbaceous Class

The herbaceous class contributes the smallest and least permanent fraction of total aboveground biomass in these systems, and was assigned a fixed biomass density coefficient (1.5 Mg/ha), representing a conservative central estimate for riparian herbaceous zones (Dwire et al., 2004). Herbaceous aboveground biomass in Intermountain West riparian meadows varies substantially with moisture availability. Dwire et al. (2004) measured aboveground biomass in wet, moist, and dry meadow communities along streamside topographic gradients in montane riparian meadows of northeast Oregon, reporting values that ranged from sedge-dominated wet meadows to mixed forb-graminoid dry meadows. Wet meadows in that study retained 2–4 times as much carbon as their drier counterparts. The Rangeland Analysis Platform (Jones et al., 2021) provides annual herbaceous aboveground biomass production estimates across western US rangelands and could serve as an alternative source for spatially explicit herbaceous biomass values, but the greatest density of those estimates are of a similar order of magnitude (0-3 Mg/ha).

2.8 Scaling from individual trees to pixels

For tree classes (deciduous, evergreen), pixel level biomass is computed as:

$$\text{Pixel_AGB (Mg)} = [\exp(\beta_0 + \beta_1 \cdot h + \beta_2 \cdot h^2) \times \text{TPA}(h)] / 1000 / 0.404686 \times 0.01 \quad (6)$$

Where h is predicted canopy height (meters), $\text{TPA}(h)$ is the height-dependent trees per acre function, $\exp()$ is the inverse of the log link, division by 1000 converts kg to Mg, division by 0.404686 converts per-acre to per-hectare, and multiplication by 0.01 scales from per-hectare to the 0.01 ha (10 x 10 meter) pixel area.

For shrub class:

$$\text{Pixel_AGB (Mg)} = [13.40 \times \ln(\text{age}(h)) - 7.020] \times 0.01 \quad (7)$$

Where $\text{age}(h)$ is linearly interpolated from height.

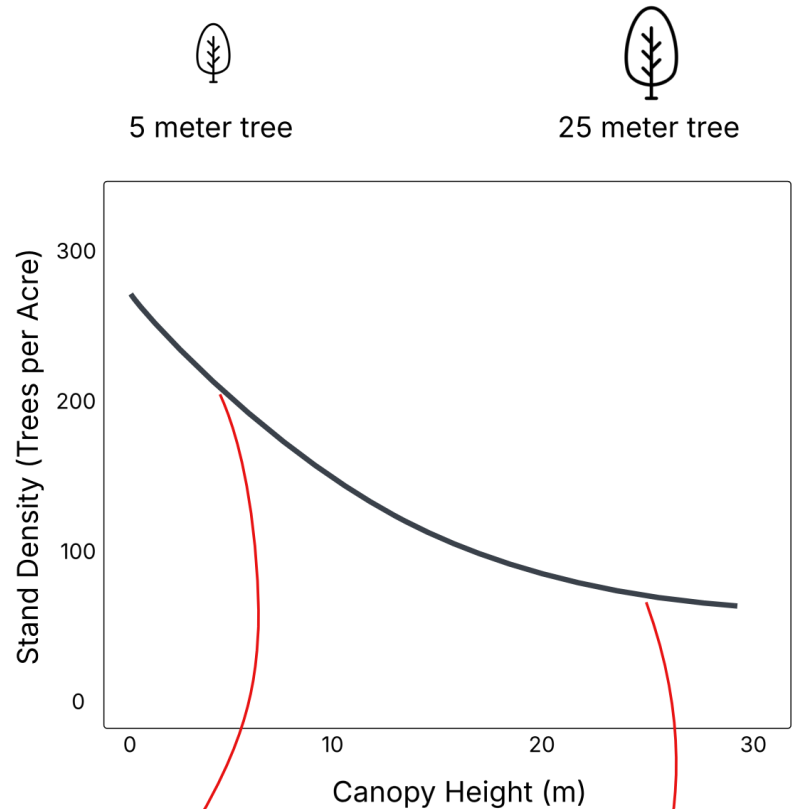
For herbaceous class:

$$\text{Pixel_AGB(Mg)} = 1.5 \times 0.01 = 0.015 \quad (8)$$

Mg/tree

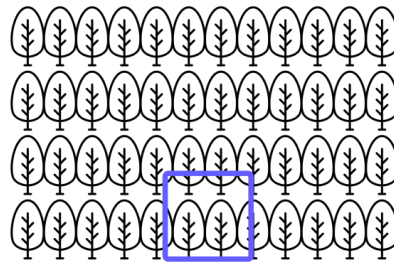
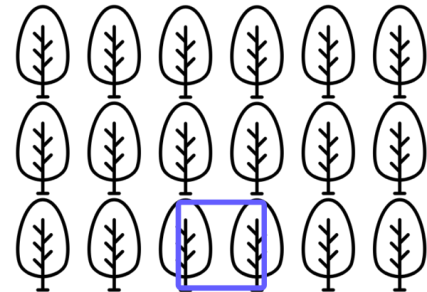
According to Bayesian quadratic model:
 $\text{biomass_kg} \sim \text{HT_m} + I(\text{HT_m}^2)$

Height- dependent stand density



Mg/ha

Theoretical plot of uniform
height and stand density (TPA)



Mg/pixel

Downscaled from theoretical plot



Figure 2. Conceptual diagram of the process of translating tree-level data to pixel-level biomass estimates.

2.8 Uncertainty propagation

Because the tree-class allometries are Bayesian, we propagate coefficient uncertainty rather than reporting point estimates alone. From each *brms* fit, we extract the full posterior

covariance matrix over (β_0 , β_1 , β_2) and propagate it into per-pixel biomass via the delta method, yielding an allometric uncertainty term for every pixel. For GEE mapping, point-estimate coefficients are written as a Javascript coefficient file and the covariance matrices are exported as JSON/CSV for GEE to ingest.

2.9 Class-assignment sensitivity analysis

Because each pixel's biomass depends on which class-specific function is applied, we quantified how sensitive the biomass output is to the vegetation classification itself. Using the classifier's soft probabilities from the associated analysis, we calculated per-pixel biomass in two ways: first, according to the highest probability class, and second, as a probability-weighted sum of the classes according to the soft classification. We summarize this as the median and upper-quantile absolute and percentage change in per-pixel biomass under reassignment, stratified by height bin to test whether sensitivity depends on canopy height.

3. Results

3.1 Per-species allometric fits and final class-specific biomass models

Both tree classes were well described by the quadratic Gamma GLM (Tables 1, 2). The fitted curves show the expected accelerating biomass-height relationship, with the quadratic term constraining the upper end where inventory data are sparse (Figures 3-4). Posterior predictive checks confirmed adequate model fit for both tree species (Bayes $R^2 = 0.649, 0.722$). The final spatial biomass models for each class are presented in Figure 5.

Table 1. Bayesian GLM parameters for allometric models.

Model	b0	b1	b2	tpa_floor	tpa_max	tpa_k
Ponderosa pine	1.346 ± 1.55e-02	0.351 ± 1.84e-03	-0.005 ± 4.56e-05	103.8374	219.4595	0.165506
Black cottonwood	1.319 ± 0.265	0.399 ± 0.032	-0.006 ± 0.0008	44.9257	228.6310	0.083137

Table 2. Model evaluation.

Model	Bayes R^2	MAE (kg)
Ponderosa Pine	0.722 ± 0.005	236.68
Black Cottonwood	0.649 ± 0.063	334.99

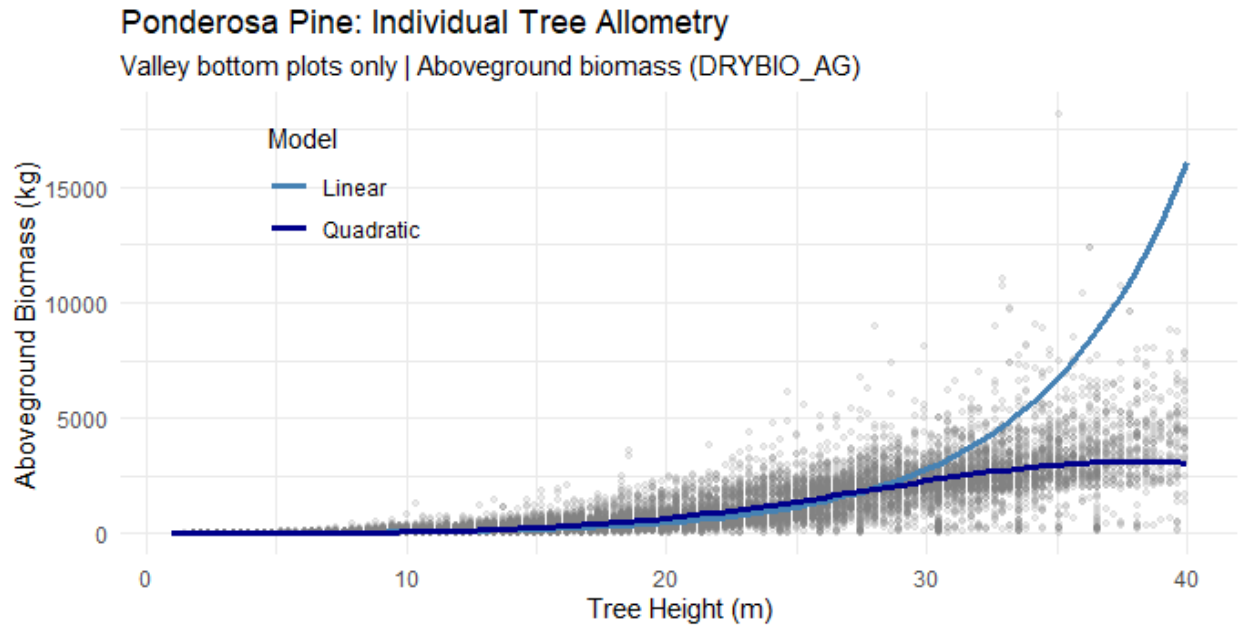


Figure 3. Linear vs. Quadratic model for Ponderosa

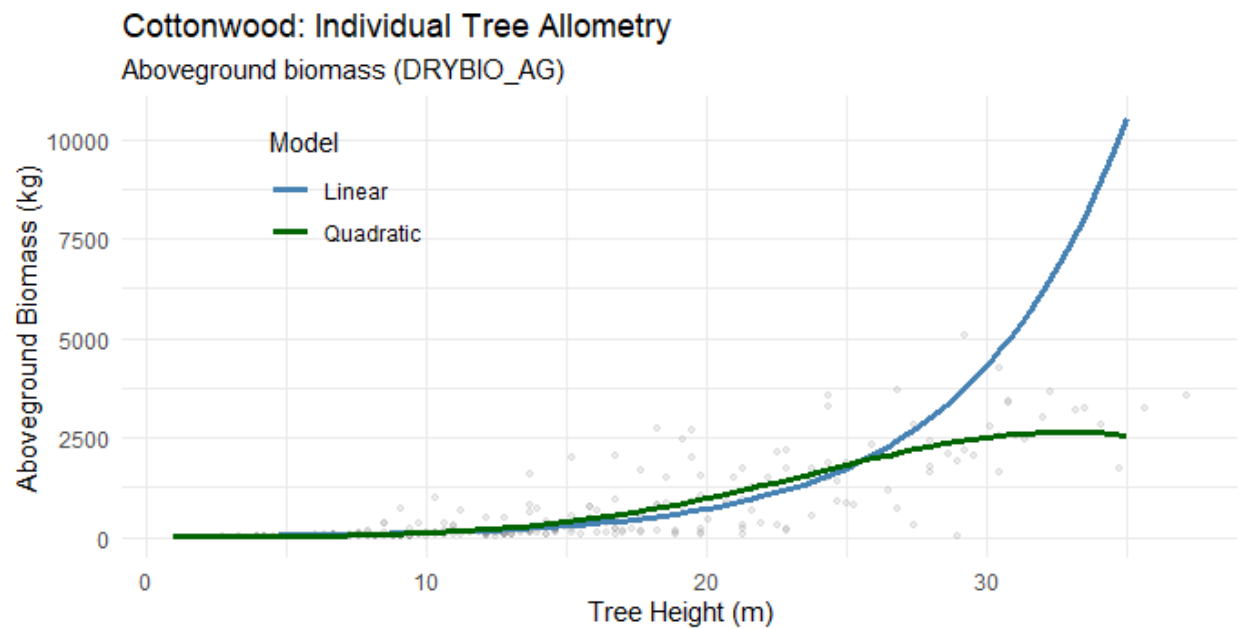


Figure 4. Linear vs. Quadratic model for Cottonwood

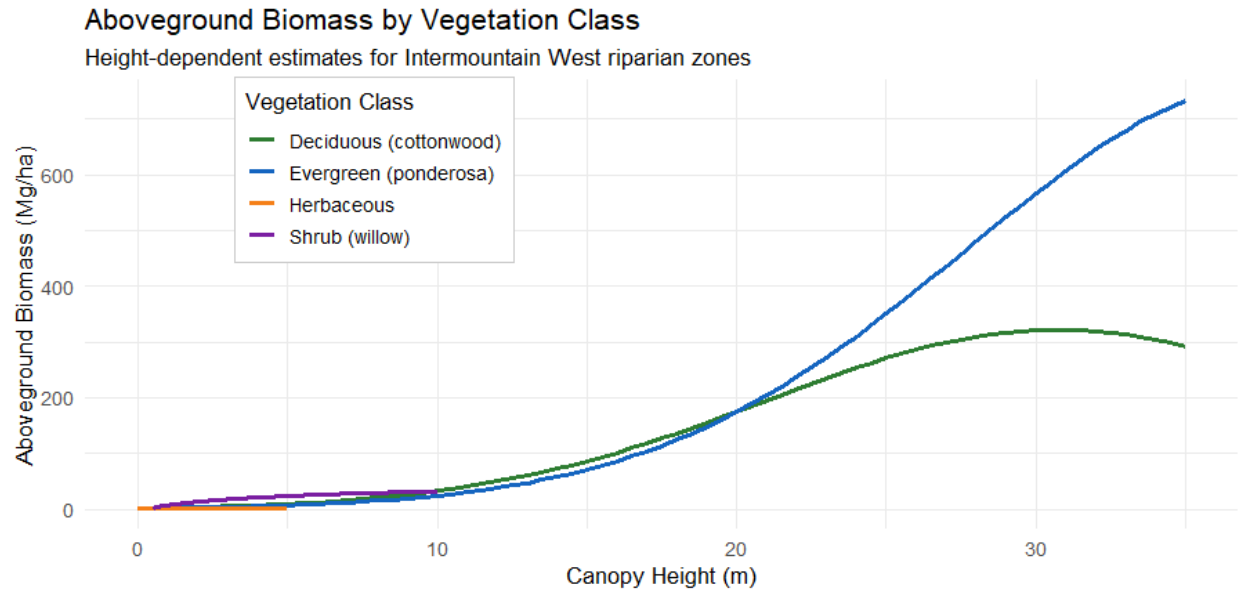


Figure 5. Final models for the relationship between 10-m pixel canopy height and AGB.

3.2 TPA scaling behavior and predicted per-pixel biomass

The split-weight blend with monotonicity constraint produced a smoothly declining TPA gradient for each tree class while preventing the tall-canopy collapse that occurs when declining TPA is applied directly (Figures 6, 7). The resulting cottonwood TPA gradient runs from roughly 4.6 trees per pixel (1 acre = 40.4686 pixels or square dekameters) at a height of 3 meters to 1.5 trees per pixel at a height of 30 meters. The corresponding stand-level biomass increased monotonically across the full height range (~5.48 Mg/ha at 3 m to ~380 Mg/ha at 30 m). Previous work has documented mature stands (height of 25 ± 2 m) of Great Plains Cottonwood (*Populus deltoides*) containing aboveground biomass of 190.39 ± 21.24 Mg/ha, and broader estimates of 100-300 Mg/ha for forested wetlands (Boggs & Weaver, 1994). An overestimation of the theoretical plot Mg/ha at maximum heights is expected because it represents unrealistic conditions: peak growth for an entire hectare. This is constrained in practice because of the downscaling to pixels, where only a few pixels within a hectare will have such height.

Table 2. Cottonwood diagnostic values

Height (m)	Tree KG	TPA	Biomass Mg/ha	Biomass Mg/pixel
3	11.8	188	5.48	0.0548
5	23.9	166	9.82	0.0982
8	62.6	139	21.6	0.216
10	112	125	34.5	0.345
15	386	97.7	93.2	0.932
20	983	79.8	194	1.94
25	1848	67.9	310	3.10
30	2562	60.1	380	3.80

Table 3. Ponderosa diagnostic values

Height (m)	Tree KG	TPA	Biomass Mg/ha	Biomass Mg/pixel
3	10.8	174	4.65	0.0465
5	20.1	154	7.67	0.0767
8	47.9	135	15.9	0.159
10	81.5	126	25.4	0.254
15	263	114	73.8	0.738
20	677	108	181	1.81
25	1391	106	363	3.63
30	2279	105	589	5.89
35	2980	104	767	7.67

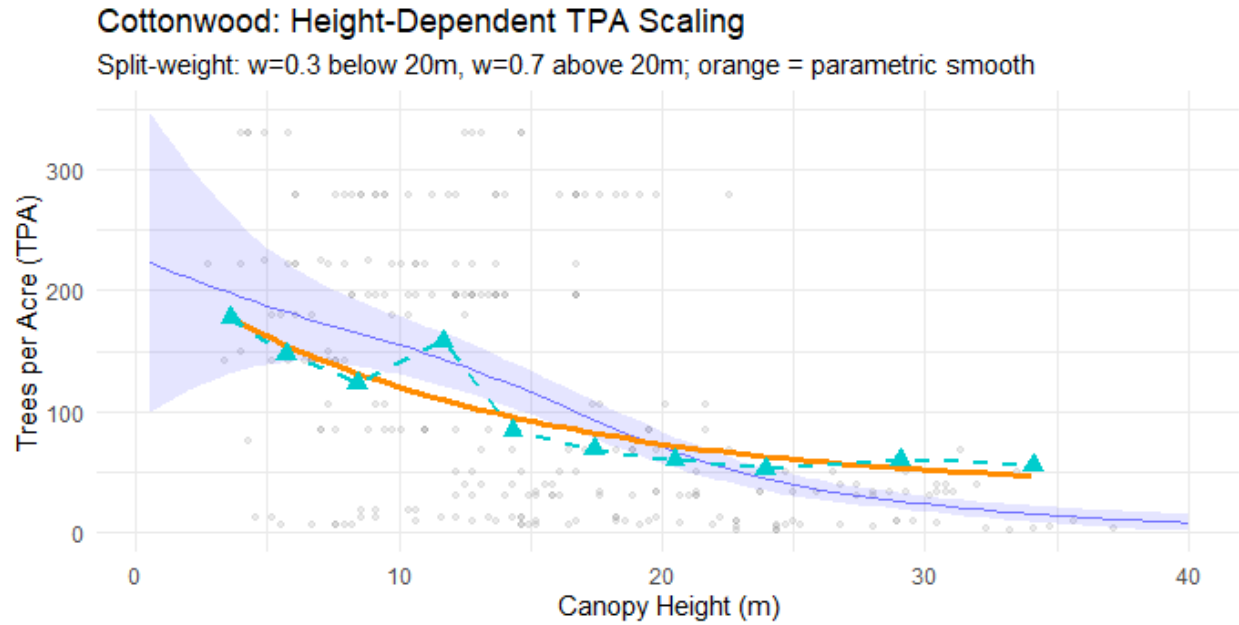


Figure 6. raw vs. constrained vs. smoothed TPA across height for cottonwood.

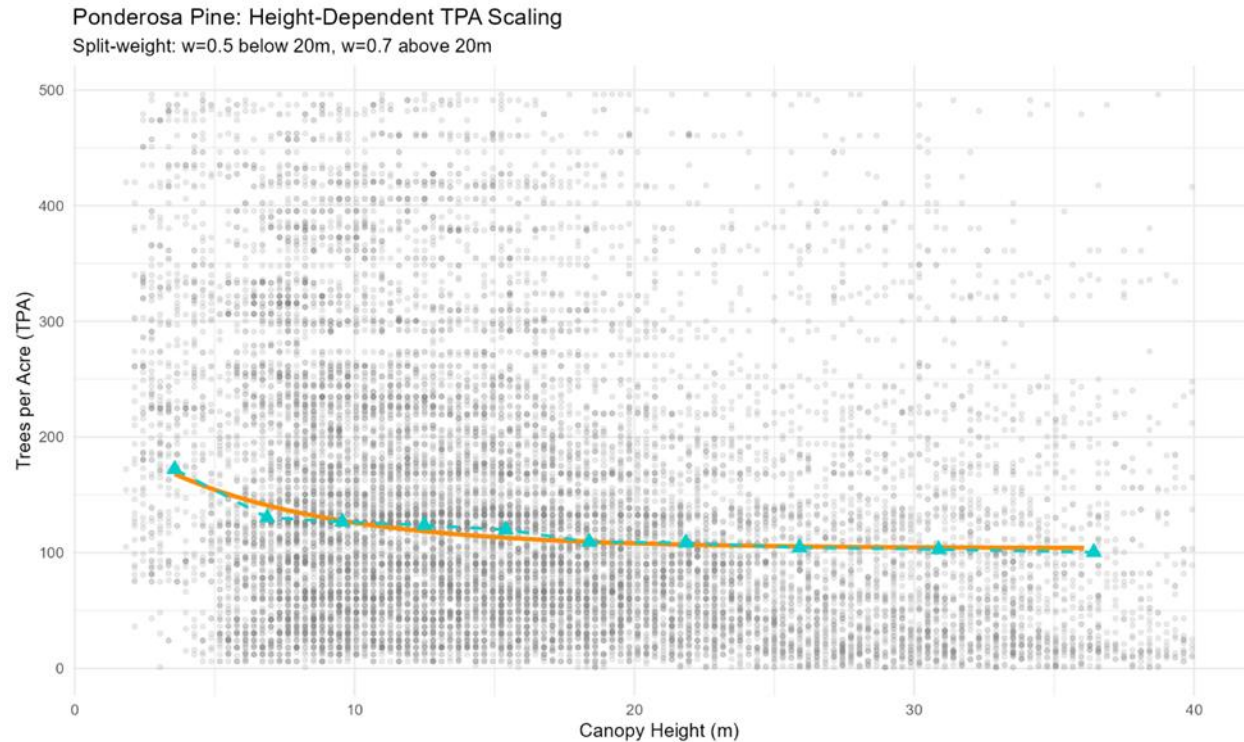


Figure 7. raw vs. constrained vs. smoothed TPA across height for ponderosa.

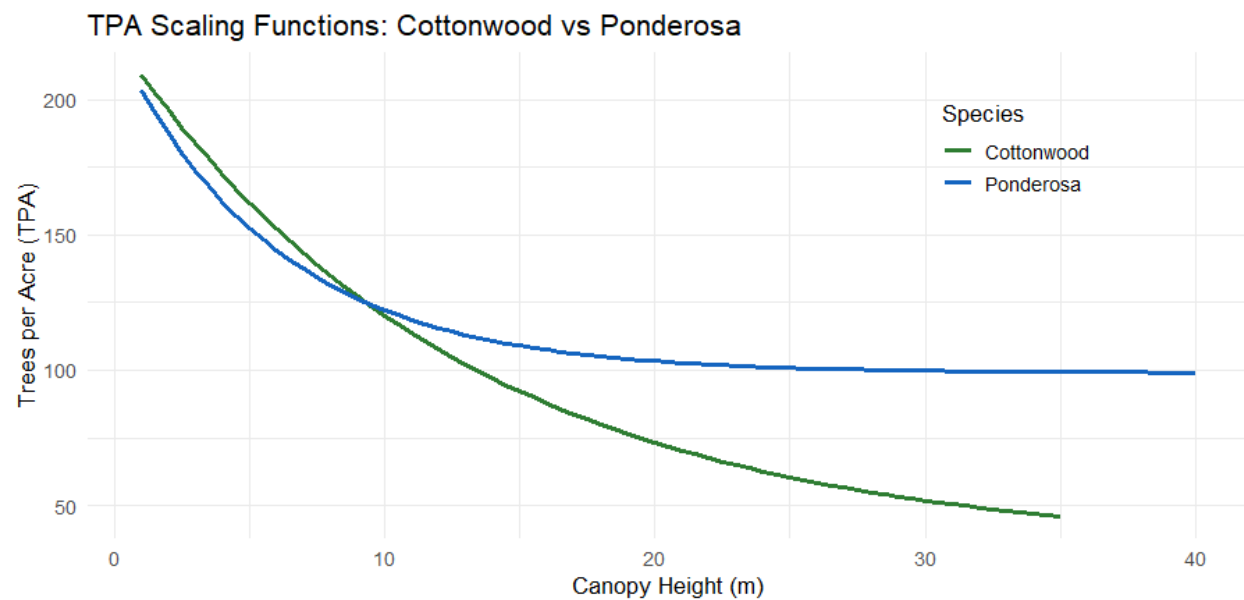


Figure 8. Differences among height-dependent stand density values between Cottonwood and Ponderosa

3.3 Cross-class biomass overlap and sensitivity to class assignment

Predicted per-pixel biomass overlapped substantially across the classes for heights < 25 m, which makes sense given the allometric models described in Figure 5. Ponderosa begins to store

dramatically more biomass above 25 m due to higher TPA values (Figure 8), so confusion among the tallest pixels can dramatically influence the output (Figures 9-11). Overall, there was low sensitivity of biomass output to weighted sum vs hard class assignments, but weighted sums typically resulted in slightly higher biomass values.

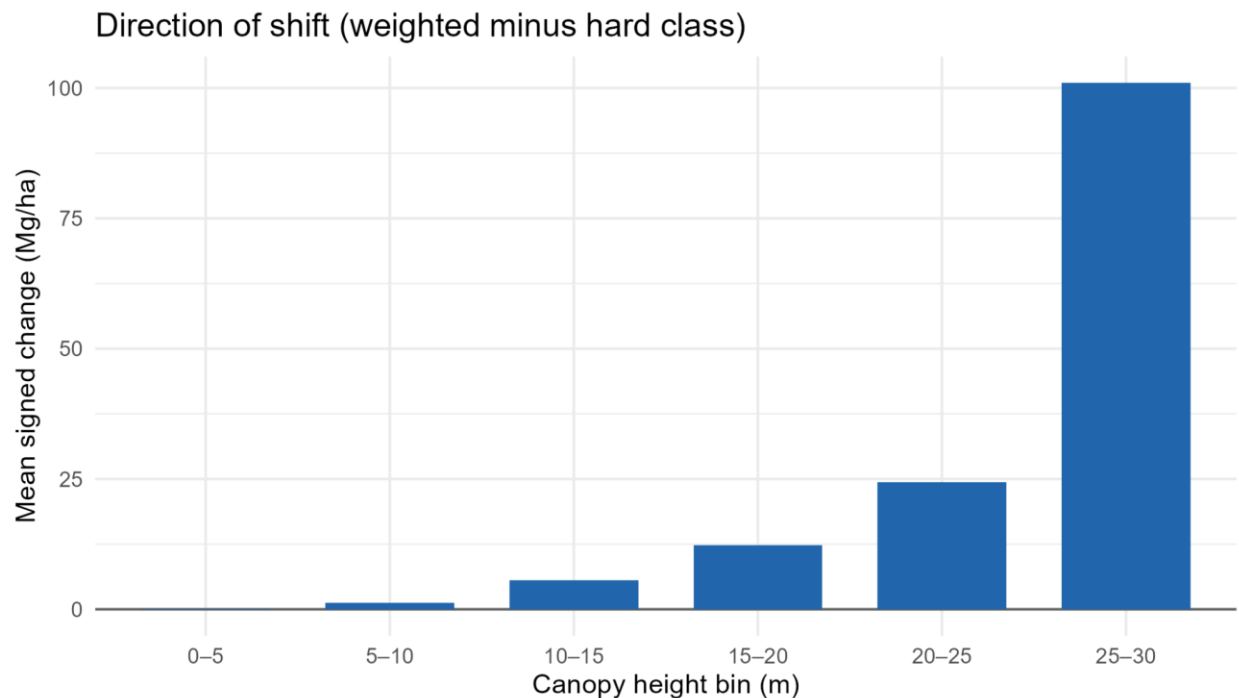


Figure 9. Difference in mean biomass estimates for weighted vs. hard class assignment at 5 m height bins.

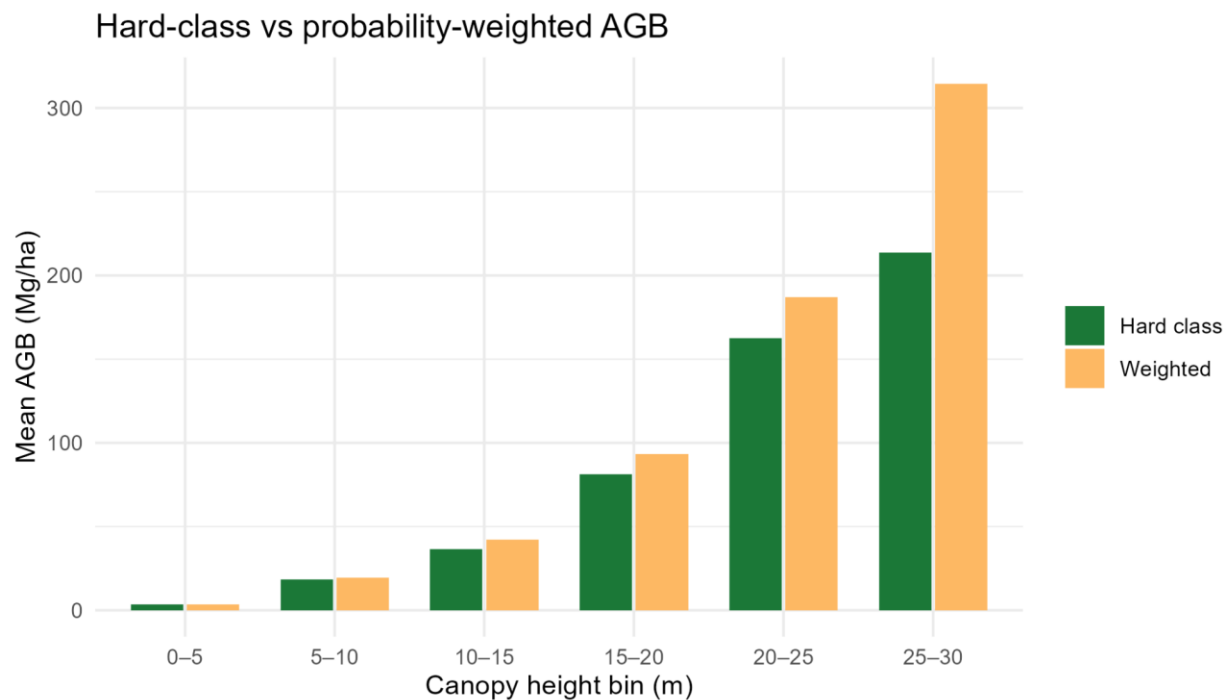


Figure 10. Difference between hard class and weighted class mean biomass at 5 m height bins.

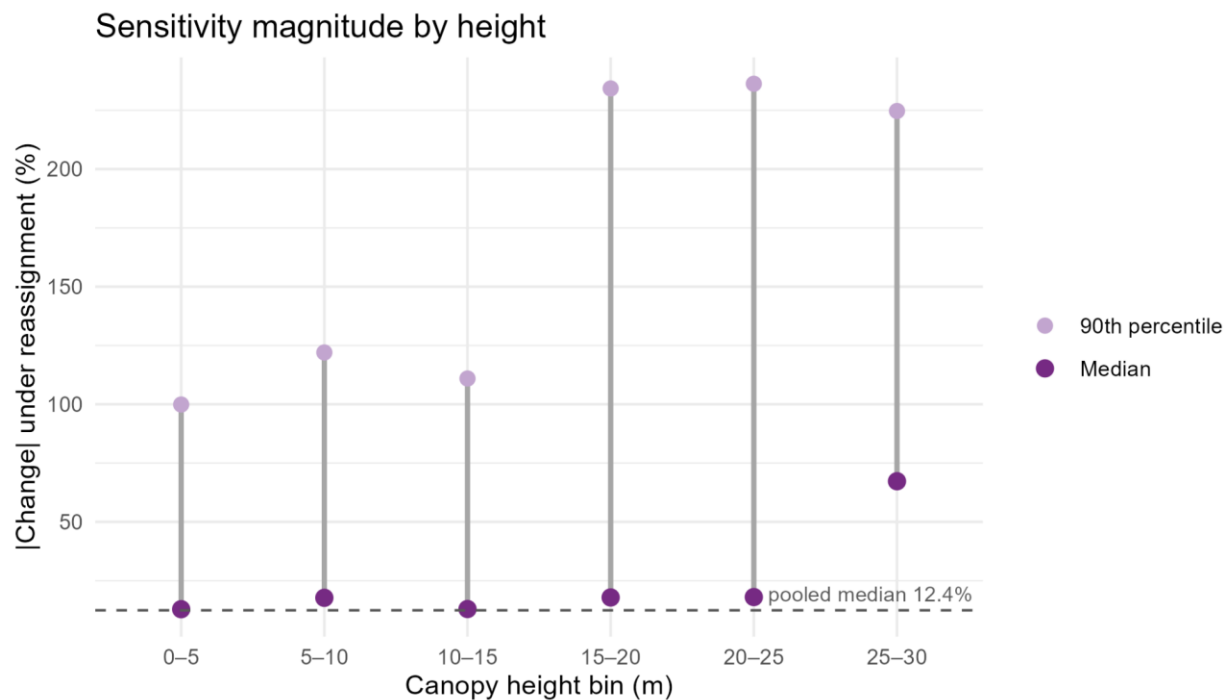


Figure 11. Median and 90th percentile percentage change in biomass estimates under reassignment.

4. Discussion

4.1 Non-geolocated inventory data as a viable training source

For biomass mapping applications requiring the highest prediction confidence, true plot-to-pixel training is ideal. But indeed, there is almost always a more robust approach that requires greater investment of time, money, and effort. Multi-temporal high resolution aerial lidar and hyperspectral imagery combined with multitemporal ground truthing and understory surveys would offer the best data possible, but such a dataset is not a realistic goal for most projects and parts of the world. This coordinate-free approach captures ecological patterns across large scales and characterizes under-monitored systems.

4.2 Robustness to class-assignment uncertainty, and its relation to species-specific allometry

The cross-class overlap finding in this system indicates that biomass estimation at 10 m resolution does not require high classifier confidence among ecologically similar classes. For pixels with a height below 25 m, the biomass estimates are not dramatically affected by class reassignment. The method is therefore resilient to the imprecision forced by non-geolocated data and imperfect classification. At canopy heights greater than 25 m, class reassignment remains high-consequence, so this should not be misunderstood as a license to ignore classification generally, and the chosen classes in this study were overly simple and did not include woody classes that may hold less consistent biomass predictions at similar heights.

4.3 Generality beyond the FIA access disruption

This approach is applicable wherever high-resolution ground-truthing is unavailable but tree-level data exists. This enables, at the very least, preliminary monitoring and assessment of neglected regions and species with minimal data requirements.

4.4 Limitations and future directions

Our specific approach assumes either an oversimplified monoculture for each pixel or a split-weight pixel based on relative class prediction probabilities. However, future work could construct more realistic “hypothetical plots” that encompass associated plant communities. Additionally, the FIA database was not useful for the shrub or herbaceous class in our study, so other supplemental methods were needed. The ecological filtering and TPA downscaling are also imperfect proxies for spatial matching.

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