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# **Monitoring Carbon Hotspots in Patchy Landscapes from Sparse Lidar and Dense Satellite Time Series**

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## **Abstract**

Monitoring aboveground biomass (AGB) stocks as an indicator of carbon storage is essential for climate mitigation, adaptation, and land management. Across much of Earth's land surface, carbon stocks are concentrated in fine-scale hotspots, including isolated trees in pastures, shrub patches in tundra, and riparian vegetation in drylands. These carbon hotspots are vulnerable to change but are difficult to monitor with remote sensing at broad scales due to three interconnected challenges: (1) spatial heterogeneity, (2) temporal change, and (3) modeling uncertainty. To address these challenges, we developed a workflow that integrates moderate-resolution satellite sensors, aerial lidar collections, and forestry-derived allometric models to produce annual maps of AGB in riparian corridors in the semi-arid western United States. To resolve spatial heterogeneity, we modeled canopy height and vegetation class at 10-m resolution, achieving canopy height mean absolute error of 1.56 m and overall vegetation classification accuracy of 84%. To measure uncertainty, we quantified prediction intervals using conformal prediction for canopy height and classification, ensemble disagreement for epistemic uncertainty, and Bayesian posterior distributions for allometric biomass models. The resulting annual maps provide pixel-level AGB estimates with statistically verified uncertainty bounds. These products reveal gradual changes in riparian biomass and can guide management decisions, from prioritizing restoration efforts to identifying early warning signs of ecosystem degradation. This framework could be adapted for monitoring AGB in other patchy landscapes, incorporated into different or changing land cover categories for future work, and updated as more and better data sources become available.

## **1.0 Introduction**

Terrestrial vegetation aboveground biomass (AGB) is a major carbon pool, storing ~320 Gt C globally (Bar-On et al., 2018). Efforts that improve our understanding of carbon budgets and climate feedbacks, such as monitoring the contributions of AGB to the pools and flows of the carbon cycle, are essential for improving global climate models and predicting atmospheric CO<sub>2</sub> concentrations. Remote sensing (RS) has become the primary tool for mapping biomass across broad spatial and temporal extents due to the inherent limitations of ground-based inventory networks, but predominant approaches developed for forest and agricultural lands and are less effective when applied in spatially heterogeneous systems (Kennedy et al., 2018; Tian et al., 2023; Zhang et al., 2025).

Spatial heterogeneity in AGB is a defining feature of many terrestrial ecosystems, including pastures with isolated trees, tundra with patches of shrubs, and riparian vegetation in drylands. These small patches can store disproportionate amounts of carbon relative to their spatial extent, and are often too small to be reliably represented with moderate resolution satellite imagery (Adams et al., 2018; Blackard et al., 2008; Kumar and Mutanga, 2017). Medium-resolution land cover products (e.g. MODIS VCF, Landsat-based products) systematically underestimate biomass in landscapes with scattered trees and mixed vegetation because they cannot resolve fine-scale structural variation within pixels (Graves et al., 2018; Greaves et al., 2016; Gwenzi and Lefsky, 2014; Kennedy et al., 2018). This creates a mismatch between the scale at which carbon is stored and the scale at which it is typically mapped.

Aerial lidar (i.e. airborne laser scanning (ALS)) can resolve AGB at much finer spatial scales than medium-resolution satellite imagery. By providing sub-meter measurements of vegetation structure, ALS has proven effective at identifying carbon hotspots across diverse ecosystems and complex landscapes (da Costa et al., 2021). The key limitations of ALS are the rarity of repeat collections and frequent spatial discontinuity. In most areas, data are collected once, if ever, making temporal analysis of vegetation structure change, and associated changes in AGB, difficult without a framework for extending lidar-derived structure across space and time using other data sources. This limitation is especially important in patchy landscapes undergoing slow, difficult-to-track directional changes that can accumulate into substantial shifts in carbon storage such as shrub expansion, tree dieback, and successional recovery (Campbell et al., 2024; Shriver et al., 2022). Therefore, monitoring frameworks that combine the structural precision of lidar with the temporal continuity of satellite imagery could lead to improved monitoring of AGB in dynamic, heterogeneous landscapes.

Measurements of canopy structure can be translated into AGB estimates through allometric models, but processes such as shrub expansion, tree dieback, and successional recovery can produce subtle annual changes in canopy structure that become consequential only when accumulated over multiple years (Caughlin et al., 2016; Vorster et al., 2020; Yang et al., 2022). Satellite-lidar fusion enables the temporal trajectories needed to detect gradual changes in AGB: lidar provides the structural detail needed, but only at specific times and locations, while satellite imagery provides temporal continuity and full spatial coverage, but lacks direct structural measurement. ALS fusion with optical satellites provides the best of both worlds: a mechanism for subpixel estimation of AGB and a dense time series, enabling spatially- and temporally-resolved monitoring (Matasci et al., 2018; Caughlin et al., 2021; Potapov et al., 2021). However, translating a pixel-based canopy height model into reliable AGB estimates for different vegetation classes introduces multiple sources of error that are often poorly constrained.

Common sources of error in biomass estimates include spatial variability, epistemic uncertainty across modeling steps, and reliability of prediction bounds (Ayrey et al., 2021; Zhang et al., 2025). Many remote sensing studies of biomass dynamics do not reliably quantify uncertainty. This can have negative implications for management due to the tendency to treat maps as truth and the increasing reliance on remote sensing for ecosystem monitoring (Kennedy et al., 2018; Singh et al., 2024; Zhang et al., 2025). Common approaches such as bootstrap confidence intervals and RMSE-based error bars assume specific distributional forms that often do not hold true in practice, provide no statistical guarantee that the stated intervals actually contain the true value at the claimed rate, and do not account for pixel-by-pixel variability in uncertainty (Brown et al., 2009; Stehman and Foody, 2019; Singh et al., 2024). Conformal prediction is a distribution-free, model-agnostic method for quantifying uncertainty in both classification and regression problems by producing statistically valid prediction intervals that contain the true value with a user-specified confidence level (Romano et al., 2019; Valle et al., 2023; Singh et al., 2024). Unlike bootstrap or parametric approaches, conformal methods make no assumptions about normality or stationarity, making them well suited to ecological data with complex error structures. Biomass monitoring frameworks which use conformal prediction to constrain estimates have increased transparency (Tasuev et al., 2026).

Policy and land management decisions regarding incentive-based natural climate solutions programs, conservation investment, restoration prioritization, and carbon budgets would all benefit from estimates of biomass dynamics across the landscape. For example, ecosystem restoration is motivated by a variety of nature-based solutions such as biodiversity, resilience, and climate change mitigation, but its potential to substantially offset emissions remains in question due to the scale of human emissions and confounding factors like albedo (Hasler et al., 2024; Tölgyesi et al., 2025). Carbon markets rely on stable, simple credits, and the verifiability of carbon storage claims depends directly on the quality of the

uncertainty bounds attached to them. Scrutiny of past approaches and the challenges associated with accurately estimating mitigation have resulted in overhauling of carbon accounting methodologies, which now include uncertainty as a key constraint on carbon credit issuance (Wells et al., 2023; West et al., 2023; ACR, 2023; Verra, 2025; Delacote et al., 2025). Consequently, statistically rigorous methods for presenting uncertainty in biomass estimates are critical for carbon accounting.

Riparian ecosystems within the sagebrush biome of the United States are an ideal place to study carbon hotspots because they are heterogeneous ecosystems undergoing consequential, gradual changes. In the sagebrush biome, wet habitats comprise 1-2% of the landscape, yet they provide vital resources to more than half the wildlife species in the region (Theobald et al., 2010; Maestas et al., 2023). These habitats are believed to store disproportionately high carbon per unit area, but estimates vary widely and the magnitude of relative differences in carbon storage have not been investigated at broad scales in the American West. Within the sagebrush biome, some wetlands are estimated to store 3-6 times more carbon than neighboring forests and drier meadows, and wetlands globally contribute 20-30% of soil carbon while making up 5-8% of land area (Norton et al., 2014; Nahlik and Fennessy, 2016; Law et al., 2018; Kauffman et al., 2022). In the Western US, riparian ecosystems are “emerald islands in a sagebrush sea” (Maestas et al., 2018) and support a mosaic of distinct vegetation types packed into narrow, discontinuous corridors that potentially store high amounts of aboveground carbon. Growth rates and long-term survival of native vegetation such as cottonwoods and willows are strongly controlled by water availability and groundwater fluctuations (Driscoll et al., 2026). In the Willamette Valley, Oregon, a highly productive ecoregion, late seral stage cottonwood-dominated stands contained up to ~594 Mg/ha of AGB (Fierke and Kauffman, 2005). Along the Yellowstone River in Eastern Montana, in a drier, less productive ecoregion, mature stands (height of  $25 \pm 2$  m) of Great Plains Cottonwood (*Populus deltoides*) contained  $190.39 \pm 21.24$  Mg/ha of AGB (Boggs and Weaver, 1994). Broader estimates of mean AGB in forested wetlands range from 100-300 Mg/ha (Boggs and Weaver, 1994; Reiners, 1972; Taylor, 1985). In upland treeless sagebrush steppe ecosystems, biomass is estimated at ~9 Mg/ha, which increases to ~124 Mg/ha when tree cover increases to near-closed canopy conditions (Rau et al., 2012). Relative to more homogenous but sparse carbon storage of neighboring upland systems, riparian areas serve as important stocks despite heterogeneous storage.

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 affect AGB and corresponding carbon storage. Changes to hydrological regimes (floodplain connectivity, groundwater availability), climate regimes (fire intensity, snow/rain dominance), and invasive species dynamics have contributed to regional declines in native riparian vegetation (Webb et al., 2019; Rohde et al., 2021; Zimmerman et al., 2023; Mohammadi et al., 2025). Land management activities also contribute to riparian changes. For example, stream restoration that raises water tables and increases frequency, duration, or magnitude of overbank flooding can shift abiotic conditions back in favor of hydriophilic species (Driscoll et al., 2025). In mesic areas impacted by grazing or other disturbances, passive measures such as livestock exclosures can promote revegetation (Kauffman et al., 2002). Tracking the response to ecosystem change and/or restoration efforts requires consistent structural measurements across years, such as those offered by satellite-lidar fusion datasets.

Riparian systems in the sagebrush biome exhibit all three challenges of monitoring carbon hotspots: they are structurally heterogeneous at scales below the resolution of most satellite products, they are undergoing gradual directional changes that demand temporal monitoring, and they are the subject of current and proposed management decisions that require reliable uncertainty estimates (Hinshaw and Wohl, 2021; Kolarik et al., 2023; Maestas et al., 2023).

The overarching goal of this study is to improve our ability to map AGB as an indicator of carbon hotspots in dynamic heterogeneous ecosystems. We developed a workflow for scaling estimates of AGB across space and time in riparian systems of the American West. This workflow offers processes for leveraging multi-source open data, for quantifying uncertainty across model layers, and for monitoring gradual temporal changes in biomass. We integrate spatially and temporally sparse ALS (for canopy height calibration) and Sentinel-2 optical imagery (for annual prediction) into a unified framework. We then incorporate freely available forestry and geolocated training data to classify pixels and model biomass within them. We quantify uncertainty through canopy height prediction, vegetation classification, and biomass estimation using conformal prediction and Bayesian methods. Our specific objectives were to:

1. Identify fine-scale carbon hotspots below the scale of conventional satellite pixels by training algorithms to predict canopy height and vegetation class from Sentinel satellite imagery.
2. Extend spatially and temporally sparse lidar observations into annual biomass trajectories by predicting canopy structure in Sentinel-2 imagery from 2017 to 2025 and estimating AGB with class-specific allometric models.
3. Produce uncertainty-aware maps of AGB by quantifying uncertainty for each modeling step, including canopy height prediction, vegetation classification, and allometric models.

## 2.0 Methods

The workflow used in this analysis consists of three main components: canopy height regression to develop canopy height models (CHM), vegetation classification, and biomass modeling. Figure 1 provides an overview of the workflow.

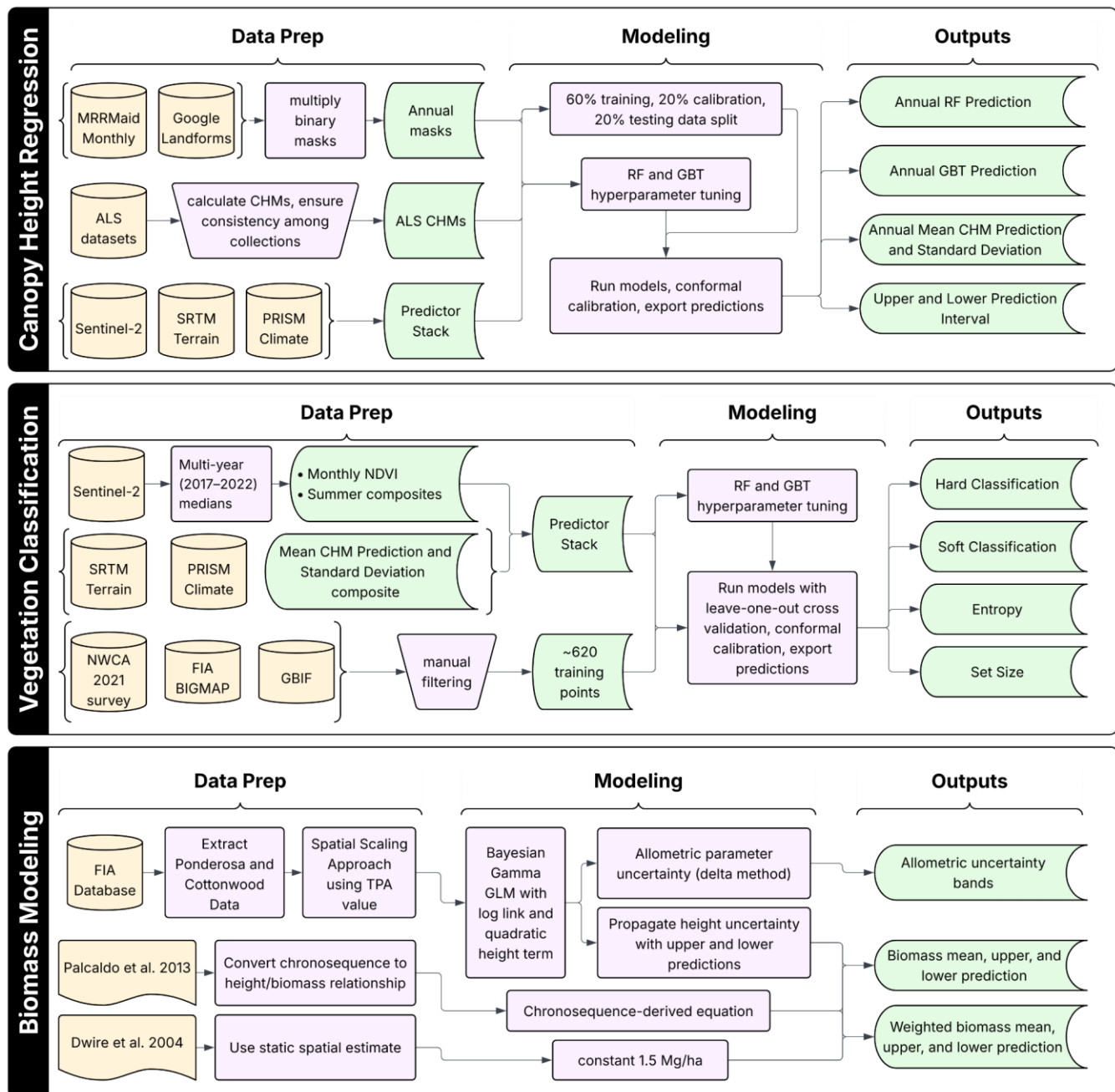


Figure 1. Workflow overview for the three main model components. Data sources are in beige, processing and analysis steps are in purple, and data products are in green. Output acronyms: RF = random forest, GBT = gradient boosted tree, CHM = canopy height model.

## 2.1 Study Area

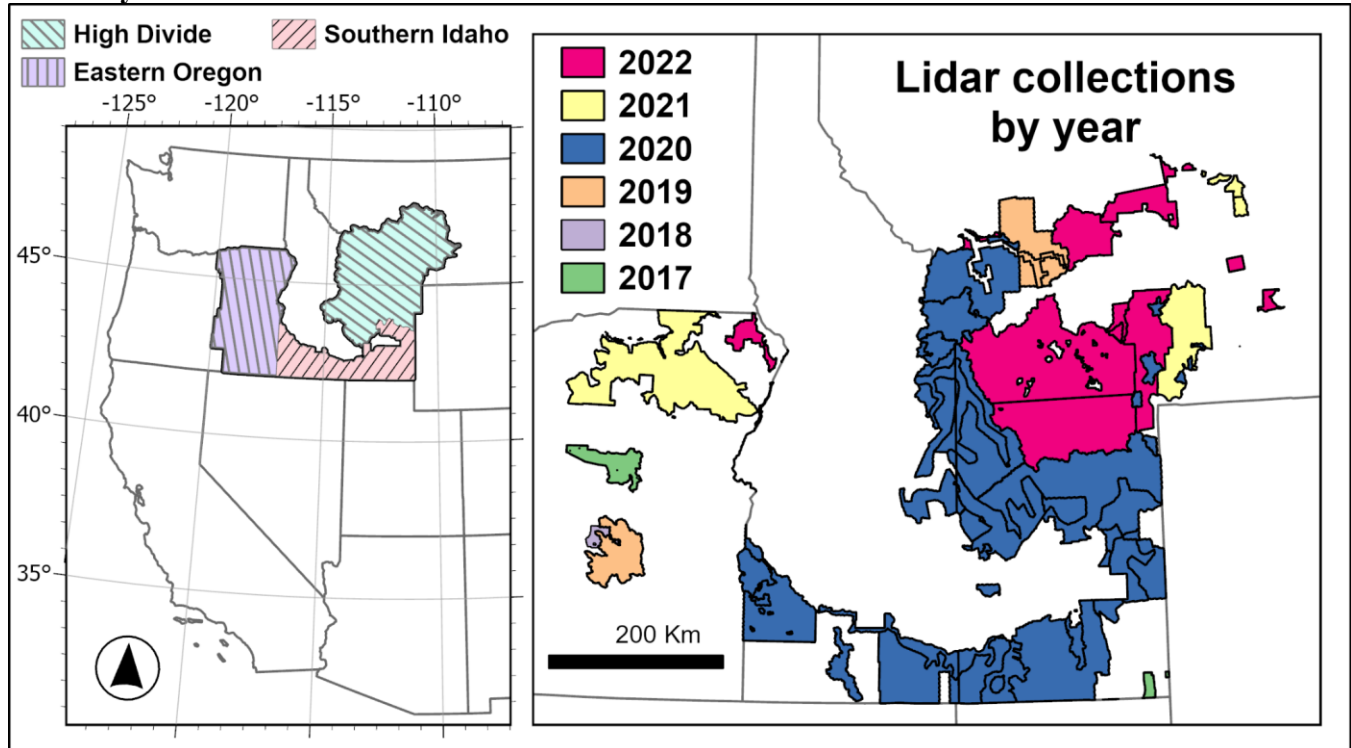


Figure 2. The study area within the Western United States consists of Eastern Oregon, Southern Idaho, and the High Divide of Idaho and Montana, an area of 289,562 square kilometers. Individual lidar collections are separated by solid lines.

We constrained our modeling to the valley bottoms and riparian zones across portions of Idaho, Oregon, and Montana within the sagebrush biome of the Intermountain West. The specific sub-regions of Eastern Oregon, Southern Idaho, and the High Divide of Idaho and Montana represent management-relevant units that collectively contain much of the climatic and topographic variability found within the broader sagebrush biome. These three areas regularly experience a range of late summer drought conditions ranging from Moderate to Exceptional according to the U.S. Drought Monitor (Simeral, 2026).

## 2.2 Data Sources

### 2.2.1 Lidar-derived canopy height models

A total of 44 ALS collections within the study area spanning 2017-2022 with either pre-existing canopy height models (CHMs) or upstream data products provided the target variable for canopy height prediction. We constrained CHMs to 40 meters to exclude any human-built structures, and excluded values outside our defined mesic mask. We included collections with variable spatial resolutions, and aggregated all to 10-m using mean reduction. We aggregated in the CHM's native coordinate reference system (CRS) prior to reprojection to EPSG:4326 (WGS84), which aligns natively with the Google Earth Engine (GEE) basemap and Sentinel-2 display grid. At the latitudes of this study area ( $\sim 41$ - $47^\circ$  N), a 10-m pixel in EPSG:4326 is slightly rectangular and varies in size, but area calculations ensure geodetic accuracy regardless of CRS.

Differing acquisition and processing parameters between lidar collections can affect vegetation inventory results, necessitating careful preprocessing and normalization in studies combining multi-platform and multi-temporal data. Models developed using one lidar acquisition are often not considered applicable to another. For example, the impact of seasonal changes in canopy conditions on penetration

of lidar into the canopy has raised concerns about combining data from leaf-on with leaf-off collections for forest inventories (Wasser et al., 2013). Guidelines for area-based approaches of forest inventories recommend using leaf-on data, or at least not mixing leaf-on and leaf-off data (Wasser et al., 2013; White et al., 2015). Therefore, despite the highly accurate data produced by ALS, lack of consistency between datasets often prohibits regional-scale modeling (Ayrey et al., 2021). However, first return data (maximum canopy height) is not much influenced by leaf-on or leaf-off status (Næsset, 2005). We used solely first-return data for model training, allowing the inclusion of both leaf-on and leaf-off collections. By leveraging many lidar collections across multiple years and only using the most transferrable information (first return data) from each, we were able to produce a model that is both locally-specific and regionally-transferrable.

### ***2.2.2 Mesic mask***

To constrain analysis to relevant vegetation and landform types, we defined mesic extent primarily with MRRMaid Monthly, a satellite-based data product of mesic ecosystems (i.e. surface water and mesic vegetation) at 10-meter resolution using Sentinel-1 and Sentinel-2 (Kolarik et al., 2023, 2026). MRRMaid generates monthly classification maps for June-September for 2017-present. For each year, we retained every pixel that was classified as mesic at least twice for the annual mask (i.e., valid pixel). To address false positives that can occur in upland areas, we used the Shuttle Radar Topography Mission (SRTM) Google Landforms product to create a secondary mask defined by classes upper slope (flat), lower slope, lower slope (flat), valley, and valley (narrow) (Theobald et al., 2015). We multiplied the binary primary and secondary masks to create the annual mesic masks. We created an inclusive union of all annual mesic masks for the vegetation classification, enabling prediction everywhere that any year had valid mesic data, assuming other parameters were met. Annual CHM predictions used year-specific masks so the valid prediction extent varied by year. When evaluating temporal change, year-over-year biomass change was computed for pixels valid in both years, and trend analysis considered only pixels valid in all years to prevent spurious trends. Of the 35,656 km<sup>2</sup> inclusive union mask, 7,273 km<sup>2</sup> are consistently classified as mesic in all years.

### ***2.2.3 Satellite data***

Sentinel-2 Level-2A surface reflectance imagery served as the primary source of spectral predictors. Sentinel-2 provides multispectral imagery at 10–20 m resolution with up to a 5-day revisit time, enabling construction of dense temporal composites (Drusch et al., 2012). We performed cloud masking using Cloud Score+ (Pasquarella et al., 2023), a pixel-level cloud probability product that provides finer-grained cloud detection than the traditional QA60 band flags, and excluded pixels with cloud scores below 0.65 (65% clear probability).

### ***2.2.4 Terrain and climate data***

We derived terrain predictors from the SRTM 30-meter DEM (Farr et al., 2007): elevation, slope, and aspect (decomposed into sine-easterness and cosine-northernness components to handle the circular discontinuity between 359° and 0°) (Olaya, 2009). We derived climate predictors from PRISM 1991–2020 30-year normals (Daly et al., 2008): mean annual temperature, total annual precipitation, and temperature range (difference between warmest and coldest month).

### ***2.2.5 Biomass allometric models***

We relied upon individual tree measurements from the USDA Forest Service (USFS) Forest Inventory and Analysis (FIA) program as the empirical basis for species-specific height-to-biomass allometric models. Exact methods are detailed in Nati-Johnson et al., 2026.

### ***2.2.6 Vegetation training data***

We selected four functional vegetation types relevant to riparian and mesic ecosystems in the sagebrush biome: Evergreen (Class 0): conifer-dominated stands, primarily ponderosa pine (*Pinus ponderosa*). Deciduous (Class 1): broadleaf deciduous stands, primarily black cottonwood (*Populus trichocarpa*). Herbaceous (Class 2): grasslands and meadows. Shrub (Class 3): shrub-dominated areas, primarily willow (*Salix* spp.). These four classes are an oversimplification, but represent the majority of vegetation functional groups within our area of interest. We used a combination of random sampling and opportunistic supplemental sampling to derive training data for the vegetation classification. Sources included FIA BIGMAP, a USFS modeled map product of pixel-level tree species biomass (Wilson et al., 2018); iNaturalist (through the Global Biodiversity Information Facility (GBIF)), self-collected field data, and manual digitization of high-resolution imagery. Training data points derived from iNaturalist, a community science platform, were not suitable as raw training data because users frequently photograph from nearby roads, trails, or adjacent positions rather than recording the exact coordinate of the organism. Therefore, we manually verified and filtered observations to ensure geolocation accuracy relative to the target 10-m pixel resolution. Additional details on the sampling protocol are available in Nati-Johnson et al. (2026). The final count for training points after all filters were as follows: 171 evergreen, 166 deciduous, 188 herbaceous, 106 shrub.

## **2.3 Canopy Height Prediction**

### **2.3.1 Predictor stack**

For each year (2017-2022), a predictor stack was assembled at 10-meter resolution comprising 24 bands: 10 fixed spectral bands from Sentinel-2 (June-July median composites), 6 phenology bands (NDVI and EVI for three seasonal periods: Mar-Apr, Jun-Jul, Sep-Oct), one Level-3 EPA Ecoregion band, four terrain bands from SRTM (elevation, slope, and transformed aspect), three climate bands from PRISM 30 year (1991-2020) normals (mean annual temperature, mean annual precipitation, and seasonal temperature range). Terrain and climate predictors were temporally static, while spectral/phenological predictors were year-specific.

### **2.3.2 Ensemble architecture**

We predicted canopy height using a two-model ensemble containing a Random Forest (RF) and a Gradient Boosted Tree (GBT), each implemented in GEE. RF builds decision trees independently using bootstrapped samples, with each tree seeing approximately 63% of training data. Trees are grown deep (low bias, high variance) and predictions are averaged to reduce variance (Breiman, 2001). GBT builds trees sequentially, where each tree corrects the residual errors of previous trees. Trees are typically shallow (low variance, higher bias) and the method primarily reduces bias through iterative correction (Friedman, 2001). We optimized hyperparameters for both models using a grid search over the training data, which we internally split 80/20 for candidate fitting and evaluation. We selected the RF and GBT configurations with lowest mean absolute error and the retrained final production models on the full training partition.

### **2.3.3 Conformal prediction for uncertainty quantification**

Ensemble disagreement provides an intuitive but statistically uncalibrated measure of prediction uncertainty. To produce prediction intervals with guaranteed coverage properties, we applied split conformal prediction, a distribution-free framework that determines the interval width needed to achieve a target coverage rate on held-out calibration data (Romano et al., 2019). We split data in three ways: training (60%) for model fitting and hyperparameter tuning, calibration (20%) for conformal threshold estimation, and test (20%) for independent coverage verification and accuracy assessment. The procedure was: (1) split available lidar-covered pixels into training and calibration sets; (2) train the two-model ensemble on the training set; (3) compute absolute nonconformity scores on the calibration set as  $|y_{\text{true}} - y_{\text{pred}}|$  (4) determine the conformal threshold as the  $(1 - \alpha)(1 + 1/n)$  quantile of the

calibration nonconformity scores, where  $\alpha$  is the target miscoverage rate. The resulting prediction interval for a new pixel is: prediction  $\pm$  threshold. Conformal approaches provide a statistical guarantee that if calibration and test data are drawn from the same distribution, the prediction intervals contain the true value with probability at least  $(1 - \alpha)$  (Singh et al., 2024).

#### **2.3.4 Output products**

For each year 2017-2025, the canopy height prediction workflow exports a 7-band image: ensemble mean predicted canopy height (meters), ensemble standard deviation (meters), conformal prediction lower and upper bounds, prediction interval width, RF prediction, and GBT prediction.

### **2.4 Vegetation Classification**

#### **2.4.1 Classification scheme**

We classified pixels into the four functional vegetation types: Evergreen (Class 0): conifer-dominated stands, primarily ponderosa pine (*Pinus ponderosa*). Deciduous (Class 1): broadleaf deciduous stands, primarily black cottonwood (*Populus trichocarpa*). Herbaceous (Class 2): grasslands and meadows. Shrub (Class 3): shrub-dominated areas, primarily willow (*Salix* spp.).

#### **2.4.2 Predictor stack for classification**

The classifier used 27 predictor bands comprising: predicted canopy height and its associated ensemble standard deviation (from the CHM workflow; including uncertainty as a predictor allows the classifier to weight height information by its reliability); 12 monthly NDVI composites (multi-year medians from 2017–2022, providing stable phenological signatures robust to single-year anomalies); six June–July spectral bands (multi-year medians from 2017–2022); four terrain variables; and three climate variables. The CHM predictions used a mosaic approach prioritizing years with lowest ensemble uncertainty (2020 as primary reference year), ensuring the most reliable height estimates informed vegetation classification.

#### **2.4.3 Ensemble classification with conformal prediction**

We classified vegetation using a two model ensemble (RF+GBT) paralleling the architecture used for canopy height prediction. We again optimized hyperparameters using the same internal grid search approach as the CHM models. We trained both models by setting the mode of each classifier to ‘MULTIPROBABILITY’, returning a 4-element array of class probabilities per pixel. RF probabilities were the fraction of trees voting for each class, and GBT probabilities were derived from the softmax of the terminal node scores across the four classes. Ensemble probability for each class was the average of the two models, meaning totals did not always add to exactly 100%. The conformal prediction sets included any class with averaged probability meeting or exceeding the calibrated threshold. We later fed these probabilities into an alternative probability-weighted biomass calculation that computes biomass for all four classes and weights by ensemble probabilities, so a pixel that is 70% deciduous / 30% shrub gets a blended biomass estimate. We then quantified uncertainty through maximum probability (confidence in the top class), Shannon entropy (overall uncertainty across classes:  $-\sum p \cdot \log(p)$ ), and normalized entropy. We performed conformal calibration using LOOCV predictions held out from the full ensemble, and applied to the classification output to produce prediction sets: sets of classes that are guaranteed to contain the true class with probability at least  $(1 - \alpha)$ . The nonconformity score for classification is  $1 - P(\text{true class})$ , where lower scores indicate higher model confidence on the correct class. A prediction set with a single element indicates high confidence, while a larger set indicates the classifier cannot reliably distinguish among the included classes (Valle et al., 2023).

#### **2.4.4 Validation**

We assessed classification accuracy using Leave-One-Out Cross-Validation (LOOCV), which is well suited for the smaller sample size of vegetation training points. Accuracy metrics include overall accuracy, producer's accuracy, and consumer's accuracy.

#### **2.4.5 Output products**

The classification procedure we used produced a single temporally stable vegetation map (not annual maps), intended for combination with annual canopy height predictions. The choice of a static vegetation classification prioritizes consistent phenological composites at the cost of capturing dramatic changes in cover type, which is not typical within a single decade. Output bands included: hard classification (0–3), per-class probabilities (four bands), maximum probability, entropy, normalized entropy, and conformal prediction set membership. These outputs were then paired with class-specific allometric models.

### **2.5 Aboveground Biomass Estimation**

We estimated AGB for each 10-m pixel by applying class-specific allometric models that translate canopy height into biomass density. 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-m pixels. Details of these methods, including class-specific implementation, are available in Nati-Johnson et al. (2026).

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), we used a Bayesian Gamma GLM with log link, as in Chabi et al., 2016, and a quadratic height term to predict individual tree biomass from height. We then scaled this prediction 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 AGB (Chave et al., 2004; Clark and Kellner, 2012; Borsah et al., 2023). To our knowledge, there were no published allometric models for *Populus trichocarpa* (black cottonwood) which necessitated creating one using FIA data (Nati-Johnson et al., 2026). Additionally, the limitations of remote sensing and a 10-m pixel prevented the use of an allometric model that includes DBH or a common proxy, crown diameter, but models derived solely from the relationship between height and biomass have been shown to exhibit only slightly reduced performance (Liu et al., 2024).

### **2.6 Uncertainty Propagation**

#### **2.6.1 Sources of uncertainty**

The biomass estimation pipeline has three primary sources of uncertainty that propagate through the workflow: (1) Canopy height prediction uncertainty, quantified by the ensemble disagreement and conformally calibrated prediction intervals. (2) Vegetation classification uncertainty, quantified by soft classification probabilities, entropy, and conformal prediction sets. (3) Allometric model uncertainty,

arising from the Bayesian posterior distributions of height-biomass model parameters, the height-dependent TPA function, and for willow, the chronosequence assumptions.

### **2.6.2 Propagation approach**

We propagated uncertainty through the biomass estimation pipeline using a scenario-based approach implemented in GEE. For canopy height uncertainty, we computed biomass three times per pixel per year: once using the ensemble mean CHM prediction, and once each using the conformally calibrated lower and upper bounds (CI\_Lower, CI\_Upper). We passed each height scenario through the class-specific allometric model determined by the hard classification, producing biomass\_mean, biomass\_lower, and biomass\_upper estimates. For classification uncertainty, we computed a probability-weighted expected biomass by evaluating all four class-specific allometric models at a given height and weighting each by the ensemble-averaged class probability from the soft classification

$$\text{Weighted Biomass} = \sum P(\text{class } k) \times f(\text{class } k(\text{height})) \quad (9)$$

where  $f$  is the allometric function for class  $k$ . We computed this at all three height scenarios (mean, lower, upper), weighted estimates for each. The prediction interval width (biomass\_weighted\_upper minus biomass\_weighted\_lower) captures the joint effect of height and classification uncertainty on the final biomass estimate. We pre-computed these seven bands and exported them as annual assets, enabling interactive exploration of uncertainty in the GEE application with minimal runtime computation.

For allometric model uncertainty, we extracted the posterior covariance matrix of the Bayesian GLM coefficients ( $\beta_0, \beta_1, \beta_2$ ) from each model and exported them for use in GEE. We computed uncertainty in the log-scale linear predictor using the delta method:  $\text{Var}[\log(\mu)] = x' \Sigma x$ , where  $x = [1, h, h^2]$  and  $\Sigma$  is the  $3 \times 3$  posterior covariance matrix (Feiveson, n.d.). On the response scale, this translates to an approximate coefficient of variation:  $CV \approx \sqrt{\exp(x' \Sigma x) - 1}$ . This produces a smooth, height-dependent allometric uncertainty band that captures how confident we are in the height-to-biomass relationship itself, independent of how confident we are in the height prediction. Comparison with a more computationally-intensive Monte Carlo-derived CV on the sample data showed near-perfect agreement. We computed this allometric CV as a separate output band for each pixel, allowing users to distinguish uncertainty arising from the height prediction versus uncertainty arising from the allometric model.

## **2.7 Temporal Analysis**

### **2.7.1 Canopy height time series**

We generated annual canopy height predictions (2017–2025) by applying the trained ensemble to each year's predictor stack. Because the vegetation classification is temporally stable (a single map derived from multi-year composites), temporal dynamics in biomass are driven entirely by changes in predicted canopy height.

### **2.7.2 Change detection**

We computed year-over-year biomass change as the difference between consecutive years' biomass estimates. We excluded pixels absent from either year's mask from the change calculation to prevent artificial gains or losses where the mesic mask expanded or contracted. We computed linear trends in biomass per-pixel using ordinary least squares regression across all years (2017–2025). Trend calculations considered only pixels included in the mesic mask (i.e., valid) in all years to prevent spurious trends. The trend slope (Mg/pixel/year) and  $R^2$  provide complementary information: slope

indicates the rate and direction of biomass change, while  $R^2$  indicates whether the change follows a consistent trajectory.

## 2.8 Implementation

We conducted all remote sensing analyses in Google Earth Engine (GEE) using the JavaScript API. GEE's cloud computing infrastructure enables processing of the full Sentinel-2 archive across the study area without local data storage or computation constraints. We performed allometric modeling in R using the *brms* package for Bayesian GLMs with LOO model comparison, the *rFIA* package for FIA data access, and the *sf* package for spatial filtering (Pebesma, 2018; Stanke et al., 2020; Doser et al., 2026). All spatial exports used EPSG:4326 at 10-meter resolution.

## 3.0 Results

### 3.1 Resolving spatial heterogeneity

#### 3.1.1 Canopy height model performance

The canopy height prediction models both performed well, with GBT slightly outperforming RF (Table 1). Retaining both for a mean ensemble comes with a tradeoff between mean error and goodness-of-fit. Our CHM predictions capture much of the fine-scale heterogeneity shown in the lidar training data. Small patches of trees and shrubs are often well-delineated (Figure 3). Canopy heights are generally underpredicted for canopies >15-m, ensuring conservative biomass estimates (Figure 4).

Table 1. Error metrics for the canopy height models (CHM) for Gradient Boosted Tree, Random Forest, and Ensemble model approaches.

| CHM Model | RMSE | MAE  | $R^2$ |
|-----------|------|------|-------|
| GBT       | 2.56 | 1.39 | 0.596 |
| RF        | 2.60 | 1.54 | 0.584 |
| Ensemble  | 2.90 | 1.56 | 0.617 |

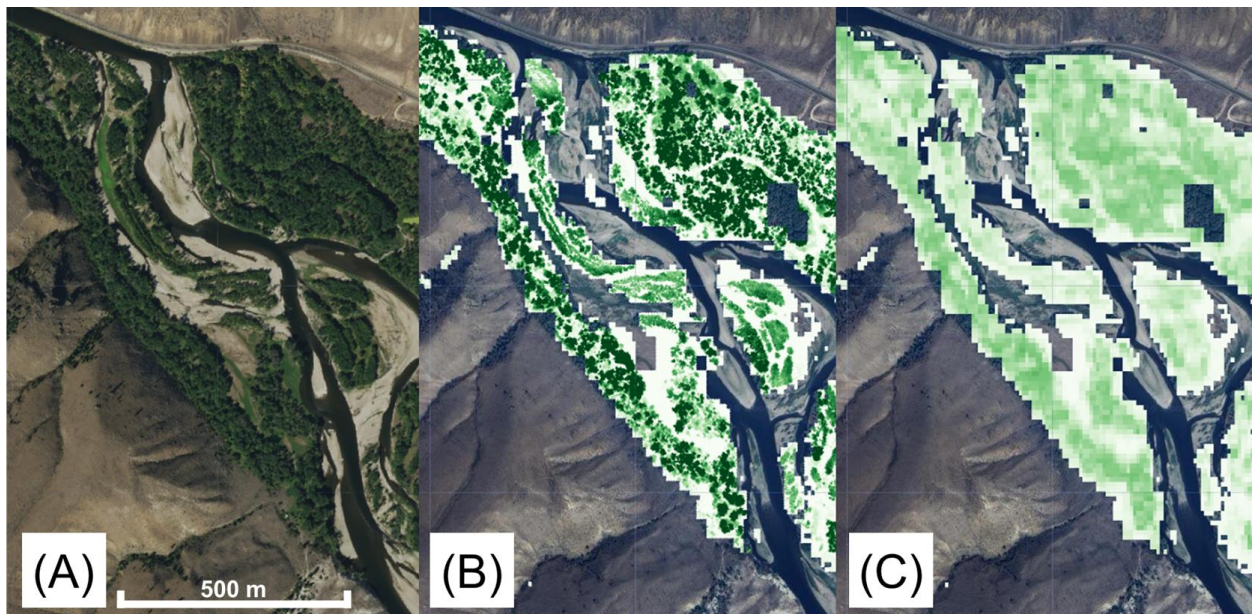


Figure 3. Example along the Salmon River, near Carmen, Idaho (-113.918, 45.329). Panel (A): National Agriculture Imagery Program, Panel (B): Lidar canopy height model, Panel (C): Mean prediction canopy height model.

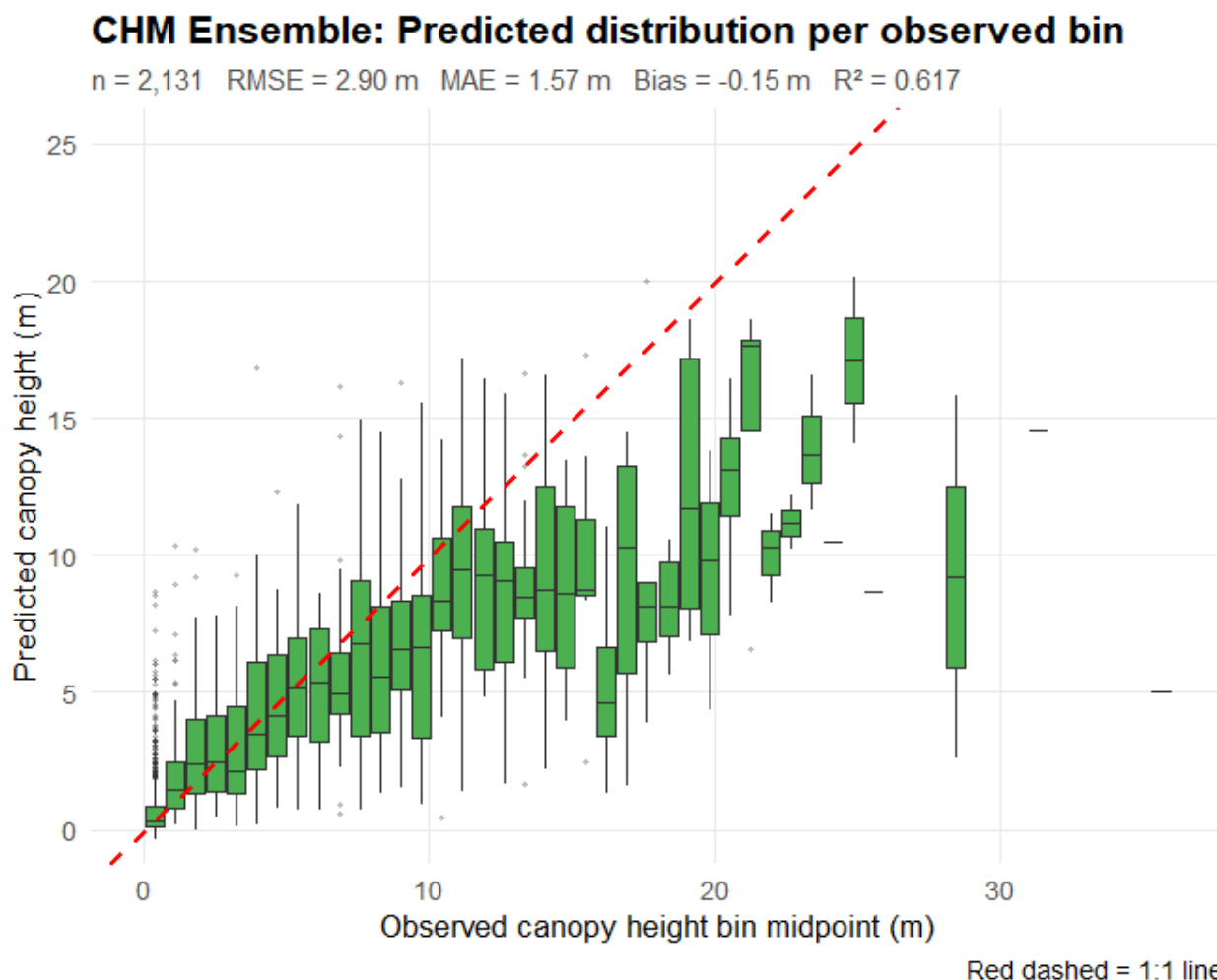


Figure 4. Actual vs. predicted canopy height values. Taller canopies are generally underpredicted.

### 3.1.2 Vegetation classification

The vegetation classifier had an overall accuracy of 84%, which reflects the inherent uncertainty associated with mixed pixels and the oversimplified four-class approach. The shrub class exhibited the most confusion with other classes (Table 2, Figure S1).

Table 2. Relative distribution and accuracy assessment metrics for the vegetation classification relative distribution of classes and accuracy.

| Class      | km <sup>2</sup> | Producer's Accuracy | Consumer's Accuracy | Balanced Accuracy | F1 Score |
|------------|-----------------|---------------------|---------------------|-------------------|----------|
| Evergreen  | 4,333           | 0.85                | 0.85                | 0.90              | 0.85     |
| Deciduous  | 1,107           | 0.82                | 0.84                | 0.88              | 0.83     |
| Herbaceous | 24,213          | 0.91                | 0.89                | 0.92              | 0.89     |
| Shrub      | 6,003           | 0.73                | 0.77                | 0.84              | 0.75     |

### 3.1.3 Allometric outputs

For both cottonwood and ponderosa, quadratic Bayesian models outperformed linear Bayesian models. Equations S1-S4 provide the input parameters for both tree classes for Equation 7. The final spatial biomass models for each class are presented in Figure 5.

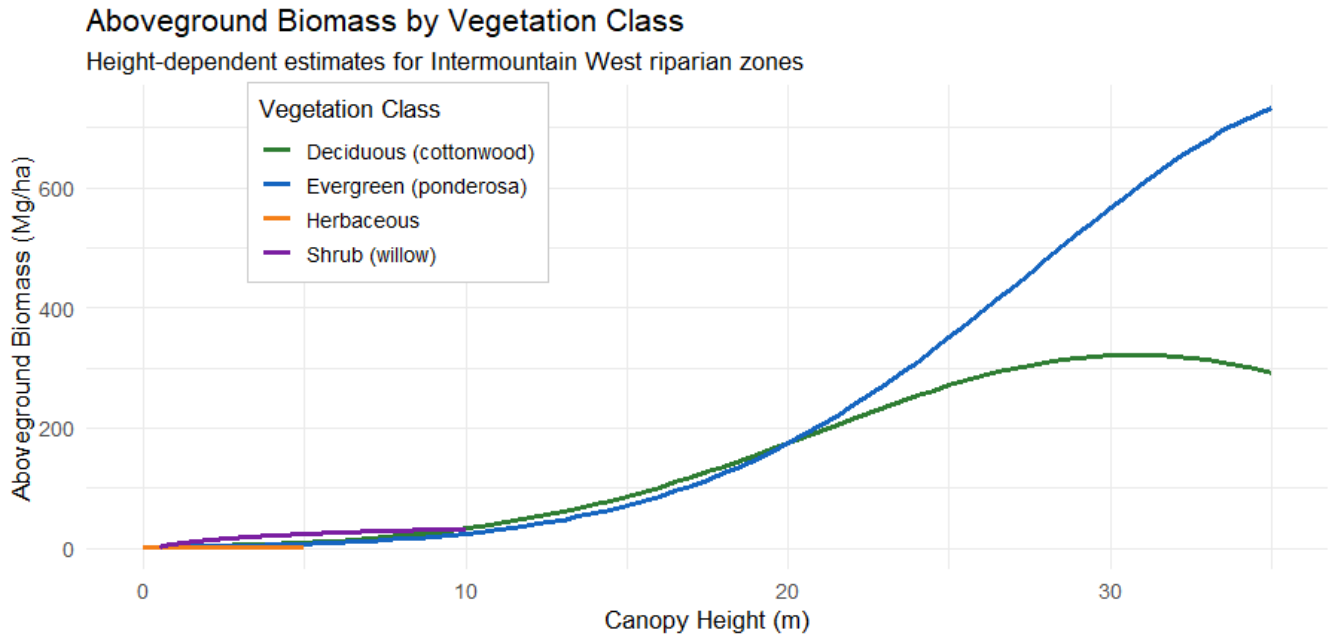


Figure 5. Final models for the relationship between 10-m pixel canopy height and AGB.

### 3.2 Temporal monitoring of gradual change

The lidar-optical fusion produces canopy height time series that reveal structural trajectories, as evidenced by temporal consistency, detected trends across the study area, and inspection of sites with known change. The annual CHM prediction metrics are consistent across years, despite substantial variation in the number of valid pixels per year as determined by the masking approach (Figure S2). All temporal trend products include only pixels that are valid across all years (102.1 million), while year-over-year change includes pixels valid in both years in question. Case studies of a highly productive riparian area (Figure 6), a tree stand removal (Figure 7), and a high severity burn (Figure 8) showcase the utility of the biomass product.

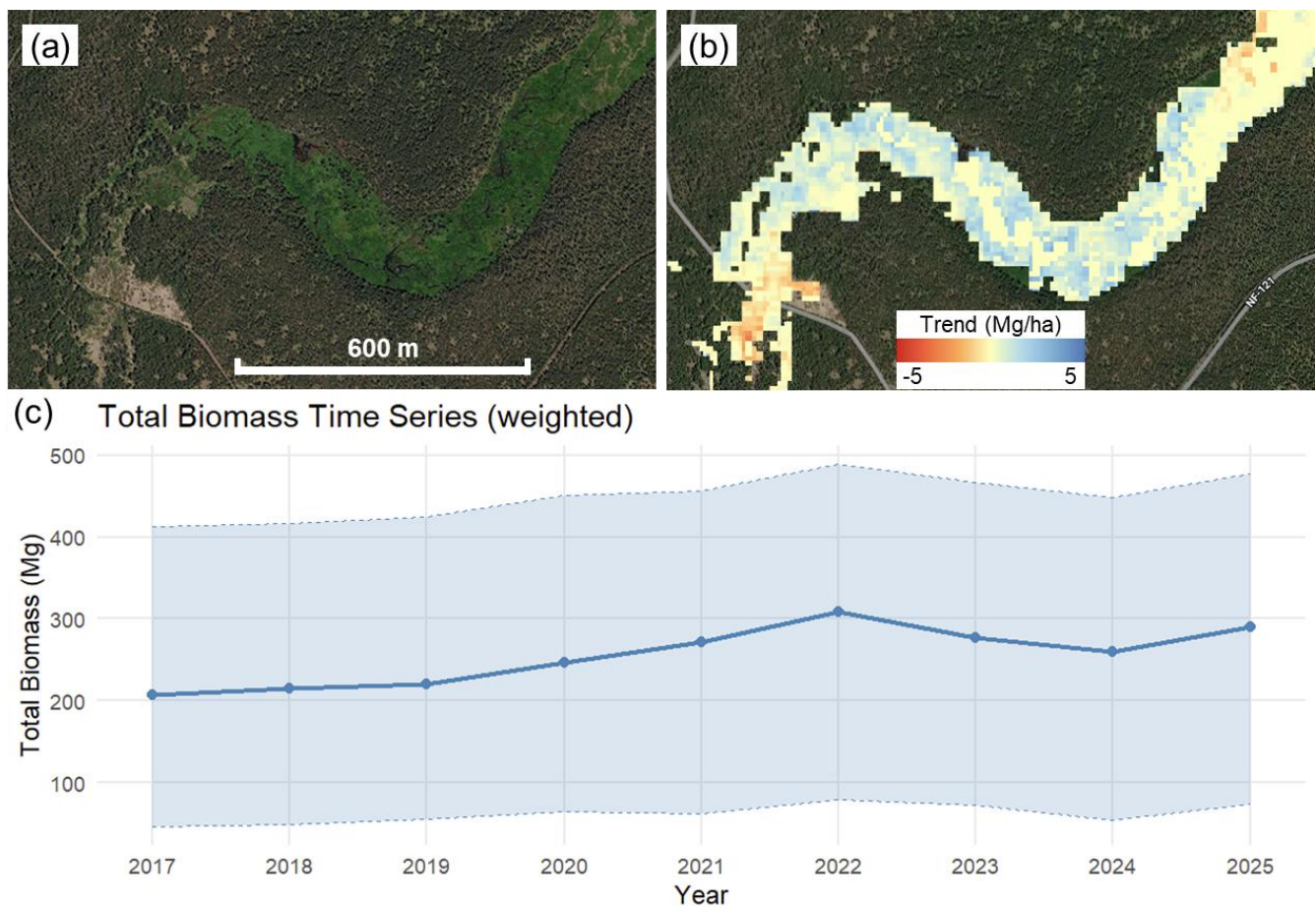


Figure 6. A productive riparian zone (a - aerial imagery) (b - biomass trend) along Split Creek in Southeast Idaho ( $44.398^{\circ}$ ,  $-111.249^{\circ}$ ) exhibits a 49.5% increase in biomass from 2017-2022 (c). The shaded area in (c) represents conformal prediction intervals.

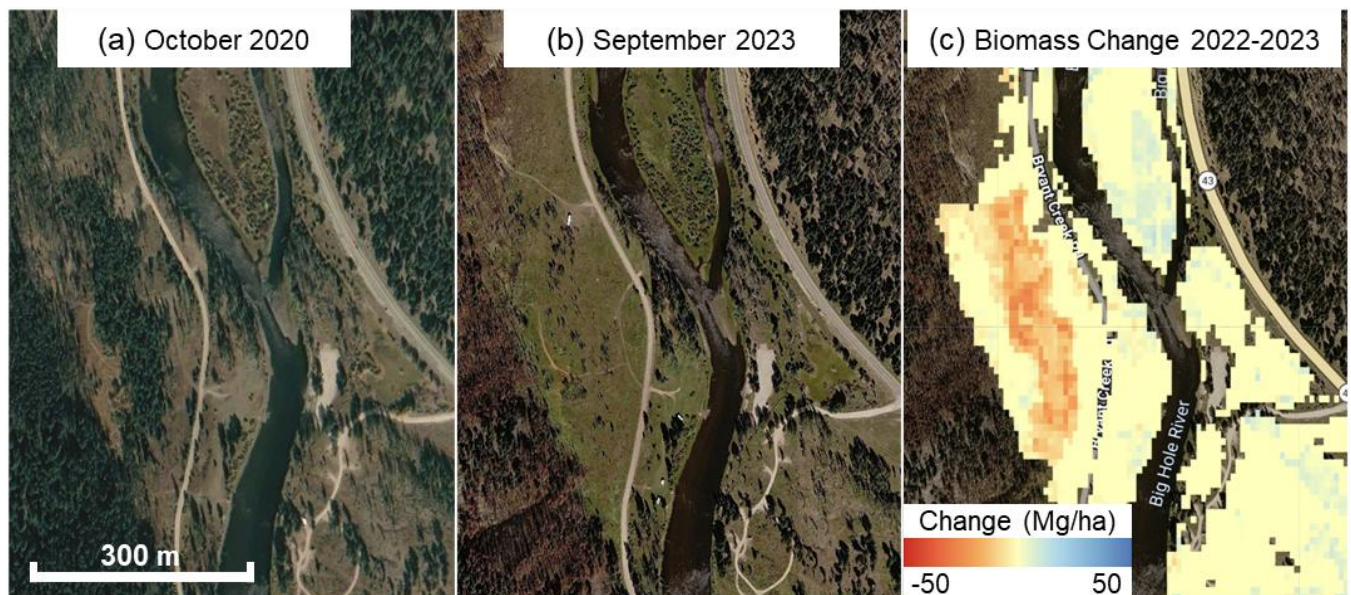


Figure 7. An area of tree removal on the banks of the Big Hole River in Montana ( $45.859^{\circ}$ ,  $-113.085^{\circ}$ ), with aerial photos before (a) (October 2020) and after (b) (September 2023) is captured in (c): year-over-year biomass change for 2022-2023.

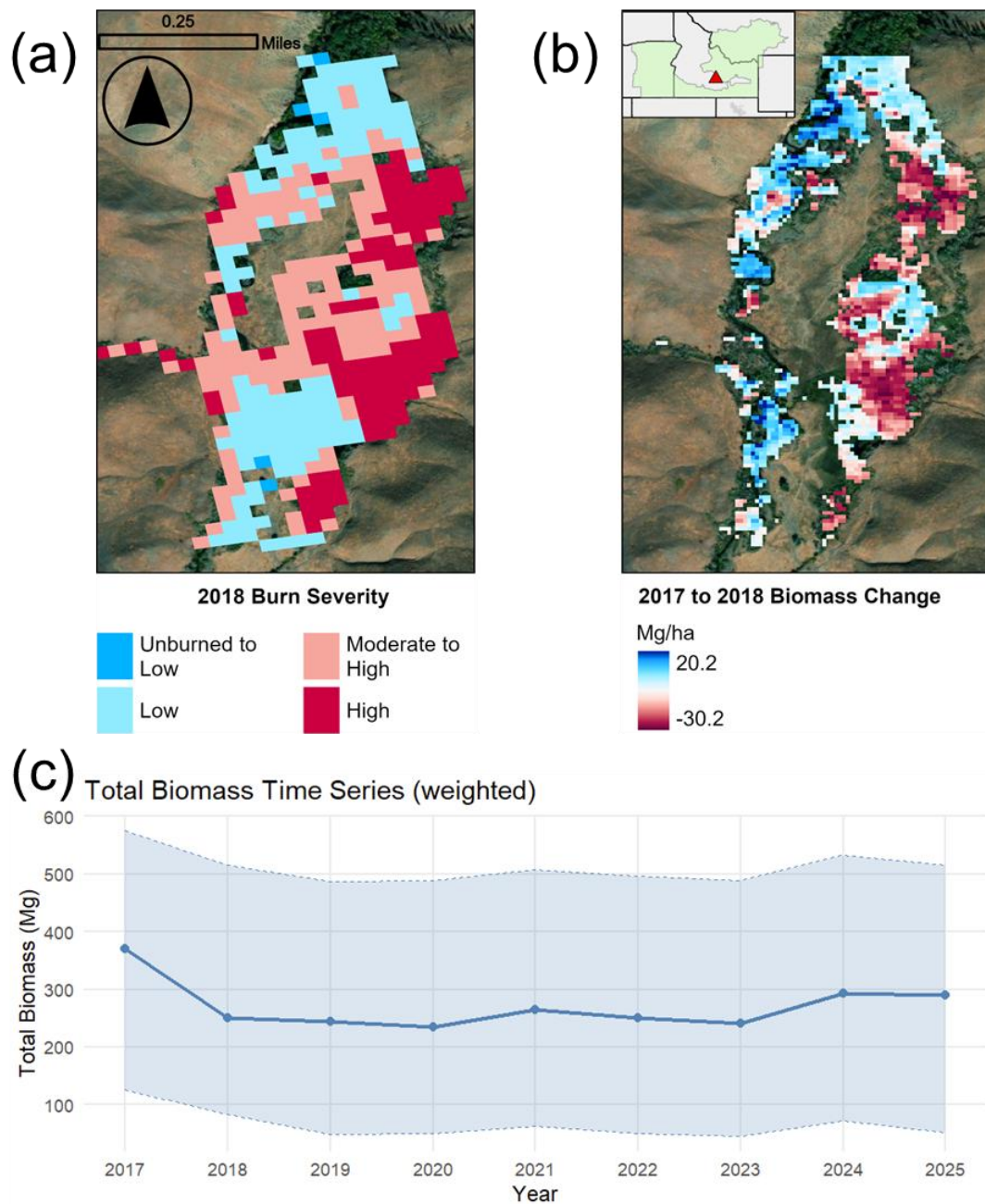


Figure 8. A selected site ( $43.555^{\circ}$ ,  $-114.051^{\circ}$ ) within the burn extent of the 2018 Sharps Fire in Idaho. (a) Fire severity from Monitoring Trends in Burn Severity. (b) Riparian biomass changes before and after fire. (c) Total biomass time series. The area depicted saw a 32.4% decline in biomass from 2017-2018, and areas of high burn severity overlap with areas of greatest decline. The shaded area represents conformal prediction intervals.

### 3.3 Uncertainty Propagation

#### 3.3.1 Canopy height model regression

We derived an absolute conformal threshold of 6.24 meters with a verified empirical coverage of 94.9%, meaning each pixel-level canopy height prediction has a prediction interval width of 12.48 meters. The symmetric nature of the conformal threshold around the mean produces some negative values for the lower prediction interval. We report these for transparency, but it should be understood that the lower prediction interval is not intended for use. Because the mean predictions are generally underestimated, particularly for taller canopies ( $> 15$  m), the best representation of reality is likely between the mean and upper prediction interval.

### ***3.3.2 Vegetation classification***

A target empirical coverage of 90% resulted in a mean set size of 1.19 for all classes (Figures S3, S4). In the validation data, a set size of one corresponded to 76.0 - 88.5% of samples among the four classes, and no samples had a set size of 4 (all classes possible) (Table S1). Among the classified outputs, all four classes had mean set sizes of less than 2, and a set size of one corresponded to 33.6-93.3% of samples among the four classes (Table S2). Deciduous pixels had the lowest proportion of single set-size pixels, but this was also the least common class, making up only 3% of all pixels. An individual observation having a set size of greater than one does not necessarily mean it was misclassified, but merely that more than one class reached the conformal probability threshold. Mixed pixels and temporal dynamics can also cause a set size of greater than one.

### ***3.3.3 Allometric modeling***

The tree-level models perform reasonably well for being purely height-derived, and weighted biomass estimates provide a secondary check on estimates in case of misclassification. For ponderosa, Bayes  $R^2 = 0.722 \pm 0.005$  and MAE = 236.68 kg. For cottonwood, Bayes  $R^2 = 0.649 \pm 0.063$  and MAE = 334.99 kg. Bayesian GLM parameters are listed in Table S3.

## **4.0 Discussion**

### **4.1 Relationship to existing carbon quantification frameworks**

The need for highly accurate data products outpaces the capacity to produce them, and we live in a time period characterized by a need to act in spite of great uncertainties (Polasky et al., 2011; Mehta et al., 2025). There is also a general lack of consensus on what constitutes error and uncertainty in geospatial modeling, and the best ways to evaluate them ((Meyer and Pebesma, 2022; Rolf, 2023). The analysis presented here contributes to this challenge in three ways. First, we provide a method for estimating a time series of biomass in heterogeneous ecosystems with limited ground truthing available. Second, the analysis demonstrates the value conformal calibration adds to ecosystem monitoring data products. Finally, we offer food for thought regarding the differing ways in which we quantify uncertainty across related fields.

Currently, biophysical uncertainties limit the feasibility of carbon-based incentives for riparian management (Lininger and Lave, 2024). The framework presented here addresses part of this uncertainty: ex-post remote sensing evaluation of how much biomass changed. Ex-post evaluation refers to the systematic assessment of project outcomes, often through comparison to a counterfactual baseline scenario. Ex-ante baseline scenarios, projections of carbon benefits associated with projects, have been identified as the main cause of over-crediting, and are no longer accepted by some crediting programs (ACR, 2023; Delacote et al., 2025). The Riparian Conservation and Restoration Benefits Calculator Tool, one such ex-ante approach based on the Carbon in Riparian Ecosystems Estimator for California (CREEC) web based tool, was developed by the California Air Resources Board (CARB) to provide guidance for estimating the net greenhouse gas benefit of proposed projects (Matzek et al., 2018; CARB staff, 2025). Ex-post evaluations of such projects are suggested as a way to increase credibility by reliably measuring project outcomes (Delacote et al., 2025). Time-series datasets that span before and

after a management intervention, such as the one developed here, can enable ex-post evaluation through changepoint and counterfactual analysis (Kolarik et al., 2025). Ex-ante estimates can be misleading if the model predicts poorly or if the project does not achieve its goals, and ex-post observations can be misleading due to measurement and modeling error, which we quantify through conformal intervals.

There are potentially problematic implications for applying conformally-derived uncertainty estimates to ex-post evaluation of carbon credits. Both approaches produce conservative estimates, but in different ways. CARB's estimates address uncertainty through conservative model construction and empirically calibrated biomass estimates. Our estimates are conservative in that canopy heights are generally underpredicted above 15 m, and the conformal intervals carry a verified coverage guarantee. The marginal coverage provided by conformal calibration is useful for avoiding the decomposition of epistemic and aleatoric uncertainty, but has practical limitations when evaluating specific predictions; the population-wide coverage guarantees are inherently broad (Barber et al., 2020). An understanding of these outputs points to the mean and upper estimates as realistic constraints in most locales, whereas the lower estimates produced by the conformal approach are often unrealistically low. This challenges direct comparison of each methods' outputs. While the calibrated interval provided by conformal methods supports change detection, it does not provide a lower bound that is useful for crediting, at least under current guidance.

## **4.2 Resolving for spatial and temporal heterogeneity**

Our modeled outputs identify carbon hotspots and effectively capture heterogeneity in canopy height, vegetation class, and biomass within the wetlands, riparian areas, and wet meadows within the dryland landscape of our study area. Mean absolute error of canopy height predictions (1.56 m) indicate an equivalent or superior performance when compared to other studies modelling forest structure combining lidar data and Sentinel imagery, including those using more computationally intensive deep learning techniques (Lang et al., 2023, 2019; Perez et al., 2022). The 10-m scale, while still relatively coarse, is fine enough to capture much of the spatial heterogeneity in the system. Conformal set sizes in the vegetation classes serve to both quantify uncertainty and to identify likely mixed pixels, which are pervasive due to the 10-m resolution. Our novel approach using non-geolocated FIA tree level data enables pixel-based biomass modeling for black cottonwoods, a species with no known allometrics models that allow biomass estimation from height alone, which is useful across systems where limited training data is available (Nati-Johnson et al., 2026).

The small, discontinuous mesic ecosystems making up our area of interest are influenced by a range of local and climatic conditions affecting their structure and function (Donnelly et al., 2016; Kauffman et al., 2022; Driscoll et al., 2025). Within the 289,562 km<sup>2</sup> regional study area, mesic extent as defined by the unified areal extent of pixels classified as mesic in any year comprised 12.3% (35,656 km<sup>2</sup>) of the total area. Gradual growth and decline are difficult to monitor, but our structural time series provide the necessary data for monitoring change and assessing reforestation potential. Case study sites of restoration, burning, and forest cutting all present in the output as expected, and the annual maps exhibit consistent performance.

## **4.3 Tracking and communicating propagated uncertainties**

The conformal predictions are the most robust uncertainty measure we present. They are calibrated against held-out residuals, so they capture prediction error from all sources for both the canopy height regression and the vegetation classification. The reader may question the choice of an RF+GBT ensemble when the GBT alone produces slightly lower error metrics (MAE of 1.39 m vs. 1.56). While the GBT may, on average, produce better results, the tendency of GBT to overfit to certain patterns warrants caution, especially for regional-scale mapping where noise and outliers may not be well

represented in training and validation data (Savitha and Talari, 2025). Because the four vegetation classes represented here are unequally distributed (Table S2), retaining RF models, which have better bias reduction, enables the end user to see where ensemble components disagree while achieving slightly improved overall model fit. Evaluating differences between RF and GBT provides a rough proxy for epistemic uncertainty due to the differing strengths of each model and can be used diagnostically to flag pixels where the ensemble model is uncertain.

The allometric approach includes three main sources of uncertainty: (1) the error in the tree-level height/biomass predictions, which relies on some assumptions and varies by class; (2) the assumptions around scaling to pixels, which inherently oversimplify structure and ignore understory contributions; and (3) the spatial allometric functions themselves, for which we report delta method posterior parameters and provide pixel-by-pixel maps of standard deviation and coefficient of variation. The allometric uncertainty sources are the most difficult to constrain due to the reliance on modeled data and underlying assumptions. This further emphasizes the importance of conformal predictions for the regression and classification steps, as they empower the user to apply domain knowledge to reasonably constrain estimates. While the ensemble mean canopy height predictions are generally underestimated, particularly in taller canopies, the conformally-derived upper prediction interval provides a reasonable, statistically-backed constraint on canopy height. The lower prediction intervals for canopy height, and by consequence the lower prediction intervals for biomass, are a consequence of the symmetric conformal intervals and should not be used. Mean estimates can therefore be understood as a realistic floor for the highest-biomass pixels. The shrub class exhibited the most confusion with other classes, which is to be expected given the structural variability of shrubs and overlapping height ranges with other classes. The biomass models for the different vegetation classes notably exhibit strong overlap in predicted biomass at canopy heights less than 25-m, indicating that even when there is confusion among classes, the biomass predictions remain largely applicable.

#### **4.4 Limitations and future directions**

Nearly the entire US has been covered by at least one lidar collection under the 3DEP, but bulk access to data products beyond bare earth DEMs is still a challenge. The file size of extensive, high resolution lidar creates prohibitive constraints on regional-and-larger analyses such as ours. Gathering and processing the lidar to ensure compatibility was the most time consuming component of this work. We had to rely on a patchwork of data access platforms at the state and federal level, with differing approaches for acquisition. Developing a dashboard for all the lidar data in the US, including post processed rasters such as DSM and DTM, would allow for easier implementation of such a workflow over larger areas. Even more effective would be enabling access through cloud computing platforms such as Google Earth Engine.

Additionally, high resolution time series imagery would allow for further improvements in spatial resolution. CHMv2 demonstrated that canopy height can be reliably predicted at meter-resolution from RGB imagery (Brandt et al., 2026). As data availability improves, approaches such as CHMv2 could be incorporated into a temporal monitoring framework similar to that presented here. Independent field measurement remains necessary to check exchangeability of conformal guarantees with calibration data and to constrain the allometric layer. Expanding this framework to a broader spatial extent and further refining uncertainty could be accomplished through approaches such as Area of Applicability analysis (AOA) and Localized Spatial Conformal Prediction (LSCP) (Meyer and Pebesma, 2022; Jiang and Xie, 2025).

#### **4.5 Applications**

These mapped outputs are a substantial improvement over existing canopy height and biomass products for the riparian areas within our study system, and these combined modeling approaches can be readily applied wherever sufficient training data is available. The magnitude of riparian areas' importance for carbon storage and potential for carbon credits within the American West is an open question, and these areas are not well represented in existing products (Lininger and Lave, 2024; Allred et al., 2025). The Rangeland Analysis Platform (RAP) estimates annual fractional cover in Western US rangelands at a 10-m resolution from Sentinel-2. While the model performs well in the vast majority of the landscape, it was not parameterized for riparian and wetland areas (Allred et al., 2025). Our riparian-focused product, a freely-available GEE app, is a foundational step towards filling this gap and could aid in quantifying carbon storage potential in riparian areas and wetlands in the western U.S. and in dryland regions globally.

Identifying sites that can recover with minimal human intervention and sites that require active restoration depends on the ability to track change among vegetation types. While the original MRRMaid Monthly product enabled the evaluation of restoration projects in terms of changes to mesic vegetation extent, our new product enables monitoring of growth within pixels (Kolarik et al., 2023). This has applicability for adaptive management, as more projects need to monitor benefits and outcomes of restorations, gradual changes are difficult to track, and monitoring resources are often limited (Roni et al., 2018; Holl and Brancalion, 2020; McKenna et al., 2023; UNEP, 2021). Change point analyses and quasi-experimental methods can be used with such a data product for informing action and monitoring the result of action (Kolarik et al., 2025). The processes presented here could be readily applied across a wide range of heterogeneous ecosystems.

## **5.0 Conclusion**

This study developed a framework for monitoring AGB stocks as an indicator of carbon hotspots in spatially heterogeneous ecosystems, which we applied to the riparian corridors of the semi-arid western United States. The workflow integrates data from satellite sensors, aerial lidar collections, and forestry inventories to produce annual maps of canopy height, vegetation class, and AGB. These products allow detection of gradual changes that can guide management and should be applied to drylands globally.

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Supporting Information for

**Monitoring Carbon Hotspots in Patchy Landscapes from Sparse Lidar and Dense Satellite Time Series**

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### LOOCV Confusion Matrix

Overall Accuracy: 83.9% | n = 622

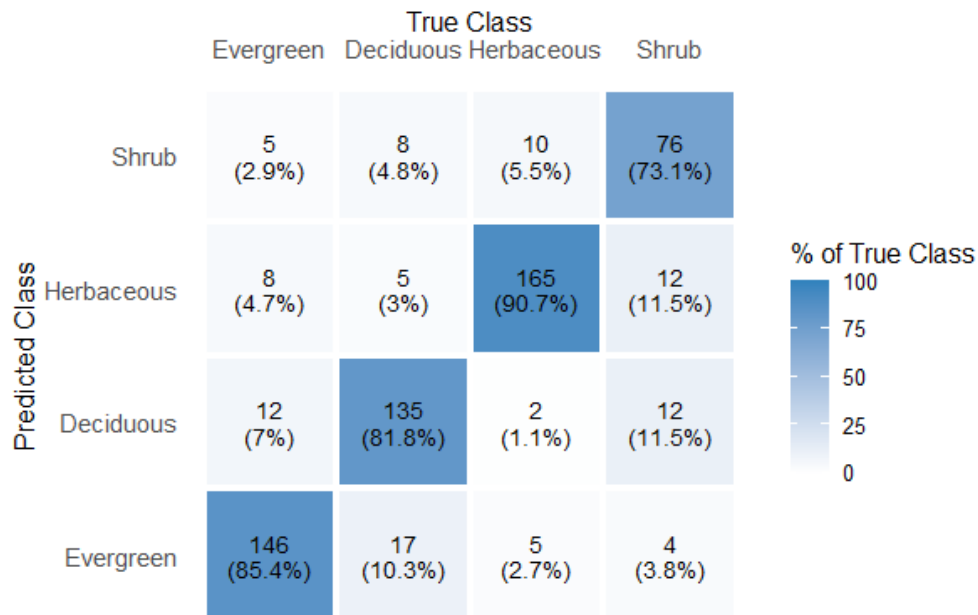


Figure S1. Vegetation classification confusion matrix.

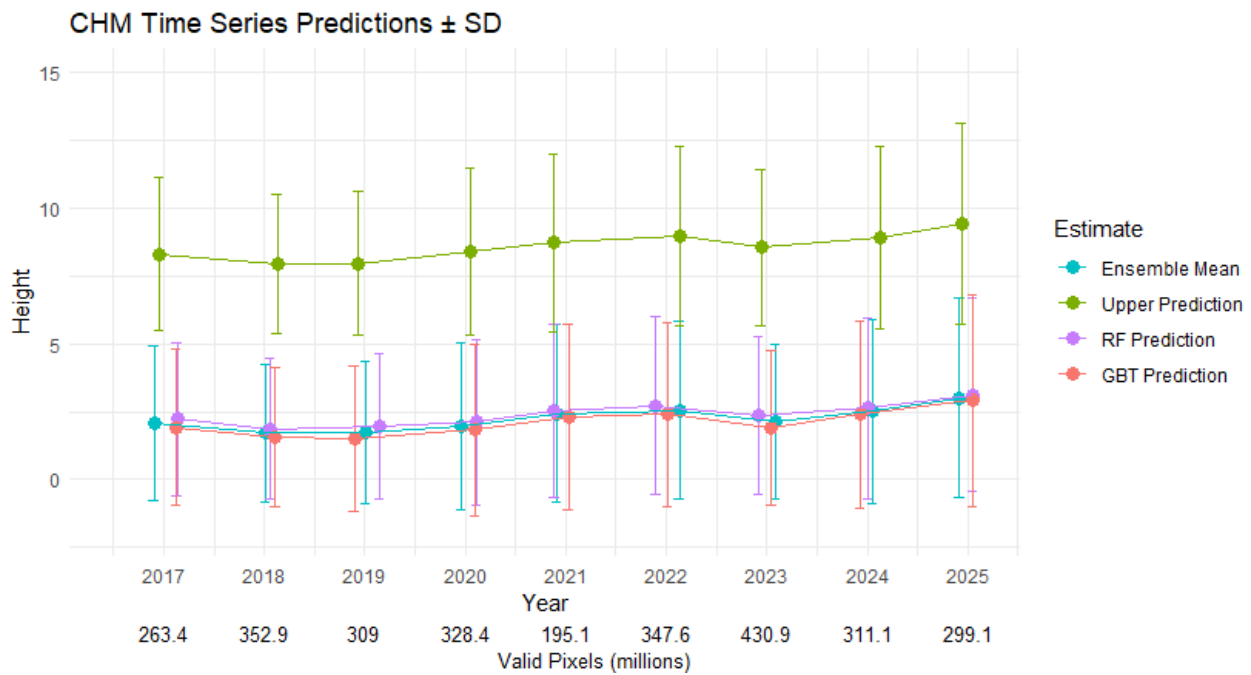


Figure S2. Canopy height predictions across the time series are largely stable, with changes in mesic extent determining annual valid pixels. The ensemble mean is derived from the mean Random Forest (RF) and Gradient Boosted Tree (GBT) predictions, and the upper prediction is derived from the conformal interval of the ensemble. Due to the underprediction of taller canopy heights, the true values are commonly between the mean and upper.

### Conformal Coverage Calibration

Empirical coverage vs. target coverage (ideal = diagonal). Labels show mean prediction set size.

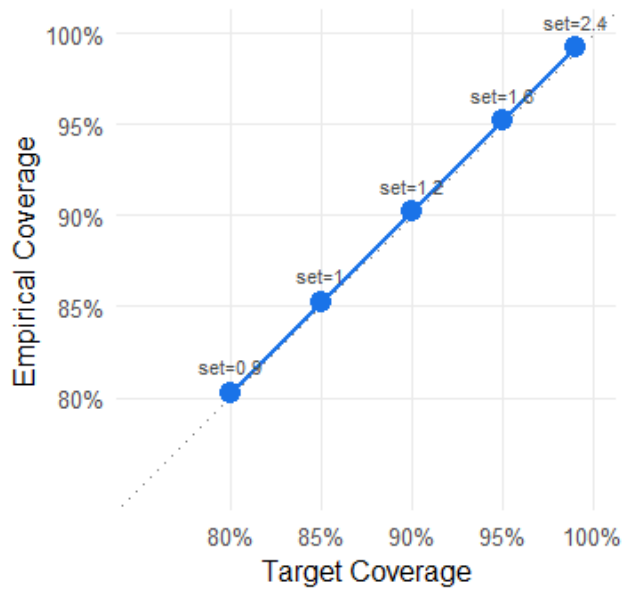


Figure S3. Empirical and target coverage exhibit strong agreement, and set sizes at 5% increments show the progression of uncertainty that comes with attempting to increase target coverage. (0.9, 1.0, 1.2, 1.6, 2.4)

### Distribution of Conformal Scores by True Class

Score = ensemble probability assigned to the true class. Samples left of threshold are miscovered.

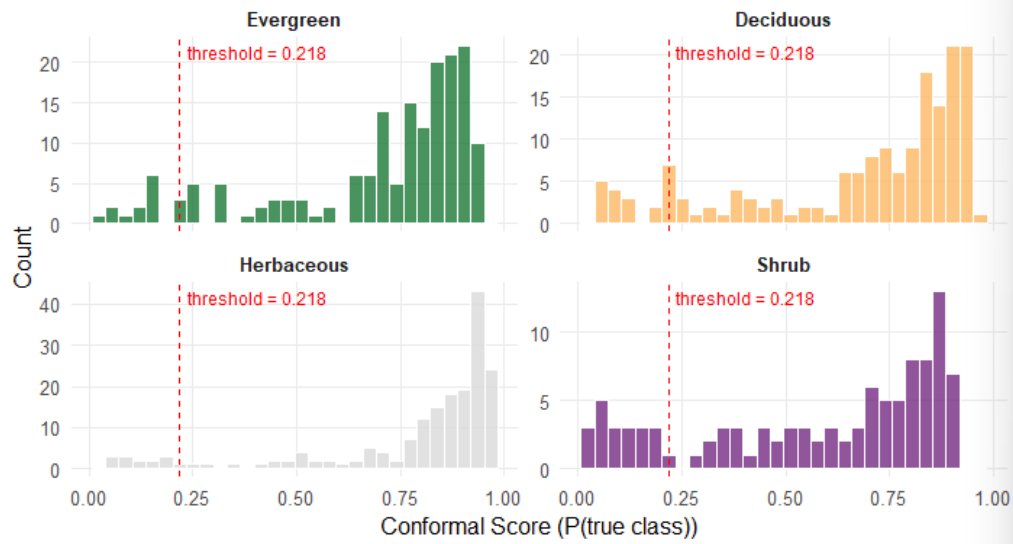


Figure S4. Distribution counts of conformal scores by true class.

Table S1. Distribution of set sizes in LOOCV classification data.

| <b>Set Size</b>  | <b>Evergreen</b> | <b>Deciduous</b> | <b>Shrub</b>  | <b>Herbaceous</b> |
|------------------|------------------|------------------|---------------|-------------------|
| 1                | 141<br>(82.5%)   | 129<br>(78.2%)   | 79<br>(76.0%) | 161<br>(88.5%)    |
| 2                | 27<br>(15.8%)    | 32<br>(19.4%)    | 24<br>(23.1%) | 20<br>(11.0%)     |
| 3                | 3<br>(1.8%)      | 4<br>(2.4%)      | 1<br>(0.96%)  | 1<br>(0.5%)       |
| Mean set<br>size | 1.19             | 1.24             | 1.25          | 1.12              |

Table S2. Distribution of set sizes in output classification

| <b>Set Size</b>  | <b>Evergreen</b>      | <b>Deciduous</b>      | <b>Shrub</b>           | <b>Herbaceous</b>       | <b>All classes</b>     |
|------------------|-----------------------|-----------------------|------------------------|-------------------------|------------------------|
| 1                | 28,105,910<br>(64.9%) | 3,715,908<br>(33.56%) | 36,503,639<br>(60.81%) | 225,973,984<br>(93.33%) | 294,299,441<br>(82.5%) |
| 2                | 13,447,013<br>(31.0%) | 6,181,881<br>(55.83%) | 21,245,300<br>(35.40%) | 14,987,582<br>(6.19%)   | 55,861,776<br>(15.7%)  |
| 3                | 1,757,444<br>(4.1%)   | 1,159,000<br>(10.47%) | 2,249,624<br>(3.75%)   | 1,142,546<br>(0.47%)    | 6,308,614<br>(1.8%)    |
| 4                | 21,191<br>(0.05%)     | 14,898<br>(0.13%)     | 26,835<br>(0.04%)      | 21,428<br>(0.009%)      | 84,352<br>(0.02%)      |
| Total<br>pixels  | 43,331,558            | 11,071,687            | 60,025,398             | 242,125,540             | 356,554,183            |
| Mean<br>set size | 1.39                  | 1.77                  | 1.43                   | 1.07                    | 1.19                   |

Table S3. Bayesian GLM parameters for allometric models.

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

Equations S1-S4:

Bayesian Gamma GLM with log-link and quadratic height term:

$$\text{Cottonwood tree biomass (h)} = \exp(1.378819 + (0.347377 \times h) + (-0.004520 \times h^2)) \quad (\text{S1})$$

$$\text{Ponderosa tree biomass (h)} = \exp(1.327521 + (0.399839 \times h) + (-0.006079 \times h^2)) \quad (\text{S2})$$

Height-dependent TPA scaling (exponential decay with monotonicity constraint):

$$\text{Cottonwood TPA(h)} = 44.9257 + (228.6310 - 44.9257) \times \exp(-0.083137 \times h) \quad (\text{S3})$$

$$\text{Ponderosa TPA(h)} = 103.8374 + (219.4595 - 103.8374) \times \exp(-0.165506 \times h) \quad (\text{S4})$$