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BIOMASS ATLAS

Biomass dynamics underpinned by Multi-Scale Lidar

TECHNICAL REPORT

INCENTIVISING INVESTMENT IN REAL CLIMATE ACTION

Summary

Models are only as good as the reference data used to train them. Sylvera's forest Biomass Atlas distinguishes itself through the use of industry-leading, scientifically validated reference datasets collected using multi-scale LiDAR (MSL) methods described in peer-reviewed literature. These reference data encompass more than 250,000 hectares of forests worldwide, representing an investment exceeding USD 10 million in data acquisition and processing

Sylvera's Biomass Atlas product provides spatially and temporally explicit estimates of forest aboveground biomass density and its uncertainty at 30 metre resolution on an annual cadence (2000 to present).

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Biomass Atlas

Change log

Version	Date	Comments
V 1.0	November 2025	Documentation for Biomass Atlas product

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Biomass Atlas

Key acronyms in this report

AGBD	Aboveground biomass density (Mg ha^{-1})
MSL	Multi-scale lidar
CH	Canopy height (meters)
GEDI	Global Ecosystem Dynamics Investigation Lidar sensor
TLS	Terrestrial laser scanning
UAV-LS	Unoccupied aerial vehicle laser scanning
ALS	Airborne laser scanning (helicopter-based in this report)
QSM	Quantitative structural models
ML	Machine learning
VCM	Voluntary carbon market
ARD	Analysis ready data

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Biomass Atlas
Product specification

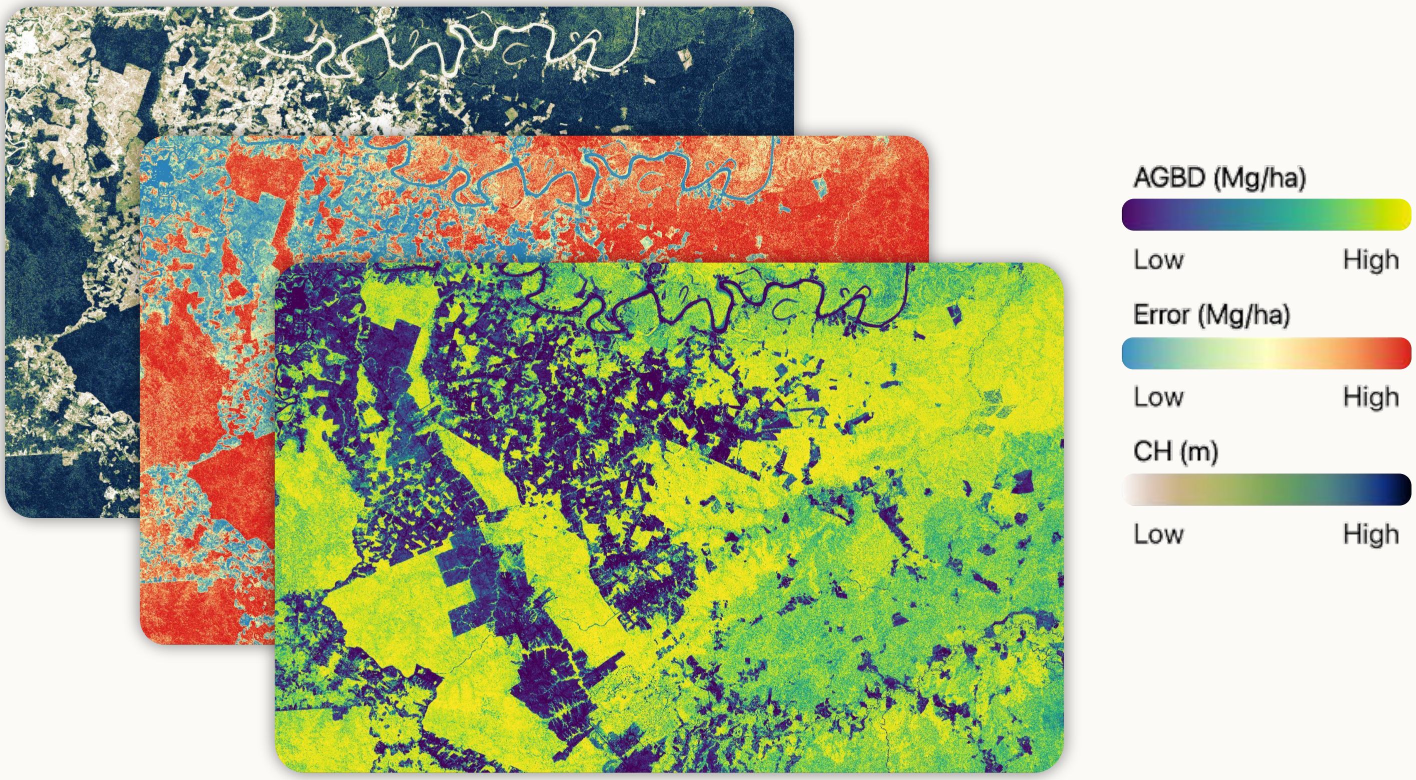
Sylvera's Biomass Atlas provides spatially explicit maps of Above-Ground Biomass Density and Canopy Height with an annual cadence.

Above-Ground Biomass Density (AGBD) is defined as the aboveground standing dry mass of live woody vegetation (trees and shrubs). Reference AGBD values are primarily derived from Sylvera's proprietary Multi-Scale LiDAR (MSL) technology, to generate a continuous global dataset with annual coverage, these MSL data are statistically upscaled in space and time using model features extracted from Analysis-Ready Data (ARD) from the Landsat constellation (5, 7, 8, 9) and topographic variables. Where MSL data is currently unavailable, AGBD reference values are derived instead from GEDI L4A LiDAR footprints.

Canopy Height (CH) represents the relative height at the 95th percentile of woody vegetation, expressed in meters. CH reference values for model training are derived from GEDI L2A LiDAR footprints .

The dataset has global coverage with annual observations from the year 2000 onwards. For each pixel a value of AGBD (Mg ha^{-1}) along its uncertainty in the form of ± standard error is provided.

Spatially explicit Aboveground Biomass density (AGBD), AGBD Standard Error, and the Canopy Height (CH) raster products



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Multi-scale lidar: Reference data from the field

Traditional forest mensuration methods provide the current foundations of carbon accounting, whether it be at project or jurisdictional scales, and are particularly well-suited to area-based accounting approaches. However, it can be argued that these methods are not fit-for-purpose for training Earth observation models owing to both their small scale and poor georeferencing. Additionally, these methods rely on allometric models. Allometries are simple models that relate easily measured variables such as stem diameter and tree height to tree biomass, built using opportunistic samples of destructive harvested trees. Such samples are often biased towards very small trees, since they are relatively easy to harvest and weigh, resulting in models that can produce biased and misleading AGBD estimates (Burt et al., 2020).

To overcome these issues, Sylvera has pioneered the collection of allometric-free Multi-Scale Lidar (MSL) data to obtain credible, traceable and highly accurate landscape-level estimates of AGBD. MSL is a peer-reviewed method (Demol et al. 2024) consisting of 3D-explicit modelling of individual tree biomass from terrestrial laser scanning (TLS) data at plot scale. These estimates are then upscaled with UAV-based laser scanning (UAV-LS) or airborne laser scanning (ALS) to cover tens of thousands of hectares. MSL can estimate AGBD of trees with a 3% error and is unbiased compared to destructive measurements, while allometric estimates are usually biased (Demol et al, 2022), with differences up to 15% (Burt et al, 2021) or even 30% (Calders et al, 2015; Gonzalez de Tanago et al, 2018).

MSL method showing TLS, UAV-LS and ALS

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Multi-scale lidar: Reference data from the field

Data collection

MSL involves collecting lidar data from multiple platforms coincidently, i.e., over the same area and within a timeframe that assumes negligible changes in forest composition (typically less than a few months). At the smallest scale, ground plots are delineated for both TLS and conventional forest inventory measurements. These ground plots can then be covered by UAV-LS or ALS. The number, size, and location of ground plots are chosen to capture the variation in forest state, succession, structure and taxonomy across the region of interest (ROI).

Conventional forest inventory data are collected in 1 ha plots following the RAINFOR protocol (Almeida et al, 2021), and cover every tree in the plot with a stem diameter of at least 10 cm. Measurements of each tree include: coordinates within the plot, taxonomic identity determined by a trained botanist, stem diameter, and point of measurement of stem diameter. Trees with diameter at breast height < 10 cm are excluded from data collection. TLS data are collected following established protocol (Wilkes et al, 2017) and the CEOS Aboveground Woody Biomass Product Validation Good Practices Protocol (Duncanson et al 2021).

In an effort to cover all relevant regions and biomes, MSL data has been collected in the locations outlined below (as of November 2025).

Region	Location	Representative Biome	Coverage (ha)	Status
Africa	Gilé NP, Mozambique	Tropical dry forest & savanna	50,000	Ready
Africa	Ipassa-Makokou Biosphere Reserve, Gabon	Tropical moist forest	700	Ready
Africa	Adenam Community Forest, Cameroon	Tropical moist forest	1,150	Ready
Oceania / SE Asia	Queensland, Australia	Tropical moist forest	65,000	Ready
North America	Virginia/West-Virginia	Temperate broadleaf	10,000	Processing
North America	Adirondacks	Temperate mixed	40,000	Processing
South America	Tambopata NP, Peru	Tropical moist forest	50,000	Ready
South America	Chiquibul Forest Reserve, Belize	Tropical moist forest	4,000	Ready
South America	Amazon forest, Acre, Brazil	Tropical moist forest	50,000	Ongoing
South America	Atlantic forest, Brazil	Tropical moist forest	50,000	Planned
Europe	United Kingdom	Temperate mixed & coniferous	50,000	Planned

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Multi-scale lidar: Reference data from the field

Data processing and modelling

TLS data are segmented into single-tree point clouds and modelled into 3D explicit volumes representing the tree's shape, known as Quantitative Structural Models (QSMs). QSMs are converted to AGBD estimates using a wood density value retrieved from taxonomic attribution, falling back to the basal-area-weighted average wood density of the plot. Forest structural metrics are extracted from UAV-LS or ALS point clouds, including: digital terrain and canopy height models, relative height distributions, tree fractional cover, canopy height rugosity, fixed and variable gap fraction, canopy closure, canopy ratio, z-entropy, skewness and kurtosis (McNicol et al, 2021) and novel voxel-based metrics describing the 3D distribution of woody plant material (Whelan et al, 2023).

TLS-derived gridded estimates of AGBD are obtained by constructing a georeferenced 10 m-resolution grid across each plot, decomposing each QSM into its constituent segments and allocating volume to respective cells. To predict AGBD at the larger scales (UAV-LS or ALS), we supply these TLS training data to an extreme gradient boosting machine learning (ML) model using the spatially coincident airborne forest structure metrics as predictor variables.

Uncertainty quantification

Uncertainty in MSL-derived AGBD estimates arises from the underlying point clouds themselves, quantitative structural modelling, wood density estimation, and the ML-based upscaling process. Uncertainty in tree-level AGBD estimates is calibrated against destructively measured AGBD values, using a sample of 65 trees compiled from the literature (Burt et al., 2018; Lau et al., 2019; Gonzalez de Tanago et al., 2018) and proprietary harvest data collected by Sylvera. Model uncertainty introduced by the upscaling process is calibrated using a spatial cross-validation approach which compares upscaled AGBD estimates to their TLS-derived counterparts.

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Biomass Atlas

Methods

Modelling framework

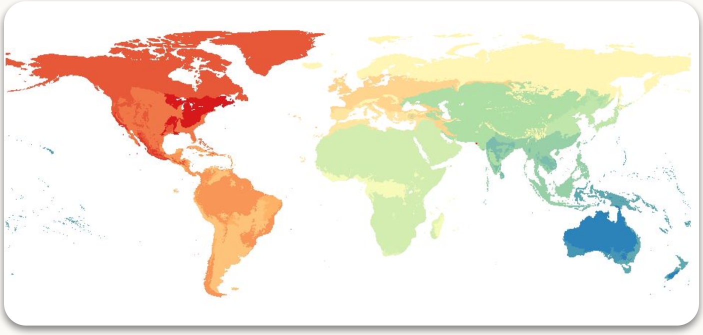
Our Earth Observation (EO) AGBD modeling framework employs a spatial jackknife / *k*-fold cross-validation approach, consistent with established methods (Rodriguez-Veiga et al., 2021). This robust framework is specifically designed to achieve three objectives: i) ensure a spatially robust, unbiased, and transferable model; ii) facilitate the estimation of confidence intervals for aggregated areas, such as projects and jurisdictions (McRoberts et al., 2022); and iii) yield cross-validation metrics that are not confounded by spatial correlation (Ploton et al., 2020).

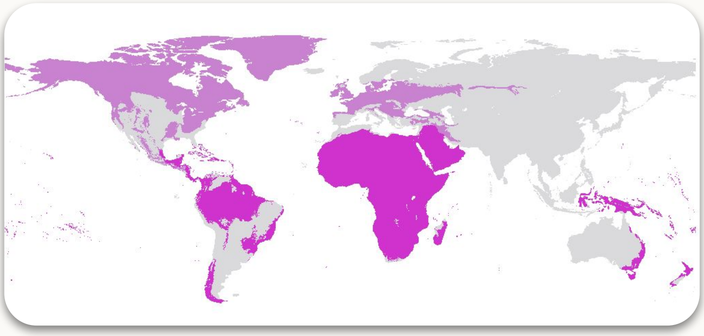
The overall AGBD modeling process is executed in a two-step approach:

- Step 1: Canopy Height modeling performed at the regional level.
- Step 2: Above-Ground Biomass Density (CH-to-AGBD) modeling performed at the regional level.

Regional Modelling

Our framework employs regional-level modeling rather than a single global model. This approach significantly increases local accuracy by specifically adjusting estimations to reflect the characteristic properties of the regional vegetation. The stratification is achieved through a hierarchical combination of regional and biome groups. This combined stratification informs our two-step process: we train seven regional models for canopy height, and 20 biome-specific models for Above-Ground Biomass Density (as detailed in the left diagram).





The map in the right visually depicts the spatial coverage of our reference data. Premium-quality MSL reference data—representing both current coverage (bright pink) and upcoming expansion (faded pink)—encompasses a substantial portion of the nature-based solutions relevant to carbon markets. In regions where MSL data is not yet available (light grey, as of November 2025), standard-quality GEDI reference data is currently utilized

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Methods

Canopy Height

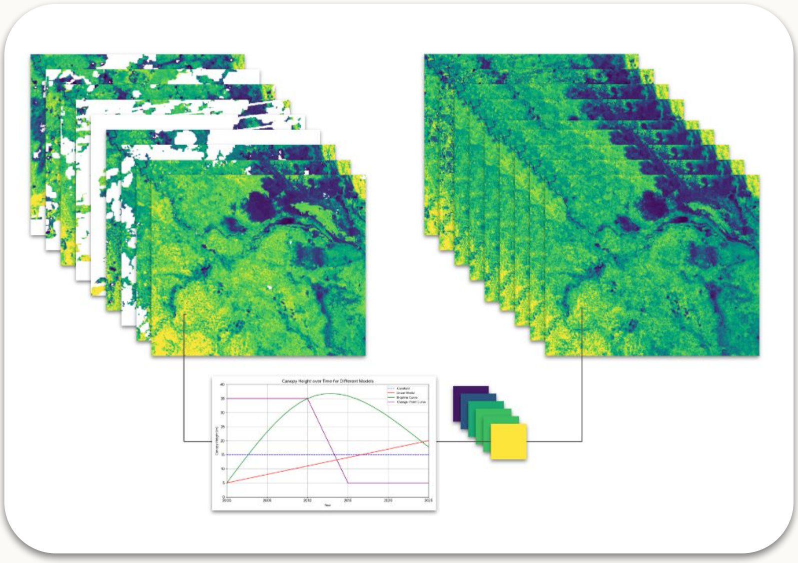
The CH modeling utilizes neural networks trained on GEDI L2A canopy height footprint labels. The models are based on features derived from annual Landsat constellation composites (sensors 5, 7, 8, 9) and topographic data. For each region quality-filtered GEDI footprint labels from a selection of randomly distributed 1° x 1° tiles are organized into *k* spatial clusters, and used to train an ensemble of *k* models.

Canopy height temporal model fitting

Satellite optical imagery from the Landsat constellation introduces data consistency and quality challenges arising from factors such as cloud cover, seasonality, topography, illumination, sensor calibration, and limited pre-2013 availability. Consequently, the unprocessed CH product can contain significant noise and data gaps.

To mitigate these issues, we implemented a pixel-level temporal model-fitting approach. This process begins with an analysis of 1° x 1° CH prediction tiles to identify and remove extreme temporal outliers, which are frequently caused by strong seasonality. The remaining time-series data are used to fit several statistical models at the pixel level: i) a constant model (representing temporal stability), ii) a linear model (representing constant change), iii) a B-spline model (representing gradual changes and dynamic forests), and iv) change-point models (representing faster changes such as deforestation). The optimal model for each pixel is then selected based on the Akaike's Information Criterion (AIC).

Canopy height temporal model-fitting to ensure gap-filling and minimizing temporal variance



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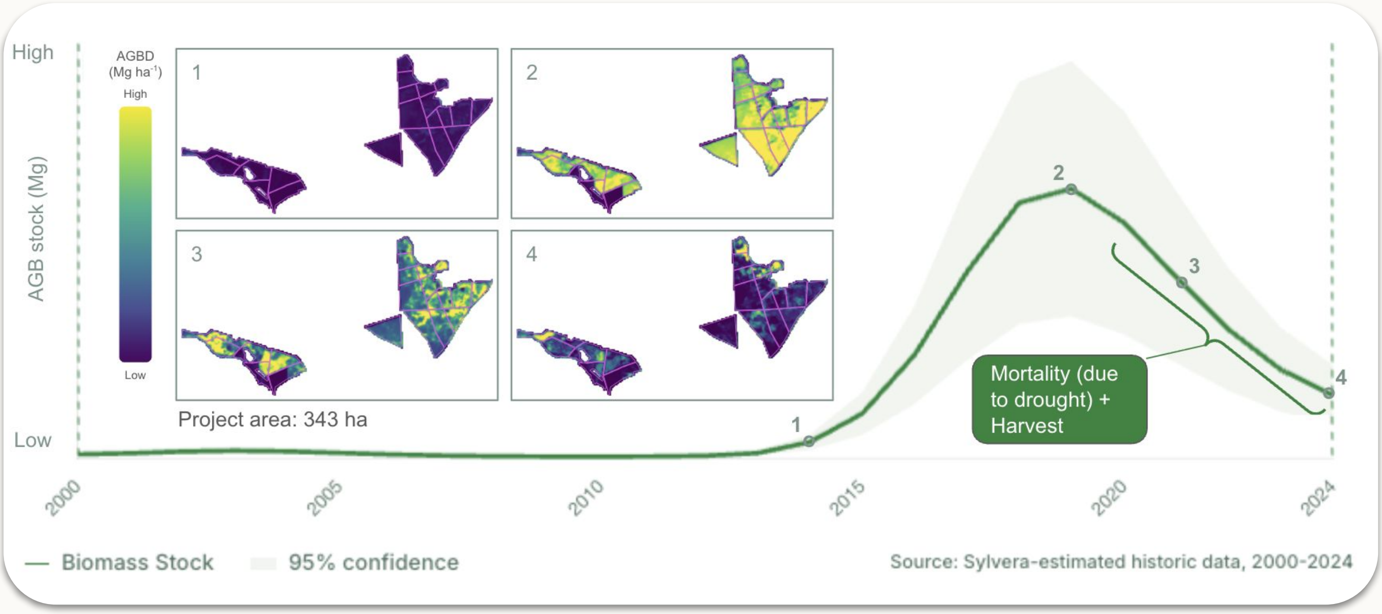
Biomass Atlas
Methods

Aboveground Biomass

Our AGBD modelling uses the 20 biome specific regions. This consists of CH-to-AGBD non-linear regression models derived from the relationship between premium MSL AGBD data (or standard GEDI AGBD L4A data, in the absence of MSL), and our 30 m x 30 m CH predictions over the same area. We apply the biome-specific models spatially and temporally over our CH product to derive the final AGBD time series product.

Spatially and temporally explicit Aboveground Biomass stock derived from AGBD time-series data



Uncertainty quantification

We perform a robust quantification of the uncertainty as explained in [McRoberts et al., (2022)](). At pixel level we provide the residual variance in the form of standard error. The residual variance includes the uncertainty from our CH and AGBD reference data (MSL and GEDI), and from our modelling steps (incl. CH and AGBD modelling, and the temporal modelling fitting procedure).

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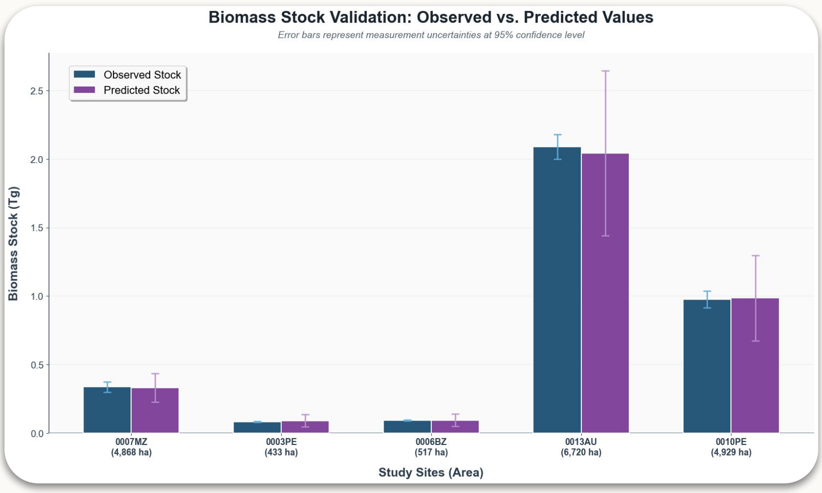
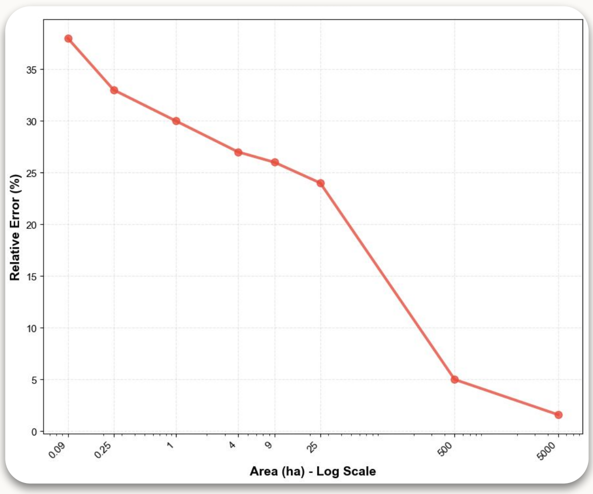
Data quality and validation

Validations

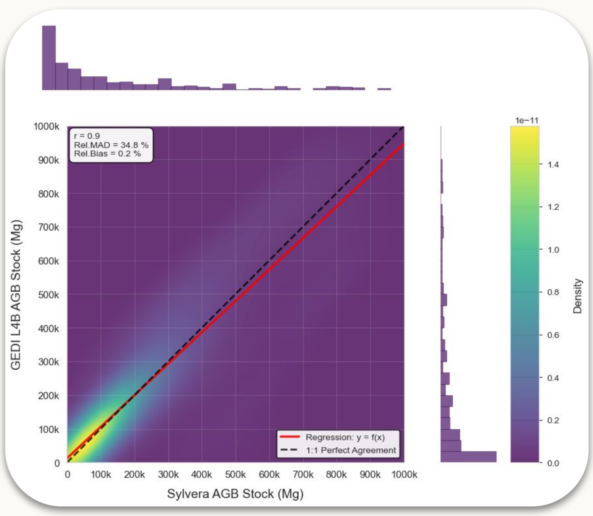
To validate our AGBD estimations across various spatial scales, we utilized independent (MSL) validation sites located in Central America, South America, Africa, and Australia. These sites were entirely excluded from the model training process. At our minimum mapping area of 0.09 ha (one pixel), the results demonstrate a low systemic error, with predictions considered unbiased (average bias 2.3%), and the relative error at this scale ranges from 25% to 41%.

While pixel-level accuracy is important, the project-level accuracy of biomass estimates is ultimately the most critical metric for carbon accounting. Projects are specifically designed to reduce net emissions, enhance carbon stocks, or increase net removals to issue credits based on the aggregate change in biomass within the project boundary. We therefore analyze our errors across different spatial scales. Our predictive model demonstrates a scale-dependent reduction in average error: from 30% at 1 hectare (ha) and 24% at 25 ha, to errors of less than 10% in areas over 400 ha.





We compared our AGBD estimations against those derived from the global GEDI L4B product across hundreds of carbon offset projects. At the project level, the two datasets show agreement (r = 0.9), with a mean relative difference of 35% and a mean bias difference of 0.2%. It is important to note that this represents a comparison against an independent AGBD product, rather than a formal validation, as the GEDI L4B product possesses a lower inherent quality than our primary training data.



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Usage notes

The Biomass Atlas regional models, derived from MSL or GEDI data, are generally considered highly representative of the geographic and temporal conditions to which they are applied, including necessary geographic and temporal extrapolations. This foundational strength provides robust estimates of AGBD and CH. However, to ensure the highest quality interpretation and maximize the utility of these models, users should be mindful of potential variability in accuracy related to specific geographic regions, model types, and vegetation characteristics.

Key considerations

The following scenarios require particular attention to ensure the most reliable results:

- Areas with specific GEDI data constraints: Users should note the scarcity of GEDI data for model calibration over northern latitudes (boreal forests). Additionally, the GEDI L4A product's AGBD estimations may be less accurate in certain dry forest and savanna regions of South America (as noted by Bullock et al 2023). Careful corroboration with local data is advised in these specific zones.
- Non-regional/natural vegetation: Our AGBD models are optimized for natural vegetation within their respective biomes. For vegetation types that deviate significantly, such as monoculture plantations of exotic fast-growing species, users may find the CH product to be a more accurate and robust metric than the AGBD product.
- Regions exhibiting strong seasonality: our reference datasets (GEDI and MSL) are acquired under leaf-on conditions. Strong seasonality can introduce effects in Landsat composites, particularly in earlier years with fewer acquisitions. This may lead to data anomalies (e.g., lower predicted AGB) or data gaps. Areas with deciduous forest cover are the most prone to these effects.
- Mangrove ecosystems with significant tidal patterns: Similar to seasonality, pronounced tidal effects can influence Landsat composites, potentially resulting in inaccuracies.
- Estimates outside forest: The models are specifically trained to estimate CH and AGBD for areas with a minimum tree canopy height (greater than 3 meters). Estimates for areas below this threshold, such as grasslands, croplands, low density agroforestry systems, or early-stage plantations, should be treated as potentially less reliable or informati ve

Other considerations:

- Residual data anomalies: While the mapping process is rigorous, the final products may contain minor residual artifacts or data gaps, often resulting from cloud contamination, strong seasonality, model transitions, topographic influences, or issues related to the Landsat 7 SLC-off sensor problem.
- Our advanced temporal model-fitting approach is highly effective at filling data gaps and significantly reducing temporal noise. However, in rare instances, this method may introduce minor temporal nuances, such as slight temporal lags or premature change detections
- Temporal extrapolation is conservatively managed by assigning the temporally closest valid CH value. For instance, if a pixel's first valid observation is in 2005, earlier years are filled using this 2005 value
- Signal saturation: In alignment with all satellite-derived AGBD methods, a saturation of the remote sensing signal is an anticipated factor at very high AGBD levels (as discussed in Rodriguez-Veiga et al, 2019). The precise saturation threshold is biome-specific, depending on the regional training samples, topography, and forest type.

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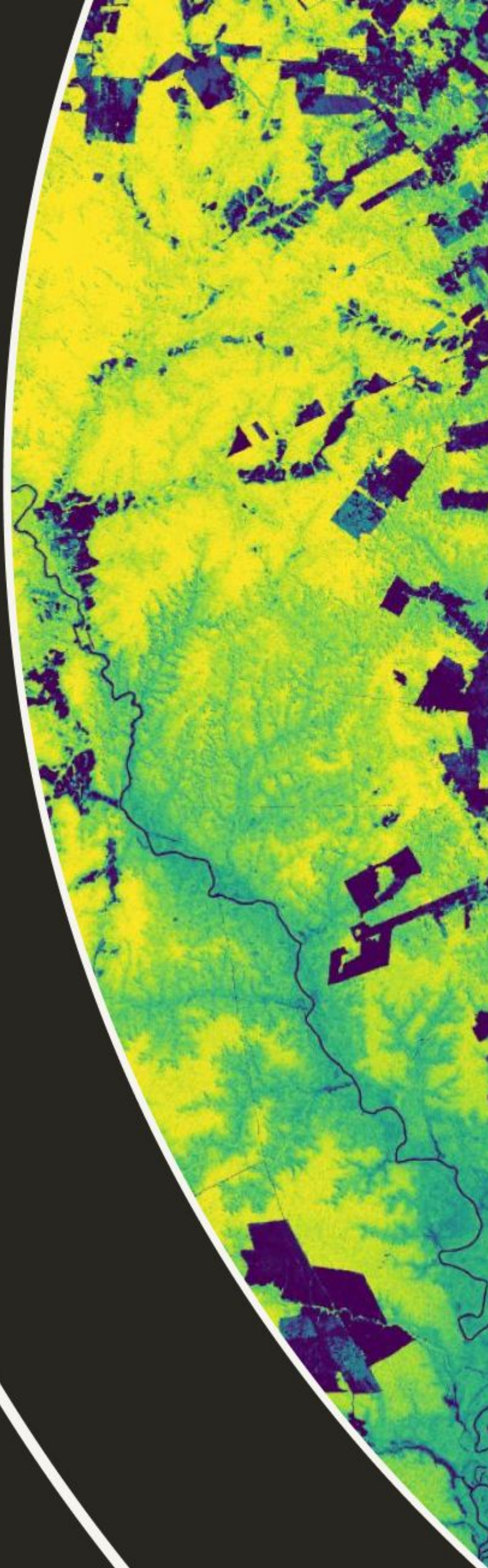

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