The **Chloris Geospatial** Technology

DIRECT ABOVE-GROUND BIOMASS STOCK AND CHANGE MEASUREMENTS SINCE THE YEAR 2000, ANYWHERE ON EARTH

Direct above-ground biomass stock and change measurements over long time series and at planetary scale

The Chloris technology delivers direct estimates of above-ground live woody biomass (AGB) stock and change at operational scale resolution, anywhere on the planet. Our approach is designed to generate robust, spatially explicit estimates of biomass stock, change, and related carbon emissions and removals, with pixel-level quantified uncertainty.

Our sensor-fusion and proprietary ML and AI technology leverages high-quality biomass training data points collected from spaceborne- and airborne-LiDAR biomass estimates and earth observations to generate wall-to-wall maps of AGB, with annual time stamps at 30m resolution (2000 to present) and 10m resolution (2017 to present). To generate robust, annual biomass change estimates, we process every pixel value with a Bayesian time series approach. This approach removes noise in the remote-sensing data and identifies statistically significant changes for every pixel, as well as robust trends in carbon stock changes over the entire time series.

The Chloris approach is based on more than a decade of peer-reviewed research, including IPCC-recognized studies. As a result, our technology has been extensively stress-tested and vetted by both the remote-sensing and carbon-cycle science communities. In addition, Chloris data are validated against independent, high-quality data collected via airborne-LiDAR and in-situ measurements from sites around the world.

Significance for forest carbon monitoring and accounting

The Chloris technology overcomes significant limitations of other forest carbon monitoring approaches, typically relying on field plots and more conventional land use cover models. Compared to such approaches, the Chloris technology brings new levels of transparency, quality, and consistency to forest carbon monitoring and accounting that otherwise have not been possible to achieve in a scalable and cost-effective manner.

- **Improved transparency:** By quantifying gradual changes in AGB and carbon stocks in all woody vegetation, the Chloris approach allows going beyond deforestation monitoring. This means that users can directly monitor emissions from degradation and other disturbance events, as well as carbon removals achieved from the growth and re-growth of trees. These processes have either been inferred or simply excluded until now. By filling this gap, the Chloris technology provides improved transparency into the impact of forest conservation and restoration programs.

- **Spatially explicit:** By directly estimating AGB stock and change at operational scale resolution, the Chloris technology delivers spatially explicit, gross values of biomass and carbon gains and losses for every time stamp, with pixel-level uncertainty. This allows for improved understanding of where and when changes are happening and what activity the change can be attributed to. It thereby creates a more robust fact base for the design and management of forest conservation and restoration programs.

- **Data consistency:** Rather than relying on challenging definitions of forests and literature-based emission factors, Chloris applies the same LiDAR-based methodology across geographies. The result is a consistent dataset that captures biogeographic variation in biomass and scales with consistency across the entire planet. Users benefit from this consistency with improved ability to reliably compare project areas across geographies and over time. The technology also supports reliable design of digital twins, dynamic baselines, and nesting of projects within jurisdictional programs.

- **Scalability and cost-effectiveness:** By delivering the data via an efficient, cloud-based software infrastructure, the Chloris technology delivers this quality data at lower per-ha cost and higher speed of production than conventional approaches. It allows users to accelerate project development and help optimize constrained budgets for on-the-ground activities.

Advanced sensor-fusion technology

The Chloris technology ingests high-quality remote-sensing measurements from NASA's Global Ecosystems Dynamics Investigation (GEDI), the Geoscience Laser Altimeter System (GLAS) aboard the Ice, Cloud, and Land Elevation Satellite (ICESat), airborne-LiDAR (ALS) acquisitions, European Space Agency's (ESA) Sentinel 1, 2 satellite missions, and United States Geological Survey's Landsat 5, 7, 8, 9 satellites (among others).

In addition to these spaceborne and airborne datasets, the Chloris models also include various ancillary datasets to capture the impact of climate, eco-zones, slope, and other variables.

Allometries leveraging full LiDAR-waveform data

Many allometric equations rely heavily on tree height as the predictor of AGB. This has important shortcomings, as tree height alone is insufficient to produce reliable biomass estimates across different regions and ecozones. In reality, the biomass of a tree is not only a function of a tree's height, but also its shape, its canopy structure, the species type, the wood density, and the vertical profile of the vegetation layers in general. In an effort to better capture these biomass predictors and reduce the uncertainty in the allometric process, Chloris developed new allometric equations using a set of metrics extracted directly from the full waveform of LiDAR measurements. The result is improved quality of the biomass data used to train our ML algorithms.

The necessary field work to collect this calibration data was conceptualized and implemented under the auspices of our Co-Founder and Chief Science Officer, Dr Alessandro Baccini. The extensive field campaign spanned tropical countries. The campaign team took Tens of thousands of individual tree measurements in hundreds of field plots accurately placed within the footprint of the spaceborne-LiDAR sensor. It used a high-quality stratification strategy to ensure reliable estimates of the biomass variability across dense humid forests, primary and secondary forests, dry forests, and ecological gradients.

For the regions outside the tropics, Chloris is largely leveraging existing field measurements, ALS, and GEDI biomass estimates. ALS AGB estimates are derived from calibrating tree height metrics with coincident field measurements, and GEDI estimates are based on the NASA GEDI level 4a data. Chloris developed a sophisticated process to filter and identify only reliable GEDI AGB estimates.

Chloris uses the LiDAR AGB estimates described above as a training dataset in machine learning models that convert image reflectance data into wall-to-wall AGB estimates. As such, they overcome the limitation of forest inventories/field data as a training and calibration dataset and allow us to generate AGB estimates backward and forward in time at an annual interval.

Using a combination of field, ALS, and spaceborne LiDAR provides millions of data points with AGB estimates that best capture the spatial variability of AGB across vegetation types and ecosystems.

Robust uncertainty calculation at the pixel and site level

Chloris computes location-specific uncertainty for every pixel, reported as standard error. Our uncertainty methodology follows two main steps. First, both the biomass estimate and the associated uncertainty estimate are calculated for every pixel and every year. This step accounts for errors related to LiDAR allometries, reflectance noise, and the machine learning modeling process itself. Second, annual estimates are harmonized using a time series fit to remove noise and identify significant changes in biomass. Errors are propagated through this fitting procedure to yield optimal results. This fitting process delivers three main outputs:

1. The p-value from a modified F-test. The p-values are used to detect statistically significant biomass changes for every pixel and over the full time series. To be statistically significant, a p-value of less than 0.05 is required by default. Those above this default threshold are taken as having a stable biomass over the time interval. The threshold can be set to higher or lower p-values.

2. Annual biomass predictions. If no statistically significant change is detected, the median value of the biomass is used. Chloris also provides the difference in biomass measured between each year as well as over the entire time period using this same procedure.

3. Annual estimates of the biomass standard error. These values are extracted using the fit covariance matrix. Error estimates between years and over the full time range are derived using error propagation from the same covariance matrix.

The pixel-level standard error estimates are then aggregated to the site level in a process that takes into account the spatial autocorrelation to compute the overall site-level uncertainty for the AGB stock and change. The 95% confidence interval (C.I.) on the biomass prediction is computed from the aggregated standard error. The methodology is peer-reviewed and published in Baccini et al. (2017).

Forest area cover, degradation, and deforestation estimates

Chloris' forest cover methodology applies a site-specific AGB threshold to distinguish between forest and non-forest areas. The threshold is determined by combining tree density data with a minimum mapping unit to distinguish between forest and non-forest pixels. The default forest/non-forest classification follows the FAO definition of forest.

The site-specific biomass threshold approach allows Chloris to define forests consistently across geographies while considering the specificity of local ecosystems. It creates a system that can be easily adapted to any national or regional forest definitions. The approach also ensures consistency between the AGB stock and change and forest/non-forest data layers produced by Chloris.

The forest/non-forest classification enables Chloris to monitor forest AGB and identify forest area gains and losses and related carbon removals and emissions. It also allows for a consistent allocation of losses (i.e., biomass losses and CO2e emissions) to either degradation or deforestation events. For that purpose, any detected AGB losses that do not result in the AGB-pixel value going below the forest threshold count as degradation. All AGB losses that result in AGB-pixel values below the biomass threshold signal a transition from forest to non-forest and are hence attributed to deforestation.

For example, if an AGB-pixel value 25t/ha is identified as corresponding to a forest definition consisting of at least 20% canopy cover, any pixels above 25t/ha are classified as forest, and any pixels below that threshold are classified as non-forest. Any losses (emissions) that result in a pixel value above the threshold count as degradation (e.g., going from 30t/ha to 26t/ha); any losses that result in a pixel value below the threshold (e.g., from 100t/ha to 10t/ha) count as deforestation.

[1] The FAO defines forest as: "Land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10 percent, or trees able to reach these thresholds in situ. It does not include land that is predominantly under agricultural or urban land use." Global Forest Resources Assessment 2020 - Terms and Definitions, Working Paper, Rome: FAO, 2018.

AGB / Carbon Stock

Annual data on above-ground biomass density since the year 2000. Pixel values in biomass/ha and CO2e/ha. 30m & 10 resolution. Pixel-level uncertainty.

AGB / Carbon Change

Annual data on above-ground biomass gains and losses since the year 2000. Pixel values in biomass/ha and CO2e/ha. 30m & 10 resolution. Pixel-level uncertainty.

Forest Cover/ Change

Annual forest cover dynamics since the year 2000, including forest area gains, deforestation and degradation, and related carbon removals and emissions.

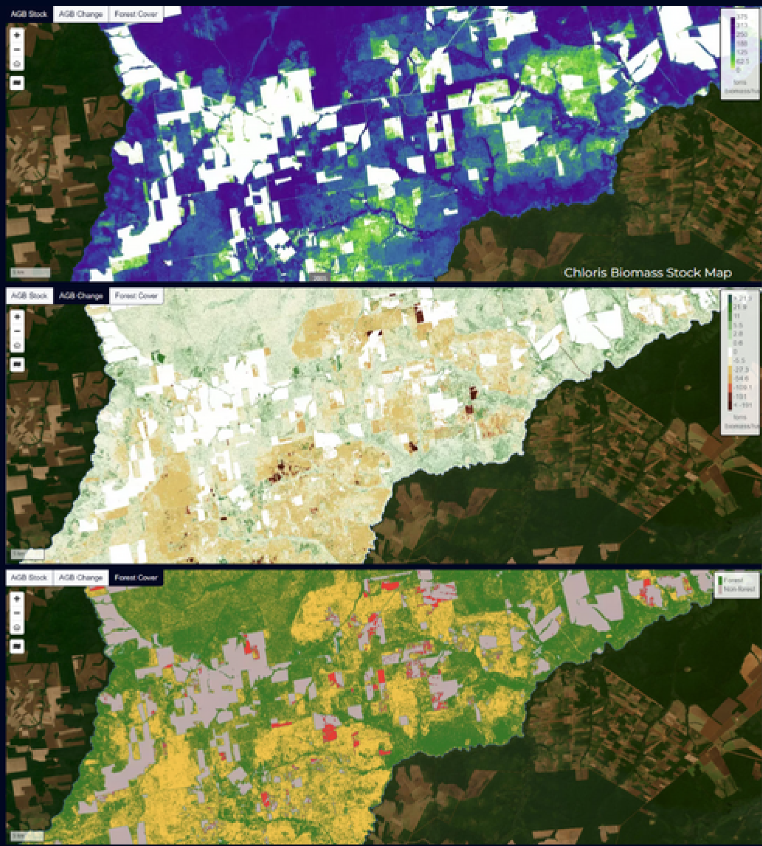

Figure 1. Data products and sample outputs for Chloris data on AGB stock and change and forest cover/change.

Outputs validated against fully independent, higher-quality data

Understanding the accuracy of biomass estimates and related carbon removal and emission estimates is both important and challenging. It is important because the accuracy of the biomass data has direct repercussions for the integrity of climate financing and claims related to forest conservation and restoration programs. And it is challenging because the accuracy of biomass estimates can generally only be calculated against other estimates, not the actual truth.

To illustrate the latter point: to understand the actual biomass of trees, trees need to be weighed. Actual biomass measurements can, however, only be gained via destructive sampling or harvesting operations. This means that every "measurement" of biomass–whether derived from field estimates or remote-sensing approaches–is always an estimate of the truth.

Actual biomass *measurements* are generally held privately, unavailable for validation of biomass estimates. This creates a challenging situation where data available for validation are estimates too, not the truth. Therefore, the first question to ask when confronted with accuracy assessments of biomass estimates always is: *compared to what*? In other words: what data was used for the validation, and how appropriate is it to validate the real accuracy of biomass estimates, particularly ML-derived biomass data?

For example, an often-used but insufficient validation approach compares ML-derived biomass estimates against the biomass estimates of a subset of the training data that was not used in the training phases. For instance, a model trained with GEDI data is validated against a subset of the same GEDI data, set aside and not used to train the algorithm. This type of validation only explains the *model's internal performance*, i.e., how well the algorithm can reproduce the training data. It does not provide any insights into how well the ML model predicts biomass in the areas not covered by the training data.

More insightful accuracy metrics are provided by validation methods that compare biomass estimates against fully independent, higher-quality data collected across regions and not used to train the algorithm. This is how Chloris approaches the validation of its ML-derived biomass estimates. Today, Chloris' data are validated against three types of fully independent, higher-quality datasets.

a) Validation against independent airborne LiDAR-derived biomass estimates

We have tested our technology against ALS biomass estimates published by independent research centers and find that we can consistently provide accurate estimates of AGB at all scales (Figure 2). While, at times, accessing ALS AGB estimates to validate Chloris AGB has been challenging, as of today we are not able to access ALS AGB data collected over time to directly validate our estimates of AGB change. In an effort to validate change, we compared our biomass trends against ALS measurements of tree height over time (Figure 3). The assumption is that if there is a change in tree height, we should also observe a AGB change. Results indicate that our AGB change estimates are consistent with the long-term dynamics monitored through airborne LiDAR at sites with multi-year monitoring measurements (Figure 3).

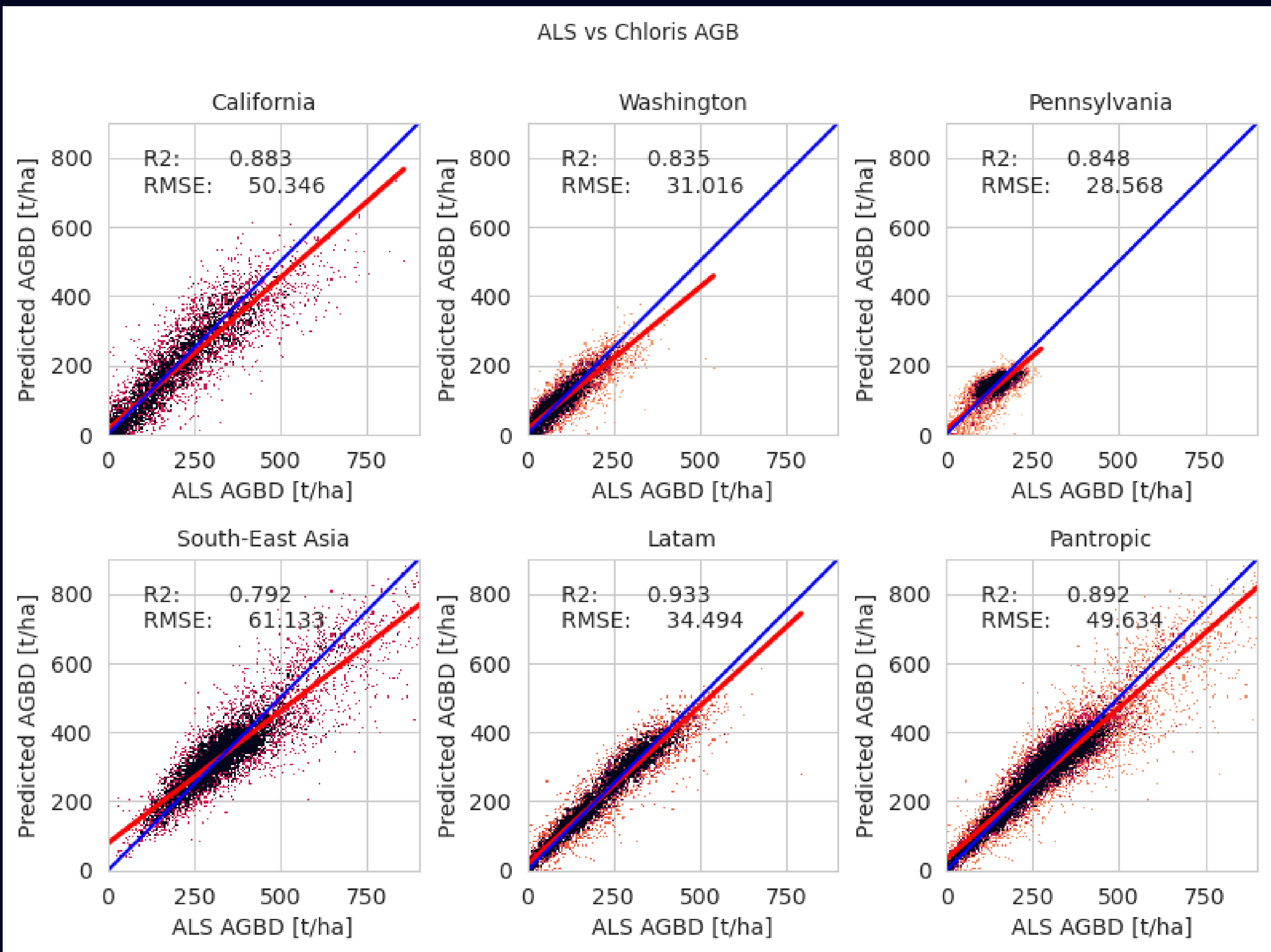

Figure 2. Chloris AGB estimates compared to airborne LiDAR estimates over three regions in the US (top) and one site in Southeast Asia and one in Latin America (bottom). The bottom-right plot shows the combined comparison of the tropical sites.

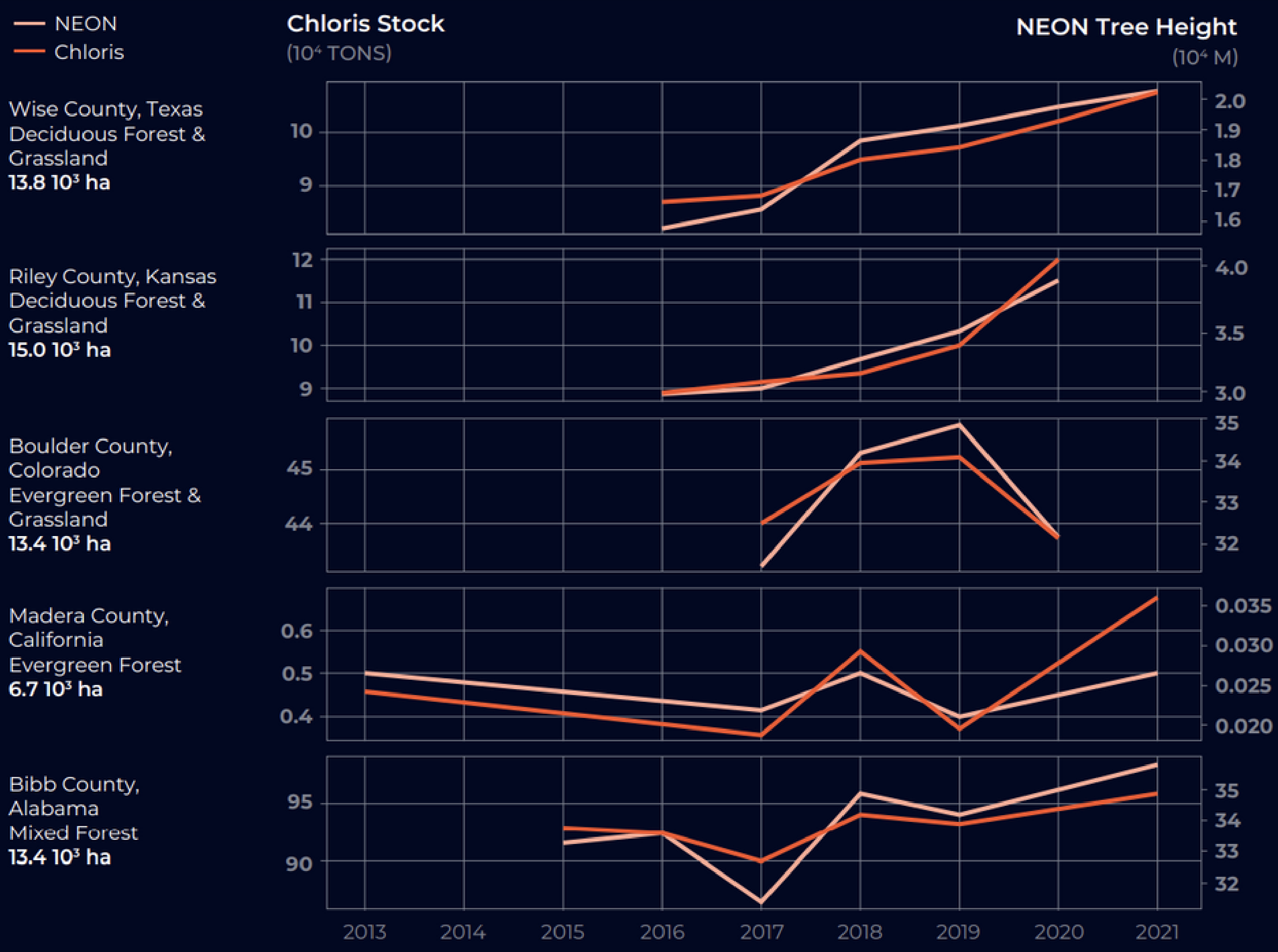

Figure 3: To validate Chloris AGB change estimates, we compared our biomass estimates over time against tree-height dynamics collected over time at sites of the National Ecological Observatory Network (NEON).

b) Validation against ground LiDAR and UAV LiDAR

In October 2023, the Ecosystem Restoration Standard (ERS) conducted an AGB Benchmarking Exercise to assess the quality of the data produced by different service providers. For that purpose, ERS acquired a high-quality biomass dataset derived from LiDAR + UAV LiDAR measurements over a 50k hectare site in Mozambique. The comparison showed that Chloris data performed better than any other actor participating in the benchmarking exercise.

c) Validation against field plots

Comparing biomass estimates derived from remote-sensing data against biomass estimates derived from field plots–a plot-to-pixel comparison–is more challenging than comparing two remote-sensing-derived biomass datasets. Factors complicating plot-to-pixel comparisons include the often small size of plot size, geolocation error, and human error when setting up field plots. That said, plot-to-pixel comparisons become more relevant in regions where not enough publicly available LiDAR datasets exist. Yet, the generally high-quality and relatively large-sized (1ha plus) field plots of the GEO-TREES network offer an interesting resource for validation, even though the number of actual plots is limited to a few hundred plots across the tropics.

In comparison against field plot values from the GEO-TREES network, the Chloris Africa model shows an R2 of 0.7 and RMSE of 83.62 t AGB/ha. For reference, when compared against GEO-TREES field plots, our Latam model shows an R2 of 0.6 and an RMSE of 84.62 t AGB/ha. The same Latam model, when compared against high-quality ALS in Latam, shows an R2 of 0.933 and RMSE of 34.394 t AGB/ha–our best R2 performance in the comparison against ALS. This suggests that if we could validate our Africa model against ALS data, we could expect even better model performance metrics for that model.

Chloris Geospatial

ABOUT CHLORIS

Chloris Geospatial provides science-based forest carbon insights built with Earth observation data and machine learning. The Chloris Platform unlocks nature-based solutions to climate change with speed, scale, and integrity. With 20+ years of ecological and remote sensing expertise, we empower companies worldwide with direct estimates of forest carbon stock and change anywhere on Earth. From large-scale deforestation to forest degradation, growth, and regrowth of trees: Chloris sees what the atmosphere sees.

Get started with the Chloris Platform: app.chloris.earth

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