FOREST CARBON PARTNERSHIP FACILITY

Assessing Technologies to Accelerate the Process of Monitoring, Reporting, and Verifying Emission Reductions Programs

Report for the Next Generation of Monitoring, Reporting, and Verification of Land Use Emission Reductions Programs ASA (P178735)

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8 Amazon Web Services

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This report leveraged the World Bank's ongoing collaborations with (1) the European Space Agency (ESA) on the Global Development Assistance program (formerly EO4SD), (2) California Polytechnic University's Digital Transformation Hub, and (3) Sylvera's ongoing program of collecting high-quality volumetric data.

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European Space Agency

Sylvera

CAL POLY
Digital Transformation Hub

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List of Acronyms and Abbreviations

ASA	Advisory Services and Analytics (World Bank)
CALM	Criteria to Consistently Assess Levels of Maturity (Global Forest Observations Initiative)
CUA	concepts under assessment
ERP	emission reductions program
ESA	European Space Agency
FCPF	Forest Carbon Partnership Facility (World Bank)
FNDS	Ministry of Agriculture and Rural Development (Mozambique)
GDA	Global Development Assistance
ha	hectare(s)
IDEAM	Institute of Hydrology, Meteorology, and Environmental Studies (Colombia)
ISFL	BioCarbon Fund Initiative for Sustainable Forest Landscapes
LiDAR	light detection and ranging (remote sensing technology)
m	meters
MRV	measurement, reporting, and verification
MT	metric tons
NDVI	normalized difference vegetation index
QSM	quantitative structural model
REDD+	Reducing Emissions from Deforestation and Forest Degradation
RMSE	root mean square error
S3	simple storage service
SAR	synthetic aperture radar (remote sensing technology)
SCALE	Scaling Climate Action by Lowering Emissions (World Bank)

REPORT HIGHLIGHTS

The Problem

In jurisdictional scale REDD+ programs, such as those under the World Bank's Forest Carbon Partnership Facility (FCPF) and BioCarbon Fund Initiative for Sustainable Forest Landscapes (ISFL), the process of establishing baselines and collecting and processing data estimates (measurement), reporting on carbon emission reductions (reporting), and verifying and certifying reported results (verification) takes too long.

Key Issues

This Advisory Services Analytics (ASA) report assesses potential technologies to expedite the measurement, reporting, and verification (MRV) process for jurisdictional scale REDD+ programs, focusing on innovative tools to improve efficiency, accuracy, scalability, and ultimately timing.

Challenges of the MRV Process. Under REDD+ programs, the current MRV process is lengthy and complex, leading to delays and additional uncertainties in verification of emission reductions and access to climate finance.

Highlighted Challenges. Key challenges include inconsistent methods across countries, high costs and long timeframes, and over-reliance on optical imagery (via satellite).

Measuring Emission Factors. Challenges in measuring emission factors include logistical and cost issues with collecting field data, limited spatial coverage, and variability in data quality.

Activity Data Collection Issues. Satellite optical data has limitations, such as cloud cover, dependency on daylight, and seasonal variability, causing delays in producing activity data.

Data Integration Complexities. Integrating activity data with emission factors is complex and involves challenges in collecting, storing, and manipulating data, and in complying with reporting standards.

Reporting and Verification Delays. Traditional methods for collecting and reporting data are time-consuming, with significant delays in presenting monitoring reports and issuing emission reductions credits.

Suggested Solutions

Technological Solutions. Suggested solutions include data management tools to reduce the MRV time cycle, and technologies—such as LiDAR, SAR, and high-resolution satellite imagery—to improve consistency, accuracy, and precision.

Innovative Data Collection Methods. New methods include terrestrial laser scanning, unmanned laser scanning, and airborne laser scanning to collect high-quality, in situ data and improve biomass estimation.

Digital Data Architecture. A centralized cloud service with decentralized "data lake" platforms has potential to solve the challenges associated with integrating data.

Recommendations

The simplest opportunity for expediting MRV processes in REDD+ programs is the incorporation of technologies to expedite reporting, validation, and verification processes. Off-the-shelf digital technologies are also readily available to enhance measurement procedures; however, the implementation of these technologies requires careful consideration of existing systems, transparency, and alignment with country-specific needs to ensure sustainability and efficiency.

It is recommended that entities intending to adopt new MRV methodologies (for example, standards setters and government agencies) develop a policy—informed by the Global Forest Observations Initiative's Criteria to Consistently Assess Levels of Maturity (CALM) framework—for assessing and incorporating technology and enabling its meaningful and impactful use. This could involve enabling exploration exercises, such as those combining the acquisition of terrestrial laser scanning data and tree- and plot-level biomass estimations, and elaborating the path toward sound assimilation of novel technologies into the MRV process.

I. CONTEXT

Background

The World Bank (2021b) policy brief *Policy Paths towards Second-Generation Measurement, Reporting and Verification (MRV 2.0)* revealed that the measurement, reporting, and verification (MRV) cycle under the Forest Carbon Partnership Facility (FCPF) and BioCarbon Fund Initiative for Sustainable Forest Landscapes (ISFL) takes too long. Based on the findings reported in World Bank (2021a), the brief states that the process is prolonged, in many cases requiring years to become functional even in countries with substantial technical capacities. Once operational, the process relies on a complex measuring system that generates uncertainty in both how to use it and how to verify results. In addition, lengthy and complex procedures are required to integrate remote sensing data with in situ field measurements, which hinders stakeholders' ability to address the drivers of greenhouse gas emissions effectively and causes delays in the ability of potential recipients to apply for and access climate finance.

Some of the main challenges highlighted in the brief include (1) lack of methodological consistency and comparability across countries; (2) high costs and overly long timeframes, exacerbated by low levels of accuracy; and (3) overreliance on optical satellite imagery. To address these challenges, findings suggested the introduction of data management tools to enhance efficiency and scalability, thereby reducing the time needed to implement the MRV cycle from years to a matter of months. In addition, the findings suggested ways to facilitate monitoring using technologies capable of improving consistency, accuracy, and precision, specifically including LiDAR (light detection and ranging, which is a form of remote sensing using a pulsed laser to measure variable distances to the Earth to generate 3D images); synthetic aperture radar (SAR), used to create two- or three-dimensional images of objects, such as landscapes; and high-resolution satellite imagery (Box 1).

These MRV issues can have serious implications for countries aiming to receive result-based payments. The delay between the generation of emission reductions and their issuance and payment would be significant, creating a disincentive for countries and communities to take action because their efforts would not be immediately rewarded. Additionally, such a time lag could lead buyers to perceive that the emission reductions are "old," causing payments to be significantly discounted and countries to receive lower levels of carbon finance.

Box 1. Reported challenges of existing MRV process for emission reductions programs

Measurement Challenges

Emission Factors

Emission factors are estimates of the rate at which a given activity releases greenhouse gases into the atmosphere. They are traditionally produced using inventory data collected in the field, which presents logistical and cost challenges—especially in remote or difficult-to-access areas—in addition to concerns about the quality and representativeness of estimates, which can impede the issuance of emission reduction credits. These challenges negatively affect programs as they prepare initial monitoring reports and work to improve, and reduce uncertainty about, the accuracy of the estimates. Ground-based measurement methods limit spatial coverage and may not provide a comprehensive picture of forest carbon stocks across large landscapes. This limitation can lead to gaps in data coverage and fewer accurate estimates. Moreover, the quality and consistency of data collected through traditional methods can vary depending on field personnel's skills and experience. This variability can affect the reliability of carbon stock estimates.

Activity Data

Optical satellite data is limited by cloud cover, lack of daylight, and seasonal weather variability, and it also has limited temporal resolution (that is, the amount of time needed to revisit and acquire data for the exact same location), all of which causes time lags in the production of activity data. On average, the best-case scenario indicates that a program needs at least six months from the end of the reporting period to collect, prepare, analyze, and report activity data.

Data Integration

To produce emission estimates, activity data needs to be linked with emission factors. This integration creates complexities in terms of data collection, storage, and manipulation, as well as in developing estimates and complying with reporting standards during the auditing process.

Reporting and Verification

Using traditional methods to collect data, report results, and verify emission reductions is time-consuming—the median being 24 months for programs to present their first monitoring reports, and an additional 12 months to validate, verify, and ultimately issue emission reductions credits. All of this has negative impacts on access to results-based climate finance. Even in cases where measurement estimates have been elaborated well, documenting the process to meet different reporting frameworks requires substantial additional processing and formatting, which contributes to inefficiencies. In addition, reporting frameworks require occasional updates that are difficult to disseminate and can cause delays in the preparation of monitoring reports, which in turn often lack supporting documentation and evidence to justification for the values, equations, and assumptions used to report emission reductions.

Source: World Bank (2021).

Notes: To guarantee climate integrity in accounting, MRV standards—such as those used by FCPF and ISFL—apply discount factors to reported emissions based on "estimates of uncertainty," a conservative approach that ensures emission reductions or removals are not overestimated.

Objectives

The objective of this Advisory Services and Analytics (ASA) study was to identify and introduce recent technology as a solution to the challenges of the existing MRV processes, as outlined in the previous section, and to assess the capacity and "readiness" of these innovative technologies to meet this objective. The ultimate goal was to provide proof of concept for a next-generation MRV process (MRV 2.0) and to ensure that the conclusions drawn could be generalized and transferred across differing countries contexts (Box 2).

Box 2. Technologies to accelerate existing monitoring, reporting, and verification processes

Measurement Technologies

Directly estimating biomass through remote sensing could expedite existing measurement procedures. This ASA study addressed previously encountered major hurdles to directly estimating biomass. World Bank (2021a) identifies one of the main gaps in forest measurements to be lack of sufficient high-quality in situ data, whether in digital or other form. This is key because such data serve as the basis for all estimations of biomass in MRV processes. Ideally, field data should be collected periodically as part of a national forest inventory using unbiased statistical methods to deliver unbiased biomass estimates. Currently, national forest inventory data are used to estimate biomass using field parameters that correlate with biomass using allometric equationsa developed via destructive sampling (that is, invasive methods that alter or destroy specimens). Allometric equations have been identified as one of the major sources of uncertainty in biomass estimates. Correlations of biomass with data from satellite-based remote sensing technologies (synthetic aperture radar [SAR] and light detection and ranging [LiDAR]) by means of artificial intelligence (support vector machines, convolutional neural networks) and geostatistics (Kriging, an interpolation method) were suggested as promising technologies to help overcome this shortfall in information on biomass.

Reporting and Verification Technologies

A potential solution to resolving challenges related to data integration was determined to be a centralized cloud service combined with a decentralized, multipurpose "data lake," which is a centralized repository of large volumes of raw data stored in its native format until it is needed (see Section 3, Digital Architecture Solutions, including Figure 3).

Source: Authors based on World Bank (2021b).

[a] Allometric equations allow biomass to be estimated at the tree level built on correlations between variables measured in national forest inventories, such as the diameter of the tree stem at breast height or the ratio of height to biomass. Allometric equations are built by performing destructive sampling to determine estimates of their measurements and dry biomass. Developing such equations is very difficult, and their representativeness is limited, particularly for large trees based on a natural reluctance to include them in samples despite the high shares of biomass they represent in mature forests.

Theory of Change

The following assumptions and hypothesis underpinned the plan to create a second-generation MRV process.

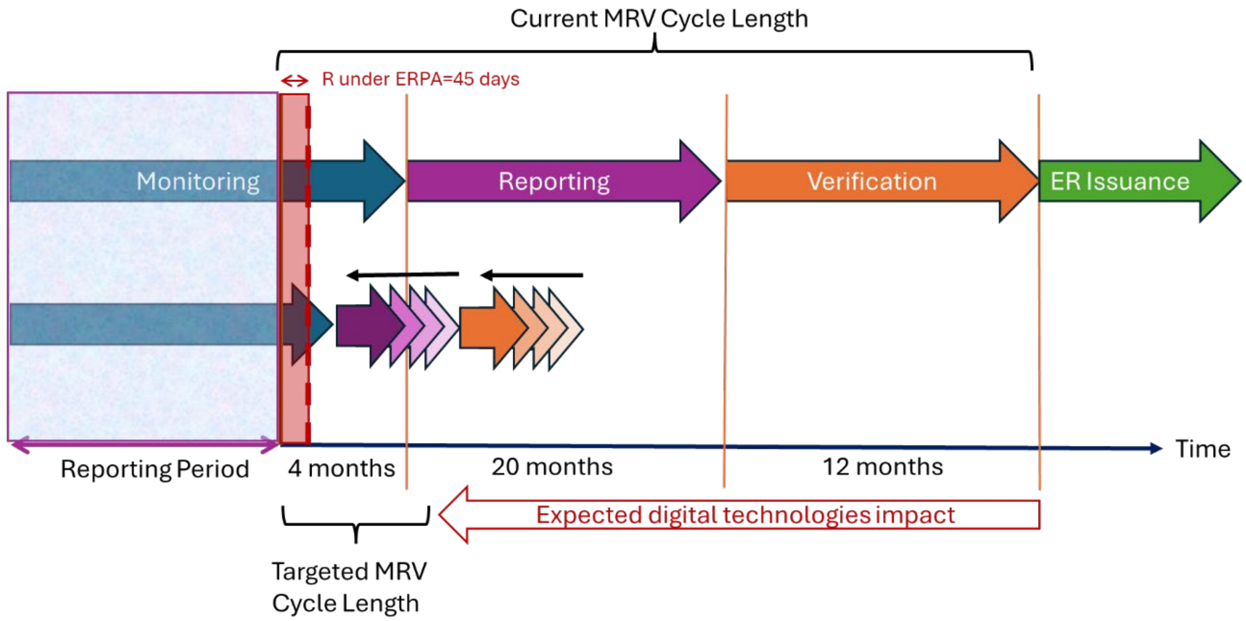
Assumptions

1. New developments in technology can improve the capacity to deliver timely estimations of and changes in carbon stocks—importantly, with improved accuracy.
2. The technological developments referred to include new possibilities for directly estimating biomass, which is an essential climate variable that both informs direct estimates of changes in carbon stocks and affects other essential climate variables, such as land cover.
3. New satellites and the falling costs of airborne data will promote unprecedented data availability, in turn enhancing direct biomass estimations.
4. The combination of innovative approaches and increased availability of data is expected to overcome several major challenges to estimating carbon stocks through the following means:
   - Enabling carbon stocks to be measured with greater frequency (less than one year)
   - Standardizing the estimation of carbon stocks to make data from various sources compatible and easily able to be integrated, while also allowing uncertainties to be quantified
   - Decreasing the time needed to generate, report, and verify estimates because MRV systems become operational within months rather than years, significantly reducing the time lag for data to become available after completion of the monitoring period

Hypothesis

Combining various available technologies—including new remote sensing data, geostatistics, and cloud computing—will expedite FCPF's and ISFL's MRV cycle, thereby unlocking the carbon credits that carbon finance stakeholders and countries require to be able to deliver climate change mitigation targets (Figure 1).

Figure 1. The existing monitoring, reporting, and verification cycle



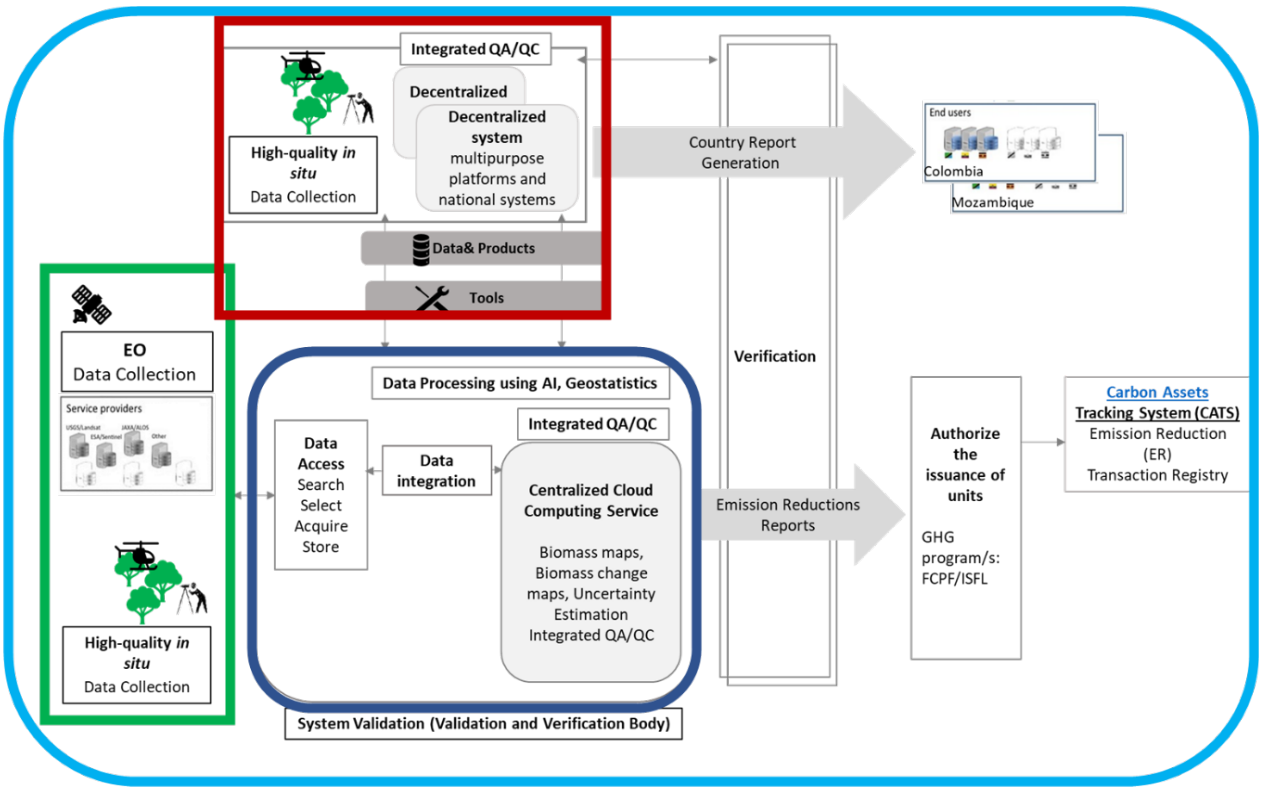
Source: Devised by authors.

Notes: The current monitoring, reporting, and verification (MRV) cycle under which reporting is expected within 45 days of the end of the monitoring period actually takes much longer. Median times currently stand at 24 months. This study sought to explore alternative solutions to drastically reduce this timeframe in the next-generation MRV for land use ERPs.

II. IMPLEMENTATION

To assess their viability and desirability prior to scaling, technologies were selected for each phase of the MRV cycle (Figure 2). To implement each technology, the ASA leveraged the World Bank's ongoing collaborations with (1) the European Space Agency (ESA) on the Global Development Assistance program[9] (formerly EO4SD[10]), (2) California Polytechnic University's Digital Transformation Hub,[11] and (3) Sylvera's ongoing program of collecting high-quality volumetric data.[12] This approach significantly alleviated the cost of implementing the proof of concept. Each goal and its associated technological solution is outlined below.

Figure 2. Schematic of technologies tested



Notes: The red box shows the schematic for measuring high-quality field data collected using terrestrial laser scanning (TLS). The green box shows the schematic for measuring biomass cloud computing, upscaled using airborne LiDAR (remote sensing), satellite data, and state-of-the-art modeling. The dark blue box shows the schematic for measuring and reporting digital data architecture. The pale blue box shows the schematic for the complete monitoring, reporting, and verification cycle. EO = Earth observation; ER = emission reductions; FCPF = Forest Carbon Partnership Facility; GHG = greenhouse gas; ISFL = BioCarbon Fund Initiative for Sustainable Forest Landscapes; QA/QC = quality assurance/quality control.

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9 https://gda.esa.int/

10 https://eo4sd.esa.int/

11 https://dxhub.calpoly.edu/

12 https://www.sylvera.com/

High-Quality In Situ Data

Lack of high-quality in situ data used to calibrate estimates is a major problem when elaborating remote sensing–based estimates. National forest inventories—which are usually the source of such data—are costly and difficult to implement. This has led practitioners to seek publicly available remote sensing data that correlates with the structural parameters of forests (for example, in terms of canopy height) and hence also with biomass. National forest inventory plots, however, are not conceived with the goal of obtaining remote sensing data. As a result, even in cases where plot samples are optimally designed and implemented, national forest inventory measurement cycles don't align with MRV reporting cycles. Additionally, issues arise in extrapolating plot-level estimates to "wall-to-wall" maps—in which every pixel represents an individual estimate—from challenges that include lack of representation of forest diversity, poor correlation between biomass and remotely sensed parameters, bias in estimates due to spatial autocorrelation in remote sensing data, model bias, and lack of consensus on how to quantify uncertainties associated with results. These problems are further compounded in the auditing phase.

This study explored the use of a state-of-the-art collection of high-quality in situ datasets, following best practices[13] to inform biomass estimates derived through remote sensing. The intention was to circumvent (1) the challenge of extrapolating data coverage from plot-level to satellite-level (for example, for the entire ERP area) and (2) the limitations of using allometric equations to estimate biomass from national forest inventories. The ASA also explored a novel method of creating data synergies within a 50,000-hectare (ha) region of interest. It was expected that these processes would improve the accuracy and bias of estimates so they could be extrapolated to the larger ERP area with the support of colleagues from Sylvera.

The new technological approaches included the following:

1. A terrestrial inventory of six one-hectare plots combining terrestrial laser scanning (TLS) with traditional methods to overcome biases and the lack of representativeness of allometric equations (Figure 2, red box)

2. Data collected using unmanned aerial vehicle laser scanning (UAV-LS) over six 300-ha sections, each encompassing the one-ha plots described in point 1

3. Data collected through airborne laser scanning (ALS) across 50,000 ha of forest encompassing both the one-ha plots described in Point 1 and the 300-ha sections described in Point 2 (Figure 2, green box)

The goal of this approach was to cross-reference, exploit synergies, and increase the accuracy of data by taking multiple measurements of the same and expanded areas using multiple means.[14] In short, data were scaled from the six one-ha plots to the six 300-ha sections and ultimately to the 50,000-ha region of interest. A fuller, step-by-step description of the high-quality field data collection exercise conducted in the ERP area of the Zambezia region of Mozambique is provided in Appendix A; detailed analysis and discussion of the exercise is provided in Appendix B.

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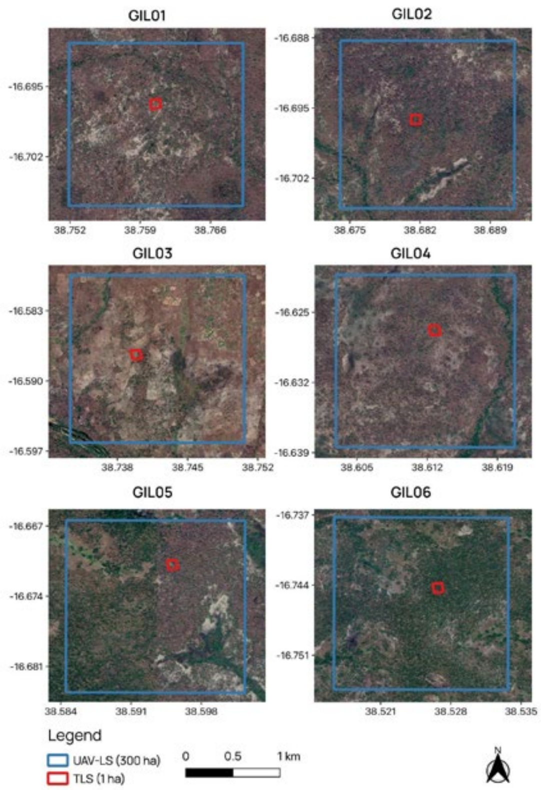
[13] https://forestplots.net/

[14] This new generation of data collection was implemented in collaboration with Sylvera and the Mozambique government. The Forest Biomass Reference System for Tree-by-Tree Inventory Data provided support to ensure that the methodology aligned with the validation protocol and that the data could be integrated into the forestplots.net network and support the development of data-sharing arrangements.

Map 1. Satellite imagery indicating the one-hectare and 300-hectare sections in the region of interest in Zambezia, Mozambique



Source of satellite imagery: Maxar Technologies (2018).

Notes: The maps depict the six 300-ha sections in blue (GIL01 to GIL06) and the six one-ha plots in red (GIL01-01 to GIL06-06) overlaid on satellite imagery.

Biomass Cloud Computing

As a second step toward improving data quality—in this case, within the ERP of Zambezia, Mozambique, currently being implemented by FCPF—the study explored how to improve the integration of the high-quality data collected in the 50,000-ha region of interest with readily available global datasets from optical and active sensors (collected within one year), such as SAR and LiDAR (using GEDI data),[15] which could be used to expedite the monitoring of biomass changes. The models tested included combined prediction and uncertainty techniques from different fields, such as artificial intelligence and geostatistics (implemented in collaboration with ESA through its partner GeoVille[16] and the Mozambique government.)

[15] https://gedi.umd.edu/

[16] https://www.geoville.com/

Digital Data Architecture

The third step targeted a cloud-based data platform through which data could be stored, accessed, and processed for the purpose of generating, revising, and validating estimates (Box 3). The focus was exploring available alternatives for developing infrastructure for cloud computing based on a client-server model. This approach emphasized data hosting; linkages to data processing; documentation of models; and estimates of emissions, emission reductions, and their associated uncertainty levels.

Once the implementation of the three technological approaches was finalized, a three-day workshop was held with all team members in collaboration with the World Wildlife Fund to identify both lessons learned and resulting recommendations. The methods used reconstructed the ASA study's implementation from conception to delivery of results, emphasizing (1) the identification of successes and failures and (2) the analysis of the failures, informed by both the ASA results and team members' extensive experience as MRV experts. The results of the workshop discussions—as well as those held with key partners, stakeholders, and leaders in forest-related MRV—inform the lessons learned and recommendations presented in this report.

Box 3. Digital data architecture

The ASA study brought key stakeholders in the monitoring, reporting, and verification cycle together to identify specific problem areas with the goal of finding targeted solutions to the MRV data access, storage, processing, and validation. The resulting suggestions were drawn from readily available tools and technologies, focusing on a high-level conceptual design. The main targets were "de-risking" technologies (those less prone to being affected by variables that could in turn affect their deployment or performance delivery) and developing assets to accelerate deployment in a field setting. Assessing alternatives for constructing a repository that would expedite the manipulation of data to generate estimates and reports involved collaboration with California Polytechnic University's Digital Transformation Hub as part of their collaboration with Amazon Web Services.

A success scenario was elaborated then dissected into key components based on "customer pain points." Modular solutions tailored to each pain point were then assembled according to the following needs:

1. *Flexibility in methods.* A single methodology would not address differing country contexts because the methods used are as diverse as the forests themselves.
2. *Support for open-source data input.* Countries need to be able to use existing datasets, so the state-of-the-art data collected and tested could not be the default. Model classifiers (used to identify forest characteristics) vary by ecosystem, and the best source of input data varies by region.
3. *Model parameters.* The definitions of forest, deforestation, and degradation must be considered as model parameters.

Note: The Digital Transformation Hub collaborates with a variety of governments, educational institutions, and nongovernmental organizations to involve hundreds of students, faculty members, and staff in addressing future challenges; it also established the first Cloud Innovation Center, supported by Amazon Web Services.

After reviewing the prioritized needs and discussing potential solutions, the next step involved defining areas for further technical exploration, which is described below.

Data Lifecycle and Processing

The central theme in most "pain points" was lack of a central repository to house and enable processing of data throughout the MRV process, along with lack of an effective process for managing the data as it is processed throughout the MRV cycle. The desired characteristics/capabilities identified for prototypes included the following:

- Show how different types of data can flow into a central repository governed by a security framework that allows for granular access
- Demonstrate how processes can be established to "sanitize" raw data into useable formats
- Show how metadata can be generated automatically using data crawlers that run custom classifiers on datasets defined to infer the data format and schema
- Demonstrate how alternate data sources can be brought into the repository and combined with existing elements
- Demonstrate how using a single "source of truth" (that is, a single entry point allowing access to all the evidence needed to validate and verify estimates) could facilitate downstream processes and auditability, streamlining many aspects of the current process
- Demonstrate how a standardized computer container can be scaled to perform data transformations (that is, gradient-boosting machine learning models) beyond the current limitations of localized computer hardware
- Provide examples of how large amounts of data can be transferred to the cloud with limited connectivity, within a reasonable timeframe, and at a cost that works within the business requirements
- Demonstrate how familiar tools currently used in the MRV process can continue to access data in the cloud with the correct access permissions

Modeling

Once datasets are collected, sourced, and transformed into usable formats, they are modeled and used to estimate and quantify changes in biomass. Modeling biomass is an evolving science that requires the right technical tools to run models, calculate uncertainty levels, and ease the burden of collaboration. This technology must be easy to consume and have a low barrier for entry to establish, while demonstrating (1) how cloud infrastructure can be generated easily with a common set of tools allowing easy adoption and startup, and (2) how open-source Earth observation data can be accessed for use within another application (such as a Jupyter notebook environment), including access to open-source model frameworks to estimate biocarbon changes.

Role-Based Access Control and Data Obfuscation

While centralizing data in a single location solves many problems, it creates potential issues in providing different levels of role-based access and the means to obfuscate raw data. For example, those reaching certain conclusions need to understand how the data were used but not be able to access the underlying source. Other needs include demonstrating the ability to (1) collaborate with others to analyze centralized datasets and gain new insights, while not revealing the underlying data to one another, and (2) apply fine-grain, role-based access to data in the cloud.

Validation and Verification

Validation and verification bodies—required for reviewing methodological approaches—are traditionally siloed/segmented from the source data and computations. Using a modern approach that reunites data and computations with these bodies would enable a more transparent review of the process, data, models, and methodologies used to estimate biomass and calculate emission reductions. Needs include demonstrating (1) the ability to re-run analyses undertaken in the modeling phase with explanatory cells to accompany executable portions of code connected to the original source data, and (2) how all code and data can be tagged to verify immutability and allow transparent verification that can be reproduced.

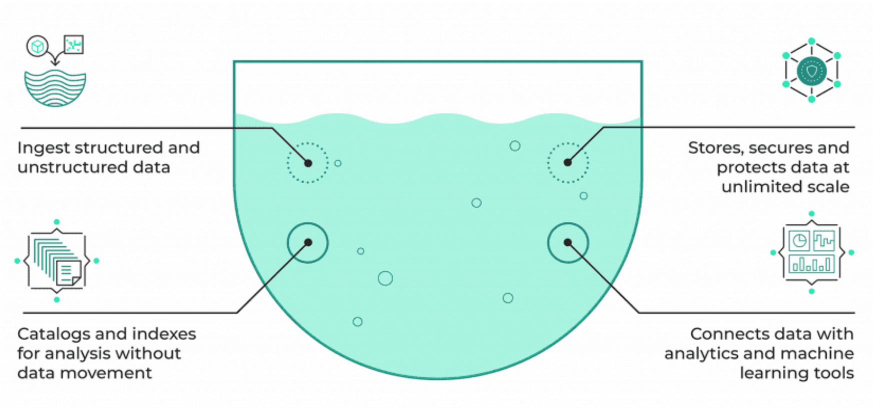
III. DIGITAL ARCHITECTURE SOLUTIONS

The needs assessments identified end-user requirements for a centralized data repository, data sharing, and privacy.[17] These included elements related to the following:

1. Data preservation (that is, avoiding potential deletion)
2. Reporting integrity (tracking and preserving all changes and versions)
3. Confidentiality and access (managing different levels of access according to clearance levels, for example, auditors vs the general public)
4. Data cataloging (metadata, source tracking, automatic tagging, origin, and relationships)
5. Scalability (flexible and capable storage capacities and functionalities to ingest new data as data volumes and types increase)

All data management solutions need to be capable of cost-effectively working with existing systems and processing large volumes of data with ever-changing algorithms and use state-of-the-art tools—in some instances in situations with poor connectivity. Based on these requirements, the solutions process identified the best option to be a data lake, which is a centralized repository designed to store large volumes of raw data in its native format until it is needed (Figure 3).

Figure 3. The core features of a data lake



Source: Singman (2024).

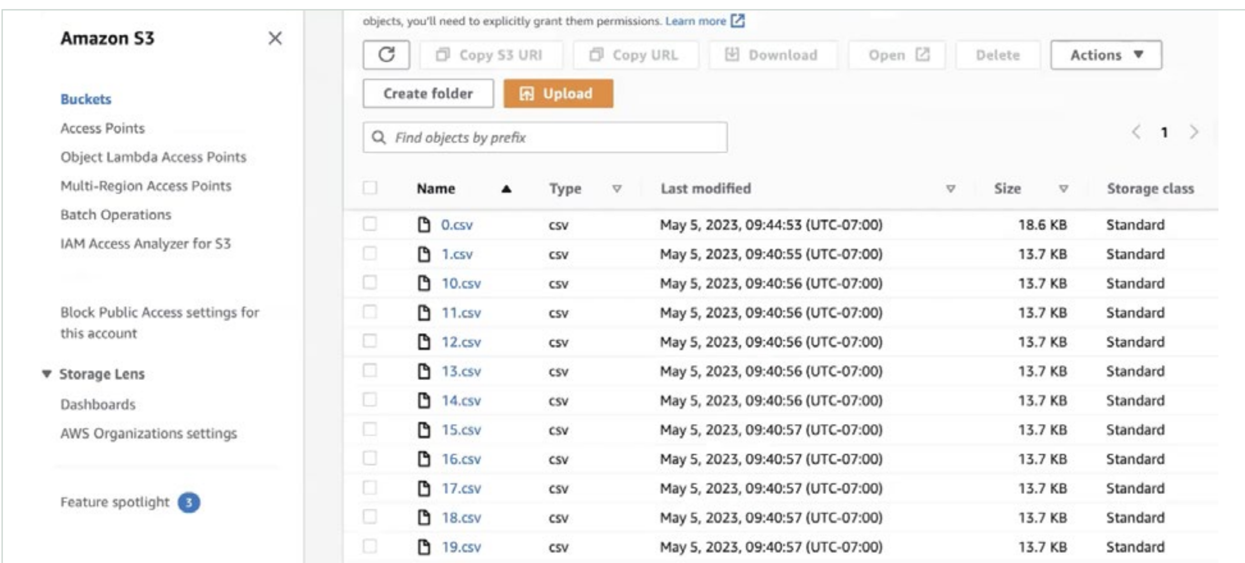
[17] Because the digital solutions aspect of this study involved a collaboration with Amazon Web Services, the solutions tested are part of their family of products. This, however, by no means implies that these products are the only available options; the *functionalities* are the focus, not the *provider*.

A data lake can ingest and transform data as it arrives.[18] It features an ingestion framework that, if necessary, can standardize data into a common repository, allow input data to be converted into the format required for analytical frameworks or models, and enable data to be curated and features extracted for use in model training. The link to the original data is maintained to enable corrections and modifications to be made when needed. Data lakes can include data governance structures built using their automatic metadata-generation capabilities. This allows data to be used in dashboards, applications, and artificial intelligence models, as well as automation in an iterative process of collecting, organizing, analyzing, and infusing data—commonly referred to as the "artificial intelligence ladder."

Simple Storage Service

The identified foundation for the data lake is the "simple storage service" (S3) proposed by Amazon Web Services. Countries showed interest in this option because it removes the need for them to supply the hardware and onsite technical support. Characteristically, S3 is an easy-to-use proven solution already in wide use that delivers the required amount of storage, has proved to be durable (with automatic backups), is cost-optimized, and includes standardized access methods and fine-grain security policies and access history. Data are stored in the region of placement but can be accessed across regions (Figure 4).

Figure 4. Example of a simple storage service web interface



Source: Amazon Web Services.

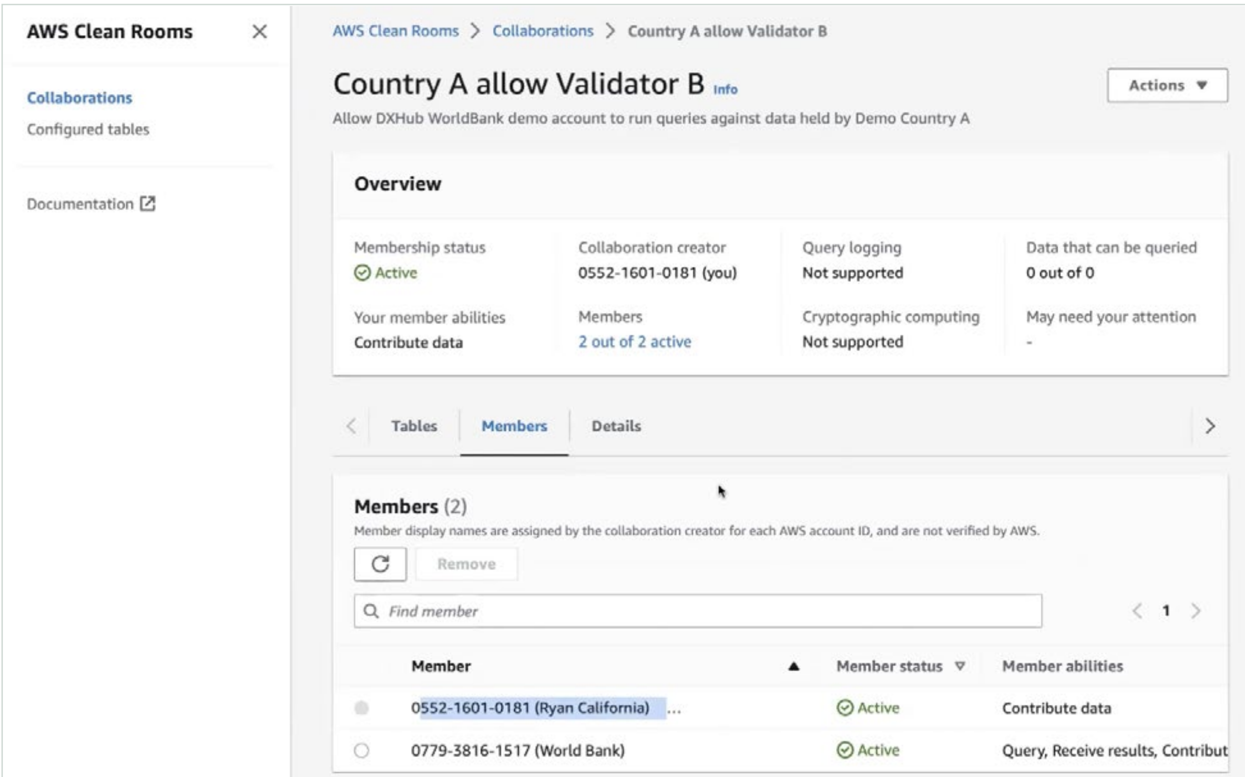
Data interconnectivity was explored using a serverless data integration service (Amazon Web Service Glue),[19] which allows easy discovery, movability, and integration of data from multiple sources and integrates with Amazon's simple storage service data lakes. For collaborative data analysis, Amazon Web Service's Clean

18 For an example of a data lake, see https://aws.amazon.com/solutions/implementations/data-lake-solution/

19 https://docs.aws.amazon.com/glue/latest/dg/what-is-glue.html

Rooms[20] was explored because it allows secure analysis and collaboration on collective datasets, providing ease of use without the need for collaborators to share or copy each other's underlying data (Figure 5). This was of relevant for the validation and verification process.

Figure 5. Example of Amazon Web Service's Clean Rooms interface

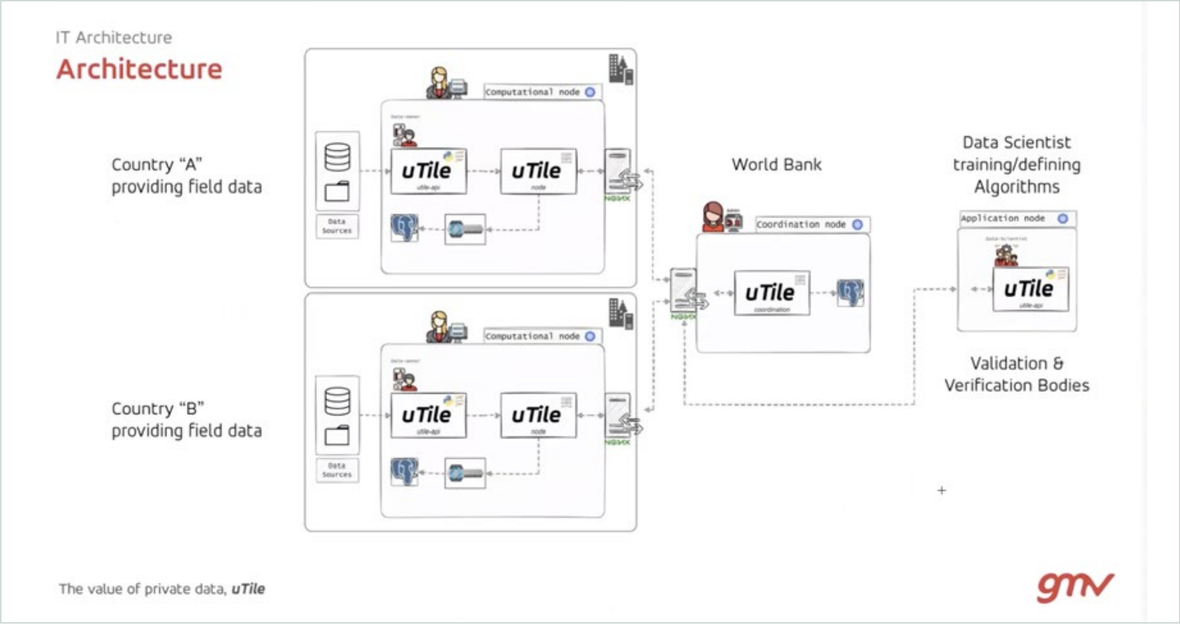


Source: https://aws.amazon.com/clean-rooms/

For modeling, Amazon Sagemaker[21] was connected to the S3 data to run codes in an adaptive setting based on specific requirements for computational capacity. For example, Sagemaker can connect to codes held in Jupyter notebooks.[22] Another modeling option explored was GMV's uTile,[23] through which distributed data can be safely and privately manipulated without being exposed or moved (Figure 6).

[20] https://aws.amazon.com/clean-rooms/
[21] https://aws.amazon.com/pm/sagemaker/
[22] https://jupyter.org/
[23] https://www.gmv.com/en-es/products/cybersecurity/utile

Figure 6. Example of a digital interface enabling secure computational capacity (uTile)



Source: https://www.gmv.com/en-es/products/cybersecurity/utile

Modeling Test

After all the modeling options were identified, a test model was assembled to elaborate and deliver estimates based on preexisting datasets and modeling approaches readily available using a specific reporting framework (Figure 7). For the test, the model was used to run a sample estimation of emissions resulting from land cover changes using data recorded in the Democratic Republic of Congo. The following elements were incorporated:

1. Amazon Sagemaker defined the computational settings required for data processing by running a code help in a preexisting Jupyter notebook. This included all the necessary software and libraries set into an Amazon Web Services Anaconda platform capable of optimizing computational performance. The size of the computer platform can be modified based on the size of the task; for example, in the case of final Monte Carlo uncertainty simulations for estimated emissions reductions, computational power needed to be maximized.

2. Sagemaker Geospatial was used for simplified access to open access satellite via an application processing interface; bypassing the need for data-specific connection settings.

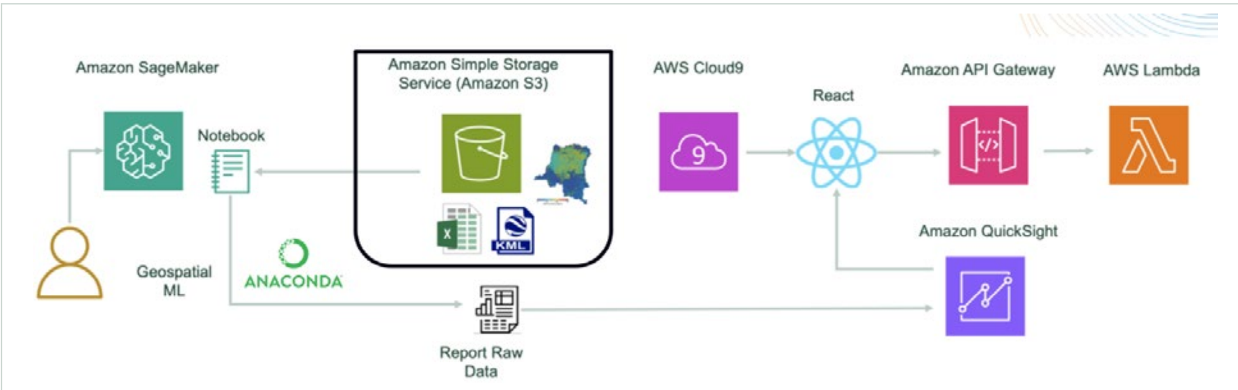
3. Data used (previously stored in an S3 bucket) included biomass data, land cover classification data, and sample distribution data related to the Jupyter notebook.

4. The code was run, delivering raw data results for ingestion into the reporting framework.

5. Amazon Web Services Cloud 9 was used as an easy to access environment to develop a simple reporting application with REACT—the basis for the reporting website—supported with Amazon Web Services Lambda to run code in the back and Amazon Web Services application programming interface gateway to manage user requests.

6. Finally, Amazon Web Services QuickSight was used to build the reports.

Figure 7. Model interface showcasing the identified solutions



Notes: ML = machine learning.

Biomass estimates were derived from biomass maps. Land cover classes and their transitions were derived from sample field data. The model successfully delivered estimates of both emissions factors (including uncertainty estimates) and reported estimated emissions per period in a very simple reporting interface. All data, repository, codes, and reporting connectivity were included.

Analysis of the Proposed Data Architecture

Solutions for all data challenges assessed were readily available—including for data storage, tagging, preservation, flows, model inputs and outputs, differentiated access, estimation, and display—and the ASA study demonstrated that a fully integrated measuring system was possible. The caveat, however, is that the ASA model was constructed under ideal conditions. In contrast, participating FCPF and ISFL countries already have systems in place that inform not only MRV processes but also issues of forest governance. Current systems also reflect existing technical capabilities, as well as such factors as institutional and legal arrangements.

Consequently, instead of adopting all the elements identified through this ASA study, countries could incorporate relevant components to complement rather than replace the existing functional systems that MRV teams are familiar with, thereby allowing a tailored, modular approach. The storage systems were highlighted as the most desirable element because overcoming the existing challenges of FCPF's and ISFL's MRV cycle requires balancing technological advancements with the need for transparency and alignment with country-specific needs. The highest priority goals are ensuring MRV systems evolve effectively, adhere to environmental monitoring goals and local capacities, and are sustainable for the lifespan of programs.

Challenges of Data Processing Solutions during the Verification Stage

MRV processes need to comply with reporting standards while also being transparent and auditable. As such, aligning MRV systems with FCPF's, or similar, methodological frameworks and verification standards is more than a procedural need—it is a strategic imperative. This alignment secures the integrity of the verification process, ensuring that reported emissions reductions are both credible and accurately reflected. This process involves the implementation of MRV systems by national institutions, adapting global standards to local contexts while maintaining technical qualities and reliability.

Discussions with validation and verification bodies indicated that a digital platform could both facilitate and disrupt the verification process. Verifiers need a transparent means of evaluating reported estimates and an easy way to access evidence and ask for clarification. The ability to go straight to the source and reconstruct the estimates with adequate access to aggregated data, including built-in version control, would improve the process while simultaneously building trust for the verification bodies. The specific requirements identified include for following:

1. A single system for inputting data, whereby all relevant information can be documented, stored, or linked (which implies a single data repository or multiple data repositories with interconnectivity that allows control over versions).

2. The ability to show how and with what data a particular report was generated.

3. Built-in version control so that any data modifications can be traced.

4. The ability to audit versions of reports.

5. The ability to check that the system recorded data accurately and immutably with minimal opportunity for human error, manipulation, or change.

6. The ability to allow validators/verifiers to have third party access to the system, including the ability for verifiers to tag/comment on issues in the system to facilitate easier tracking.

Integrating complex data processing methods, such as artificial intelligence, poses challenges in terms of maintaining transparency, accuracy, completeness, and consistency—all of which are essential to MRV processes, especially in the verification stage. The sophistication of these systems often makes it difficult to audit and understand decision-making processes, assumptions, and potential sources of bias. These challenges result in *more* rather than *fewer* findings by auditors, which generates additional work for MRV teams in order to provide reasonable levels of assurance that the systems used are not biased.

In addition, beyond FCPF's and ISFL's requirements, digital systems would involve additional compliance standards, such as ISO 27001 clause 4.3 on standard security techniques, which would in turn add capacity requirements for both MRV teams and auditors. Note that compliance with digital standards was not assessed in this ASA study.

Generic off-the-shelf solutions can be considered fully operational under the Global Forest Observations Initiative's Criteria to Consistently Assess Levels of Maturity (CALM).[24] These are being used for the data collected and processed for both FCPF's and ISFL's measuring and reporting components. Use in the verification stage was shown to be viable, but compliance may involve additional requirements as systems shift into the realm of standards.

Inefficiencies Based on the Method of Communication

The ASA study identified that, under both FCPF and ISFL, the existing reporting and verification process is inefficient based on the communication methods used. Specifically, the use of word processing–based reporting templates (using Microsoft Word) for both monitoring reports and verifying findings lacks any assurance of completeness prior to submission by reporting parties and cannot guarantee linkages to sources of evidence of reporting estimates or facilitate exchanges between country teams and validation verification bodies. In addition, both FCPF and ISFL are pilot programs, so templates are subject to updates, requiring reporting parties to keep up to date with versions and modifications. This causes major transaction costs, not to mention frustration by all parties involved in the MRV cycle. Average time for the reporting and verification under the first monitoring report was 18 months—clearly indicating the need for improvement.

Another point of inefficiency identified is the (ever-changing) existing MRV reporting template. Countries are required to input the results of measurements into the template, which is in turn governed by standards. Verification is done based on a monitoring report correlated with that template. The ASA study concluded that these time-consuming manual processes could be improved through the use of a digital reporting template that would reduce churn and allow for data to be sourced and audited more dynamically and consistently. Dynamic reports could be generated on request from source data and be much easier to validate.

The needs identified include the following:

1. Demonstrate how reports would look and function as a dynamic web-based application that can generate graphs, tables, and so on.
2. Demonstrate technology frameworks that allow outputs to be compiled into a template and format that draws from a central repository of modeled results.
3. Demonstrate dynamic reports that reflect data generated directly from model outputs rather than through a "copy and paste," which is subject to immediately becoming outdated.
4. Facilitate the transfer and interconnectivity of relevant data in the different reports—for example, nonvariable parameters, methodology, and descriptions should be incorporated automatically in subsequent reports.
3. Document formatting changes that require presentations to be reworded to meet revised output standards. Standardized inputs should automatically be generated according to reporting requirements so that the burden of repetitious editing, word processing, and formatting changes is eliminated.

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[24] The Global Forest Observations Initiative is the leading group in research, capacity building, data, and methods guidance on MRV for forests. CALM draws on the concept of NASA's Application Readiness Levels to develop "concepts under assessment" (CUA) related to REDD+ MRV.

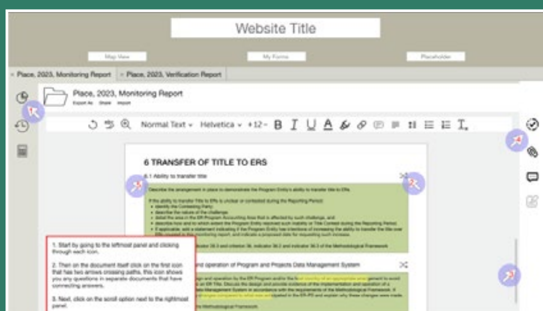
Proposed Reporting Hub

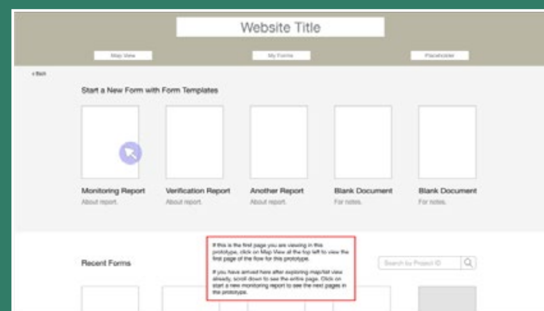
The ASA explored the possibility of developing a reporting hub that would satisfy the reporting and verification requirements under FCPF along with the issues related to data generation, manipulation, and storage. This led to the development of a test website (effectively a digital version of the current template) incorporating the desired levels of interconnectivity and functionality for the reporting and verification components of the MRV process—constituting a paradigm shift in approaches to the needs of the MRV process, which traditionally have begun with the monitoring component. The ASA explored how the levels of interconnectivity and functionality needed for the reporting and verification processes might facilitate a revision of the entire monitoring and reporting cycle, while at the same time providing the means to deliver feedback, collect responses, and track changes to reporting documentation.

As part of the ASA, a new reporting template was devised based on FCPF's reporting template. This proved to be the most promising component of the solutions tested because it provided the necessary format and internet connectivity for teams to input, manipulate, update, and correct data using codes, algorithms, and spreadsheets, while also enabling auditors to communicate to deliver findings (Box 4). The cost of implementation would be marginal compared with a fully integrated system, could be implemented in the short term, and would immediately have a positive impact on both FCPF's and ISFL's programs. This could be a particularly timely asset because the Bank's MRV teams currently face 24 FCPF and 12 ISFL reports, along with new ones as programs enter the SCALE (Scaling Climate Action by Lowering Emissions) pipeline.

Box 4. Proposed online reporting hub

The proposed reporting hub works as a centralized system and repository, where relevant reports can be initiated, saved, and revised, then progressed to the validation phase where they can be further modified, verified, tracked, and finally issued. As new reporting phases are initiated, information from previous reports can be incorporated, reducing the transaction costs associated with currently used word processing–based approaches. The interface, shown below, can be accessed and explored at https://xd.adobe.com/view/af9dcb8e-1d9a-475e-916e-1ff83e1fd862-face/





A fundamental aspect of reporting and verification processes is transparency. By connecting the formulae in the reports with their associated source data and codes, the interface allows calculations of estimates to be completely reconstructed by third party auditors. This continuity extends all the way to input data collected in the field or assessed via remote sensing and includes access to processing codes and data repositories.

One of the biggest hurdles in the MRV process is the iterative nature of interactions between the reporting and standard management teams on the one hand, and the reporting and validation and verification teams on the other. These communications are usually transferred as (clean and tracked) word-processing documents via email, which are logged with the corresponding answers attached. This cumbersome process generates a significant volume of email messages and report versions, along with substantial confusion and potential for error.

In contrast, the proposed online reporting hub provides a practical, secure, easy-to-use solution that would expedite the process while preserving the tracked versions of reports, the responses to queries, and the opening and closing of findings.

Source: Devised by authors.

IV. CONCLUSION

Lessons Learned

Combining innovative technologies—including remote sensing, geostatistics, artificial intelligence, and cloud computing—to build a next-generation of MRV will certainly accelerate the process of accessing climate finance and make it easier for governments and stakeholders to monitor their forests and the implementation of related environmental policies. Realizing this endeavor will take time, however, and is subject to numerous caveats, discussed below.

Using terrestrial laser scanning. The collection of digital volumetric data via terrestrial laser scanning will improve the accuracy of biomass estimates at tree and plot levels. Nevertheless, data collection and databases are still under construction, and the methods of analysis have yet to mature. Use of terrestrial laser scanning as a field method or to enhance allometric equations is a medium- to long-term endeavor, so data collection will not necessarily be faster than with traditional national forest inventory methods. Consequently, it is not possible to use this approach to inform current bank programmatic work under FCPF and ISFL.

Directly estimating biomass using maps. It is not yet possible to incorporate direct estimates of biomass into FCPF's and ISFL's MRV processes. The datasets used for extrapolation from ground data to larger areas introduce bias in the models, and currently available optical and SAR dataset signals saturate in high biomass areas. New satellites expected to help in overcoming this issue are anticipated to become available soon, including satellites with P-band SAR, which is more successful in penetrating tree canopies. ESA Biomass and NASA-ISRO (NISAR) missions[25] are expected to help with these limitations, and commercial alternatives such as TandemX[26] are being explored by the World Bank in collaboration with University of Maryland and NASA.

Using airborne LiDAR data. Although Airborne LiDAR data, which is needed to upscale field-based plot data to satellite data, greatly reduces uncertainties stemming from extrapolation. It has not yet proved to be as necessary for MRV systems, however, based on recent findings of complementarities between plot data from national forest inventories and readily available global tree height and biomass products.

Producing regional biomass estimates. How to produce regional biomass estimates, including estimates of uncertainty, remains unclear, which can affect the auditing process. GFOI is working on elaborating good practice guidance informed by recent publications. The use of CALM to deploy MRV technologies is advised, however.

Using digital data interfaces. Digital data interfaces that satisfy measurement needs can be constructed, but it will be necessary to comply with relevant additional standards.

Using digital reporting interfaces. Digital reporting interfaces have the potential to ease and expedite reporting and auditing processes irrespective of such variables as weather, human resource and institutional capacities, the need for transparency, and alignment with existing in country systems.

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[25] https://www.esa.int/applications/observing_the_earth/futureeo/biomass

[26] https://tandemx-science.dlr.de/

Falling costs of airborne data. The assumption that new satellites and the falling costs of airborne data (especially from drones) will result in unprecedented data availability to support biomass estimation remains unproven. As reported by Málaga Durán (2024), however, global datasets calibrated to regional estimates using national forest inventory plot data are readily available and should be explored.

Increased data availability. While the availability of datasets used to upscale biomass estimates to regional levels enables biomass patterns to be monitored more frequently, countries are already generating deforestation and forest degradation layers that can be linked to biomass estimates produced by other means (for example, maps used for stratification approaches). However, detecting patterns in biomass differs significantly from actually measuring and quantifying levels, particularly under reporting standards. For the most part, current reporting frameworks require biannual reporting at best, which eliminates the need to further increase frequency. In contrast, using remote sensing approaches for early warning systems to inform design and policy implementation are becoming standard in most forested countries given the higher availability of daily remote sensing data.

Standardizing estimations of carbon stocks. The goal of standardizing carbon stock estimations to make data from different sources compatible and easy to integrate and to more accurately quantify uncertainties as yet remains unattainable. The ASA study proved that there are many ways to estimate biomass, even when similar input datasets are used. In the end, to facilitate data comparability and interoperability what is needed is transparency, in terms of their characteristics and how they were obtained. The idea of standardized estimates is based on an ideal reference estimate, but the development of novel approaches makes the existence of a reference standard estimate a utopian ideal rather than a reality. Rather than standardizing the estimates, what needs to be standardized is the proposed use of the estimates, informed by their associated characteristics. The criteria used should be both quantitative and context specific. For example, the average biomass estimates for a mono-specific plantation in which all trees are the same age will be much more accurate than that of a tropical rainforest with over 400 species per hectare. Quantitatively speaking, of the two types of estimates, the plantation estimate will be superior because it will be more accurate; qualitatively speaking, however, the rainforest estimates are the more desirable of the two types. In this case, such context could inform the rapport between the estimates and the MRV framework in terms of how uncertainty is interpreted. Standardization is neither possible, nor necessary given the diversity of countries and forests.

Reducing the time needed to generate estimates. Sound data infrastructure linked to a reporting framework can render the reporting and verification stages of the MRV process considerably faster and more efficient because MRV systems can become operational within months rather than years, and the time lag between the end of a monitoring period and the availability of data is much shorter. This premise was supported by the evidence collected under the ASA study.

In summary, the ASA study highlighted the importance of carefully considering the use of new technologies. The study emphasized the need for methods and equipment that are novel, yet well established as a means of minimizing unforeseen circumstances. Making use of the latest technologies across all aspects of the MRV process would increase the risk of failure and, rather than solving existing challenges, increase the likelihood of generating new challenges.

Recommendations

The simplest opportunity for expediting MRV processes in REDD+ programs is the incorporation of technologies to expedite reporting, validation, and verification. Country teams, supporting agencies, standard managers, and validation and verifications bodies all agreed on this point. Off-the-shelf digital technologies are readily available to enhance measurement procedures. Their implementation needs to be country-specific and ensure complementarities with existing systems. The long-term sustainability of proposed approaches and their integration into national systems are essential. Coherence with existing national forest monitoring systems is another necessary component because new systems cannot disrupt or displace institutional, political, legal, and technical arrangements. Country measurement systems are multipurpose and inform multiple forest-related aspects, including their management and derived assets and benefits.

Use of novel technologies can accelerate the measurement process but result in additional requirements to achieve reasonable levels of assurance of lack of bias in the estimates and systems. Additional standards may need to be applied to the systems themselves. Use of methods under development in official MRV processes should be phased out or delayed until an assessment of their development and use has been completed. The need for a well-thought-out process for the incorporation of new approaches is clear and includes capacity building for producers, users, and assessors of estimates. Knowing the limitations of methods is also relevant, particularly in terms of transparency, consistency (particularly when considering a reference period), replicability, and overall the lack of bias—all of which need to be capable of being assessed. It is advised that CALM is used as a guidance tool.

Biomass mapping has been on the table for more than a decade. Its intended use has ranged from enhancing understanding of biomass distribution to informing estimates of emissions factors, to direct estimations of change. However, consensus remains lacking on how uncertainties should be estimated and incorporated into emissions estimates. To date there is no guidance on how to make use of maps for carbon accounting. This is exacerbated by an abundance of new maps constructed using different data inputs and methods, which creates a need for clarity in the selection of maps. Based on this, the Global Forest Observations Initiative is developing a process for delivering guidance on how to make use of maps correctly.

As demand for carbon credits increases, the offer of high integrity emissions reductions becomes more relevant; however, recent events have illustrated how challenging the delivery of such emission reductions actually is. REDD+ programs, such as those under the FCPF and ISFL, have made significant efforts to deliver their verified emission reductions, but the process is time-consuming. This ASA study found alternative pathways for the World Bank to explore in efforts to accelerate the MRV process. These pathways diverge from the commonly held belief that efficiency and timeliness could be achieved through automated monitoring and measuring systems supported by artificial intelligence.

Facilitating the validation and verification process of REDD+ programs can be achieved by means of digital architecture. The change in scope demonstrated the interoperability of data flows and management, beginning with both the template used to present reports to auditors and their interactions with it. This approach was well-received by report producers and auditors, as well as by team members. The kind of communications hub described in this report would dramatically lower the time and cost burden to reporting and verification processes while simultaneously increasing efficiency and transparency. ASA participants recommended that a pilot study be undertaken.

For the World Bank, it is recommended that a policy, informed by the CALM framework, be developed for assessing and incorporating technology and enabling its meaningful and impactful use. This could involve a two-pronged approach:

1. Enabling exploration exercises such as those combining the acquisition of terrestrial laser scanning data and tree- and plot-level estimations of biomass

2. Elaborating the path toward sound assimilation of novel technologies into the MRV process

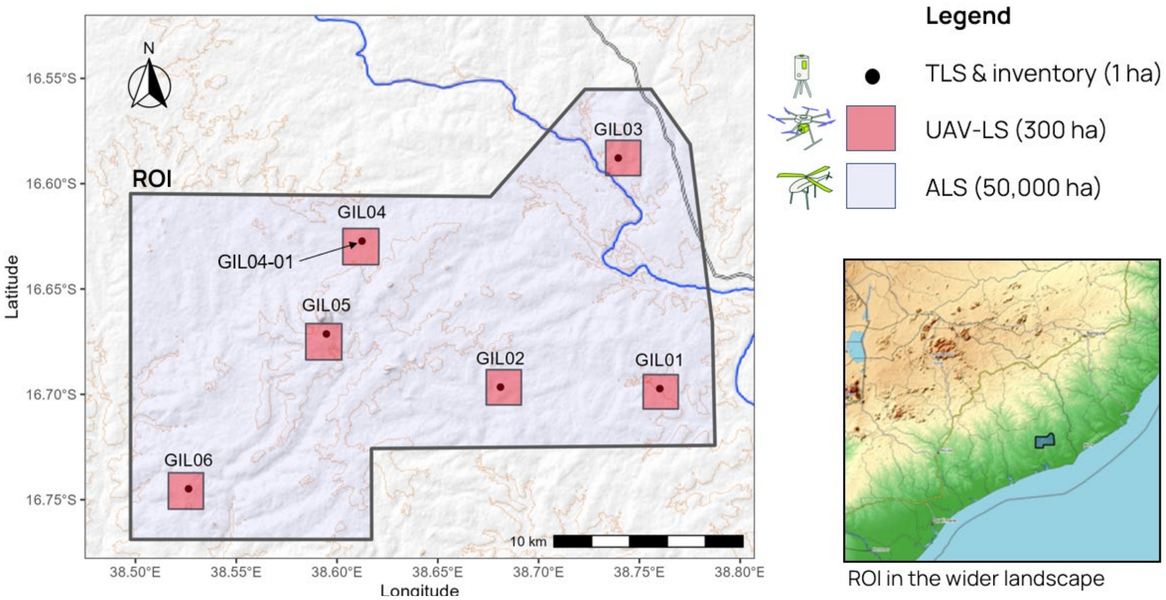
These approaches should optimize resource use while shielding countries from potential failures arising during the exploration phase and avoiding contributing to unrealistic expectations (as illustrated by the hype cycle).[27] It is therefore recommended that clients be supported in incorporating new digital data technologies, tools, or components that are readily available and can complement the systems already in use.

[27] https://www.gartner.com/en/research/methodologies/gartner-hype-cycle

Appendix A. High-Quality Field Data Collection Exercise

A high-quality field data collection exercise was carried out over the 50,000-hectare region of interest inside the Gilé National Reserve and buffer zone in Mozambique's ERP under FCPF's results-based payments portfolio (Map A1).

Map A1. Location of high-quality field data collection exercise



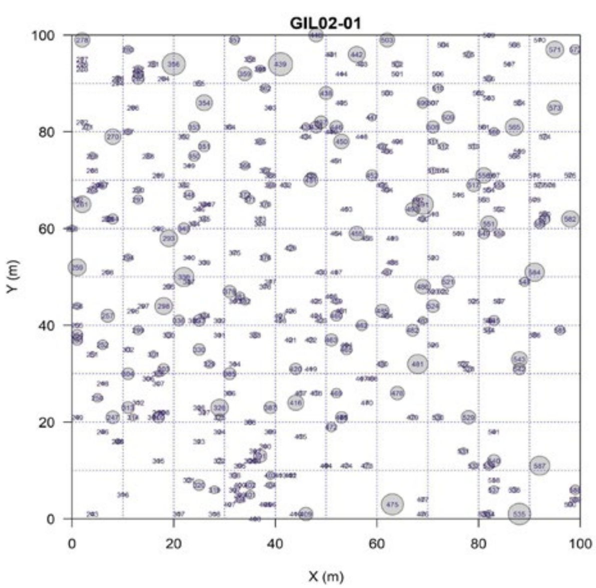
Notes: Aerial laser scanning (ALS) data were acquired across the entire region; slow-flying unmanned aerial vehicle laser scanning (UAV-LS) data were acquired across six 300-ha sections (GIL01 to GIL06); and terrestrial laser scanning (TLS) data were collected in six one-hectare plots (GIL01-01 to GIL06-01) within these sections.

Acquisition and Processing of Terrestrial Laser Scanning Data

TLS data were collected from each of the established six one-ha forest plots, specifically selected for their representativeness of the forests in the area, using a RIEGL VZ-400i scanner [28] (Figure A1). The six plots were established using RAINFOR-defined protocols in accordance with the Committee on Earth Observation Satellites above-ground woody biomass product validation good practices protocol (Duncanson et al. 2021). For each one-hectare (planimetric) plot the principal axes were aligned north and east for the x and y axes, respectively, and demarcated using a galvanized pole.

Photo A1. Terrestrial laser scanning data collection in GIL01-01

Figure A1. Example of a plot stem map



Notes: This example is for GIL02-01. Each tree stem is represented by a circle scaled by tree stem diameter at breast height, overlaid with each unique tree identifier or "tree tag."

[28] http://www.riegl.com/nc/products/terrestrial-scanning/produktdetail/product/scanner/48/

For each tree inside these plots with a stem diameter greater than or equal to 10 centimeters the following data were collected:

1. Stem diameter via a circumference/diameter tape

2. Point of measurement of the stem diameter—either 1.3 meters (m) above the ground or 0.5m above the buttress

3. Taxonomic identity, as determined by the botanist

4. Coordinates within the subplot (that is, x–y as described above)

5. Relevant RAINFOR–defined fieldwork database codes and notes

An estimate of basic wood density was assigned to each tree via taxonomic identity and the mean value of entries available in the Global Wood Density Database (Zanne et al. 2009). Attribution was determined, in order of priority, at the species, genus, or plot level (84.4, 14.2, and 1.4 percent for the 1,406 individual trees, respectively). Finally, taxonomic identity was cross-checked using the Taxonomic Name Resolution Service,[29] and typographical errors were corrected.

Results of Terrestrial Laser Scanning

The TLS point clouds collected provide a complete representation of the external 3D structure of each tree within the six one-ha plots (Figure A2). Each laser point was labeled as wood, leaf, coarse woody debris, or terrain using a Sylvera-developed PointNet++ model based on methods described by Krisanski et al. (2021). This deep learning model (Qi et al. 2017) assigns class probabilities for individual points based on various features within the given point cloud (Figure A3, panel a). Next, woody points were categorized using a Sylvera-developed graph-based approach, which clusters and assigns them to a particular tree (Figure A3, panel b). The inventory data were used to assess the quality of the point cloud segmentation (noting that the same number of trees and their location had to be recorded in both datasets). Any discrepancies—such as in the number of trees recorded using national forest inventory methods and estimated from the terrestrial laser scanning data—were reassessed and resolved, highlighting the need for curatorial work after the data are processed. A quantitative structural model (QSM) was then built for each tree to include volume estimates combined with the inventory data (Figure A3, panel c). This identified the species and allocated wood density, which assisted in estimating biomass at the individual tree level.

[29] https://tnrs.biendata.org/

Figure A2. Example of a terrestrial laser scanning point cloud

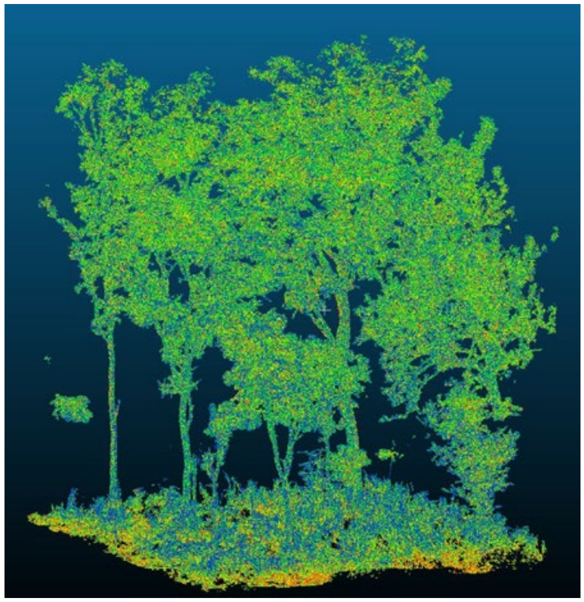
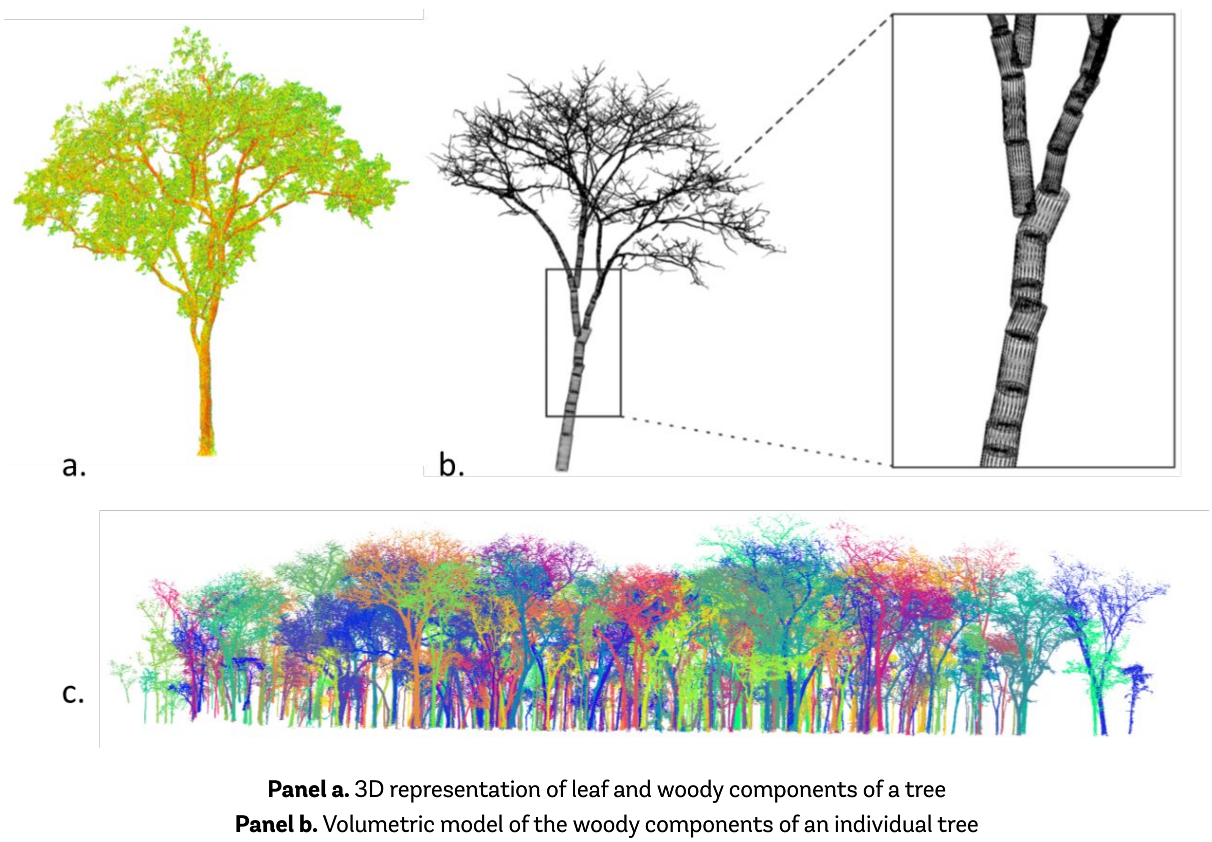
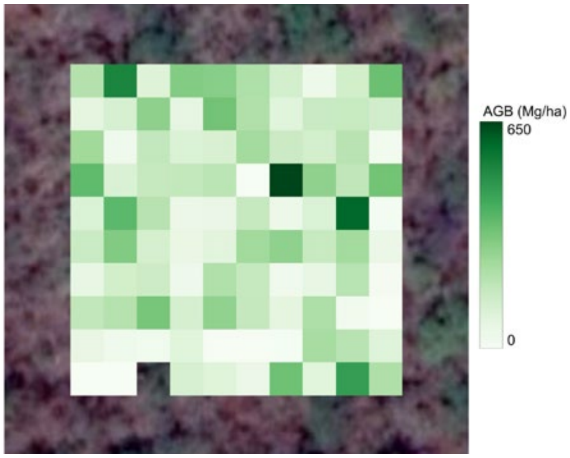


Figure A3. Steps in constructing the external 3D representation of each tree



Panel a. 3D representation of leaf and woody components of a tree
Panel b. Volumetric model of the woody components of an individual tree
Panel c. Sample transect of trees within one of the six one-ha plots surveyed

Map A2. Above-ground biomass map overlaid on satellite imagery



QSM cylinders of each tree within each cell were used to create above-ground biomass maps derived from TLS at a 10m resolution (Map A2). To convert the QSM–derived maps of woody volume into above-ground biomass, cylinders were assigned a basic woody tissue density (dry mass divided by green volume) based on the taxonomic identity of the tree in question. Unidentified tree cylinders with stems located outside the plot but with branches encroaching into the plot were assigned a plot-level basal-area-weighted average wood density. Trees identified as dead in the inventory data were excluded from the estimates (Table A1).

Note: This example is for GIL02-01.

Above-ground biomass at 568 pixels (a 10m resolution) across the six one-ha plots (GIL01-01 to GIL06-01)—equivalent to 5.68 ha—equaled 458.6 MT, resulting in an average density of 80.7 MT/ha. The range was as low as 1.01 MT/ha in GIL03-01 to as high as 165.3 MT/ha in GIL02-01. Relative plot-level uncertainty in above-ground biomass density (at a 90 percent confidence interval) was less than 15 percent of the estimate itself. The key exception was GIL03-01, where the relative uncertainty of the estimate was172.5 percent because the density was exceptionally low (1.01 MT/ha). The uncertainty in the aggregate total density over all six plots was 6.1percent (4.9 MT/ha).

Table A1. Above-ground biomass estimates derived through terrestrial laser scanning, including density and uncertainty levels

	Above-ground biomass derived through terrestrial laser scanning			Number of pixels (10m resolution)	
Plot	Total (MT)	Density (MT/ha)	Uncertainty (MT/ha)	Total	Nonzero
GIL01-01	47.7	56.1	7.9 (14.0%)	85	85
GIL02-01	163.6	165.3	17.6 (10.6%)	99	99
GIL03-01	1.19	1.01	1.8 (172.5%)	118	17
GIL04-01	57.6	56.5	9.7 (17.1%)	102	90
GIL05-01	80.2	94.4	13.3 (14.0%)	85	84
GIL06-01	108.3	137.1	18.4 (13.4%)	79	79
Aggregated total	458.6	80.7	4.9 (6.1%)	568	454

Notes: Estimates reflect a 90 percent confidence interval. Zero pixels indicate that no above-ground biomass was observed within that pixel. MT = metric tons; ha =hectare; m = meter.

Comparing Above-Ground Tree-Scale Estimates Using LiDAR and Allometric Methods

To assess the level of improvement in the estimates, above-ground tree-level biomass estimates were derived using allometric equations for the 1,226 living trees inventoried across the six plots. Two commonly used allometric equations were considered for this analysis (Table A2): (1) the widely used pantropical allometric equation described in Chave et al. (2014) and (2) an allometric model described in Mugasha et al. (2013), which is specific to the Miombo woodland used by the Mozambique government to undertake their national forest inventory and is relevant to Gilé National Reserve within the context of the Zambezia Integrated Landscape Management Program.

Table A2. Allometric equations used to assess the accuracy of the estimates of above-ground biomass

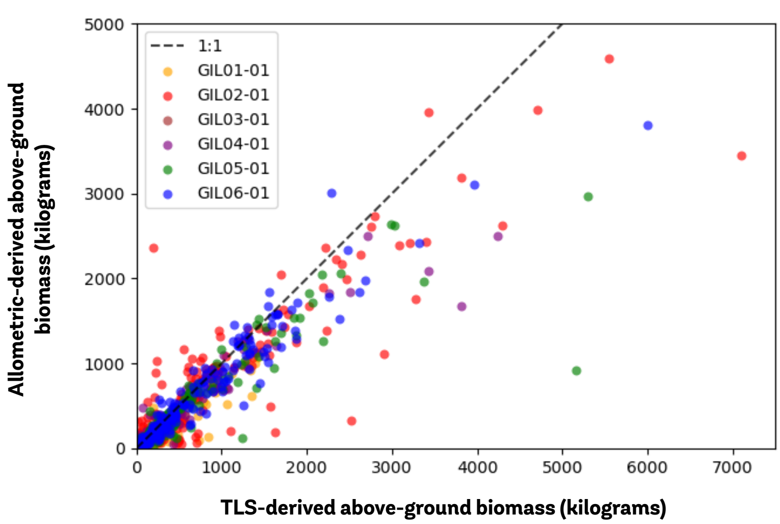
Equation 1	Equation 2
Chave et al. (2014)	Mugasha et al. (2013)
$AGB=0.0673(D^2 H_\rho)^{0.976}$	$AGB=0.0763(D^{2.2046} H)^{0.4918}$

Notes: AGB = above-ground biomass; D = tree diameter at breast height; and H = tree height.

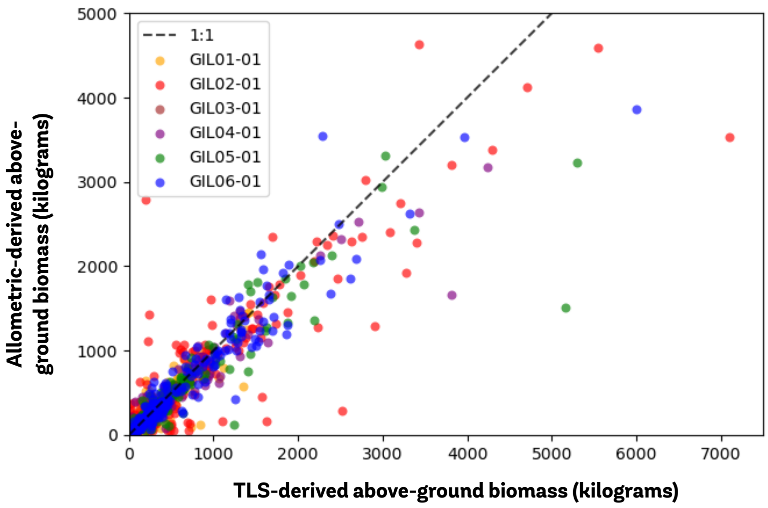
Compared with above-ground biomass derived from TLS, which totaled 538.8 MT for the 1,226 living trees, the allometric-derived totals were 452.4 MT using the Chave et al. (2014) equation and 496.0 MT using the Mugasha et al. (2013) equation (Figure A4). This represents a 17.4 and 8.3 percent difference for the two methodologies, respectively, indicating that the allometric estimates were systematically smaller than the respective TLS estimates. Note that these results were further elaborated and peer-reviewed in Demol et al. (2024).

Figure A4. Comparison of TLS– and allometric-derived estimates of above-ground biomass for the 1,226 living trees across GIL01-01 to GIL06-01

Panel a. Results derived using the pantropical allometric model (Chave et al. 2014)



Panel b. Results derived using the Miombo woodland-specific allometric model (Mugasha et al. 2013)

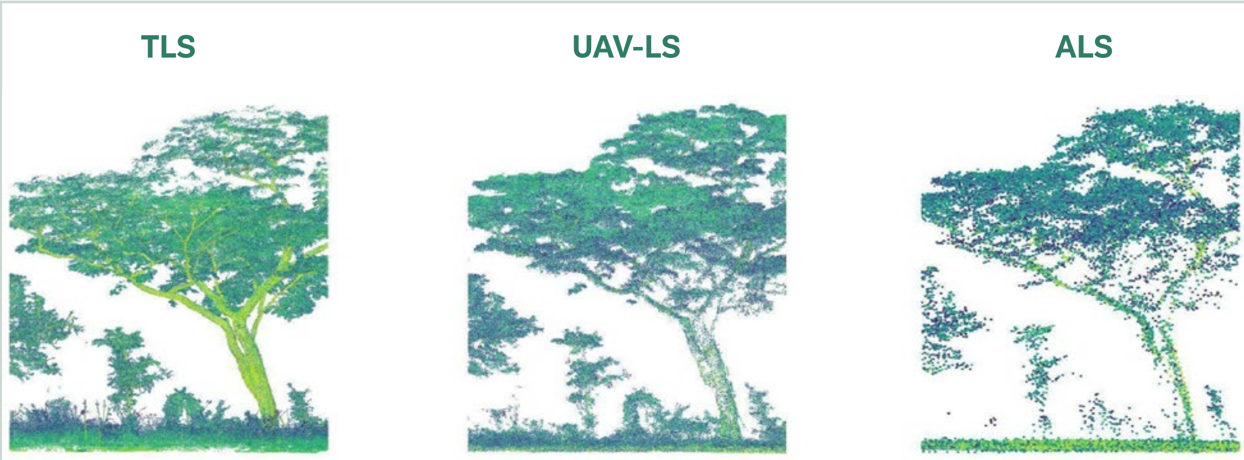


Notes: For large trees—which contribute the most biomass to each plot (some up to 7,000 kg)—allometric estimates systematically underestimate biomass. For this reason, the scale for estimates derived through terrestrial laser scanning (the x axis) is larger than the scale for the allometric estimates (y axis).

Airborne Laser Scanning

ALS, including UAV, delivered complementary data to establish correlations from which plot-level above-ground biomass estimates could be extrapolated (Figure A5). The ALS and UAV-LS datasets were used to derive a suite of metrics describing the structure of the forest using Sylvera-developed software capable of processing large-scale, high-density point clouds (Table A3). Examples of these variables for one of the 300-ha sections (Map A1, GIL02) for which UAV-LS data were collected for the entire region of interest are presented in Map A3.

Figure A5. Point clouds from terrestrial laser scanning and airborne laser scanning



Panel a. Terrestrial laser scanning (TLS) | **Panel b. Slow-flying unmanned aerial vehicle laser scanning (UAV-LS)** | **Panel c. Fast-flying aerial laser scanning (ALS)**

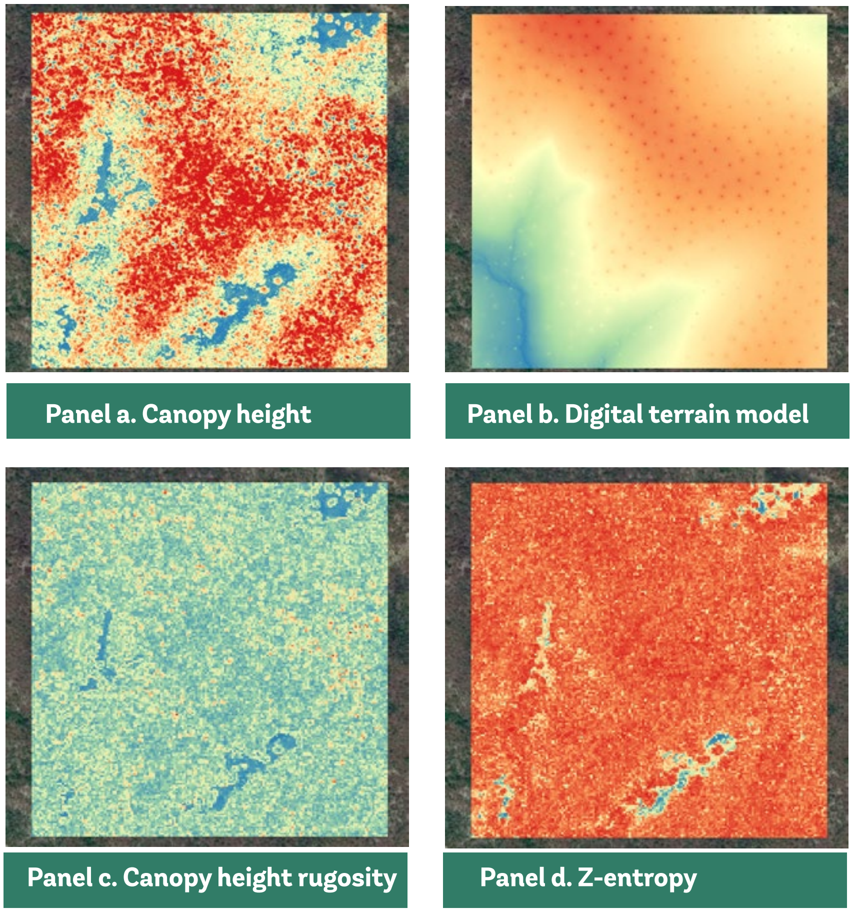
Notes: The figure depicts multiscale LiDAR point clouds for a 10 square meter section of forest within a one-hectare plot (GIL01-01).

Table A3. Unmanned aerial vehicle and aerial laser metrics describing forest structure

Metric	Resolution (m)
Canopy height map	1
Digital terrain model	1
Relative height	10
Tree fractional cover	10
Canopy height rugosity	10
Fixed gap fraction	10
Variable gap fraction	10
Canopy closure	10
Canopy ratio	10
Z-entropy	10

Note: Rugosity is the presence of a rough, ridged, or wrinkled surface.

Map A3. A selection of metrics derived from the unmanned aerial vehicle laser scanning data collected across GIL02



Notes: Results are scaled from low (blue) to high (red). Rugosity indicates a rough, ridged, or wrinkled surface. Note, also, the regular presence of termite mounds in Panel b.

Biomass Cloud Computing

Biomass cloud computing was implemented at a local scale through the expertise of the three major collaborators. Sylvera collected data in the field and elaborated the biomass mapping algorithm to that scale, while the European Space Agency's Global Development Assistance (GDA) program—which seeks to mainstream the use of Earth observation into development operations—targeted Agile Earth Observation Information Development applied to priority sectors. Through its GDA program, ESA brokered the participation of GeoVille, a satellite-based information solutions company that delivers end-to-end plug-in satellite information services for major market sectors. GeoVille helped in developing the algorithms used to extrapolate local biomass estimates for Mozambique's ERP area. Above-ground biomass modeling involved a two-stage process. The first stage involved using acquired ALS data to model biomass estimates for the 50,000-ha region of interest. The second stage used those results, with the addition of readily available remote sensing data, as input parameters to model biomass for the entire Zambezia ERP area.

The first stage involved mapping each of the 300-ha sections in the 50,000-ha region of interest. The biomass estimates were generated from the UAV-LS- and ALS-derived machine learning models, which were optimized using spatial cross-validation. The models were programmed to treat above-ground biomass as the dependent variable, and the metrics of forest structure (shown in Table A3) as input parameters. For this, a gradient boosting approach was implemented using Sylvera-developed software.[30] Issues resulting from spatial autocorrelation were controlled, which is a key issue when using biomass maps as the basis for estimating average regional biomass.

Upscaling the Biomass Estimates

Upscaling the Biomass Estimates to the Section Level

For the process of upscaling the biomass estimations, the estimates generated from the TLS data (Figure A6) and corresponding UAV-LS metric (Table A3) were recalculated to match 1m spatial resolutions. Then correlations between the above-ground biomass values and the corresponding UAV-LS metrics were assessed to ensure spatial independence between the training and validation data, thus reducing the risk of producing overly optimistic validation statistics. Modeled estimates for each of the 300-ha UAV-LS sections were generated, along with uncertainty estimates.

Plot-level UAV-LS biomass modeling resulted in performance statistics derived from the mean of the validation folds of root mean square error (RMSE), median symmetric accuracy, and signed symmetric percentage bias of 59.6 MT/ha, 48.9 percent, and 4.6 percent, respectively (Table A4). The Pearson correlation coefficient (r) between coincident TLS-derived above-ground biomass and the UAV-LS-derived canopy height was 0.59, which was the most important predictor of variable weight. The TLS to UAV model showed significant variance but low bias (Figure A6).

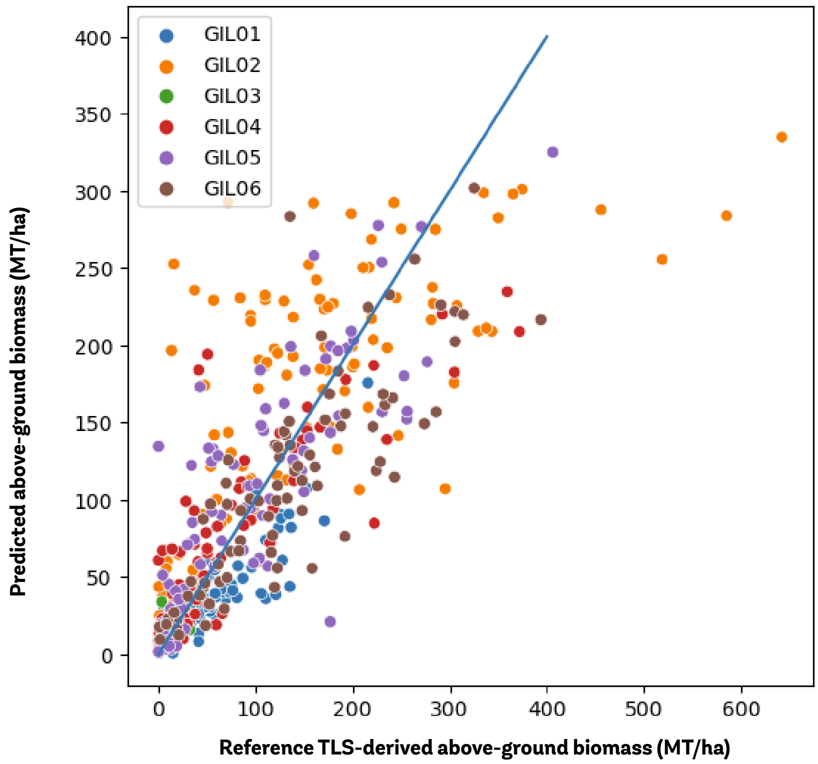
[30] Gradient boosting has been shown to be fast and robust in avoiding over- and underestimation (Li et al. 2020), as well as over- and underfitting (Pham et al. 2020).

Table A4. Statistics from the final tuned model

Cross-validation metrics	Results (mean values)
Number of features	44
Root mean square error (MT/ha)	59.6
Explained variance (%)	64.0
Median symmetric accuracy (%)	48.9
Symmetric signed percentage bias (%)	4.6
Total bias (%)	–2.2

Notes: Results shown are mean values from the spatial cross-validation of the models across all six plots shown in Map A1. MT = metric tons; ha = hectares.

Figure A6. Spatial cross-validation of predicted above-ground biomass vs reference terrestrial laser scanning estimates



Notes: The blue line represents the "identity line" (1:1 proportion). MT = metric tons; ha = hectares.

The UAV-LS-derived products cover 209,050 pixels (10m resolution) across the six sections (GIL01 to GIL06) and are equivalent to 2,090.5 ha. Total above-ground biomass estimates for the sections ranged from 6,500 MT in GIL03 to 38,989 MT in GIL02, and totaled 146,443 MT (Table A5). Corresponding above-ground biomass densities ranged from 19.3 MT/ha to 113.9 MT/ha, with an average of 70.1 MT/ha. Uncertainty for the aggregated above-ground biomass density, at a 90 percent confidence interval, was 3.2 MT/ha (4.6 percent). Section-level uncertainty ranged from 7.0 MT/ha for GIL05 (8.2 percent) to 4.5 MT/ha for GIL03 (23.3 percent). Uncertainty at the pixel-level was higher, averaging 133.7 percent, and was typically higher for pixels with lower biomass estimates.

Table A5. Above-ground biomass estimates from unmanned aerial vehicle laser scanning, including density and uncertainty

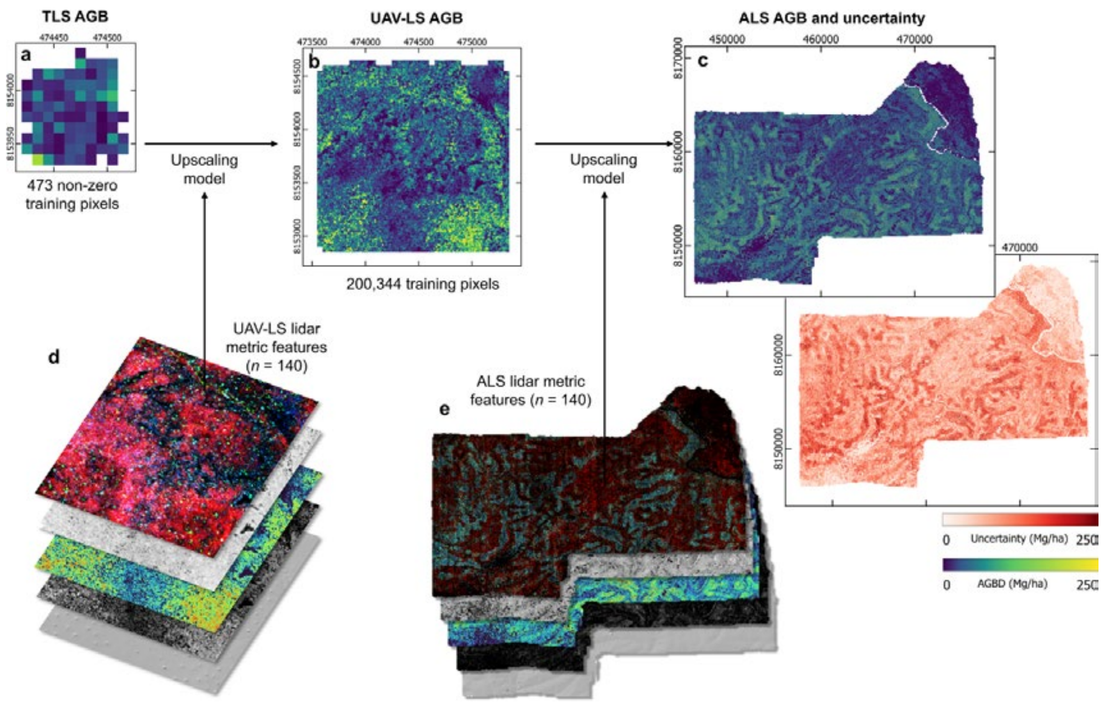
300-ha sections	Above-ground biomass estimates from unmanned aerial vehicle laser scanning			Number of pixels (10m)	
	Total (MT)	Density (MT/ha)	Uncertainty (MT/ha)	Total	Nonzero
GIL01	27,690.4	83.2	10.1 (12.1%)	33,300	33,300
GIL02	38,989.2	113.9	11.2 (9.9%)	34,225	34,223
GIL03	6,587.2	19.3	4.5 (23.3%)	34,175	33,923
GIL04	18,976.9	52.6	6.4 (12.2%)	36,100	36,095
GIL05	30,559.7	84.7	7.0 (8.2%)	36,100	36,096
GIL06	23,639.9	67.3	6.7 (9.9%)	35,150	35,098
Aggregated total	146,443.3	70.1	3.2 (4.6%)	209,050	208,735

Notes: Estimates reflect a 90 percent confidence interval. MT = metric tons; ha = hectares.

Upscaling the Biomass Estimates to the Region of Interest and Emission Reductions Program Area

Above-ground biomass for the region of interest was estimated using ALS data following the same process as for the UAV-LS biomass estimates, but in this case the UVA-LS–derived estimates were used as calibration parameters for ALS-derived metrics to extrapolate estimates for the 50,000-ha region of interest. Further upscaling from the UAV-LS to ALS followed the same process, whereby the UAV-LS–derived above-ground biomass was the dependent variable and the ALS–derived metrics of forest structure were the features (Figure A7).

Figure A7. Upscaling above-ground biomass estimates from terrestrial laser scanning to unmanned aerial vehicle laser scanning to aerial laser scanning



Source: de Mol et al. (2024).

Notes: Plot-level above-ground biomass estimates were generated using the terrestrial laser scanning (TLS) data (see Panel a) and were then used as calibration parameters for modeling above-ground biomass using the parameters derived from unmanned aerial vehicle laser scanning (UAV-LS), as presented in Table A1 (see Panel b). Finally, the UAV-LS–derived estimates were used as calibration parameters for modeling above-ground biomass based on metrics derived from aerial laser scanning (ALS) for the 50,000 hectare region of interest (see Panel c).

The final tuned model, upscaled from the UAV-LS to the ALS data, generated performance statistics from the mean of the validation folds of RMSE, median symmetric accuracy, and signed symmetric percentage bias of 26.6 MT/ha, 28.0 percent, and 4.8 percent, respectively (Table A6).

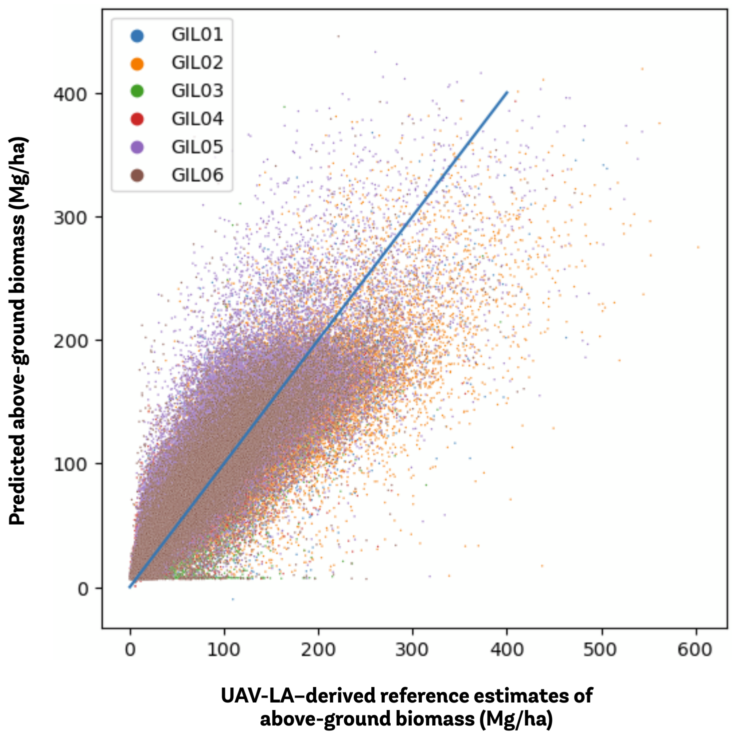
Table A6. Statistics of the final tuned model

Cross-validation metric	Results
Number of features	44
Toot mean square error (MT/ha)	59.6
Explained variance	64.0
Median symmetric	48.9
Symmetric signed	4.6
Total bias (%)	–2.2

Notes: MT = metric tons; ha = hectares.

The cross-validation metrics report an improved performance in upscaling from the UAV-LS to the ALS model compared with results for upscaling from the TLS to the UAV-LS model. Results of upscaling to the ALS model indicated an RMSE of 26.0 MT/ha compared with 59.6 MT/ha for the TLS to UAV-LS model, while the explained variance (Figure A8), increased from 64.0 to 84.6 percent. This is likely the result of the much smaller spatial upscaling factor required in this step, at around 28x (~1,800 to ~50,000 ha) compared with around 300x for the TLS to UAV-LS model (~6 to ~1,800 ha). The median symmetric accuracy and total bias also improved (28.0 and −0.64 percent, respectively, compared with 48.9 and −2.2 percent, noting that smaller values are better for both metrics).

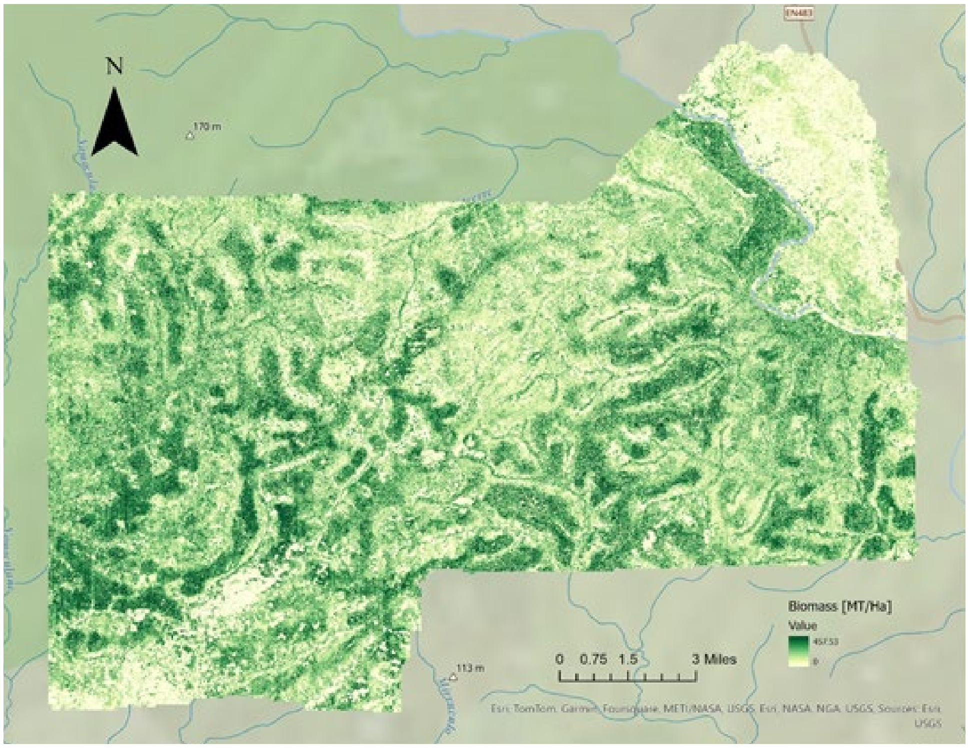
Figure A8. Spatial cross-validation of above-ground biomass predictions derived from aerial laser scanning compared with reference estimates derived from unmanned aerial vehicle laser scanning



Notes: The blue line represents the identity line (1:1 proportion); MT = metric tons; ha = hectares.

ALS-derived products cover 5,007,457 pixels (10m resolution) across the region of interest, equivalent to 50,075 ha (Map A4). Total above-ground biomass is 3,864,953 MT, with an average density of 77.18 MT/ha. Uncertainty for the aggregated density, at a 90 percent confidence interval, is 3.2 MT/ha (4.6 percent) (Table A7, Map A5).

Map A4. Estimated above-ground biomass in the region of interest within Gilé National Reserve, Zambezia, Mozambique



Source: Sylvera.

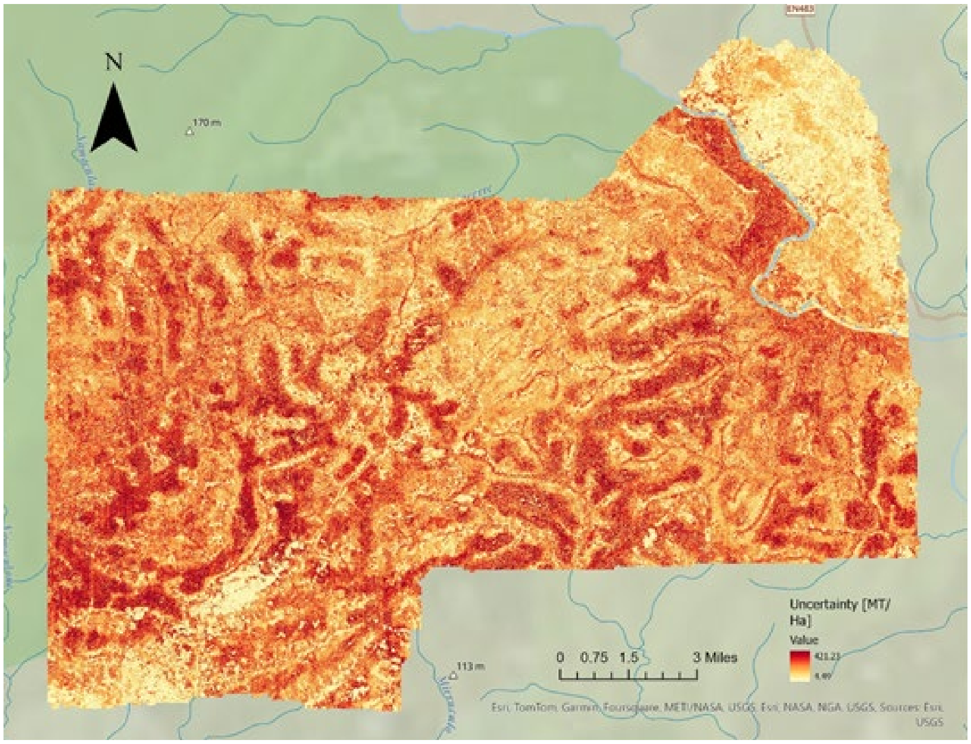
Note: Estimates were determined using Sylvera's multiscale LiDAR methods.

Table A7. Above-ground biomass from aerial laser scanning, including density and uncertainty, for the region of interest

Area/location	Above-ground biomass from aerial laser scanning			Number of pixels (10m)
	Estimated total (MT)	Density (MT/ha)	Uncertainty (MT/ha)	Total
50,000-ha region of interest	3,864,953	77.18	3.2 (4.6%)	5,007,457

Notes: Estimates reflect a 90 percent confidence interval. MT = metric tons; ha = hectares.

Map A5. Uncertainty of above-ground biomass estimates in the region of interest within Gilé National Reserve, Zambezia, Mozambique



Source: Sylvera.

Note: Estimates were determined using Sylvera's multiscale LiDAR methods.

The ASA study assessed the use of state-of-the-art methods for upscaling ALS-derived estimates to the ERP area of the Zambezia region of Mozambique. The goal was to test a combined Earth observation/field measurement approach, which used sufficient highly accurate above-ground biomass estimates from ground observations (ALS data) to train AI-based Earth observation image interpretation algorithms to extrapolate the known above-ground biomass values across the entire ERP area. The model used input data divided into two main groups: (1) in situ above-ground biomass data, including national forest inventory data and (2) remote sensing–based datasets, such as optical and radar imagery (Table A8).

Table A8. Summary of data sources acquired for use with statistical analysis and model development

Sensor/source	Resolution	Timeframe	Metrics/statistics
Sentinel 2	10 and 20 meter bands	January 26, 2018, to December 31, 2018; January 26, 2022, to December 31, 2022	Individual bands (20th percentile) NDVI (90th percentile)
Alos-2 Palsar-2 L-Band[a]	25 meters	January 1, 2018, to December 31, 2018; November 1, 2022, to December 31, 2022	Mean backscatter (VV, VH, HH-VH)
Landsat tree canopy cover (%)[b]	30 meters	2010–2015	Canopy cover (%)
National forest inventory above-ground biomass estimates	20 x 50 meter subplots	2017–2018	Above-ground biomass (MT/ha)

Notes: MT = metric tons; ha = hectares; NDVI = normalized difference vegetation index.

[a] Masanobu and Takahiro (2011).

[b] Sexton et al. (2013).

High-resolution (10–20 meters) Sentinel-2 optical data allows information related to the spectral properties of the above-ground biomass to be retrieved, including all 12 spectral bands—that is, B02/blue, B03/green, B04/red, B05/vegetation red edge 1, B06/vegetation red edge 2, B07/vegetation red edge 3, B08/nir, B8A/narrow nir, B11/swir 1, B12/swir 2—as well as the normalized difference vegetation index (NDVI). Percentiles of the spectral bands (20th percentiles) and the NDVI (90th percentiles) were calculated based on the time-series data.

Data from ALOS PALSAR-2 offering L-band backscatter were used for structural parameters. Compared with C-band radar (that is, Sentinel-1), the L-band SAR signal has a longer wave length, allowing it to more deeply penetrate the canopy and offer additional information about the geometric properties of the vegetation's canopy structure. Individual Level 2.2 ScanSAR 25m resolution scenes were sourced for the January–December 2022 period to gain coverage of the whole region of interest, resulting in 66 separate scenes.

The Landsat Tree Canopy Cover layer, derived from Landsat data, consists of estimates of the percentage of horizontal ground in each 30m pixel covered by woody vegetation greater than 5 meters in height (Sexton et al. 2013).

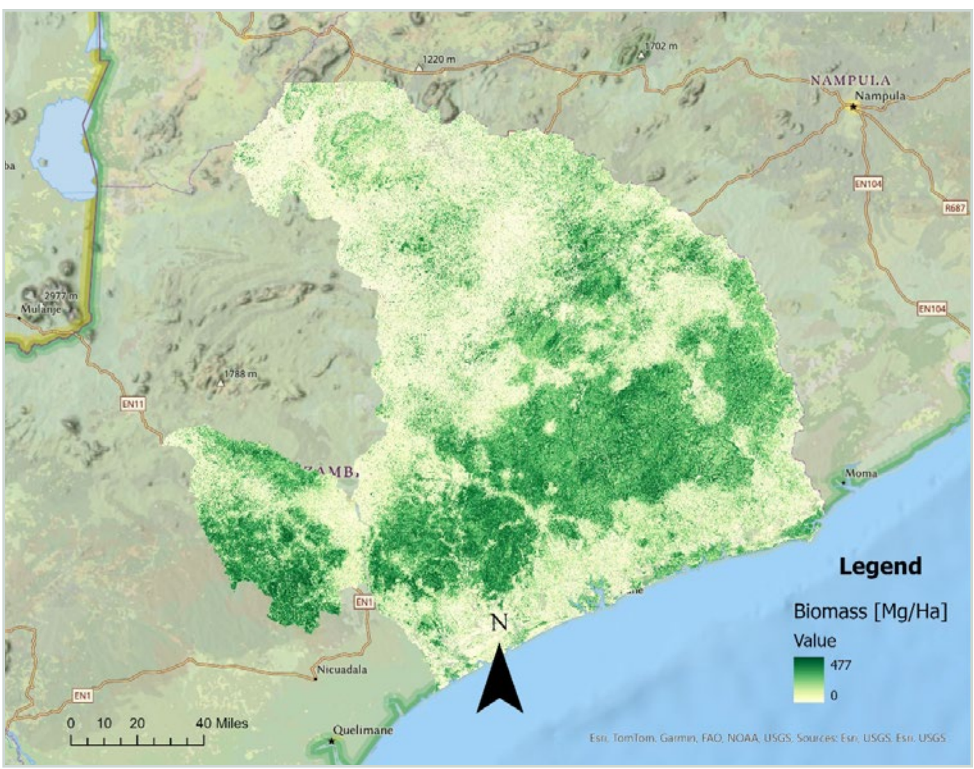
National forest inventory field data were collected over two years (2017 and 2018) on 128 clusters comprising 512 individual plots. Data included cluster and plot IDs, latitude and longitude, collection date, forest type, several structural metrics, and above- and below-ground biomass measurements. Field data sampling plots were spatially recreated using sampling strategy information from Mozambique's 2021 national forest inventory report and the latitude and longitude coordinates from the acquired tabulated national forest inventory data. Earth observation data were extracted at the cluster aggregation level. This method sought to leverage the sampling strategy of the national forest inventory data to account for the variability of the forest stand (Avitabile, Pilli, and Camia 2020). For this method, a one-ha polygon was created to represent the cluster using the individual plot points, where the above-ground biomass estimate assigned was the mean value of the associated plots. Correlations among all variables were tested, and the integration and propagation of error and uncertainties in both the input (Earth observation) data and the target variable (biomass values) were applied using the Monte Carlo simulation approach as recommended by Penman et al. (2003) and Duncanson et al. (2021). Spatial autocorrelation in validation and prediction was assessed using semi-variograms to establish minimum distances.

Two modeling approaches were tested: Random Forest and U-net Image analysis regressor. The final product utilized the U-net results due to their better performance. U-net was developed by Ronneberger, Fischer, and Brox (2015) to tackle the problem of accurate segmentation of biomedical images with high resolution. Modeling outputs were validated splitting the dataset into train and test sets, validating on unseen "ground truth" data. Comparisons were also made with existing global products.

Modeling Results of Upscaling to the Emission Reductions Program Area

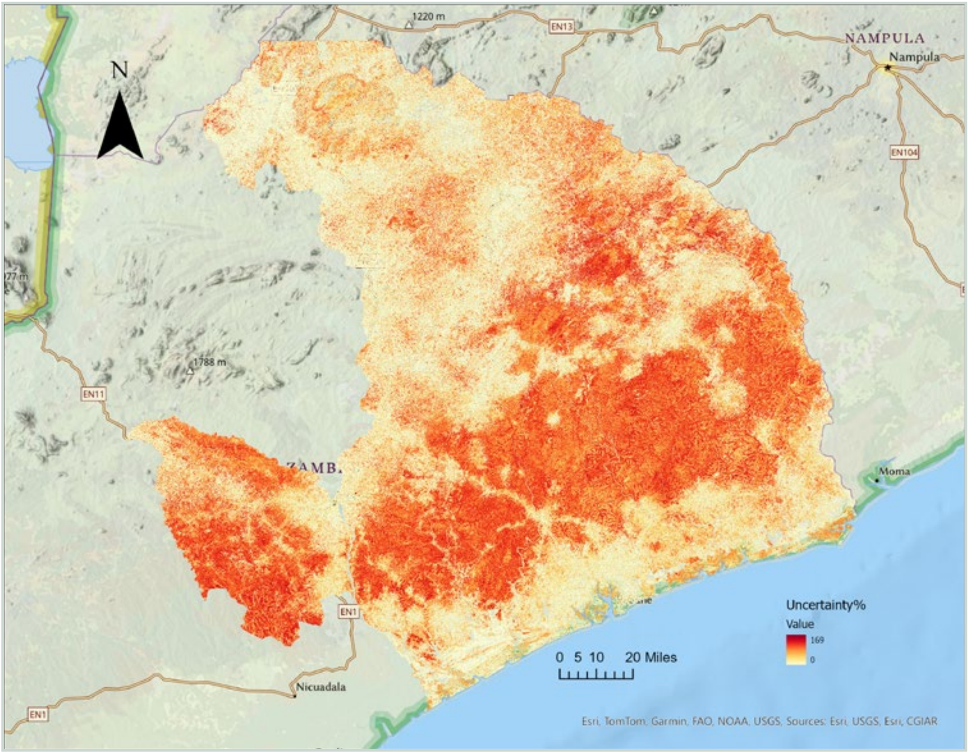
Modeling results indicate the mean above-ground biomass was estimated at a 95 percent confidence interval as 43.37 ± 18.38 MT/ha, ranging from 0 to 413 MT/ha (Map A6 for biomass estimates; Map A7 for uncertainty estimates). The total estimated above-ground biomass for the ERP area is 231.1 million MT. The validation results showed that the U-net modeling approach, using all predictor inputs to estimate the mean above-ground biomass density over the entire ERP area, explained 76 percent of the variance ($r^2 = 0.76$) with an RMSE of 28.98 (MT/ha) and a bias of –5.26 (MT/ha).

Map A6. Estimated above-ground biomass in the emission reductions program area of East Zambezia, Mozambique



Source: Sylvera.

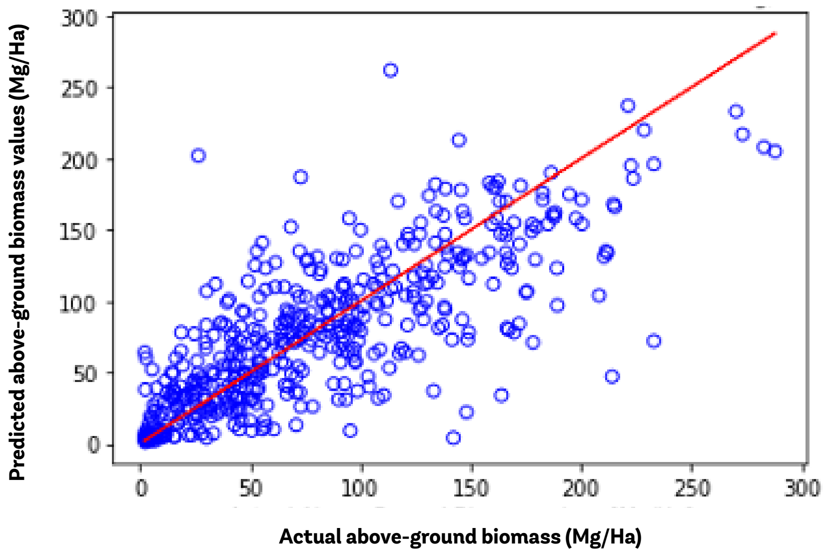
Map A7. Uncertainty of above-ground biomass estimates in the emission reductions program area of Eastern Zambezia, Mozambique



Source: Sylvera.

A statistical comparison of the two modeling outputs (ALS and U-net) for the 50,000-ha region of interest is presented in Figure A9 and Table A9. A comparison of the performance of the ASA model with readily available global biomass data is provided in Table A10. Note that the RMSE results for the ASA model are smaller than results for the global models.

Figure A9. Scatter plot showing agreement of actual vs predicted above-ground biomass values



Notes: MT = metric tons; ha = hectares.

Table A9. Descriptive statistics for modeling outputs derived from pixels within the airborne laser scanning mapping region of interest

Descriptive statistic	Airborne laser scanning	Upscaling to the ERP area	Performance of upscaling to the ERP area
Maximum	457.53	443.00	N/A
Minimum	0.00	1.00	N/A
Mean	77.22	72.22	N/A
Range	457.53	442.00	N/A
Standard deviation	60.13	54.15	N/A
Sum	385,644,885	359,622,444	93.3 percent

Note: ERP = emission reductions program. N/A = not applicable.

Table A10. Performance of ASA model in upscaling biomass estimates to emission reductions program area compared with other global biomass models

Model	Mean (MT/ha)	Minimum (MT/ha)	Maximum (MT/ha)	Total (million MT)	RMSE vs NFI data (MT/ha)
Avitabile 2016[a]	61.34	0	410	271.4	107.6
GlobBiomass[b]	51.17	0	131	280.4	119.5
European Space Agency (ESA) Climate Change Initiative (CCI) Biomass[c]	52.88	0	143	271.5	110.5
ASA model upscaling to emission reductions program area	38.89	0	389	206.8	101.2

Notes: MT = metric tons; ha = hectares; RMSE = root mean square error; NFI = national forest inventory.

a. http://lucid.wur.nl/datasets/high-carbonecosystems.

b. https://climate.esa.int/en/projects/biomass/.

c. https://globbiomass.org/wpcontent/uploads/GB_Maps/Globbiomass_global_dataset.html.

Appendix B. Analysis and Discussion of High-Quality Field Data Collection Exercise

Photo B1. TLS data collection

The use of TLS to collect volumetric data proved to be successful. This included enabling the acquisition of data from large trees not usually covered in the sampling from which allometric equations are developed. This helped deal with uncertainties resulting from extrapolation using equations in cases where a tree's diameter is beyond the scope of the sampling. Because of their more comprehensive representation of tree volume, the results obtained were consistent with the TLS-derived tree-level biomass estimates, which are usually higher than estimates produced with allometric equations. (Similar results have been reported by Sylvera and others for tropical humid forests, boreal forests, and redwoods forests, among others.) This deals with the consistent bias in allometry-based biomass estimates (for example, regarding the estimation of tree height [Terryn et al. 2024]) and should contribute to improving compliance through guidance on good practice and avoiding under- or overestimation. Such successes should, for example, support Mozambique in being able to update their estimates for the same type of forests if additional issues relating to statistical representativeness are dealt with.

Deploying Terrestrial Laser Scanning in the Field

The collection of TLS data was expected to improve the quality of tree- and plot-level data more quickly than traditional national forest inventory methods. It does, however, require optimal weather conditions. First, it needs to be done during the dry season because water in the forest canopy causes the LiDAR beam to bounce in all directions, making data acquisition impossible. Second, windy conditions move tree branches causing TLS to produce multiple targets from a single branch, which makes modeling the tree structure impossible. These aspects can shorten the temporal windows for effective data collection and can result in longer than expected field campaigns and unforeseen costs. In addition, data collection requires access to the TLS sensor (at a cost of more than US$100,000), and personnel need to be trained.[31]

TLS generates large volumes of data, which is challenging for data storage and transfer. The assessment identified a data lake to be the most appropriate solution. Sylvera exchanged the data collected with both the World Bank and the Mozambique MRV team via the Amazon Web Services S3.

[31] Note that the ASA study delivered training to Mozambique's MRV team.

Although data storage and transfer can be solved, TLS data processing is challenging, and it has not been standardized. The science behind the results it delivers for forest biomass measurements is still under development (Arrizza et al. 2024). Using TLS data also requires adequate discrimination of woody vs nonwoody vegetation components, which is a particularly challenging task that requires scientists to develop novel approaches, including radiometric methods that need accurate calibration and geometric methods that—as in the case of this ASA—use size, shape, position, density, roughness, and curvature of point clouds from the 3D coordinates of the points. Machine learning techniques are common, and novel approaches such as neural networks are being tested (Arrizza et al. 2024).

Photo B2. Measuring the diameter of trees at breast height

Notes: One of the biggest issues with traditional methods is that measuring the diameter of trees at breast height is not always a straightforward task. In this case, a large tree needs to be measured above the buttress as the starting point of the beast height, which requires the use of a ladder. This usually results in an underestimation of tree biomass because the stumps are not included in the estimation.

Although software is available with wood-leaf separation tools (for example, CANUPO, TreeQSM, SimpleTree, TLSeparation, LeWoS, FORTLS, and TLS2trees), Sylvera used proprietary software to conduct the data processing. This indicates that data analysis techniques are still evolving and that TLS data sharing would open the door for deep learning–based methods to accelerate classification techniques. Nevertheless, using these methods for reporting under FCPF and ISFL could be problematic because systems and methods need to be audited. A reasonable level of assurance is needed that the models used are not biased, causing estimates to also be biased. In the case of this ASA study, the fact that the TLS estimates were higher than the ones derived through allometry could generate multiple findings and require them to be clarified during an auditing process.

These issues led to assessments of TLS use following CALM protocols (as previously discussed), informed not only by this study's TLS experience but also by the related literature and MRV experiences. GFOI is the leading group in research, capacity building, data, and methods guidance on MRV for forests. CALM draws on the concept of NASA's Application Readiness Levels to develop what is known as "concepts under assessment" (CUA) related to REDD+ MRV. Within that scope it became apparent that, although the results presented in this report demonstrate the great potential of TLS for improving tree- and plot-level biomass estimates—given that processing has yet to be standardized—TLS use by FCPF and ISFL countries is still between what CALM categorizes as levels 3 and 5 (Table B1). This indicates that TLS use remains in the preoperational stage, with some components still in the research and development stage (for example, point cloud data classification per

Sylvera's approach). Given that all FCPF countries have already had their first monitoring reports validated and verified, their biomass estimates have been settled for the remainder of the programs' reporting schedule. It is therefore unlikely that updated and potentially improved TLS estimates would be used.

TLS is currently being acquired by such organizations as Sylvera, with the objective of creating a representative database to contribute to updates by the Intergovernmental Panel on Climate Change of the default values countries use in their greenhouse gas inventories.

Discussions with the Colombian and Mozambique MRV teams regarding difficulties in deploying the technology based on the need to acquire optimal data brought to light another way to use the TLS data. Instead of deriving the biomass estimates directly, it is possible to use volumetric data to recalibrate the allometric equations normally used in national forest inventories to remove biases caused by the sampling carried out during their development. Sylvera is exploring this approach.

Table B1. CALM's scoring criteria for assessing the readiness of technologies for deployment

Phase	Level	Milestones	Examples of supporting information
Research and development	1. Basic research (conception)	• CUA has stated goals for application in REDD+ MRV systems • Prerequisites of CUA detailed	• Literature review • Concept notes available
	2. Application concept (invention)	• High-level outline of CUA formulated and created • Intended key priority aims and scope of CUA identified	• Research proposals submitted or approved
	3. Proof of concept (viability established)	• CUA design is independently reviewed • CUA design is documented in detail • Convincing case made for the viability of CUA	• Publications exist outlining the application being considered and provide analysis to support the concept • Appropriate calibration and validation data are available
	4. General planning in external context (prototype/plan)	• Components of CUA brought together and external interaction issues worked out • Impacts of CUA understood and mitigated	• Experimental data/publications are available for small-scale scenarios
Pre-operational	5. Specific planning in relevant environment (potential determined)	• Impacts and required changes have been reviewed and pros and cons understood • Accepted to proceed to beta testing	• Experimental data/publications for small-scale scenarios are available. • Experimental data/publications available at national/jurisdictional level. • Methods assessed for applicability in REDD+ MRV context.
	6. Demonstration in relevant environment (potential demonstrated)	• Prototype CUA beta-tested in a simulated operational environment • Results reviewed and assessed	• Data/estimates are acquired/made in consistent and sustainable manner for routine national monitoring • Publications outlining the processing workflow and application in REDD+ MRV context available
Operational	7. Adopted in an operational context (functionality demonstrated)	• CUA adopted in operational environment • CUA has demonstrated pre-operational phase level 6	• Active implementation and capacity in country organizations mandated to conduct REDD+ MRV • CUA has been used in the development of estimates submitted in reports to the UNFCCC or other bilateral arrangement/program
	8. Application completed and qualified (functionality proven)	• CUA used in operational environment and results reviewed and shown to operate as expected • Results from CUA qualified and approved • Documentation and training completed	• CUA has been used in the development of estimates submitted in reports to the UNFCCC or other bilateral arrangements/program • Core data are available for routine monitoring
	9. Operational deployment and use (sustained use)	• Sustained use of CUA in operational environment	• CUA has been subjected to technical assessment/technical analysis process of UNFCCC (or equivalent third party validation/verification) process at least once

Notes: CUA = concepts under assessment; MRV = monitoring, reporting, and verification; REDD+ = Reducing Emissions from Deforestation and Forest Degradation; UNFCCC = United Nations Framework Convention on Climate Change.

Data Collection Via Unmanned Aerial Vehicle Laser Scanning and Aerial Laser Scanning

Photo B3. Airborne LiDAR

Airborne LiDAR data processing involves estimating the height of the forest canopy based on both the intensity of and time required for a signal to travel to and from the forest canopy and soil surface. This is now standard procedure, and many FCPF countries have experimented with such datasets. The novel component of this ASA study was using TLS and airborne LiDAR data in combination. TLS-derived estimates of biomass and tree-level canopy height at 10 x 10m pixels were correlated with estimates of canopy height derived from high-density UVA-LS data and low-density ALS data using Sylvera-developed methods (taking issues associated with biomass mapping into consideration). Using this methodology, a biomass map was successfully created for the 50,000-ha region of interest. Putting such maps to use, however, proves problematic. Discussions of how to use data from biomass maps to estimate biomass—such as the average biomass of a certain type of forest combined with deforestation data to estimate resulting emissions—have not yet defined optimal ways to use the maps. GFOI is currently working on guidance for good practice in elaborating those estimates for MRV processes. One area of early consensus is that estimates derived from biomass maps should not be used at the pixel level. This is because, even if such maps are not biased, uncertainties at the pixel level usually calculate to more than 100 percent of the estimate, rendering the associated biomass estimates unreliable and unusable. This is especially the case if the underlying goal is to track biomass changes over time. It also has implications when upscaling estimates produced with remote sensing data, as was the case for the ERP area in Zambezia, Mozambique.

Deploying Unmanned Aerial Vehicle Laser Scanning and Aerial Laser Scanning in the Field

Although it is common to acquire data using airborne LiDAR, the process is difficult. Similar to acquiring data using TLS, conditions need to be perfect, so the window for operation is small. In addition, restrictions limit the deployment of drones. In addition, logistical and national security implications of drone deployment affected this ASA to the point that the campaign to acquire data in Colombia had to be abandoned. Hybrid drones were able to be used based on their greater autonomy and the fact that their dual propulsion systems delivered an additional layer of insurance against accidents, especially while carrying expensive LiDAR equipment. Good quality fuel was fundamental to safe drone operations, but the available fuel was of low quality, necessitating a controlled emergency landing that damaged the LiDAR and delayed the field campaign for several weeks while a new sensor was flown in and a sound understanding of what caused the emergency was achieved. The situation was further exacerbated by the approach of the rainy season.

Photo B4. Hybrid drone used as unmanned aerial vehicle for data acquisition

Note: The LiDAR sensor can be seen underneath the drone.

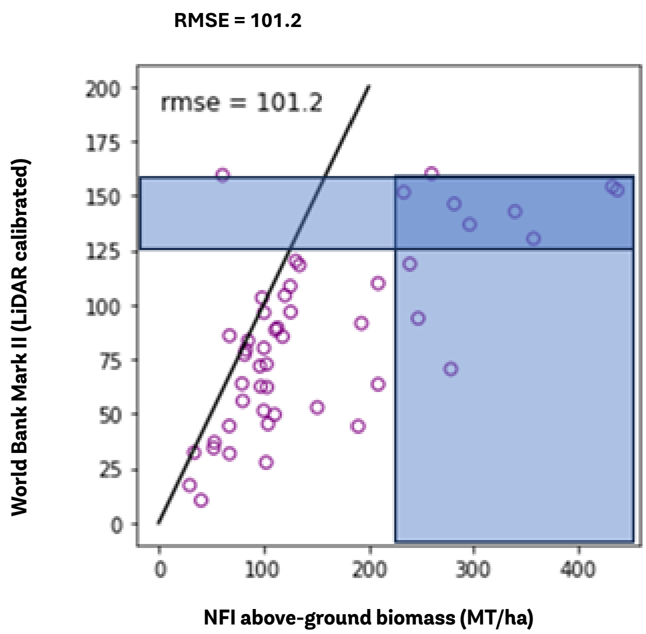
Upscaling Airborne LiDAR Data to the Emission Reductions Program Area

Modeling results showed moderate improvements in performance compared with national forest inventory data and other available biomass datasets. Moreover, it was determined that an essential step in generating model-based biomass estimates is removing model bias using ground data (Málaga Durán 2024).

As is common in biomass maps calibrated for larger areas, estimates for lower biomass areas tend to be overestimated, and those for higher biomass areas tend to be underestimated—likely the effect of signal saturation. The U-net model was chosen because it appears to be less affected by saturation, likely attributable to its ability to account for spatial trends, correlations, and patterns. The U-net results therefore appear to more accurately predict both lower and higher values across the ERP area, and to maintain the textures of the ALS calibration dataset. As in the case of ALS-derived estimates, however, these estimates cannot be used at the pixel level, given substantial levels of uncertainty. Direct use of map-based time-series data to estimate changes in biomass is therefore not advised. Regionally averaged values that account for uncertainties stemming from model propagation, correlation, and autocorrelation are a better option. Additionally, consensus has not yet been reached regarding assessing uncertainties associated with emissions factors sourced from biomass maps.

The fact that the ALS data for both the region of interest and six one-ha plots are nonprobability samples is another source of bias. This means the whole model of inference cannot guarantee lack of bias and therefore requires additional validation checks. Additionally, the methods are not fully transparent for auditing purposes, and the potential for bias renders the estimated values invalid. Since Mozambique is already undergoing verification of its third monitoring report and its fourth and final monitoring period was scheduled for 2023–2024, updating emissions factors is impractical.

Figure B1. Comparing U-net model estimates with national forest inventory estimates for Mozambique's emission reductions program area



Notes: Mapping estimates lose sensitivity when biomass totals more than 200 MT/Ha. MT = metric tons; ha = hectares; RMSE = root mean square error; NFI = national forest inventory.

Apart from issues of bias in input data, the U-net map loses accuracy when estimating biomass at levels higher than 200 MT/ha (Figure B1), bringing into question the value of these mapping efforts, which seem marginal considering the significant investment required to generate the high-quality field data. The overall cost of producing the ALS-derived region of interest biomass estimates was close to US$700,000, half of which was subsidized by Sylvera and the rest covered by the World Bank. Although TLS-derived tree-level estimates delivered excellent results, their lack of representativeness makes their utility beyond allometric improvements questionable. The use of airborne LiDAR is classified by CALM as levels 6 and 7 (Table B1). Operational use occurs on a regular basis, but the use of sample-based biomass estimates has been set aside due to bias in biomass maps. Rethinking their use for extrapolation in ways that limit the risk of bias and additional uncertainties is something to consider.

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