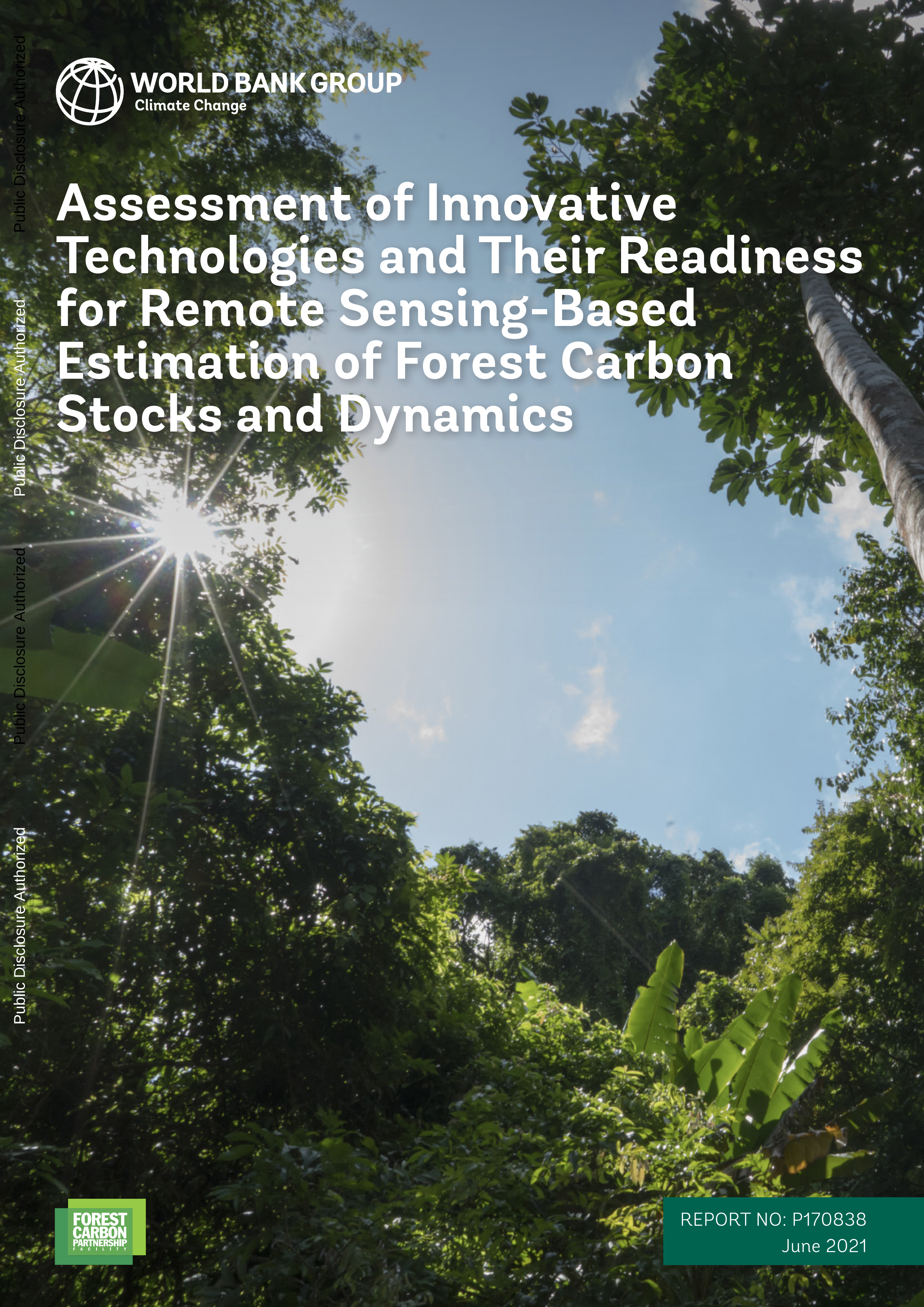

WORLD BANK GROUP
Climate Change

Assessment of Innovative Technologies and Their Readiness for Remote Sensing-Based Estimation of Forest Carbon Stocks and Dynamics

FOREST CARBON PARTNERSHIP FACILITY

REPORT NO: P170838
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WORLD BANK GROUP
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This final report has benefited from the advice of **86 world experts** who provided key inputs during the international consultation workshop organized as part of this project and the collation of this report. The complete list of experts is found in Appendix A.

Acronyms and Abbreviations

AD	activity data
AfriTRON	African Tropical Rainforest Observation Network
AGB	aboveground biomass
AI	artificial intelligence
ALOS	Advanced Land Observing Satellite
ALOS PALSAR	Advanced Land Observing Satellite Phased Array L-band Synthetic Aperture Radar
BGB	belowground biomass
C	carbon
CC	cloud computing
CCI	Climate Change Initiative
CEOS	Committee on Earth Observation Satellites
COP	Conference of Parties
CTFs	Center for Tropical Forest Science
DLR	Deutsches Zentrum für Luft- und Raumfahrt
ECV	essential climate variable
EF	emission factor
ENVI	Environment for Visualizing Images
EO	Earth observation
EPFL	École Polytechnique Fédérale de Lausanne
ER	emissions reduction
ESA	European Space Agency
ESA ROSE-L	European Space Agency Radar Observation System for Europe in L-band
FAO	Food and Agriculture Organization of the United Nations
FCPF	Forest Carbon Partnership Facility
ForestGEO	Forest Global Earth Observatory
FREL	Forest reference emission level
FRL	Forest reference level
GCOS	Global Climate Observing System
GEDI	Global Ecosystem Dynamics Investigation

GEE	Google Earth Engine
GEF	Global Environment Facility
GEO	Group on Earth Observations
GFOI	Global Forest Observations Initiative
GHG	greenhouse gases
GS	geostatistics
ICAO	International Civil Aviation Organization
ICESat	Ice, Clouds, and Land Elevation Satellite
IPCC	Intergovernmental Panel on Climate Change
ISRO	Indian Space Research Organization
JAXA	Japan Aerospace Exploration Agency
LiDAR	Light Detection and Ranging or Laser Imaging Detection and Ranging
M & MRV	monitoring and measurement, reporting, and verification
MAAP	Multi-Mission Algorithm and Analysis Platform
NASA	National Aeronautics and Space Administration
NISAR	NASA-ISRO Synthetic Aperture Radar
NFI	National Forest Inventory
NICFI	Norway's International Climate and Forest Initiative
OBIWAN	Online Biomass Inference using Waveforms and iNventory
PAMs	policies and measures
RAINFOR	Amazon Forest Inventory Network
REDD+	Reducing emissions from deforestation and forest degradation in developing countries
RS	remote sensing
SAOCOM	Satélite Argentino de Observación COn Microondas
SAR	synthetic aperture radar
SEOSAW	A Socio-Ecological Observatory for Southern African Woodlands
SEPAL	System for Earth Observations, Data Access, Processing & Analysis for Land Monitoring
SOC	soil organic carbon
UAV	unmanned aerial vehicle
UNFCCC	United Nations Framework Convention on Climate Change
WWF	World Wide Fund for Nature

EXECUTIVE SUMMARY

Forest-related greenhouse gas (GHG) emissions, emission reductions, and enhanced removals (carbon sequestration) are estimated by measurement, reporting, and verification (MRV) systems, usually based on a combination of remote sensing data, field or *in situ* measurements, and modeling approaches. Operationalizing the MRV process, is lengthy, however, often taking years even in countries with currently high capacities for such a task, and once it is operational, it relies on a complex, nonstandardized, uncertain, and lengthy process of integrating remote sensing and *in situ* measurements. This negatively affects the ability to address the drivers of these emissions, and at the same time apply and access climate finance in a timely manner.

Under the United Nations Framework Convention on Climate Change (UNFCCC), the lack of consistency limits the comparability between countries and makes the reconciliation of national reports and global estimates that are needed for the 2023 Global Stocktake under the Paris Agreements difficult. Moreover, the ongoing costs of MRV systems can be high, while the accuracy of the estimates is often low, and thus not able to unlock the full potential of climate finance. Traditionally, MRV processes have been based on land use and land cover change (LULCC) approaches, which are heavily reliant on satellite optical imagery. New developments in technology are improving our capabilities for mapping carbon (C) stocks, and C-stock change with improved accuracy. In particular, biomass, which can be obtained through *in situ measurements, remote sensing, and models, is an essential climate variable (ECV) that provides a direct measurement of C changes and impacts on other ECV, such as land cover.* Upcoming satellites and the ever-falling costs of airborne data (especially from drones) will result in unprecedented availability of data to support biomass estimation. The combination of innovative approaches and increased availability of data is expected to overcome several major challenges to estimating C stocks by:

- Enabling the monitoring of C stocks with increased frequency (<1 year frequency, compared to the current lower frequency of the reporting cycle);
- Standardizing C-stock estimation so that data from different sources are compatible and can be easily integrated, and uncertainties can be quantified; and
- Decreasing the time needed to generate estimates, because MRV systems can become operational in months, not years, and there is a much smaller time lag between the end of a monitoring period, and the availability of data.

In this context, the World Bank launched a study to assess the readiness of various innovative technologies—including remote sensing (RS), geostatistics (GS), artificial intelligence (AI), and cloud computing (CC)—to identify how these can be combined and leveraged to foster a next-generation MRV, which would help to unlock climate finance and enable governments and stakeholders to **monitor the implementation of environmental policies and assess the status of the world's forests.**

The study began with a review of the current and potential innovative technologies in order to gain a comprehensive understanding of the readiness of these technologies, and the challenges to rolling out their implementation.

Following the review of the technologies, the World Bank hosted a virtual two-day international workshop of experts with the objective of deepening the overall understanding of existing gaps through discussions of the methodological issues and limits, as well as the disruptive technologies and data management tools that could contribute to overcoming these obstacles. During the workshop, specific sessions also covered the policy and institutional barriers that will need to be addressed in order to deploy these technologies and offer solutions on how to disrupt the MRV process.

As a result, a set of the main technological challenges, and recommendations for overcoming them, were identified. **The technological challenges can be grouped into four areas: data availability and access; processing and computational performance; uncertainty management; and standardization and protocols.**

The major challenges identified are related to the lack of free and open access to data, tools, and cloud computing systems. There is a need for transparent methods and algorithms for turning remotely sensed variables into accurate aboveground biomass (AGB) estimates. Establishing sustainable long-term *in situ* monitoring networks is a challenging task with multiple contributing factors. To start with, the lack of secured funding exacerbates the issues with the limited availability of representative data and metadata to estimate and reduce uncertainty, and the difficulty of establishing standardized and universally accepted measurement protocols. Government reluctance to share and exchange local data that are currently located on national servers with centralized cloud computing systems, and the low bandwidth in many regions, which makes building distributed systems challenging, are additional complications. Finally, innovative methods can be difficult to implement owing to the lack of communication among domains, which hinders the integration of GS and AI solutions into the process of estimating C stock and dynamics.

A set of recommendations was developed to make better use of current and upcoming remote sensing technologies through the smart combination of geostatistics and AI, deployed to the cloud, and anchored on traditional forest inventory data sets. Implementing the proposed technologies into comprehensive methodological frameworks would contribute to overcoming some of the challenges and achieving **the main goal of this analysis,** which is to **improve the MRV process, reducing the time needed for MRV implementation, and consequently speeding up the mobilization of GHG emission reduction-based payment in the short term; and to foster sustainability, and build an operational service to carry out carbon stock based finance at global scale in the long term.**

To do so, we have outlined a nonexhaustive list of recommendations for the short term (1—2 years) and for the longer term (3—5 years) and have also identified potential coordinators and actors to the best of our knowledge, and based on the state-of-the-art review and the feedback received from experts. It is clear from both the review and the discussions held during the virtual workshop that a **"one size fits all" method for AGB mapping and monitoring is unlikely to be achievable**, or even desirable, given the different requirements, geographic locations, and types of forest under observation; therefore, a new generation of MRV processes will need to be flexible in order to enable its adaptation to various conditions. The recommendations we have devised allow for this flexibility and, if implemented, will lead to an enhancement and simplification of the MRV process by setting up and running systems in individual countries.

Short Term (1–2 years)	Areas of Needed Improvement	Potential Coordinators and Actors
	Data Availability and Access • Seek international partnerships with remote sensing data providers; support existing efforts in *in situ* data collection; and build on existing infrastructure so as to facilitate reliable, free, and open access to data, algorithms, and centralized cloud computing services through sustainable funding. • Foster partnerships with research groups and institutions developing and maintaining forest plot networks and support them in additional data collection or access (that is, build a Global Forest Biomass Reference System).	**Data Availability and Access** • Group on Earth Observations (GEO). • e agencies: European Space Agency (ESA), National Aeronautics and Space Administration (NASA), Japan Aerospace Exploration Agency (JAXA). • Committee on Earth Observation Satellites (CEOS). • *In situ* data collection networks and coordination mechanisms: GEO-TREES, AfriTRON, CTFS-ForestGEO, ForestPlots.net, RAINFOR, SEOSAW.
	Processing and Computational Performance • Support the integration of new approaches (such as AI and GS) into traditional ones. • Support the convergence of techniques between research groups (RS, AI/computer vision, GS, CC) as this will enable the enhancement of the developed tools.	**Processing and Computational Performance** • RS, GS, AI, and CC research centers and groups.
	Uncertainty Management • Pilot the implementation of geostatistical (GS) and AI solutions through demonstration activities and pilots to link *in situ* and RS data, harnessing the potential of CC. • Include estimates of error propagation from the input data to the final output in MRV systems.	**Uncertainty Management** • RS, GS, AI, and CC research centers and groups, national agencies.
	Standardization and Protocols • Establish a common understanding of how data will be used and processed to address various needs, through the collection of users' requirements. • Develop standards and protocols for data collection and development of the components of the system. • Promote data protection and security protocols for data migrations and protection.	**Standardization and Protocols** • CEOS, GFOI. • International Organization for Standardization (ISO), Cloud Security Alliance (CSA), European AI Alliance, World Economic Forum Global AI Action Alliance.
	Enabling Environments • Support data policies *in situ* and RS data) for access and sharing. • Engage with stakeholders to inform them about how local data will be used to build confidence throughout the MRV system. • Create mechanisms for incentivization, such as rewards for establishing public-private partnerships to promote communication and collaboration among relevant institutions and stakeholders.	**Enabling Environments** • GEO, FAO, GFOI, space agencies, plot networks, national authorities, research groups. • Financial institutions, donors. • UNFCCC, IPCC, World Bank • Climate AI, European AI Alliance, World Economic Forum Global AI Action Alliance, Global Partnership on AI, International Association of Mathematical Geosciences (IAMG), geoENVia.

	Areas of Needed Improvement	Potential Coordinators and Actors
	• Create the necessary financial support mechanisms seeking public and private investments, such as impact investing, blended finance, and voluntary markets. • Create SMART KPIs (Specific, Measurable, Attainable, Relevant, Time-bound Key Performance Indicators) to monitor system implementation. • Designate a perceived neutral entity that coordinates these actions, especially on the quality control of the *in situ* data, making it available and accessible to stakeholders (similar to the World Meteorological Organization network). • Establish communication among experts and users, which would help to generate confidence and encourage data sharing as well as building on ongoing efforts.	
Long Term (3—5 years)	**Data Availability and Access** • Support plans for the future follow-up to the GEDI and BIOMASS missions, and/or plans for alternative missions with similar characteristics. • Continue supporting and reinforce the continuation of international partnerships by making satellite data publicly available and the long-term maintenance of a Global Forest Biomass Reference System. **Processing and Computational Performance** • Build distributed systems with local micro-clouds in regions without local data migration possibilities. • Promote interoperability between local data centers and central servers. **Uncertainty Management** • Continue exploring innovations such as the automation of processing through GS with "meta-models." • Enhance quantification of spatial patterns from training images and combine input data for AGB estimation using high spatial resolution satellite imagery, possibly selected via AI methods. • Estimate the impact of overestimating and underestimating carbon stocks on results-based payments.	**Data Availability and Access** • Space agencies (NASA, ESA). • GEO, CEOS. **Processing and Computational Performance** • National AI and CC research centers, national and local authorities. **Uncertainty Management** • RS, GS, and AI research centers and groups. • *In situ* data collection networks and coordination mechanisms: GEO-TREES, AfriTRON, CTFS-ForestGEO, ForestPlots.net, , RAINFOR, SEOSAW.

Long Term (3—5 years)	Areas of Needed Improvement	Potential Coordinators and Actors
	Standardization and Protocols • Establish an international framework for adopting standard data management and processing approaches deployed in cloud computing systems located in different regions.	**Standardization and Protocols** • International alliances and partnerships, and organizations for standardization.
	Enabling Environments • Analyze whether new data and tools could create ethical issues, keeping in mind the risk of "dual uses" that do not occur in current approaches. • Invest in research, training, and knowledge generation in user countries. • Support policy frameworks for AI solutions and cloud security. • Foster collaboration among space agencies, international organizations, and governments. • Carry out a full data and capacity-building needs assessment, based on identified target audiences and stakeholders in specific countries before developing a complete strategy to build distributed systems. • Allocate funding to support the regular acquisition of unmanned aerial vehicles (UAVs) and LiDAR data through CEOS and the private sector.	**Enabling Environments** • RS, AI, research centers and groups. • World Bank, FAO. • National governments and offices. • Financial institutions, donors.

1. INTRODUCTION

1.1 BACKGROUND

In 2005, the parties to the United Nations Framework Convention on Climate Change (UNFCCC) began to formally set up a framework for financially incentivizing emissions reduction due to deforestation and forest degradation through conservation, the sustainable management of forests, and enhancement of forest carbon (C) stocks in developing countries.

In 2013, the Warsaw Framework for REDD+, which was adopted at the 19th Conference of the Parties (COP19), provided a comprehensive methodological and financing guideline for implementing activities for Reducing Emissions from Deforestation and forest Degradation (REDD+). According to the Warsaw Framework, activities aimed at reducing greenhouse gas (GHG) emissions from deforestation and forest degradation, and fostering sustainable management practices in developing countries are to be implemented in three phases (UNFCCC 2021):

(i) Development of national strategies, policies, and measures (PAMs), and identification of capacity building needs (readiness phase);

(ii) Implementation of demonstration activities, national PAMs, strategies, or action plans that could involve further capacity building and technology development; and

(iii) Monitoring and assessing the performance of PAMs at the national scale, allowing countries to obtain results-based payments.

In 2015, Article 5 of the Paris Agreement, which was adopted by 196 parties at COP 21, highlighted the pivotal role of results-based financing mechanisms in reducing GHG emissions, deforestation, and forest degradation. Although REDD+ is not considered a market-based mechanism (one in which credits are generated and transacted to compensate for GHG emissions) under Article 5, it is expected to be part of the Article 6 transactions. Moreover, voluntary markets and offsetting programs (for example, ICAO's CORSIA) include the generation of credits from REDD+. These market transactions require more robust monitoring, reporting, and verification (MRV) systems, and assurance of environmental integrity.

Financing mechanisms are provided by various institutions: For example, the World Bank's Climate Change Fund Management Unit includes two funds—the Forest Carbon Partnership Facility (FCPF), and the Initiative of Sustainable Forest Landscapes (ISFL)—both of which aim to pilot results-based payments and market-based mechanisms of land use interventions at a large scale. These funds have capitalized more than $1 billion dollars for result-based financing against emissions reduction (ER) units. In particular, the FCPF is an ambitious program working with 47 REDD+ country participants and 17 donors; it includes a Readiness Fund and a Carbon Fund, both focused on the implementation of REDD+ programs.

To obtain these funds, countries need to first define their forest reference levels (FRLs) and forest reference emission levels (FRELs) (FCPF 2020). Parties are required to assess FRELs and/or FRLs—which measure the amount of emissions from deforestation and forest degradation—as well as removals due to the enhancement of C stocks in a given area within a reference period. Actual results are then compared with the assessed FRELs in order to mobilize payments for actions that prove consistency between the FRELs and FRLs; include transparent information that will allow for recalculation of estimates; and provide a description of the National Forest Monitoring System (NFMS) (FAO 2013).

Under the UNFCCC, as well as under other standards, it is required that the methodologies for estimating GHG emissions are consistent with the guidelines developed by the Intergovernmental Panel on Climate Change (IPCC), and that they comply with the following principles (FAO 2013):

- **Adequate** to represent C-stock changes (representing land use classes and conversions);
- **Consistent** over time (without discontinuities in time-series data);
- **Complete** (all the land of a country should be included); and
- **Transparent** (data, tools, and methods should all be thoroughly described).

The IPCC has identified five types of carbon pools: (i) aboveground biomass (AGB); (ii) belowground biomass (BGB); (iii) dead wood; (iv) litter (that is, dissolved organic matter; and (v) soil organic carbon (SOC), which can be measured and reported as part of national GHG inventories (FAO 2013).

When submitting their national GHG inventories, parties are encouraged to report on as many of their significant C pools as possible, according to their national circumstances, and with methodological consistency. AGB is the most visible and dynamic pool, and a key component in C inventories, representing 30 percent of the total terrestrial ecosystems (Kumar and Mutanga 2017). SOC is also an important pool, especially in some regions. For example, in peatlands it is estimated that the carbon stored in soils could be twice as much as that stored in all the world's forests (UNEP 2019), and peat C is released rapidly following drainage and/or clearance of the overlying forest. In moist, tropical forests, SOC represents less than 50 percent of the total C stock (that is, terrestrial living plant material—(AGB and BGB)—and soil carbon stock) (Scharlemann et al.. 2014). SOC and BGB are difficult to monitor via satellite-based approaches (FAO 2009); thus, BGB is usually inferred from the AGB, via ratios or specific functions.

The choice of methodologies for collecting data and compiling GHG inventories follows the MRV approach, which is based on three "pillars" (FAO 2013):

- Satellite Land Monitoring Systems, which estimate the activity data (AD);[1]
- Terrestrial forest inventory, such as a National Forest Inventory (NFI), which estimates emission factors (EF);[2] and
- GHG inventory, which combines ADs and EFs to estimate GHG emissions and removals.

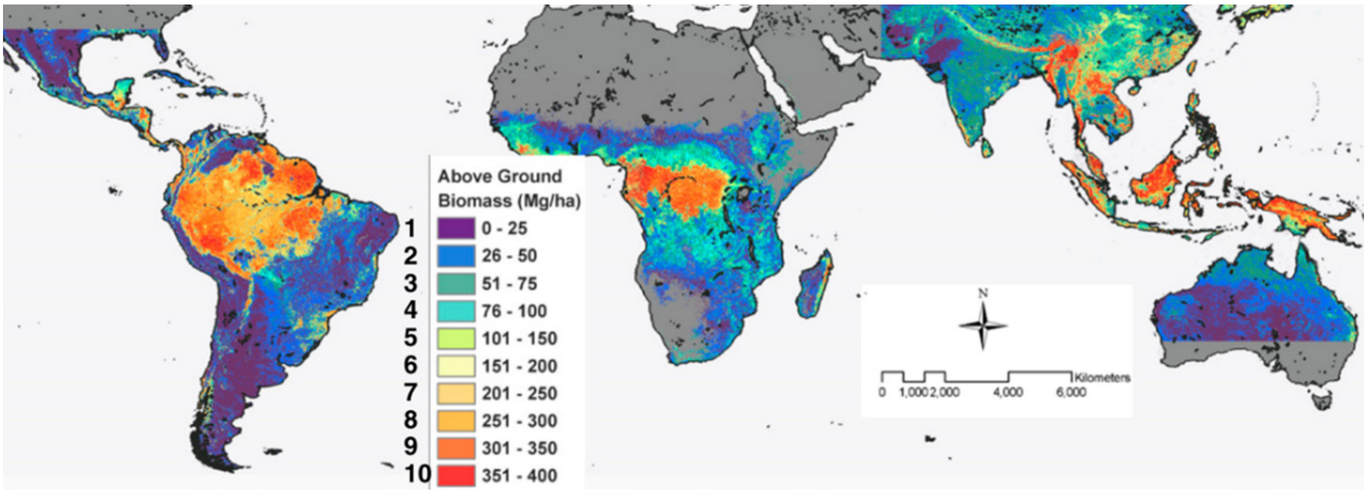
Traditionally, the production of AD relied upon small ground-data sets and classical classification algorithms, partially due to the lack of satellite imagery, and sufficient computing power to process these images. EFs have been often estimated through costly traditional forest inventories, which may or may not be repeated and provide estimates at a coarse scale. The availability of free optical data, and the possibility of implementing straightforward methods to derive AD from land use and land cover change (LULCC) have resulted in MRV frameworks that are primarily based on optical data. However, biomass, which can be obtained through *in situ* measurements, remote sensing (RS), and models, is an essential climate variable (ECV) that provides a direct measurement of carbon changes and impacts on other ECV, such as land cover (FAO 2009). As discussed during the virtual workshop, the RS of vegetation methods based on optical and C-band SAR data sets are not ideal for applying existing biomass mapping algorithms. Fundamentally, these data sets tend to describe only the top of the canopy, and they struggle to obtain information on forest biomass, particularly in dense forests. In addition, persistent cloud cover over the tropics hinders the use of optical imagery.

Over the past decade there have, for the first time, emerged continuous RS-based maps of aboveground forest carbon storage (Saatchi et al.. 2011; Baccini et al.. 2012; Avitabile et al.. 2016). These were made possible through an innovative spaceborne LiDAR sensor called ICESat that was launched by NASA in 2003, which, despite its primary mission being about the thickness of ice, collected sparse footprints across the globe from 2003 to 2009, giving information on tree density and height that could be related directly to forest biomass (Lefsky 2010). These individual LiDAR footprints could not themselves be used to create biomass or biomass change maps because they only sampled a tiny fraction of 1 percent of the world's land surface. However, they could be used to train machine-learning algorithms based on other optical and radar remote-sensing layers to effectively fill in the gaps, and create biomass maps without the cost and logistical challenge of collecting LiDAR data across a whole region, for example, Colombia (Asner et al.. 2012).

1 Activity data (AD) refers to trends in land use change (i.e., area changes)

2 The emission factor (EF) provides an estimation of carbon stocks (i.e., emissions or removals per activity data) such as emitted due to deforestation.

Figure 1-1 Example of a Pantropical Biomass Map.



Source: Saatchi et al.. 2011

While these biomass maps represent a massive step forward for carbon accounting and tropical ecology, enabling for the first time an accurate estimate of the biomass in each region, and biomass gradients, they have very high uncertainty on a pixel level. Indeed, evidence from independent *in situ* plots suggests that they did not even correctly map large-scale regional gradients (Mitchard et al.. 2014), and did not agree with each other well in many areas. In particular, it has become clear that repeating the same method each year will not lead to reliable biomass change estimates: Since individual pixels have errors of 30—40 percent, changes related to forest growth or degradation (which typically have smaller percentage changes) will not be captured this way. One study attempted to repeat these methods (Baccini et al.. 2017), creating annual maps of forest carbon stock change over a decade, but the results are not widely considered credible in the scientific community (Hansen et al.. 2019), and it is accepted that extrapolated maps based on passive optical remote sensing will not produce accurate enough change data for this method to work. Therefore, innovative methods and data should be used to provide accurate AGB estimations and carbon stock changes. However, the production of biomass maps and the estimation of C-stock change based on RS data have not been taken to an operational stage, and MRV systems rely on traditional methods that combine AD and EF. Therefore, the mechanism for calculating emissions for MRV is:

- **Slow** due to a lack of automation, computing power, adequate infrastructure, know-how, and standardization. Even if MRV systems are operational and sustainable, the time for conducting the measuring and reporting varies from 3 to 16 months, depending on the country, and for verification, 6—12 months is required;
- **Costly** in terms of the time and money required for field campaigns. MRV systems are complex, and they depend on the existence of sustained capacity and capabilities in key institutions during the reporting period (5 years); and
- **Uncertain:** The sources of uncertainty are related to the following: the quality and suitability of satellite data; data pre-processing and post-processing; the definition of land cover classes; *in situ* data measurement; and emissions calculations using an integration of AD and EF, which oversimplifies reality.

Some of the challenges associated with the estimation of GHG emissions for results-based payments for REDD+ could be overcome by using and combining new technologies and other data sets that present better relationships with forest structure and biomass, such as long-wavelength SAR missions (L -and P-band SAR). Innovative approaches will help:

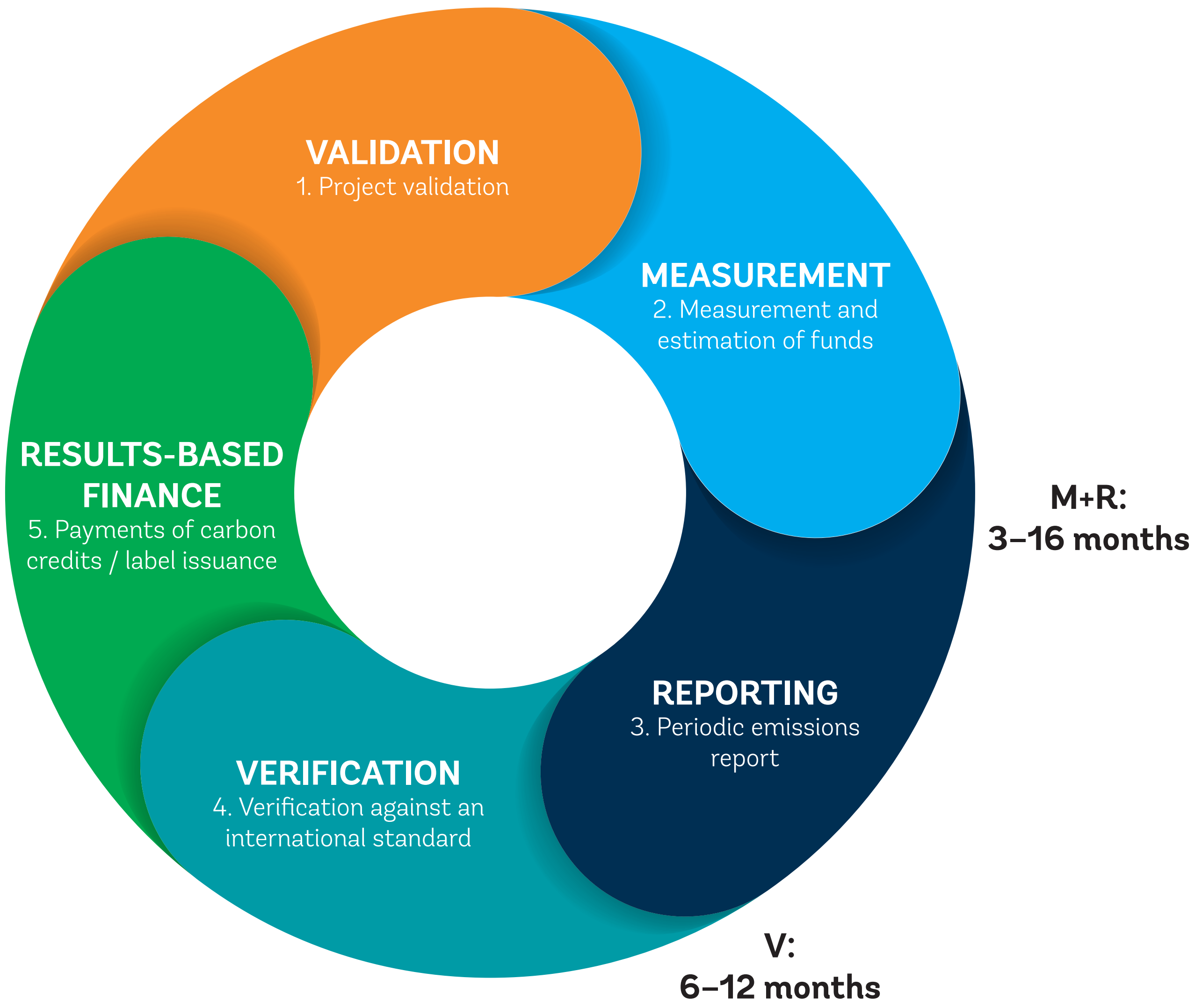
- **Reduce the cost** of national or subnational-wide ground-data surveys by a fraction of the original cost.
- **Substantially decrease the time needed** to implement the MRV cycle (from years/months to weeks). (Figure 1-2).
- **Improve deforestation and afforestation estimates,** and therefore GHG emissions and removals through satellite-based AGB measurements, and information about the associated uncertainty.

In order to analyze the possibilities for overcoming the existing challenges that are hindering the current REDD+ MRV approach, the World Bank hired a consortium led by GMV Aerospace and Defence (GMV) to assess the readiness of innovative technologies and approaches in fields such as geostatistics (GS), artificial intelligence (AI), and cloud computing (CC) to boost the use of remote sensing of vegetation to estimate forest carbon stocks and dynamics. The consortium, led by GMV and formed by the University of Edinburgh, the Insight Centre for Data Analytics-University College Cork, and GS consultants from the Cyprus University of Technology and Aristotle University of Thessaloniki, and enabling environments (provided by Federica Chiappe Consulting Ltd.) performed a state-of-the-art review on current and potential innovative technologies. The results of this review were shared during a virtual International Workshop of Experts on "Disrupting Carbon Stock Dynamics Estimation for Results-Based Payments" held November 16—17, 2020. An online survey was also conducted to receive feedback and recommendations on how to improve and disrupt the current MRV process (Figure 1-2).

The workshop participants analyzed five key areas that play a relevant role in building a REDD+ enabling environment for rolling out innovative technologies:

i. Policy, regulatory, and institutional frameworks
ii. Finance and economics
iii. Technology and markets
iv. Information and capacity
v. Social, cultural, and behavioral factors

Figure 1-2 Traditional M & MRV Approach for Results-Based Payments and Time Frames



1.2 OBJECTIVES

The objective of this report is to assess the feasibility of improving and enhancing the role of RS and emerging technologies such as GS, AI/machine learning, and CC, in order to estimate GHG emissions and to achieve more rapid mobilization of results-based payments.

The specific objectives of the report are to:

i. **Analyze the results of a state-of-the-art review on innovative technologies,** and feedback collected during the virtual International Workshop of Experts on "Disrupting Carbon Stock Dynamics Estimation for Results-Based Payments."
ii. **Gain a comprehensive understanding of the readiness of RS** of vegetation, and **GS, AI, and CC technologies for disrupting the MRV process** and overcoming the aforementioned challenges.
iii. **Present the identified frontier technologies and state-of-the-art approaches** for disrupting the MRV process, and map AGB, using RS-based technologies.
iv. **Define an implementation framework** leading to the disruption of the MRV process based on recommendations for rolling out innovative technologies and identified enablers (institutional frameworks, mandates, and incentives) to ensure the operationalization of RS-based technologies and processing approaches.

The report is structured as follows: First, we present the results of the state-of-the art review and the feedback received from experts. Second, we identify the challenges associated with the implementation of these technologies and provide recommendations for ways to disrupt the MRV process. Finally, we discuss the enabling environments that will be required in order to potentially reduce the time needed for MRV implementation, and therefore speed up mobilization of results-based payments.

2. INNOVATIVE TECHNOLOGIES FOR IMPROVING THE MRV PROCESS

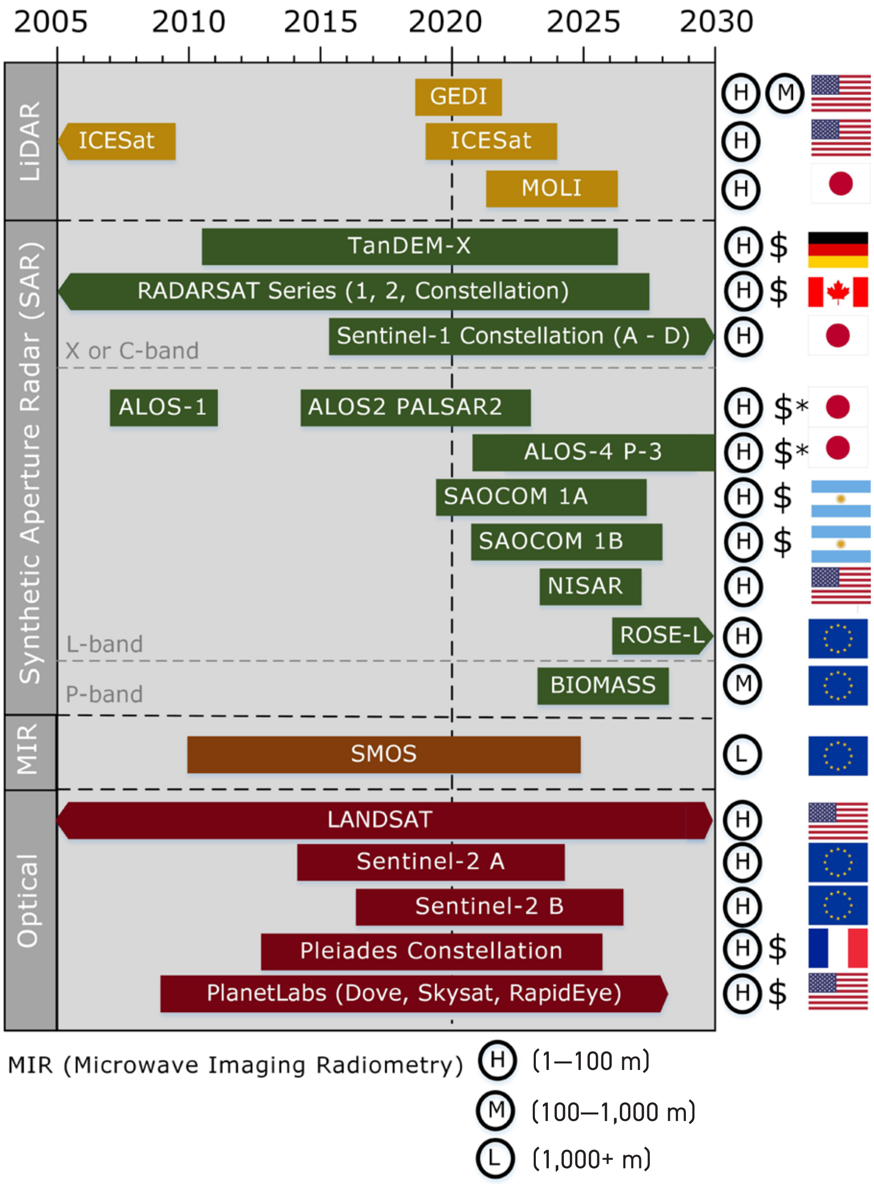
Remote sensing (RS) refers to a technology that employs active or passive sensors that can scan the Earth's surface and process the data captured to infer spatially continuous, meaningful data, and information that is directly usable for understanding and monitoring (at various scales) many of the natural and anthropogenic activities taking place on our planet.

We are now entering a golden age of RS, with a plethora of spaceborne, airborne, and ground-based platforms and sensors that are either currently operating or scheduled to become operational within the next 1–5 years (Figure 2-1). The launch of new missions by space agencies is causing an unprecedented increase in imagery availability and revisit rates. The availability of new spaceborne platforms specifically designed for forest aboveground biomass (AGB) mapping has the potential to greatly enhance our capacity to develop a monitoring system capable of reporting changes within the time frame of the monitoring, reporting, and verification (MRV) process.

However, it is important to acknowledge that, because of the wide range and sensitivity of available sensors, a "one size fits all" method of AGB mapping and monitoring is unlikely to be achievable. Moreover, methods will depend on user requirements, such as the geographic extent, the type of vegetation, the AGB densities under consideration, and the objective of the report—for example, whether the need is for the most recent up-to-date AGB estimate, or for a long-term AGB trend for establishing baselines. From our state-of-the-art review and the subsequent discussions held during the International Workshop of Experts on "Disrupting Carbon Stock Dynamics Estimation for Results-Based Payments," it is clear that achieving global and temporally consistent carbon stock estimations annually, and with errors below 20 percent, as required by the Intergovernmental Panel on Climate Change (IPCC) and the RS community,[3] remains a significant technological and logistical challenge, particularly in the short to medium term (2-3 years).

3 The target set by the IPCC and GCOS (Global Climate Observing System) is for a global and temporally consistent AGB monitoring system, with data sets generated annually at a -100-50 meter resolution, with relative errors < 20 % in areas with AGB densities >50 Mg ha1-, and a fixed error of 10 Mg ha1- in lower-density areas.

Figure 2-1 Spaceborne Satellite Platforms and Sensors Relevant to the Measurement of Aboveground Biomass and Its Dynamics



Note: This summary of spaceborne satellite platforms and sensors that are either dedicated to the measurement of AGB and its dynamics, or have been demonstrated as useful in its derivation, either in isolation, or as part of a multi-sensor approach, is based on our state-of-the-art review. The launch date of future missions should be considered nominal, and subject to change. The $ symbol indicates that the full data catalog is not free to access; $* indicates free products are available. The spatial resolution refers to the scale at which these products are typically aggregated for wider use.

RS systems can be located on the ground, but in this report, when discussing RS, we will refer to either airborne sensors (onboard a plane or unmanned aerial vehicle, or UAV), or spaceborne sensors (onboard satellites). These systems are defined depending on the source of the energy they detect. Passive sensors detect the radiation that objects naturally emit or reflect (for example, reflected sunlight). Active sensors emit their own source of energy, and thus operate independently of solar illumination, which is then scattered from the target and received back at the sensor. Synthetic aperture radar (SAR), which emits microwave pulses, and LiDAR, which emits laser beams, are examples of active sensors. Active sensors are key to monitoring forests because they have the capacity to penetrate the forest canopy, and in some cases clouds, which is useful since most tropical forests are located in areas with frequent continuous cloud cover, which represents a major problem for passive sensors. SAR can penetrate clouds and provide volume and height estimates to measure biomass and LiDAR instruments are able to accurately map the 3D structure of stands of trees, even identifying the size and shape of individual trees; however, unlike SAR, they cannot penetrate clouds.

A major feature of SAR systems is that radiation penetrates more or less through the canopy, depending on the specific wavelength at which the system is operating. For instance, X-band (short wavelength) radiation interacts with the surface of the forest canopy and is backscattered by small-scale components such as foliage and small branches, whereas P-band (long wavelength) radiation penetrates deeper into the canopy and is scattered back by larger components, such as large branches, tree stems, and the surface of the terrain. Since most of the biomass is contained in the stems and largest branches, P-band SAR is the preferred sensor for mapping AGB; however, there has never been a spaceborne SAR sensor operating at this wavelength, meaning that for many years AGB has been modeled instead, with relative success, using L-band (the next shortest wavelength from P) and C-band (Bouvet et al.. 2018; McNicol et al.. 2018; Rodríguez-Veiga et al.. 2019). The challenge with C-band and L-band SAR systems is that when used in isolation, their signal saturates at relatively low AGB levels,[4] estimated to be at around 50 Mg ha^{-1} for C-band, and 150 Mg ha^{-1} for L-band, values that that preclude the measurement of AGB in most intact tropical forests, where densities exceed 200 Mg ha^{-1}. This means that above this point, differences in AGB are no longer captured. Conversely, P-band airborne data is shown to respond to AGB changes in forests well over 200 Mg ha^{-1}, and indeed above 500 Mg ha^{-1} in French Guiana (Minh et al.. 2016).

ESA's BIOMASS mission, which will operate on P-band, is scheduled to launch in 2023, and is expected to be a game changer in this regard, by improving AGB estimates, particularly over tropical areas (which have high AGB densities) and overcoming the saturation issues with shorter wavelength systems. It is worth noting that spaceborne SAR sensors do not measure biomass or carbon stocks directly, but rather parameters that correlate with biomass, such as forest structure and volume, and canopy height. Overall, SAR and LiDAR sensors have proven to be more suitable for accurate AGB modeling because of their capability for penetrating the canopy and providing information about the forest 3D structure. Optical sensors, which are limited to measurements of the visible (2D) surface, can provide no information on the vertical structure or density of the forest.

Along with the ESA BIOMASS mission, two spaceborne missions are now collecting LiDAR data at global scales: NASA's Global Ecosystems Dynamics Investigation (GEDI), onboard the International Space Station (Dubayah et al.. 2020), and their Ice, Clouds and Land Elevation Satellite (ICESat-2). The GEDI mission is the first spaceborne LiDAR specifically tasked with collecting data on tree canopy height, canopy cover, and various other metrics of the vertical forest structure, all within 25-meter footprints, much smaller than ICESat's 70 meters. A global network of coincident *in situ* field and airborne LiDAR data sets will be used to develop and refine calibration models for converting GEDI-derived metrics of forest structure to AGB density, both at the footprint level (25 meters) and as part of a continuous, but coarser-resolution 1-kilometer product (Duncanson et al.. 2020; Patterson et al.. 2019). These data will only ever cover a small percentage of the world's surface (4 percent for GEDI), and thus need to be combined with other RS data, namely SAR, and to a lesser extent multispectral optical imagery, to extrapolate the data contained in these small footprints to the wider region. Such a multisensor approach—leveraging discrete LiDAR samples as a basis for creating wall-to-wall data sets—has formed the basis of several national and regional products created over the last decade, including the benchmark pantropical AGB maps of Saatchi et al.. (2011) and Baccini et al.. (2012). With a new generation of platforms and sensors now available, innovative methods and data are emerging, including those that combine GEDI with SAR data, such as TanDEM-X, to produce contiguous forest biomass maps at both 1-kilometer and 1-hectare resolution, with the latter achieving accuracies ranging from 11 to 27 percent (Qi et al.. 2019). Despite clear promise, the challenge for MRV is that TanDEM-X, along with many other SAR data, is currently a commercial product, meaning that the costs associated with obtaining a global annual data set is likely to hinder widespread fusion attempts in support of this process. (See Figure 2-2.)

The vast amount of optical satellite imagery now available, which is in many cases free of charge, has the potential to contribute to the overall process of integrating innovative approaches analyzed in this report, possibly by discovering new patterns and correlations between satellite imagery and forest AGB (Figure 2-2). Indeed, several recent studies have already explored the possibility of combining LiDAR with freely available optical data from Planet, Landsat, and Sentinel using machine-learning approaches, both to estimate AGB (Csillik et al.. 2019) and, more

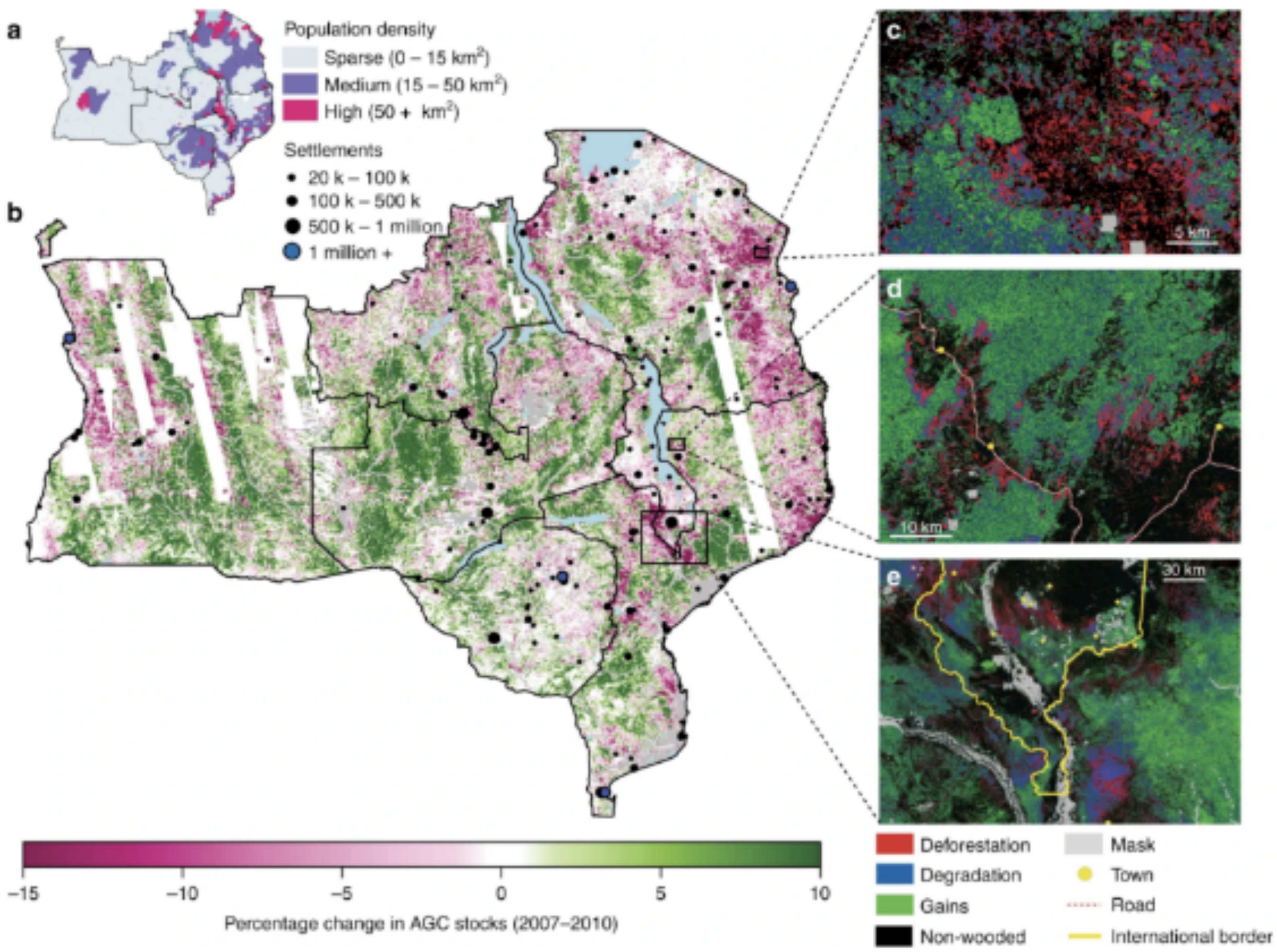
4 Estimated to be around 50 Mg ha1- for C-band, and 150 Mg ha1- for L-band, values that preclude the measurement of AGB in most intact tropical forests, where densities exceed 200 Mg ha1-.

prevalently, to measure tree height (Ploton et al.. 2017; Lang et al.. 2019), a reliable proxy for AGB for which several calibration models exist (Asner and Mascaro 2014; Jucker et al.. 2017). Despite these advances, these methods remain very much in the proof-of-concept stage and require independent validation before they can be considered suitable for wider application. However, the main barrier to developing reliable and temporally consistent monitoring strategies based on LiDAR is that our current spaceborne LiDAR sensors, GEDI and ICESat-2, both of which are likely to underpin future mapping efforts, are not operational satellites, and have no guarantee of long-term coverage. Airborne data collection using aircraft, while capable of replicating discrete LiDAR coverage at the regional to national scales, is prohibitively expensive ($200—$500 per square kilometer), and is unlikely to be part of any long-term monitoring regime.

It is therefore clear from both the literature review and the evidence obtained from the expert panel **that SAR is the remote sensing technology with the greatest maturity in terms of readiness to address the challenges of the MRV process,** particularly sensors operating at L-band (Figure 2—2), which have provided relatively accurate estimates of AGB in areas with low to moderate AGB density (0—150 Mg ha^{-1}) (Bouvet et al.. 2018; McNicol et al.. 2018).

Crucially, these areas comprise about 90 percent of the land surface globally, which shows the significant potential of the SAR data sets for operational AGB mapping in many regions. However, tropical forests and other areas with AGB densities that are considerably greater than 150 Mg ha^{-1} will remain challenging to measure due to the saturation of the SAR signal. There is no clear and readily available method for operational large-scale AGB mapping and monitoring within the next 2 years, at least until the launch of BIOMASS.

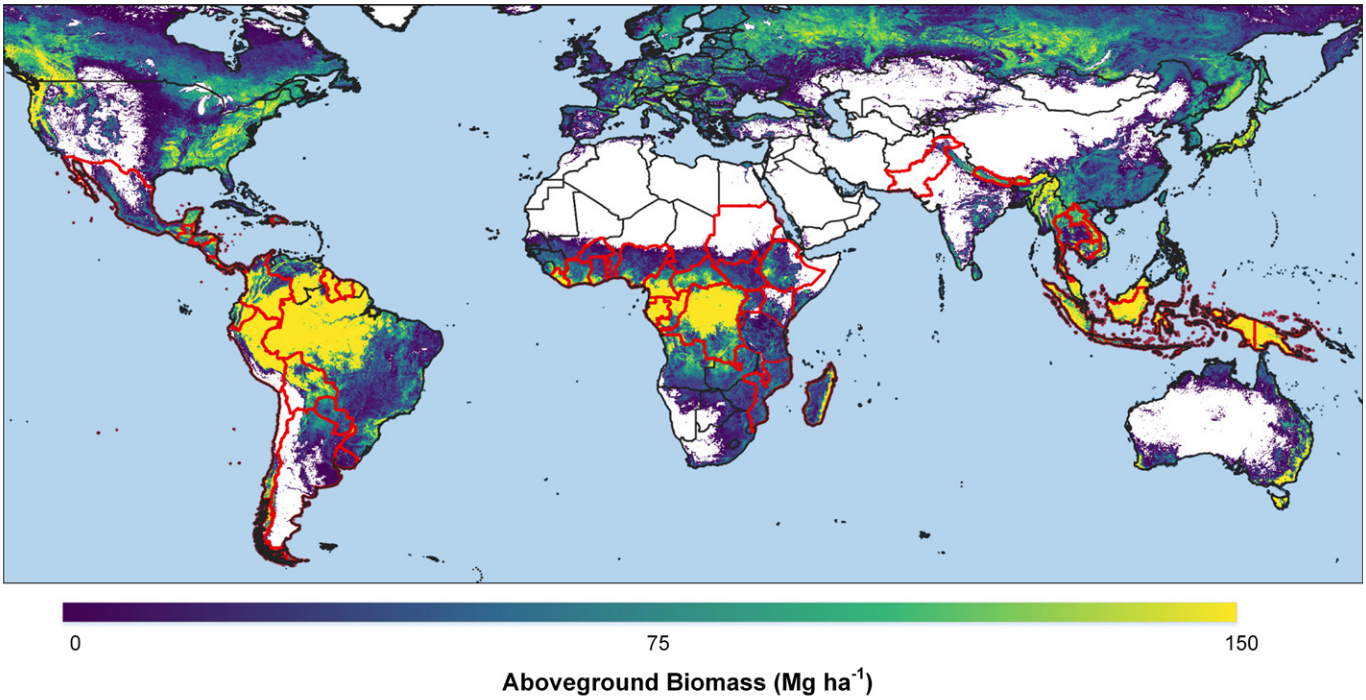
Figure 2-2 Percentage of Biomass Change, Derived from L-band SAR



Source: McNicol et al.. 2018.
Note: Areas where seasonal differences prohibited data analysis are shown in white. SAR = synthetic aperture radar.

Current state-of-the-art regional to global mapping efforts necessarily rely on freely available RS data, prominent among which are the ALOS PALSAR annual mosaic products available from the Japan Aerospace Exploration Agency (JAXA), which are delivered fully processed with a latency period of 1—2 years and are available through Google Earth Engine (GEE) (Bouvet et al.. 2018; McNicol et al.. 2018; Santoro et al.. 2020). The ESA Climate Change Initiative (CCI) ESA DUE GlobBiomass project targets the creation of consistent global AGB maps at 1-hectare resolution for three epochs (2010, 2017, and 2018), which are theoretically capable of supporting quantification of AGB change in support of MRV in the short term (1—2 years).[5] The data sets for 2010 and 2017 have already been created and are available for public use. However, per-pixel uncertainties on these products are high, around 40—50 percent—values which, at present, should preclude their use in AGB change mapping.[6] Furthermore, as previously noted, despite their global coverage, these Biomass CCI data sets cannot be used to estimate AGB in forests with densities >150—200 Mg ha^{-1} due to the saturation of L-band SAR.

Figure 2-3 Aboveground Biomass (AGB) Stocks for 2010 from the ESA DUE GlobBiomass Project



Note: The ESA DUE GlobBiomass project is a precursor to the ESA Biomass CCI project (Santoro et al.. 2020). The 47 countries delineated in red form part of the Forest Carbon Partnership Facility (FCPF), of which 33 have at least 75 percent of forested areas with AGB densities < 150 Mg ha-1.

5 To generate maps of AGB and AGB change, the project uses data from past, current, and future satellite missions, including optical sensors (for example, Sentinel 2A/B), C-band (Sentinel 1A & B), and L-band (ALOS-2 PALSAR-2) SAR data, and spaceborne LiDAR (for example, NASA's GEDI). https://climate.esa.int/en/projects/biomass/about/

6 Reducing the uncertainties on per-pixel estimates may be possible if aggregated to coarser resolution, assuming that errors are random, and the product does not contain systematic biases. However, such data sets are more difficult to validate using standard comparisons, as there exists little ground data with a spatial resolution larger than 1 hectare.

There are other open issues related to the quality of the input SAR data itself that may be contributing to increasing the uncertainties in the AGB estimations. One of the most obvious is that the "mosaics" comprise images collected throughout the year, meaning that they are subject to the variable influence of surface moisture, which can enhance the backscatter intensity in dry conditions. Mitigating the seasonal and weather-related effects on SAR data will likely require a complete regeneration of the products; however, to date, the cost of acquiring the necessary number of ALOS PALSAR images required to generate the mosaics over large areas for a given year has been considered prohibitively expensive ($2,300 for a single 70 x 70 kilometer acquisition). Certainly, for global mapping, cost may not be an issue if implemented by groups of nations, for example the 47 countries that are part of the Forest Carbon Partnership Facility (FCPF). New opportunities may also arise with the recent announcement that JAXA will provide free and open access to the ScanSAR observation data from ALOS and ALOS-2 (60- to 100-meter resolution); however, the time frame of this release has yet to be established. The launch of NASA-ISRO's synthetic aperture radar (NISAR), an L-band mission scheduled for launch in 2022 at the earliest, will change this situation, by distributing L-band SAR data for free and providing AGB data with an accuracy of up to 20 percent.

As a result of these open issues, the currently available global AGB products have a high level of discrepancies (Saatchi et al.. 2011; Baccini et al.. 2012). However, promising data sets for AGB estimation have been recently made available, and more will shortly be made available through various space missions that are soon to launch. As shown in Figure 2-1, many new satellite missions (SAR, LiDAR, and optical) will render abundant high- and medium-resolution data during the next decade. **However, none of these sensors or methods will be capable of accurately mapping AGB across all vegetation types in all regions, at least with a spatial and temporal resolution sufficient for the detection of small patterns and changes in AGB, including those associated with forest degradation and growth. This was confirmed by the experts participating in the workshop, who discussed the need to base operational AGB monitoring on a combination of sensors.**

The upcoming BIOMASS and NISAR missions (in 2022—2023), specifically designed around AGB mapping and monitoring, will provide data free of charge, and this will result in a new generation of AGB data sets capable of supporting the MRV process in the mid to long term (5—10 years). Longevity in free L-band data is likely to be provided by the ESA ROSE-L mission, which is considered a high-priority candidate in the Copernicus program, and is scheduled for launch toward 2027. These data, combined with inputs from ALOS-4, PALSAR-3, and other L-band platforms, including the Earth observation satellite constellation of Argentina's space agency, SAOCOM (Satélite Argentino de Observación COn Microondas; Spanish for Argentine Microwaves Observation Satellite), have the potential to contribute to a long-term AGB monitoring system capable of annual reporting at global scales should a suitable solution to the commercial restrictions be found. Figure 2-1 shows the type of access, availability, and the expected launch timeline of these missions.

Together with new satellite missions, and new developments in data science, artificial intelligence (AI) and geostatistics (GS) are also improving the capability for obtaining more accurate predictions and quantifying uncertainty. Their implementation in MRV frameworks, which is not yet complete and comprehensive, could help to mobilize greenhouse gas (GHG) emission reduction-based payments. For example, **geostatistical methods (including model-based inference) represent relatively mature technologies in the forestry domain,** but for the most part they have not yet found their way into an operational MRV context because of their complexity. Currently, the linking of ground-based AGB to RS data in an MRV context is typically achieved through rather simple models that often yield poor predictive performance. Nevertheless, **GS offers a multitude of methods and algorithms for integrating data of multiple variables and improving spatial prediction/ mapping, including:**

- i **Spatial regression models** (linear or nonlinear) that account for spatial correlation, differences in data resolution, and measurement error.
- ii **Regression models,** combined with advanced spatial interpolation methods, which address the issue of spatial misalignment.
- iii **Spatiotemporal geostatistical models** accounting for the temporal dimension of the data.
- iv **Computational procedures** for handling large data sets.
- v **Bayesian extensions** of all of the above.

Geostatistical regression models (see ii. above) have direct links to model-based inference and hybrid inference, which are widely employed in the forestry context. Moreover, GS provides a comprehensive framework for error and/or uncertainty modeling/propagation. **Geostatistical simulation, in particular, extends classical nonspatial simulation to account for spatial and/or spatiotemporal correlation, as well as different data resolutions, and constitutes an all-around approach for spatial error propagation, particularly when results need to be reported at various spatial resolutions (pixel versus regional versus national).** Spatiotemporal geostatistical models for AGB (see iii above) are being actively developed, particularly for combining time-series analysis with spatial statistics for understanding temporal patterns and actual changes that occurred between the times of image acquisition. Finally, **satellite-based AGB estimation could benefit from the advent of multiple-point GS, whereby spatial patterns are first "learned" from training images and are then "exported" to the ground via geostatistical simulation, and fused with actual data to provide realistic models of spatial heterogeneity and complexity.** This is a very active area of research, which is being applied in fields such as soil science and engineering, recently in combination with RS techniques, which could improve the accuracy of AGB estimates.

Geostatistical approaches and AI solutions can be considered as relatively mature technology that could be used at the various stages of AGB estimation from space, mainly to support image processing and pattern recognition within the remotely sensed information. The algorithms that can be considered for modeling AGB dynamics and classification purposes would have to be, of course, tuned to the specific application. Given the need for image processing and recognition of patterns within RS data, it is easily predicted that the various methodologies involved in image processing would be incorporated into AGB estimations. This implies that deep neural networks and the various approaches used for its performance improvement would be applied. **AI would not only be used for image processing. Other tasks, such as inter/intra-annual dynamic estimation, uncertainties estimation, data filtering, data processing/curation, and data insight/variables/system behavior could be accomplished using AI solutions. Similarly, patterns and correlations within the collected information would be performed by various machine-learning approaches that would help reduce the burden of dimensionality in the collected information, and at the same time facilitate handling information from annexed approaches** (for example, cloud computing processing). At the current stage, various AI applications already exist in several platforms that help bring tools and scientific communities together: GEE,[7] EO-learn (open-source Python library),[8] Radiant MLHub,[9] Open Data Cube,[10] and ENVI in the Cloud,[11] among others. Apart from all of the work performed so far, efforts have to be made to facilitate the application of AI technologies within the MRV framework.

Cloud computing (CC) is a mature technology that is shifting the paradigm in processing large data volumes and ensuring scalability. The foundational technologies and systems enabling cloud services are consolidated and standardized. CC underpins a vast number of services and information backups that allow large enterprises to host all their data and run their applications in the cloud. It is based on the concept of dynamic provisioning, which is applied not only to services but also to computing capability, storage, networking, and information technology (IT) infrastructure in general. Resources are made available through the internet and offered on a pay-per-use basis from CC vendors. However, there are currently very few end-to-end examples of AI algorithms that are employed to derive AGB from satellite data and are deployed in a cloud environment.

As more satellite sensors are launched, the availability of data will progressively increase. Some advances already exist, such as cloud computing platforms that provide global maps, and some progress has been made toward the automation of AGB estimation. However, there is still a long way to go before the efficient combination of these technologies will allow us to build a wall-to-wall AGB processing chain that speeds up MRV implementation and mobilizes emissions reduction-based payments. In the following section of this report, we highlight the main challenges of the presented technologies, which have been grouped into four topics: data availability and accessibility; processing and computational performance; uncertainty management; and standardization and protocols.

7 Google Earth Engine (GEE) is a cloud computing platform for processing and analyzing satellite imagery and other Earth observation (EO) data.
8 EO-learn is a collection of Python packages that fuse AI and remote sensing techniques, and have been developed to seamlessly access and process spatiotemporal image sequences.
9 Radiant MLHub is an open library for ready-to-use, open-source geospatial training data, and advanced machine-learning applications on EO.
10 Open Data Cube is an open-source geospatial data management tool in which data is organized as a multidimensional array of values.
11 ENVI in the Cloud provides users with the full functionality of software packages like ENVI, in a powerful cloud-hosted IT environment.

3. IDENTIFIED TECHNOLOGICAL CHALLENGES

Data Availability and Access

The first of these challenges is the need for **free and open access to remote sensing (RS) data and algorithms that can be produced in a timely and cost-effective manner,** within the time frame of the monitoring, reporting, and verification (MRV) cycle. This is critical to ensuring reproducibility. The open-data policy adopted by ESA and NASA has gone some way toward addressing this requirement; however, the data sets on which the most promising results are based, including TanDEM-X and ALOS PALSAR, are not available free of charge, while those that are, for example C-band SAR and optical data from the Sentinel missions and Landsat, are not necessarily the most appropriate data sets for aboveground biomass (AGB) mapping and monitoring (CEOS 2021b). Other useful satellite data sets, while open, were not available in the past—for example, NASA's GEDI spaceborne LiDAR was only given its two-year slot on the International Space Station starting in late 2018, though its timeline has fortunately been extended. ESA's BIOMASS mission will likely only operate for four years, and there is no plan for a successor satellite. In some ways, this makes these data sets even less useful for operational MRV systems than commercial data sets, since once they are no longer operational there is no possibility of gaining access to the data, even if budget is available.

Another challenge **is the need for transparent methods and algorithms for converting RS variables to AGB estimates, which requires accurate *in situ* data for calibration and validation.** A smaller number of scientific *in situ* plots are available, and are very useful for calibration and validation, but that is not their primary purpose, so they are often not located where they would ideally be for this purpose, and are not measured repeatedly. Remeasurement of AGB *in situ* plots should be done at least every 2–5 years in order to account for changes and update calibration models and validation databases, with more frequent observations likely to be required in areas that are undergoing forest disturbance or encroachment (Herold et al.. 2019). However, **securing the necessary funding to maintain and remeasure these ground networks is often difficult, and it represents a challenge to the establishment of long-term *in situ* monitoring networks.**

A global biomass reference system would also require the capacity to handle and process immense amounts of data from *in situ*, airborne, and spaceborne sensors. The challenge here is not only the required computational power but also the ability to efficiently integrate these data sets into methodological frameworks. To do so, there are two challenges that have to be overcome. First, geostatistics (GS) and artificial intelligence (AI), like all analytical frameworks, rely on representative reference data, such as common sites and plots where different methods can be tested and/or validated. Therefore, **the limited availability of representative data (both in terms of quantity and quality), along with the scarcity of metadata about their generation, constitutes a key barrier toward the application of GS in an MRV context, since it hinders confidence building in comparative studies as well as uncertainty reduction when communicating results to experts and stakeholders.** Second, **data collection should meet the calibration and validation requirements set for all of the domains** (that is, RS, GS, and AI) that depend on the application and expected functions and outputs of the methodological approach (image processing, regressions, time-series analysis, etc.)

Processing and Computational Performance

Another barrier is related to scaling up from local estimations to the national scale and beyond. Different model parameterizations, such as stratification by forest type, are required for scaling GS applications to large areas, along with computational methods for inverting very large covariance matrices. **Different model parameterizations also entail decisions that are critical in model development, rendering the task of automation rather challenging.** Additional improvements are needed to determine optimum methods for integrating (with linear or nonlinear models) *in situ* and RS data in AI models, while explicitly accounting for spatial correlation; accommodating the temporal dimension of the data and models of AGB change; and considering differences in data resolution, measurement error, and spatial misalignment between different data sources, as well as the complexity of different environments when scaling up (spatial heterogeneity), among other issues. Geostatistical methods also include model-based inference methods that are widely employed in forestry. Additionally, **the development of new algorithms and solutions may require not only *in situ* data collection but also well-defined user requirements in order to develop solutions that fit the objectives, scale, and expected performance of the devised tool.** Therefore, the time planned for building a monitoring system should also consider the time frame needed to collect and implement user requirements.

The availability of large volumes of data **requires powerful computing systems with efficient computational performance,** and the resources for massive data storage. Centralized clouds are frequently used for storing and processing RS data, reducing computational time and cost. Such methods have already been used to estimate AGB in Sub-Saharan Africa using very high-resolution satellite imagery.[12]

Uncertainty Management

Differences of calibration between observations of the same sensor type in time and space are difficult to correct. Ensuring satellite data comparability will require separate calibrations based on data that is collected concurrently with the period of image acquisition. National Forest Inventories (NFIs) have the potential to contribute to this; however, **at the international level, concerns and issues related to plot size, data access, standardization, and measurement protocols, or lack thereof, can create additional challenges and uncertainties.** Moreover, difficulties arise when attempting to account for error and uncertainty in various MRV steps, **including the quality of spatial data** (along with uncertainty or vagueness in definitions—for example forest versus nonforest), **positional errors, attribute errors, temporal uncertainty, and completeness.**

Finally, the lack of familiarity with geostatistical methods of the people involved in operational MRV highlights the need for such methods to be appropriately communicated.

Overall, geostatistical methods are well developed and can contribute to improving uncertainty estimations. Yet there are two main areas that require improvement:

i. **Accounting for different sources of uncertainty,** including spatial data quality (along with uncertainty/vagueness in definitions—for example, forest versus nonforest), positional errors, attribute errors, temporal uncertainty, and completeness; and
ii. **Identifying optimal GS simulation methods for spatial error propagation and expanding classical Monte Carlo methods[13] to include spatial correlation and differences in data resolution.** This would be useful because simulation results may apply to a fine spatial resolution, and subsequently be aggregated to a coarser scale—for example, to the country level—for reporting purposes.

Regarding specific AI solutions, the main limitation that is clearly jeopardizing a "relatively" fast implementation in the MRV processes is **the lack of communication between the RS and AI domains, which is hindering the adequate integration of AI solutions into the carbon stock estimation process.**

Standardization and Protocols

Despite the efforts of Open Science,[14] **the lack of open methodologies and algorithms** is still a common issue that remains unresolved and is **hindering standardization**. In addition, **the lack of broadly accepted guidelines in developing tools for specific tasks (for example, defining system variables) and data management (that is how, and in which format products will be accessed, stored, and shared)** can pose challenges to the reliability and consistency of open processing systems.

Cloud computing (CC) is a well-developed technology for managing resources using standard protocols and producing scalable products. There are International Organization for Standardization (ISO) standards for cloud interoperability, although **the level of**

12 "Counting Trees and Shrubs in the Sub-Sahara Using Cloud Computing", https://www.nccs.nasa.gov/news-events/nccs-highlights/counting-shrubs-trees-using-cloud-computing.
13 Monte Carlo methods are one of the two methods to combine uncertainties accepted by the IPCC and is based on numerical simulations that draw pseudo-random samples from probability density functions representing the population of each parameter involved in the estimation.
14 Open Science is a new approach to the scientific process based on cooperative work and new ways of sharing knowledge by using digital technologies and collaborative tools.

implementation and application worldwide is not known. Potential barriers highlighted during the virtual workshop were related to **massive data storage and governmental reluctance to share and migrate data from national servers and research centers to private cloud providers located in foreign countries.** Moreover, **dependency on a particular cloud provider** could, on the one hand, constrain the modification of components; and on the other hand, reduce interoperability issues.

At a global scale, one could also employ a client-server model of distributed computing through **edge computing,** through which multiple local users share their computing resources to be run as one system. Edge computing is an emerging cloud architecture that can contribute to solving some national data-sharing issues (for example, NFI, soil sampling, field campaigns). Within this architecture, data can be processed and analyzed independently in local data centers that connect to the core data center. However, **bandwidth resources and connectivity issues in some regions of the world may pose challenges to building these systems.**

In summary, the main challenges to be considered while building these systems are:

- **Data storage, sharing, and migration from local servers to a centralized system;**
- **Processes distributed in different clouds** could produce interoperability issues; and
- **Absence of internet connectivity:** Establishing computing system architecture based on high data transfer remains a challenge in some parts of the world because of connectivity and bandwidth limitations.

4. RECOMMENDATIONS FOR ROLLING OUT INNOVATIVE TECHNOLOGIES AND BUILDING ENABLING ENVIRONMENTS TO OVERCOME CHALLENGES

In general, technological advancements have been relatively quick, because of widespread confidence in their methods and the resultant data, as well as in their ability to improve carbon measurements and MRV processes. However, the enabling environment has not always been conducive to change, and the policies that support technological advancement have progressed at a much slower rate, and consequently have not kept up with this speed. There is an increased risk that since the scientific community has greater faith in the data and tools than policy makers do, as this gap widens, challenges to the uptake and use of new technologies could intensify further. Therefore, it was reiterated in the virtual workshop discussions that technological advancements in REDD+ monitoring, reporting, and verification (MRV) cannot function without positive enabling environments; the latter are key to implementation.

Implementing the proposed technologies into comprehensive methodological frameworks would contribute to overcoming the challenges and achieving **the main goal of this analysis, which is to improve the MRV process, reducing the time of MRV implementation, and consequently speeding up the mobilization of greenhouse gas (GHG) emission reduction-based payments** in the short term; **and to foster sustainability and build an operational service to carry out carbon stock-based finance at a global scale** in the long term. To do so, we have outlined recommendations for the short term (1—2 years) as well as for the long term (3—5 years) to the best of our knowledge, based on the state-of-the-art review and the feedback received from experts (Figure 4-1).

First, we have identified four areas for improving MRV processes, especially C-stock measurements, from a technological perspective: data availability and access; processing and computational performance; uncertainty management; and standardization and protocols.

Second, we have highlighted appropriate enabling environments for rolling out these innovative technologies. We have proposed five categories: policies and regulations; institutions and stakeholders; capacity and information; finance and sustainability; and social, cultural, and behavioral factors.

Figure 4-1 Implementation Framework

	SHORT TERM	LONG TERM
INTERMEDIATE OUTCOMES	**Data Availability and Access** • Seek international partnerships that foster free and open access to data, algorithms, and centralized cloud services through sustainable funding. • Support forest inventory updates and new initiatives to build a Global Forest Biomass Reference System. **Processing and Computational Performance** • Support the integration of new approaches (biomass estimation, hybrid modeling, data augmentation) into traditional ones. • Support the convergence of techniques among research groups. **Uncertainty Management** • Support demonstration activities and pilots to link *in situ* and remote sensing data. • Include estimates of error propagation from the input data to the final output in MRV systems. **Standardization and Protocols** • Establish a common understanding of how data will be used and processed. • Promote data standards, protection, and security.	**Data Availability and Access** • Support future satellite missions with similar characteristics. • Ensure and reinforce international partnerships to make satellite data publicly available, and increase the Global Forest Biomass Reference System. **Processing and Computational Performance** • Build distributed systems with local micro-clouds in regions without local data migration possibilities. • Promote interoperability between local data centers and central servers. **Uncertainty Management** • Develop meta-models. • Combine input data selected by AI solutions. • Estimate the impact of overestimating and/or underestimating carbon stocks on results-based payments. **Standardization and Protocols** • Establish an international framework to adopt standard data management and processing approaches deployed in cloud computing systems located in different regions.
ENABLING ENVIRONMENT	• Support data policies (for both field and remote sensing data) regarding access and sharing. • Incentivize stakeholders to promote public-private partnerships. • Create key performance indicators. • Select a neutral entity to coordinate actions. • Establish cross-communication among experts and users. • Seek public and private funding sources. • Engage with stakeholders to build confidence throughout the MRV system.	• Analyze whether new data and tools could create ethical issues in the future, keeping in mind the risk of "dual uses." • Support policy frameworks for AI solutions and cloud security. • Foster collaboration among space agencies, international organizations, and governments. • Assess capacity-building needs. • Invest in research, training, and knowledge transfer. • Allocate funding to support regular acquisition of UAVs and LiDAR through CEOS.
GOAL	• Improve the MRV process to reduce the time required for implementation.	• Foster sustainability.
IMPACT	• Speed up the mobilization of greenhouse gas emission reduction-based payments.	• Build an operational and sustainable service to carry out carbon stock-based finance at a global scale.

4.1 SHORT-TERM RECOMMENDATIONS (1—2 YEARS)

INTERMEDIATE OUTCOMES

- **Data Availability and Access**

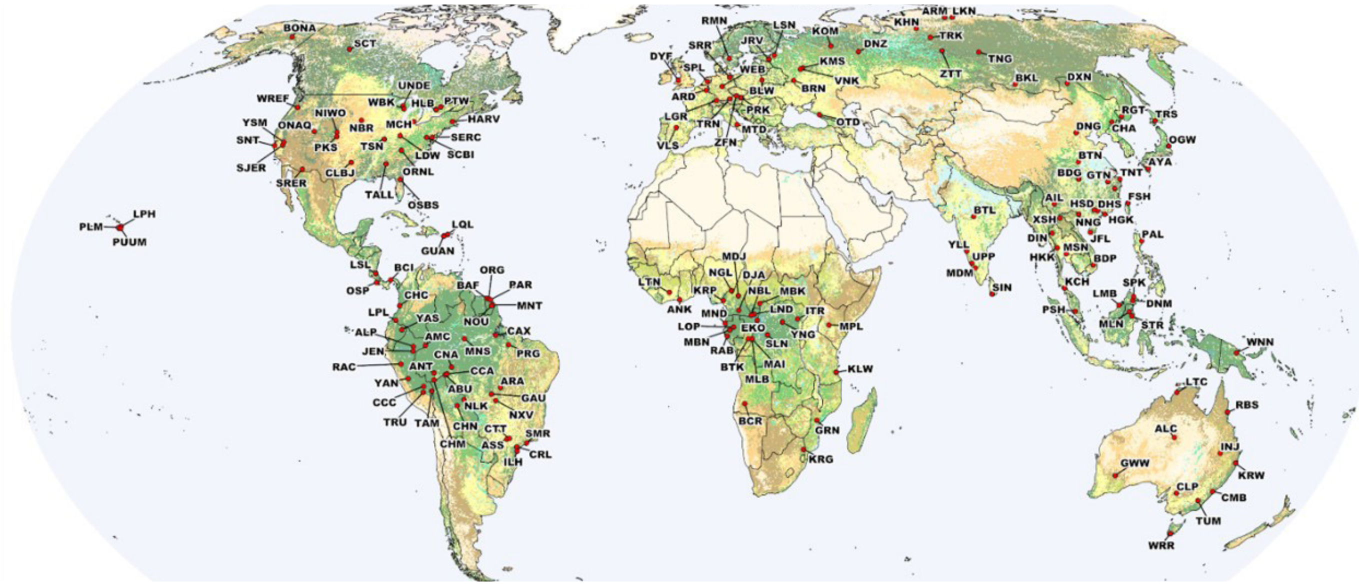
Ensuring reliable remote sensing (RS) data inputs **will require establishing international partnerships with RS data providers; supporting existing efforts in *in situ* data collection; and building on existing infrastructure.** For example, the intergovernmental Group on Earth Observations (GEO) is playing a key role in promoting open access to data, information, and knowledge. GEO has contributed to increasing data availability for users and reducing the cost barrier through agreements with key data providers (NASA, ESA, DLR, JAXA) to make some of their data free to use and share. **Further efforts to ensure data availability should warrant that existing agreements—for example, with JAXA—are fulfilled, and new arrangements with other commercial service providers are sought** (GEO 2020). An example of such an agreement is the collaboration between Kongsberg Satellite Services (KSAT), Planet, and Airbus with Norway's Ministry of Climate and Environment, to provide access to high-resolution imagery for monitoring the tropics in order to curb deforestation. The contract awarded was approximately €37 million euros, which is comparable to the sum estimate for the **development of a Global Forest Biomass Reference System** (CEOS 2020).

Ground-data sampling campaigns should **foster partnerships with research groups and institutions that are developing and maintaining the forest plot networks responsible for *in situ* data collection and curation**—such as ForestPlots.net, SEOSAW, AfriTRON, CTFS-ForestGEO, and RAINFOR—to make some of their forest inventory data publicly available and contribute to enhancing them with data from other regions. Granting access to repeat inventories conducted in the periods 2005—2010, 2015, and more recent plots, which will ensure an overlap with key spaceborne missions, would be particularly relevant for calibrating and validating RS-based methodologies. Emphasis should be placed on 1-hectare sampling plots to ensure spatial matching between RS pixels and *in situ* samples. In addition, **we recommend addressing efforts toward not only updating out-of-date inventories** in areas with limited capacity for establishing remeasurement programs, but also **supporting new initiatives to monitor forest structure in regions with clear opportunities for aboveground biomass (AGB) mapping and monitoring in support of MRV (for example, tropical dry forest) that lack the resources for such inventories** (Figure 4-2). For example, citizen science and open, free tools for data collection such as OpenForis[15] could contribute to increasing *in situ* data collection, processing, and sharing in regions with limited resources. We estimate that the cost of remeasuring a single 1-hectare plot is $2,000—$4,000 if conducted by a local team. **This will require institutional coordination and significant financial and administrative support from organizations such as the World Bank, and national governments that have both the necessary capacity and the resources to assist in these efforts and can help develop a Global Forest Biomass Reference System.**

Open-data access and suitable data (in terms of quality, acquisition time, and quantity) for model calibration and validation will directly impact the development and performance of geostatistical (GS) models and artificial intelligence (AI) solutions. The deployment of algorithms and AGB estimates using big data should be carried out through cloud computing (CC) systems to speed up the MRV processing chains. Centralized and distributed clouds have the potential to speed up AGB estimates; improve MRV implementation; allow reproducibility; and reduce implementation time. During the course of the virtual workshop, experts stated that the availability of open-source clouds is an important requirement for establishing a methodological framework using CC systems. Therefore, **short-term actions should focus on promoting open clouds—which would help generate trust, and encourage data sharing—as well as building on existing platforms.**

15 http://www.openforis.org

Figure 4-2 Potential Biomass Reference Measurement Sites to Set Up Increase Confidence in Biomass Estimates



Note: These will need to be re-censused since they will be outdated by 2022/2023 (CEOS 2020).

- **Processing and Computational Performance**

The short-term recommendations on the automation of analysis through GS approaches are based on selecting state-of-the-art, and preferably open-source, GS software that should be enhanced in computational efficiency, parallelized for speed, and ported onto CC systems to address large-scale applications. There are also additional developments and trends in the field of AI (for example, **hybrid modeling frameworks**) that could be incorporated in future methodological frameworks to design AI components with high performance, and with a broader range of applicability, in order to improve implementation of the MRV process. Input data aided by automatic and self-evolving AI configuration components could be useful for building dynamically modified systems, constraints, parameters, and estimations, leading to an enhanced system. **Data augmentation** could be used as a promising approach for increasing the supply of information to AI algorithms as long as they do not incorporate further uncertainties into the system. This implies that methodologies such as **image inversion/flipping** could be included, but those based on synthetically created information should be implemented only with caution. Environmental and land-based conditions are considerably dynamic. This variability has to be included in nontraditional components in order to produce trustworthy solutions. Furthermore, AI is well recognized for making inferences based on "what is currently true," but if the situation is changing dynamically, the system has to develop alternatives to cope with recognized uncertainties or incorporate them into the system as a new set of information. Finally, **convergence of techniques between research groups** (RS, AI/computer vision, GS, CC) would enable the enhancement of the tools that have been developed. These interactions will need to be fostered by end users who are interested in such applications.

Operational and in-development examples of centralized platforms for retrieving satellite data, such as the System for Earth Observations, Data Access, Processing and Analysis for Land Monitoring (SEPAL), which is hosted by the United Nations' Food and Agriculture Organization (FAO), harnesses cloud-based capabilities and modern geospatial data infrastructures like Google Earth Engine (GEE), allowing users to access and process satellite imagery to monitor forests. NASA and ESA are currently building the Multi-Mission Algorithm and Analysis Platform (MAAP), which has features similar to GEE, and the Copernicus Data and Information Services platform (DIAS), which are also targeted toward monitoring forests. MAAP aims to improve the ease of access to huge amounts of data that are or will be available using CC resources. This platform will enable users to develop code, analyze results, and share and process global-scale data, which in turn should increase reproducibility and transparency. However, there are still issues surrounding the availability of input data, both for creating and parameterizing existing models for predicting AGB, or AGB change, many of which require regional calibration, or lack up-to-date information. Therefore, the first step required is the establishment of partnerships to ensure RS and *in situ* data access and their integration into open-access cloud systems. This system will ideally retrieve RS and *in situ* data from various providers and will use AI solutions and geostatistical approaches to estimate global and annual carbon maps in tropical regions (see examples in Appendix C). **The need to store large volumes of data (for example, satellite imagery of time-series) makes centralized clouds the best option for avoiding big data migration among servers. Also, the lack of stable connectivity and bandwidth in many parts of the world makes the option of a centralized cloud system the most plausible one in the short term.**

- **Uncertainty Management**

It is recommended that **the implementation of geostatistical methods be approached through demonstration activities and pilots to link *in situ* and RS data.** These methods should account for spatial correlation; differences in spatial resolutions (and possible misalignments) between *in situ* and remotely sensed data; errors in reference and other data; and spatial heterogeneity in attribute values when scaling to large regions, due to different biomes. It is also recommended to **employ geostatistical simulation algorithms to propagate spatial uncertainty stemming from various sources and steps in the MRV process to the final carbon estimates reported.**

- **Standardization and Protocols**

Data migration and storage should be accompanied by privacy and security protocols (for example, different levels of access to the platform, and the adoption of international regulations) to establish standard data protection guidelines, including security strategies, depending on the system architecture and the license to use national data sets and added-value products developed in the platform.

Improved model performance will go hand in hand with extended periods of development and testing phases following trustworthy AI solutions, which should be "lawful (respecting all applicable laws and regulations), ethical (respecting ethical principles and values), and robust (both from a technical perspective while taking into account its social environment)" (European Commission 2019). In particular, human intervention in supervised approaches will likely be required for reasons of assessment and transparency (because people might not believe the full black box). Therefore, broadly accepted guidelines should be added to the development and deployment of any AI component. **Promoting and developing data management protocols and regulations through policies and professional initiatives will help create a common understanding of how data will be used.**

ENABLING ENVIRONMENTS

- **Policies and Regulations**

The implementation of REDD+, globally, is guided by a series of overarching policies, including the Paris Agreement and Agenda 2030. Still, **to enable the development of a Global Forest Biomass Reference System,** and to leverage the discussed technologies, specific policy and regulation requirements regarding the use of these technologies need to be taken into consideration. These include:

- Revisions to the decision 11/CP19 on the modalities for forest-monitoring systems under the Warsaw Framework regarding the need to use the latest technologies, and cooperation between national and international agencies in order to harmonize data needs for reporting to the UNFCCC. Some steps have already been taken, such as the introduction of guidance for the use of allometric models and biomass maps that were included in the 2019 Refinement to the 2006 IPCC Guidelines for National GHG Inventories (IPCC 2019); and
- Development of policies to improve compliance and voluntary carbon standards to encourage the use of disruptive technologies for forest monitoring.

The following actions are recommended in order to create an environment that can promote the development of a global forest biomass monitoring system:

- Adoption of standard operating procedures for *in situ* and remote sensing data for forest monitoring.
- Development of policies for aligning *in situ* and RS data.
- Development of a policy for data access and sharing among public and private institutions.
- Development of legal provisions on the use and validity of spatial data.

- **Institutions and Stakeholders**

Institutions and stakeholders play a key role in providing the regulations, funding mechanisms, and training activities and education needed to implement new technologies and ensure future sustainability. They need to be incentivized to collaborate and communicate, while also being held accountable for outcomes. **Incentivization can be achieved through financial rewards, but also, and very importantly, through**

well-developed key performance indicators. Incentives will be particularly important for piloting new technologies at the national and international levels. Setting up an environment in which people and institutions can contribute to something that they consider to be useful will result in a win-win situation. Furthermore, if a clear purpose and framework for sharing data is provided, it can help create openness as people become more willing to share data. Providing rewards for contributing data is a great example of incentivization. The reward does not need to be financial, but it can still be very interesting for countries if, for example, they can access additional data, and if their institutions trust the organization holding the data. This could be fostered through public-private partnerships. However, open source (data, algorithms, and cloud) is crucial to overcoming data-sharing reluctance. Cloud computing as both infrastructure and platform is the core system through which the other three technologies could be implemented through several major steps.

Cloud-based data catalogs have to be compiled or retrieved from public and private Earth observation (EO) data providers (NASA, ESA, JAXA, DLR). Therefore, **partnerships with these agencies and intergovernmental institutions, and other international organizations such as GEO and FAO** (for example, the Global Forest Observation Initiative) **should be fostered.**

In situ data sets have to be used in combination with RS data and highlighted technologies in order to calibrate and validate models for biomass estimation. However, there is a lack of data in many tropical regions because of remoteness, lack of capacity, paucity of data, or armed conflicts (Rodríguez-Veiga et al.. 2017). Therefore, carbon maps in many regions will rely on a combination of innovative technologies and allometric models that are representative of the forests of that region. **Updating forest inventories and supporting existing and new initiatives for *in situ* data collection** will increase the quantity of calibration and validation samples. **There are international initiatives already in place to coordinate *in situ* data collection and harmonization that could contribute to establishing partnerships for migrating *in situ* data to this system—**for example, AfriTRON, CTFS-ForestGEO, ForestPlots, and RAINFOR. Remote sensing and *in situ* data could be integrated into AI solutions and geostatistical models run in a cloud environment. But to do so, **collaboration must be established between key private and public players in order to enable knowledge transfer and develop operational solutions following the recommendations proposed in this report.** Some of the key players in the field of standardization and software development, guidelines, and initiatives are the International Organization for Standardization (ISO), ClimateAI, the European AI Alliance, the World Economic Forum Global AI Action Alliance, the Global Partnership on AI, the Partnership on AI, the International Association of Mathematical Geosciences (IAMG), and geoENVia.[16] The development of AI solutions in a cloud environment should also consider the following key relevant industry partners with specific products: Google, Microsoft, IBM, Amazon, and the Environmental Systems Research Institute (ESRI).

- **Capacity and Information**

Additionally, the architectural design and the combination of software and hardware needed to process big data should be selected in such a way as to improve the computational cost of the analyses, not only to improve MRV implementation, but also to reduce the associated carbon footprint derived from it. **Open-source tools usually include tutorials and documentation for self-learning. However, designing field data sampling and the development of new algorithms tailored to monitoring specific environmental issues will likely require technical training.** As with geostatistics, the removal of barriers in the use of AI solutions may be achieved by **supporting communication between experts and users working in these domains.**

- **Finance and Sustainability**

Financing could be made available to open satellite data archives and could even fund new missions as well as *in situ* data campaigns. This would remove barriers in the way of developing a consistent carbon measurement strategy. All in all, setting up a Global Forest Biomass Reference System (for example, a network of 100 biomass reference measurement sites, plus 210 additional distributed sites) will require significant investment—about 34 million euros, or $41 million for *in situ data collection, personnel time, airborne campaigns, data curation, and processing over a 5-year period* (CEOS 2020). Other estimates indicate that in order to fully re-census 600 1-hectare plots across all four tropical continents would require 9 million euros ($11 million) per remeasurement cycle (Chave et al.. 2019).

16 ClimateAI (https://climate.ai/), European AI Alliance, the World Economic Forum Global AI Action Alliance (https://www.weforum.org/projects/global-ai-action-alliance), the Global Partnership on AI (https://gpai.ai/), the Partnership on AI (www.partnershiponai.org), the International Association of Mathematical Geosciences (IAMG -- https://www.iamg.org/), with key players in geostatistics among its membership; and geoENVia (https://geoenvia.org), an association promoting the use of geostatistics for environmental applications.

For any system to be implemented, and to be sustainable beyond the time frame of an intervention, adequate financing is needed. In general, financing for digital MRV will come from demonstrating its value, and both public and private sources will be required.

- **Public Sources**

There are numerous potential sources of public finance to support innovation in forest MRV. At the multilateral levels, the Green Climate Fund (GCF) and the Global Environment Facility (GEF) play a strong role and will continue to do so. In addition, there is the need for continued support from bilateral funding such as Norway's International Climate and Forest Initiative (NICFI), the United States Agency for International Development (USAID), and the United Kingdom, among others.

- **Private Funding**

Impact investment, blended finance, and carbon credits are all possible sources of finance. The voluntary market might serve as a useful platform (and source of financing) for pilots, while the cost of maintaining technologies over the long term needs to be factored into the products in order to ensure the sustainability of the solutions. In this regard, technology companies have a strong role to play in providing computational power, software, and training capacity.

- **Social, Cultural, and Behavioral Factors**

Effective implementation relies on confidence being built throughout the MRV system. This means that the stakeholders and/or beneficiaries need to know that their data will not be used against them. The system must be reliable, and it must ensure continuity over a number of years so that users and data providers consider it worthy of investing the required resources.

4.2 LONG-TERM RECOMMENDATIONS (3—5 YEARS)

INTERMEDIATE OUTCOMES

- **Data Availability and Access**

Long-term remote sensing (RS) data acquisition should focus on exploring opportunities and **supporting plans for future follow-up to the GEDI and BIOMASS missions, and/or plans for other missions with similar characteristics. By implementing this recommendation, the availability of input data with similar features will ensure the relevance of the geostatistical and AI algorithms developed and tailored to these satellite data sets once those "explorer" missions reach the end of life. It would be essential to ensure and reinforce the continuation of international partnerships, making satellite data publicly available.**

Regarding access to *in situ* data, our long-term recommendations are focused on **maintaining and increasing the Global Forest Biomass Reference System (a network of 100 biomass reference measurement sites, plus 210 additional distributed sites), which as discussed earlier, would require about 34 million euros for** *in situ* data collection, personnel time, airborne campaigns, and data curation and processing over a five-year period (CEOS 2020).

- **Processing and Computational Performance**

To resolve cases in which *in situ* data-sharing challenges cannot be easily overcome, **edge computing has been proposed** as an emerging cloud computing architecture for applications at large scale. **Within this architecture, nonsharable *in situ* data could be processed and analyzed in local data centers** in a similar manner to the one in a centralized cloud in this case, each local data center could act as a micro-cloud where analysis and results would be computed locally. Distributed systems enable quicker responsiveness and processing, lower network traffic, and facilitate real-time monitoring. **Local data centers should therefore be created to store privacy-protected data and run relevant AGB-related analytics. In addition, interoperability with the centralized cloud needs to be maintained.**

- **Uncertainty Management**

As previously recommended, **once a well-established and sustainable plot network has been developed, long-term measures to automate processing through geostatistics could evolve toward "meta-**

models" and linking GS (or other) model parameter estimates across different plots, conditions, data types, accuracies, and modeling approaches to actual carbon predictions and their quality; this would improve feature engineering, machine-learning approaches, and model development in GS and AI. In addition, **multiple-point geostatistics could enhance the quantification of spatial patterns from training images for AGB estimation by combining various sources of satellite imagery, possibly selected via AI solutions.**

Quantifying the (possibly monetary) impact of overestimating versus underestimating the true carbon amount is recommended; this will set the stage for evaluating the suitability of data sources for computing emission reduction-based payments and improving uncertainty management. In addition, the development of a **set of prototype case studies involving GS models will help showcase the benefit of improving uncertainty management in the MRV cycle**.

- **Standardization and Protocols**

Establish an international framework to adopt standard data management and processing in cloud computing systems located in different regions. Some specific areas for which guidelines should be considered include resilience to attack and security; accuracy, reliability, and reproducibility; data protection and security (authentication, encryption); quality and data integrity; traceability, explainability, accessibility, and universal design; stakeholder participation; auditability; readiness for tackling specific problems; and sustainable and environmentally friendly solutions for fostering computational efficiency.

ENABLING ENVIRONMENTS

- **Policies and Regulations**

Exploring the interaction of the above actions with some of the more specific REDD+ policies will also be important. For example:

- Country-level REDD+ readiness policies, strategies, and regulations;
- Other sector-specific policies and regulations;
- Free and prior informed consent; and
- Environmental and social safeguards.

Furthermore, **the ethics of data and usage is always a concern.** Although the current resolution of satellite data does not specifically enter into the ethical risk zone (for example facial recognition) for non-MRV purposes, **it is recommended that the possibility of new data and tools creating ethical issues in the future should be analyzed, and thought should be given to possible "dual uses" before the technology and data become operational.** For example, while satellites do not recognize facial images, drones can and do; this generates even higher risks and highlights the need for policies on spatial data privacy. In addition, the application of the selected algorithms should follow broadly accepted guidelines. Many organizations have started to create AI regulations to avoid negative consequences related to the use of AI: For example, the European Commission has issued an Ethics Guide based on seven requirements: transparency, explainability, safety, fairness, human rights, privacy, and security (European Commission 2019). It should be noted that negative consequences are linked to someone in the value chain being able to make certain kinds of decisions, while ethical risks are simply related to the use of very high-resolution imagery. **Confidence can be built through policy frameworks such as the Cloud Security Alliance (CSA), with various levels of certification and trust.**

- **Institutions and Stakeholders**

Coordination between satellite and ground inventory systems at the technological level is one of the key needs, enabling near real-time data collection; the reduction of uncertainty around the interpretation of that data; and therefore, higher confidence in the estimates from satellite-based methods. This will require **close collaboration among the space agencies, national governments, and international agencies that are funding the *in situ* data collection programs. International initiatives such as the Global Forest Observations Initiative (GFOI) can play a role in engaging countries, always taking into consideration each country's circumstances.**

On another front, long-term recommendations include **stakeholders' engagement at early stages of AI deployment tools** so that they understand the limitations of the system (independently of the extent of the foreseen application of the system) and **promoting the incorporation of scientific advances ready for operationalization** (for example, incorporate auto, self-evolving/automatic configuring AI components once they are considered mature for deployment).

Moreover, as increasing amounts of data become available, facilities provided by the private cloud sector will become more important for data storage and data processing and analytics. **The success of innovations in the development of a global forest biomass monitoring system will require collaboration**

between space agencies, international institutions such as the FAO and the World Bank, and national partners. Participants in the workshop recommended that **to increase confidence in MRV data, there needs to be a perceived neutral entity that takes charge of the process and, specifically, of the quality control of the *in situ* data, making it available and accessible to the global community, similar to the World Meteorological Organization network.** An important driver will be increasing local capacity for data analysis and allowing the analysis to be co-located with data collection, while supporting country-level policy makers.

Greater decentralization seems to spur the use of new data and technologies. However, with these opportunities there are also challenges for REDD+ countries. Implementation in countries with higher degrees of decentralization tends to generate better outcomes, as the challenges for digital MRV and potential solutions tend to be locality-specific and require knowledge of the places in which they are to be implemented. Also, places with greater decentralization often have greater local capacity and the autonomy to deliver. However, decentralization efforts require higher degrees and volumes of capacity to be built, especially with newer technologies, but usually there are only a limited amount of people at the local level and they are already overburdened with an increasing number of mandates and responsibilities.

- **Capacity and Information**

There are significant needs in data collection, storage, retention, security, interoperability, portability, and interconnectivity between systems. To address these needs, **capacity development is the main recommendation that was suggested by many of the participants in the workshop.** Capacity needs to be developed or improved, especially at the national and subnational levels. The selection and tuning of AI models are both highly skilled tasks involving experts who may require capacity building in forest and environmental departments in order for local implementation to be effective, without having to outsource these services to external experts (who may themselves not understand the local environmental context). **It is recommended that a full data and capacity-building needs assessment based on the identified target audiences and stakeholders be carried out before developing a complete strategy.** This assessment could start with lessons learned from previous programs by NASA, ESA, and other national agencies. In addition, **cutting-edge approaches, including the development of new algorithms and methodologies, will require investment in research, training, and knowledge transfer across the industrial, academic, and end-user communities.**

There are capacity-building needs associated with all of the presented technologies:

- **Remote sensing.** Capacity building is currently leaning on IPCC Good Practice Guidance for Land Use, Land-Use Change and Forestry (GPG-LULUCF); Agriculture, Forestry and Other Land Use (AFOLU) guidelines; and GFOI Methods and Guidance on the use of biomass maps. However, these guides are very generic and hard to apply given the highly diverse country contexts. While most countries now maintain a National Forest Inventory (NFI), there is great variation among the countries, due to different definitions of forests and biomass, varying data availability, and the reliability of *in situ* data, as well as different country needs. Initiatives such as NASA and ESA's collaboration on the Multi-Mission Algorithm and Analysis Platform (MAAP) requires *in situ* data in order to develop the algorithms and validate the products, without which data cannot be trusted by policy makers. **Local institutions need to be willing to share their data, but open-source solutions are usually hard to enforce, especially when incentives are insufficient, or lacking altogether**.

- **Artificial intelligence.** In the AI realm, technologies that are able to accelerate and cover topics concerning policy (including the sharing of information) and human resources, such as **training and tackling current needs in the sector, should be prioritized.**

- **Cloud computing (CC)**. In the CC space, the need to move computation closer to data generation will create capacity challenges. Even when there are policy frameworks (such as the Cloud Security Alliance, data requires a full process before it is ready for analysis: It needs to be harmonized and placed in the cloud; then training samples must be generated and quality controlled; finally, data sets need to be trained using machine learning or AI, and methods for post-processing the data need to be developed. Therefore, **there is a clear need for standard operating procedures on the preparation of remote sensing and *in situ* data from various sources, and its sharing across platforms.** Critically, local expertise needs to be built, and stakeholders need to be consulted, which will require financial commitments. Finally, but importantly, the **allocation of resources, capacity building, and training activities are needed to build, maintain, and operate data centers within distributed systems in some regions.**

- **Finance and Sustainability**
  It is important to ensure sustainability in the longer term, which can only happen if there is an ongoing, **adequate understanding of the value of the technologies and the embedding of these technologies in systems owned by key decision-makers in the countries. Funding should be allocated to support the regular acquisition of unmanned aerial vehicles (UAVs)/aerial LiDAR *in situ* data through the Committee on Earth Observation Satellites.** The cost of such acquisitions will vary; however, a reasonable guide would be $250–$600 per square kilometer, with UAV acquisitions tending toward the lower end, and airborne (that is, airplanes) the upper end.

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- **Social, Cultural, and Behavioral Factors**

  At the global level, lessons learned from the mobilization of demand for deforestation-free supply chains can also be drawn, and synergies derived for implementation in the carbon measurement and MRV space. In fact, investors managing approximately $6 trillion are increasingly demanding a wide range of **research, analysis, benchmarking tools, and best-practice materials that will help them understand and manage the risks and opportunities** associated with intensive agriculture. Such powerful investor groups wield powerful influence levers on national policy.[17] Therefore, engagement with them is key.

17 https://www.fairr.org/research/

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APPENDIX A: WORKSHOP PARTICIPANTS LIST

The names of presenters and experts providing substantial feedback have been **<u>bolded and underscored.</u>**

Name	Affiliation	Sector
Aguilar-Amuchastegui Naikoa	World Wide Fund for Nature (WWF)	Remote Sensing, Geostatistics, and REDD+ MRV
Asiyanbi Adeniyi	BIOSEC	Policy Matters
<u>Atkinson Peter</u>	Lancaster Environment Centre at the University of Lancaster	Remote Sensing, Artificial Intelligence, Machine Learning and/or Big Data and Geostatistics
Baydin Atilim Gunes	University of Oxford	Artificial Intelligence, Machine Learning and/or Big Data
Benito Pablo Llopis	South Pole	Policy Matters and Project implementation
<u>Benjamins Richard</u>	Telefónica	Remote Sensing, Artificial Intelligence, Machine Learning and/or Big Data and Policy matters
Brooks Chris	Oxford Policy Management	Policy Matters
Cabezas Antonio Tabasco	GMV Aerospace and Defense	Remote Sensing
Camara Gilberto	Group on Earth Observations	Remote Sensing, Artificial Intelligence, Machine Learning and/or Big Data, Geostatistics, Cloud Computing and Policy Matters
Camps-Valls Gustau	University of Valencia	Remote Sensing, Artificial Intelligence, Machine Learning and/or Big Data and Geostatistics
Carr Edward	Clark University	Climate Change
Castren Tuukka	World Bank	Forest Data
Chiappe Federica	Federica Chiappe Consulting	Policy
Chua Darryl	Temasek	Policy Matters
Cooke Katherine	Oxford Policy Management	Policy Matters
<u>De Bruin Sytze</u>	Laboratory of Geo-Information Science and Remote Sensing at Wageningen University	Remote Sensing, Artificial Intelligence, Machine Learning and/or Big Data and Geostatistics
De Grandi Elsa Carla	GMV Aerospace and Defense	Remote Sensing
<u>Di Gregorio Monica</u>	University of Leeds	Policy Matters
Disney Mat	University College London	Remote sensing, Artificial Intelligence, Machine Learning and/or Big Data

Dumra Bidyut	DBS Bank	Artificial Intelligence, Machine Learning and/or Big Data
Duncanson Laura	University of Maryland	Remote Sensing
Dutta Omjyoti	GMV Aerospace and Defense	Remote Sensing / Cloud Computing
Espejo Andrés	World Bank	Carbon Finance / Forestry
Fernandes Erick	World Bank	Sustainable Development
Flasher Joe	Amazon	Cloud Computing
Fleming Sam	Earth Box	Remote Sensing, Artificial Intelligence, Machine Learning and/or Big Data and Cloud Computing
Garcia Monica	Technical University of Denmark	Remote Sensing
Garret Keith	World Bank	Sustainable Development
Ghosh Soumya Kanti	Indian Institute of Technology Kharagphur	Remote Sensing, Artificial Intelligence, Machine Learning and/or Big Data and Cloud Computing
Giménez Marta Gómez	GMV Aerospace and Defense	Remote Sensing
Giuliani Gregory	University of Geneva / UN Grid-Geneva	Remote Sensing, Artificial Intelligence, Machine Learning and/or Big Data and Cloud Computing
Gonzalez-Castañé Gabriel	Insight Centre for Data	AI/Machine Learning
Gorelick Noel	Google	Remote Sensing, Artificial Intelligence, Machine Learning and/or Big Data, Geostatistics, Cloud Computing, and Policy Matters
Haas Oliver	DBS Bank	Finance
Häme Tuomas	VTT Technical Research Centre of Finland	Remote Sensing, Artificial Intelligence, Machine Learning and/or Big Data
Harshadeep Nagaraja-Rao	World Bank	Sustainable Development
Herold Martin	Laboratory of Geo-Information Science and Remote Sensing at Wageningen University	Remote Sensing, Artificial Intelligence, Machine Learning and/or Big Data and Policy Matters
Howard Luke	Plan Vivo foundation	Voluntary Carbon Market
Iversen Peter	UNFCCC	Policy Matters
Jiménez Julián Gonzalo	World Bank	Climate Change
Jonckheere Inge	Food and Agriculture Organization of the United Nations (FAO)	Remote Sensing and Cloud Computing
Kubasiak Anna	Microsoft	Artificial intelligence, Machine Learning and/or Big Data
Kyriakidis Phaedon	Cyprus University of Technology	Geostatistics

Lacoste Alexandre	Element AI	Artificial Intelligence
Lynch Jim	Earth-I	Remote Sensing and Policy Matters
Mariethoz Gregoire	Institute of Earth Surface Dynamics at the University of Lausanne	Remote Sensing, Artificial Intelligence, Machine Learning and/or Big Data, Geostatistics and Cloud Computing
Martínez Carlos López	Polytechnic University of Catalonia	Artificial Intelligence and Big Data
McNichol Iain	University of Edinburgh	Remote Sensing
Mendes Flavia	Remote Sensing Solutions GmbH	Remote Sensing
Mitchard Edward	University of Edinburgh	Remote Sensing
Nanos Nikos	Aristotle University of Thessaloniki	Geostatistics
Nuño Bruno Sánchez-Andrade	Microsoft	Remote Sensing, Artificial Intelligence, Machine Learning and/or Big Data; Geostatistics, Cloud Computing and Policy Matters
Nussbaum Madlene	Bern University of Applied Sciences	Remote Sensing, Artificial Intelligence, Machine Learning and/or Big Data and Geostatistics
Ochiai Osamu	Japan Aerospace Exploration Agency (JAXA)	Earth Observation
Olofsson Pontus	Boston University Earth & Environment	Remote Sensing and Geostatistics
Paganini Monica	World Bank	Policy Matters
Parisa Zack	SilviaTerra	Forest Data
Pascual Adrián	Arizona State University	Remote Sensing and Geostatistics
Patenaude Genevieve	University of Edinburgh	Remote Sensing and Cloud Computing
Peneva-Reed Ellie	World Bank	Remote Sensing / Climate
Ploton Pierre	Institute of Research for Development	Remote Sensing, Artificial Intelligence, Machine Learning and/or Big Data and Geostatistics; Earth Observation
Prados Ana I.	University of Maryland Baltimore County	Remote Sensing and Policy Matters
Ramage Steven	Group on Earth Observations	Earth Observation
Ramoelo Abel	South African National Parks	Remote Sensing, Artificial Intelligence, Machine Learning and/or Big Data and Geostatistics
Rana Omer	University of Cardiff	Artificial Intelligence, Machine Learning and/or Big Data, and Cloud Computing
Reddy Rama Chandra	World Bank	Climate Change
Reed Bradley	United States Geological Survey	Remote Sensing

Romero Beatriz Revilla	GMV Aerospace and Defense	Remote Sensing
Sadler Marc	World Bank	Climate Funds
Schneider Fabian	Jet Propulsion Laboratory (JPL)	Remote Sensing
Scipal Klaus	European Space Agency (ESA)	Remote Sensing
Sebastian Ana	GMV Aerospace and Defense	Remote Sensing
Shapiro Aurelie	World Wide Fund for Nature (WWF)	Remote Sensing, Artificial Intelligence, Machine Learning and/or Big Data
Sinha Chandra Shekhar	World Bank	Climate Change
Staddon Sam	University of Edinburgh	Remote Sensing
Stahl Göran	Swedish University of Agricultural Sciences; Department of Forest Resource Management	Remote Sensing, Artificial Intelligence, Machine Learning and/or Big Data and Geostatistics
Stein Alfred	University of Twente	Geostatistics
Tejada Graciela	CCST do Instituto Nacional de Pesquisas Espaciais (INPE) Brazil	Remote Sensing and Earth System Science
Thau Dave	World Wide Fund for Nature (WWF)	Big Data and Artificial Intelligence
Tolosana Rafael	University of Zaragoza	Cloud Computing
Tuia Devis	École polytechnique fédérale de Lausanne (EPFL)	Remote Sensing, Artificial Intelligence, Machine Learning and/or Big Data
Verhegghen Astrid	Joint Research Centre (JRC)	Remote Sensing and Cloud Computing
Volpi Michele	Swiss Data Science Center, ETH Zürich and EPFL	Remote Sensing, Artificial Intelligence, Machine Learning and/or Big Data
Vyhmeister Eduardo	Insight Center for Data	AI/Machine Learning
Williams Mathew	University of Edinburgh	Remote Sensing
Yagüe Julia	GMV Aerospace and Defense	Remote Sensing
Zhang Yujia	Cornell University	Remote Sensing, Artificial Intelligence, Machine Learning and/or Big Data and Geostatistics

APPENDIX B: GLOSSARY OF TERMS

Aboveground biomass (AGB) is "all living biomass above the soil including stem, stump, branches, bark, seeds, and foliage" (IPCC, 2003 p. 557, G.2).

Belowground biomass (BGB) is "all living biomass of live roots. Fine roots of less than (suggested) 2 mm diameter are sometimes excluded because these often cannot be distinguished empirically from soil organic matter or litter" (IPCC, 2003 p. 558, G.3).

Biomass is "the organic material both aboveground and belowground, and both living and dead, e.g., trees, crops, grasses, tree litter, roots etc. Biomass includes the pool definition for above- and below-ground biomass" (IPCC, 2003 p. 558, G.3).

Carbo pool is "the reservoir containing carbon." (IPCC, 2003 p. 559, G.4).

Carbon stock is "the quantity of carbon in a pool" (IPCC, 2003 p. 559, G.4).

Dead wood "includes all non-living woody biomass not contained in the litter, either standing, lying on the ground, or in the soil. Dead wood includes wood lying on the surface, dead roots, and stumps larger than or equal to 10 cm in diameter or any other diameter used by the country" (IPCC, 2003 p. 562, G.7).

Essential climate variable (ECV) is a "physical, chemical or biological variable or a group of linked variables that critically contributes to the characterization of Earth's climate" (GCOS 2021).

Forest reference level (FRL) is "a benchmark for emissions from deforestation and forest degradation and removals from sustainable management of forest and enhancement of forest C stocks" (FCPF 2020, p. 25).

Forest reference emission level (FREL) is "a benchmark for emissions exclusively from deforestation and forest degradation" (FCPF 2020, p. 25).

The Global Climate Observing System (GCOS) is a "co-sponsored programme which regularly assesses the status of global climate observations and produces guidance for its improvement. It is co-sponsored by the World Meteorological Organization (WMO), Intergovernmental Oceanographic Commission of UNESCO (IOC-UNESCO), United Nations Environment Programme (UN Environment), and International Science Council (ISC). GCOS expert panels maintain definitions of Essential Climate Variables (ECVs). They identify gaps by comparing the existing climate observation system with these ECVs. ECVs are the observations required for systematically observe Earth`s changing climate. The expert panels regularly develop plans on how to sustain, coordinate and improve physical, chemical and biological observations" (CEOS 2021c).

Litter "includes all non-living biomass with a diameter less than a minimum diameter chosen by the country (for example 10 cm), lying dead, in various states of decomposition above the mineral or organic soil. This includes litter, fumic, and humic layers. Live fine roots (of less than the suggested diameter limit for belowground biomass) are included in litter where they cannot be distinguished from it empirically" (IPCC, IPCC p. 567).

Measurement is "the processes of data collection over time, providing basic datasets, including associated accuracy and precision, for the range of relevant variables. Possible data sources are in-situ measurements, field observations, detection through remote sensing and interviews" (UN-REDD 2009, p. 3).

Monitoring a) "is a function of the National Forest Monitoring Systems, which is primarily a domestic tool to allow countries to assess a broad range of forest information, including in the context of REDD+ activities.

The monitoring function can be implemented through a variety of methods and serve a number of different purposes, depending on national circumstances" (FAO, 2013 p. vi).

Monitoring b) is "the need for periodic information on the results obtained through national policies and measures" (FAO, 2013 p. 5).

Open science refers to "the way research is carried out, disseminated, deployed and transformed by digital tools and networks. It relies on the combined effects of technological development and cultural change towards collaboration and openness in research" (European Commission 2014).

Reporting is "the process of formal reporting of assessment results to the UNFCCC, according to predetermined formats and according to established standards, especially the IPCC Guidelines and GPG. It builds on the principles of transparency, consistency, comparability, completeness and accuracy" (UN-REDD 2009, p. 4).

Soil organic matter "includes organic carbon in mineral and organic soils (including peat) to a specified depth chosen by the country and applied consistently through the time series. Live fine roots (of less than the suggested diameter limit for belowground biomass) are included with soil organic matter where they cannot be distinguished from it empirically" (IPCC, IPCC p. 574, G.19).

Verification is "the process of formal verification of reports, for example the established approach to verify national communications and national inventory reports to the UNFCCC" (UN-REDD 2009, p. 4).

APPENDIX C: OTHER PLATFORMS

An inventory of platforms can be found on the CEOS webpage (CEOS, 2021 b). Here, we highlight the following examples.

Multi-Mission Algorithm and Analysis Platform (MAAP) for Biomass, NISAR, and GEDI

NASA and ESA are currently collaborating to build the Multi-Mission Algorithm and Analysis Platform (Albinet 2019). Exponential data growth is a significant factor in the earth sciences and carbon monitoring community with the launch of several high-data-volume missions, including ESA BIOMASS (Le Toan et al.. 2011); NASA-ISRO SAR (NISAR) (Rosen et al.. 2017), and NASA Global Ecosystem Dynamics Investigation (GEDI) (Stavros et al.. 2017), as well as complementary and/or similar missions. Both ESA BIOMASS and NASA-ISRO SAR (NISAR) have planned launches for 2022, while NASA GEDI was launched in December 2018 for a two-year mission, with data being made available to users from late 2019.

This platform will enable users to develop code, analyze results, and share and process global-scale data. It is similar to Google Earth Engine (GEE) but targeted to forest communities, which will hold all of the satellite and *in situ* data using cloud computing resources. However, challenges remain on how to turn observations into actionable products, given that satellites can only measure structure; they cannot measure biomass directly. Where conversions have been carried out, measurements have been affected by large uncertainties, and most contain regional biases, making their use as evidence for result-based payments unsatisfactory. In every case, ground observation data is needed to develop the algorithms and validate the products, without which, data cannot be trusted for policy making. **The success of this will require collaboration between space agencies, institutions such as FAO and the World Bank, and national partners; space agencies alone cannot solve this challenge, as they do not have either the expertise or the mandate to establish such a system.**

GEDI's OBIWAN

One of the objectives of the GEDI mission is to produce estimates of mean biomass with uncertainty on 1 x 1 kilometer grid cells. Using the GEDI data set and footprint-level biomass library, OBIWAN (Online Biomass Inference using Waveforms and iNventory)[18] will provide biomass estimates over areas defined by users. Users will be returned a standard carbon report documenting the statistical estimator used, along with query-specific information about sample number and model parameters. OBIWAN is expected to provide critical emission factors for forests under both the REDD+ and IPCC reporting frameworks in many parts of the world. OBIWAN, the first space-based carbon density estimates, is characterized by its level of statistical rigor, and the spatial resolution required for market-based and international carbon accounting.

SEPAL

The System for Earth Observations, Data Access, Processing and Analysis for Land Monitoring (SEPAL) is an open-source, cloud computing platform developed for the automatic monitoring of land cover.

It combines cloud services such as GEE and Amazon Web Services Cloud (AWS) with free software, including geospatial services. The main focus of this platform is on building an environment with previously configured tools and on managing the use of computational resources in the cloud to facilitate ways to search, access, process, and analyze Earth observation data, especially in countries that have difficulties with internet connection and few computational resources. It works as an interface that facilitates access and the integration of other services.

18 https://climate.esa.int/sites/default/files/D1_S1_T6_Healey.pdf

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