CCI

BIOMASS

ALGORITHM DEVELOPMENT PLAN

BIOMASS CHANGE (ADPC)

VERSION 1.0

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5.0	2023-12-12	Adapted the ADP to year 5 algorithm. Added aspects developed on biomass change.	
6.0	2026-04-29	Added details on biomass change detection methods.	

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SYMBOLS AND ACRONYMS

ADP	Algorithm Development Plan
AGB	Above Ground Biomass
AFOLU	Agriculture, Forestry and Other Land Use
ALOS	Advanced Land Observing Satellite
ARD	Analysis Ready Data
ASCAT	Advanced Scatterometer
ATBD	Algorithm Theoretical Basis Document
BCEF	Biomass Conversion & Expansion Factor
CCI	Climate Change Initiative
CCI-Biomass	Climate Change Initiative – Biomass
CTV	Cultivated Terrestrial Vegetation
DARD	Data Access Requirements Document
E3UB	End to End ECV Uncertainty Budget
ECV	Essential Climate Variables
EO	Earth Observation
ESA	European Space Agency
FAO	Food and Agriculture Organisation
GCOS	Global Climate Observing System
GEDI	Global Ecosystem Dynamics Investigation
GEE	Google Earth Engine
GHGs	Greenhouse Gases
GLAS	Geoscience Laser Altimeter System
GSV	Growing Stock Volume
ICESat	Ice, Cloud, and land Elevation Satellite
JAXA	Japan Aerospace Exploration Agency
LCCS	Land Cover Classification System
NDVI	Normalised Difference Vegetation Index
NFI	National Forest Inventory
NTV	Natural/Semi-Natural Terrestrial Vegetation
OED	Overarching Environmental Descriptor
PSD	Product Specification Document
PVASR	Product Validation and Algorithm Selection Report
PVIR	Product Validation and Intercomparison Report
PVP	Product Validation Plan
SAR	Synthetic Aperture Radar

SMOS	Soil Moisture & Ocean Salinity
SRTM	Shuttle Radar Topography Mission
URD	User Requirement Document
WCM	Water Cloud Model

Table 1-1: Reference Documents

ID	TITLE	ISSUE	DATE
RD-1	Algorithm Theoretical Basis Document (ATBD)		
RD-2	End to End ECV Uncertainty Budget (E3UB)		
RD-3	Climate Research Data Package (CDRP)		
RD-4	Algorithm Development Plan (ADP)		
RD-5	Algorithm Development Plan Biomass Change (ADPC)		
RD-6	ATBD of the GlobBiomass project		
RD-7	Product Validation and Intercomparison Report		

1. Introduction

Above-ground biomass (AGB, units: Mg ha^{-1}) of vegetation is one of 54 Essential Climate Variables (ECV) that has been defined by the Global Carbon Observing System (GCOS). The majority of AGB is stored within woody vegetation and in the trunks and branches of woody plants and primarily trees. Quantifying AGB Change (ΔAGB) expressed as the difference in AGB in Mg ha^{-1} between two or more time-separated periods) and associated uncertainties is critical for both the climate and carbon science communities. In terms of climate, carbon released through natural events (e.g., fires, storms) and processes (e.g., vegetation dieback) or human activities (e.g., deforestation, harvesting) contributes an additional burden to the already high concentrations of Greenhouse Gases (GHG) in the atmosphere. However, through growth, vegetation sequesters carbon from the atmosphere and woody plants can accumulate and store substantive amounts in the trunks, branches and root systems (above and below ground). As well as playing an important role in carbon budgets, vegetation also impacts on surface energy budgets and land surface water balances that influence climate. Knowledge of carbon stocks and stock changes is further relevant to the provisioning of ecosystem services (e.g., water quality, biodiversity, fuelwood provision) and economies (forestry, agriculture).

GCOS requires AGB to be provided wall-to-wall over the entire globe for all major woody biomes at 500 m to 1 km spatial resolution with a relative error of less than 20% where AGB exceeds 50 Mg ha^{-1} and a fixed error of 10 Mg ha^{-1} where the AGB is below that limit. AGB changes, which have largely been estimated from comparisons of AGB through time, are also needed. The GCOS goal is for mapping every six months, with the breakthrough level (when specified uses within climate monitoring become possible) being 1-2 years. The minimum requirement (the threshold) is every 5-10 years.

In 2024, six years since its inception, the European Space Agency's (ESA) Climate Change Initiative (CCI) Biomass Project generated eight global maps of AGB for the year 2010 and annually from 2015-2021 at 100 m spatial resolution. Each was produced using annual time series of Synthetic Aperture Radar (SAR) data at C- and L-band wavelengths, primarily supported by spaceborne optical and lidar data and state-of-the-art biomass retrieval models (Santoro *et al.*, 2024). The provision of the time series of 7 years (2015-2020), with capacity to refer to the 2010 estimate, increased the scope for detecting and quantifying trends in AGB and associated uncertainties. Such capacity was not possible in the previous CCI Biomass Phase 1, when an initial AGB map was generated for 2010 with annual time-series maps then produced subsequently for 2017-2020. These latter maps allowed assessment of change with a time-separated interval of 1-4 years (i.e., combinations of 2017-2020) and 7-10 years (combinations of 2010 with years between 2018-2020). The initial focus of AGB change estimation in Phase 2 focused on a stock-difference method as there were insufficient data to establish trends, but methods were nevertheless explored.

Algorithms for estimating AGB from the EO data are described in the Algorithm Theoretical Basis Document (ATBD) [RD-1] while the End-to-End ECV Uncertainty Budget (E3UB) document [RD-2] describes the precision associated with the estimates of AGB and AGB change. The ATBD and the E3UB are live documents, updated annually to provide a comprehensive description of the algorithms implemented to generate AGB and AGB change maps. The current version of the ATBD and the E3UB documents describe the CORE algorithm used to generate Version 5 of the Climate Research Data Package (CDRP) [RD-3]. This consists of global datasets of AGB and related AGB change maps for and between the years 2010 and 2015 to 2021 respectively. The Algorithm Development Plan (ADP) (RD-

4] describes the proposed development of the algorithm for AGB retrieval and included a section dedicated to quantifying AGB change and uncertainty. Given developments associated with AGB change resulting from the provision of a longer and more frequent time series of AGB, this document provides a separate ADP focusing on Biomass Change (ADPC) Change.

1.1. Background to this document

AGB retrieval at the global level initially relied on the annual mosaics of Advanced Land Observing Satellite (ALOS-1/2) Phased Arrayed L-band SAR (PALSAR-1/2) data alongside time series of European Space Agency (ESA) C-band SAR. However, more recently, annual multi-temporal observations of the L-band data have been made available by the Japanese Aerospace Exploration Agency (JAXA), with this allowing substantial improvements in the estimation of AGB and hence AGB change. The development of the retrieval algorithm and relevance to change is outlined below.

For estimation of AGB, the original CORE algorithm (Version 1; based on the GlobBiomass global retrieval algorithm [RD-6] (see http://globbiomass.org/products/global-mapping/) produced estimates of Growing Stock Volume (GSV). AGB was then estimated from GSV using Biomass Conversion and Expansion Factors. In Version 2 of the algorithm, AGB was estimated directly (without the need for conversion and expansion factors) by expressing the SAR backscatter as a function of forest height and canopy density and exploiting relationships between these (Kay *et al.,* 2021) and AGB in the retrieval model, taking account of the effect of local topography. Further advances (Version 3) included refinement using the Global Ecosystem Dynamics Investigation (GEDI) and the ICESat-2 observations and the introduction of methods for avoiding unnatural fluctuations in AGB estimates. A model-based framework that utilised the Plot2Map tool developed in CCI Biomass (Araza *et al*., 2022) was used alongside coarse resolution maps of AGB bias (0.1° cell size) to quantify biases in the AGB maps, with this giving confidence in the reliability of the map. In Version 4, when time series of L-band SAR became available, the retrieval models based on the BIOMASAR approach evolved towards a more precise characterisation of the parameters in the Water Cloud Model (WCM) that related AGB to SAR backscatter. The retrieval was also relaxed in regions with sloping terrain as the SAR data were of higher radiometric quality. The availability of a time series of AGB estimates from both the BIOMASAR-C and -L algorithms further allowed more robust merging rules to be defined, and the provision of more extensive spaceborne LIDAR data and National Forest Inventory (NFI) data facilitated more accurate characterisation of the model expressing vegetation height as a function of AGB. This reduced systematic retrieval errors that resulted from incorrect characterisation of maximum AGB within and between regions.

For AGB change estimation based on Version 3 (between 2010 and 2017/18), differencing of the AGB estimates rather than signals were used because of the multi-sensor approach pursued in this project. Consideration was also given to the uncertainty of the estimates within each compared year and between years. Following the provision of a greater number of more robust maps (Version 4, with these increasing in subsequent versions), opportunities for developing time series methods for establishing magnitudes and directions of change arose.

1.2. Content of this document

This document provides an overview of existing and proposed developments for quantifying AGB and associated uncertainties, with particular focus on advancing the use of the time series of AGB estimates and addressing the requirements of the CCI Biomass project.

ADP Change (Version 1) builds on the ADP [Version 5; RD-4] with focus on state-of-the-art advances in the estimate of AGB change and its uncertainty. Consideration is given particularly to a) a review of remotely-sensed biomass change estimation approaches and their relevance to the those taken in CCI Biomass and, b) current methods implemented – specifically the stock difference and Mann-Kendall/Theil-Sen slope - and how these will be improved.

2. Advancing the estimation of AGB changes

2.1. Introduction

In Version 3 of the CCI Biomass ATBD, the approach adopted for assessing AGB change between two epochs was based on differencing AGB estimates between years (the stock-difference method), with consideration given to their uncertainty. This approach was adopted as global AGB products had only been generated for 2010 and 2017/2018. However, in Version 4, the maps of AGB for these years were updated and new layers were generated for 2019 and 2020, with these allowing some investigation into quantifying trends in AGB. This included the review and development of methods for ascertaining the directions and magnitudes of AGB changes and associated uncertainties, which could be explored over the period 2010/2017-2020 and when subsequent time-series maps were generated. Those currently selected are presented herein.

Changes in AGB can be slow (over several to many years) or fast (within days, weeks or one growing season). Depending on their direction, they can be gains, losses or no change. In addition, some AGB loss processes lead to only partial losses and others to a full loss of all AGB. Globally, changes in AGB can manifest themselves through an often complex combination of processes that interact on several spatial and temporal scales, including the timing of the change, the nature and intensity of the causal pressures (linked to drivers of primarily climate and economy), the response of forests to the change, and interactions with the surrounding environment such as forest loss affecting the local microclimate. Depending on the observation period, different and even opposing processes can act on the same forest area in specific time periods of varying lengths.

Earth Observation data collected with space-based instruments are not always consistent and can be subject to errors that lead to uncertainties in classifications of landscapes or modelled estimates of biophysical variables. These limit our ability to ascertain the extent to which the change detected corresponds to what has happened on the ground. As the ESA CCI AGB estimates are affected by these uncertainties, which can be substantial, the proposal is to develop and further integrate the currently selected methods for quantifying $\triangle$AGB (i.e., stock-difference and trend analysis) and attributing these to different pressures (e.g., through an existing evidence-based approach developed through the *Living Earth* project; Lucas *et al*., 2022). This framework describes change on the basis of impacts and driving pressures inferred from diverse Earth Observation (EO) data and builds on the Driver-Pressure-State-Impact-Response (DPSIR) framework (Oesterwind *et al.*, 2016). The ESA CCI AGB estimates can be used in conjunction with other data to support whether changes, detected through time series comparisons, agree with and can be explained through the evidence accumulated from these EO data (e.g., relating to climate, land management or biogeography).

2.2. Review of existing approaches for estimating AGB change from EO data

Methods for remotely-sensed biomass change estimation, described in the IPCC Good Practice Guidance (IPCC, 2019), fall into two broad categories: stock differencing and gain-loss approaches.

The stock differencing approach involves having measurements of a variable (in this case, AGB) for the same location at different dates and then calculating the difference between the two measurements. This can be achieved either with direct measurements of AGB or *via* proxies and modelling (McRoberts et al, 2015), with this approach being widely applied in combination with LiDAR, NFIs and/or permanent plot measurements. As examples, Xu *et al*. (2021) used a stock differencing approach to estimate AGB change as the difference between two AGB density maps generated two years apart. Similarly, Araza *et al.* (2023) used differencing between two epochs to compare the AGB change from different global products, using LiDAR, NFI and country-level estimates from the United Nations (UN) Forest Resource Assessment (FRA) reports as reference data. Dubayah *et al*. (2010) applied an indirect biomass change estimation method to estimate AGB change from two acquisitions from the Laser Vegetation Imaging Sensor (LVIS) instrument taken seven years apart. Both sets of LiDAR footprints were translated into canopy height (m) and then into AGB density (Mg ha^{-1}) using empirical models. AGB change was calculated from the two density estimates. However, whilst the stock differencing method can provide accurate change estimates (McRoberts *et al*., 2018), it lacks robustness when the uncertainties of measurements are high, which is often the case when solely using pixel-based AGB estimates from satellite imagery (Santoro, 2021; Turton et al, 2022). This method is also limited by data richness, specifically in terms of spatial and temporal coverage, and is thus restricted to areas where repeat measurements are available and hence constrains applicability at the global scale.

When AGB data are missing, a gain-loss approach is recommended as an alternative (IPCC, 2019). This method involves using an estimate of the area of forest change stratified by forest type and then comparing AGB density within each forest type before and after the forest change to quantify AGB gains and losses (Brown 1997). Gains are generally associated with forest regeneration and can be estimated using averaged growth rates standardised by forest types. AGB losses that are attributed to pressures such as deforestation or those associated with degradation (e.g., selective logging, drought, fires) are calculated as the product of the area of the land use change (activity) and an associated emission factor (i.e., the average amount of greenhouse gases sequestered or released per unit of activity) (McRoberts et al., 2020). This method leads to greater uncertainty in the change detected but yields net estimates comparable to those obtained through stock differencing and is compliant with the IPCC guidelines for reporting and monitoring (McRoberts et al., 2018; IPCC, 2019). Other studies applying this method include Tang *et al*. (2020), who applied a spatially explicit model to the Colombian Amazon using AGB and land cover dynamics from Landsat sensor data to estimate carbon emissions and their uncertainty between 2001 and 2015. The approach was considered applicable to any country. Harris *et al*. (2021) developed a global-scale monitoring framework based on the gain-loss approach to estimate global forest carbon emissions and removals from 2000 to 2019.

In addition to the two broad approaches described in the IPCC Good Practice Guidelines, time series analysis methods can be applied to examine AGB changes within a selected time period. Includes are trend analyses, which have been employed to discern and quantify slow changes in AGB over time. They account for differences in AGB over multiple time intervals and are suitable for characterising the overall direction of change over long periods. The slope parameter characterises the incremental average AGB change per time unit. Trend analysis methods generally involve using either parametric tests such as linear regression (in cases where the data follow a Gaussian distribution) or non-parametric tests (where independence from assumptions about the distribution of the data was required). The latter include the Theil-Sen slope, which is the median of partial slope estimates of the time series, in combination with the Mann-Kendall test for significance (Kendall 1938; Mann 1945; Theil, 1950; Sen, 1968). Mann-Kendall has proved efficient for detecting changes in vegetation indices, such as the Normalized Difference Vegetation Index (NDVI) (Forkel *et al.*, 2013; Guo *et al.*, 2018, Dashpurev et al. 2023) or Leaf Area Index (LAI) (Liu *et al*., 2024). As AGB databases grow, the method has been increasingly adopted for assessing changes in long AGB time series. For example, Liu *et al.* (2013) used the Mann-Kendall method to analyse a time series of Vegetation Optical Depth (VOD) from AMSR-E between 1988 and 2008 highlighting that, over tropical forests, the VOD changes coincided with rapid AGB loss from deforestation, while for boreal forests, rapid AGB losses from disturbances such as fires were noted. Xu *et al.* (2021) used the Mann-Kendall method to explore trends in AGB between 2000 and 2019 combining satellite data from MODIS and QuikSCAT. Xuejian et al (2024) also used Mann-Kendall to highlight AGB changes estimated with machine learning between 2001 and 2018 in fast growing bamboo forests in China.

2.3. Methods selected in CCI Biomass

The two approaches identified and adopted for detecting and quantitatively describing changes in AGB between epochs are the stock-difference method, which involves simple differencing with the standard deviation as a measure of uncertainty, and the Theil-Sen slope (Theil, 1950; Sen, 1968) together with the Mann-Kendall test (Kendall, 1938, Mann, 1945), which allow the detection of slow monotonic trends. These methods are described in more detail in the following sections.

2.3.1. Stock difference method

As demonstrated for Version 3, a straightforward way of estimating AGB change between two epochs is to calculate the difference between two AGB maps, which can be time-separated by a year (e.g., 2017 and 2018) or a decade (e.g., 2010 and 2020). The time series data are, in this case, assumed stationary (that is the mean and variance are constant over time). The significance of the change can be accounted for by using the standard deviation around the estimated AGB means for the two dates or epochs being compared. If these error bars do not overlap (Figure 5-1), the AGB difference can be considered statistically significant under the assumption of unbiased estimates or equal biases in both AGB stock maps. Partial or full overlap indicate a potential change or that change is improbable.

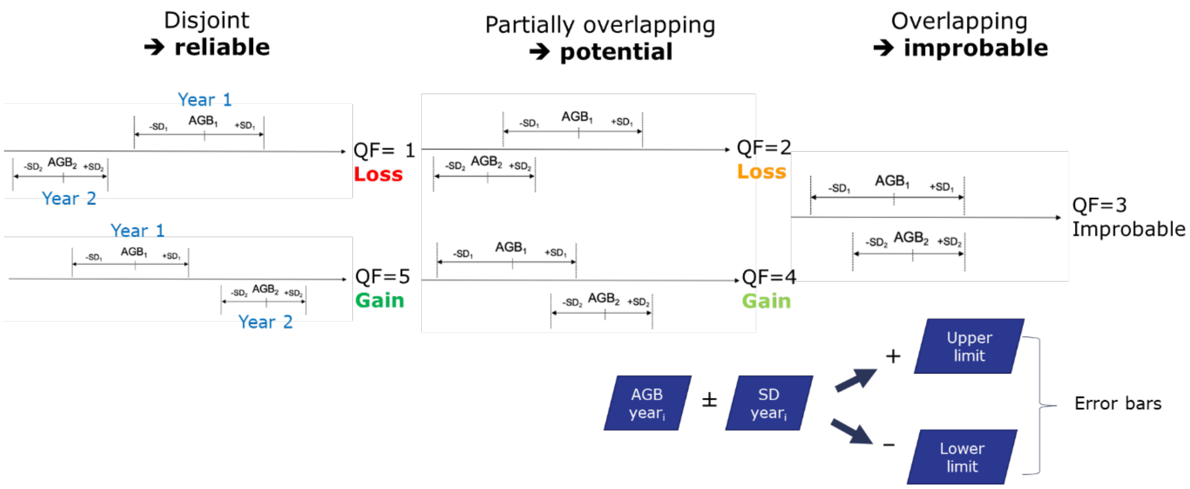

Figure 5-1: Overview of the stock-difference approach to AGB change detection.

The standard deviation, which quantifies the precision of the stock-difference estimate, is calculated as the square root of the sum of the variances of the two individual maps, which assumes the errors in the two estimates are independent. This standard deviation can then be used to generate a quality flag for the difference estimates (i.e., reliable, potential or improbable change), which assists with the interpretation of the significance of the difference detected for an area. Both the standard deviations of the change and the quality flags are currently provided by the ESA CCI BIOMASS CRDP [RD-3] alongside the AGB and standard deviation for each year. An example of the stock difference map is given in Figure 5-2.

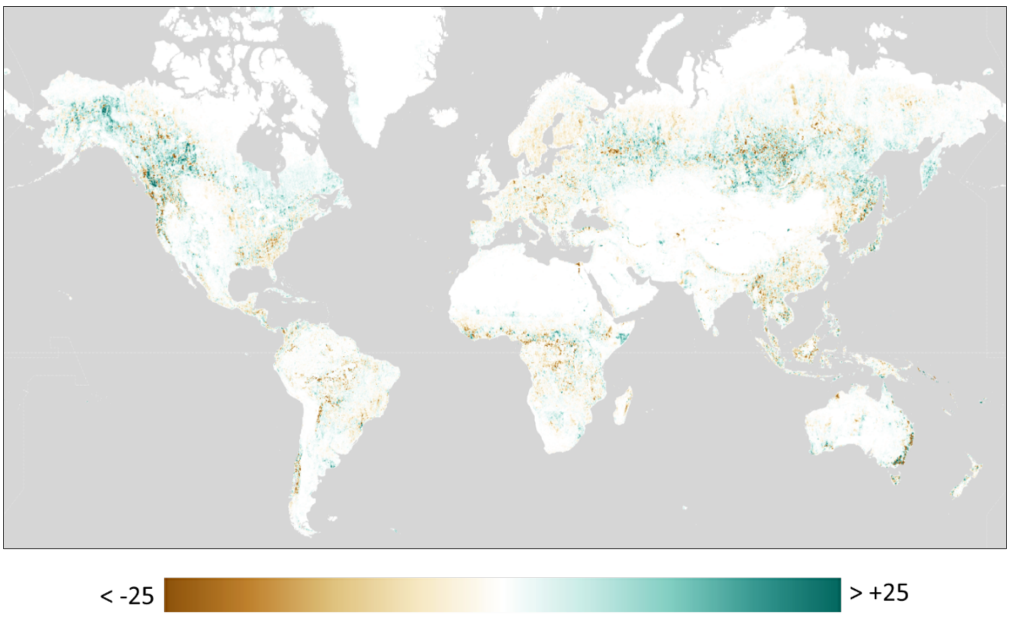

Figure 5-2: Net difference in ESA CCI AGB between 2015 and 2021, expressed as Mg ha^{-1}. No quality flag or forest mask applied. Map as displayed in Google Earth Engine (GEE) using the mask-weighted mean of the input pixels for pyramiding (i.e. reduced-resolution versions of the image).

There are a number of drawbacks to the stock-difference approach used within CCI Biomass, which include:

a) The change that can be detected depends on the standard deviations of the individual AGB estimates. The larger their values, the wider the spread about the mean and thus the more likely the standard deviation intervals will overlap.
b) Biases in the individual AGB estimates will propagate to the AGB difference estimate, and the variance of the estimated difference will be larger than that of each individual estimate. Both bias and precision issues were identified and discussed in the ATBD and PVIR [RD-7], and both affect the quality of the AGB difference estimated from the CCI Biomass AGB data products.
c) CCI Biomass generates maps of AGB by combining data from different sensors, namely ENVISAT ASAR and ALOS PALSAR for 2010 and the Sentinel-1 and ALOS-2 PALSAR-2 for 2015 onwards, and this introduces errors that may be difficult to identify and quantify.
d) Depending on the frequency, polarisation and other factors (e.g., incidence angle, moisture content of vegetation and soils), the radar signal saturates and sensitivity to differences in AGB decreases near the saturation level. Similarly, the capacity to detect changes in AGB between dates or epochs may be compromised as measurements may also be affected by environmental conditions at the time of observations.
e) Only net changes in AGB over large temporal intervals between observations (e.g. decadal) are detected, with fluctuations at finer temporal intervals often not identified.

In CCI Biomass, global, repeated observations from multiple spaceborne missions are found to have substantially higher predictive power and hence, as more AGB estimates become available, the opportunities for trend analysis are increased.

2.3.2. Trend analysis

Where more than two AGB estimates from different time points are available, trends in AGB can be used to identify whether there is an increase, decrease or no change within the observation period, noting that over long time series these trends may not be monotonic, as different change processes may act on the forest. Methods for establishing whether trends over time series observations are significant include the F-test of the slope parameter from a linear regression, the non-parametric Mann-Kendall test and Theil-Sen slope, or repeated applications of the stock difference method for adjacent time steps (as described above).

a) Multiple comparisons of stock-difference estimates:

Between successive time-separated periods, the significance of the difference in AGB is assessed and collated for each year to establish whether there is no change or there are successive gains or losses or combinations of these (Figure 5-3). These are summarised for the final year of interest (here 2020) to highlight whether there has been a net gain or loss in AGB overall based on the significance of difference, with interruptions to the sequence identified. This could also result in the generation of successive quality flag assessments and standard deviations of differences between years. The large time-interval between 2010 and 2015 onwards may compromise this approach because of natural events/processes or human activities that might have occurred from which forests may (or otherwise) have recovered sufficient AGB for these not to be detected.

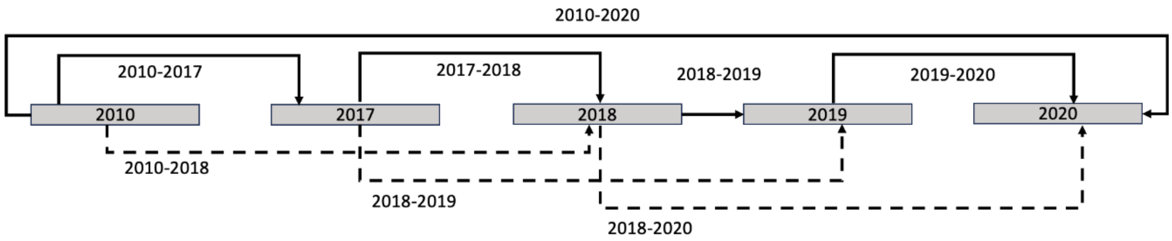

Figure 5-3: Repeated comparisons of stock-difference estimates and associated uncertainty metrics over time series of AGB maps can be used to determine relative magnitudes and directions of change.

b) Mann-Kendall and Theil-Sen slope:

The non-parametric, non-seasonal Mann-Kendall test can be used to detect if there is a decreasing or increasing monotonic trend in multi-temporal AGB estimates and evaluate the significance of this trend (Kendall, 1938; Mann, 1945). This method calculates the sign of the change between each pair of AGB estimates compared, giving 1 or -1 for a gain or loss respectively, or 0 if both values are equal, (Equation (5-1), Gilbert, 1987). The signs of all pairs are then summed for all the year intervals, with this indicating whether AGB is increasing or decreasing overall. This can be calculated as follows:

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} sign\,(x_j - x_k) \tag{5-1}$$

$$sign\,(x_j - x_k) = \begin{cases} +1 \text{ if } x_j - x_k > 0 \text{ (gain)} \\ 0 \text{ if } x_j - x_k = 0 \text{ (no change)} \\ -1 \text{ if } x_j - x_k < 0 \text{ (loss)} \end{cases}$$

Here, n is the length of the time series and x_j and x_k are the measurements observed at years t_j and t_k.

The strength of the trend can be measured with the Kendall rank correlation Tau-b coefficient (Kendall, 1938), which is calculated using the number of concordant and discordant pairs of observations, here *(AGB, time)*, with adjustment for ties. For a pair of observations, annotated (x_j, t_j) and (x_k, t_k) and where $j < k$, the pair is considered concordant if ($x_j < x_k$ & $t_j < t_k$) or if ($x_j > x_k$ & $t_j > t_k$), or discordant if ($x_j < x_k$ & $t_j > t_k$) or ($x_j > x_k$ & $t_j < t_k$). When $x_j = x_k$ (and/or $t_j = t_k$), i.e. the observations are tied and the pair is considered neither concordant nor discordant. The values of Kendall Tau-b range from -1 for a perfectly negative association (AGB strongly decreases with time) to +1 for a perfectly positive association (AGB strongly increases with time), with 0 meaning no association.

Kendall's Tau-b is calculated as follows:

$$tau\ b = \frac{n_c - n_d}{\sqrt{(n_0 - n_1) \times (n_0 - n_2)}} \tag{5-2}$$

where:

n = Sample size

n_0 = Total number of possible pairs = $\binom{n}{2} = \frac{n(n-1)}{2}$

n_c = Number of concordant pairs

n_d = Number of discordant pairs
u_j = Number of tied values in the *j*-th group of ties in x
v_k = Number of tied values in the *k*-th group of ties in t
$n_1 = \sum_j \frac{u_j(u_j-1)}{2}$
$n_2 = \sum_j \frac{v_j(v_j-1)}{2}$

The variance of the Mann-Kendall statistic can be estimated as follows:

$$\mathrm{VAR}(S) = \frac{1}{18}\left(n(n-1)(2n+5) - \sum_{k=1}^{g}(F_k(F_k-1)(2F_k+5)\right) \quad (5\text{-}3)$$

where g represents the number of tie groups (i.e., repeated values observed) and F_k the number of times these values appear in the *k*-th tie group.

The significance of the trends over the selected time series can be determined using the standard normal statistic, z, which is calculated by dividing the Mann-Kendall statistic by its standard deviation (based on a two-sided test).

$$z = \begin{cases} \frac{S-1}{\sqrt{VAR\,(S)}} & (S>0) \text{ increasing trend} \\ 0 & (S=0) \text{ no change} \\ \frac{S+1}{\sqrt{VAR\,(S)}} & (S<0) \text{ decreasing trend} \end{cases} \quad (5\text{-}4)$$

The probability of observing an extreme value (i.e., the P-value of z) of the Mann-Kendall statistic is calculated as (Clinton, 2020):

$$Pvalue = 1 - P(|z| < Z) \quad (5\text{-}5)$$

For a two-sided test to establish whether a positive or negative trend exists at the 95% confidence level, the P-value is compared to the value of 0.975. Pixels indicating a significant trend can be highlighted by using a mask where the P-value is within a specified threshold (e.g., P-value lower than 0.025, 0.05, or 0.001) and hiding the pixels outside this threshold (Clinton, 2020).

The Theil-Sen slope estimator (Theil, 1950; Sen, 1968) determines both the direction (increasing or decreasing) and magnitude of the change and is calculated as the median of all possible slopes among data pairs in the time series.

$$MEDIAN(\sum_{k=1}^{n-1}\sum_{j=k+1}^{n}\frac{(x_j - x_k)}{(t_j - t_k)}) \quad (5\text{-}6)$$

where x_j and x_k are the measurements at years t_j and t_k.

A global example of the changes in AGB generated using the Thiel-Senn slope estimator is given in Figure 5-4m, with this highlighting progressive losses and gains in AGB. However, there are a number of considerations to this approach. The CCI Biomass AGB estimates are generated from time series of C- and L-band SAR data and are aggregated on an annual basis. They are thus assumed minimally affected by seasonality, which is a requirement for using the non-seasonal Mann-Kendall test. We also assume that the AGB estimations are not serially correlated over time. The combination of the Mann-Kendall and Theil-Sen slope is robust to outliers but a minimum of three time-separated estimates of AGB are required.

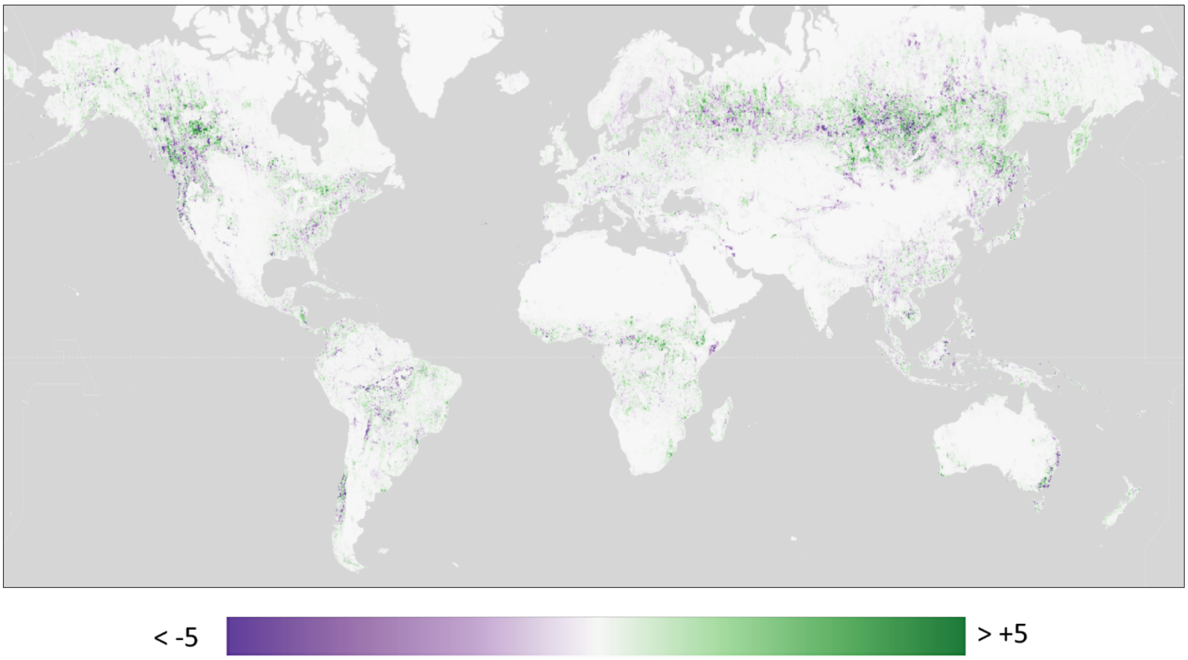

Figure 5-4: a) Global annual change in ESA CCI BIOMASS AGB based on the Theil-Sen slope estimator between 2015-2021, expressed as tons per hectare per year. No quality flag or forest mask applied. Map as displayed in Google Earth Engine (GEE) using the mask-weighted mean of the input pixels for pyramiding (i.e. reduced-resolution versions of the image). Many of the forested areas showing strong annual AGB loss are consistent with areas subject to severe disturbances, such as megafires (Siberia, Western Canada, Eastern Australia), extensive logging or forest conversion (Canada, Russia, Manaus and along the Amazon River etc.). The gain detected often corresponds to vegetation regrowth in previously disturbed forest areas (Russia, Canada,). Some of the changes may be due to anomalous AGB estimates (due to moisture conditions at the time of SAR image acquisition etc.)

Other drawbacks to using the Mann-Kendall and Theil-Sen slope include:

a) The approach is not applicable where the intervals between observations are not consistent over time (e.g., AGB data missing for years 2011-2016)

b) It is sensitive to ties (repeated identical values) which may lead to small Sen's slopes being rounded to 0 even if the trend is flagged as significant by the Mann-Kendall test.
c) It is sensitive to autocorrelation and seasonality in the time series.
d) It may miss true trends for shorter time series with an insufficient frequency of observations

As with the stock-difference approach, an increase in AGB at decadal points only might indicate no change in AGB but forests may have been cleared or degraded then recovered during the intervening period so that no change is detected. The assumption of no change is likely to be most frequently observed for forests that are of low AGB (e.g., shrublands) or that rapidly accumulate AGB (as in the case of tropical regenerating forests) even though a substantive loss might have occurred during a change event. Similarly, where the radar backscatter is above a saturation level, any growth in the intervening period is unlikely to be captured.

2.4. Discussion

2.4.1. Stock-difference approach

The stock-difference approach (with associated quality flags) is a viable method for a) providing uncertainty in quantified differences in AGB between successive dates and b) giving a degree of confidence (i.e., reliable, potential, or improbable) that changes detected are associated with a loss or gain of AGB. The success in applying the stock-difference approach is dependent on a) the periods (epochs) being compared and b) the rates, magnitudes, directions, and persistence of change. In ESA CCI BIOMASS, AGB estimates are compared over one decade (2010 and 2020) and annually from 2015 to 2021. Key considerations are:

a) The stock-difference approach performs best where forest loss is complete, rapid and persistent (i.e., remains as non-forest over the year or decade). In these situations, the estimated AGB of the forest prior to removal gives an estimate of the magnitude of the loss, subject to the uncertainty in this estimate prior to the change event.
b) Where partial removal of vegetation occurs, the reliability of detection depends on the AGB prior to the change, which varies with the setting (e.g., climate, slope, aspect, prior land management) within biomes, the proportional loss of AGB, and the uncertainty in AGB estimation prior to and following the AGB change.
c) Detecting partial losses of AGB over time will further depend upon the amount accumulated by forests following the change (through growth) over the period of comparison (decades or years) and the associated uncertainty of the pre- and post-change AGB. Where forest loss is partial but has recovered, changes in AGB might be overlooked, particularly where estimates are a decade apart.
d) Gains in AGB are generally most rapid during the early stages of growth (e.g., on land recently cleared of natural forests or fully/partially harvested for timber and then replanted) but are unlikely to be detected when AGB estimates are compared between consecutive years, particularly given the often high levels of uncertainty in the estimates. The exception is where forests are rapidly growing, as is often the case for commercial plantations and natural regenerating forests in productive regions (e.g., the tropics).
e) Gains and losses can take place over varying time series and may not be monotonic, particularly in highly dynamic environments (e.g., wooded savannas with a high frequency of fire events).

2.4.2. Mann-Kendall and Theil-Sen Slope Trend Analysis

The Mann-Kendall and Theil-Sen slope methods are best applied where AGB estimates are available for consecutive years, as is the case for 2015 to 2021 and it cannot be assumed that the data are following a Gaussian distribution. Whilst the CCI Biomass 2010 AGB data can be integrated, the use of different C- and L-band sensors in their generation can be misleading, partly as these differed between epochs (i.e., ALOS PALSAR and ENVISAR ASAR for 2010 and ALOS-2 PALSAR-2 and Sentinel-1 SAR for 2015-2021). A time series of AGB estimates that are more frequently generated and obtained using the same sensor types and operating modes is preferred, but this is often difficult to achieve. Another option is to consider and benchmark AGB trends with those obtained from time series of AGB estimates from other sensors (e.g., L-VOD, C-band scatterometers) or extrapolated from *in situ* measurements (e.g., with the Plot2Map tool) under the assumption that such trends correspond to reality. However, in the latter case, obtaining sufficient data from spatial locations and time-steps that facilitate this approach has proved problematic. Reference to time series of other metrics (e.g., Landsat-derived fractional cover of vegetation or spectral indices) can also indicate the nature of change (e.g., directions, magnitudes).

Moving ahead with the methodological developments around AGB change detection algorithms, the following activities are required:

- Extension of the time series of annual AGB estimates for more robust change detection between 2010 and 2015-2021 using the stock difference and trend analysis (Theil-Sen slope) approaches.
- Carrying out a systematic plausibility assessment of AGB change by analysing global areas where expected AGB change should be close to zero, slowly losing AGB, and slowly gaining AGB over time to see whether the AGB change maps identify those fundamental types of change consistently with other spatial datasets.
- Validation of the AGB change detection results with multitemporal airborne Lidar images or repeated field plot measurements in some test sites in different biomes, subject to multitemporal data availability.
- Devise a method for identifying an acceleration or deceleration of AGB gains and losses over time from the AGB change data.
- Designing an application of temporal segmentation of the AGB time series into time segments in which specific AGB change processes are identifiable, using LandtrendR.
- Development of an evidence-based framework to deconstruct existing multi-temporal land cover maps into constituent environmental descriptor layers (e.g., lifeform, cover, height) and compare these to give evidence for pre-defined impacts (with 12 relevant to forests and reflecting changes in vegetation extent, amount, type or condition). Each can then be attributed with a select range of driving pressures (e.g., fire, insect infestation, storms, deforestation).
- Development and demonstration of use cases of preliminary AGB change products in areas of known AGB changes and their drivers, pressures and impacts and based on national products (e.g., England, Wales, Australia), and comparison with those generated using deconstructed and reconstructed global datasets.
- Outreach and knowledge sharing of the AGB change detection methods

3. Conclusions

The two methods currently considered for identifying and qualifying changes in AGB in CCI Biomass are the stock-difference and trend-analysis approaches, with both applied at a global level through GEE. The stock-difference approach has been demonstrated globally. ESA Biomass AGB per-pixel (100 m) estimates for each year (2010 and 2015-2021) and associated standard deviations have been generated and the standard deviation of the stock-difference method been provided in the ESA product. Per-pixel quality flags have also been generated according to whether the histograms associated with the pixel at the two epochs are disjoint or fully or partially overlapping and can be used to interpret the reliability of the difference detected by pixel.

The Mann-Kendall and Theil-Sen slope have been used to estimate trends, with the former determining the presence (or otherwise) of a trend and its significance over the selected time period and the Theil-Sen slope establishing the direction and magnitude of the trend. This approach is best applied to the annual time series of AGB estimates from 2015 to 2021 but can also be considered for use with all available estimates (i.e., 2010 to 2020). In this latter case, we need to consider the effects of both differences in sensor types used in the AGB estimation and changes in AGB that might have occurred during periods of no observation by satellites.

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