



**EYE-CLIMA**  
Verifying emissions  
of climate forcers

# Updated report on existing biomass and biomass change datasets

## DELIVERABLE 1.8

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## Summary

This report reviews existing datasets on woody biomass and biomass change and assess their suitability for greenhouse gases inventories and as potential benchmarks (common denominators) for national UNFCCC reporting. Datasets describing the drivers of biomass change are also considered, as they are essential for distinguishing changes driven by human activities from those resulting from natural processes. Based on this review, three biomass-related datasets are identified as the most relevant for the stated aims.

(1) ESA CCI Biomass and biomass change maps show strong potential for use within the EYE-CLIMA framework. A key advantage is the integration of multiple remote sensing instruments, including radar, lidar, and optical sensors from different space agencies (ESA, NASA, JAXA). These maps provide uncertainty estimates for both above-ground biomass (AGB) and AGB change and are continuously improved through systematic reprocessing of earlier reference years (e.g., 2010). Future releases aim to extend the time series in both directions, covering earlier years (e.g., 2000, 2005) as well as more recent periods. A notable strength is the successful calibration and validation of CCI Biomass maps against national and regional ground observations, which reduces bias and improves accuracy (Schepaschenko et al., 2021; Avitabile et al., 2023). However, differences between sensors used in earlier and later reference years introduce inconsistencies that affect the reliability of biomass change estimates derived using a stock-change approach.

(2) Biomass change datasets based on L-band Vegetation Optical Depth (L-VOD) also demonstrate great potential, mainly due to their relatively long and temporally consistent observation period starting in 2010, acquired using the same sensor. Nevertheless, uncertainties related to the calibration of L-VOD to biomass and the reliance on a space-for-time approach to infer change reduce the robustness of biomass change estimates derived from stock differences.

(3) Avitabile et al. (2023) provide a European biomass map for 2020 that is calibrated to sub-national statistics. This calibration ensures internal consistency and minimizes bias with respect to national statistics and UNFCCC reporting, making the dataset particularly suitable as a reference layer.

An additional key dataset is the European Forest Disturbance Atlas (Viana-Soto and Senf, 2025) which provides spatially explicit information on the drivers of biomass change across Europe for the period 1985–2023.

Our own study based on visual interpretation of very high-resolution imagery suggests that CCI Biomass products tend to overestimate the spatial extent of biomass changes; however, the direction of changes is generally captured correctly. In particular, about 72% of detected biomass losses are linked to forest management activities, while 92% of biomass gains occur within existing forest stands, reflecting post-harvest recovery and natural growth rather than land-use change.

Finally, for estimating biomass change, flux-based approaches have been developed that infer aboveground biomass dynamics from disturbance and recovery rates, particularly for secondary forests. These methods have been applied in Europe, boreal, and tropical regions where long-term disturbance time series derived from Landsat data are available.



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## 1. Introduction

This report aims to review biomass and biomass change datasets that are available or might be made available during the course of the project. These datasets should be suitable for direct utilisation in UNFCCC reporting or for benchmarking greenhouse gas (GHG) inventories at European scale. Our primary focus has been on the remote sensing-based products that facilitate wall-to-wall mapping at regular (annual) intervals.

Biomass definitions vary across datasets. From a biological standpoint, the living biomass of a forest encompasses trees (stem, bark, branches, foliage, roots), understory and green forest floor biomass. Remote sensing-based products typically estimate above-ground woody biomass of trees (in units of dry matter) with a diameter at breast height greater than 10 cm. Other components, such as roots, foliage, smaller trees, shrubs, and herbaceous cover, are not included. This divergence is acceptable as long as the definition is consistently applied for time series analysis or cross-dataset comparison. A conversion of dry matter to C requires conversion factors from the C content of biomass, close to 0.48.

Direct measurement of biomass is unattainable, barring destructive methods involving cutting trees, dividing them into pieces, and weighing them. Even in the destructive method, a sampling approach is employed to select representative trees, branches, and wood density samples. Consequently, biomass estimations are inevitably associated with uncertainties. Remote sensing methods rely on various forest features obtained through optical, radar or lidar instruments. Each feature and its corresponding biomass estimation method have inherent advantages and shortcomings. Notably, the most relevant instruments (L/P-band radar and lidar) have a relatively short history of measurements, rendering biomass change detection particularly challenging when different instruments are employed over time.

An additional critical question we aim to address concerns the drivers of biomass change. This knowledge is crucial for distinguishing changes linked to forest management from those attributable to natural processes. Quantifying drivers of change should enhance our understanding of the effectiveness of forest management practices and identify major threats.

## 2. Biomass and Biomass Change Datasets

Remote sensing-based above-ground biomass and biomass change maps serve as critical independent sources of information regarding carbon stocks and fluxes. While they may exhibit somewhat lower accuracy compared to ground-based national inventories, they offer several distinct advantages, including:

- **Consistent Cross-Border Approach:** Remote sensing allows for a uniform approach across borders, facilitating standardized assessment methods.
- **Wall-to-Wall Estimation:** One of the notable strengths is the ability to provide comprehensive, wall-to-wall estimations, offering a holistic view of the biomass distribution.
- **Timely (Annual) Estimates:** Remote sensing methods enable timely assessments with annual estimates, ensuring a more dynamic and up-to-date understanding of biomass changes over time.

These advantages make remote sensing an invaluable complement to ground surveys, enhancing our ability to monitor and understand the dynamics of carbon stocks and fluxes in a more comprehensive and efficient manner.

Table 1 comprises a list of biomass and biomass change datasets that have been considered in this report.



**Table 1.** Major biomass and biomass change datasets

Dataset name	Spatial resolution	Spatial coverage	Temporal coverage	Biomass change
Baccini	25 m	global	2000	no
CCI Biomass	100 m	global	2007, 2010, 2015-2022	yes
CTREES JPL	10 km	global	2000-2020	yes
GEDI L4 gridded biomass	1 km	up to 51.6° N	2020	no
ICESat-2 Boreal biomass	30 m	50°-75° N	2020	no
DQ1 Sentinel 2 Russia biomass	30 m	Russia	2024	no
Harmonised Forest Biomass dataset 2020 for Europe	100 m and sub-national statistics	Europe, 38 countries	2020	no
LVOD	25 km	global	2010-2022	yes

## 2.1. Biomass datasets

### 2.1.1. ESA CCI Biomass

The ESA CCI Biomass dataset (version 6) offers estimates of forest above-ground biomass for the years 2007, 2010, and 2015-2022. These estimates are derived from a blend of Earth observation data, varying by year and sourced from the Copernicus Sentinel-1 mission, Envisat's ASAR instrument, and JAXA's Advanced Land Observing Satellite (ALOS-1 and ALOS-2). The AGB maps rely on revised allometries based on spaceborne LiDAR data from the GEDI and ICESat-2 missions. The dataset is developed as part of the European Space Agency's (ESA's) Climate Change Initiative (CCI) programme by the Biomass CCI team. The data product consists of above ground biomass (AGB, unit: tons/ha i.e., Mg/ha) provided as raster dataset. AGB is defined as the mass, expressed as oven-dry weight, of the woody parts (stem, bark, branches, and twigs) of all living trees, excluding stump and roots). Per-pixel estimates of AGB uncertainty are also provided, expressed as the standard deviation in Mg/ha (raster dataset). Data are provided in both Netcdf and Geotiff format (Santoro et al., 2021; Santoro & Cartus, 2023).

The dataset is accessible at: <https://dx.doi.org/10.5285/95913ffb6467447ca72c4e9d8cf30501>

### 2.1.2. GEDI gridded biomass

The GEDI gridded biomass dataset is derived from the Global Ecosystem Dynamics Investigation (GEDI) L4B product (Version 2.1), offering 1 km estimates of mean AGB. NASA's GEDI, a full waveform lidar instrument aboard the International Space Station, conducted data collection between April 2019 and March 2023, covering global regions between 51.6° N and 51.6° S latitudes. Each laser illuminates ~25 m on the ground, and measures tree heights and volumes within those 25 m areas. GEDI L4A parametric footprint biomass models convert each high-quality waveform to an AGB prediction, and the L4B algorithm uses the sample present within the borders of each 1 km cell to statistically infer mean AGB and the standard error of the mean. The GEDI L4B product is 1 km spatial resolution, and the gridding procedure is described in the GEDI L4B Algorithm Theoretical Basis Document (ATBD). Dubayah et al. (2022) describe the hybrid model-based mode of inference used, where estimates of the standard error



of the mean account for both GEDI L4A modelling uncertainty and uncertainty related to how the 1 km cells are sampled by GEDI's observations (as opposed to making wall-to-wall observations). The data themselves are samples, that is, are not spatially continuous.

The dataset is accessible at: <https://doi.org/10.3334/ORNLDAA/C2299>

### 2.1.3. ICESat-2 Global Biomass Models

The ICESat-2 boreal dataset stems from NASA's ICESat-2, a photon-counting lidar instrument that launched in 2018. ICESat-2 is dedicated to collecting global 3D structure measurements of Earth's terrain and vegetation. This provisional product, still in development, utilises samples from ICESat-2's vegetation height product along with 30m data from Harmonized Landsat Sentinel-2, and the Copernicus DEM. This product focuses on high latitude boreal forests where NASA's GEDI instrument doesn't collect data, and is meant to complement the temperate and tropical forest maps from GEDI. Description of the data set available here: <https://ceos.org/gst/icesat2-boreal-biomass.html>

Preprint is available: Duncanson et al., 2025 <https://dx.doi.org/10.2139/ssrn.5784282>

### 2.1.4. DQ1 Sentinel 2 Russia 2024

Maps of biomass in Russia are uncertain, in part because of lack of publicly available ground data and lack of GEDI data north of 52°. LSCE has developed a deep-learning model to map forest canopy height at 10 m resolution from DQ1 LiDAR waveforms with full coverage of Russia with a footprint size of 80 to 100 m diameter. The model is trained using input features filtered Sentinel 2 images during clear sky periods for the growing season. The height map has better performance than ICESat-2 maps of height. Canopy height has been converted to AGB at 30 m using height biomass allometric relationships derived with IIASA ground based data. The data will be available after the EYE CLIMA publication is accepted (submission expected Jan 2026).

### 2.1.5. Harmonised Forest Biomass dataset 2020 for Europe

The Harmonised Forest Biomass dataset is a collaborative effort led by the Joint Research Centre in conjunction with National Forest Inventory representatives from a majority of European countries (Avitabile et al., 2023). This database provides statistics and maps of the forest area, biomass stock in the year 2020, and statistics on gross and net volume increment in 2010-2020, for 38 European countries. The statistics of most countries are available at sub-national scale and are derived from National Forest Inventory data, harmonised using common reference definitions and updated to a common year using a modelling approach. The map originated from the CCI BIOMASS map, which was calibrated with the NFI statistics and depicts the spatial distribution of the AGB at 100 m resolution.

The biomass statistics refer to the aboveground standing biomass of all living trees, including the aboveground stump, the stem from stump to top, branches and foliage (AGB) as total AGB stock (tons) and AGB stock per hectare (AGB/ha) (t/ha) in the forest areas of each country (Avitabile et al., 2023).

The dataset is accessible at: <https://doi.org/10.6084/m9.figshare.c.6465640>

## 2.2. Biomass change datasets

Biomass change is being estimated by several approaches that involves the integration of various sources of information, including:

- ground-based measurements, primarily from National Forest Inventories (NFIs);
- remote sensing observations, incorporating optical, radar, and lidar instruments;
- model-based approaches, used to simulate biomass dynamics and attribute observed changes.



## 2.2.1. ESA CCI Biomass

The ESA CCI Biomass project provides estimates of forest AGB for selected reference years (2007, 2010, 2015-2022) and also supports the assessment of AGB changes for multiple years as well as over decadal intervals. Each AGB change product is composed of two sets of maps: (i) the standard deviation of the AGB change and (ii) a quality flag indicating the reliability and direction of AGB change. The AGB change itself is not provided explicitly, as it can be computed as the difference between two AGB maps. The quality flag layer of the AGB change maps is stored in byte format and adopts the following legend: 0: AGB is equal to zero in both maps, 1: AGB loss, 2: Potential AGB loss, 3: Improbable change, 4: Potential AGB gain, 5: AGB gain (CCI Biomass Product user guide v.4, 2023).

The current dataset (version 6) is accessible at:

<https://dx.doi.org/10.5285/95913ffb6467447ca72c4e9d8cf30501>

The next release (version 7) is planned for spring 2026. It will provide updated annual biomass estimates and extended the temporal coverage in both directions (2005, 2007, 2010, 2015-2023). In this version, biomass change maps will no longer be distributed directly, instead, users will be provided with software tools to calculate biomass change and associated quality flag from the AGB time series.

## 2.2.2. Machine learning model of AGB change using multiple sensors

Xu et al. (2021) developed a machine learning model trained using spatial in-situ measurements of AGB with optical and microwave (low frequency VOD) to provide temporal changes of AGB at 10 km resolution since 2000. This product shows areas of loss and gains, but losses in some tropical deforestation areas do not seem to be captured properly, possibly because of the machine learning model trained in space and used in time for change maps.

The dataset is accessible at: <https://doi.org/10.5281/zenodo.4161694>

## 2.2.3. Vegetation Optical Depth based biomass change map

The Vegetation Optical Depth (VOD)-based biomass change dataset provides a time series of AGB estimates spanning from 2010 to 2022. The analysis is derived from the L-band Vegetation Optical Depth (LVOD) signal acquired by the Soil Moisture and Ocean Salinity (SMOS) mission (Yang et al., 2023). LVOD is a valuable indicator for monitoring changes in biomass because it is sensitive to woody water content and structural vegetation properties. Retrieval of AGB from LVOD is complemented by referencing a high-resolution AGB product, such as CCI Biomass (Santoro et al., 2021), with calibration performed using multiple independent reference maps. A key advantage of the LVOD approach is that biomass change is estimated consistently using a single sensor over time. In addition, the fusion of SMOS and SMAP observations (Li et al., 2022) enables a continuous AGB time series that extends beyond the nominal lifetime of the SMOS mission. Several sources of uncertainty affect LVOD-based biomass estimates. These include signal saturation at very high biomass densities ( $>250 \text{ t ha}^{-1}$ ), the inability to retrieve VOD over frozen soils and flooded areas (which are filtered from the dataset), residual noise from radio-frequency interference, and sensitivity to vegetation water content per unit biomass volume. Although statistical filtering is applied to reduce these effects, interannual variability in vegetation water content may still alias into annual AGB estimates.

The dataset is documented at: <https://dx.doi.org/10.1038/s41561-023-01274-4>

Recent analyses based on this dataset indicate substantial live biomass carbon losses driven by drought in northern temperate ecosystems during the period 2016–2022 (Li et al., 2025).



### 3. Uncertainties of biomass and biomass change datasets

The uncertainties linked to biomass and biomass change datasets are essential for determining their accuracy. Data producers estimate these uncertainties, and independent efforts, like Araza et al. (2022), contribute insights.

For example, the ESA CCI Biomass dataset provides per-pixel uncertainty estimates expressed as standard deviation for both AGB and AGB change, but the standard product documentation does not include explicit estimates of spatial error correlation scales or a formal spatial covariance model. For AGB change, it reports a quality flag indicating if confidence intervals of consecutive AGB estimates overlap.

Independent validation of biomass datasets is crucial to ensure diverse data sources are employed in map production and validation. However, challenges in validating biomass maps arise from several factors:

- **Size Discrepancy:** Ground plots, like those from National Forest Inventories (NFIs), are often too small compared to map pixels. This size discrepancy can affect the representativeness of ground data.
- **Coarse Geolocation:** The geolocation of ground data, particularly from NFIs, is often too coarse. This limitation can hinder precise alignment with finer-resolution map pixels.
- **Spatial Distribution Issues:** The spatial distribution of ground data may not meet statistical requirements. This can lead to uneven coverage and affect the reliability of validation efforts.
- **Temporal Mismatch:** Ground data may suffer from a temporary mismatch, being too old for current map validation. This temporal misalignment can impact the relevance of ground data for assessing contemporary biomass maps.

Addressing these challenges requires concerted efforts in improving ground data quality, refining geolocation accuracy, enhancing spatial distribution representativeness, and ensuring temporal alignment. Initiatives like GEO-TREES (<https://geo-trees.org/>) and methodologies proposed by Labrière et al (2023) and Duncanson et al. (2021) contribute to advancing the field of biomass dataset validation.

Araza et al. (2022) propose an uncertainty framework designed to address biases in existing AGB maps. This framework, when applied, corrects for biases along with their associated standard deviations at coarser scales. The method allows for the utilisation of small plots by aggregating data to a coarser resolution and averaging values from multiple small plots. However, the effectiveness of spatial uncertainty modelling is impacted by the uncertainty associated with plot-level AGB. This uncertainty primarily arises from measurement and sampling errors. In regions where only small plots are available, this uncertainty tends to be particularly pronounced. In summary, Araza et al.'s framework aims to enhance the reliability of AGB maps by addressing biases and associated uncertainties, especially when dealing with data from small plots and aggregating to coarser scales.

In the study conducted by Avitabile et al. (2023), a calibration approach is employed to align map values with sub-national statistics. This calibration process aims to ensure that maps are not only consistent but also unbiased in comparison to both national statistics and the reporting requirements of the United Nations Framework Convention on Climate Change (UNFCCC) at the national level.

By calibrating map values to sub-national statistics, the study seeks to enhance the accuracy and reliability of the maps, making them more aligned with actual on-the-ground conditions and improving their utility for national-level reporting, particularly in the context of climate change assessments and commitments.



Hunka et al. (2023) conducted a comparative analysis of NASA's GEDI and ESA's CCI biomass maps. The comparison revealed strong relations between both products and NFI estimates in four countries. However, the study emphasised the importance of validating these correlations with independent reference data. Despite the identified relations, direct comparisons were limited by dissimilarities in the uncertainty estimation frameworks employed by NASA GEDI and ESA CCI Biomass. The study advocates for active collaboration among map producers, as well as engagement with policy experts. Formalising approaches for the operational use of Above-Ground Biomass Density (AGBD) maps in national-level reporting is crucial. Furthermore, the study underscores the need for transparent and comprehensive public releases of AGBD estimates, including associated variances. This approach aligns with guidance from the Intergovernmental Panel on Climate Change (IPCC) and ensures that the information is both actionable and impactful for policy decisions.

## 4. Drivers of biomass change

Understanding and quantifying the drivers of biomass change is essential for attributing observed changes to management or natural processes. Historically, most large-scale datasets have focused on biomass losses, as these are easier to detect remotely than gradual gains from growth or regrowth.

Viana-Soto A. and Senf C. (2025) used satellite data to map four decades of forest disturbances across continental Europe. Between 1986 and 2023, 22% of Europe's forest area was disturbed by anthropogenic and/or natural causes. The majority of disturbances were stand-replacing. Human land use (harvest) accounted for 79.2% of disturbances, while wind and bark beetle disturbances accounted for 12%, and fire-related disturbances for 8.8% of all disturbances recorded in Europe. Storm-related disturbances were most prevalent in western and central Europe, where they locally accounted for more than 50% of all disturbances. Fire-related disturbances were a major disturbance agent in southern and south-eastern Europe.

The dataset available at: <https://doi.org/10.5281/zenodo.13333034>. It contains three disturbance classes: (1) wind or bark beetle disturbances, (2) fire disturbances, (3) other disturbances, mostly harvest, at 30 m spatial resolution.

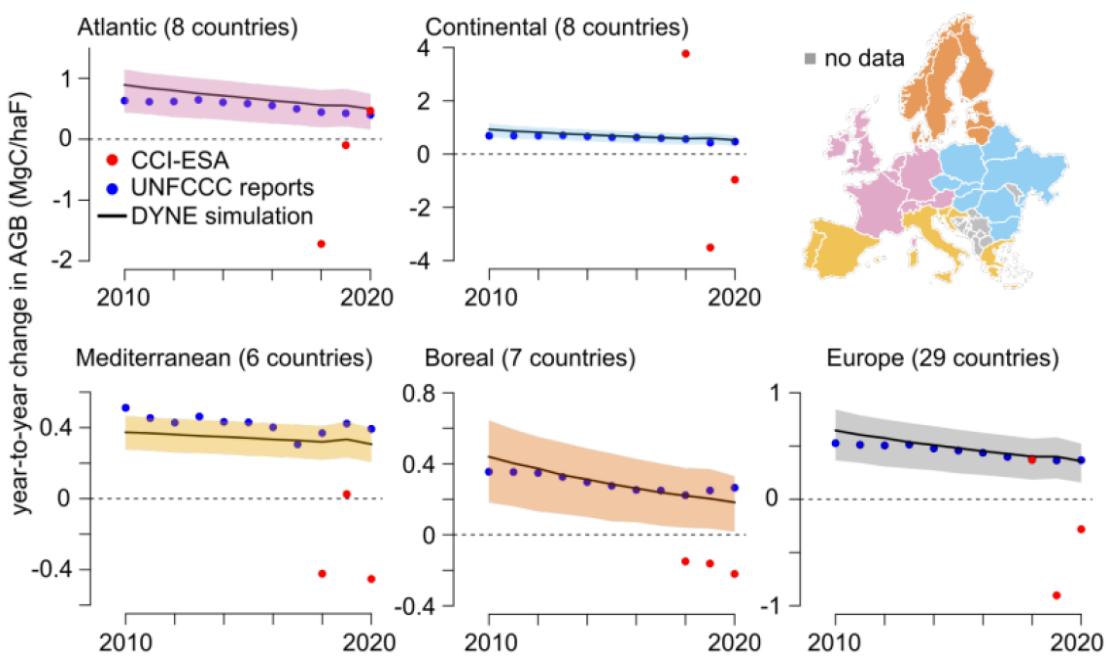
Curtis et al. (2018) produced a global map of drivers of forest cover loss for the period 2001 to 2015. Although tree cover loss is detected at 30 m spatial resolution, the corresponding drivers dataset indicates only a primary driver at 10 km spatial resolution. This resolution is too coarse for our purposes. As a result, nearly all of Europe is represented by "forestry" driver, while Asian Russia is dominated by the "wildfire" driver.

Using LVOD AGB change, Yang et al. (2022) inferred drivers of change from the Curtis et al. dataset and other data, e.g. annual forest loss maps, and attributed 25 km AGB change to fires, deforestation, regrowth and forestry. The key result is that northern forests that show an increase of AGB change are young or middle aged, opposite to what global simulation models predict, as these models mostly lack the effect of forest demography on C sinks from recovery of past natural disturbances and harvest.

### 4.1. Own study on the drivers of biomass change from CCI Biomass maps

Analysis of AGB change from CCI maps since 2017 indicate that most European areas are losing biomass, which is inconsistent with national forest inventories. This is possibly because of striped patterns from the ALOS orbits that are not yet fully corrected in the algorithm, and because CCI may underestimate biomass and biomass increments in old forests. We are working with the group producing the maps to improve these effects.



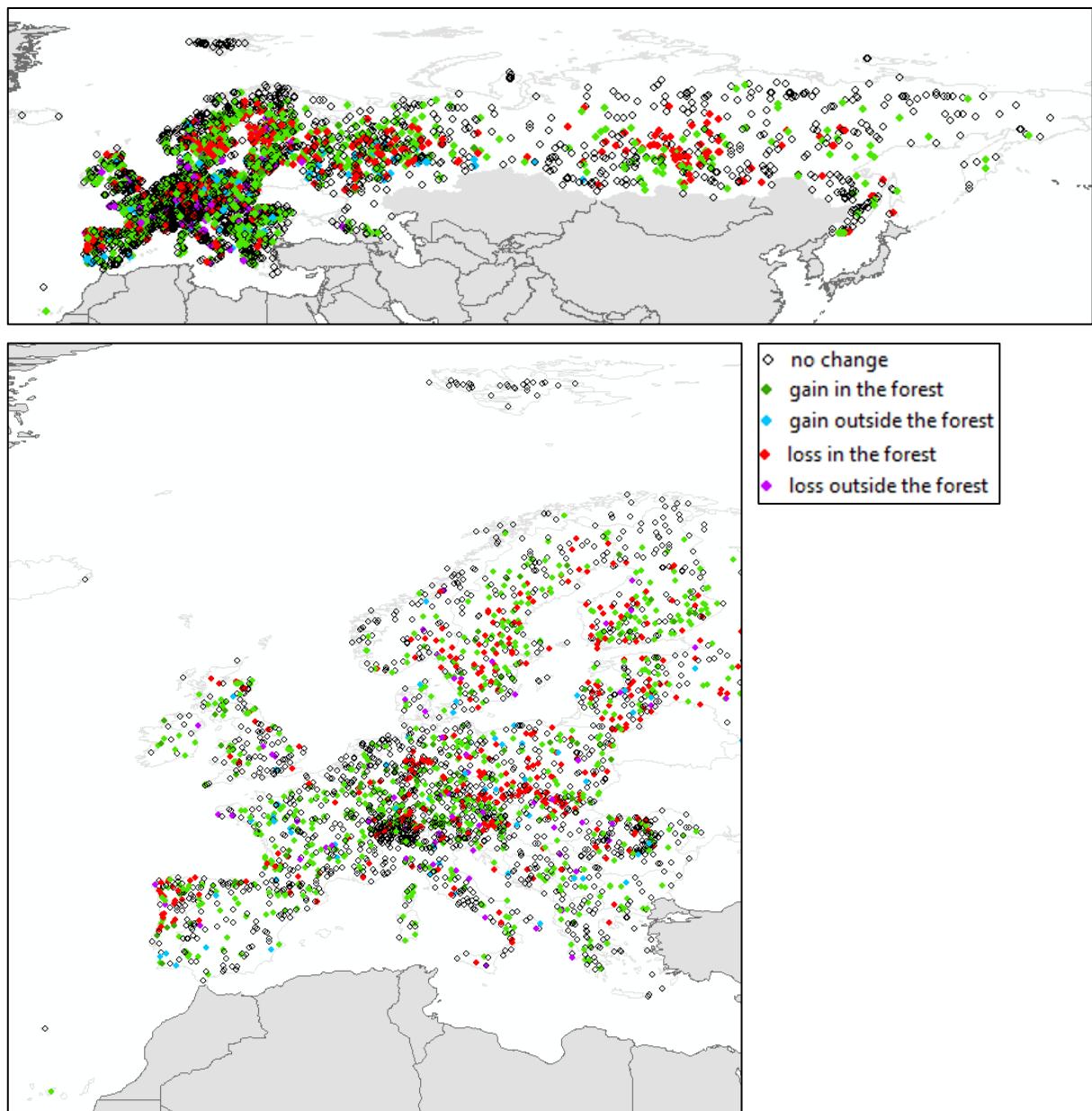


**Figure 1.** Biomass change from ESA CCI maps since 2017 obtained by taking the year-on-year difference of AGB between subsequent years (red dots) indicating an unrealistic biomass loss and a too large inter-annual variation. The blue dots are the NFI based AGB change submitted to UNFCCC based on  $\approx 5$  years revisits of thousands of forest plots and the black line is the result of a data driven model of regrowth and loss of AGB at 18 km resolution, calibrated to NFI data for the first year by adjusting the ratio of disturbance severity to AGB loss (Ritter et al. in review 2024)

Existing drivers of change datasets focus solely on biomass losses, whereas our objective encompasses both loss and gain. Additionally, we aim to validate the CCI Biomass and drivers of tree loss datasets. We use the Geo-Wiki approach (Laso Bayas et al., 2022; Lesiv et al., 2022). This method involves visual interpretation of very high-resolution imagery and vegetation indices by trained experts. The imagery freely provided by Google, Bing and ESRI. Experts examine images to confirm biomass changes (loss or gain) between 2010 and 2020, specifying possible reasons such as clear-cutting, fire, land use change, forest regrowth, etc. The target resolution is aligned with CCI Biomass maps (100 m) for recent changes (2010-2020).

For our assessment, we implemented a random sample design with reduced sampling intensity across three dimensions: (1) geographic regions: Russia, Turkey, and Ukraine; sampling fraction 1/10); (2) change magnitude (-25 to +25 t/ha; sampling fraction 1/20); and (3) CCI Biomass quality flag (areas classified as *improbable change* with sampling fraction 1/20). During 2024-2025, experts visually inspected and classified 5300 locations. Each location was assessed by at least one expert, and about 20% of locations were assessed by two experts to check consistency. This effort is ongoing and will continue in the coming year to achieve a more statistically robust assessment. The spatial distribution of sampled locations is shown in Figure 2, and the results of the visual interpretation are summarized in Table 2.





**Figure 2.** Distribution of the sample location for visual interpretation



**Table 2.** Results of classification of drivers of biomass change

Drivers of change	Number of locations	Share (percentage of samples with the respective driver), %
Gain: afforestation	96	1.8
Gain: forest growth	1450	27.2
Gain: reforestation	181	3.4
Gain: tree crops, agroforestry	10	0.2
Gain: urban trees	5	0.1
Loss: cropland	40	0.8
Loss: forest management	740	13.9
Loss: insects and diseases	36	0.7
Loss: mining and crude oil extraction	5	0.1
Loss: other natural disturbances	15	0.3
Loss: roads/trails/buildings	33	0.6
Loss: tree/shrub crops	7	0.1
Loss: wildfire	75	1.4
Loss: windthrow	2	0.1
No change observed	2580	48.4
Not clear	58	1.1
Grand Total	5333	100.0

Biomass gain was confirmed at 1,742 locations (Table 2), with 94% attributed to reforestation or forest growth, 6% to afforestation, and about 1% to biomass gain outside forest (e.g. trees in urban areas, tree crops, and agroforestry). Biomass losses were confirmed at 953 locations, of which 78% were associated with forest management (harvesting or thinning), 9% with land use change (expansion of urban areas and infrastructure) or tree loss outside forests (e.g. urban trees, shelterbelts, and tree crops), 8% with wildfires, 4% with insects and disease, and 6% with windthrow and other natural disturbances.

Results of the visual assessment of reported biomass changes in the CCI Biomass product are shown in Table 3. The validation was based on expert interpretation of very high-resolution (VHR) optical imagery, which was used to visually assess whether forest disturbances or regrowth consistent with the reported biomass change could be identified at the sampled locations. This approach is independent from the ESA CCI Biomass methodology, which relies primarily on spaceborne radar (ALOS, Sentinel-1, ASAR) and spaceborne LiDAR (GEDI, ICESat-2) data combined with biomass models, rather than on optical change detection.



**Table 3.** Results of visual validation of CCI biomass map (changes exceeding  $\pm 50$  t/ha)

CCI Biomass quality flag	share of locations at visual interpretation, %			
	Not visible at very high-resolution imagery	gain	loss	total
AGB loss	51	1	48	100
Potential AGB loss	56	2	42	100
Improbable change	49	37	14	100
Potential AGB gain	28	70	3	100
AGB gain	17	80	2	100
Total	41	32	27	100

The visual inspection indicates that in approximately 50% of cases, reported biomass changes are not clearly discernible in VHR imagery, even when applying a high threshold for change ( $>50$  t/ha), which should theoretically be visible as major canopy disturbance or regrowth. This suggests that the CCI Biomass product tends to overestimate the spatial extent of biomass change at the native pixel scale (100 m). Part of this discrepancy likely arises from sensor differences and temporal inconsistencies in the radar acquisitions between years (e.g., different instrument configurations in 2010 and 2020), as well as from uncertainties in both the biomass retrieval algorithms and the visual interpretation itself.

Importantly, the disagreement at fine spatial scales does not imply that the CCI Biomass product is unreliable for regional or national assessments. When biomass change is aggregated to coarser resolutions (e.g., 1 km or administrative units), the correspondence between reported changes and visually interpreted disturbance patterns improves substantially, indicating that the product performs better as a spatially averaged indicator of change rather than as a precise pixel-level disturbance map. Given the absence of alternative wall-to-wall, temporally consistent biomass change datasets with comparable spatial coverage, CCI Biomass remains the most suitable dataset currently available for large-scale monitoring and policy-relevant reporting, provided that its limitations at fine spatial scales are acknowledged.

The collected data will serve the following purposes:

- Calculating regional statistics on the drivers of biomass change.
- Validating existing biomass datasets, such as ESA CCI Biomass.
- Providing feedback to the ESA CCI Biomass project to contribute to dataset improvement.
- Validating datasets on biomass loss, for example Viana-Soto and Senf (2025).



## Conclusions

ESA CCI Biomass products, including biomass change maps, present a valuable source of information for monitoring aboveground biomass dynamics, although current change estimates remain subject to substantial uncertainty. A key strength of these products is the integration of multiple remote sensing technologies—radar, lidar, and optical sensors—from several space agencies (ESA, NASA, and JAXA). The datasets provide uncertainty estimates for both AGB and AGB change and are continuously improved through systematic reprocessing of earlier reference years (e.g. 2010), with plans to further extend and refine the time series. A notable achievement is the successful calibration of CCI Biomass maps against national and regional ground-based datasets, which reduces bias and improves accuracy (Schepaschenko et al., 2021; Avitabile et al., 2023).

Biomass change datasets based on L-band Vegetation Optical Depth (L-VOD) also show strong potential, primarily due to their long and temporally consistent observation record starting in 2010 using a single sensor. However, their interpretation requires careful consideration of confounding effects related to vegetation water content and radio-frequency interference (RFI). In addition, the relatively coarse spatial resolution limits attribution in Europe, where harvesting, natural disturbances, and regrowth typically occur at finer spatial scales. Ongoing efforts to downscale LVOD-based biomass change estimates to 100 m resolution are expected to improve attribution and will be addressed within the EYE-CLIMA project.

The European biomass map for 2020 produced by Avitabile et al. (2023), calibrated to sub-national statistics, provides a consistent and unbiased reference layer that aligns well with both national statistics and UNFCCC reporting requirements.

An additional key dataset is the European Forest Disturbance Atlas (Viana-Soto and Senf, 2025), which offers spatially explicit information on the drivers of biomass change across Europe for the period 1985–2023 and supports attribution of observed biomass losses and gains.

Visual interpretation of very high-resolution imagery suggests that CCI Biomass products tend to overestimate the spatial extent of biomass changes, although the direction of change is generally captured correctly. Notably, approximately 78% of biomass loss is associated with forest management activities, while 94% of biomass gain occurs within forest areas and is primarily linked to reforestation and forest growth.



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