Forestry and Land Use Change sector: Net Forest & Mangrove, Net Grassland, and Net Wetland Carbon Stock Change - Living Biomass

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1. Introduction

Changes in terrestrial ecosystem carbon storage immediately impact global atmospheric CO_2 concentrations by releasing (as a source) or removing (as a sink) carbon. Current estimates of the global carbon budget suggest that terrestrial ecosystems, particularly forests, account for 10-20% of net global CO_2 emissions to the atmosphere annually while sequestering approximately 30% of annual CO_2 emissions. However, these estimates involve large uncertainties (Friedlingstein et al., 2022), primarily due to the lack of reliable and standardized greenhouse gas (GHG) inventory systems for the land sector in many countries, as well as inconsistencies in inventory approaches used by countries to assess and report land-sector emissions and removals to the United Nations Framework Convention on Climate Change (UNFCCC). Accurate assessment of net CO_2 emissions from global land-use change, along with understanding the role of land in climate mitigation, remains a critical challenge (Friedlingstein et al., 2022; Grassi et al., 2017).

As climate policy moves from pledges to tangible implementation, there is an urgent need to reduce uncertainties in land-use, land-use change, and forestry (LULUCF) emissions estimates and to develop standardized, observation-based GHG inventory systems. These improvements will help refine the global stocktake and enhance countries' capacities to assess compliance with their climate targets under the Paris Agreement.

Forests are the primary component of land-atmosphere carbon exchanges, contributing over 80% of the land carbon flux (Xu et al., 2021). They store substantial amounts of carbon in aboveground and belowground biomass and are central to the global carbon cycle (Saatchi et al., 2011; Malhi et al., 2009). Consequently, forests are a focal point in the design and implementation of Natural Climate Solutions (NCS) for addressing climate change. NCS refers to actions aimed at protecting, managing, and restoring natural ecosystems to reduce GHG emissions and sequester carbon. These solutions are recognized for their potential to provide immediate, cost-effective pathways to mitigate climate change by reducing emissions from deforestation and forest degradation, and by enhancing carbon sequestration through improved land management, afforestation, reforestation, and revegetation (Seddon et al., 2021; Cook-Patton et al., 2021; Griscom et al., 2017). Forests play a significant role in NCS due to their ability to absorb anthropogenic CO_2 emissions through ecological processes such as photosynthesis, gross primary production, natural disturbance and recovery, and conservation and management practices (Luyssaert et al., 2008; Pan et al., 2011; Xu et al., 2021).

CTrees has developed a systematic, bottom-up approach (**Fig. 1**) for global GHG inventorying of the land sector, focusing on estimating emissions and removals from forests and natural non-forest ecosystems worldwide. CTrees is a nonprofit organization dedicated to tracking carbon in every tree globally, providing science-based geospatial data to enable natural climate solutions at all scales (https://ctrees.org/). CTrees' annual assessments of global carbon stocks and fluxes in the land sector are shared with Climate TRACE for integration with other trace gas fluxes across sectors. The dataset provides annual estimates of stocks and fluxes from 2015 to 2023, updated quarterly, to inform national policies and enhance global emissions tracking. The methods and techniques applied are detailed in Xu et al. (2021). This document presents a high-level summary of the methodology and approaches used to generate the datasets described in Section 2 for the three components of the CTrees standardized framework including live biomass carbon, activity data and emissions, and emissions based on land cover types. Section 3 will provide a summary of jurisdictional zonal statistics for emissions and removals.

2. Dataset methods

Each section below provides an overview on the approach to generate each dataset.

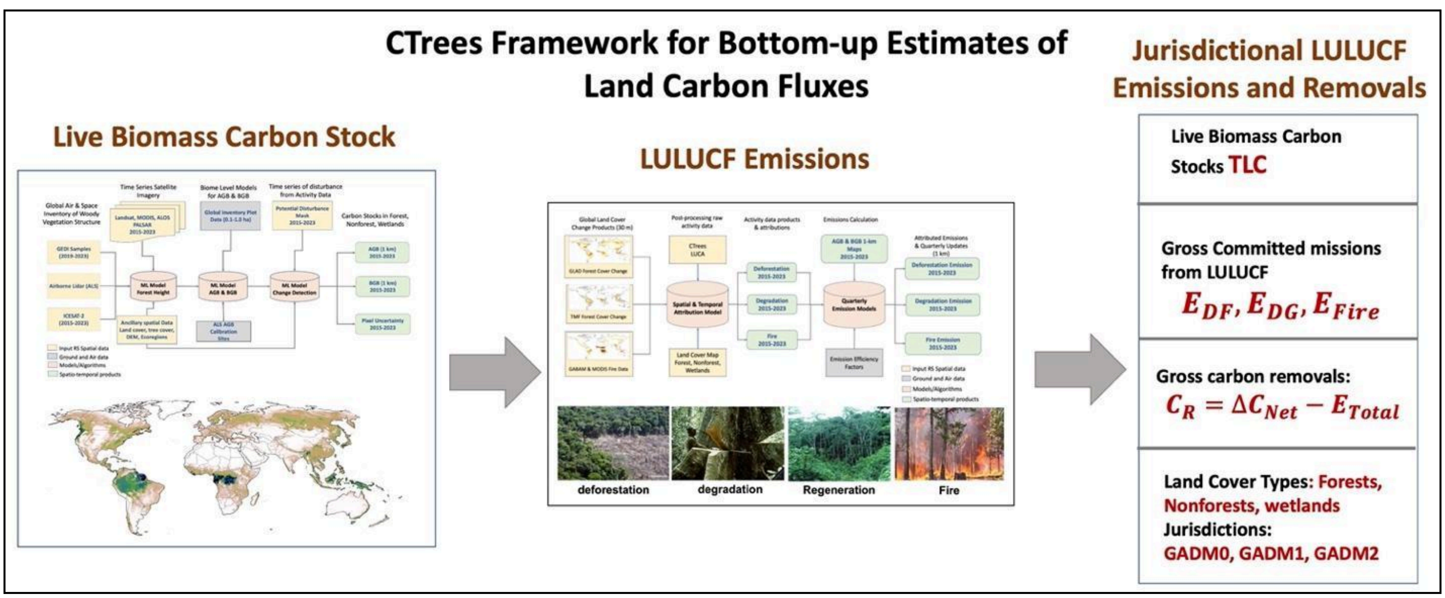

Fig 1. CTrees standardized framework for bottom-up estimates of land carbon fluxes using ground and remote sensing data and AI, providing GHG inventory and LULUCF emissions from 2015-2023. The framework consists of three main components of the live biomass carbon stock changes (discussed in section 2.1), LULUCF emissions (discussed in section 2.2), and jurisdictional level LULUCF emissions for 195 countries. Final geospatial maps and products are at 1-km spatial resolution.

2.1 Estimates of Live Biomass Carbon Stocks and Changes

This dataset provides annual estimates of live above-ground biomass (AGB), below-ground biomass (BGB), and total carbon (TLC) as the combined AGB and BGB across global vegetation (Fig. 2). AGB estimates were derived from measurements of vegetation vertical structure using data from two satellite lidar sensors: the Global Ecosystem Dynamics Investigation (GEDI) mission aboard the International Space Station (ISS) and the ICESat-2 (Ice, Cloud, and land Elevation Satellite). These lidar-derived waveform metrics enabled the development of global vegetation structure (height metrics) maps across forested and non-forested areas, including savanna woodlands and shrublands, using machine learning (ML) algorithms. The number of GEDI and ICESAT-2 samples used in each 1-km grid cell was set to be greater than 50 to allow reliable estimates of vegetation structure and later AGB across different ecoregions globally. The valid number of samples increased significantly away from tropical regions thanks to the unique satellite orbit of the International Space Station hosting the GEDI sensor. A comprehensive set of airborne lidar data collected across the tropics was used to calibrate and validate the ML models. To create these structural maps, we developed over 700 ML models tailored to different ecoregions worldwide, improving height estimates and reducing large-scale overfitting and potential systematic errors.

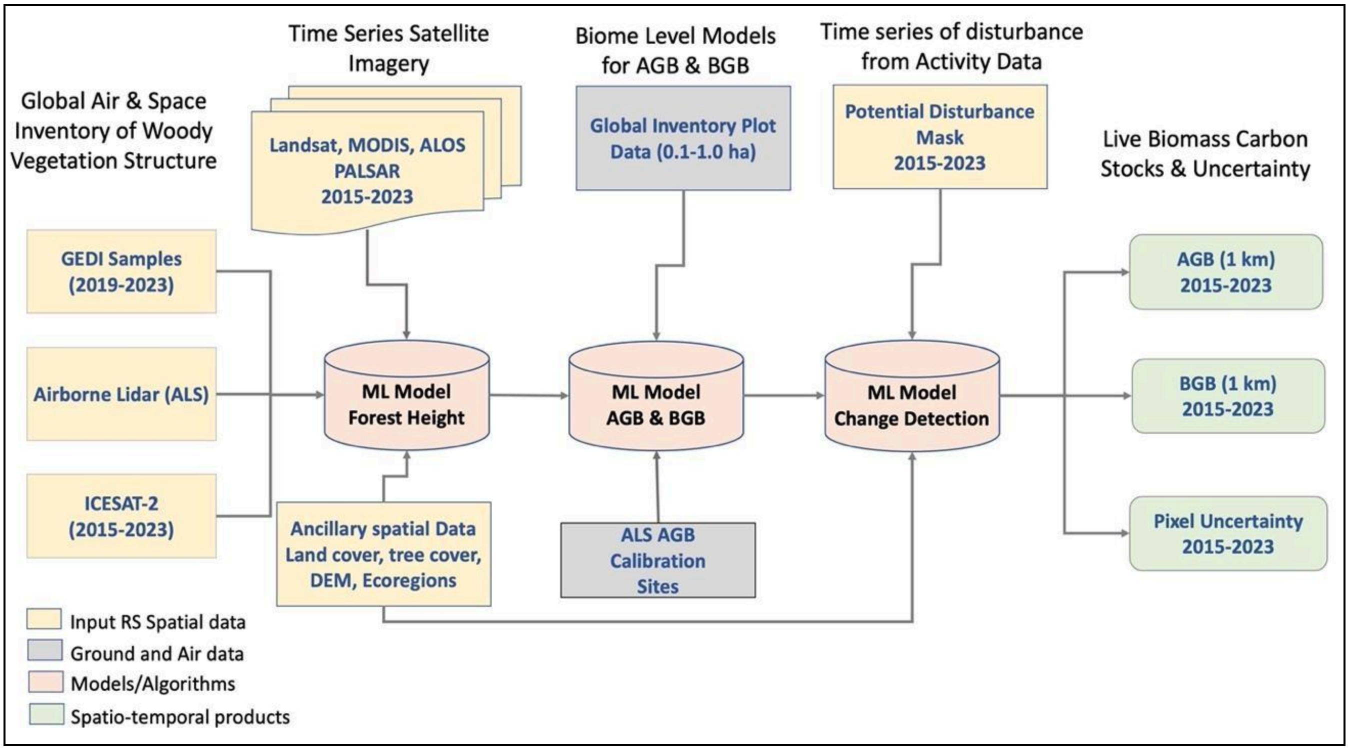

Fig 2. Schematic showing the development of spatial and temporal variations of the global live biomass carbon stocks and changes using a combination of satellite remote sensing observations, ground and air inventory samples, and machine learning techniques, for vegetation structure, biomass density, and change detection (Xu et al., 2021).

The height maps were validated and refined to reduce spatial uncertainty and artifacts before being used in an ML model to predict above-ground biomass (AGB). We used the height metrics coincident with plots with AGB values a large number of ALS based estimates of AGB from height-based allometric models to develop a large number of AGB training samples for mapping live biomass density. This model was trained using over 300,000 inventory plots from diverse sources, including national forest inventory (NFI) data, globally distributed research plots in different ecoregions, and biomass estimates from a network of airborne lidar scanning (ALS). All training data from forest inventories and ALS were smaller than 1-km pixels and were combined with higher-resolution remote sensing data to train the ML model at a resolution close to plot size. The trained model was then applied to coarser-resolution remote sensing data to provide AGB estimates that were adjusted to align proportionally with 1-km pixel sizes. The biomass maps were developed at a 1-km spatial resolution, with 2019 and 2020 as the reference years.

The next step involved developing a change-detection ML model (Xu et al., 2021) for annual AGB mapping at 1-km resolution from 2015 to 2023, with potential for future carbon density updates. This model relies on an annual disturbance mask, incorporating all disturbances from activity data (e.g., forest cover change and fire) and additional disturbances identified through significant annual reflectance changes in satellite imagery. The change-detection model predicts AGB changes by constraining large year-to-year anomalies in undisturbed areas while allowing unrestricted predictions in disturbed areas. The 2020 AGB map serves as a reference dataset to train the change-detection model, enabling annual AGB predictions across the entire time series (2015–2023).

AGB values were used to estimate BGB using existing models developed for different forest types and the Intergovernmental Panel on Climate Change (IPCC) guidelines for default values. Total carbon was calculated by using the following relation:

$$TLC = (AGB + BGB) \times CF$$

Where TLC is total live carbon in vegetation, and CF is the carbon fraction of vegetation ranging from 0.47-0.51 depending on different forest types with the average value of about 0.5. Live biomass carbon stocks are converted to tons (Mg) of CO_2e per hectare (tCO_2e/ha) before delivering to Climate Trace.

As part of the change-detection approach, we further enhance AGB estimates using a productivity model developed by the CTrees team. This model employs a space-for-time approach, combining global disturbance data with AGB estimates to improve carbon removal estimates across all ecoregions with stable vegetation over the complete disturbance history Heinrich et al. 2023). The productivity model enables annual adjustments in areas of dense forest biomass where AGB values remain stable but may have high uncertainty, capturing biomass increases from gradual vegetation recovery. Biomass increases are applied to different biomass levels, representing local vegetation growth stages as a proxy.

Datasets used for mapping vegetation structure and biomass includes:

- Microwave radar measurements from Phased Array type L-band Synthetic Aperture Radar (PALSAR) on Advanced Land Observation Satellite (ALOS) and PALSAR-2 ALOS-2 at the 25 m spatial resolution
- Thematic Mapper on Landsat 5, Operational Land Imager on Landsat 8 provided at the 30 m spatial resolution
- Moderate Resolution Imaging Spectroradiometer (MODIS) on Aqua and Terra Satellites at 250 to 500 m spatial resolutions
- Copernicus Digital elevation model (30 m spatial resolution) and land cover products (100m resolution)
- Annual disturbance masks at 30 m spatial resolution derived from globally available land cover and land use change data, forest cover change, burned area, and additional remote sensing based metrics.

- Ancillary data such as global land cover and tree cover maps at 100 m resolution to separate forests, from nonforests (shrublands and grasslands) and wetlands.

2.2 Estimates of LULUCF Emissions

To calculate the committed carbon emissions from deforestation, fire, and degradation events, we utilized a combination of satellite-derived products on forest cover change, fire disturbances, and CTrees' monitoring of land use change activities. The methodology includes three main steps (**Fig. 3**):

1. Post-process 30-m disturbance data from multiple sources and land cover maps to estimate land use changes, attributing deforestation, forest clearing, degradation across tropical regions, and burned areas due to fires.
2. Aggregate land use change activity data to 1-km resolution, reflecting percentages of non-overlapping land use activities, and combine it with 1-km carbon density estimates to calculate committed emissions from deforestation, degradation, and fire from 2015 to 2023, with plans to extend for future years.
3. Integrate and calibrate CTrees' land use change activity alert (LUCA) data with global deforestation, degradation, and fire data to provide quarterly LULUCF emission estimates starting in 2023. These quarterly estimates enable sub-annual emission assessments, supporting emission reduction policy enforcement and harmonization with emissions from other sectors reported by Climate TRACE.

To calculate emissions, we used estimates of area of land use change and burned areas in forests, and wetlands, with emission factors derived by the biomass change, and an emission efficiency factor (f_D) as given below:

$$E_{DF} = \sum_i C_i \times PDA_i \times f_D$$

$$E_{Fire} = \sum_i C_i \times PBA_i \times f_B$$

$$E_{DG} = \sum_i C_i \times PDgA_i \times f_{Dg}$$

Where C_i is the total live carbon derived from annual TLC mapping for pixel i, and E_{DF} (or E_{fire}, E_{DG}) represents emissions from deforestation, fire, and degradation respectively for the corresponding year. PDA, PBA, and $PDgA$ represent the percent deforested areas, percent burnt area, and percent degraded area, respectively within the 1-km grid cells.

The emission efficiency factor for deforestation was assumed $f_D = 1$ to allow total clearing of forest with a nonforest land use such as agriculture or pasture. Depending on the type of clearing, there may be variations for deforestation f_D that can be used for uncertainty estimates. For fire burned areas the efficiency factor or combustion factor f_B vary with land cover types, suggesting different factors used for forest types and shrub and grasslands in boreal, temperate, and tropical wet and dry ecoregions (Xu et al. 2021). For degradation in tropical forests, we assume a fixed factor (f_{Dg} = 0.15) in our analysis, which is an average number derived from various publications (e.g. Pearson et al. 2014). The total emissions from deforestation (E_{DF}), fire (E_{Fire}), and degradation (E_{DG}) were then estimated using the bottom-up modeling approximation (Xu et al., 2021).

Fire events at 1-km resolution can occur in both forest and non-forest regions, which may introduce a mixed-pixel effect when calculating emissions. To address this, each 1-km pixel was divided into two fractions—forest and non-forest—based on annual forest cover maps. The carbon in each fraction was designated as forest TLC CFCF (forest) or non-forest TLC CNFCNF (non-forest). The annual forest cover maps were created using Global Forest Change (GFC) tree cover datasets, with the data averaged at a 100-m resolution and then aggregated to 1-km resolution using a 20% threshold to generate annual forest cover classifications. Degradation events additionally accounted for forest edge emissions.

The choice of a 20% threshold for global calculations was informed by a review of national reporting practices, which vary between 10-30% tree or canopy cover in defining forests and reflects the significant uncertainties in data types used for country-level estimations.

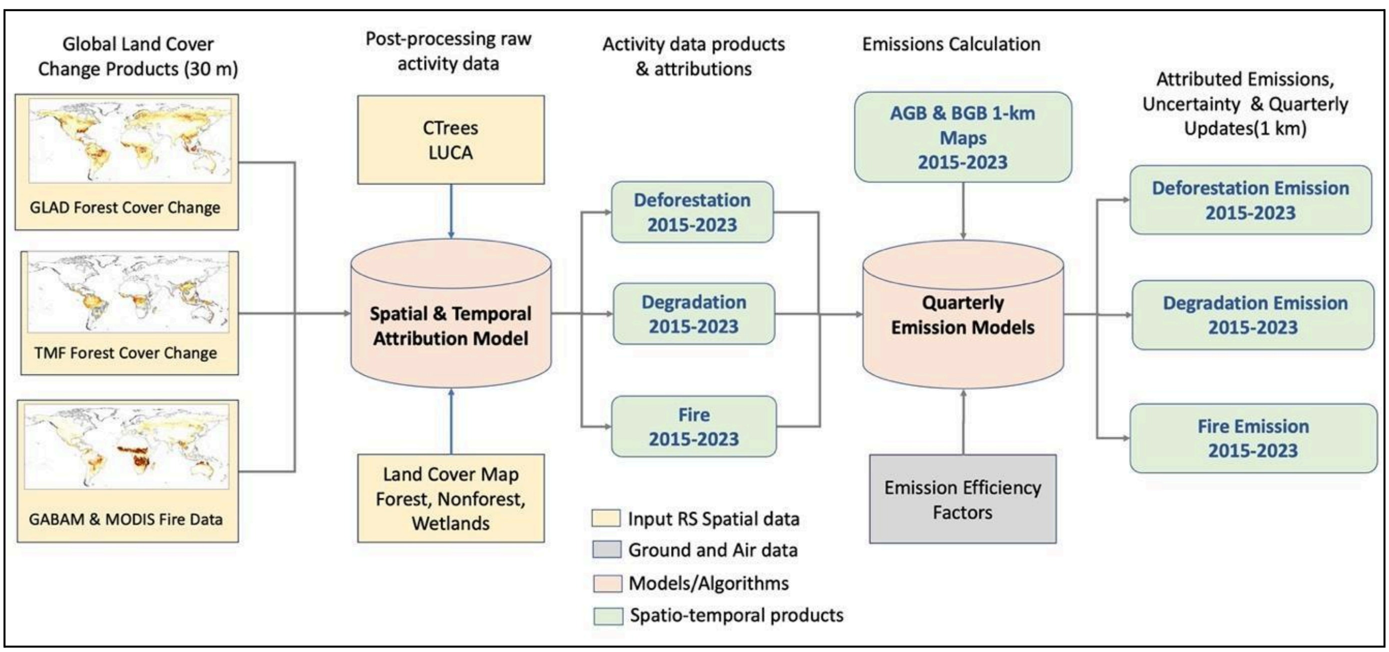

Fig 3. Schematic showing the process of developing land use change activity data from peer-reviewed existing satellite data products along with CTrees carbon stock changes and emission factors to estimate LULUCF emissions including deforestation, degradation, and fire for all forest and nonforests areas globally.

The datasets used to develop emissions for land use change activities include:

- The Global Forest Change (GFC) product at 30m spatial resolution from the University of Maryland GLAD data covering annual estimates of global forest change without attributions (Hansen et al. 2013).
- Global Annual Burned Area Maps (GABAM) at 30m spatial resolution (Long et al. 2019
- Tropical Moist Forest Product (TMF) developed by Joint Research Center (JRC) at 30m spatial resolution (Vancutsem et al. 2020) providing estimates of forest cover change attributable to deforestation and degradation.
- Ancillary data including tree cover estimates from Landsat and land cover types separating forests, nonforests, and wetlands.

Emissions for land cover types will only include fire in forest, grass/shrubland, and wetlands that were calculated by using the proportion of the burned area in each land cover type and the emission factor. The emission factor for fires is the biomass multiplied by the combustion factors in each land cover category. Emission estimates are provided in total tons of CO_2e per 1-km resolution, globally for years 2015 to 2023.

The net annual carbon flux at each pixel (C_{net}) in the 1-km grid cells denotes the difference between the potential vegetation carbon uptake ($C_{removal}$) and the emissions from deforestation (E_{DF}), fire (E_{Fire}) and degradation (E_{DG}). Therefore, the removal term is the residual of the estimated carbon stock change, and emissions from deforestation, fire and degradation terms in equation:

$$C_{removal} = \Delta C_{net} - E_{DF} - E_{Fire} - E_{DG}$$

For more details on the overall methodology, refer to Xu et al. (2021) for the overall framework of data processing and spatio-temporal machine learning model implementations.

2.3 Estimates of Emissions from Land Cover Type

CTrees data provides annual estimates of total live biomass carbon (TLC) stored in three major land cover types: forests/mangroves, shrub/grasslands, and wetlands. The following datasets were used to calculate the carbon stocks:

- Total live biomass carbon stocks (e.g., CTrees global TLC; see section 2.1)
- Land cover map from Copernicus Global Land Cover (CGLS) at 100 m spatial resolution in 2019.
- High resolution – 100m resolutions TLC map generated for 2020 (unpublished but publicly available data).

We combined CGLS land cover types into three separate land cover layers: all forest types (forest and mangroves), grasslands and shrublands (shrub-grassland), and wetland types (wetland). Each layer was averaged from 100m to 1-km spatial resolution, and we obtained three land cover fractions – forest/mangrove, shrub/grassland, and wetland. In each 1-km spatial resolution, each land cover fraction CO_2 was denoted as C_F, C_{SG}, or C_W representing forest, shrub-grassland, and wetland land cover classes, respectively. A ratio was obtained for the following: $R_f = C_F/C$; $R_{sg} = C_{SG}/C$; $R_w = C_W/C$ using the CGLS layers and the existing high-resolution (100m) global TLC map. With the knowledge of CO_2 estimates (C_i) for the 1-km pixel i in each year, the following equations were used:

$$C_{F,i} = C_i \times R_f \times A_i$$
$$C_{SG,i} = C_i \times R_{sg} \times A_i$$
$$C_{W,i} = C_i \times R_w \times A_i$$

Where $C_{F,i}$, $C_{SG,i}$, $C_{W,i}$ represent the total CO_2 of forest/mangroves, shrub/grassland, and wetland in each pixel i, respectively, and A is the area of pixel i.

3.0 Climate TRACE Reporting

3.1 Annual Reporting

The spatially developed estimates of emissions and removals are used to generate zonal statistics for Climate TRACE reporting. The Climate TRACE platform reports total carbon stocks, emissions, and removals across forests/mangroves, shrub/grasslands, and wetlands at three levels of administrative units (GADM). These levels, GADM0, GADM1, and GADM2, refer to different administrative boundary tiers within the Global Administrative Areas Database (GADM) (https://gadm.org/about.html), which provides detailed geographic boundaries for regions worldwide. Specifically, GADM0 corresponds to national boundaries encompassing entire countries, GADM1 refers to subnational units such as provinces, states, or regions (depending on a country's administrative structure), and GADM2 represents divisions at the level of counties, districts, or municipalities. These designations allow researchers and policymakers to analyze data across various administrative levels and granularities.

To calculate the zonal statistics at these GADM levels, we use 1-km pixel-level estimates of carbon stocks and emissions/removals within each GADM boundary, formatted accordingly for Climate TRACE reporting. The net change in living biomass from 2015 to 2023 is calculated for each sector by assessing the change in total carbon (TLC) between years, as follows:

$$\Delta C_{net,\, yr2} = C_{yr1} - C_{yr2}$$

where C_{yr1} represents the previous year's carbon stock and C_{yr2} the current year's stock, resulting in $\Delta C_{net,yr2}$, the net change in living biomass carbon stock.

For consistent reporting across levels, we first calculate zonal statistics at GADM2, then aggregate the data to GADM1 and GADM0. These estimates are available on the Climate TRACE website for display and download at all three GADM levels. Additionally, for each administrative level, carbon stocks and fluxes are separated by land cover types.

The following datasets are available for download: Annual carbon stocks, emissions from forest-land fires, forest-land clearing, forest-land degradation, emissions from shrub/grassland fires, wetland fires, and residual removals from forest, shrub/grasslands, and wetlands. Additionally, CTrees provide uncertainty and confidence level for all zonal statistics.

3.1 Quarterly Reporting

To estimate emissions for quarterly reporting, we use the CTrees LUCA (Land Use Change Activity) platform, which provides global land use change estimates with 10-meter spatial resolution, updated biweekly for both global and forest-specific areas. For data prior to 2023, we aggregated LUCA estimates to a 1-km spatial resolution and compared them with similar datasets derived from Landsat-based products used for land use activity data.

Since the current version of LUCA does not attribute specific land use activities to each change, we calibrated emission factors at each pixel to ensure that total emissions calculated quarterly align closely with annual emissions from all land use activities. This adjustment enables LUCA data to be utilized effectively for calculating and reporting emissions on a quarterly basis (see Fig. 3). At the end of each year, we will reconcile quarterly estimates with annual totals obtained from Landsat data and emission factors for each activity type, ensuring consistency between quarterly and annual emissions reports.

4. Supplemental Data

Table S1 General dataset information for Net Forest & Mangrove, Net Grassland, and Net Wetland Carbon Stock Change - Living Biomass.

General Description	Definition
Sector definition	*Net Forest & Mangrove, Net Grassland, and Net Wetland Carbon Stock Change - Living Biomass.*
UNFCCC sector equivalent	*4.A Forest Land; 4.C Grassland; 4.D.1.a Peat Extraction Remaining Peat Extraction; 4.D.1.c Other Wetlands Remaining Other Wetlands; 4.D.2 Land Converted to Wetlands*

General Description	Definition
Temporal Coverage	*2015 – 2023*
Temporal Resolution	*Quarterly; Monthly (on website, see Temporal Disaggregation of Emissions Data for the Climate TRACE Inventory)*
Data format(s)	*GeoTIFF at 1-km spatial resolution.*
Coordinate Reference System	*Coordinates of each reservoir given in degrees*
Number of countries	*195 countries*
Ownership	*Country*
What emission factors were used?	*See section 2.2 Estimates of LULUCF Emissions*
What is the difference between a "NULL / none / nan" versus "0" data field?	*"0" values are for true non-existent emissions. If we know that the sector has emissions for that specific gas, but the gas was not modeled, this is represented by "NULL/none/nan"*
total_CO2e_100yrGWP and total_CO2e_20yrGWP conversions	*Climate TRACE uses IPCC AR6 CO_2e GWPs. CO_2e conversion guidelines are here:https://www.ipcc.ch/report/ar6/wg1/downloads/report/IPCC_AR6_WGI_FullReport_small.pdf*

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Geographic boundaries and names (iso3_country data attribute): The depiction and use of boundaries, geographic names and related data shown on maps and included in lists, tables, documents, and databases on Climate TRACE are generated from the Global Administrative Areas (GADM) project (Version 4.1 released on 16 July 2022) along with their corresponding ISO3 codes, and with the following adaptations:

- HKG (China, Hong Kong Special Administrative Region) and MAC (China, Macao Special Administrative Region) are reported at GADM level 0 (country/national);
- Kosovo has been assigned the ISO3 code 'XKX';
- XCA (Caspian Sea) has been removed from GADM level 0 and the area assigned to countries based on the extent of their territorial waters;
- XAD (Akrotiri and Dhekelia), XCL (Clipperton Island), XPI (Paracel Islands) and XSP (Spratly Islands) are not included in the Climate TRACE dataset;
- ZNC name changed to 'Turkish Republic of Northern Cyprus' at GADM level 0;

- The borders between India, Pakistan and China have been assigned to these countries based on GADM codes Z01 to Z09.

The above usage is not warranted to be error free and does not imply the expression of any opinion whatsoever on the part of Climate TRACE Coalition and its partners concerning the legal status of any country, area or territory or of its authorities, or concerning the delimitation of its borders.

Disclaimer: The emissions provided for this sector are our current best estimates of emissions, and we are committed to continually increasing the accuracy of the models on all levels. Please review our terms of use and the sector-specific methodology documentation before using the data. If you identify an error or would like to participate in our data validation process, please contact us.

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