Forestry and Land Use sector: Forest & Mangrove, Shrub & Grassland, and Wetland Emissions

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1. Introduction

Natural climate solutions (NCSs), defined as conservation, restoration, and protection of terrestrial lands and wetlands, have been recognized as mature approaches for carbon conversation and mitigation efforts (Griscom et al., 2017; Fargione et al., 2018; Xu et al., 2021). Forests have been identified as a significant NCS based on the fact that these environments are substantial sinks and can sequester a significant amount of CO_2 annually (Mori et al., 2021; Xu et al., 2021).

Forests store significant amounts of carbon in aboveground biomass (AGB) and below ground biomass (BGB) and play a major role in the global carbon cycle (Meena at al., 2019; Spawn et al., 2020). Thus, accurate and up-to-date estimates of forest carbon sequestration and greenhouse gas emissions caused by disturbances are critical for global carbon accounting and climate policy (Hansen et al., 2013; Maxwell et al., 2019).

Here, we provide an overview of Climate TRACE reporting of biomass change, emissions, and removals for forest, mangroves, grasslands, and wetlands. Climate TRACE partnered with CTrees, "a nonprofit organization on a mission to track carbon in every tree on the planet and to deliver science-based geospatial data for enabling natural climate solutions at all scales" (https://ctrees.org/). CTrees modeled AGB and BGB globally using methods that incorporated activity specific emissions factors globally, for years 2015 to 2021. The approach and techniques applied are described in detail in Xu et al. (2021). This document presents a high level summary of the aforementioned paper and the approaches used to generate the datasets described in section 2.

2. Dataset methods

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

2.1 Total live carbon in vegetation dataset generated by CTrees

This dataset provides annual estimates of live above ground biomass (AGB) and below ground biomass (BGB) and total carbon from above plus below ground across the global vegetation. AGB estimates were based on measurements of vegetation vertical structure from two lidar sensors respectively from the Global Ecosystem Dynamics Investigation (GEDI) mission onboard International Space Station (ISS) and the ICESAT-2 (Ice, Cloud and land Elevation) satellite converted to biomass using models based on ground forest inventory plot data, and airborne lidar estimated biomass across the globe. Raster maps were generated using machine learning (ML) algorithms and satellite remote sensing image data. Other remote sensing data inputs included:

- Microwave radar measurements from Phased Array type L-band Synthetic Aperture Radar (PALSAR) on Advanced Land Observation Satellite (ALOS) and PALSAR-2 ALOS-2, provided at a 25 m spatial resolution
- Thematic Mapper on Landsat 5, Operational Land Imager on Landsat 8 provided at a 30 m spatial resolution
- Moderate Resolution Imaging Spectroradiometer (MODIS) on Aqua and Terra Satellites provided at 250 to 500 m spatial resolutions
- Copernicus Digital elevation model and land cover products, both 30 m spatial resolution.

Ancillary data for emission calculation include:

- The Global Forest Change (GFC) product at 30m spatial resolution
- Global Annual Burned Area Maps (GABAM) at 30m spatial resolution
- Tropical Moist Forest Product (TMF) developed by Joint Research Center (JRC) at 30m spatial resolution

The biomass estimates from GEDI and ICESAT-2 were aggregated to provide estimates of mean and variance of AGB at 1-km grid cells to provide global distribution of biomass to train the machine learning models. The number of GEDI and ICESAT-2 samples used in each grid cell was greater than 100 to allow reliable estimates of AGB across the globe. The number of samples increased significantly away from tropical regions due to satellite orbits. The biomass maps were first generated for the years 2019 and 2020 and because of the increasing number of GEDI and ICESAT-2 samples. These estimates were used in a change detection ML model and satellite imagery from different years to develop estimates of AGB and carbon stocks from 2015 to 2021.

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.

2.2 Calculating committed emissions

To calculate the committed emissions of carbon from deforestation, fire and degradation events, we used the emission factors for deforestation (f_D = 1), fire (f_B = 0.3) and degradation (f_{Dg} = 0.075). We define the emission factor as the fraction of committed emission during the disturbance event versus the total carbon available within the vegetation being burned/deforested. The total emissions from deforestation (E_{DF}), fire (E_{Fire}), and degradation (E_{DG}) were then estimated using the bottom-up modeling approximation.

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

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

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

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 the emission from deforestation (or fire, degradation) for the corresponding year. *PDA*, *PBA*, and *PDgA* represent the percent deforested areas, percent burnt area, and percent degraded area, respectively. Fire events at 1-km resolution can happen in forest and/or non-forest regions, which could cause a mixed-pixel effect when calculating emissions. Therefore, we further separated each 1-km pixel into two fractions – forest, and non-forest fractions, and denoted the forest (or non-forest) carbon within each pixel as forest TLC C_F (or non-forest TLC C_{NF}). Degradation events also consider forest edge emissions.

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 is the biomass multiplied by the combustion factors in each land cover category. Emission estimates are provided in Mg CO_2e per 1-km resolution, globally for years 2015 to 2021.

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, 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 Assigning emissions to land cover type

This dataset provides annual estimates of total live biomass carbon (TLC) stored in three major land cover types: Forests, 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.

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, shrub-grassland, and wetland in each pixel i, respectively, and A is the area of pixel i.

3. Climate TRACE reporting of emissions

3.1. Country-level emission estimates

Using the dataset generated above, The Climate TRACE platform reports the total net change of living biomass for forest, shrub-grassland, and wetland at the country-level. Both were created by associating each 1-km spatial resolution pixel with the GADM (Database of Global

Administrative Areas) database (https://gadm.org/about.html) and properly parsed to the Climate TRACE reporting format. To estimate total net change of living biomass between years, from 2016 to 2021, for each sector, was performed by estimating the change in carbon stock (TLC) between years:

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

Where, C_{yr1} is the previous year subtracted from the most recent year, C_{yr2}, and $\Delta C_{net,yr2}$ is net living biomass. This approach was applied at the country-level.

CTrees generated country-level emissions estimates from the datasets in section 2. On the Climate TRACE website, the following are available for display and download at the country-level: net forest and mangroves, net shrub-grassland, and net wetlands emissions.

The following datasets are only available via download: forest-land-fires, forest-land-clearing, forest-land-degradation, grassland-fires, wetland-fires, and forest-grassland-wetland-sink emissions.

Climate TRACE does not provide error estimates for each dataset described in section 2 but are available per request.

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