



The EDGAR-LULUCF Dataset of forest-related carbon emissions and removals

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Abstract. The EDGAR database provides a consistent global inventory of anthropogenic Greenhouse Gas (GHG) emissions and removals, widely used in major global studies and assessments, but until recently lacked estimates from the Land Use, Land-Use Change, and Forestry (LULUCF) sector.

LULUCF plays a crucial role in mitigating climate change, mostly through conserving and enhancing the forest sink and by
75 reducing emissions from deforestation and peatland degradation. LULUCF is the most challenging sector in National GHG Inventory (NGHGI) reporting, due to the combination of complex biophysical processes paired with demanding data collection needs, potentially resulting in high uncertainties. Emission coverage and quality vary between countries, with advanced techniques applied in more developed nations, whereas important forested areas worldwide may lack reliable estimates.

This work presents new global, country-level estimates for carbon stock changes in living biomass from managed Forest Land
80 and Deforestation. In both cases, a globally coherent IPCC Tier 1 gain-loss approach with regionally differentiated parameters is used, combined with spatially-explicit Earth Observation-derived land use data and official statistics. Deforestation estimates are based on the new "Global Maps of Forest Cover Changes and their Drivers" from the EU Observatory on Deforestation and Forest Degradation.

For Forest Land, we implemented a few methodological improvements to existing IPCC guidance in order to address
85 limitations of the Tier 1 approach: (i) a third forest age class (>100 years) to avoid overestimating gains; (ii) a corrected IPCC fuelwood formula to eliminate double-counting; (iii) fuelwood adjustments for Southern Asia; (iv) country-specific illegal logging corrections.

Global net CO₂ removals from Forest Land over 2001-2021 averaged -7.0 Gt CO₂ yr⁻¹ showing a declining trend linked to rising harvest rates, while Deforestation emitted on average 4.7 Gt CO₂ yr⁻¹, leading to a combined -2.3 Gt CO₂ yr⁻¹ removal.
90 These estimates are compared with the countries' official reporting to the UNFCCC and with other independent datasets and the results are discussed.

Overall, this EO-based Tier 1 dataset fills a critical gap in EDGAR reporting by providing a transparent, IPCC-compliant global benchmark against which NGHGIs may be compared, or that can be used to fill gaps in Non-Annex I countries with limited reporting.

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1 Introduction

Within the United Nations Framework Convention on Climate Change (UNFCCC) Greenhouse Gas (GHG) reporting system, the Land Use, Land-Use Change and Forestry (LULUCF) sector addresses GHG emissions and CO₂ removals from land



management activities. The LULUCF sector has a dual impact on the overall carbon budget: land use generates ~10% of anthropogenic CO₂ emissions (primarily through deforestation), while terrestrial ecosystems (mainly forests) absorb ~30% of annual emissions (Friedlingstein et al. 2025). Climate mitigation thus requires reducing deforestation and maximizing carbon removals through land management, while helping in reducing fossil fuel emissions in other sectors, for example by leveraging wood use for construction material as durable carbon storage.

Overall, land-based mitigation options represent a substantial share of the global mitigation portfolio and are central in many pathways consistent with the Paris temperature goals. The Intergovernmental Panel on Climate Change (IPCC) considers their rapid implementation a necessary component of pathways that achieve the goals of the Paris Agreement (PA) alongside deep emissions reductions in the energy and industry sectors (IPCC 2023). Article 5 of the PA (UNFCCC 2015) encourages action in greenhouse gas forest sink conservation and in reducing deforestation, and this is reflected in national climate policies (Migliavacca et al. 2025) and countries' pledges under the PA (Grassi et al. 2017, Roman et al. 2025), where LULUCF accounts for ~25% of planned emissions reductions. Forest land is particularly critical: within the land sector, reducing deforestation and enhancing forest sinks represent the single largest mitigation option (IPCC, 2022). Land currently absorbs approximately 30% of annual anthropogenic CO₂ emissions, making them, together with the Earth's oceans, the main natural carbon removal mechanism presently available (Pan et al., 2011; Harris et al., 2021). Land global carbon sink has remained relatively stable over three decades, with living biomass contributing the majority of net CO₂ flux (Pan et al., 2011; Pan et al., 2024). However, forest reporting remains incomplete in developing countries, and uncertainties in the attribution of anthropogenic vs. natural fluxes create large discrepancies between global models and National GHG Inventories (Grassi et al. 2025).

The Emissions Database for Global Atmospheric Research (EDGAR) provides a consistent global inventory of anthropogenic GHG emissions and removals (1970–present) following IPCC Guidelines (Janssens-Maenhout et al., 2019; Crippa et al., 2025). Widely used in major assessments such as the IPCC Sixth Assessment Report (AR6, Minx et al., 2021) and the United Nations Environment Programme Emissions Gap Report (UNEP 2025), EDGAR lacked LULUCF estimates until 2020 due to the complexity of the sector; regional LULUCF data were added from 2020–2024, largely based on national inventories.

This work addresses this gap by developing a global dataset of country-level forest-related emissions and removals using the IPCC Tier 1 gain-loss approach. Two forest components are presented: "Forest Land" (living biomass for Forest Land remaining Forest Land and areas converted to Forest Land in the last 20 years) and "Deforestation" (conversion of Forest Land to other land uses).

While national inventories often use higher-tier methods with greater expected accuracy, especially in the case of Annex I countries, this IPCC-compliant dataset provides a transparent benchmark useful for evaluating or complementing other estimates, particularly for countries with limited resources and data.

In addition, this dataset offers valuable information for regions where national or official data are sparse or unavailable, such as in several African countries. Overall, the EDGAR LULUCF dataset represents an important step in broadening the coverage of the EDGAR global emissions dataset, with the longer-term objective to include other land-use categories.



2 Approaches to model forest fluxes

135 Various approaches are used to model LULUCF emissions and removals across scientific communities, reflecting different goals and expertise. The IPCC Guidelines (IPCC, 2006, 2019) were developed to support the compilation of the National Greenhouse Gas Inventories (NGHGs) submitted under the UNFCCC and related international climate treaties such as the Paris Agreement. Other scientific communities employ a variety of approaches such as global carbon models (bookkeeping and dynamic global vegetation models; Friedlingstein et al., 2025), remote-sensing-based modelling (Xu et al., 2021; Harris et al., 2021), and inverse modelling (Deng et al., 2022). In addition, FAO disseminates LULUCF emissions and removals by country, including explicitly from forests, as part of its agrifood systems database (FAO, 2025). The large mismatch in LULUCF estimates across communities—particularly between global carbon models and national inventories—primarily reflects differences in the definition of anthropogenic GHG emissions and removals, with countries applying broader definitions of “managed land” areas and processes than global models (Grassi et al., 2023). For example, Brazil’s NGHGI classifies primary Amazon forests under conservation laws (such as Indigenous Lands) as “managed”, while global models in general treat primary or intact forests as “unmanaged”.

This work belongs to the field of GHG Inventories and implements the default IPCC Gain/Loss approach (Tier 1), outlined in the IPCC Guidelines for National GHG Inventories (IPCC 2006, 2019), with methodological consistency at the global scale. In general the IPCC methodology estimates emissions and removals by multiplying activity data (quantifying activities leading to GHG exchanges) by emission/removal factors (quantifying emissions/removals per unit activity). The Gain/Loss approach accounts for carbon stock inputs and outputs from the various carbon pools. Another approach, the Stock difference method, quantifies carbon stock variations as the change in total C stocks in a pool through time. The high spatial-temporal variability of GHG fluxes, biological system complexity, and diverse land and vegetation management strategies make the estimation of LULUCF emissions and removals considerably more complex than for other sectors (Energy, Industry, Agriculture, Waste).

155 This complexity extends to both collecting activity data and selecting adequate methods and parameters.

Essential activity data for carbon removal estimates include annual information about areas under the various land uses within the national territory and their conversions,—a challenge with traditional National Forest Inventory (NFI) approaches that sample only limited areas annually and are updated at intervals of five years or longer. Additionally, following a land use conversion, the IPCC approach assumes a default 20-year “transition period” to allow carbon stocks to reach the expected long term average under conditions typical of the new category. For emissions from living biomass, activity data rely on wood harvest statistics, which are a systematic underestimation of actual harvest since they fail in accounting for illegally or informally logged wood—which can be substantial or even predominant in some regions compared to official statistics.

Several approaches are employed to obtain land use information, ranging from statistical extrapolation and sampling of NFI data to wall-to-wall geographically-explicit mapping via Earth Observation (EO), each involving varying degrees of complexity and uncertainty. Within the European Union, Regulation 2018/841 (EU 2018a) mandates geographically-explicit approaches for land use monitoring in LULUCF estimations. Inventory compilers are encouraged to explore synergies with



existing national efforts (EU 2023) such as NFIs, cadastral data, or spatially explicit systems including the Land Parcel Identification System (LPIS) for monitoring the implementation of the EU Common Agricultural Policy (Böttcher et al. 2024). However, data collected for other purposes often do not meet IPCC requirements regarding spatial or temporal resolution and require further processing and harmonization.

The development of Earth Observation (EO) techniques has enabled regular land cover monitoring, but producing reliable land representation requires considerable technical expertise, and satellite data at sufficiently fine spatial resolution to comply with most national land use definitions are available only for relatively recent years. Carbon removal capacity varies according to land use and management practices, forest characteristics, and tree age, while emissions depend on harvested wood quantities, converted to total plant carbon content through parameters reflecting local forest characteristics. Stratifying land parcels by ecological zones, forest type, management, and age introduces further complexity and uncertainty. Methodological challenges arise from the intrinsic complexity and spatial-temporal variability of natural systems. Default IPCC parameters and emission factors from literature carry substantial uncertainty, and the development of advanced approaches or locally-determined parameters through field experiments is costly, time-intensive, and requires specialized expertise.

The IPCC identifies three methodological Tiers of increasing complexity, coverage in terms of carbon pools (i.e. living biomass, dead wood, litter, and soil organic matter), and data requirements. Tier 1 is the default and most widely applicable approach, utilizing default tabulated parameters and emission factors for large regions derived by the IPCC Guidelines from literature, matched to specific land use parcels through ancillary data, with a set of assumptions that limit carbon pools coverage. Tier 2 is conceptually the same, it uses similar equations but employs locally-derived parameters, for instance from countries' field studies, better representing local conditions, and extends the carbon pools coverage of Tier 1. Tier 1 and Tier 2 Gain/Loss represent the "classic" IPCC approach, and are conceptually similar to bookkeeping models (e.g., Houghton and Castanho 2022). Tier 3 methods employ advanced modelling approaches, expected to produce more accurate estimates. Parties are encouraged to use approaches higher than Tier 1 whenever possible, with Annex I Parties required to do so for statistically defined important land uses and carbon pools (key categories). The IPCC Guidelines also identify three Approaches for Land Representation, ranging from national data (Approach 1) to spatially-explicit land use tracking (Approach 3).

This work implements Tier 1 methodology at the global level using Approach 3 to track land use via EO-derived spatial datasets, with modifications to address specific Tier 1 limitations.

3 The EDGAR-LULUCF Methodology

The Gain/Loss Approach calculates the net carbon flux as the difference of all gains and losses in a carbon pool as shown in Equation 1.



$$\Delta C = \Delta C_G - \Delta C_L \quad (1)$$

ΔC = annual carbon stock change in the pool, tonnes C yr⁻¹

ΔC_G = annual carbon gains, tonnes C yr⁻¹

ΔC_L = annual carbon losses, tonnes C yr⁻¹

1.1 Forest Land

1.1.1 Forest Land: Methodology

In the Forest Living Biomass pool (sum of above and below ground living biomass), Gains quantify the net carbon removed from the atmosphere through photosynthesis by living vegetation, and stored in above-ground and below-ground biomass.

Carbon losses result from biomass removed through wood harvesting. At Tier 1, other carbon pools such as Dead Organic Matter may not be considered. Also, as per IPCC guidelines, mortality losses are ignored as a first approximation.

Figure 1 shows the flowchart of the calculations.

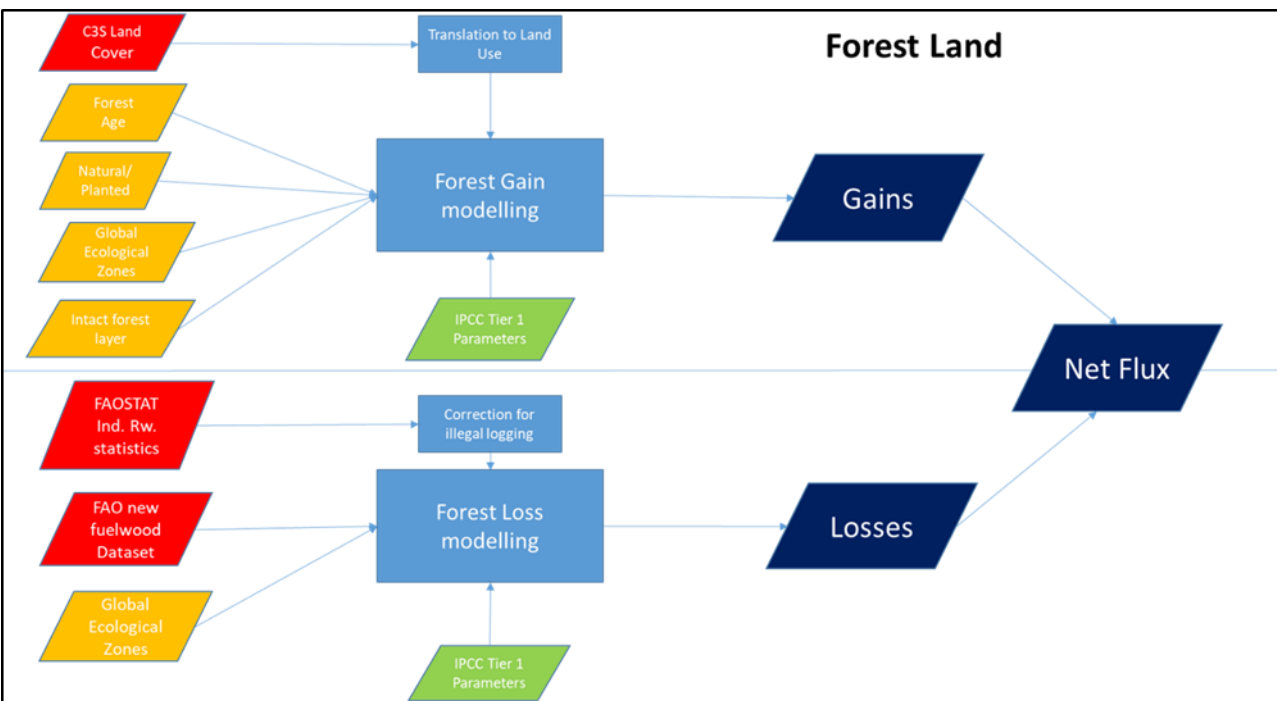


Figure 1: Flowchart for the Forest Land estimates.



Gain: annual gain in biomass carbon stocks in Forest Land result from annual net woody biomass increment. IPCC (2006, 2019) at Tier 1 estimates it using Equation 2 (see supplemental material).

220 The Above-Ground Net Biomass Growth (G_w) parameter describes annual dry matter production by forests per forest hectare per year and, once converted using a carbon fraction (CF) parameter, the carbon annually absorbed per forest hectare. The IPCC Guidelines contain tables (Tables 4.9-4.10) providing Above-Ground Net Biomass Growth values for different regions, ages, and Global Ecological Zones. Table 4.3 contains CF parameters, while Table 4.4 contains ratios of below-ground to above-ground biomass (R) values.

225 *Loss*: at Tier 1, annual biomass loss in Forest Land living biomass is the sum of losses from the removal of industrial roundwood and fuelwood. Disturbances such as wildfires are also causing losses. Within EDGAR, emissions from biomass fires are estimated by the Global Wildfire Information System (GWIS) of the Joint Research Centre (JRC), based on the Tier 1 approach by Rossi et al. (2016) and Prosperi et al. (2020), also implemented in FAOSTAT.

Equation 3 models carbon loss from industrial roundwood removals. The Biomass Conversion and Expansion Factor (BCEF) parameter converts merchantable wood volume to total dry matter content of whole trees, including parts removed after harvest. 230 Table 4.5 of the IPCC Guidelines provides default BCEF values according to climatic zone, forest type, and growing stock level ($\text{m}^3 \text{ha}^{-1}$).

For fuelwood we corrected an error in the IPCC formula as outlined below.

3.1.2 Forest Land: Methodological changes

235 *3rd Age Class*: the standard IPCC Tier 1 approach considers two forest age classes (0-20 years and above 21 years). We found that using a single class for older forests overestimates forest gain, as it does not account for forest ageing which reduces carbon absorption capability. Within the standard IPCC framework, a 21-year-old forest is assumed to absorb carbon at the same rate as a, e.g., 300-year-old forest. We therefore introduced a third class for older forests, subdividing the "above 21 years" class into a class for 21-100 years and one above 100 years. For these older forests, we used the aboveground growth values for primary forests provided by the IPCC Guidelines.

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Corrected formula for fuelwood losses: while developing the EDGAR methodology, we identified that the application of the IPCC equation for fuelwood removals (Equation 2.13 in the 2006 Guidelines) to FAOSTAT statistics would result in an overestimate of those quantities. In fact FAOSTAT defines fuelwood data as "wood harvested from main stems, branches and other parts of trees used for fuel" (FAO 2024). Thus, Multiplying FAOSTAT statistics by BCEF_R double-counts biomass from 245 tree parts other than the stem. Considering that the BCEF_R can be replaced by the Biomass Expansion Factor (BEF) multiplied by the Wood Density (D) to convert cubic meters in dry matter ($\text{BCEF} = \text{BEF} \times D$), we amended the formula by replacing



BCEF with an expansion factor limited to the wood left in the field during harvesting (~10% according to the Guidelines) multiplied by wood density (see equation 4 in the Supplemental materials)..

250 *Reduction for non-forest fuelwood collection in Southern Asia:* several studies (e.g., Battacharya 2015; Arnold et al. 2003; Vergara 1997) report that in Southern Asia, a large proportion (80-95%) of fuelwood is collected outside forests. For example, the share of fuelwood collected in Indian forests decreased from 35% in the 1970s to 17% in the 1990s. Considering all Fuelwood as originating from forest harvest would therefore overestimate carbon losses from forest living biomass. We therefore introduced specific parameters using average literature values—one for Southern Asia generally and one specifically
 255 for India—to reduce the share of total fuelwood harvest originating from forests.

3.1.3 Forest Land: Activity Data

Gain: activity data relate to Forest Land area, stratified by tree type (broadleaf or needleleaf), age class, management type (natural forest and plantation), and Global Ecological Zone. Forest land areas were identified and tracked in a spatially explicit way using the European Space Agency (ESA) Climate Change Initiative (CCI)/Copernicus Climate Change Service (C3S)
 260 Land Cover (LC) Dataset (ESA 2017). This dataset provides annual global land cover maps from 1992 to the present at ~300 m spatial resolution at the equator. It was developed by harmonizing data from multiple sensors: AVHRR (1992–1999), SPOT-Vegetation (1998–2012), MERIS (2003–2012), PROBA-V (2013-2016), and Sentinel-3 OLCI (from 2016). The dataset is part of the C3S data archive, which provides yearly updates, and represents the longest regularly updated, spatially explicit global annual land cover time series currently available.

265 The ESA CCI/C3S Land Cover dataset follows the FAO Land Cover Classification System (LCCS) (Di Gregorio and Jansen, 2000), a hierarchical classification system that uses a set of classifiers to adjust thematic detail according to available information.

LCCS classifies land cover, describing the physically observable surface of Earth, whereas the IPCC methodology employs the concept of land use, describing the human management of land. The IPCC identifies six land use categories (Forest Land,
 270 Cropland, Grassland, Wetlands, Settlements, Other Land). We therefore translated the original LCCS Legend into proxies for IPCC land use categories. We further stratified Forest Land into needleleaved and broadleaved forest, Cropland into herbaceous and woody crops, Grassland into shrubland and herbaceous grassland, and Wetlands into inland waters and wetlands.

Since LCCS classes are often mixed with coexisting land cover types, we adopted an approach based on shares of each land
 275 use category within each pixel area. Pixel area within the Land Cover map was reassigned to different land use classes according to shares defined by each LCCS class description (Figure 2). For LCCS forest classes not specifying needleleaf or broadleaf, the forest share was further partitioned according to average shares of the two forest types in the pixel's ecological zone.



LCCS Class	IPCC	Forest Land			Cropland		Grassland		Wetlands		Settlements	Other land	Sea water
		Broadleaf	Needleleaf	Forest on wetlands	Herbaceous	Woody	Shrubs	Grasses	Wetlands	Inland water			
10	Cropland, rainfed				100								
11	Herbaceous cover				100								
12	Tree or shrub cover					100							
20	Cropland, irrigated or post-flooding				100								
30	Mosaic cropland (>50 %) nat. veg. (tree, shrub, herb.) (<50 %)	20			60		10	10					
40	Mosaic nat. veg. (tree, shrub, herb.) (>50 %)/cropland (<50 %)	20			40		20	20					
50	Tree cover, broadleaf, evergreen, closed to open (>15 %)	100											
60	Tree cover, broadleaf, deciduous, closed to open (>15 %)	100											
61	Tree cover, broadleaf, deciduous, closed (>40 %)	100											
62	Tree cover, broadleaf, deciduous, open (15–40 %)	100											
70	Tree cover, needleleaf, evergreen, closed to open (>15 %)		100										
71	Tree cover, needleleaf, evergreen, closed (>40 %)		100										
72	Tree cover, needleleaf, evergreen, open (15–40 %)		100										
80	Tree cover, needleleaf, deciduous, closed to open (>15 %)		100										
81	Tree cover, needleleaf, deciduous, closed (>40 %)		100										
82	Tree cover, needleleaf, deciduous, open (15–40 %)		100										
90	Tree cover, mixed leaf type (broadleaf and needleleaf)	50	50										
100	Mosaic tree and shrub (>50 %)/herbaceous cover (<50 %)	20					20	60					
110	Mosaic herbaceous cover (>50 %)/tree and shrub (<50 %)						30	70					
120	Shrubland						100						
121	Shrubland evergreen						100						
122	Shrubland deciduous						100						
130	Grassland							100					
140	Lichens and mosses											100	
150	Sparse vegetation (tree, shrub, herbaceous cover) (<15 %)						5	5				90	
152	Sparse shrub (<15 %)						10					90	
153	Sparse herbaceous cover (<15 %)						10					90	
160	Tree cover, flooded, fresh or brackish water			100									
170	Tree cover, flooded, saline water			100									
180	Shrub/herbaceous cover, flooded, fresh/saline/brackish water								100				
190	Urban areas										100		
200	Bare areas											100	
201	Consolidated bare areas											100	
202	Unconsolidated bare areas											100	
210	Water bodies									100			100
220	Permanent snow and ice											100	

Figure 2: Conversion from the LCCS Legend to IPCC Land Use categories. Cell numbers represent pixel area shares (%) assigned to each IPCC class. For forest classes where LCCS does not specify needleleaf or broadleaf type (indicated in dark green), shares were partitioned between these forest types based on their average proportions within the ecological zone.

As NGHGs focus on managed forests only (IPCC, 2006), we used an Intact Forests layer (described among ancillary data) as a proxy for unmanaged forests, excluding them from our estimates.

Loss: the activity data is the amount of wood harvested under forest management, subdivided into Industrial Roundwood and Fuelwood, typically available in FAOSTAT as country official harvest statistics. For Industrial Roundwood, it refers to wood harvested in m³ of merchantable volume produced per year.

However, evidence indicates that official harvest statistics substantially underestimate actual harvest (Kallio and Solberg, 2018; UNODC, 2025). Illegal logging of Industrial Roundwood can be equivalent to total actual logging in some areas (Kleinschmit et al. 2016; Hoare 2015). For Fuelwood, informal collection and trade play major roles in various regions, where wood is collected and processed with chainsaw mills on-site before being transported to informal urban markets. Informal Fuelwood consumption can constitute up to 90% of the actual total Fuelwood consumption, with official statistics recording only a small amount of the wood actually collected (Lescuyer and Cerutti, 2013).

It follows from the above that using official FAOSTAT statistics as they are would substantially underestimate carbon emissions. We therefore developed approaches to account for illegal and informal logging. For Fuelwood, we replaced FAOSTAT statistics with a new dataset by Steel et al. (2025) that more reliably estimates actual fuelwood consumption. For



illegal Industrial Roundwood logging, we applied correction factors from available literature to FAOSTAT data, using regional averages or country-specific values when available. Although some reports indicate reduced illegal logging shares in the first decade of the 2000s due to improved large-scale logging concession enforcement, dramatic small-scale logging growth from population increase has stabilized or worsened the situation in some areas (Hoare 2015; Cerutti, personal communication, 2025). We therefore maintained constant correction coefficients over time.

3.1.4 Forest Land: Ancillary datasets

Parameters for estimating gains and losses are specific to different environmental contexts, including forest characteristics, ecological zones, and forest age. Each cell in the forest map must be matched with correct parameters according to ecological zone and vegetation characteristics, requiring stratification using appropriate ancillary datasets.

Global Ecological Zones: Tier 1 default parameters vary according to ecological zone (i.e. climate and forest ecosystem), which must be identified for each pixel to correctly match with parameters. The IPCC Guidelines suggest using the FAO Global Ecological Zones dataset (FAO 2025), which identifies ecological zones as broad yet relatively homogeneous natural vegetation formations similar in physiognomy, generally subdivided according to the Köppen-Geiger climate map (Kottek et al. 2006).

Shares of Planted and Naturally grown forests: plantations and natural forests have different characteristics and management, resulting in different growth rates. The FAO Forest Resource Assessment (FRA 2025) provides the actual area of planted and naturally growing forests in addition to total forest area at the country level for the whole Globe. We assume the same plantation-natural forest subdivision within each forest grid cell.

Age classes: forests grow and absorb carbon at different rates according to tree age. The IPCC Guidelines assign different forest growth rates to forests ≤ 20 years and > 20 years old. Forest age was mapped using the Global Forest Age Dataset (GFAD) 1.1 (Poulter et al. 2019), a geospatial dataset describing age distribution in ten-year intervals from 1-10 years to older than 150 years for four forest types classified by leaf type (needleleaf and broadleaf) and tree type (deciduous or evergreen). As mentioned above, we added to the original IPCC classes a third age class for forests older than 100 years.

Intact forest layer as a proxy for unmanaged forests: under UNFCCC, NGHGs report only anthropogenic emissions and removals. Due to difficulties in providing widely applicable and scientifically robust methods to disentangle anthropogenic and natural effects on land-based GHG fluxes, the IPCC Guidelines adopted the 'managed land' proxy concept as a pragmatic way to facilitate GHG reporting. Anthropogenic land GHG fluxes are defined as all those occurring on managed land, where human interventions and practices have been applied to perform production, ecological, or social functions. Given the general



lack of managed forest maps in NGHGs, we used the Intact Forest Landscapes (IFL) dataset (Potapov et al. 2017)—forest areas characterized by no remotely detected signs of human activity—to exclude unmanaged land from our maps. Previous studies (Grassi et al. 2021) demonstrated that the resulting non-intact forest map (i.e., total forest minus intact forest) is a good proxy for countries' managed forest.

Country borders: Country borders follow the United Nations Cartographic Section (UNCS) subdivision, the UN authority for international boundaries. They were obtained from the FAO Global Administrative Unit Layers (GAUL) (FAO 2025), a spatial database of administrative units for all countries worldwide, at Level 0 (country boundaries).

3.2 Deforestation

Deforestation is the permanent removal of forest, changing land use from Forest to other uses (e.g., agriculture), and resulting in a net carbon loss.

3.2.1 Deforestation: methodology

Figure 3 shows the flowchart of the calculations.

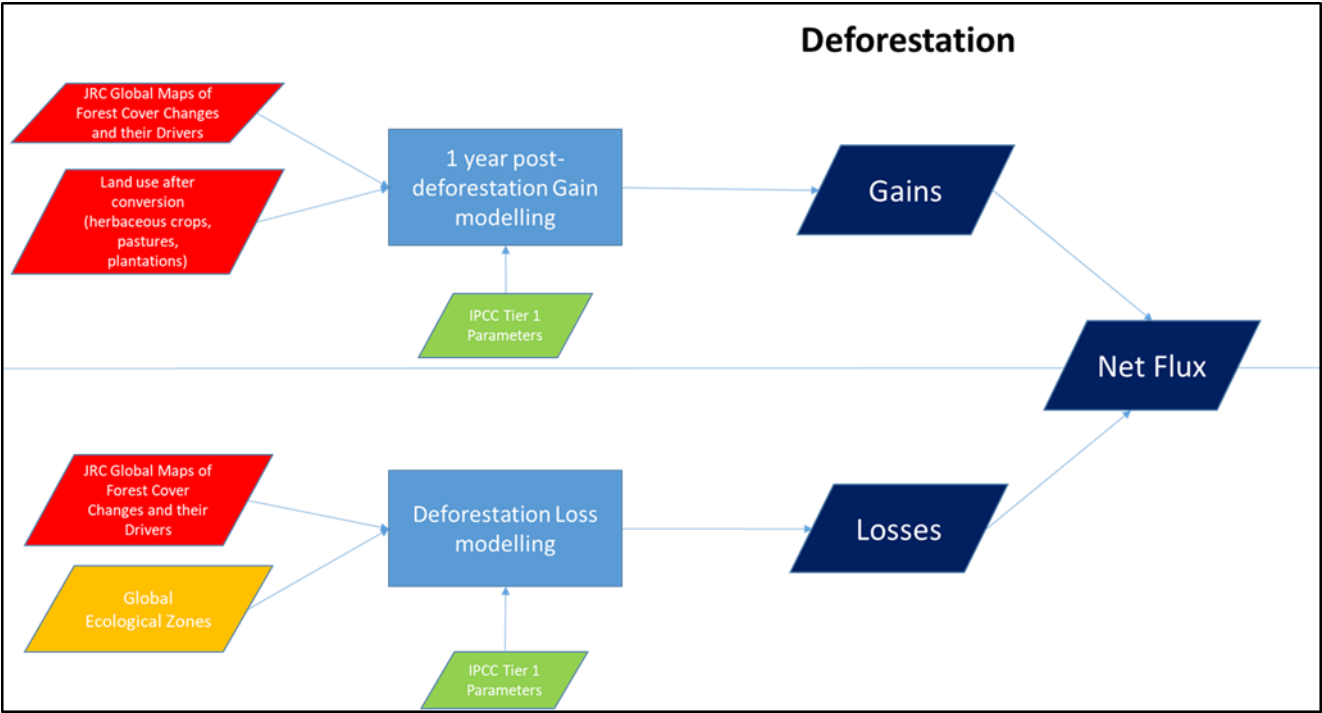


Figure 3: Flowchart for the Deforestation estimates



Gains: deforestation gains in the conversion year consist of removals from one year of vegetation growth in land following conversion. Parameters of biomass stocks for new vegetation replacing forests after conversion are provided by IPCC (2006, 2019) describing biomass accumulation during the first year following conversion, accounting for annual and perennial crops, grasslands, and other land use categories according to ecological zone (Tables 5.9 and 6.4 for cropland and grassland).

Losses: At Tier 1, forest vegetation is assumed entirely removed at the conversion with all carbon immediately released to the atmosphere ("instantaneous oxidation") in the year when deforestation occurs, leaving no carbon in biomass. Emissions are therefore obtained from the deforested area and the biomass removed per hectare, zone.

The biomass change for the deforestation year is calculated using eq.5.

Values of Average Above-Ground Biomass in Forests represent the amount of forest carbon stock removed and are provided by IPCC (2006, 2019) derived from literature for each Global Ecological Zone and Age Class (≤ 20 years or > 20 years) in Table 4.7. As for Living Biomass, ratio of below-ground to above-ground biomass (R) values are derived from Table 4.4, and CF values are derived from Table 4.3.

For newly replacing vegetation, they consider one year of growth and provide parameters describing vegetation gain in this specific initial stage for annual and perennial cropland.

3.3 Deforestation: Activity Data

Losses: The spatial resolution of 300m of the ESA/C3S land cover dataset that we used to map land uses hampers the mapping of land use conversions at pixel level. For modelling the losses from deforestation, activity data consist of deforested areas, i.e. forest land converted to other land uses. Distinguishing deforestation from clear-cutting or selective logging as a forest management practice is challenging and requires monitoring subsequent vegetation development over following years to verify whether actual conversion to other land uses occurs or whether new forest returns. In this work we used a dataset developed by the JRC for this purpose, the new "Global Maps of Forest Cover Changes and their Drivers" with 30m spatial resolution available within the "European Observatory on Deforestation and Forest Degradation (<https://forest-observatory.ec.europa.eu/>). This dataset contains deforested area maps by the types of drivers for the period 2001 to 2021, with further updates foreseen in the next future. The methodology combines two wall-to-wall products: the first is the JRC Tropical Moist Forest (TMF) dataset (v1_2023, Vancutsem et al. 2021), developed using the Landsat time series, which covers all closed forest in the humid tropics. The second, covering the rest of the ecological zones, is the Global Forest Change Dataset (GFC, Hansen et al., 2013), also Landsat-based, applying a threshold of $> 30\%$ tree canopy cover to identify forests in 2000 with a 0.5 hectare minimum mapping unit, and then monitoring forest cover changes in the following years.

In the TMF domain, deforestation is derived from trajectory analysis of the satellite data time series: a disturbance is considered as deforestation when it persists over 2.5 years or when more than four short-duration disturbance events (each of less than 2.5 years duration observation) are detected (Vancutsem et al. 2021). Additionally, tree cover loss from GFC within areas considered undisturbed by TMF is kept and classified as a potential deforestation event. Outside the TMF domain, within GFC forest loss temporary disturbances are distinguished from permanent conversion using a combination of driver classification



and post-hoc verification against the ESA WorldCover 2021 land cover map (Zanaga et al. 2022), to assess the presence or absence of vegetative regrowth in 2021 following tree cover loss from fire according to Tyukavina et al. (2022).

Driver attribution is based on the Curtis et al. (2018) global classification of forest loss drivers at ~10 km resolution, and on Tyukavina et al. (2022) which differentiates GFC fire-related tree cover losses from other tree cover losses at 30m resolution.

385 In the TMF domain, the drivers are assigned to areas already classified as deforestation. Forest degradation resulting from non-permanent disturbances (e.g., selective logging, fire, drought, blowdowns, or other natural events) is assumed to persist for less than 2.5 years and then to be followed by forest recovery; therefore, it is excluded from the deforestation map. Areas classified as deforestation by TMF overlapping with fire-related tree cover loss (2001–2023) where tree cover is detected in
 390 cover is absent in ESA WorldCover 2021, the areas are confirmed as deforestation, included in the deforestation map, and assigned a dominant driver based on the Curtis dataset. Outside the TMF domain, the drivers from Curtis dataset serve a dual role: they both classify the cause of loss and help distinguishing between conversion (Urbanization, Shifting Agriculture, and Commodity-Driven Deforestation) and temporary disturbance (Forestry and Wildfire). The final deforestation map only retains areas that are related to one of those conversion drivers. As described in the TMF domain, also GFC loss that overlap with
 395 fire-related tree cover loss (2001–2023) and where tree cover is detected in ESA WorldCover 2021 are reclassified as forest degradation and excluded from the analysis. Conversely, where tree cover is absent in ESA WorldCover 2021, the areas are retained in the analysis and assigned a deforestation driver based on the Curtis dataset.

The JRC deforestation map identifies deforestation for agricultural purposes, either as long-term permanent conversions into agricultural land for crops or livestock (commodity-driven deforestation) or for temporary cultivation (shifting agriculture).

400 *Gains:* To estimate gains we need information on the land uses following the conversion. We followed Pendrill et al. (2022) in assessing shares of conversions to permanent and herbaceous crops and other uses (pastures). This study also highlights how a significant share (around 50%) of areas deforested for agriculture do not become actively employed for production due to land speculation, tenure issues, fires, and abandoned or degraded land.

4 Results

405 In the following paragraphs, we present the results obtained, using the regional subdivision scheme outlined in Annex II of the IPCC Sixth Assessment Report Working Group III (IPCC 2022). Results are available online (Rossi et al. 2026).

The EDGAR dataset for Forest Land covers the period 1992–2022, the lifespan of the C3S land cover dataset. However, before the MERIS sensor, which offered the first maps at 300m, data were derived from coarser resolution sensors such as AVHRR and SPOT-Vegetation at 1 km. In order to reduce inconsistencies due to systematic biases we therefore consider forest land
 410 data for the period 2000–2022.

For Deforestation, we considered the whole time series covered by the JRC Deforestation Maps (2001–2021).



We compare our results at regional and country scales with National GHG Inventories, and at the global scale with other modelling efforts such as the Global Carbon Budget (GCB, Friedlingstein et al. 2025) and the Global Forest Watch (GFW, Gibbs et al. 2025).

415 GHG reporting obligations differ by country classification: developed countries and economies in transition ("Annex I" parties) submit annual National GHG Inventories with comprehensive data from 1990 onwards, subject to strict quality reviews. Until 2023, developing countries ("Non-Annex I" parties) submitted only periodic reports under various forms without clearly defined data structure. As of 2024, the Enhanced Transparency Framework (ETF) requires all parties to submit GHG inventories at least biennially following the same data structure, though data quality may still differ significantly. When
 420 comparing with National GHG Inventories it is therefore important to distinguish between Annex I and Non Annex I countries. Differences between datasets can be explained by various factors, and discrepancies in individual countries do not necessarily indicate errors. In fact countries may include different components within their estimates (e.g., some include forest fire emissions in biomass losses while others do not), and local assumptions adopted by individual countries can explain differences.

425

4.1 Results: Forest areas

We estimate a global managed forest area of approximately 3200 Mha (64% broadleaf, 36% needleleaf) in 2020, of which about 1500 Mha in Annex I countries and 1700 Mha in Non-Annex I countries. Compared to the official reporting of Annex I countries, our estimates are about 10% lower overall, reflecting differences in forest definitions, mapping methodologies
 430 (satellite resolution, National Forest Inventories), and the inclusion of overseas territories. For the EU, our estimates are 6.5% smaller than NGHGI data, but 1.3% larger when excluding overseas territories. Country-level comparisons show generally close agreement: our estimates are 3.5% higher for Canada, 1.7% higher for Scandinavia, 6.9% lower for Russia, and 14.3% lower for the USA. Oceania shows high differences with 40% less area mapped as forest in Australia and New Zealand compared to NGHGI, which likely reflects different definitions of forest management status and equilibrium assumptions. For
 435 example, Australia considers all its forests as managed in its NGHGI, while IFL classifies 30% as intact forest in 2000 (21% in 2025), which is considered unmanaged forest in our approach and therefore not accounted for. Additionally, Australia assumes around 80% of its forests (equivalently to non-production forests) at equilibrium, regardless of age class or disturbance history.

440 4.2 Results: Emissions and removals in Forest Land

At the global level, the average estimated gross CO₂ removal (Gains) from forest growth on Managed Forest Living Biomass over the whole time series 2000-2022 is -16.4 Gt CO₂ yr⁻¹. Africa and the Middle East (25%) and Latin America and the

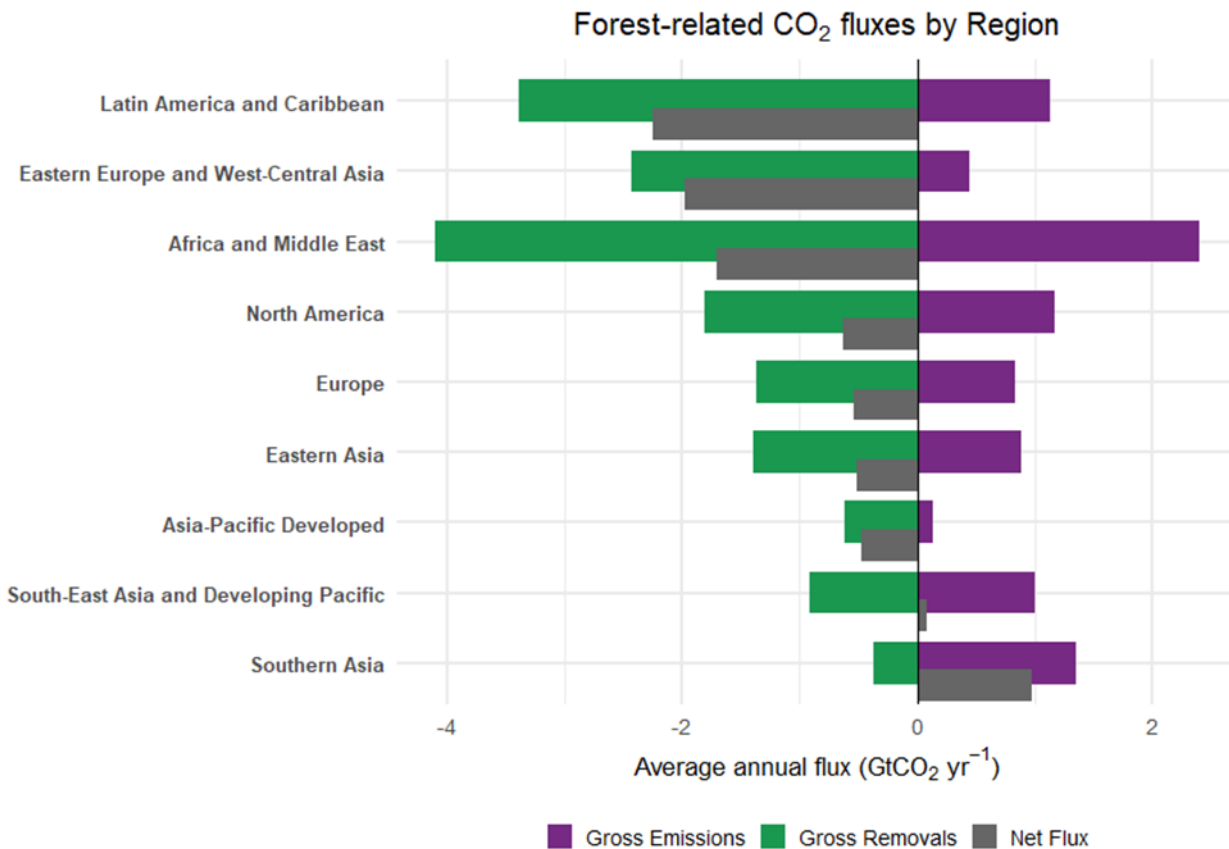


Caribbean (20%) account for the largest share, followed by Eurasia (15%) and North America (11%). Non-Annex I countries provide 63% of total absorption.

445 By ecological zone, Tropical Rainforests and Moist Deciduous Forests remove the most CO₂: 45% and 31% respectively in Africa, and 53% and 21% in South America.

When including losses we obtain a net Flux of -5.3 Gt CO₂ in 2022, equivalent to 13.9% of global fossil CO₂ emissions (thus excluding LULUCF). Results show a declining removal trend reflecting increasing global harvest rates. Over 2000-2022, forests globally are a net sink, removing on average -7.1 Gt CO₂eq yr⁻¹. Latin America and the Caribbean, Eastern Europe and
450 West-Central Asia, and Africa and the Middle East account for most net absorption. Most regions are net sinks; exceptions are South-East Asia and Developing Pacific (small source) and Southern Asia (source). Annex I and Non-Annex I countries have similar net flux impacts, around -3-3.5 Gt CO₂eq yr⁻¹ each.

Figure 4 displays average annual fluxes by region for 2000-2022.



455

Figure 4: Regional Fluxes in Forest Land (average 2000-2022).



At the country level, the Russian Federation has the highest gains and relatively low emissions due to low harvest rates in official statistics, resulting in the largest net removal among countries, averaging $-1.71 \text{ Gt CO}_2 \text{ yr}^{-1}$. Brazil and the Democratic Republic of Congo have the second and third largest net sinks, both around $-0.68 \text{ Gt CO}_2 \text{ yr}^{-1}$. Conversely, India has very high official harvest rates, generating an average net emission of $0.55 \text{ Gt CO}_2 \text{ yr}^{-1}$ over the period.

The combined statistical population for all countries and years comprises 3,788 observations, ensuring robust analysis. The two populations have virtually identical average values ($-39.3 \text{ Gt CO}_2 \text{ yr}^{-1}$ for our dataset vs. -40.29 for NGHGI), with strong correlation ($r=0.67$) and explained variance $R^2=0.45$, indicating both datasets capture the same underlying dynamics in emissions and removals from living biomass. Correlation is strong among Annex I countries ($r=0.83$) but weak among Non-Annex I countries ($r=0.44$).

Moving to time series, the aggregated global time series 2000-2022 (Fig. 5) show similar average values for EDGAR LULUCF estimates and NGHGI (-6.5 and $-6.6 \text{ Gt CO}_2 \text{ yr}^{-1}$ respectively), but trends differ noticeably. The Mann-Kendall trend test shows a statistically significant increasing trend ($\tau = 0.45$, $p = 0.001$) for EDGAR-LULUCF, while NGHGI data show no statistically significant trend. This decoupling is driven by Non-Annex I countries, where the two datasets show opposite statistically significant trends: increasing for our Tier 1 ($\tau = 0.91$, $p = 0$), decreasing for NGHGI ($\tau = -0.67$, $p = 9 \times 10^{-6}$).

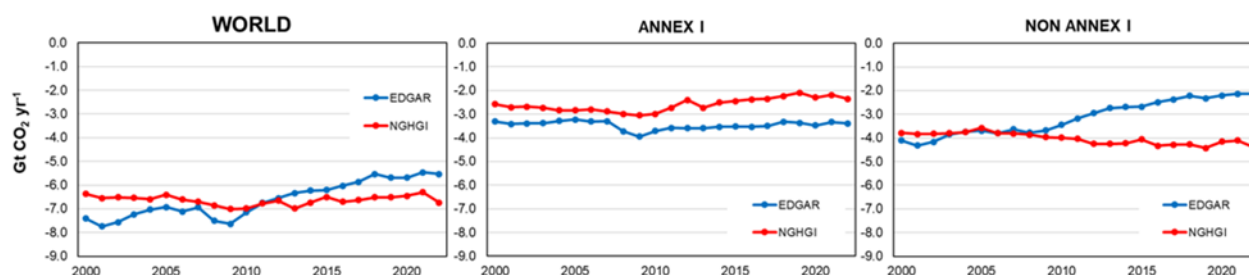


Figure 5: Net fluxes in Forest Living Biomass (World, Annex I and Non Annex I countries)

Aggregated regional time series (Fig. 6) confirm good agreement in Annex I regions (Europe, North America, Asia-Pacific Developed) and similar overall trends in other regions (Eastern Europe and West-Central Asia, Southern Asia). Statistically significant opposite trends and linear slopes occur in Latin America and the Caribbean, South-East Asia and Developing Pacific, and particularly in Africa and Middle East and Eastern Asia.

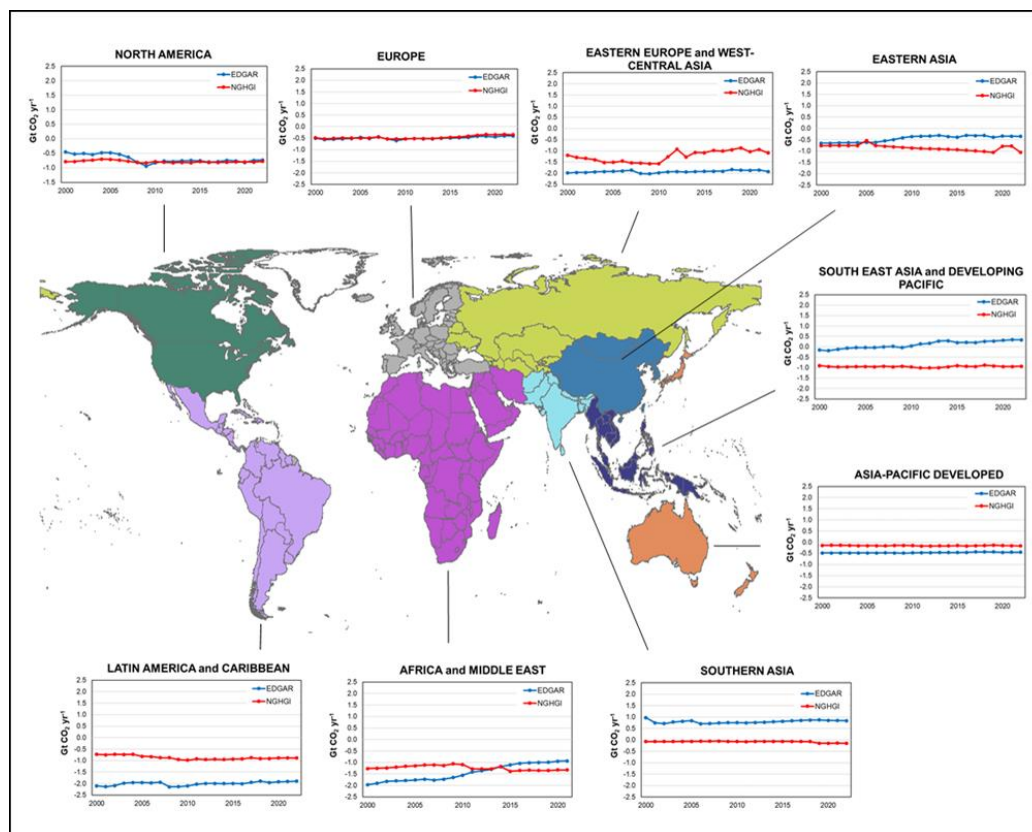


Figure 6: Net fluxes in Forest Living Biomass (Regions)

Varying correlation and different trends indicate that while EDGAR-LULUCF estimates detect a decreasing sink at global level and for most regions, this signal is absent from aggregated national inventories (NGHGI). Africa and the Middle East and Eastern Asia are the main sources of disagreement in terms of diverging trends.

The main source of temporal variation in estimated emissions and removals from living forest biomass is harvesting. While forest cover does not fluctuate substantially year-to-year, wood harvest varies according to dynamics that can change greatly between years. These include economic and market drivers such as demand changes and price cycles (UNECE/FAO 2024), policy and management decisions (Päivinen et al. 2022), natural disturbances (storms, fires, insect outbreaks) (Udali et al., 2021), and related salvage logging (Toth et al. 2020). Compared with harvest, forest area fluctuations are less drastic in normal conditions, with abrupt changes occurring only from increased harvest (Ceccherini et al. 2015), deforestation, or severe disturbances such as forest fires (FAO, 2020).

We therefore investigate whether the different trends between EDGAR-LULUCF and NGHGI correlate with harvest using official FAOSTAT statistics. For this trend comparison, we use the original FAOSTAT data rather than the corrected values employed in EDGAR-LULUCF (which adjust for illegal logging and use alternative fuelwood data). Although original



FAOSTAT data underestimate actual harvest, we assume they adequately represent overall global trends and provide an independent reference.

To compare trends across the three datasets (EDGAR-LULUCF, NGHGI, and FAOSTAT harvest statistics for roundwood production), time series were standardized to a common 0-1 scale.

EDGAR-LULUCF estimates closely follow FAOSTAT harvest statistics trends, while NGHGI data appear largely uncorrelated with them (Fig. 7).

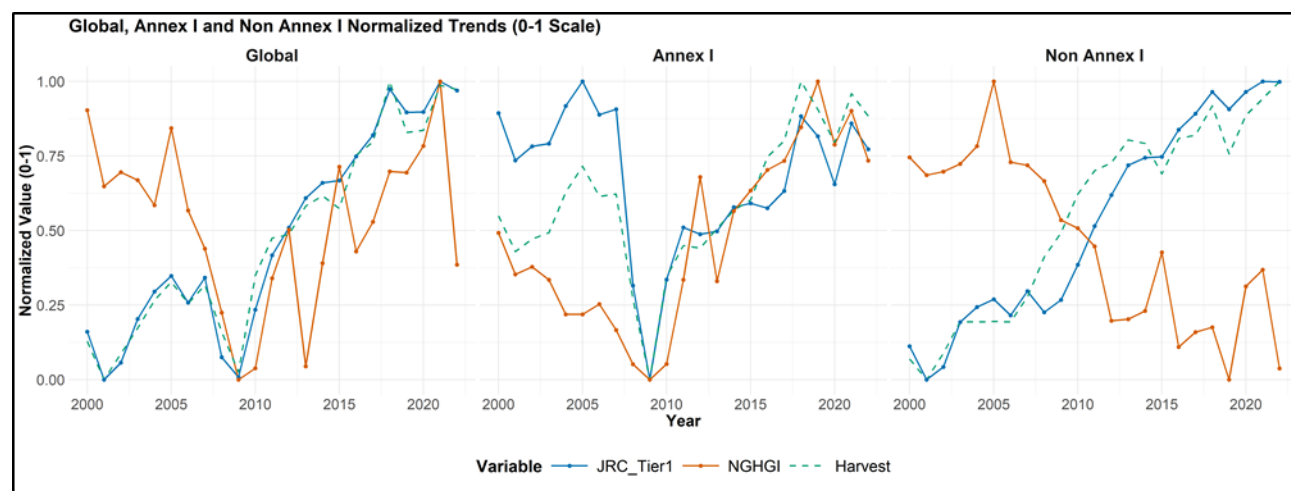


Figure 7: Normalized trends (Global, Annex I, and Non Annex I) for EDGAR-LULUCF (in blue), NGHGI (in orange), and FAOSTAT Harvest statistics (in dashed green).

Regional analysis shows that disagreement in trends among datasets is higher where NGHGI does not follow harvest dynamics. An exception is Southern Asia, where NGHGI appears to follow harvest trends while EDGAR-LULUCF does not, likely due to our specific methodological changes to the IPCC methodology (outlined in Methods) aimed at better describing local fuelwood collection patterns, which occur mostly outside forests.

NGHGI data show in several countries an increasing global CO₂ sink despite increasing FAOSTAT harvest, which would normally be expected to reduce the sink. This could only occur if forest area increased dramatically over the same period and compensated for this effect.

The Democratic Republic of Congo and Ethiopia largely determine the disagreement in Africa and Middle East between EDGAR-LULUCF and NGHGI. In both cases, NGHGI shows increasing forest sinks, contrary to FAOSTAT where harvest increases. In these countries NGHGI data are available only for three years in the two decades examined, an example of the scarcity of officially reported data in critical areas. In Brazil, which plays a key role in Latin American and Caribbean fluxes, emissions correlate well with harvest, though not in the early part of the time series. China, critical for Eastern Asia, is also not aligned with harvest.

In Southern Asia NGHGI are more correlated with harvest data than EDGAR estimates, due to the correction we introduced to account for non-forest fuelwood collection.



We also compare EDGAR estimates with forest emissions from two modelling efforts: the Global Carbon Budget 2024 (GCB, Friedlingstein et al., 2025) and the Global Forest Watch carbon flux model 2024 (GFW, Gibbs et al. 2025), available in the JRC LULUCF Data Hub (Melo et al. 2025). Both time series have been translated to the NGHGI definition of anthropogenic land fluxes (Melo et al. in review). We consider the period 2001-2022 where all data are available. As GCB and GFW include biomass fire emissions, we included fire emissions reported in the EDGAR Database via the JRC Global Wildfire Information System (GWIS) to our estimates.

Trend analysis shows that EDGAR and GFW are highly correlated ($r=0.9$), and show almost identical monotonic increasing trends (Kendall $\tau>0.7$, $p<0.0001$), detecting a decrease in net carbon sink in living forest biomass of approximately $0.18 \text{ Gt CO}_2 \text{ yr}^{-1}$. Normalized trends show these datasets closely follow global FAOSTAT harvest increases with high positive correlations in country analysis ($r>0.8$).

GCB shows a weaker but still significant ($\tau=-0.43$, $p=0.006$) opposite decreasing trend with high interannual variability, disconnected from global harvest trajectories.

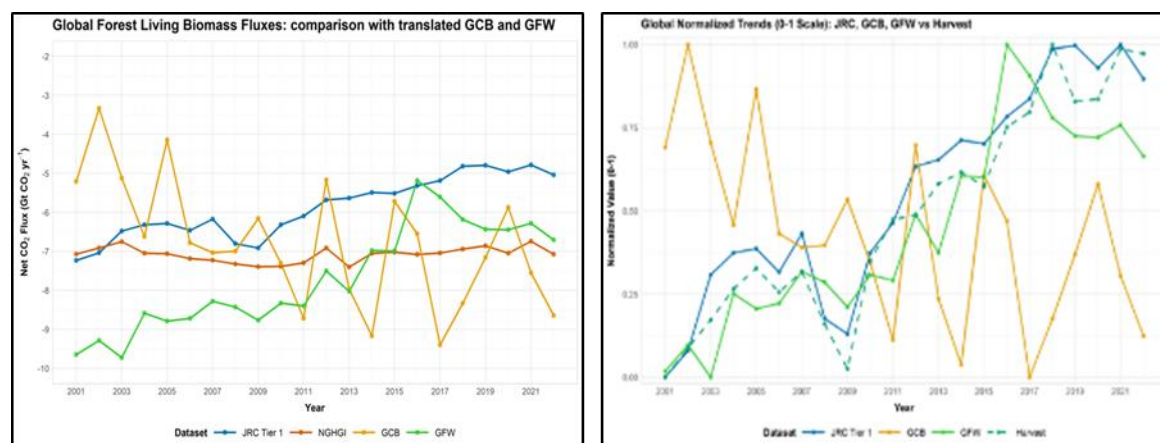


Figure 8: Global time series (left) and normalized trends (right) for EDGAR (blue), NGHGI (orange), GCB-translated (yellow), GFW-translated (light green), and FAOSTAT Harvest (dashed green)

Analysis of the normalized time series also reveals interesting patterns. The interannual variability in GCB-translated estimates results from climate sensitivity of the dynamic global vegetation models used for translating original bookkeeping models to the NGHGI approach. In contrast, EDGAR-LULUCF estimates align more consistently with FAOSTAT harvest time series variations ($SD=0.29$), while NGHGI presents neither significant trends nor remarkable fluctuations in the trend for 2001-2022. GFW shows stable behavior until 2015 ($SD=0.36 \text{ Gt CO}_2$), then interannual variability abruptly increases 2.6 times in 2016-2022 ($SD=0.9 \text{ Gt CO}_2$). This change can be explained by algorithm adjustments effective from 2015 onwards and changes in sensors used in the GFC dataset employed by GFW, leading to inconsistencies over the time series (Weisse and Potapov, GFW blog entry 28 April 2021, Palahi et al. 2021). As will be shown, this has consequences for deforestation estimates as well.



4.3 Results: Deforestation emissions

540 At the global level the new JRC "Global Maps of Forest Cover Changes and their Drivers", estimate over the available period (2001-2022) an average annual deforestation gross rate of 13.2 million hectares (Mha), almost exclusively (~98%) in Non-Annex I countries, with a decreasing trend. This is slightly higher than the FRA 2025 estimate of 12.7 Mha/yr. Agriculture is by far the main driver, while urbanization is marginal.

Figure 9 shows the comparison between EDGAR-LULUCF deforestation emissions subdivided by drivers and total NGHGI
 545 figures at the global level and in the top three emitting countries. EDGAR-LULUCF estimates an average 5 Gt CO₂ yr⁻¹ in the first decade (2001-2010) and 4.4 Gt CO₂ yr⁻¹ in the second decade (2011-2022), compared to 4.2 and 3.8 Gt CO₂ yr⁻¹ respectively reported by countries in NGHGI. NGHGI is better aligned with EDGAR-LULUCF in the first decade ($r=0.469$) and correlates well with Commodity-Driven Deforestation (CDD) ($r=0.76$, $R^2=0.57$, $p=0.012$). This is driven by strong correlation in Brazil ($r=0.88$, $R^2=0.77$, $p=0.002$), particularly for CDD ($r=0.92$, $R^2=0.85$). Global correlation deteriorates in the
 550 second decade where EDGAR-LULUCF detects a general deforestation increase in 2010-2020, with deforestation emission spikes in 2015-2016, and 2019. In Brazil in general the trend reflects the official available data (PRODES monitoring project) about the deforestation trajectory determined by the changes in forest policy in the country. After a dramatic decrease after the 2004 peak due to specific legislation and monitoring systems established by the Lula government, a rebound effect can be observed following the weakening and then the complete change of those policies by the following governments, leading to a
 555 stable increase of deforestation rates (David and Macfarlane 2025). The pronounced peak in 2015–2016 is probably due to the effects of El Niño, which caused droughts and forest weakening (Tyukavina et al. 2022), with its consequences in terms of further deforestation (de Oliveira et al. 2025). NGHGI follows the same trend although it remains relatively stable after 2010.

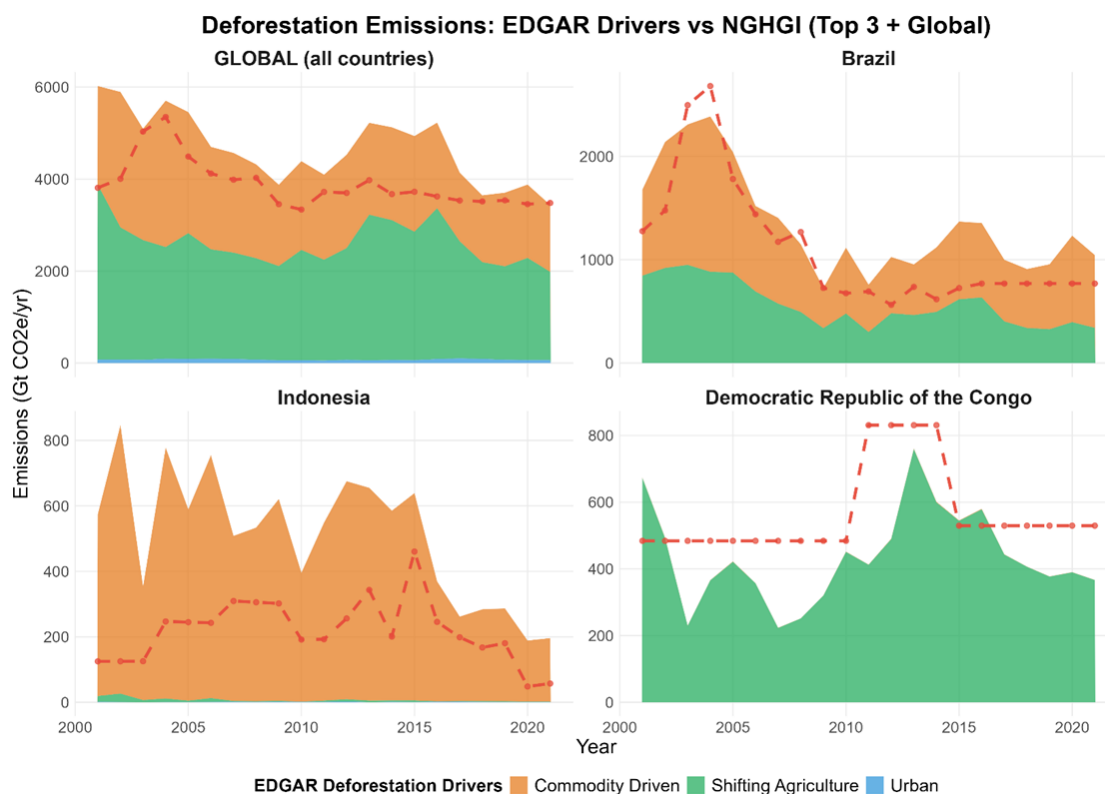


Figure 9: Deforestation emissions by drivers vs. NGHGI total emissions (Global and top 3 countries)

In Non-Annex I countries, EDGAR-LULUCF results, based on a continuous, wall-to-wall remote sensing coverage, detect fluctuations that are not shown in NGHGI data, due to the irregularity of data availability, as shown is Democratic Republic of Congo deforestation emissions within official reporting (Figure 8). This illustrates the potential usefulness of a coherent global IPCC-based dataset for gap-filling in contexts where NGHGI data are not available.

When comparing with other datasets, the trend analysis shows that EDGAR-LULUCF agrees with GCB and NGHGI (Fig. 10) in clearly describing a statistically significant declining trend in global deforestation emissions over 2001-2021, with Kendall τ between -0.4 and -0.6.

In contrast, GFW shows a significant increasing trend reaching a peak in 2016, with Kendall $\tau=0.5$. As mentioned, this likely results from changes in algorithms and data used in the underlying forest mapping dataset, which introduced time series artifacts (Weisse and Potapov, GFW blog entry 28 April 2021, Palahi et al. 2021).

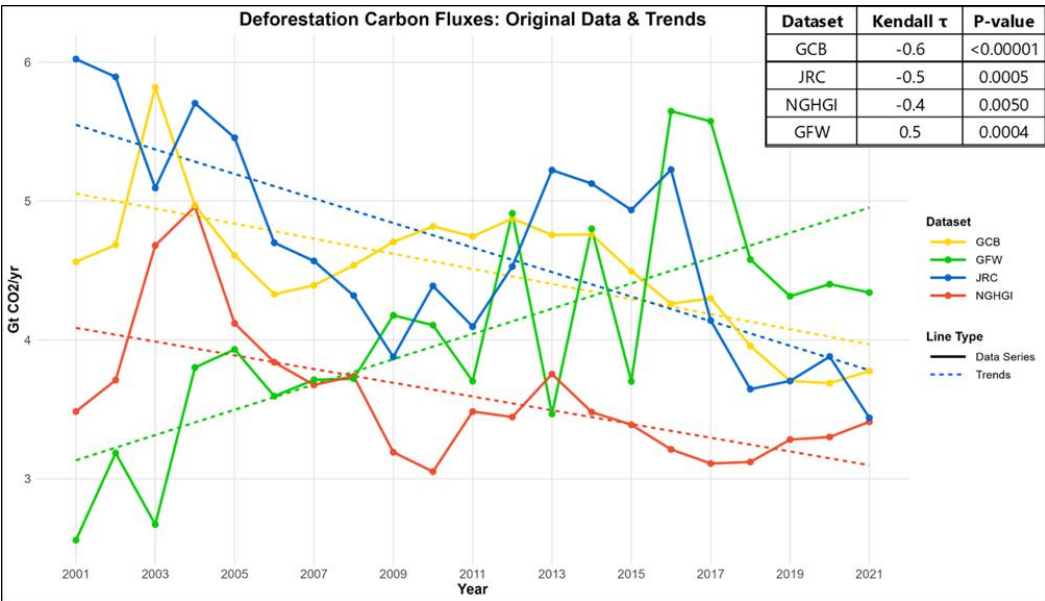


Figure 10: Global Deforestation emissions for EDGAR (blue), NGHGI (orange), GCB (yellow), and GFW (light green) for 2001-2021

5 Uncertainty analysis

Uncertainty was estimated using the Approach 1 framework (error propagation) outlined in IPCC (2006). Uncertainties for activity data were taken from the documentation of the datasets we used. For parameters, the IPCC (2019) tables provide uncertainty estimates for each parameter, forest type, climate zone and age class. Uncertainties are expressed in various ways (percentages, standard deviations) and are generally quite large, especially in tropical and subtropical areas. When best estimates are not available, IPCC assigns a default relative uncertainty of $\pm 90\%$.

For gains in living biomass, the C3S Land Cover product documentation (ESA 2017b) indicates an average uncertainty of about $\pm 12\text{--}15\%$ for forest area, slightly lower ($\pm 10\text{--}12\%$) in tropical areas and higher ($\pm 15\text{--}20\%$) in temperate and boreal regions.

Uncertainty in forest growth parameters was derived from the IPCC tables and weighted by secondary forest age shares (<20 and >20 years) across four climate zones. When propagated through error combination for gains, we obtained $\pm 85\%$ for tropical, $\pm 70\%$ for subtropical, $\pm 40\%$ for temperate and $\pm 65\%$ for boreal forests.

Losses underwent explicit correction of harvest data to account for illegal logging and were based on a specific fuelwood dataset to minimise informal logging uncertainty, but we cautiously maintained a $\pm 10\%$ residual uncertainty. Other uncertainties reflect primarily measurement issues and variability in BCEF/BCEFr parameters (IPCC 2006, Table 4.5). For losses we finally obtained $\pm 27\%$ for tropical, $\pm 22\%$ for subtropical, $\pm 22\%$ for temperate and $\pm 18\%$ for boreal areas.



Global gains uncertainty ($\pm 45\text{--}50\%$) reflects IPCC Tier 1 structural dispersion in forest growth parameters, and the default $\pm 90\%$ adopted when no uncertainty estimates are available, particularly for tropical and boreal secondary forests. Global losses uncertainty ($\pm 20\text{--}25\%$) is substantially lower, reflecting the tighter range of BCEF values and the explicit correction of harvest statistics to limit the impact of under-reported logging.

For deforestation, an accuracy assessment of the new JRC Deforestation Maps is not yet available, but we used the detailed accuracy assessments for all three input datasets used within the data production as reported in the supplementary materials of Vancutsem et al. (2021) for TMF, Curtis et al. (2018) for the Drivers map, and Hansen et al. (2013) for GFC; the figures cited below are drawn from those sources.

Inside the TMF tropical moist forest domain, the TMF transition map has an overall accuracy of 92.8%, with omission and commission errors for forest changes (deforestation and degradation combined) of 19% and 8.4% respectively, and a documented systematic area underestimation bias of 11.8%. Since these two components are not fully independent, and a separate accuracy metric for deforestation alone is not available, we use a combined detection uncertainty of approximately $\pm 22\%$ for total deforested area in the TMF domain, treating this as a first-order approximation that likely slightly overestimates the true uncertainty.

When deforestation is further broken down by driver using the Drivers map, an additional $\pm 11\%$ driver-classification uncertainty applies, based on an overall accuracy of $89\% \pm 3\%$. Combining this with the TMF detection uncertainty using the IPCC error propagation approach yields approximately $\pm 25\%$ for driver-specific deforested area estimates within the TMF domain. The Drivers map does not affect the total mapped deforestation area — TMF alone determines whether a pixel is deforestation or degradation — so the $\pm 25\%$ figure applies only to driver-specific estimates; $\pm 22\%$ is the relevant uncertainty for total deforested area in the TMF domain.

Outside the TMF domain, GFC contributes roughly $\pm 17\%$ detection uncertainty in the tropics and $\pm 12\%$ in temperate/boreal zones. Here the Drivers map plays a dual role — assigning the driver and helping distinguish permanent conversion from temporary disturbance — so its $\pm 11\%$ uncertainty affects both the mapped deforestation area and the driver breakdown, leading to an overall activity-data uncertainty of about $\pm 20\%$ in tropical regions and $\pm 16\%$ in non-tropical regions.

Emission factor uncertainties are taken from the IPCC (2019) default above-ground biomass (AGB) values for each FAO GEZ zone. For each stratum, the activity-data uncertainty and the AGB emission-factor uncertainty are combined in quadrature using the IPCC error-propagation approach, giving per-stratum combined uncertainties ranging from $\pm 37\%$ for tropical rainforest and tropical moist forest strata to $\pm 54\%$ for subtropical dry forest. Total emissions uncertainty is then derived by aggregating across all strata with the IPCC weighted error-propagation formula, where each stratum's contribution is weighted by its share of total emissions. Under the standard IPCC assumption of independence between strata, the weighted total uncertainty is approximately $\pm 20\%$.



6 Data availability

Data are available under a Creative Commons Attribution 4.0 International license (Rossi et al. 2026):
625 <https://doi.org/10.5281/zenodo.20381556>.

7 Discussion and conclusions

In this paper we present two datasets of emissions and removals from Forest Living Biomass and emissions from Deforestation, produced as part of the LULUCF Component of the JRC EDGAR Emission Database. The methodology implements the IPCC Tier 1 approach, using default IPCC parameters with EO-derived information to monitor land use and deforestation, and
630 official harvest statistics to represent losses from forest management. We proposed corrections to the standard Tier 1 approach to better account for forest dynamics, regional peculiarities and data limitations, while maintaining a globally coherent focus. At global scale, results for Forest Living Biomass show overall good agreement with data reported by countries under international conventions and agreements, in particularly for Annex I countries where differences can often be explained by local assumptions. Given the generally high-quality data from Annex I countries, this agreement confirms our methodology.
635 However, EDGAR-LULUCF data show a declining global forest sink but NGHGI report stable net removals. Our analysis highlights that NGHGI in Non-Annex I countries are largely decoupled from official harvest statistics. These different trends are especially evident in Africa, where various studies consistently indicate increasing forest harvest levels, aligned with growing population and wood demand.

The disagreement between NGHGI and harvest data highlighted by our results requires further investigation: although
640 increasing atmospheric CO₂ can enhance net primary production and therefore removals over time, maintaining a stable net forest carbon sink with increasing harvest would require substantial increases in total removals and therefore in forest areas and stocks. However, FAO reports a net decrease in global forest area over recent decades (FAO, 2020). Comparison with other global datasets shows that while GFW presents similar trends to EDGAR-LULUCF, following harvest increases, GCB, like NGHGI, does not. While NGHGI remains essentially stable, GCB shows an increasing sink trend over the last two decades.
645 These discrepancies likely reflect differences in methods and underlying assumptions and need further analysis.

Results for deforestation emissions show that the new EO-derived "Global Maps of Forest Cover Changes and their Drivers" dataset employed by EDGAR-LULUCF allows for a continuous forest monitoring also in areas which at the moment provide very irregular data in the official reporting. Deforestation emissions over 2001-2021 are dominated by Non-Annex I countries. EDGAR generally reports higher interannual variability and slightly higher emissions than NGHGI. Together with NGHGI
650 and GCB, EDGAR indicates a statistically significant declining trend in global deforestation emissions while capturing short-term spikes, underscoring the value of harmonized EO-based methods for detecting real-world deforestation dynamics. In contrast, GFW shows an increasing long-term trend, likely linked to known algorithm and data changes in the underlying tree-cover loss product that introduce artificial time series breaks.



Like similar modelling approaches, our IPCC-based Tier 1 approach has limitations compared to more complex modelling, or
655 advanced country level assessments. Some of these limitations might be tackled with relatively simple methodological
improvements, like those that we presented in this paper. Other limitations refer to the data, and the further improvement in
data availability opens opportunities for enhancements.

An important constraint is that we use constant factors over the entire time series, thus not capturing forest dynamics or CO₂
fertilization effects. Further improvements could allow parameters to vary, describing the effects of increased CO₂
660 concentrations. Additionally, default IPCC parameters provided for large regions often have substantial associated
uncertainties. Using parameters from other sources (e.g., the IPCC Emission Factor Database) with more detailed
regionalization could move toward a Tier 2 approach and potentially decrease uncertainty. Improved land use data (e.g., more
complete mapping of permanent crops) and better ancillary data (e.g., for forest age, for identifying plantations) may also
become available in the future, improving overall quality. Uncertainties in official harvest statistics are also problematic. Here
665 too, improvements are possible, such as exploring alternative data sources for harvest estimates, including EO approaches
(e.g., Ceccherini et al. 2020).

Overall, the results we obtained both in Forest Land and in Deforestation demonstrate that the EDGAR-LULUCF dataset can
serve as a transparent, IPCC-consistent global benchmark to reveal inconsistencies in national reporting and fill critical
information gaps where national inventory data are incomplete. Similarly, the ability to capture deforestation variability
670 provides a useful tool for identifying priority areas and revealing potential limitations in current reporting systems. This is
particularly valuable as the Enhanced Transparency Framework requires all countries to report biennially, with data quality
varying significantly. By combining EO-based land use monitoring with improved IPCC Tier 1 methodology, the EDGAR-
LULUCF dataset provides an independent reference for evaluating and in some cases complementing national GHG reporting.
As satellite data continue to improve and methodological refinements are integrated, this dataset supports transparent and
675 accurate global forest carbon accounting.

The EDGAR LULUCF Dataset is a valuable addition to the EDGAR Dataset, allowing its use in a wider range of assessments.

Author contributions

SR contributed to develop the methodology, implemented it, processed the data, analysed the results and wrote most of the
680 manuscript. CB, FA, and RC produced the "JRC Global Maps of Forest Cover Changes and their Drivers". JM contributed in
the selection of the parameters. JM, MC, and GG provided help, contributions and review during the implementation. SF, GG,
and SR worked on the conceptualization and development of the methodology. FNT provided advice and review. GC
contributed to coding and algorithm development. GJ-M and GG supervised and coordinated the whole work.



Competing interests

685 A declaration of all potential conflicts of interest is required by Copernicus Publications as this is an integral aspect of a transparent record of scientific work. Please see our [competing interests policy](#).

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