Revised and updated geospatial monitoring of twenty-first century forest carbon fluxes

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Short Summary

Updated global maps of greenhouse gas emissions and sequestration by forests from 2001 onwards using satellite-derived data show that forests are strong net carbon sinks, capturing about as much CO_2 each year on average as the United States emitted~~s~~ from fossil fuels in 2019. After reclassifying fluxes to countries' reporting categories for national greenhouse gas inventories, we found that roughly two-thirds of the ~~total~~ net CO_2 flux from forests is anthropogenic and one-third is non-anthropogenic.

Abstract

~~Forests are a key component of climate change mitigation strategies because they both emit and remove atmospheric carbon dioxide.~~ Earth observation data are increasingly used to estimate the magnitude and geographic distribution of greenhouse gas (GHG) fluxes and reduce overall uncertainty in the global carbon budget, including for forests. Here we report on a revised and updated geospatial, Earth observation-based ~~forest carbon flux~~ modelling framework that maps GHG emissions ~~(Gibbs et al. 2024a)~~, carbon removals ~~(Gibbs et al. 2024b)~~, and the net balance between them ~~(Gibbs et al. 2024a, Gibbs et al. 2024b, Gibbs et al. 2024c, respectively)~~ globally for forests from 2001 ~~onwards~~ to 2023 at roughly 30-meter resolution ~~(Harris et al. 2021~~, hereafter referred to as the Global Forest Watch (GFW) model (see Data and Code Availability section). ~~Beyond updating the model to include the most recent yearsthrough 2023, r~~Revisions address some of the original model's limitations, improve model inputs, and refine the uncertainty analysis. We found that between 2001 and 2023, global forest ecosystems were, on average, a net ~~carbon~~ sink of -5.5 ± 8.1 (one standard deviation) gigatonnes CO_2 equivalent yr^{-1} (Gt CO_2e yr^{-1}), which reflects the balance of 9.0 ± 2.7 Gt CO_2e yr^{-1} of GHG emissions and -14.5 ± 7.7 Gt CO_2 yr^{-1} of ~~carbon~~ removals, with an additional -0.20 Gt CO_2e yr^{-1} transferred into harvested wood products. Uncertainty in gross removals was greatly reduced compared to the original model due to refinement of temperate secondary forest carbon removal factor uncertainties. After reallocating GFW's gross CO_2 fluxes ~~estimates~~ into anthropogenic fluxes from forest land and deforestation categories to increase the conceptual similarity with national greenhouse gas inventories (NGHGIs), we estimated a global net anthropogenic forest sink of -3.6~~5~~ Gt CO_2~~e~~ yr^{-1}, ~~including~~excluding harvested wood products, ~~and consider~~with the remaining net CO_2 flux of -2.2 Gt CO_2~~e~~ yr^{-1} reported by the GFW model as non-anthropogenic. Although the magnitude of GFW's translated estimates align relatively well with aggregated NGHGIs, their temporal trends differ. Translating Earth-observation-based flux estimates into the same reporting framework as countries use for NGHGIs ~~can~~ helps build ~~consensus~~confidence ~~and build confidence on~~around land use carbon fluxes and support independent evaluation of progress towards Paris Agreement goals.

1 Introduction

Land is ~~among~~ the most uncertain component~~s~~ of the global carbon cycle (Friedlingstein et al. 2023). The highly dynamic and bi-directional nature of ~~forest~~ terrestrial carbon fluxes, both spatially and temporally, as well as the contributions of anthropogenic and non-anthropogenic processes, pos~~caus~~e unique challenges for monitoring fluxes. Top-down atmospheric observations, e.g. from sensors such as NASA's Orbiting Carbon Observatory, are not precise enough to attribute fluxes to specific drivers, and the current suite of bottom-up approaches for estimating global terrestrial carbon fluxes (Friedlingstein et al. 2023) is based on models that are not fully consistent with each other (i.e., bookkeeping models and dynamic global vegetation models (DGVMs) to estimate anthropogenic and natural fluxes, respectively) (Dorgeist et al. 2024, Walker et al. 2024). An additional complication is that these models separate anthropogenic and natural fluxes from land differently from how national greenhouse gas inventories (NGHGIs) do, which are used within climate policy treaties ~~and~~ to drive national climate actions (IPCC 2024). This makes it difficult for models to provide estimates directly relevant to climate policy frameworks and national climate action. Top-down atmospheric approaches do not make this separation, while global estimates of anthropogenic land use fluxes from bookkeeping models (Friedlingstein et al. 2023) are 6.7 Gt CO_2 yr^{-1} higher than aggregate NGHGIs (Grassi et al. 2023). This gap is due primarily to definitional and conceptual differences around what is classified as anthropogenic vs. natural fluxes from forests (Grassi et al. 2018), with recent studies focusing on reconciling these differences (e.g., Schwingshackl et al. 2022, Grassi et al. 2023). Thus, despite improved data acquisition and advances in modelling capabilities, large uncertainty and variation in estimates of land emissions and sinks remain. Moreover, the spatial distribution of forest emissions and, even more so, forest carbon removals are not well understood, impeding the ability of a range of actors, such as governments, companies, and civil society, to monitor the effectiveness of land-based climate mitigation actions that reduce emissions from forest loss and maintain or increase forest carbon sinks.

To address some of these limitations, Global Forest Watch (GFW) introduced an Earth observation-based framework and model for estimating forest carbon fluxes globally (Harris et al. 2021) that aligns with calls for geospatial monitoring of forest carbon fluxes (EC 2018; Nyawira et al. 2024; Ochiai et al. 2023; Turubanova et al. 2023). It was designed to fill a gap among existing forest carbon monitoring approaches by combining global forest change maps, benchmark carbon density maps, and other Earth observation data based on the ~~IPCC~~ Intergovernmental Panel on Climate Change (IPCC) Guidelines for National Greenhouse Gas Inventories (IPCC 2006, IPCC 2019) that countries use to estimate emissions and removals for their NGHGIs. Within the scope of the Agriculture, Forestry, and Other Land Uses (AFOLU) sector, only GHG fluxes from forest-related land uses and land-use changes (forest remaining forest, non-forest converted to forest, forest converted to non-forest) were included. The framework was designed around the UNFCCC guiding principles for NGHGI preparation: transparency, accuracy, completeness, comparability and consistency. All GFW carbon flux model inputs and outputs and code are publicly available (see Data and Code Availability section).

Recognizing that both Earth observation and ground data increase and improve through time, we designed GFW's flux monitoring framework and the model implementing it with the flexibility to accommodate updates to existing components and add new components. Here we document updates to the model, report ~~the~~ results from the current version, present a revised uncertainty analysis, and - following the recommendations of a recent IPCC expert meeting on reconciling land use emissions (IPCC 2024) - introduce a new translation ~~-~~of GFW model of CO_2 emissions and removals into NGHGI reporting categories of deforestation and forest land that provides an Earth observation perspective on forest fluxes conceptually similar to what countries are expected to report under IPCC guidelines.

2 Methods

Harris et al. 2021 includes a detailed explanation of the GFW forest flux monitoring framework, but some key elements are described here. The framework encompasses gross CO_2 emissions from loss of carbon in aboveground and belowground biomass pools, dead wood, litter, and soil organic carbon in mineral soils due to stand-replacing disturbances, carbon loss from drainage of organic soils, and methane (CH_4) and nitrous oxide (N_2O) emissions from forest fires and drainage of organic soils. Carbon removals include sequestration into aboveground and belowground forest biomass. All model inputs are resampled to the spatial resolution of a Landsat pixel (0.00025x0.00025°, roughly 30x30 m at the equator), and outputs are generated at the same resolution. The model uses Landsat resolution because it is the highest resolution for which the global forest change maps and an aboveground biomass map for the year 2000 are publicly available. Higher~~-~~-resolution maps of forest change and biomass exist but are not publicly available, are available only for ~~more~~ recent years, and/or include only certain ~~geographic~~ regions (e.g., Vancutsem et al. 2019, Yang and Zeng 2023).

The IPCC GHG inventory guidelines, the methodological basis of GFW's forest carbon flux monitoring framework, lay out two methods by which terrestrial carbon stock changes associated with land use, land-use change, and forestry (LULUCF, part of the broader AFOLU sector) can be calculated: gain-loss and stock-difference (IPCC 2006). Methods can be applied according to different Tiers (from 1 to 3) with increasing complexity and presumed accuracy. In the gain-loss method~~, at a high level~~, carbon emissions and removals are calculated separately by multiplying activity data such as forest area lost, gained, or maintained (ha) by emission or removal factors (t C ha^{-1}); the net carbon stock change, or flux, is the difference between gross emissions and gross removals. In the stock-difference method, carbon stocks are measured during repeated inventories and the difference between remeasurements is the estimate of net carbon stock change, or flux. GFW's framework employs the gain-loss approach, in which the activity data and other contextual information are estimated using global, Earth observation-based maps trained on local ground plot data and/or airborne and spaceborne lidar observations.

GFW's gain-loss modeling approach is initialized in the year 2000 with global maps of carbon densities in five forest ecosystem carbon pools (Fig. 1). The model ~~is~~ runs for all pixels with canopy density >1% in 2000 (Hansen et al. 2023) but ~~our~~ default outputs define forests as:~~We define forest as follows:~~ 1) >30% canopy cover in 2000 (Hansen et al. 2013) or subsequent tree cover gain (Potapov et al. 2022), 2) non-zero aboveground biomass in 2000 (Harris et al. 2021), 3) mangroves in 2000 (Giri et al. 2011), and 4) exclusion of oil palm plantations in 2000 (see Table 2). We use this definition of forests because a canopy density of >30% is a common threshold ~~used~~in for national definitions of forests (Harris et al. 2018) and because some of the input removal factors are applicable specifically to denser forest. All outputs and results use canopy density >30%, unless otherwise specified. However, because the model ~~is~~ runs without any a priori canopy density threshold and the forest definition is applied after the fact, ~~results~~fluxes can be ~~generated~~estimated ~~users can obtain results~~ for ~~a~~ lower canopy density thresholds ~~applied~~. ~~Within the resulting forest mask~~Within pixels with canopy cover in 2000, gross removals are mapped based on locations of forest extent and regrowth, while gross emissions are subsequently mapped based on locations of stand-replacing forest disturbances~~, while gross removals are mapped based on locations of forest extent and regrowth~~. In this system of tracking the forest/non-forest status of individual pixels over time, the model adheres to IPCC Approach 3 for land representation (IPCC 2019).

For activity data, rather than combining and reconciling national or regional geospatial forest monitoring data in the limited places where it exists continuously since 2000, we deliberately use global, independent (non-governmental) data sources to maintain global consistency and comparability within the framework, recognizing that global data are generally not the most locally accurate or relevant data, but remain useful for large-scale analyses and potentially for verification purposes of other approaches. To identify forest loss, the GFW model uses the Global Forest Change (GFC) data of Hansen et al. 2013, updated annually. Because of the framework's use of GFC, emissions are limited to those from stand-replacing disturbances or other disturbances severe enough to be detected by GFC. Tree cover gain (Potapov et al. 2022) is gross gain and is assigned to the period 2000-2020, not ~~assigned~~ to a specific year. In the model, forest pixels can have loss only (assigned to a specific year), neither loss nor gain (i.e., no change), or both loss and gain (~~although~~ in which the ~~sequence~~ order is unknown). Non-forest pixels can have either tree cover gain or no gain; in the latter case they are outside the framework as they are non-forest remaining non-forest.

Emission and removal factors likewise use spatially explicit data as much as possible to capture spatial variation in forest properties and dynamics and move beyond ecozone-level representation of forests. GFW model emission and removal factors are generally independent of national data sources, with the exception of some removal factors in temperate forests, which are derived directly from the Forest Inventory and Analysis (FIA) database maintained by the USDA Forest Service (see Harris et al. 2021 and Glen et al. 2024 for details). The model uses a combination of IPCC default (Tier 1) and localized (Tier 2) emission/removal factors, with the goal of using more Tier 2 factors over time, just as countries are encouraged to do in their NGHGIs. (Note that some Tier 1 removal factors come from national forest inventories, particularly USFS FIA data (IPCC 2019).) For example, removal factors in primary forests use IPCC defaults (IPCC 2019, Tier 1), while ~~pre-disturbance~~initial (year 2000) aboveground biomass carbon densities use a global benchmark map of woody biomass developed from field data and remote sensing (Harris et al. 2021, Tier 2). Removal factors are applied in a hierarchy from six sources: 1) mangrove-specific rates (IPCC 2014a), 2) Europe-specific rates by forest type (combination of Table 4.11 of the updated IPCC Guidelines, FAO Planted Forest Assessment and factors published in national forest inventories), 3) planted tree rates from the Spatial Database of Planted Trees (SDPT) Version 2.0 (Richter et al. 2024), 4) US-specific rates by region, forest type and age class derived from the FIA database (Glen et al. 2024), 5) young secondary forest rates (Cook-Patton et al. 2020), and) IPCC default rates for all other areas (e.g., primary forest, older secondary forest in the tropics and in temperate forests outside Europe and the US) (IPCC 2019). The framework supports the addition of other geospatial removal factors as they become available. Gross removals are added to pre-disturbance biomass until the year of loss to determine the biomass in the year of loss. Emission factors are estimated using a map of tree cover loss drivers (Curtis et al. 2018) and burned area (Tyukavina et al. 2022); the combination of these determine the extent to which carbon pools (including soil organic carbon in mineral soils) are emitted by forest disturbance. Emission factors are estimated using “committed” emissions (Hansis et al. 2015) or instantaneous oxidation (IPCC 2019), whereby carbon loss from all relevant pools is assumed to occur in the year of disturbance rather than modeling delayed carbon fluxes through time.

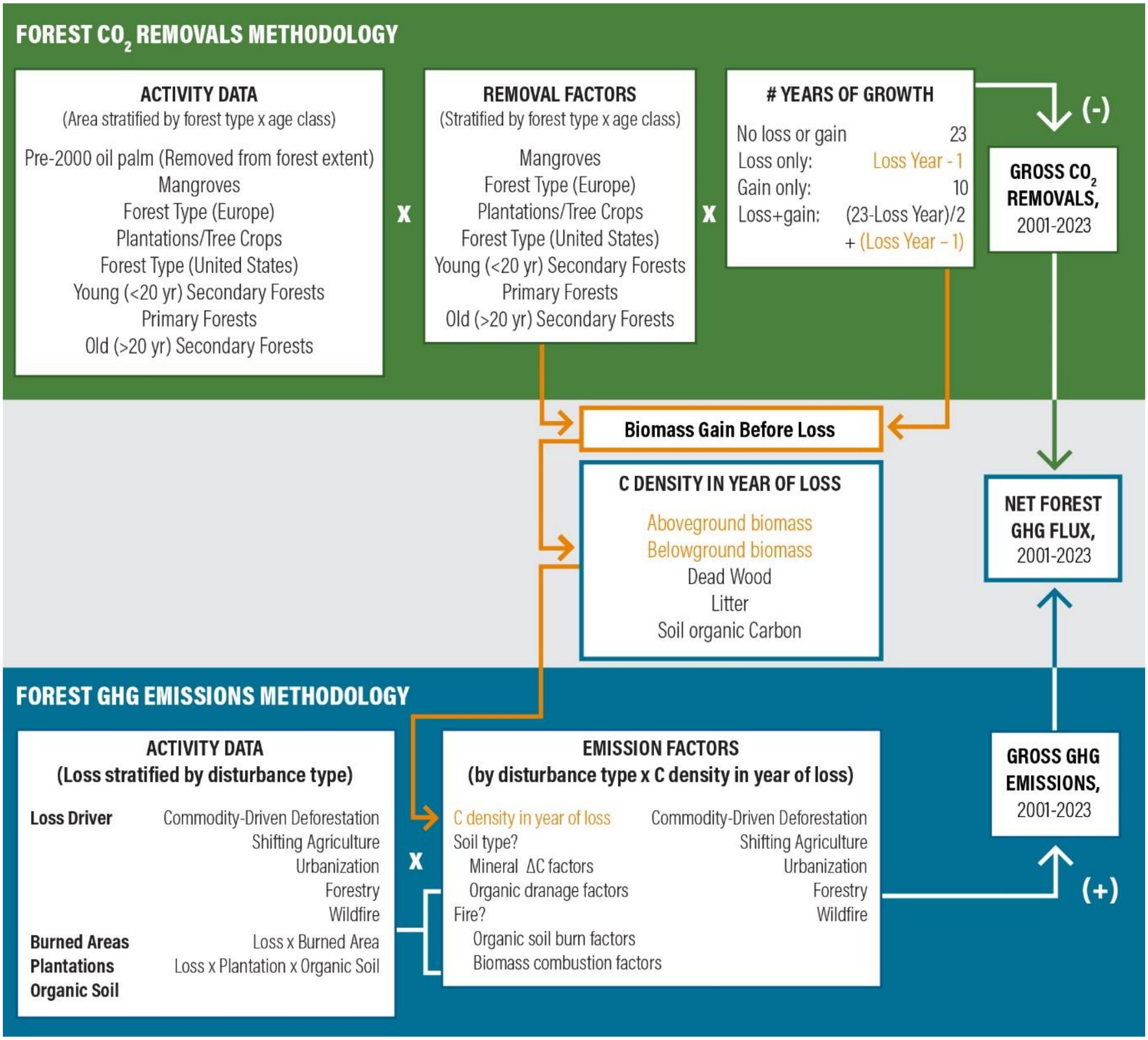


Figure 1. Updated conceptual framework for modeling forest-related GHG fluxes. The model estimates gross forest-related emissions and removals as the product of activity data and emission/removal factors for each ~30-m pixel. The net forest GHG flux is the sum of gross emissions (+) and removals (-). Text and arrows in orange are portions of the removals methodology that are passed into the emissions methodology.

2.1 Changes to GFW model input data

Since the original release of GFW's carbon model framework in 2021, which estimated forest carbon flux results through 2019, we have made several changes to the model inputs because new data were published or existing data were improved (Table 1). These changes keep the model aligned with ~~the latest~~recent advances in global Earth observation data and address some limitations in the original version but do not change the underlying conceptual framework. The updated geospatial inputs are shown in the context of all inputs in Table 2. We summarize changes to the input data with respect to extension of the model from 2019 to 2023 (Sect. 2.1.1), changes to activity data (Sect. 2.1.2), and changes to emission and removal factors (Sect. 2.1.3).

Table 1. Changes to GFW model inputs since the original version (Harris et al. 2021).

Framework component (article section)	Original version	Current version	Affects emissions	Affects removals
Temporal coverage of tree cover loss (2.1.1)	Tree cover loss through 2019 (Hansen et al. 2013, updated annually on GFW)	Tree cover loss through 2023 (Hansen et al. 2013, updated annually on GFW)	Yes	Yes
Temporal coverage of drivers of tree cover loss (2.1.1)	Dominant driver of tree cover loss through 2015 (Curtis et al. 2018)	Dominant driver of tree cover loss through 2023 (Curtis et al. 2018, updated annually on GFW)	Yes	No
Temporal coverage of burned area (2.1.1)	Burned area through 2019	Burned area through 2023	Yes	No
Transfers to harvested wood products (country-level only) (2.1.1)	Transfers to HWP through 2015 (FAOSTAT 2021)	Transfers to HWP through 2021 (FAOSTAT 2024)	No	Yes
Temporal coverage of tree cover gain (2.1.2)	2000–2012 (Hansen et al. 2013)	2000–2020 (Potapov et al. 2022)	Yes	Yes
Burned area extent (2.1.2)	MODIS burned area (Giglio et al. 2018, updated annually)	Tree cover loss from fires (Tyukavina et al. 2022, updated annually)	Yes	No
Organic soils extent (2.1.2)	• Indonesia and Malaysia (Miettinen et al. 2016) • Below 40° N (Gumbricht et al. 2017) • Above 40° N (Hengl et al. 2017)	• Indonesia and Malaysia (Miettinen et al. 2016) • Central Africa (Crezee et al. 2022) • Lowland Amazonian Peru (Hastie et al. 2022) • Below 40° N (Gumbricht et al. 2017) • Above 40° N (Xu et al. 2018)	Yes	No
Planted tree extent (2.1.2)	Spatial Database of Planted Trees v1.0 (Harris et al. 2019)	Spatial Database of Planted Trees v2.0 (Richter et al. 2024)	Yes	Yes
Belowground biomass (R:S ratio) (2.1.3)	Global ratio of 0.26 for belowground carbon to aboveground carbon for non-mangrove forests (Mokany et al. 2006)	Map of ratio of belowground carbon to aboveground carbon for non-mangrove forests (Huang et al. 2021)[1]	Yes	Yes
Planted tree removal factors and their uncertainties (2.1.3)	Spatial Database of Planted Trees v1.0 (Harris et al. 2019)	Spatial Database of Planted Trees v2.0 (Richter et al. 2024)	Yes	Yes

Older secondary (>20 year) temperate forest removal factors and their uncertainties (2.1.3)	2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories, Volume 4, Chapter 4, pages 4.34–4.38 Table 4.9 (IPCC 2019)	4th Corrigenda to the 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories, Volume 4, Chapter 4, pages 4.18–21, Table 4.9 (IPCC 2023)[2]	Yes	Yes
Global Warming Potential (GWP) values (2.1.3)	IPCC Fifth Assessment Report, Table 8.7 (100-year, no climate-carbon feedback) (IPCC 2014b)	IPCC Sixth Assessment Report, Table 7.15 (100-year, no climate-carbon feedback) (IPCC 2022)	Yes	No

[1] The R:S map was extended outwards to fill gaps in the original map.
[2] Removal factors for other climate domains and ages were not updated.

Table 2. Geospatial data components and sources currently used in the GFW model. Updated components and sources are denoted with an * and *italics*. This updates Table S3 in Harris et al. 2021.

Model component	Source
Forest extent 2000	
Tree cover extent	Hansen et al. 2013
Mangrove forest extent	Giri et al. 2018
Tropical humid primary forest extent	Turubanova et al. 2018
Intact forest landscapes (boreal/temperate)	Potapov et al. 2017
Planted tree extent (plantations and tree crops)	**Richter et al. 2024 (Spatial Database of Planted Trees v2.0)*
**Peatland extent*	Miettinen et al. 2016 (Indonesia and Malaysia) **Crezee et al. 2022 (Congo Basin)* **Hastie et al. 2022 (Amazonian Peru)*
	Gumbricht et al. 2017 (<40° N)
	**Xu et al. 2018 (≥40° N)*
Oil palm extent 2000 (areas excluded from model)	Austin et al. 2017 (Indonesia)
	Gaveau et al. 2014 (Borneo)
	Miettinen et al. 2016 (Sumatra, Borneo)
	Gunarso et al. 2013 (peninsular Malaysia)
Carbon density 2000	
Aboveground live woody biomass density	Updated from Zarin et al. 2016 (non-mangrove)
	Simard et al. 2019 (mangrove)
**Belowground biomass density ratio*	**Huang et al. 2021 (root:shoot ratio for non-mangrove forests), with Mokany et al. 2006 filling in gaps*
Soil organic carbon density	Hengl et al. 2017 (non-mangrove)
	Sanderman et al. 2018 (mangrove)
Ecological zone (for deadwood and litter)	FAO 2012
Elevation (for deadwood and litter)	Farr et al. 2007
Mean annual precipitation (for deadwood and litter)	Fick and Hijmans 2017
Activity data	
**Tree cover loss*	**Hansen et al. 2013 (2001–2023)*
**Tree cover gain*	**Potapov et al. 2022 (2000–2020)*

**Burned areas*	**Tyukavina et al. 2022 (tree cover loss from fires, updated through the year 2023)*
Emission factors	
**Drivers of forest loss*	**Curtis et al. 2018 (updated through year 2023)*
Climate zone	FAO 2012
Fire combustion and emission factors	IPCC 2019 (Tables 2.5 and 2.6)
Removal Factors	
Ecological zone	FAO 2012
Mangrove removal factors	IPCC 2014a (Wetlands Supplement, Tables 4.4 and 4.5)
US forest type	Ruefenacht et al. 2008
US stand age	Pan et al. 2011
US removal factors (by region x type x age class)	Forest Inventory and Analysis Program
Europe forest type	Brus et al. 2011
Europe removal factors (by forest type)	IPCC 2019 (Table 4.11)
	FAO Planted Forest Thematic Study
	Portugal's National GHG inventory
**Planted tree removal factors*	**Richter et al. 2024 (Spatial Database of Planted Trees v2.0) (including uncertainties)*
Agroforestry removal factors	IPCC 2019 (Tables 5.1 and 5.3)
Natural regrowth removal factors (<20 yrs)	Cook-Patton et al. 2020
Primary forest removal factors	IPCC 2019 (Table 4.9)
**Old secondary forest removal factors (>20 yrs)*	**IPCC 2019 (Table 4.9 for non-temperate forests only)*
	**IPCC 2019/IPCC 2023 (Table 4.9 Corrigenda 4 for temperate forests (including uncertainties))*
Harvested wood products (country only)	
**Production, import and export statistics of sawnwood, wood-based panels and paper & paperboard*	**FAOSTAT (2001–2021)*

2.1.1 Annually updated data

We have updated four inputs to the framework annually since the original GFW model was published: tree cover loss, dominant driver of tree cover loss, burned area, and country-level transfers to harvested wood products (HWP). In the original version, they extended to 2019, 2015, 2019, and 2015, respectively. The first three inputs now extend through 2023 and we plan to continue to update them annually, lagging one year behind the calendar year. Country-level HWP transfers now extend through year 2021 based on data from FAOSTAT that currently extend through year 2022 (Access date: 5 May 2024). These constitute the core updates to the model each year.

2.1.2 Updated activity data

Beyond the annual updates described above, we ~~have~~ made four additional updates to the model's activity data:

1. Temporal coverage of tree cover gain: Tree cover gain originally covered 2000–2012 but now covers 2000–2020. In the original version, tree cover gain covered seven fewer years than tree cover loss did (12 years of tree cover gain vs. 19 years of tree cover loss); currently, tree cover gain covers three fewer years than tree cover loss (20 years vs. 23 years). Tree cover gain is still reported in one interval, so the framework does not assign gain to a specific year within 2000–2020. The shorter duration of tree cover gain and its lack of information on timing is an ongoing limitation of the inputs to the framework (see Sects. 4.3 and 4.4).
2. Burned area extent: The original version of the GFW model used MODIS burned area (500-m resolution) (Giglio et al. 2018), but now it uses Global Land Analysis & Discovery Lab tree cover loss due to fires (TCLF) (30-m resolution) (Tyukavina et al. 2022). This burned area product is designed to be used with GFC. As in the original version of the model, emissions from fires are included only where stand-replacing disturbances are detected by GFC, meaning that emissions from relatively low severity forest fires remain unquantified in the model.
3. Organic soils extent: We added two new regional tropical peatland maps (Peru and Congo basin, Hastie et al. 2022 and Crezee et al. 2022) and replaced the peat map above 40° N (Xu et al. 2018). These maps reflect a more recent understanding of the extent of organic soils in those regions. This is one of the few inputs to the model that composites regional maps with pan-tropical and global maps.
4. Planted tree extent: Planted trees are part of managed ecosystems, and using distinct removal factors for planted trees instead of removal factors for natural forests better represents the associated carbon sequestration of these managed landscapes. The original version of the GFW model used SDPT v1.0 (Harris et al. 2019) but now it uses SDPT v2.0 (Richter et al. 2024), which includes planted tree extent in 45 additional countries. Richter et al. defines planted trees as plantation forests and tree crops. This dataset aggregates maps of tree crops and planted forests globally in a bottom-up approach that captures roughly 90% of planted tree area globally circa 2020. Each polygon in the database has the most taxonomically resolved information available, from broad type of production (e.g. orchard) to species.

2.1.3 Updated emission and removal factors

We ~~have~~ made four updates to emission and removal factors:

1. Belowground biomass (R:S ratio): The original version of the GFW model used a single R:S ratio of 0.26 to estimate belowground biomass applied globally to non-mangrove forests (Mokany et al. 2006). (~~m~~Mangroves had separate ratios from IPCC 2014a.)~~.~~ The updated model uses a global R:S map from Huang et al. 2021 to incorporate spatial variability in R:S, ranging from less than 0.15 to greater than 0.5. Because the R:S map does not cover all land where forest is present in our framework (e.g., some near-shore islands), we interpolated missing R:S pixels from nearby ones; where interpolation was not possible (e.g., remote Pacific islands), we retained the original default ratio of 0.26. We applied this ratio map to aboveground biomass in the year of tree cover loss to calculate carbon emissions from loss of belowground biomass. We also used the R:S map to calculate carbon removals by belowground biomass based

on carbon removals by aboveground biomass. Including this input makes the belowground carbon stocks and removal factors reflect local forest types better than using a single, global ratio.

2. Planted tree removal factors and their uncertainties: SDPT v2.0 (Richter et al. 2024) has a removal factor and uncertainty associated with every planted tree (planted forest and tree crop) polygon included in the database. The removal factors of polygons that were in SDPT v1.0 are largely unchanged in SDPT v2.0, but polygons newly included in SDPT v2.0 have been assigned removal factors based on information about what kind of planted tree is present using the most taxonomically resolved information available.
3. Older secondary (>20 year) temperate forest removal factors and their uncertainties: The original version of the framework applied Tier 1 removal factors published in Table 4.9 of IPCC 2019 for primary and some secondary (>20 years) temperate forests. In 2023, IPCC released corrected default removal factors and their uncertainties for temperate secondary forests in North and South America, which are also applied in the GFW model to >20 year old forests in temperate ecozones outside of the United States and Europe where no better sources of data are currently available. In the model update, we replaced the original IPCC defaults with the corrected ones.
4. Global Warming Potential (GWP) values: The original version of the framework converted non-CO_2 emissions from CH_4 and N_2O into equivalent units of CO_2 using GWP values published in IPCC's Fifth Assessment Report. The framework now uses GWP values for CH_4 and N_2O from IPCC's Sixth Assessment Report. This affects gross emissions and net flux outputs only where non-CO_2 emissions are estimated (organic soil drainage, fires in organic soils, or biomass burning).

2.2 Updated uncertainty analysis

With the original version of the framework, we presented an uncertainty analysis that used an error propagation approach for inputs for which uncertainties (variances) were available and potentially substantial. This approach underlies Approach 1 (simple error propagation) outlined in the IPCC Guidelines and produces similar results but reflects exact calculations of variances and standard deviations, whereas IPCC Approach 1 to uncertainty analysis is an approximated approach that yields 95% confidence intervals (IPCC 2019). For the model update, we repeated this uncertainty analysis with all the changes and updates to the framework described in Sect. 2.1, using the same error propagation approach and the same components as used in the original analysis.

2.3 Anthropogenic fluxes from "managed" forests

GFW's Earth observation-based modelling framework does not (and cannot) differentiate anthropogenic and non-anthropogenic fluxes from forests. Rather, it includes fluxes from all forest land and therefore the combination of direct anthropogenic, indirect anthropogenic, and natural fluxes. Thus, results from our model are not directly comparable with those from NGHGIs or bookkeeping models, each of which define anthropogenic fluxes with different system boundaries for their specific purposes (Grassi et al. 2022, Grassi et al. 2023). Under UNFCCC decisions and IPCC methodological guidance, countries report only anthropogenic fluxes in their NGHGIs, approximated by "managed land" (IPCC 2006, Ogle et al. 2018). Therefore, if GFW's forest carbon flux monitoring framework is to serve as an independent, Earth observation-based point of reference for NGHGIs, its results must be able to be reported in a conceptually similar way covering the same scope. In doing so, we adopted the proposal of Grassi et al. (2023) in adjusting global data to the NGHGI framework for analyses focused on country policy or action. ~~, limiting the scope of our comparison to CO_2 fluxes only.~~ In translating the GFW model's fluxes into the NGHGI reporting framework, we did what IPCC guidelines direct countries to do when compiling and reporting their inventories rather than what countries necessarily do in practice for their inventories. The goal of this translation exercise was not to reproduce as closely as possible how countries prepare their NGHGIs ~~as closely as possible~~ using the GFW model, to achieve maximum quantitative similarity to NGHGIs, or to reconcile the GFW flux model with NGHGIs but rather to present ~~GHG~~CO_2 fluxes from a globally consistent, geospatial approach in the same conceptual terms that national policymakers use.

We developed a three-step process to translate the GFW model's gross CO_2 emissions and removals into three IPCC reporting categories: anthropogenic flux from managed forest land, emissions from deforestation (anthropogenic), and non-anthropogenic flux from unmanaged forest (Table 3). It builds upon the simpler comparison between the GFW model and NGHGIs conducted in the IPCC Sixth Assessment Report (Nabuurs et al. 2022), in which anthropogenic flux~~es~~ from the ~~former~~ GFW model were those outside primary forests in the tropics and intact forest landscapes in the non-tropics. This translation process does not change the GFW model's bottom-line net flux estimates; rather, it reclassifies the gross CO_2 fluxes by intersecting the GFW model fluxes with other contextual geospatial data to provide fluxes more conceptually aligned with those of NGHGIs. The first step (Sect. 2.3.1) assigned each country to one of three cases based on how their NGHGI applies the managed land proxy (Fig. 2). The second and third steps reclassified the GFW model's emissions (Sect. 2.3.2) and removals (Sect. 2.3.3), respectively, into three IPCC reporting categories according to the three cases assigned in step 1 (Fig. 2). Emissions and removals within each IPCC reporting category were then summed to calculate net anthropogenic and non-anthropogenic forest-related CO_2 fluxes for each country. The GFW model calculates annual emissions, corresponding to the year of tree cover loss, but does not calculate annual removals and instead calculates removals as an annualized average over the entire model period. Thus, to generate timeseries from the GFW model using the NGHGI reporting categories, we calculated the average annual removals in each reporting category by dividing gross removals by the number of model years. The resulting time series for each reporting category is therefore the difference between the annual emissions for that year and the average annual removals.

For this analysis, we used data from the GFW model for 2001–2022 to align with the temporal coverage of NGHGIs. We limited our comparison to CO_2 fluxes only (i.e. excluding CH_4 and N_2O emissions from the GFW model) but note that some developing countries report do not separately report CO_2 and non-CO_2 emissions. Because the GFW model cannot currently report emissions from organic soil separately from all other emissions, we combined NGHGIs' deforestation and organic soil emissions (including emissions from forest land, from peat decomposition and peat fires typically associated to deforestation, and from agriculture soils) to achieve the same scope as the model. We excluded transfers into the harvested wood products pool from both data sources in this translation analysis because that is not a core element of our geospatial framework.

Table 3. Translating GFW flux model gross CO_2 emissions and removals to national greenhouse gas inventory (NGHGI) reporting categories. To calculate total net CO_2 flux for IPCC reporting categories, GFW flux model emissions and removals were reclassified according to managed land status (managed vs. unmanaged) and driver of tree cover loss. Following IPCC guidelines, for Case 2 countries we used information about the driver of tree cover loss to reassign initially delineated unmanaged forest to managed forest where direct human activity is observed to result in tree cover loss (i.e. forestry, commodity-driven deforestation (CDD), urbanization, and shifting agriculture). Thus, all associated fluxes from unmanaged forests reassigned to managed forests are reported in the corresponding anthropogenic IPCC reporting category (anthropogenic forest land flux and deforestation).

		Anthropogenic Forest Land Flux *Forest Remaining Forest and Non-Forest Land Converted to Forest*			**Deforestation** *Forest Converted to Non-Forest Land*			**Non-Anthropogenic Forest Land Flux** *Forest Remaining Forest*		
Step 1: Managed land delineation (2.3.1)	Country case	1	2a	2b	1	2a	2b	1	2a	2b
	Managed land proxy	All forests managed	Managed land polygons	Non-intact/ non-primary forests	All forests managed	Managed land polygons	Non-intact/ non-primary forests	All forests managed	Managed land polygons	Non-intact/ non-primary forests
Step 2: Reclassify gross emissions (2.3.2)	Managed land	Forestry ✓* Wildfire ✓ Unknown ✓ Shifting ag +[1] CDD ✗ Urbanization ✗			Forestry ✗ Wildfire ✗ Unknown ✗ Shifting ag +[2] CDD ✓* Urbanization ✓*			*N/A*		
	Unmanaged land	*N/A*			*N/A*			*N/A*	Forestry ✗ Wildfire ✓ Unknown ✓ Shifting ag ✗ CDD ✗ Urbanization ✗	
Step 3: Reclassify gross removals (2.3.3)	Managed land	✓			✗			*N/A*		
	Unmanaged land	*N/A*			*N/A*			*N/A*	✓	

✓ = Included
✗ = Excluded
+ = Included in certain scenario

* Includes emissions from not only the initial delineation of managed forests, but also from tree cover loss in unmanaged forests reassigned to managed forests due to direct human activity.
[1] To calculate the maximum emissions in anthropogenic forest land, we count emissions from shifting agriculture (shifting ag) in secondary forest toward the anthropogenic forest land flux and emissions from shifting agriculture in primary forests toward deforestation.
[2] To calculate the maximum emissions from deforestation, we count all emissions from shifting agriculture in both primary and secondary forest toward deforestation. This also corresponds to a larger sink in anthropogenic forest land.

2.3.1 Managed land delineation

In the first step (top of Table 3), we assigned countries to one of three cases based on careful review of NGHGIs ~~(Melo et al., in preparation)~~ and the availability of in-country information on the distribution of m~~M~~anaged and u~~U~~nmanaged forests. These cases describe which land is considered managed and unmanaged according to information that countries provide in their NGHGIs regarding their use of the managed land proxy (Fig. 2). Case 1 included 46 countries (primarily UNFCCC Annex 1 countries, i.e. advanced economies with annual GHG reporting commitments) that explicitly consider all forest land managed and another three countries (China, India, Indonesia) for which we assumed that all forest land is considered managed, based on the information provided in their NGHGIs. Case 2 included all other countries, which do not consider all forest to be managed and thus consider some forest to be unmanaged. For the three Case 2a countries (Brazil, the United States, and Canada), we used the georeferenced boundaries of managed and unmanaged lands that they use in their NGHGIs. The remaining 143 countries (UNFCCC non-Annex 1 countries, i.e. countries with historically less stringent GHG reporting commitments) either report no information or not enough details regarding the use of the managed land proxy and its extent. For example, Russia's inventory explicitly includes unmanaged land but reports areas by administrative unit rather than spatially, which is not adequate for our analysis. For these Case 2b countries, we approximated managed forest in tropical regions as forests outside humid tropical primary forests from 2001 (Turubanova et al. 2018) and in extratropical regions as forests outside intact forest landscapes from 2000 (Potapov et al. 2017). For Case 2 countries, the initial managed forest delineation was modified in steps 2 and 3 to include unmanaged land reassigned to managed land due to direct anthropogenic activity. We note that while countries' definitions of forest land differ, we instead used a single, global definition of forest as defined in Sect. 2, with a tree cover density >30% (Hansen et al. 2013).

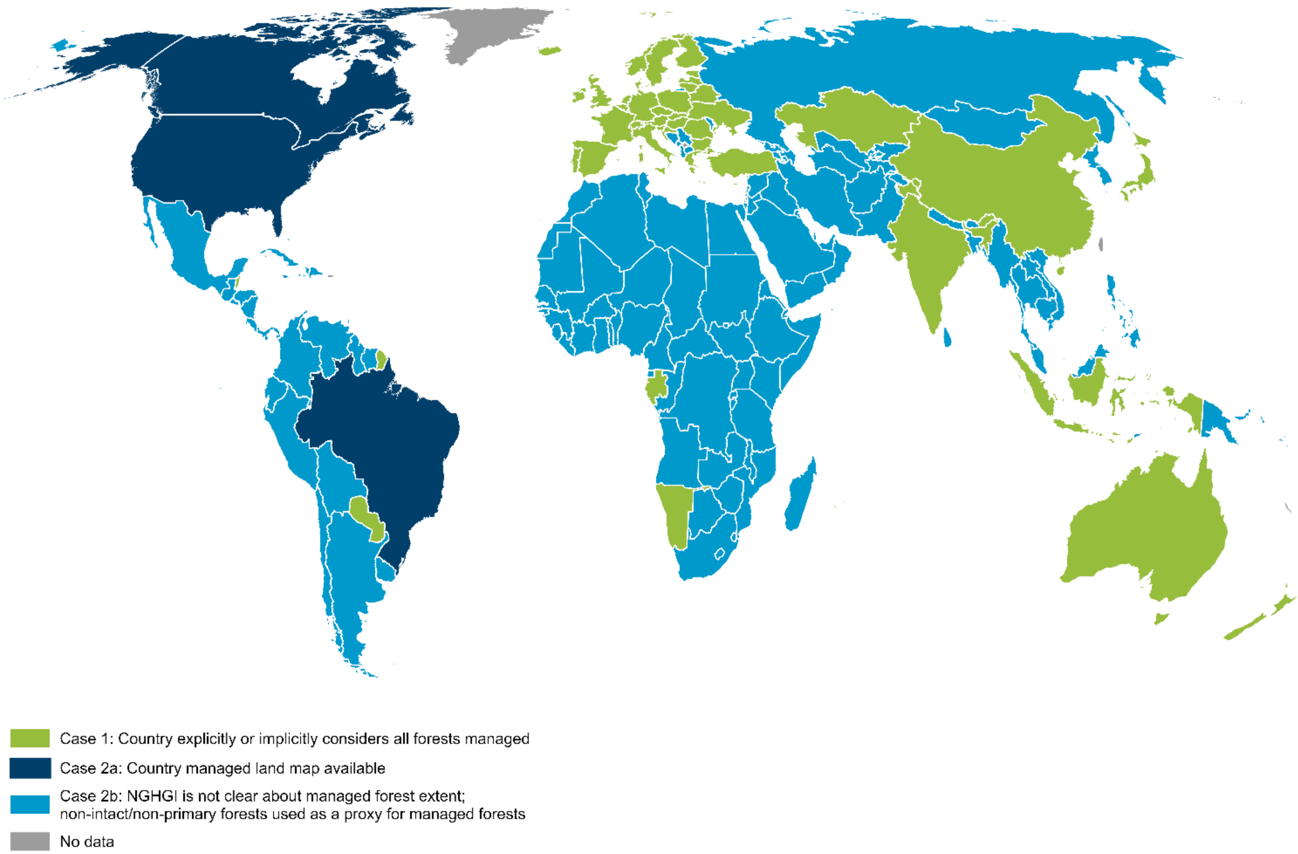


Figure 2. Country representation of managed land in their national greenhouse gas inventories (NGHGIs). Countries consider fluxes by forests in several ways in their national greenhouse gas inventories (Melo et al. in preparation). Some countries explicitly or implicitly consider all forests to be managed and thus include all forest fluxes in their NGHGIs (Case 1). The rest do not consider all forests to be managed. Only a few countries (Case 2a) use maps of managed lands to delineate anthropogenic fluxes from non-anthropogenic fluxes. The rest are not clear in their NGHGIs about the spatial extent to which forests are or are not considered managed and thus which forest fluxes are included in their inventories (Case 2b).

2.3.2 Reclassifying gross carbon dioxide emissions

In the second step (middle of Table 3), we combined the initial delineation of managed forests described in Sect. 2.3.1 with a map of drivers of tree cover loss (Curtis et al. 2018, updated through 2023) to partition the GFW model's gross CO_2 emissions into IPCC reporting categories because not all of the GFW model's gross emissions are from deforestation. For Case 1 countries, which classify all forests as managed, all emissions occurring within country borders were anthropogenic and no emissions were non-anthropogenic. For Case 2 countries, all emissions within managed forest boundaries (defined in Sect. 2.3.1) were anthropogenic and the remaining emissions within initially delineated unmanaged forest boundaries were either anthropogenic or non-anthropogenic depending on the driver of the tree cover loss. We expanded our definition of managed forests to include initial unmanaged forest as defined in Sect. 2.3.1 where there is a direct human activity, such as forest harvest or deforestation (IPCC 2006). Thus, we considered all emissions from direct human activity to be anthropogenic. The remaining emissions—from natural or semi-natural drivers of tree cover loss, such as wildfire, occurring within unmanaged forest boundaries—were the only emissions we considered to be non-anthropogenic.

Using this delineation of anthropogenic vs. non-anthropogenic, we reclassified the GFW model's gross emissions into three categories that are conceptually aligned with IPCC reporting categories (Table. 3): anthropogenic emissions on managed forest land ("forest remaining forest" plus "non-forest land converted to forest"), anthropogenic emissions from deforestation ("forest converted to non-forest land"), and emissions on unmanaged forest land that are non-anthropogenic by definition ("forest remaining forest").

Anthropogenic emissions from managed forest land. For all countries, this category included emissions from wildfire and the ~~small amount of~~negligible emissions not assigned to a driver (Curtis et al. 2018) occurring within managed forest areas. This category also included emissions from forestry regardless of where they occurred (inside or outside initial delineated managed land boundaries as defined in Sect. 2.3.1) because harvest activity is a direct human activity and thus any tree cover loss from forestry activity results in the reclassification of unmanaged forest to managed forest.

Anthropogenic emissions from deforestation. For all countries, this category was the sum of all emissions from tree cover loss due to commodity-driven deforestation and urbanization, regardless of where they occurred, as well as emissions from the loss of intact/primary forests in areas of shifting agriculture because this is considered a permanent change in land use.

Non-anthropogenic emissions from unmanaged forests. For Case 1 countries, we assumed based on their NGHGIs that all forests are considered managed and thus no emissions are considered non-anthropogenic. The two categories above represent all CO_2 emissions from the GFW model for those countries. For Case 2 countries, which have some unmanaged forest (as defined in Sect. 2.3.1), non-anthropogenic emissions were the sum of the remaining emissions outside managed forests: emissions from tree cover loss due to wildfires and the (small) unassigned drivers class (Curtis et al. 2018). Although some fires in unmanaged land can be caused by humans, we classified emissions from them as non-anthropogenic to be consistent with IPCC guidelines; separating emissions from human-caused fires in unmanaged land and reporting them as anthropogenic forest land emissions could be improved in further iterations of this analysis.

It is often not clear to which land use categories emissions from shifting agriculture cycles are allocated in NGHGIs, because this distinction is not required by the IPCC Guidelines (IPCC 2019). Following Curtis et al. (2018), shifting agriculture landscapes are defined as "small- to medium-scale forest and shrubland conversion for agriculture that is later abandoned and followed by subsequent forest regrowth." To highlight the sensitivity of how emissions from shifting agriculture landscapes are estimated, we created two scenarios for our emissions reclassification. In one scenario, we calculated the maximum emissions from deforestation by including all emissions from the loss of both primary and secondary forests within shifting agriculture landscapes and therefore no emissions from shifting agriculture are considered to ~~be~~ occur~~ring~~ in forest remaining forest. In the other scenario, we calculated the maximum emissions from managed forest land by including emissions from the loss of secondary forests in shifting agriculture landscapes in the anthropogenic forest land flux. This transferred a subset of emissions considered to be deforestation under the alternative scenario to forest land. The remaining emissions from loss of intact/primary forests due to shifting agriculture were still considered deforestation emissions, as described above. The two scenarios do not change the total net anthropogenic forest flux (fluxes from forest land plus deforestation) because the same emissions are assigned to either category. In both scenarios, emissions from the loss of intact/primary forests due to shifting agriculture were always classified as deforestation because we considered them to arise from a permanent change from forest to a non-forest land use.

2.3.3 Reclassifying gross removals

In the third step (bottom of Table 3), we partitioned carbon removals occurring on forest land as either anthropogenic or non-anthropogenic. No forest carbon removals were included in deforested land; any removals in pixels with tree cover loss were assigned to either anthropogenic forest land removals or non-anthropogenic forest removals, as described below. Since NGHGIs do not treat removals uniformly, we used the three managed land proxy cases to align GFW flux model removal estimates with how countries report removals in their NGHGIs (Fig. 2).

For Case 1 countries, which explicitly or implicitly consider all forest land to be managed, we classified all removals across the full GFW model extent as anthropogenic forest land. No removals for these countries were considered non-anthropogenic. For Case 2 countries, we separated removals into anthropogenic and non-anthropogenic categories following the same spatial proxy used to delineate managed forests (Sect. 2.3.1). In this approach, we classified all removals in managed forest land as anthropogenic, including unmanaged forest reclassified as managed forest due to tree cover loss from forestry and shifting agriculture. All removals in unmanaged forest land were classified as non-anthropogenic.

3 Results

3.1 Emissions, removals, and net fluxes from GFW's updated flux model

In the updated GFW flux model, average annual global gross emissions from stand-replacing forest disturbances were 9.0 Gt CO_2e yr^{-1} between 2001 and 2023 (with 98% from CO_2 and 2.4% from CH_4 and N_2O), average annual gross removals were 14.5 Gt CO_2 yr^{-1}, and the average annual net forest ecosystem sink was -5.5 Gt CO_2e yr^{-1} (Table 4). Globally, the HWP pool was an additional net carbon sink of -0.20 Gt CO_2 yr^{-1}, resulting from the transfer of carbon out of forest ecosystems and into the HWP pool. Although the original and revised values in Table 4 are not directly comparable due to different temporal coverage and model updates, it does give a high-level view of the degree to which the collective changes to the model have affected (or not affected) fluxes. Figure 3 maps the updated gross emissions, gross removals, and net GHG flux for forests, and are derived from Gibbs et al. 2024a, b and~~, Gibbs et al. 2024b, and Gibbs et al. 2024c~~ -c, respectively.

Our framework allows flexible, yet consistent, estimates of carbon fluxes in a variety of forest types, spatial scales, and regions. For example, defining forest as tree cover >10% instead of >30% (Hansen et al. 2013) results in gross emissions of 9.4 Gt CO_2e yr^{-1}, gross removals of -17.5 CO_2 yr^{-1}, and a net sink of -8.1 CO_2e yr^{-1}. Tropical and subtropical forests continued to be the largest contributors to global forest carbon fluxes, contributing 74% of gross emissions (6.7 Gt CO_2e yr^{-1}) and 60% of gross removals (-8.8 Gt CO_2 yr^{-1}). However, temperate forests are the largest net sink, comprising 40% of the global net sink (-2.2 Gt CO_2e yr^{-1}). Together, humid tropical primary forests (Turubanova et al. 2018) and intact forest landscapes (Potapov et al. 2017) outside the tropics were a net ~~carbon~~ sink of -0.26 Gt CO_2e yr^{-1} (average annual emissions of 2.8 Gt CO_2e yr^{-1} and removals of 3.1 Gt CO_2 yr^{-1}). Forests within protected areas (UNEP-WCMC 2024) accounted for 31% (-1.7 Gt CO_2e yr-1) of the global net ~~carbon~~ sink. In 2023, gross emissions from Canada's wildfires exceeded emissions from all humid tropical primary forests loss that year (3.0 vs. 2.4 Gt CO_2e, respectively; MacCarthy et al. 2024). Updated emissions, removals, and net flux statistics by country and smaller administrative levels can be found on www.globalforestwatch.org.

Table 4. Average annual ~~F~~forest GHG fluxes by climate domain and globally, with uncertainties expressed as standard deviations, for the original (2~~0~~010-2019) and ~~updated~~ revised models (2001-2023). Values in parentheses are the percent of the global flux that occurred in each climate domain. * denotes fluxes with major changes in the uncertainties in the revised GFW model (see Sect. 3.3). In addition, average annual gross emissions from the revised model for 2001-2019 is provided. The original and updated values are not directly comparable due to different temporal coverage and model updates.

Forest GHG fluxes Gt CO_2e yr^{-1} (± standard deviation)

Climate domain	Gross emissions			Gross removals [a]		Net GHG flux [a]	
	Original *(2001–2019)*	Revised *(2001-2019)*	~~Updated~~Revised *(2001–2023)*	Original *(2001–2019)*	R~~Updated~~evised *(2001–2023)*	Original *(2001–2019)*	~~Updated~~Revised *(2001–2023)*
Boreal	0.88 ± 0.42 (11)	1.3 (15)	1.4 ± 0.75 (16)	-2.5 ± 0.96 (16)	-2.5 ± 0.95 (17)	-1.6 ± 1.1 (21)	-1.1 ± 1.2 (20)

Temperate	0.87 ± 0.60 (11)	1.0 (11)	0.93 ± 0.62 (10)	-4.4 ± 48* (28)	-3.1 ± 0.55* (22)	-3.6 ± 48* (47)	-2.2 ± 0.83* (41)
Subtropical	1.0 ± 0.59 (12)	0.9 (10)	1.0 ± 0.93 (11)	-1.6 ± 0.56 (10)	-1.7 ± 0.56 (12)	-0.65±0.81 (8.6)	-0.70± 0.80 (13)
Tropical	5.3 ± 2.4 (66)	5.4 (64)	5.7 ± 2.4 (63)	-7.0 ± 7.6 (45)	-7.1 ± 7.6 (49)	-1.7 ± 8.0 (22)	-1.4 ± 7.9 (26)
Global	**8.1 ± 2.5 (100)**	**8.5 (100)**	**9.0 ± 2.7 (100)**	**-16 ± 49* (100)**	**-14.5 ± 7.7* (100)**	**-7.6 ± 49* (100)**	**-5.5 ± 8.1* (100)**

[a] The revised model does not have gross removals and net flux values for 2001-2019 because they are an annual average over the entire model period rather than a timeseries and thus cannot be subset by year.

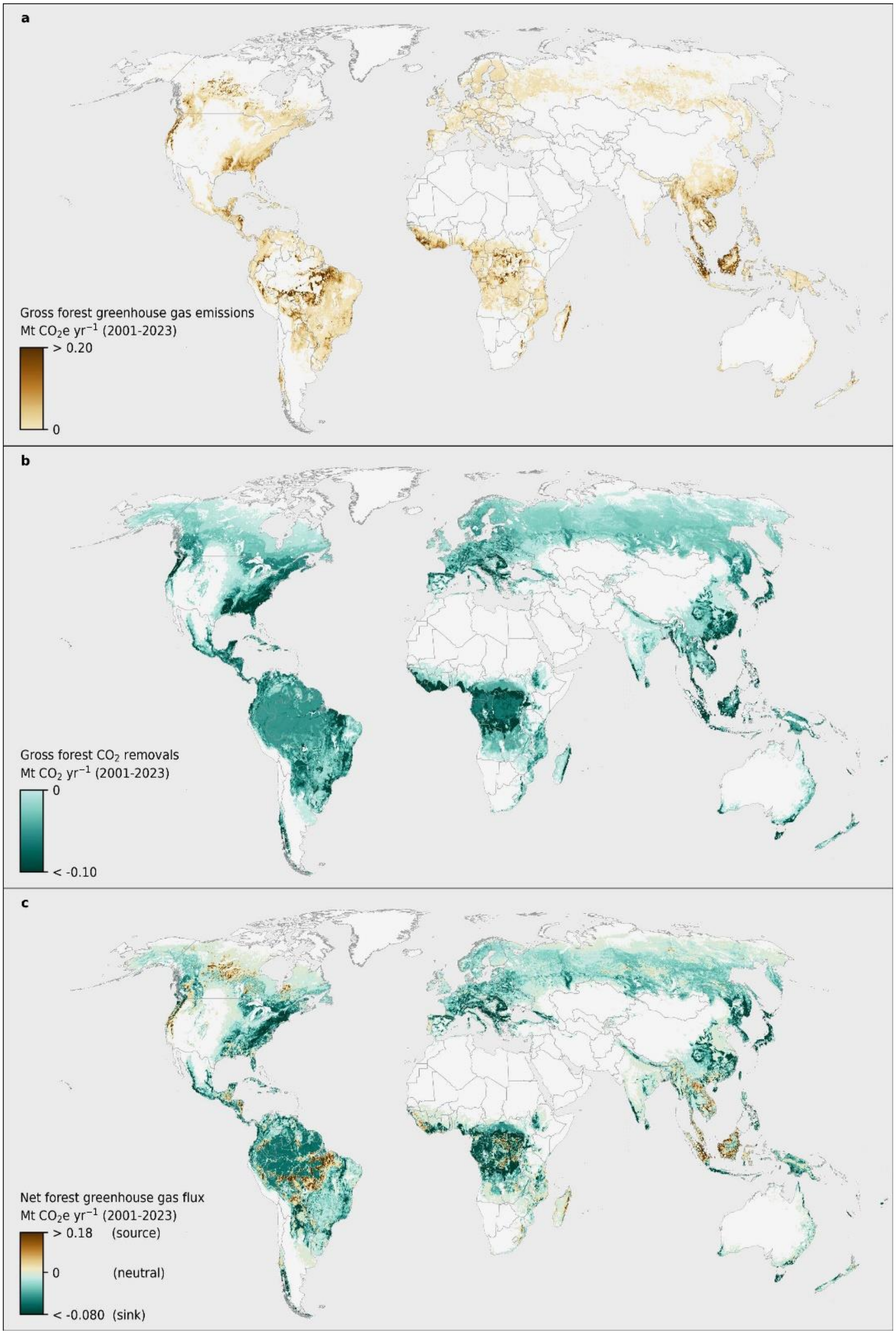


Figure 3. Forest-related GHG fluxes (annual average, 2001–2023). a) Gross GHG emissions. b) Gross ~~carbon dioxide~~CO_2 removals. c) Net GHG flux. Fluxes are aggregated to 0.04 x 0.04° (approximately 4x4 km) cells for display purposes.

3.2 Effect of GFW model changes on forest carbon flux estimates

Updates to the GFW flux model changed gross emissions, gross removals, and net flux over all spatial scales. Average annual gross emissions in the updated GFW model are 12% higher than in the original version, primarily due to higher gross annual emissions since 2019 (8.5 Gt CO_2e yr^{-1} between 2001 and 2019 vs. 11.4 Gt CO_2e yr^{-1} between 2020 and 2023). Updated gross annual removals are 7.3% lower than in the original model, primarily due to the use of corrected, lower IPCC Tier 1 removal factors for temperate forests, which are applied to 290 Mha of secondary forests in the framework, primarily throughout Eurasia and Canada. Annual average net GHG flux decreased accordingly by 28% from the original version because of both higher gross emissions and lower gross removals.

Although we did not quantify the degree to which each change to the model individually affects emissions and removals because we implemented multiple changes simultaneously, we describe how the inputs changed and some general impacts on gross emissions and removals.

Activity data:

1. Temporal coverage of tree cover gain: The area of tree cover gain increased globally from 78 Mha in the original version (gain through 2012) to 130 Mha in the current version (gain through 2020). Carbon removals associated with areas of tree cover gain increased from -0.57 to -0.62 Gt CO_2 yr^{-1}. As in the original model, carbon removals occurring in these young (<20 years) forests remain relatively small compared to gross removals occurring in older, established forests that are much more extensive in total area (96% of gross removals occurred in older forests).
2. Data source for burned area: Use of the new source of fire data with higher spatial resolution (TCLF) combined with an increase in forest fires across Australia, Spain, the United States and Canada between 2020 and 2023 led to an increase of global average annual burned area that coincided with tree cover loss from 4.3 Mha yr^{-1} (2001–2019) to 6.0 Mha yr^{-1} (2001–2023). Global average emissions increased from 1.0 to 1.7 Gt CO_2e yr^{-1} in areas where tree cover loss was ~~identified as burned~~attributed to fire.
3. Data sources for organic soil~~s~~ extent: Improved data led to an increase in the extent of organic soils from 477 Mha to 760 Mha and the area of tree cover loss on organic soils increased from 0.77 Mha yr^{-1} to 2.4 Mha yr^{-1}. Emissions from organic soil drainage in areas with tree cover loss increased from 0.21 to 0.91 Gt CO_2e yr^{-1}, occurring primarily in Indonesia and Malaysia (17% and 3.1% of global total, respectively). Higher emissions from organic soil drainage is due to a combination of increased organic soil extent, planted tree extent, and tree cover loss compared to the original model.
4. Data sources for planted tree extent: Planted forest and tree crop extent increased from 140 Mha to 230 Mha and tree cover loss in planted tree polygons increased from 42 Mha to 64 Mha.

Emission and removal factors:

1. Data source for R:S ratios: The previous global R:S used across the full model extent was 0.26. Now, the average ratio of aboveground removals to belowground removals is 0.27 but with considerable geographic variation.
2. Planted tree removal factors and their uncertainties: The average aboveground removal factor in planted trees originally was 3.2 t C ha^{-1} yr^{-1} but using SDPT v2.0 it is 2.3 t C ha^{-1} yr^{-1}. Global planted forests and trees were originally estimated to be a net ~~carbon~~ sink of -0.30 Gt CO_2e yr^{-1} but using SDPT v2.0 they are now a net sink of -0.54 Gt CO_2e yr^{-1}, with the increased area of planted trees compensating for the lower average removal factor.
3. Older secondary (>20 year) temperate forest removal factors and their uncertainties: Older secondary temperate forests using IPCC Tier 1 removal factors (i.e., areas affected by this change) originally covered 310 Mha and now cover 290 Mha. Gross removals in these forests declined from -2.7 to -1.3 Gt CO_2 yr^{-1}.
4. Global Warming Potentials: Updated model results of non-CO_2 emissions associated with biomass burning and drainage of organic soils were negligibly impacted by using updated GWPs.

3.3 Updated uncertainty analysis

Nearly all changes to the framework are represented in the error propagation approach and therefore affect the global and climate domain uncertainty analyses to some degree. However, the largest change to the uncertainty analysis in terms of input values was the corrected IPCC Tier 1 temperate forest removal factors, which the model applies across large areas of Eurasian and Canadian forests. Some of the largest changes for removal factors and their uncertainties include temperate mountain forest >20 years old [~~(~~previously 4.4 t aboveground biomass (AGB) ha^{-1} yr^{-1} $\pm$ 100.7 ($\pm$ standard deviation); now 2.1 $\pm$ 0.02 t AGB ha^{-1} yr^{-1})] and temperate oceanic forest >20 years old [~~(~~previously 9.1 t AGB ha^{-1} yr^{-1} $\pm$ 20.2; now 4.9 $\pm$ 0.25 t AGB ha^{-1} yr^{-1}~~)~~]. We did not formally assess the contributions of individual model changes to uncertainty because the change in IPCC Tier 1 temperate forest removal factor uncertainties was so dominant.

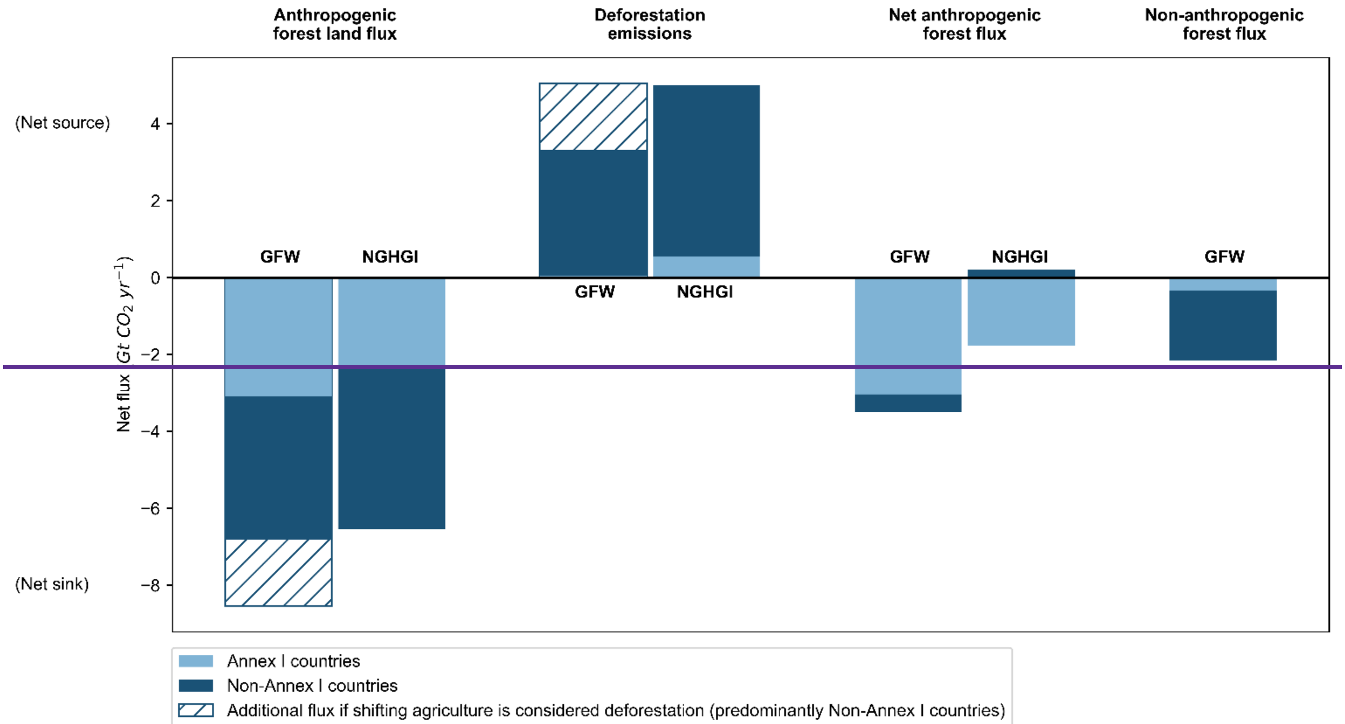
Uncertainty (reported as one standard deviation) in temperate gross removals declined from 48 Gt CO_2 yr^{-1} in the original GFW model to 0.55 Gt CO_2 yr^{-1}, with uncertainty for gross emissions in temperate forests ~~his biome~~ increasing slightly from 0.60 to 0.62 Gt CO_2e yr^{-1} and uncertainty for net flux decreasing from 48 to 0.83 Gt CO_2e yr^{-1} (Table 4). Reduced uncertainty in temperate forest gross removals propagated to reduced uncertainty in global gross removals and net flux. In the uncertainty analysis for the current version of the model, tropical gross removals has the highest uncertainty, driven by relatively high uncertainty in IPCC's Tier 1 removal factors, which the GFW model applies to tropical primary forests and older secondary forests. Large uncertainties for climate domain and global net flux estimates should be interpreted with caution; their uncertainties are proportionately very large in part because net flux they reflect the sum of negative (removals) and positive (emissions) terms, compounding the addition of their uncertainties.

3.4 Anthropogenic fluxes from "managed" forests

When gross CO_2 emissions and ~~carbon~~ removals from the GFW flux model for 2001–2022 were reclassified into NGHGI reporting categories, the anthropogenic net flux in managed forest land ranged between -6.~~8~~9 and -8.~~5~~6 Gt CO_2~~e~~ yr^{-1} (with and without emissions from shifting agriculture in secondary forests, respectively) and emissions from deforestation ranged between 3.3 and 5.0 Gt CO_2~~e~~ yr^{-1} (without and with emissions from shifting agriculture in secondary forests, respectively) (Fig. 4, Table A1). The resulting net anthropogenic forest flux—the combined flux from both anthropogenic forest land and deforestation—was -3.~~5~~6 Gt CO_2~~e~~ yr^{-1}. The non-anthropogenic net sink was -2.2 Gt CO_2~~e~~ yr^{-1}, comprised of -2.5 Gt CO_2~~e~~ yr^{-1} removals and 0.3~~7~~2 Gt CO_2~~e~~ yr^{-1} emissions from fires and tree cover loss without an assigned driver in unmanaged forests. ~~The difference in global net flux estimates between the untranslated GFW model (-5.5 Gt CO_2e yr^{-1}) and the NGHGI-translated one is that the latter includes only anthropogenic forest-related CO_2 fluxes in managed land, while the former also includes fluxes from unmanaged land and emissions from CH_4 and N_2O.~~ The combined NGHGI-translated anthropogenic and non-anthropogenic forest ~~flux~~ sink ~~differs~~ is about ~~by about~~ 0.~~2~~3 Gt CO_2~~e~~ yr^{-1} ~~from~~ larger than the untranslated net flux (-5.8 vs. -5.5 Gt CO_2e yr^{-1}, respectively) because the former does not include CH_4 and N_2O emissions, does not include fluxes from 2023 ~~and~~ , and does not include fluxes from 32 countries (mostly small island countries)~~,~~ which ~~did~~ do not have comparable NGHGIs.

Under the scenario which included emissions from shifting agriculture from secondary forests in deforestation (Fig. 4, hatched bars), GFW's maximum estimate for global deforestation emissions aligned with the combined NGHGI deforestation and organic soil emissions (5.0 Gt CO_2~~e~~ yr^{-1}). In that scenario, GFW's corresponding maximum estimate for global net sink in anthropogenic forest land was larger than estimated by NGHGIs. Under the alternative scenario, which included emissions from shifting agriculture in secondary forests in the anthropogenic forest land flux (Fig. 4, non-hatched bars), GFW's minimum estimate for global net sink in anthropogenic forest land was similar to the NGHGI net forest sink (-6.6 Gt CO_2 yr^{-1}), but GFW's corresponding minimum estimate for global deforestation emissions was lower than estimated by NGHGIs. The combined GFW flux model net anthropogenic forest sink in managed lands is ~~1.9~~2.0 Gt CO_2~~e~~ yr^{-1} greater than in NGHGIs (-1.5 Gt CO_2 yr^{-1}).

For Non-Annex 1 countries, the GFW model high and low estimates for forest land and deforestation bracketed the corresponding NGHGI fluxes. However, GFW estimated the net anthropogenic forest flux for Non-Annex 1 countries to be a small net anthropogenic sink while NGHGIs estimates them to be a small net anthropogenic source. For Annex 1 countries, deforestation emissions from the GFW model were much lower than from NGHGIs (0.046–0.049 and 0.55 Gt CO_2~~e~~ yr^{-1}, respectively) and the net forest sink was somewhat larger (-3.~~1~~2 and -2.3 Gt CO_2~~e~~ yr^{-1}, respectively).


Anthropogenic forest land flux
Deforestation emissions
Net anthropogenic forest flux
Non-anthropogenic forest flux
(Net source)
(Net sink)
Net flux $(Gt\ CO_2\ yr^{-1})$
4
2
0
−2
−4
−6
−8
GFW
NGHGI
GFW
NGHGI
GFW
NGHGI
GFW
Annex I countries
Non-Annex I countries
Additional flux if shifting agriculture is considered deforestation (predominantly Non-Annex I countries)

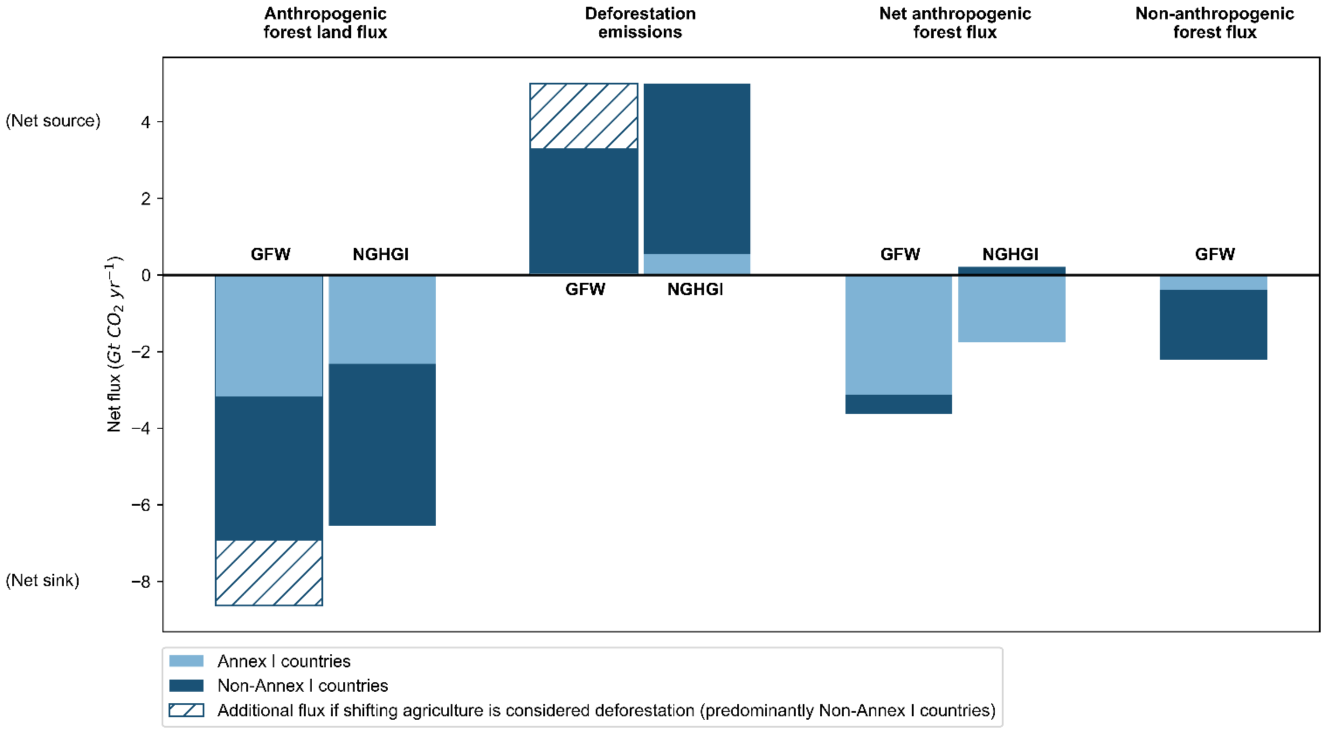
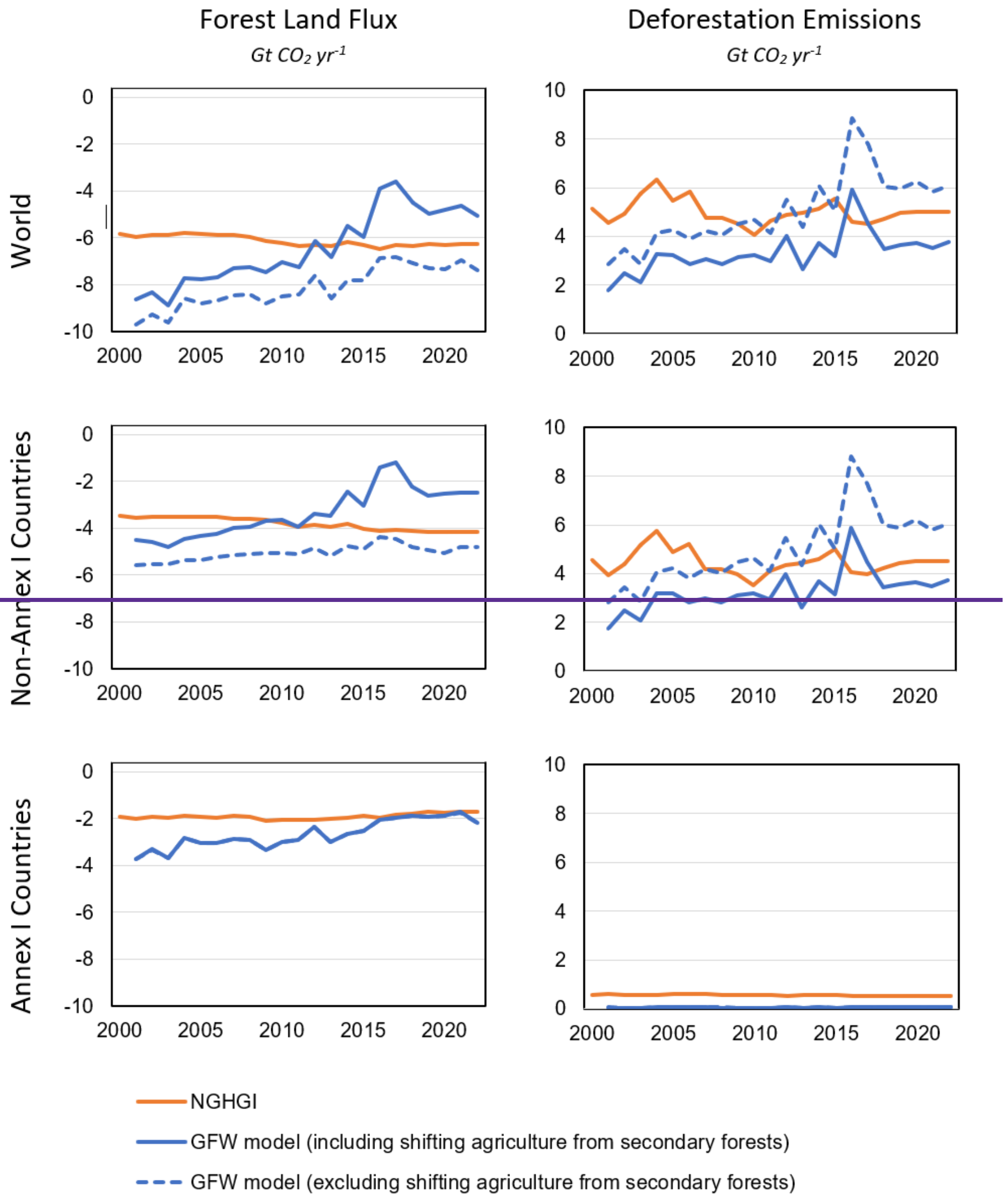

Anthropogenic forest land flux
Deforestation emissions
Net anthropogenic forest flux
Non-anthropogenic forest flux
(Net source)
(Net sink)
Net flux $(Gt\ CO_2\ yr^{-1})$
4
2
0
−2
−4
−6
−8
GFW
NGHGI
GFW
NGHGI
GFW
NGHGI
GFW
Annex I countries
Non-Annex I countries
Additional flux if shifting agriculture is considered deforestation (predominantly Non-Annex I countries)

Figure 4. Comparison of average annual forest carbon fluxes (2001–2022) between national greenhouse gas inventories (NGHGI) and the updated GFW flux model. For the GFW flux model, net anthropogenic ~~c~~forest flux is calculated as the sum of the net anthropogenic forest land flux in managed forests and deforestation (Sect. 2.3). Non-anthropogenic forest flux is calculated as emissions and removals occurring outside managed forests. Because country reporting on emissions from the loss of secondary forests associated with cycles of shifting agriculture is ambiguous, these emissions are shown for the GFW model as hatched bars to indicate how they impact totals depending on the reporting category (forest land or deforestation). Results from the GFW model are for CO_2 fluxes only and NGHGI results have also been limited to CO_2 fluxes except for a few developing countries where non-CO_2 emissions could not be separated.

Although the magnitude of the global GFW model estimates for deforestation emissions and the anthropogenic sink in forests align with the aggregated NGHGIs for 2001–2022 under different scenarios, their trends ~~through time~~from 2001 to 2022 do not agree (Fig. 5). Both globally and for Non-Annex 1 countries, the NGHGIs suggest that from 2001 to 2022 forest land became a slightly larger sink and deforestation emissions lacked a clear trend. However, the GFW flux model results suggest the opposite: a reduced sink in forest land and increased deforestation emissions. The forest land flux and deforestation emissions from NGHGIs and the GFW model for Non-Annex 1 countries appear to converge in the last 10 years (roughly -6 Gt CO_2 yr^{-1} and 5 Gt CO_2 yr^{-1}, respectively). For Annex 1 countries, the forest land sink decreased much more according to the GFW model than NGHGIs, while deforestation emissions stayed fairly constant in both.


Forest Land Flux
Gt CO_2 yr^{-1}
Deforestation Emissions
Gt CO_2 yr^{-1}
World
Non-Annex I Countries
Annex I Countries
NGHGI
GFW model (including shifting agriculture from secondary forests)
GFW model (excluding shifting agriculture from secondary forests)

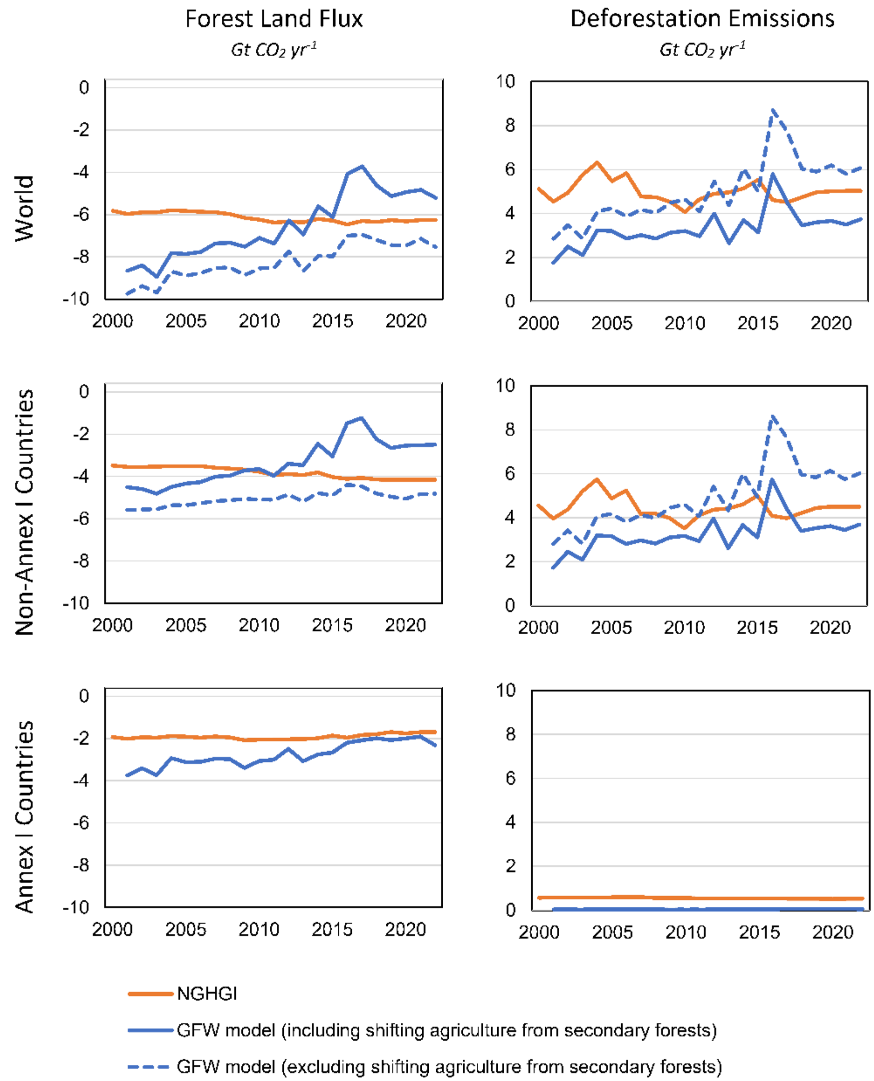


Figure 5. Comparison of forest carbon fluxes timeseries (2001–2022) between national greenhouse gas inventories (NGHGIs) and the updated GFW flux model for Non-Annex 1, Annex 1 countries, and globally. NGHGI values shown here exclude any fluxes from harvested wood products, and deforestation emissions are the combined emissions from both deforestation and organic soils to conceptually align with the scope of fluxes from the GFW framework. For the world and Non-Annex 1 countries, GFW model results are shown in two timeseries: one where emissions from shifting agriculture in secondary forests is included in that reporting category and one where those emissions are not included. For the GFW model in Annex 1 countries, the two scenarios are essentially the same and thus we show only one

line. The GFW model has been limited to CO_2 only; NGHGI data includes only CO_2 except for a few developing countries where non-CO_2 emissions could not be separated.

4 Discussion

We focus our discussion on the following topics. First, we examine how the updated GFW forest flux model compares with results from a recent global estimate of forest fluxes by Pan et al. (2024) and the Global Carbon Budget (GCB). Second, we discuss how fully geospatial, Earth observation-based forest flux estimates can be translated into the reporting categories of NGHGIs and how transparency in both approaches can result in methodological improvements. Third, we discuss strengths and limitations of GFW's Earth observation-based forest carbon flux model. Fourth, we outline future research ~~topics~~ priorities which provide partial solutions to the model's current limitations.

4.1 Comparison with other recent global flux estimates

Pan et al. (2024) is a relevant comparison for the GFW model because both include only forests and report gross rather than net fluxes. Pan et al. (2024) estimated gross removals by forests, gross emissions from tropical deforestation, and the global forest carbon sink by synthesizing forest plot data (inventories and long-term monitoring sites) from 1990 onwards. The removals estimates are conceptually similar (e.g., both include established and new forests), but the emissions estimates have different geographic scope (global for GFW, tropical for Pan et al. 2024) (Table 5). The global net fluxes from Pan et al. 2024 and the updated GFW model are remarkably similar given their entirely different approaches, and thus provide multiple lines of evidence for a net forest sink of ~~around~~ approximately 6 Gt CO_2 yr^{-1}. Differences in gross emissions and removals between the data sources likely arise from different scopes and system boundaries, but may be balanced out when combined in the global net flux. Pan et al. estimated higher tropical gross emissions than the GFW model did for the tropics and subtropics for 2001-2019. When the GFW model's gross emissions (CO_2 only) are limited to the tropics and subtropics and one geospatially implemented definition of deforestation (tree cover loss due shifting agriculture in primary forest, and all commodity- and urbanization-driven tree cover loss), it estimates 3.2 Gt CO_2 yr^{-1}, well below the tropical deforestation estimate of Pan et al. 2024. More broadly including all tree cover loss in the tropics and subtropics, the GFW model estimates gross emissions of 6.3 Gt CO_2 yr^{-1}.

Table 5. Comparison of GFW flux model results to Pan et al. 2024 and the Global Carbon Budget (GCB). Estimates from the three data sources are not directly comparable due to differences in scope, data, methodologies and reporting structure. GFW model fluxes are limited to 2001–2022 for comparability with the GCB. The GFW model and Pan et al. 2024 are for forests only, while the GCB also includes non-forest land ~~as well~~.

Flux	GFW model, 2001-2022 (Gt CO_2 yr^{-1})	Pan et al. 2024, 2000-2019 (Gt CO_2 yr^{-1})	Global Carbon Budget, 2001-2022 (Gt CO_2 yr^{-1})
Emissions	8.6 (gross, all observed disturbances)[a]	7.4 (gross, tropical deforestation)[b]	4.9 (net, anthropogenic)[c]
Removals	-14.7 (gross, all forest ecosystems (-14.5) and HWP (-0.20))[d]	-13 (gross, global)	-11.4 (net, non-anthropogenic)[e]
Net	-6.1 (net, all forests)[ef]	-5.6 (net, global)	-6.4 (net, all land)

[a] Gross emissions from all forest disturbances (anthropogenic and non-anthropogenic) ~~observed from Landsat data~~ for ~~the period~~ 2001–2022. Estimate includes CO_2 only for comparability with GCB; non-CO_2 emissions are 0.19 Gt CO_2e yr^{-1}. This value is lower than that of Table 4 (9.0 Gt CO_2e yr^{-1}) because this one includes emissions for 2001–2022 only and excludes non-CO_2 gases.

[b] Includes emissions from degradation.

[c] Estimates only net direct anthropogenic effects, including deforestation, afforestation/reforestation, organic soils, and wood harvest. Gross fluxes higher but not reported.

[d] Gross removals from all forest processes (direct, indirect and natural). HWP = transfers to harvested wood products. Removals are the annual average from 2001-2023.

[e] Represents the land sink associated with indirect human-induced effects such as CO_2 fertilization, nitrogen deposition, etc.

[ef] Calculated as the net balance between gross forest ecosystem emissions and removals (8.6 – 14.5 Gt CO_2 yr^{-1}) in this table plus an additional net removal of -0.20 Gt CO_2 yr^{-1} into HWP. This value differs from that of Table 4 (-5.5 Gt CO_2e yr^{-1}) because this one uses lower gross emissions (see note a).

Another point of comparison is the GCB, released by the Global Carbon Project each year. The GCB provides annual estimates of GHG emissions and carbon sinks, when relevant, for all sectors. The GFW flux model is not designed to represent the land portion of the global carbon cycle, nor is it directly comparable with the land use fluxes included in the GCB because of differences in definitions, scope, reporting structure, and methods (Friedlingstein et al. 2023). Three overarching differences are: 1) The GCB reports net sources and sinks for all land (including croplands, grasslands, semi-arid savannas and shrublands), while the GFW model reports gross emissions and removals for forests only; 2) the GCB categorizes fluxes by process into net anthropogenic emissions from land use change and forestry and the "natural" land sink, while the GFW model categorizes fluxes by activity data; 3) the GCB uses global bookkeeping models to estimate net anthropogenic carbon fluxes from land use and dynamic global vegetation models (DGVMs) to estimate net carbon fluxes from the natural land sink (Walker et al. 2024), while the GFW flux model uses a single integrated approach to estimate emissions and removals. Nevertheless, comparison of the GFW model with the GCB is useful because they use entirely different data sources and approaches, and, as such, convergence between them would represent multiple lines of evidence towards the magnitude of the land sink.

We estimated a global net CO_2 sink by forest ecosystems of -6.1 Gt CO_2 yr^{-1} between 2001 and 2022, which is similar to the net CO_2 land sink of -6.4 Gt CO_2 yr^{-1} in the GCB for all terrestrial fluxes over the same period (Table 5). The GCB's net emission estimate (4.9 Gt CO_2 yr^{-1}) is lower than GFW's gross emissions estimate (8.6 Gt CO_2 yr^{-1}) partially because the GCB's land-use change emissions (sources) reflect the net balance between anthropogenic emissions and anthropogenic removals associated with forest regrowth. Similarly, the GFW model's gross removals reflect removals across all forest lands, including removals implicit (but unreported) in the GCB net land-use change estimate (Friedlingstein et al. 2023). Additional reclassification of fluxes from the GFW model into net anthropogenic fluxes from land-use change and the natural land sink may be possible for further comparisons with the GCB, as has been done between the GCB and NGHGIs (Schwingshackl et al. 2022).

In the comparison of the original GFW model with the GCB, we included a non-spatial estimate of emissions from tropical forest degradation of 2.1 Gt CO_2e yr^{-1} from Pearson et al. 2017 that potentially included some emissions from small-scale disturbances which we assumed our original model did not capture. For this and subsequent comparisons between the GFW flux framework and the GCB, we are discontinuing the inclusion of a non-spatial estimate of degradation emissions from a source external to our framework to maintain its internal consistency and fully geospatial nature. We acknowledge that the GFW model itself is likely omitting both emissions (e.g., from degradation not detected by TCL) and removals (e.g., from low canopy density or regenerating forest), but those are gaps that the model should be able to fill over time (see Sect. 4.4). Adding external data such as Pearson et al. 2017 risks double-counting emissions in the global total. As more geospatial data on distinguishing deforestation from degradation (Vancutsem et al., 2021) becomes available globally, and geospatial data on the emission and removal factors associated with forest degradation (Holcomb et al., 2024) and recovery (Heinrich et al., 2023b) ~~becomes available~~is developed, it may be possible to reintegrate forest degradation and its associated fluxes.

4.2 Translating between Earth observation-based fluxes and NGHGIs

The 6.7 Gt CO_2 yr^{-1} gap in global land use emissions between NGHGIs and the GCB has been largely explained (Grassi et al. 2023) and translation between NGHGIs on the one hand and bookkeeping models and DGVMs on the other is becoming routine (e.g., Schwingshackl et al. 2022); this work is the start of a similar process for explaining the gap between NGHGIs and Earth observation-based models, primarily through reallocation of emissions and removals to match NGHGIs' land use categories and filtering the results with maps of managed forest as a proxy to delineate anthropogenic from non-anthropogenic fluxes. This approach follows the recommendations of a recent IPCC expert meeting on reconciling land use emissions (IPCC 2024). Our goal in translating GFW model results into a NGHGI reporting framework was to provide independent estimates of forest-based GHG fluxes based on globally consistent, Earth observation-based ~~forest flux~~ data in the reporting categories that national policymakers use. It was not to reproduce how countries classify their managed land, report their forest fluxes in practice, or compare fluxes for individual countries. For example, we did not rely solely on the use of managed land polygons for Case 2a~~1~~ countries to define managed forest; if our observations detected direct human activity in unmanaged polygons, we assigned those fluxes as anthropogenic forest land fluxes or deforestation. Thus, although this translation makes the GFW model more conceptually similar with NGHGIs in that the outputs are supposed to represent the same fluxes, they are still not necessarily entirely comparable because we did not exactly reproduce what countries do in practice within their NGHGIs. This ~~It~~ demonstrates~~s~~ that the GFW model is sufficiently flexible to approximate the system boundaries of anthropogenic fluxes in the IPCC reporting framework and that Earth observation-based models can be used to independently monitor anthropogenic GHG fluxes from forests if adequate country data are made publicly available. ~~The 6.7 Gt CO_2 yr^{-1} gap in global land use emissions between NGHGIs and the GCB has been largely explained (Grassi et al. 2023) and translation between NGHGIs on the one hand and bookkeeping models and DGVMs on the other is becoming routine (e.g., Schwingshackl et al. 2022); this work is the start of a similar process for explaining the gap between NGHGIs and Earth observation-based models, primarily through reallocation of emissions and removals to match NGHGIs' land use categories and filtering the results with maps of managed forest as a proxy to delineate anthropogenic from non-anthropogenic fluxes. This approach follows the recommendations of a recent IPCC expert meeting on reconciling land use emissions (IPCC 2024).~~

Although the conceptual alignment produces quantitatively similar annual average fluxes for the GFW model and NGHGIs globally and for Non-Annex 1 countries, the trends from NGHGIs and the GFW model differ (Fig. 5). For Non-Annex 1 countries, where the trends in each data source are most evident, NGHGIs reported the forest land sink strengthening slightly while deforestation emissions fluctuated but were generally steady. The GFW model, on the other hand, reported a weakening sink in forest land and deforestation emissions that increased correspondingly. The decreasing forest land sink in the GFW model is due to the use of average annual gross removals over time (i.e. a constant value), combined with increasing (i.e. annually variable) tree cover losses not associated with deforestation~~The tight association between the decreasing forest land sink and increasing deforestation emissions in the GFW model is due to the use of average annual gross removals over time (i.e. a constant value), with only gross emissions varying year to year~~. In NGHGIs, forest land and deforestation can both change through time~~ and are therefore not driven by the trajectory of just one flux~~. The differing trends between the GFW flux model and aggregated NGHGIs is likely driven by generally increasing annual tree cover loss used in GFW (Hansen et al. 2013), as that has the greatest interannual variability present in either dataset. Quantitative similarity between the GFW model and NGHGIs may be further improved when the GFW model's gross removals can vary through time as well (Sect. 4.4). Moreover, for Non-Annex 1 countries, results from the GFW model and NGHGIs have converged for forest land and deforestation since around 2010, with the two GFW model scenarios bracketing NGHGI fluxes from both reporting categories after that year. This indicates that the GFW model, and the tree cover loss data that underlies its gross emissions, were perhaps under-detecting loss ~~as detected by~~relative to NGHGIs in the early part of the time series.

Exploration of the differences between the GFW model and specific countries' NGHGIs is beyond the scope of this paper; future work may include more detailed reclassification of the GFW model's fluxes and comparisons with specific regions or countries. As an initial resource for country-level data, the European Union Joint Research Centre LULUCF Data Hub presents graphs of national land fluxes according to their NGHGIs, the Global Carbon Budget, and the translated fluxes from the GFW model (https://forest-observatory.ec.europa.eu/carbon/fluxes). Further sub-setting results from our framework to differentiate anthropogenic and non-anthropogenic fluxes for comparison with NGHGIs for individual regions, countries, and other local-scale analyses is possible and encouraged. Indeed, comparison of the GFW model and countries' inventories is a way to explore the complementarity and discrepancies between Earth observation data and inventories, encourage transparency for both, and improve both approaches (Heinrich et al. 2023a). For example, one advantage of the GFW model, which includes forest fluxes undifferentiated by human contribution, is that it encompasses both anthropogenic and non-anthropogenic fluxes. When this translation exercise is conducted, GHG fluxes from managed ~~land~~ forests can be put in the context of all ~~land~~ forest fluxes and compared with fluxes from unmanaged ~~land~~forests. Because NGHGIs are not required to estimate fluxes from unmanaged land (just report the area of unmanaged land), aggregation of NGHGIs does not provide context for managed land fluxes with unmanaged land fluxes. In other words, the GFW model can indicate the scale of non-anthropogenic fluxes that countries are not reporting in their NGHGIs (which ~~are~~ nevertheless affect atmospheric CO_2 concentrations and global temperature), while NGHGIs are necessary for the GFW model to approximate the anthropogenic fluxes that are being monitored by countries and the focus of the Paris Agreement. An alternative approach for reconciling global models and NGHGIs would be for NGHGIs to report all land fluxes in the country, in both managed and unmanaged land (Nabuurs et al. 2023), but adoption of this seems unlikely.

~~Future improvements to our flux reclassifications, which may improve regional or country-level comparisons, could include customizing tree cover density thresholds that align more closely with countries' forest definitions to filter forest extent and thus the associated fluxes on a country-by-country basis. Additionally, we used maps of primary forests and intact forest landscapes from 2001 and 2000, respectively, to approximate the extent of unmanaged forests at the initial year of our model framework. Further refinement to the GFW model's estimates of fluxes from managed lands could include recategorizing forests as "managed" or "unmanaged" using updated primary/intact forest boundaries in different years to reflect changes to countries' managed land area over time whenever known. Furthermore, for simplicity, we considered all forest removals as forest land and did not differentiate the relatively small amount of removals from forest gain as "other land converted to forest", which is a category that countries report in their NGHGIs. Another improvement would be to separate the emissions from drainage of organic soils and the emissions from deforestation in the GFW model; in the current translation, deforestation emissions and organic soil emissions are combined in both data sources. Separating them would further narrow the conceptual similarity, which would matter most in countries with high emissions from organic soils. Finally, emissions from fires occurring in unmanaged land could theoretically be differentiated into anthropogenic vs. non-anthropogenic using additional geospatial data, rather than our simplified assumption that all fires in unmanaged forests are non-anthropogenic in origin.~~

While our geospatial, Earth observation-based framework permits estimation of fluxes for any geospatially defined forest and the inclusion (or exclusion) of any area of interest, it cannot distinguish between managed versus unmanaged land without relevant spatial data. Thus, the ability of the GFW model, and Earth observation models in general, to be translated into IPCC categories largely depends on the transparency with which countries report on their managed lands. Only t~~T~~hree countries have publicly available maps of managed and unmanaged forest (Canada, Brazil, and the United States) (Ogle et al. 2018)~~that currently apply the managed land proxy (Canada, Brazil, and the United States) have publicly available managed land maps (Ogle et al. 2018)~~. For all remaining countries, the use and application of the managed land proxy was assumed based on the available information from country reports. In the absence of this information, primary or intact forest have been used as proxy for unmanaged forest. With sufficient transparency and flexibility in both the Earth observation-based products and NGHGIs, the differences between them can be explored.

A ~~crucial~~ key driver of forest disturbance, and thus emissions, in the GFW model is shifting agriculture. However, the comparison between GFW and NGHGI is complicated by the fact that countries typically do not provide specific information on shifting agriculture in their land representation; according to the IPCC guidelines it can be implicitly included either in forest or in other land uses (e.g., cropland) (Grassi et al. 2023). Thus, we developed two scenarios for the treatment of fluxes from shifting agriculture (Fig. 4). Hopefully, as countries begin to submit their Biennial Transparency Reports under the Paris Agreement, their use of the managed land proxy, the treatment of shifting agriculture, and other exclusions from inventories will be progressively clarified and translation between approaches will become more accurate. Although they are time-consuming to implement, the goal should be for the kinds of Earth-observation based adjustments described by Heinrich et al. 2023a for Brazil to be achievable for all countries. This will ultimately facilitate comparisons between global models such as the GFW model and NGHGIs, provide national policymakers with timely geospatial data in their own reporting terms, and build confidence in the magnitude and trends of land-based anthropogenic emissions and sinks (Grassi et al. 2023).

Future improvements to our flux reclassifications, which may improve regional or country-level comparisons, could include customizing tree cover density thresholds that align more closely with countries' forest definitions to filter forest extent and thus the associated fluxes on a country-by-country basis. Additionally, we used maps of primary forests and intact forest landscapes from 2001 and 2000, respectively, to approximate the extent of unmanaged forests at the initial year of our model framework. Further refinement to the GFW model's estimates of fluxes from managed lands could include recategorizing forests as "managed" or "unmanaged" using updated primary/intact forest boundaries in different years to reflect changes to countries' managed land area over time whenever known. Furthermore, for simplicity, we considered all forest removals as forest land and did not differentiate the relatively small amount of removals from forest gain as "other land converted to forest", which is a category that countries report in their NGHGIs. Another improvement would be to separate the emissions from drainage of organic soils and the emissions from deforestation in the GFW model; in the current translation, deforestation emissions and organic soil emissions are combined in both data sources. Separating them would ~~further narrow~~refine the conceptual similarity. This ~~, which~~ would matter most in countries with high emissions from organic soils. Finally, emissions from fires occurring in unmanaged land could theoretically be differentiated into anthropogenic vs. non-anthropogenic using additional geospatial data, rather than our simplified assumption that all fires in unmanaged forests are non-anthropogenic in origin.

4.3 Strengths and limitations of the GFW flux monitoring framework

The strengths of the current GFW flux model are broadly similar to those described in Harris et al. 2021. Strengths include its transparency, operational nature, flexibility, and updatability as new information becomes available. Here we focus on the complementarity of the GFW model with other land flux monitoring approaches. A strength of flux monitoring based on Earth observation, and therefore geospatial, data is its geographic specificity, while maintaining spatial consistency. Knowing where changes in land use and land cover—and the emissions and removals they have caused—occurred may help identify what factors are responsible for these changes and how to attribute them to specific human activities. While detailed information from ground surveys and activity data generated using local training data may provide more detail and accuracy at local scales, understanding the magnitude and distribution of global change requires a combination of both ground- and space-based observations (Houghton and Castanho 2023). In this sense, it fills in the gaps among other flux monitoring approaches. In terms of global consistency, the GFW model's key data are global in breadth and independent of data from the United Nations Food and Agriculture Organization, giving it a separate source for forest change data from bookkeeping models (Hansis et al. 2015, Gasser et al. 2020, Houghton and Castanho 2023). Moreover, by having an open-source model based on publicly available data, others can evaluate the model, make improvements, and/or adapt it to use national or local rather than global data. Users can keep some defaults while replacing others with better or more specific information, and understand how results are impacted by the various changes made for regions or at scales that interest them most.

Limitations are also broadly similar to those described in Harris et al. 2021. First, combining multiple spatially explicit data sources compounds the errors present in each individual source used in the framework. The GFW model partially manages this over larger areas through uncertainty propagation analysis to identify the relative contributions of different model components to uncertainty in each climate domain but cannot provide a pixel-level accuracy or uncertainty map. Extending the uncertainty framework to smaller regions (e.g., biomes or countries) would require uncertainty information for each of the individual data sources to be available at the desired scale of uncertainty propagation analysis. Second, the gain-loss approach of starting with baseline carbon densities and adding gains and subtracting losses over time has the potential to generate unrealistic estimates over longer periods due to drift from the original benchmark map. The GFW model could potentially address this through recalibration of carbon densities and forest extent at one or more intermediate years (e.g., 2010, 2015). Finally, the GFW model continues to have temporal limitations for both activity data and removal factors. The shorter gain period compared to tree cover loss in the original publication (12 vs. 19 years, respectively) has largely been addressed with the extension of tree cover gain through 2020. More limiting than the mismatch of tree cover loss and gain durations is the one-time nature of tree cover gain. Because the year of tree cover gain is not known, the model does not necessarily include post-disturbance gross regrowth and removals, which may underestimate removals and decrease the net sink. This effect would be particularly pronounced in forest where disturbance occurs earlier in the model and regrowth is substantial. The ~~, but the~~ ~~t~~tree cover loss timeseries also has its own inconsistencies (Weisse and Potapov 2021). The improvement in Earth observation data and changes to processing confounds apparent trends in gross emissions based on tree cover loss; it is difficult to determine how much the trends in emissions are due to real increases vs. better detection of disturbances through time. For removal factors, the concern is not so much temporal inconsistency as temporal constancy; the model makes the simplifying assumption of static removal factors, i.e. removal factors do not change as forests grow or climate changes over the 23-year model period. Thus, the GFW model does not incorporate growth-response curves or climate feedbacks, unlike in Earth System Models.

4.4 Research priorities and ~~A~~anticipated model developments

Beyond annual updates to the GFW model, we anticipate continued, substantial changes to and research around both activity data and emission and removal factors. These do not change the underlying conceptual framework but rather its implementation as the model.

For activity data, anticipated model developments include:

1. Global forest change data: The model will use annual forest extent, loss, and gain maps for greater temporal detail (similar to Potapov et al. 2019 or Turubanova et al. 2023) and improved representation of carbon dynamics. For example, the year of tree cover gain will be known (at least approximately) and repeated forest disturbances in the same location will be captured (unlike in Hansen et al. 2013), allowing the generation of annual time series of gross emissions, gross removals, and net flux. This should further enhance comparability of ~~flux~~ temporal trends in GFW's fluxes with the GCB and NGHGIs.
2. Drivers of forest loss: The model currently uses a global map of drivers of forest loss at 10-km resolution (Curtis et al. 2018, updated to 2023) but research on mapping drivers of forest loss is advancing. An anticipated 1-km resolution global map of drivers of forest loss (Sims et al., in review) will detect drivers that are not dominant at 10-km (and are therefore not mapped) but are important at smaller scales, such as loss due to small-scale infrastructure and built-up areas amid loss due to agricultural commodity expansion. Moreover, a separate ~~driver~~ class of forest loss due to natural disturbances ~~would~~ will further help with parsing natural and anthropogenic fluxes for translation into NGHGI reporting categories.
3. Delineation of organic soils and their drainage status: The GFW model currently compiles several different data sources (Table 2), which have different definitions and resolutions, to map organic soil extent. The GFW model would benefit from a globally consistent organic soil map based on comprehensive aggregation of soil samples and standardized mapping methods (Hengl et al. in prep). However, it is not just the extent of organic soils but their

drainage that affects emissions in the GFW model. Thus, we are exploring improved mapping of organic soil drainage using recent improvements in delineating road networks (OSM 2010; Meijer et al. 2018; Engert et al. 2024), drainage canal networks (Dadap et al. 2021), and land cover (Potapov et al. 2022). More comprehensive maps of organic soil extent and drainage will improve where the GFW model reports these emissions, particularly affecting non-CO_2 GHG emissions.

4. Improved initial forest age map: The GFW model currently classified forested pixels into primary forest, secondary forest > 20 years, and secondary forest < 20 years old in 2000 using a few simple rules (described in Harris et al. 2021). However, a forest age map such as Besnard et al. 2021 could be used to refine the assignment of starting age categories—particularly for secondary forests—or to determine where forest is along age-growth curves.
5. Extent of planted forests and trees: The model currently uses SDPT v2.0 (Richter et al. 2024) but plans are underway for SDPT 3.0, which will improve differentiation between natural and artificial stands in the United States and Canada, along with other improvements for delineating planted tree extent in other countries.

For emission and removal factors, anticipated model developments include:

1. Improved spatial and temporal resolution of forest carbon removals: The dominant role of removal factor uncertainties in the uncertainty analysis highlights the need to further improve understanding of spatial and temporal variation in forest carbon removals. Combining plot-level biomass estimates with spaceborne observations to produce static biomass maps is well established (e.g., Saatchi et al. 2011, Santoro et al. 2021) and mapping biomass change is being explored (Xu et al. 2021) but these do not provide spatiotemporally variable removal factors. An ecology-based, yet still spatial, way to map removal factors could combine tree-level information collected in field plots with machine learning methods to map forest population structure through time, including variables that influence biomass change like upgrowth, mortality and recruitment for different forest types (Ma et al. 2020, Liang et al. in review). Such an approach can generate spatial and temporal predictions of how biomass changes across space and time that can be validated with forest plot data. In conjunction with a time series of tree cover gain (in activity data list above), this would result in fully temporal gross removals. Alternatively, growth curves for natural regeneration of forests could be revised and expanded to include a greater range of forest ages, using similar methods to Cook-Patton et al. 2020 (Robinson et al. under review)~~Alternatively, growth curves for natural regeneration of forests could be developed, using methods similar to Cook-Patton et al. 2020~~.
2. Improved maps of soil carbon dynamics in mineral soils: The GFW model currently uses a benchmark map of soil organic carbon density in mineral soil in 2000 and assumes loss of specific fractions of carbon under certain types of tree cover loss, following a Tier 1 approach from IPCC 2019. However, a timeseries of soil organic carbon density in mineral soil would support more realistic mapping of SOC ~~dynamics~~losses and gains.

~~2.~~3. Improved maps of emissions from organic soil drainage: The GFW model currently assumes that organic soils are drained only wherever tree cover loss, organic soils, and planted trees (Richter et al. 2024) coincide. Future improvements could include expanding the proxies used to map ~~for~~ organic soil drainage, as well as including emissions from extraction of organic soils.

Additionally, opportunities remain to compare GFW model emissions and removals with NGHGIs, bookkeeping models, and regional or local data (e.g., Araza et al. 2023, Heinrich et al. 2023b). Such work would further our understanding of the complementary roles of Earth observation-based forest carbon models and other approaches to forest flux monitoring.

5 Data and code availability

Gross emissions, gross removals, and net flux are available for download as 10x10 degree geotifs in 0.00025x0.00025-degree resolution. Data that correspond to the model version presented in this publication are as follows: g~~G~~ross emissions ~~files~~ (Gibbs et al. 2024a)-- ~~are at~~ https://doi.org/10.7910/DVN/LNPSGP;~~https://doi.org/10.7910/DVN/LNPSGP/~~ ~~G~~gross removals ~~files~~ (Gibbs et al. 2024b)-- ~~are at~~ https://doi.org/10.7910/DVN/V2ISRH;~~. N~~ net flux ~~files~~ (Gibbs et al. 2024c)--~~ are at~~ https://doi.org/10.7910/DVN/TVZVBI. Data are also available as assets on Google Earth Engine at https://code.earthengine.google.com/ae55707e335894d7be515386195390d2. Note that more recent versions of these datasets may be available from www.globalforestwatch.org. ~~Data are also available as assets on Google Earth Engine at https://code.earthengine.google.com/ae55707e335894d7be515386195390d2.~~ Code is available at https://github.com/wri/carbon-budget.

6 Conclusion

The updated Earth observation-based GFW forest carbon flux framework continues to show a substantial net sink for CO_2 in forests globally, while also reporting ~~sizeable~~ gross emissions over half as large as gross removals since 2001~~0~~. This highlights ongoing opportunities to protect the forest carbon sink across a broad area and also reduce emissions from forest loss, especially in hotspots of emissions that are discernable with our geospatial framework. The revised uncertainty analysis—with its dramatic reduction in uncertainty in gross removals—demonstrates the importance of refining forest carbon sequestration rate estimates. The flexibility of the model supports analyses at a range of spatial scales, while its operational nature means it can incorporate new and existing Earth observation products and provide timely maps and data. Our translation of the GFW model's fluxes into the reporting framework that NGHGIs use—~~—~~following the recommendations of a recent IPCC expert meeting on reconciling land use emissions (IPCC 2024)—~~—~~provides another lens through which to look at country-level, land-based climate mitigation and is a resource for national policymakers interested in timely, spatial data on land fluxes. It also demonstrates the two approaches' ability to improve, assess, and potentially confirm each other. Ultimately, confidence and transparency are needed in assessments of progress towards the Paris Agreement, and Earth observation-based forest carbon models are another tool to build consensus.

Author contributions

NH and DAG conceived the model updates, and DG and MR executed the model updates. DAG executed the updated uncertainty analysis. GG, SR, and JM created the national greenhouse gas inventory data set, and MR and GG compared it to the GFW model. VH contributed to the translation of the GFW model for Brazil. DAG led manuscript preparation with contributions from all co-authors.

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Appendix A

Table A1. Comparison of forest carbon fluxes in Annex 1 countries, Non-Annex 1 countries, and globally between the GFW flux model and national greenhouse gas inventories (NGHGIs). Ranges in reported GFW values here come from two different scenarios: one scenario where emissions from shifting agriculture in secondary forests is included in forest land, while the other scenario includes all emissions from shifting agriculture in deforestation. Results from the GFW model are for CO_2 fluxes only and NGHGI results have also been limited to CO_2 fluxes except for a few developing countries where non-CO_2 emissions could not be separated.

	~~**Net flux in forest land (Gt CO_2 yr^{-1})**~~		~~**Deforestation emissions (Gt CO_2e yr^{-1})**~~		~~**Net anthropogenic forest flux (Gt CO_2e yr^{-1})**~~		~~**Non-anthropogenic forest flux (Gt CO_2e yr^{-1})**~~	
	~~**GFW**~~	~~**NGHGI**~~	~~**GFW**~~	~~**NGHGI**~~	~~**GFW**~~	~~**NGHGI**~~	~~**GFW**~~	~~**NGHGI**~~
~~**Annex 1 countries**~~	~~-3.1 – -3.1~~	~~-2.3~~	~~0.046 – 0.049~~	~~0.55~~	~~-3.0~~	~~-1.8~~	~~-0.34~~	~~N/A~~
~~**Non-Annex 1 countries**~~	~~-3.7 – -5.5~~	~~-4.2~~	~~3.3 – 5.0~~	~~4.5~~	~~-0.46~~	~~0.2~~	~~-1.8~~	~~N/A~~
~~**Global**~~	~~-6.8 – -8.5~~	~~-6.6~~	~~3.3 – 5.0~~	~~5.0~~	~~-3.5~~	~~-1.6~~	~~-2.2~~	~~N/A~~

	Net flux in forest land (Gt CO_2 yr^{-1})		**Deforestation emissions (Gt CO_2 yr^{-1})**		**Net anthropogenic forest flux (Gt CO_2 yr^{-1})**		**Non-anthropogenic forest flux (Gt CO_2 yr^{-1})**	
	GFW	**NGHGI**	**GFW**	**NGHGI**	**GFW**	**NGHGI**	**GFW**	**NGHGI**
Annex 1 countries	-3.2 – -3.2	-2.3	0.046 – 0.049	0.55	-3.0	-1.8	-0.34	N/A
Non-Annex 1 countries	-3.7 – -5.5	-4.2	3.3 – 5.0	4.5	-0.46	0.2	-1.8	N/A

Global	-6.9 – -8.6	-6.6	3.3 – 5.0	5.0	-3.6	-1.5	-2.2	N/A