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

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11 **Short Summary**

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

16 **Abstract**

17 Forests are a key component of climate change mitigation strategies because they both emit and remove atmospheric carbon
18 dioxide. Earth observation data are increasingly used to estimate the magnitude and geographic distribution of greenhouse gas
19 (GHG) fluxes and reduce overall uncertainty in the global carbon budget, including for forests. Here we report on a revised
20 and updated geospatial, Earth observation-based forest carbon flux modelling framework that maps GHG emissions (Gibbs et
21 al. 2024a), carbon removals (Gibbs et al. 2024b), and the net balance between them (Gibbs et al. 2024c) globally from 2001
22 onwards at roughly 30-meter resolution (Harris et al. 2021, hereafter referred to as the Global Forest Watch (GFW) model).
23 Beyond updating the model to include the most recent years, revisions address some of the original model's limitations,
24 improve model inputs, and refine the uncertainty analysis. We found that between 2001 and 2023, global forest ecosystems
25 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
26 reflects the balance of 9.0 ± 2.7 Gt CO_2e yr^{-1} of GHG emissions and -14.5 ± 7.7 of carbon removals, with an additional -0.20
27 Gt CO_2e yr^{-1} transferred into harvested wood products. Uncertainty in gross removals was greatly reduced compared to the
28 original model due to refinement of temperate secondary forest carbon removal factor uncertainties.

29 To increase the conceptual similarity between fluxes from the GFW model and national greenhouse gas inventories (NGHGIs)

30 and further policy relevance, we translated (re-allocated) GFW's estimates of gross emissions and removals into fluxes from

31 forest land and deforestation, i.e. the land use categories that countries use to report anthropogenic forest-related fluxes from

32 managed land in their NGHGIs. We estimated a global net anthropogenic forest-related sink of -3.5 Gt CO_2e yr^{-1} (-3.7 Gt CO_2e

33 yr^{-1} including transfers into harvested wood products). Emissions from deforestation ranged between 3.3 and 5.0 Gt CO_2yr^{-1}

34 and the net anthropogenic sink in managed forest land ranged between -6.8 and -8.5 Gt CO_2e yr^{-1}, reflecting ambiguity about

35 the reporting category to which countries assign emissions from loss of secondary forests within shifting agriculture systems.

36 We categorized the remaining net flux of -2.2 Gt CO_2e yr^{-1} reported by the GFW model as non-anthropogenic (0.37 Gt CO_2e

37 yr^{-1} emissions and -2.5 Gt CO_2e yr^{-1} removals). The magnitude of the GFW model's annual average deforestation emissions

38 and the global anthropogenic forest sink aligned well with aggregated NGHGIs, although their temporal trends differed;

39 NGHGIs reported a slightly increasing forest land sink and fluctuating deforestation emissions, while the GFW model reported

40 a declining sink and increasing deforestation emissions.

41 Updates to the model and the revised uncertainty analysis demonstrate a spatially explicit forest carbon flux monitoring

42 framework that is increasingly transparent, operational, timely, and flexible enough to answer research and policy questions.

43 Moreover, the translation of Earth observation-based flux estimates into the same reporting framework as countries use for

44 NGHGIs can help build consensus on land use carbon fluxes, support the independent evaluation of progress towards Paris

45 Agreement goals, and assist national policymakers in locating sources and sinks of forest carbon and their drivers.

46 **1 Introduction**

47 Land is among the most uncertain components of the global carbon cycle (Friedlingstein et al. 2023). The highly dynamic and

48 bi-directional nature of forest carbon fluxes, both spatially and temporally, as well as the contributions of anthropogenic and

49 non-anthropogenic processes, cause unique challenges for monitoring fluxes. Top-down atmospheric observations, e.g. from

50 sensors such as NASA's Orbiting Carbon Observatory, are not precise enough to attribute fluxes to specific drivers, and the

51 current suite of bottom-up approaches for estimating global terrestrial carbon fluxes (Friedlingstein et al. 2023) is based on

52 models that are not fully consistent with each other (i.e., bookkeeping models and dynamic global vegetation models (DGVMs)

53 to estimate anthropogenic and natural fluxes, respectively). An additional complication is that these models separate

54 anthropogenic and natural fluxes from land differently from how national greenhouse gas inventories (NGHGIs) do, which are

55 used within climate policy treaties and to drive national climate actions. This makes it difficult for models to provide estimates

56 directly relevant to climate policy frameworks and national climate action. Top-down atmospheric approaches do not make

57 this separation, while global estimates of anthropogenic land use fluxes from bookkeeping models (Friedlingstein et al. 2023)

58 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

59 differences around what is classified as anthropogenic vs. natural fluxes from forests (Grassi et al. 2018), with recent studies

60 focusing on reconciling these differences (e.g., Schwingshackl et al. 2022, Grassi et al. 2023). Thus, despite improved data

61 acquisition and advances in modelling capabilities, large uncertainty and variation in estimates of land emissions and sinks

62 remain. Moreover, the spatial distribution of forest emissions and, even more so, forest carbon removals are not well

63 understood, impeding the ability of a range of actors, such as governments, companies, and civil society, to monitor the

64 effectiveness of land-based climate mitigation actions that reduce emissions from forest loss and maintain or increase forest

65 carbon sinks.

66 To address some of these limitations, Global Forest Watch (GFW) introduced an Earth observation-based framework and

67 model for estimating forest carbon fluxes globally (Harris et al. 2021) that aligns with calls for geospatial monitoring of forest

68 carbon fluxes (EC 2018; Nyawira et al. 2024; Ochiai et al. 2023; Turubanova et al. 2023). It was designed to fill a gap among

69 existing forest carbon monitoring approaches by combining global forest change maps, benchmark carbon density maps, and

70 other Earth observation data based on the IPCC Guidelines for National Greenhouse Gas Inventories (IPCC 2006, IPCC 2019)

71 that countries use to estimate emissions and removals for their NGHGIs. Within the scope of the Agriculture, Forestry, and

72 Other Land Uses (AFOLU) sector, only GHG fluxes from forest-related land uses and land-use changes (forest remaining

73 forest, non-forest converted to forest, forest converted to non-forest) were included. The framework was designed around the

74 UNFCCC guiding principles for NGHGI preparation: transparency, accuracy, completeness, comparability and consistency.

75 All GFW carbon flux model inputs and outputs and code are publicly available.

76 Recognizing that both Earth observation and ground data increase and improve through time, we designed GFW's flux

77 framework and the model implementing it with the flexibility to accommodate updates to existing components and add new

78 components. Here we document updates to the model, report the results from the current version, present a revised uncertainty

79 analysis, and introduce a new translation of GFW model emissions and removals into NGHGI reporting categories of

80 deforestation and forest land that provides an Earth observation perspective on forest fluxes conceptually similar to what

81 countries are expected to report under IPCC guidelines.

82 **2 Methods**

83 Harris et al. 2021 includes a detailed explanation of the GFW forest flux monitoring framework, but some key elements are

84 described here. The framework encompasses gross CO_2 emissions from loss of carbon in aboveground and belowground

85 biomass pools, dead wood, litter, and soil organic carbon in mineral soils due to stand-replacing disturbances, carbon loss from

86 drainage of organic soils, and methane (CH_4) and nitrous oxide (N_2O) emissions from forest fires and drainage of organic soils.

87 Carbon removals include sequestration into aboveground and belowground forest biomass. All model inputs are resampled to

88 the spatial resolution of a Landsat pixel (0.00025x0.00025°, roughly 30x30 m at the equator), and outputs are generated at the

89 same resolution. The model uses Landsat resolution because it is the highest resolution for which the global forest change

90 maps and an aboveground biomass map for the year 2000 are publicly available. Higher resolution maps of forest change and

91 biomass exist but are not publicly available, only for more recent years, and/or include only certain regions (e.g., Vancutsem

92 et al. 2019, Yang and Zeng 2023).

93 The IPCC GHG inventory guidelines, the methodological basis of GFW's forest carbon flux monitoring framework, lay out

94 two methods by which terrestrial carbon stock changes associated with land use, land-use change, and forestry (LULUCF, part

95 of the broader AFOLU sector) can be calculated: gain-loss and stock-difference (IPCC 2006). Methods can be applied

96 according to different Tiers (from 1 to 3) with increasing complexity and presumed accuracy. In the gain-loss method, at a

97 high level, carbon emissions and removals are calculated separately by multiplying activity data such as forest area lost, gained,

98 or maintained (ha) by emission or removal factors (t C ha^{-1}); the net carbon stock change, or flux, is the difference between

99 gross emissions and gross removals. In the stock-difference method, carbon stocks are measured during repeated inventories

100 and the difference between remeasurements is the estimate of net carbon stock change, or flux. GFW's framework employs

101 the gain-loss approach, in which the activity data and other contextual information are estimated using global, Earth

102 observation-based maps trained on local ground plot data and/or airborne and spaceborne lidar observations.

103 GFW's gain-loss modeling approach is initialized in the year 2000 with global maps of carbon densities in five forest ecosystem

104 carbon pools (Fig. 1). We define forest as follows: 1) >30% canopy cover in 2000 (Hansen et al. 2013) or subsequent tree

105 cover gain (Potapov et al. 2022), 2) non-zero aboveground biomass in 2000 (Harris et al. 2021), 3) mangroves in 2000 (Giri

106 et al. 2011), and 4) exclusion of oil palm plantations in 2000 (see Table 2). Within the resulting forest mask, gross emissions

107 are subsequently mapped based on locations of stand-replacing forest disturbances, while gross removals are mapped based

108 on locations of forest extent and regrowth. In this system of tracking the forest/non-forest status of individual pixels over time,

109 the model adheres to IPCC Approach 3 for land representation.

110 For activity data, rather than combining and reconciling national or regional geospatial forest monitoring data in the limited

111 places where it exists continuously since 2000, we deliberately use global, independent (non-governmental) data sources to

112 maintain global consistency and comparability within the framework, recognizing that global data are generally not the most

113 locally accurate or relevant data, but remain useful for large-scale analyses and potentially for verification purposes of other

114 approaches. To identify forest loss, the GFW model uses the Global Forest Change (GFC) data of Hansen et al. 2013, updated

115 annually. Because of the framework's use of GFC, emissions are limited to those from stand-replacing disturbances or other

116 disturbances severe enough to be detected by GFC. Tree cover gain (Potapov et al. 2022) is gross gain and is not assigned to

117 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),

118 or both loss and gain (although the sequence is unknown). Non-forest pixels can have either tree cover gain or no gain; in the

119 latter case they are outside the framework as they are non-forest remaining non-forest.

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120 Emission and removal factors likewise use spatially explicit data as much as possible to capture spatial variation in forest

121 properties and dynamics and move beyond ecozone-level representation of forests. GFW model emission and removal factors

122 are generally independent of national data sources, with the exception of some removal factors in temperate forests, which are

123 derived directly from the Forest Inventory and Analysis (FIA) database maintained by the USDA Forest Service (see Harris et

124 al. 2021 and Glen et al. 2024 for details). The model uses a combination of IPCC default (Tier 1) and localized (Tier 2)

125 emission/removal factors, with the goal of using more Tier 2 factors over time, just as countries are encouraged to do in their

126 NGHGIs. (Note that some Tier 1 removal factors come from national forest inventories, particularly USFS FIA data (IPCC

127 2019).) For example, removal factors in primary forests use IPCC defaults (IPCC 2019, Tier 1), while pre-disturbance (year

128 2000) aboveground biomass carbon densities use a global benchmark map of woody biomass developed from field data and

129 remote sensing (Harris et al. 2021, Tier 2). Removal factors are applied in a hierarchy from six sources: mangrove-specific

130 rates (IPCC 2014a), Europe-specific rates by forest type (combination of Table 4.11 of the updated IPCC Guidelines, FAO

131 Planted Forest Assessment and factors published in national forest inventories), planted tree rates from the Spatial Database

132 of Planted Trees (SDPT) Version 2.0 (Richter et al. 2024), US-specific rates by region, forest type and age class derived from

133 the FIA database (Glen et al. 2024), young secondary forest rates (Cook-Patton et al. 2020), and IPCC default rates for all

134 other areas (e.g., primary forest, older secondary forest in the tropics and in temperate forests outside Europe and the US)

135 (IPCC 2019). The framework supports the addition of other geospatial removal factors as they become available. Gross

136 removals are added to pre-disturbance biomass until the year of loss to determine the biomass in the year of loss. Emission

137 factors are estimated using a map of tree cover loss drivers (Curtis et al. 2018) and burned area (Tyukavina et al. 2022); the

138 combination of these determine the extent to which carbon pools (including soil organic carbon in mineral soils) are emitted

139 by forest disturbance. Emission factors are estimated using "committed" emissions (Hansis et al. 2015) or instantaneous

140 oxidation (IPCC 2019), whereby carbon loss from all relevant pools is assumed to occur in the year of disturbance rather than

141 modeling delayed carbon fluxes through time.
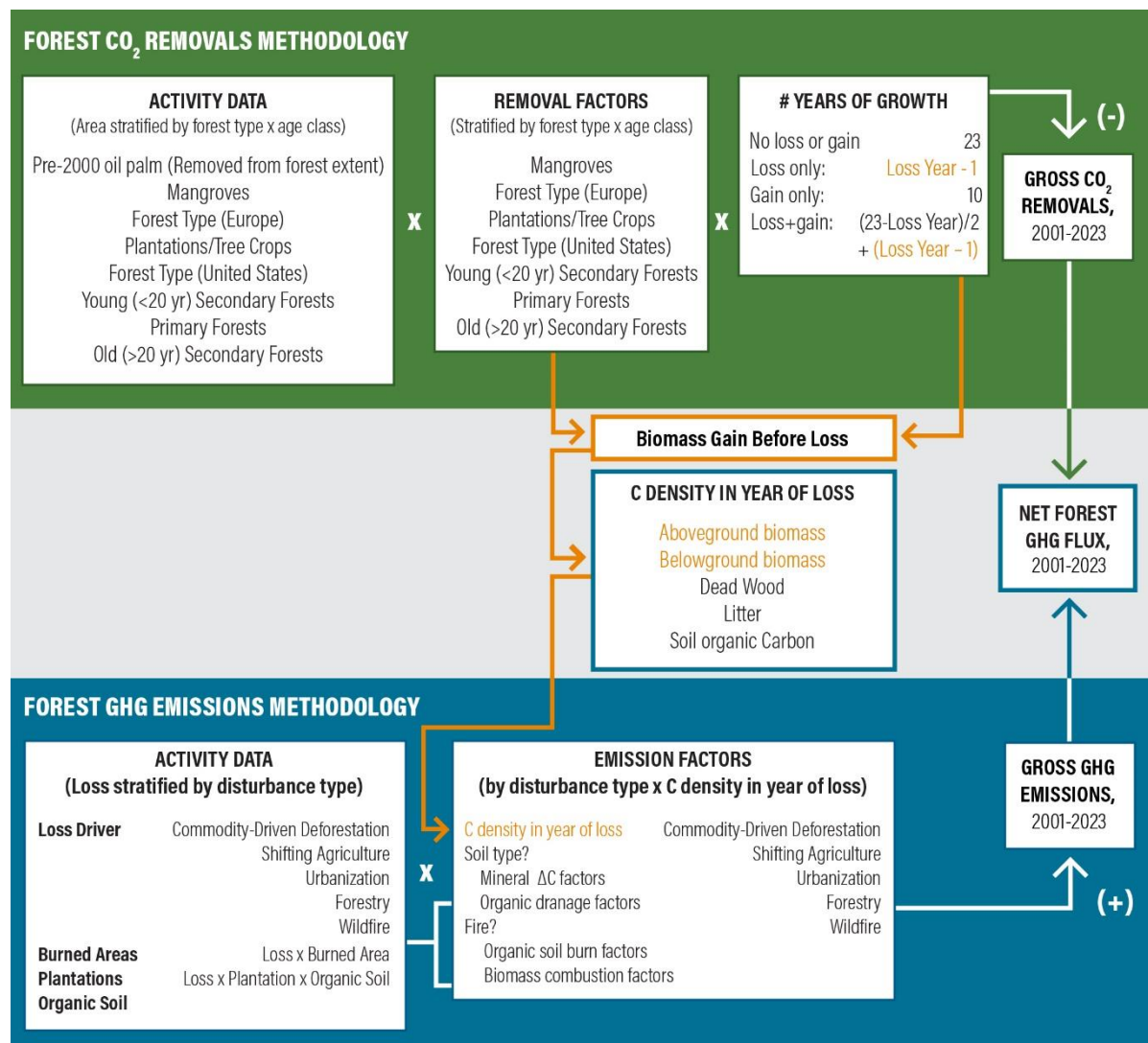
Figure 1. Updated conceptual framework for modeling forest-related GHG fluxes. The model estimates gross forest-related emissions and removals as the product of activity data and emission/removal factors for each ~30-m pixel. The net forest GHG flux is the sum of gross emissions (+) and removals (-). 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 advances in global Earth observation and address some limitations in the original version but do not change the underlying conceptual framework. The updated geospatial inputs are shown in the

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152   context of all inputs in Table 2. We summarize changes to the input data with respect to extension of the model from 2019 to

153   2023 (Sect. 2.1.1), changes to activity data (Sect. 2.1.2), and changes to emission and removal factors (Sect. 2.1.3).

154

155   **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)	2019 Refinement to the 2006 IPCC Guidelines for National	4th Corrigenda to the 2019 Refinement to the 2006 IPCC	Yes	Yes

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| temperate forest removal factors and their uncertainties (2.1.3) | Greenhouse Gas Inventories, Volume 4, Chapter 4, pages 4.34–4.38 Table 4.9 (IPCC 2019) | Guidelines for National Greenhouse Gas Inventories, Volume 4, Chapter 4, pages 4.18–21, Table 4.9 (IPCC 2023)[2] | | |
| 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 |

156 [1] The R:S map was extended outwards to fill gaps in the original map.
157 [2] Removal factors for other climate domains and ages were not updated.
158
159
160 **Table 2. Geospatial data components and sources currently used in the GFW model.** Updated components and sources are denoted
161 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	Austin et al. 2017 (Indonesia)
(areas excluded from model)	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)*

162

2.1.1 Annually updated data

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

2.1.2 Updated activity data

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

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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) (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

204   carbon removals by aboveground biomass. Including this input makes the belowground carbon stocks and removal

205   factors reflect local forest types better than using a single, global ratio.

206   2.   Planted tree removal factors and their uncertainties: SDPT v2.0 (Richter et al. 2024) has a removal factor and

207   uncertainty associated with every planted tree (planted forest and tree crop) polygon included in the database. The

208   removal factors of polygons that were in SDPT v1.0 are largely unchanged in SDPT v2.0, but polygons newly

209   included in SDPT v2.0 have been assigned removal factors based on information about what kind of planted tree is

210   present using the most taxonomically resolved information available.

211   3.   Older secondary (>20 year) temperate forest removal factors and their uncertainties: The original version of the

212   framework applied Tier 1 removal factors published in Table 4.9 of IPCC 2019 for primary and some secondary (>20

213   years) temperate forests. In 2023, IPCC released corrected default removal factors and their uncertainties for

214   temperate secondary forests in North and South America, which are also applied in the GFW model to >20 year old

215   forests in temperate ecozones outside of the United States and Europe where no better sources of data are currently

216   available. In the model update, we replaced the original IPCC defaults with the corrected ones.

217   4.   Global Warming Potential (GWP) values: The original version of the framework converted non-CO_2 emissions from

218   CH_4 and N_2O into equivalent units of CO_2 using GWP values published in IPCC's Fifth Assessment Report. The

219   framework now uses GWP values for CH_4 and N_2O from IPCC's Sixth Assessment Report. This affects gross

220   emissions and net flux outputs only where non-CO_2 emissions are estimated (organic soil drainage, fires in organic

221   soils, or biomass burning).

2.2 Updated uncertainty analysis

223 With the original version of the framework, we presented an uncertainty analysis that used an error propagation approach for

224 inputs for which uncertainties (variances) were available and potentially substantial. This approach underlies Approach 1

225 (simple error propagation) outlined in the IPCC Guidelines and produces similar results but reflects exact calculations of

226 variances and standard deviations, whereas IPCC Approach 1 to uncertainty analysis is an approximated approach that yields

227 95% confidence intervals (IPCC 2019). For the model update, we repeated this uncertainty analysis with all the changes and

228 updates to the framework described in Sect. 2.1, using the same error propagation approach and the same components as used

229 in the original analysis.

2.3 Anthropogenic fluxes from "managed" forests

231 GFW's Earth observation-based modelling framework does not (and cannot) differentiate anthropogenic and non-

232 anthropogenic fluxes from forests. Rather, it includes fluxes from all forest land and therefore the combination of direct

233 anthropogenic, indirect anthropogenic, and natural fluxes. Thus, results from our model are not directly comparable with those

234 from NGHGIs or bookkeeping models, each of which define anthropogenic fluxes with different system boundaries for their

235 specific purposes (Grassi et al. 2022, Grassi et al. 2023). Under UNFCCC decisions and IPCC methodological guidance,

236 countries report only anthropogenic fluxes in their NGHGIs, approximated by "managed land" (Ogle et al. 2018). Therefore,

237 if GFW's forest carbon monitoring framework is to serve as an independent, Earth observation-based point of reference for

238 NGHGIs, its results must be reported in a conceptually similar way covering the same scope. In doing so, we adopted the

239 proposal of Grassi et al. (2023) in adjusting global data to the NGHGI framework for analyses focused on country policy or

240 action. In translating the GFW model's fluxes into the NGHGI reporting framework, we did what IPCC guidelines direct

241 countries to do when compiling and reporting their inventories rather than what countries necessarily do in practice for their

242 inventories. The goal of this translation exercise was not to reproduce how countries prepare their NGHGIs as closely as

243 possible using the GFW model, to achieve maximum quantitative similarity to NGHGIs, or to reconcile the GFW flux model

244 with NGHGIs but rather to present GHG fluxes from a globally consistent, geospatial approach in the same conceptual terms

245 that national policymakers use.

246 We developed a three-step process to translate the GFW model's gross emissions and removals into three IPCC reporting

247 categories: anthropogenic flux from managed forest land, emissions from deforestation (anthropogenic), and non-

248 anthropogenic flux from unmanaged forest (Table 3). It builds upon the simpler comparison between the GFW model and

249 NGHGIs conducted in the IPCC Sixth Assessment Report (Nabuurs et al. 2022), in which anthropogenic fluxes from the

250 former were those outside primary forests in the tropics and intact forest landscapes in the non-tropics. This translation process

251 does not change the GFW model's bottom-line net flux estimates; rather, it reclassifies the gross fluxes by intersecting the

252 GFW model fluxes with other contextual geospatial data to provide fluxes more conceptually aligned with those of NGHGIs.

253 The first step (Sect. 2.3.1) assigned each country to one of three cases based on how their NGHGI applies the managed land

254 proxy (Fig. 2). The second and third steps reclassified the GFW model's emissions (Sect. 2.3.2) and removals (Sect. 2.3.3),

255 respectively, into three IPCC reporting categories according to the three cases assigned in step 1 (Fig. 2). Emissions and

256 removals within each IPCC reporting category were then summed to calculate net anthropogenic and non-anthropogenic forest-

257 related fluxes for each country. The GFW model calculates annual emissions, corresponding to the year of tree cover loss, but

258 does not calculate annual removals and instead calculates removals as an annualized average over the entire model period.

259 Thus, to generate timeseries from the GFW model using the NGHGI reporting categories, we calculated the average annual

260 removals in each reporting category by dividing gross removals by the number of model years. The resulting time series for

261 each reporting category is therefore the difference between the annual emissions for that year and the average annual removals.

262 For this analysis, we used data from the GFW model for 2001–2022 to align with the temporal coverage of NGHGIs. Because

263 the GFW model cannot currently report emissions from organic soil separately from all other emissions, we combined

264 NGHGIs' deforestation and organic soil emissions (including emissions from forest land, from peat decomposition and peat

265 fires typically associated to deforestation, and from agriculture soils) to achieve the same scope as the model. We excluded

266 transfers into the harvested wood products pool from both data sources in this translation analysis because that is not a core

267 element of our geospatial framework.

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

275

		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

276
277 * 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
278   activity.
279 [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
280   land flux and emissions from shifting agriculture in primary forests toward deforestation.
281 [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
282   corresponds to a larger sink in anthropogenic forest land.
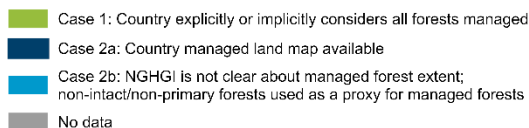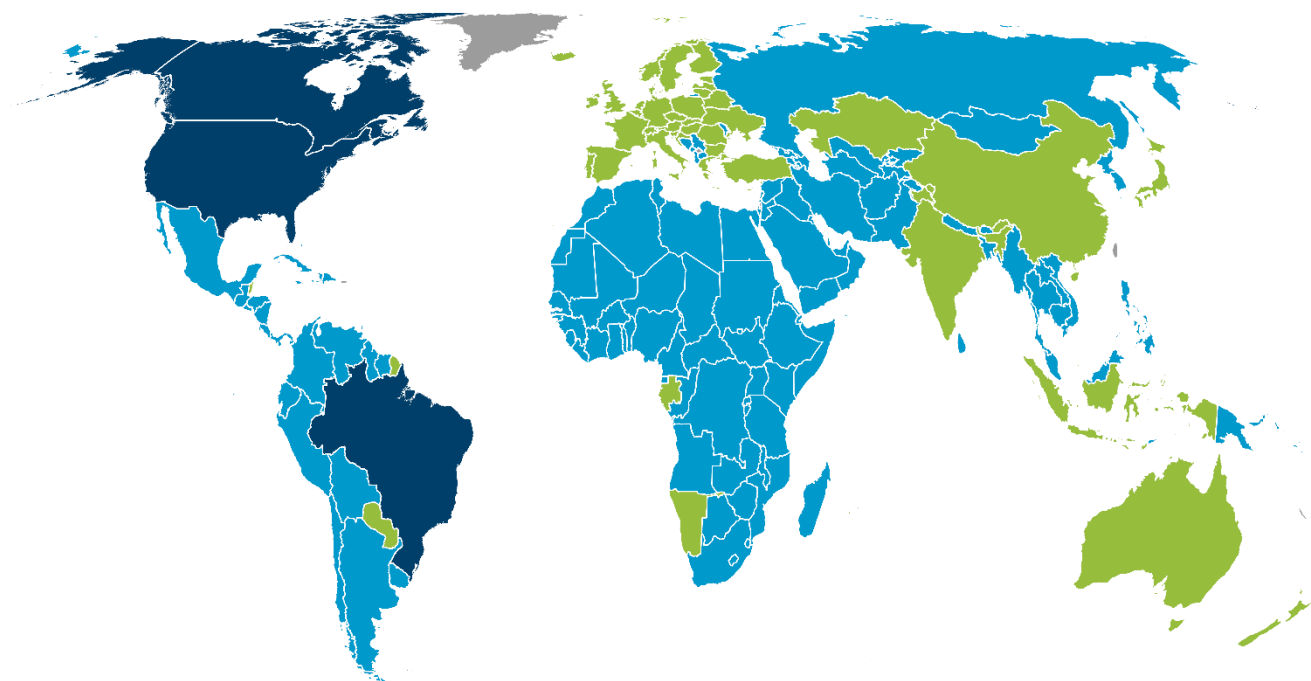283

284 **2.3.1 Managed land delineation**

285 In the first step (Table 3), we assigned countries to one of three cases based on careful review of NGHGIs (Melo et al., in

286 preparation). These cases describe which land is considered managed and unmanaged according to information that countries

287 provide in their NGHGIs regarding their use of the managed land proxy (Fig. 2). Case 1 included 46 countries (primarily

288   UNFCCC Annex 1 countries, i.e. advanced economies with annual GHG reporting commitments) that explicitly consider all

289   forest land managed and another three countries (China, India, Indonesia) for which we assumed that all forest land is

290   considered managed, based on the information provided in their NGHGIs. Case 2 included all other countries, which do not

291   consider all forest to be managed and thus consider some forest to be unmanaged. For the three Case 2a countries (Brazil, the

292   United States, and Canada), we used the georeferenced boundaries of managed and unmanaged lands that they use in their

293   NGHGIs. The remaining 143 countries (UNFCCC non-Annex 1 countries, i.e. countries with historically less stringent GHG

294   reporting commitments) either report no information or not enough details regarding the use of the managed land proxy and

295   its extent. For example, Russia's inventory explicitly includes unmanaged land but reports areas by administrative unit rather

296   than spatially, which is not adequate for our analysis. For these Case 2b countries, we approximated managed forest in tropical

297   regions as forests outside humid tropical primary forests from 2001 (Turubanova et al. 2018) and in extratropical regions as

298   forests outside intact forest landscapes from 2000 (Potapov et al. 2017). For Case 2 countries, the initial managed forest

299   delineation was modified in steps 2 and 3 to include unmanaged land reassigned to managed land due to direct anthropogenic

300   activity. We note that while countries' definitions of forest land differ, we instead used a single, global definition of forest as

301   defined in Sect. 2, with a tree cover density >30% (Hansen et al. 2013).

Case 1: Country explicitly or implicitly considers all forests managed
Case 2a: Country managed land map available
Case 2b: NGHGI is not clear about managed forest extent; non-intact/non-primary forests used as a proxy for managed forests
No data

302

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).

309

310

2.3.2 Reclassifying gross emissions

In the second step (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 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 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 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 emissions from the GFW model. 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

341   caused by humans, we classified emissions from them as non-anthropogenic to be consistent with IPCC guidelines; separating

342   emissions from human-caused fires in unmanaged land and reporting them as anthropogenic forest land emissions could be

343   improved in further iterations of this analysis.

344   It is often not clear to which land use categories emissions from shifting agriculture cycles are allocated in NGHGIs, because

345   this distinction is not required by the IPCC Guidelines (IPCC 2019). Following Curtis et al. (2018), shifting agriculture

346   landscapes are defined as "small- to medium-scale forest and shrubland conversion for agriculture that is later abandoned and

347   followed by subsequent forest regrowth." To highlight the sensitivity of how emissions from shifting agriculture landscapes

348   are estimated, we created two scenarios for our emissions reclassification. In one scenario, we calculated the maximum

349   emissions from deforestation by including all emissions from the loss of both primary and secondary forests within shifting

350   agriculture landscapes and therefore no emissions from shifting agriculture are considered to be occurring in forest remaining

351   forest. In the other scenario, we calculated the maximum emissions from managed forest land by including emissions from the

352   loss of secondary forests in shifting agriculture landscapes in the anthropogenic forest land flux. This transferred a subset of

353   emissions considered to be deforestation under the alternative scenario to forest land. The remaining emissions from loss of

354   intact/primary forests due to shifting agriculture were still considered deforestation emissions, as described above. The two

355   scenarios do not change the total net anthropogenic forest flux (fluxes from forest land plus deforestation) because the same

356   emissions are assigned to either category. In both scenarios, emissions from the loss of intact/primary forests due to shifting

357   agriculture were always classified as deforestation because we considered them to arise from a permanent change from forest

358   to a non-forest land use.

359

360   **2.3.3 Reclassifying gross removals**

361   In the third step (Table 3), we partitioned carbon removals occurring on forest land as either anthropogenic or non-

362   anthropogenic. No forest carbon removals were included in deforested land; any removals in pixels with tree cover loss were

363   assigned to either anthropogenic forest land removals or non-anthropogenic forest removals, as described below. Since

364   NGHGIs do not treat removals uniformly, we used the three managed land proxy cases to align GFW flux model removal

365   estimates with how countries report removals in their NGHGIs (Fig. 2).

366   For Case 1 countries, which explicitly or implicitly consider all forest land to be managed, we classified all removals across

367   the full GFW model extent as anthropogenic forest land. No removals for these countries were considered non-anthropogenic.

368   For Case 2 countries, we separated removals into anthropogenic and non-anthropogenic categories following the same spatial

369   proxy used to delineate managed forests (Sect. 2.3.1). In this approach, we classified all removals in managed forest land as

370   anthropogenic, including unmanaged forest reclassified as managed forest due to tree cover loss from forestry and shifting

371   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, Gibbs et al. 2024b, and Gibbs et al. 2024c, respectively.

Our framework allows flexible, yet consistent, estimates of carbon fluxes in a variety of forest types, spatial scales, and regions. 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 CO2e 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.

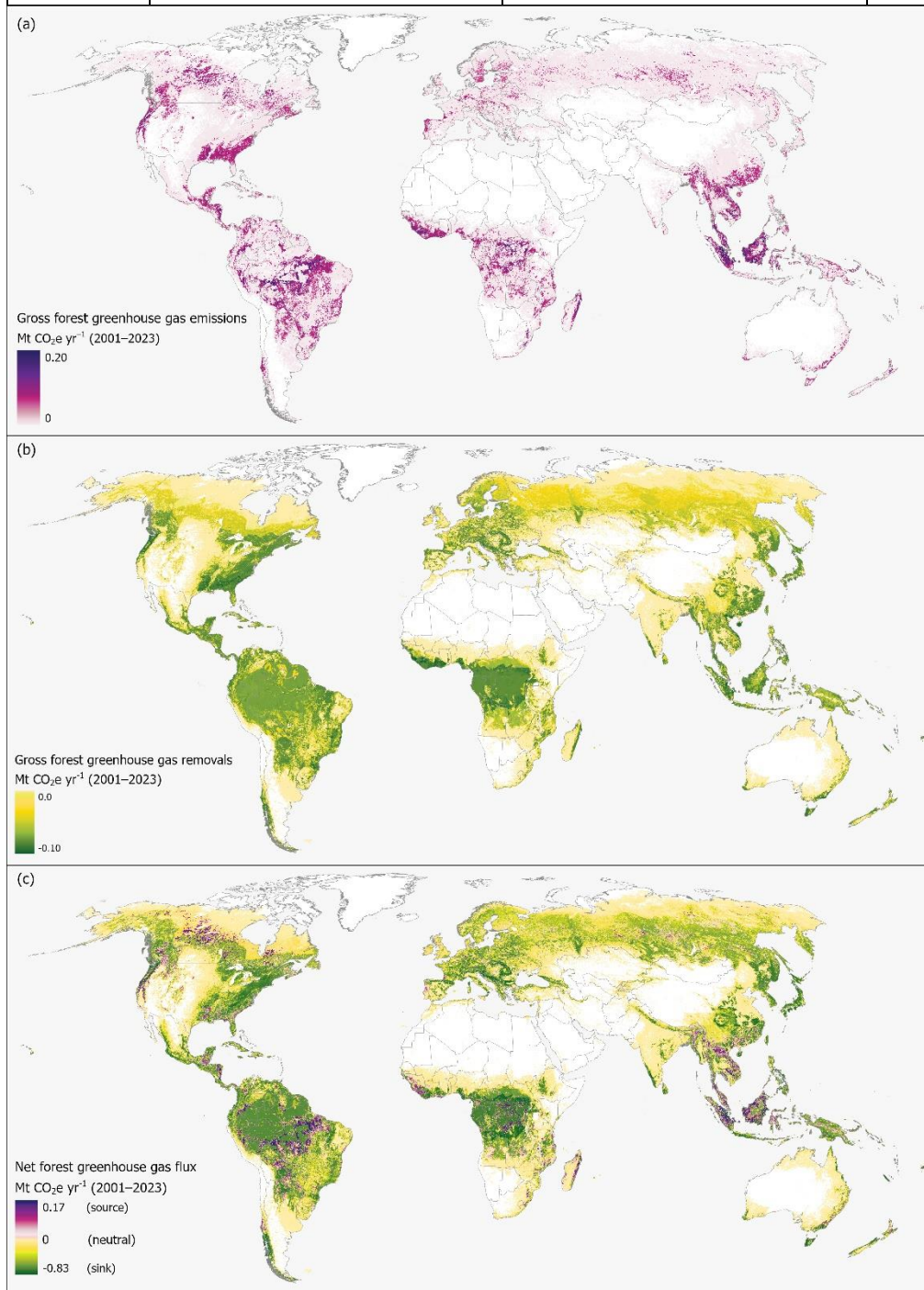**Table 4. Forest GHG fluxes by climate domain and globally, with uncertainties expressed as standard deviations, for the original and updated models.** Values in parentheses are the percent of the global flux that occurred in each climate domain. * denotes fluxes with major changes in the uncertainties in the revised GFW model (see Sect. 3.3). The original and updated values are not directly comparable due to different temporal coverage and model updates.

Forest GHG fluxes Gt CO₂e yr⁻¹ (± standard deviation)

Climate domain	Gross emissions		Gross removals		Net GHG flux	
	Original *(2001–2019)*	Updated *(2001–2023)*	Original *(2001–2019)*	Updated *(2001–2023)*	Original *(2001–2019)*	Updated *(2001–2023)*
Boreal	0.88 ± 0.42 (11)	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)	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)	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)	5.7 ± 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)**	**9.0 ± 2.7 (100)**	**-16 ± 49* (100)**	**-14.5 ± 7.7* (100)**	**-7.6 ± 49* (100)**	**-5.5 ± 8.1* (100)**

(a) Gross forest greenhouse gas emissions
Mt CO_2e yr^{-1} (2001–2023)
0.20
0

(b) Gross forest greenhouse gas removals
Mt CO_2e yr^{-1} (2001–2023)
0.0
-0.10

(c) Net forest greenhouse gas flux
Mt CO_2e yr^{-1} (2001–2023)
0.17 (source)
0 (neutral)
-0.83 (sink)

397

Figure 3. Forest-related GHG fluxes (annual average, 2001–2023). a) Gross GHG emissions. b) Gross carbon dioxide removals. c) Net GHG flux. Fluxes are aggregated to 0.04 x 0.04° 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 emissions and lower 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.

3. Data sources for organic soils 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.

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430 *Emission and removal factors:*

431　　1. Data source for R:S ratios: The previous global R:S used across the full model extent was 0.26. Now, the average
432　　　ratio of aboveground removals to belowground removals is 0.27 but with considerable geographic variation.
433　　2. Planted tree removal factors and their uncertainties: The average aboveground removal factor in planted trees
434　　　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
435　　　originally estimated to be a net carbon sink of -0.30 Gt CO$_2$e yr^{-1} but using SDPT v2.0 they are now a net sink of -
436　　　0.54 Gt CO$_2$e yr^{-1}, with the increased area of planted trees compensating for the lower average removal factor.
437　　3. Older secondary (>20 year) temperate forest removal factors and their uncertainties: Older secondary temperate
438　　　forests using IPCC Tier 1 removal factors (i.e., areas affected by this change) originally covered 310 Mha and now
439　　　cover 290 Mha. Gross removals in these forests declined from -2.7 to -1.3 Gt CO$_2$ yr^{-1}.
440　　4. Global Warming Potentials: Updated model results of non-CO$_2$ emissions associated with biomass burning and
441　　　drainage of organic soils were negligibly impacted by using updated GWPs.

3.3 Updated uncertainty analysis

443 Nearly all changes to the framework are represented in the error propagation approach and therefore affect the global and
444 climate domain uncertainty analyses to some degree. However, the largest change to the uncertainty analysis in terms of input
445 values was the corrected IPCC Tier 1 temperate forest removal factors, which the model applies across large areas of Eurasian
446 and Canadian forests. Some of the largest changes for removal factors and their uncertainties include temperate mountain
447 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
448 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}
449 yr^{-1}). We did not formally assess the contributions of individual model changes to uncertainty because the change in IPCC Tier
450 1 temperate forest removal factor uncertainties was so dominant.

451 Uncertainty (reported as one standard deviation) in temperate gross removals declined from 48 Gt CO$_2$ yr^{-1} in the original
452 GFW model to 0.55 Gt CO$_2$ yr^{-1}, with uncertainty for gross emissions in this biome increasing slightly from 0.60 to 0.62 Gt
453 CO$_2$e yr^{-1} and uncertainty for net flux decreasing from 48 to 0.83 Gt CO$_2$e yr^{-1} (Table 4). Reduced uncertainty in temperate
454 gross removals propagated to reduced uncertainty in global gross removals and net flux. In the uncertainty analysis for the
455 current version of the model, tropical gross removals has the highest uncertainty, driven by relatively high uncertainty in
456 IPCC's Tier 1 removal factors, which the GFW model applies to tropical primary forests and older secondary forests. Large
457 uncertainties for climate domain and global net flux estimates should be interpreted with caution; their uncertainties are
458 proportionately very large in part because net flux they reflect the sum of negative (removals) and positive (emissions) terms,
459 compounding the addition of their uncertainties.

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460 **3.4 Anthropogenic fluxes from "managed" forests**

461 When gross emissions and removals from the GFW flux model for 2001–2022 were reclassified into NGHGI reporting

462 categories, the anthropogenic net flux in managed forest land ranged between -6.8 and -8.5 Gt CO_2e yr^{-1} (with and without

463 emissions from shifting agriculture in secondary forests, respectively) and emissions from deforestation ranged between 3.3

464 and 5.0 Gt CO_2e yr^{-1} (without and with emissions from shifting agriculture in secondary forests, respectively) (Fig. 4, Table

465 A1). The resulting net anthropogenic forest flux—the combined flux from both anthropogenic forest land and deforestation—

466 was -3.5 Gt CO_2e yr^{-1}. The non-anthropogenic net sink was -2.2 Gt CO_2e yr^{-1}, comprised of -2.5 Gt CO_2e yr^{-1} removals and

467 0.37 Gt CO_2e yr^{-1} emissions from fires and tree cover loss without an assigned driver in unmanaged forests. The difference in

468 global net flux estimates between the untranslated GFW model (-5.5 Gt CO_2e yr^{-1}) and the NGHGI-translated one is that the

469 latter includes only anthropogenic forest-related fluxes in managed land, while the former also includes fluxes from unmanaged

470 land. The combined NGHGI-translated anthropogenic and non-anthropogenic forest flux differs by about 0.2 Gt CO_2e yr^{-1}

471 from the untranslated net flux because the former does not include fluxes from 2023 and does not include fluxes from 32

472 countries (mostly small island countries), which did not have comparable NGHGIs.

473 Under the scenario which included emissions from shifting agriculture from secondary forests in deforestation (Fig. 4, hatched

474 bars), GFW's maximum estimate for global deforestation emissions aligned with the combined NGHGI deforestation and

475 organic soil emissions (5.0 Gt CO_2e yr^{-1}). In that scenario, GFW's corresponding maximum estimate for global net sink in

476 anthropogenic forest land was larger than estimated by NGHGIs. Under the alternative scenario, which included emissions

477 from shifting agriculture in secondary forests in the anthropogenic forest land flux (Fig. 4, non-hatched bars), GFW's minimum

478 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

479 GFW's corresponding minimum estimate for global deforestation emissions was lower than estimated by NGHGIs. The

480 combined GFW flux model net anthropogenic forest sink in managed lands is 1.9 Gt CO_2e yr^{-1} greater than in NGHGIs (-1.5

481 Gt CO_2 yr^{-1}).

482 For Non-Annex 1 countries, the GFW model high and low estimates for forest land and deforestation bracketed the

483 corresponding NGHGI fluxes. However, GFW estimated the net anthropogenic forest flux for Non-Annex 1 countries to be a

484 small net anthropogenic sink while NGHGIs estimates them to be a small net anthropogenic source. For Annex 1 countries,

485 deforestation emissions from the GFW model were much lower than from NGHGIs (0.046–0.049 and 0.55 Gt CO_2e yr^{-1},

486 respectively) and the net forest sink was somewhat larger (-3.1 and -2.3 Gt CO_2e yr^{-1}, respectively).
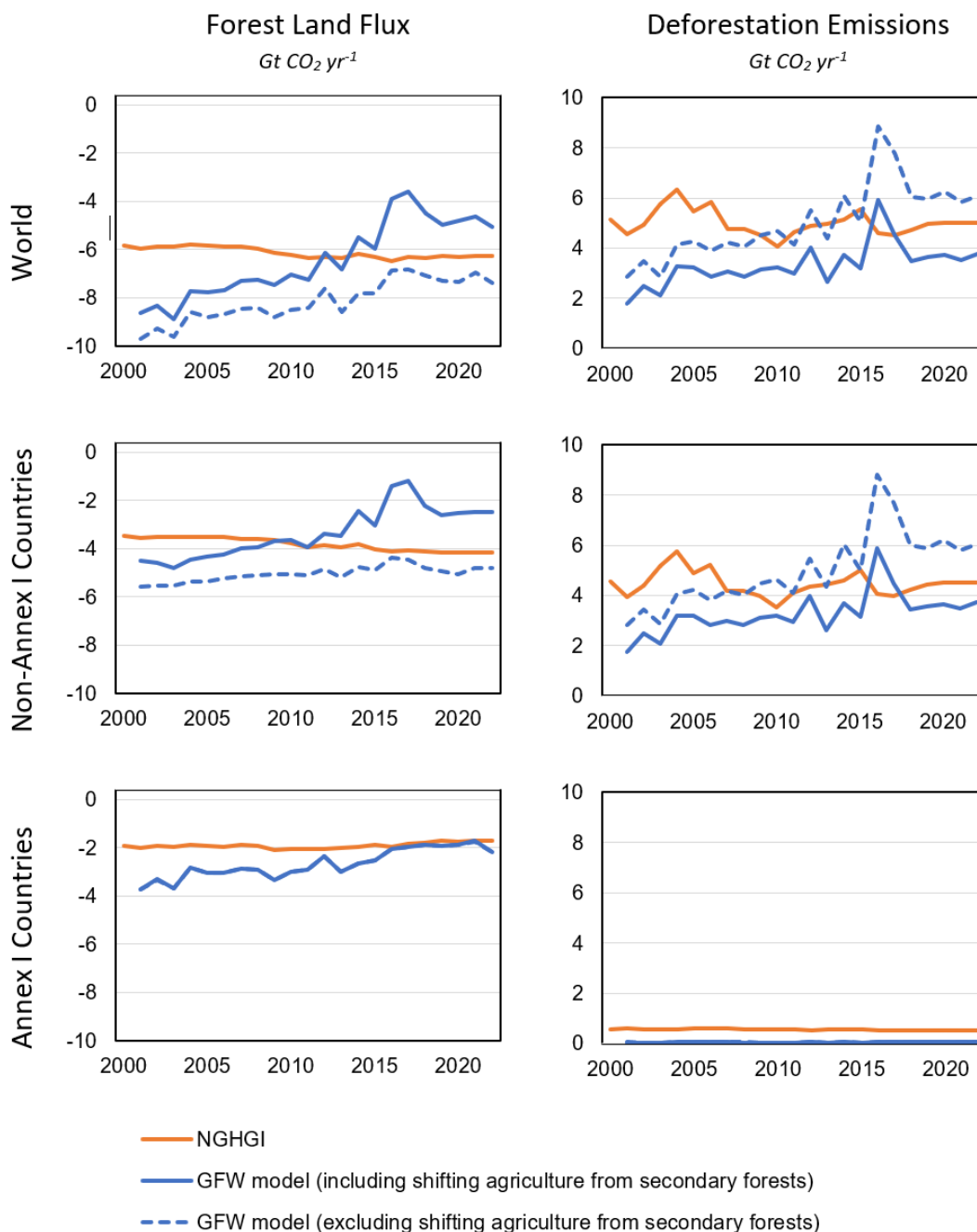
487
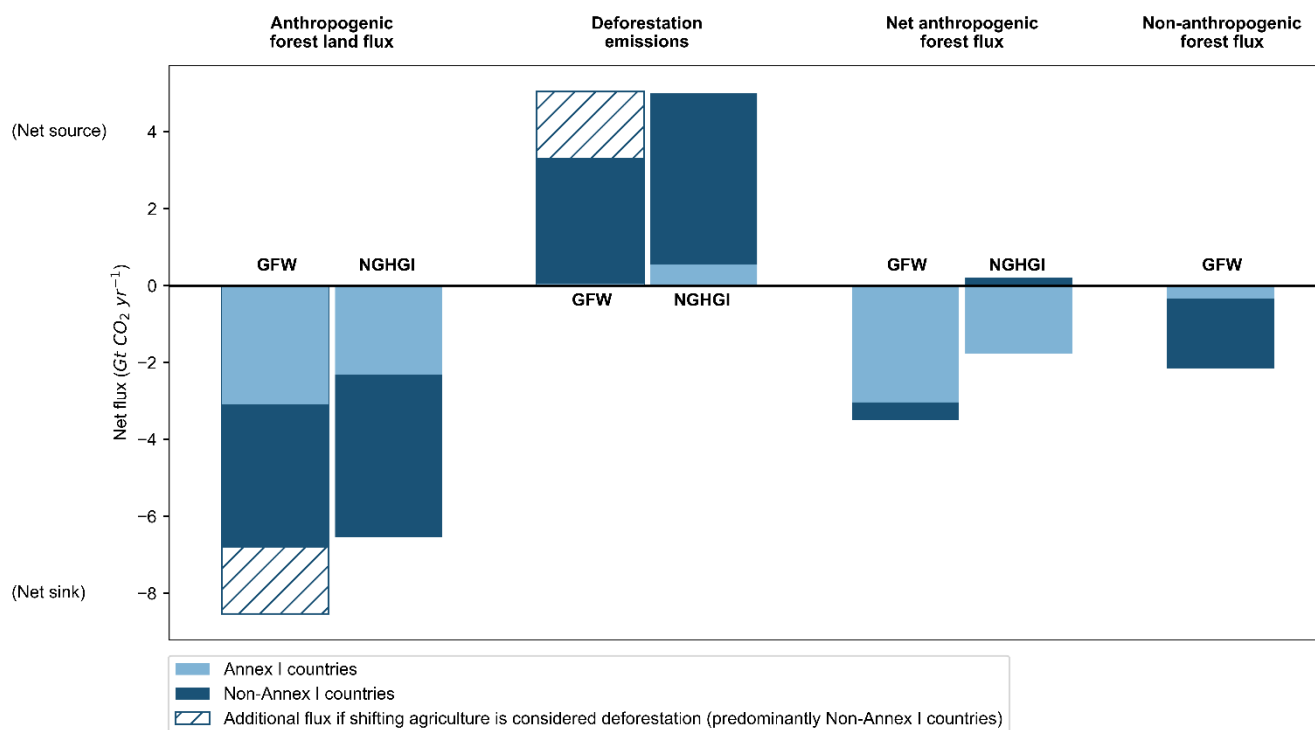
Figure 4. Comparison of average annual forest carbon fluxes (2001–2022) between national greenhouse gas inventories (NGHGI) and the updated GFW flux model. For the GFW flux model, net anthropogenic forest flux is calculated as the sum of the net anthropogenic forest land flux in managed forests and deforestation (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).

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 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

501 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

502 the GFW model than NGHGIs, while deforestation emissions stayed fairly constant in both.

503

504 **Figure 5. Comparison of forest carbon fluxes timeseries (2001–2022) between national greenhouse gas inventories (NGHGIs) and**
505 **the updated GFW flux model for Non-Annex 1, Annex 1 countries, and globally.** NGHGI values shown here exclude any fluxes from
506 harvested wood products, and deforestation emissions are the combined emissions from both deforestation and organic soils to conceptually

507 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
508 timeseries: one where emissions from shifting agriculture in secondary forests is included in that reporting category and one where those
509 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
510 line.

4 Discussion

512 We focus our discussion on the following topics. First, we examine how the updated GFW forest flux model compares with

513 results from a recent global estimate of forest fluxes by Pan et al. (2024) and the Global Carbon Budget (GCB). Second, we

514 discuss how fully geospatial, Earth observation-based forest flux estimates can be translated into the reporting categories of

515 NGHGIs and how transparency in both approaches can result in methodological improvements. Third, we discuss strengths

516 and limitations of GFW's Earth observation-based forest carbon flux model. Fourth, we outline future research topics which

517 provide partial solutions to the model's current limitations.

4.1 Comparison with other recent global flux estimates

519 Pan et al. (2024) is a relevant comparison for the GFW model because both include only forests and report gross rather than

520 net fluxes. Pan et al. (2024) estimated gross removals by forests, gross emissions from tropical deforestation, and the global

521 forest carbon sink by synthesizing forest plot data (inventories and long-term monitoring sites) from 1990 onwards. The

522 removals estimates are conceptually similar (e.g., both include established and new forests), but the emissions estimates have

523 different scope (global for GFW, tropical for Pan et al. 2024) (Table 5). The global net fluxes from Pan et al. 2024 and the

524 updated GFW model are remarkably similar given their entirely different approaches, and thus provide multiple lines of

525 evidence for a forest sink of around 6 Gt CO_2 yr^{-1}. Differences in gross emissions and removals between the data sources likely

526 arise from different scopes and system boundaries, but may be balanced out when combined in the global net flux. Pan et al.

527 estimated higher tropical gross emissions than the GFW model did for the tropics and subtropics for 2001-2019. When the

528 GFW model's gross emissions (CO_2 only) are limited to the tropics and subtropics and one geospatially implemented definition

529 of deforestation (tree cover loss due shifting agriculture in primary forest, and all commodity- and urbanization-driven tree

530 cover loss), it estimates 3.2 Gt CO_2 yr^{-1}, well below the tropical deforestation estimate of Pan et al. 2024. More broadly

531 including all tree cover loss in the tropics and subtropics, the GFW model estimates gross emissions of 6.3 Gt CO_2 yr^{-1}.

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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.

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 (-0.2))[d]	-13 (gross, global)	-11.4 (net, non-anthropogenic)
Net	-6.1 (net, all forests)[e]	-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 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.

[e] 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 anthropogenic carbon fluxes from land use and DGVMs to estimate the natural land sink, 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.

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,

564 including removals implicit (but unreported) in the GCB net land-use change estimate (Friedlingstein et al. 2023). Additional

565 reclassification of fluxes from the GFW model into net anthropogenic from land-use change and the natural land sink may be

566 possible for further comparisons with the GCB, as has been done between the GCB and NGHGIs (Schwingshackl et al. 2022).

567 In the comparison of the original GFW model with the GCB, we included a non-spatial estimate of emissions from tropical

568 forest degradation of 2.1 Gt CO_2e yr^{-1} from Pearson et al. 2017 that potentially included some emissions from small-scale

569 disturbances which we assumed our original model did not capture. For this and subsequent comparisons between the GFW

570 flux framework and the GCB, we are discontinuing the inclusion of a non-spatial estimate of degradation emissions from a

571 source external to our framework to maintain its internal consistency and fully geospatial nature. We acknowledge that the

572 GFW model itself is likely omitting both emissions (e.g., from degradation not detected by TCL) and removals (e.g., from low

573 canopy density or regenerating forest), but those are gaps that the model should be able to fill over time (see Sect. 4.4). Adding

574 external data such as Pearson et al. 2017 risks double-counting emissions in the global total. As more geospatial data on

575 distinguishing deforestation from degradation (Vancutsem et al., 2021) becomes available globally, and geospatial data on the

576 emission and removal factors associated with forest degradation (Holcomb et al., 2024) and recovery (Heinrich et al., 2023b)

577 becomes available, it may be possible to reintegrate forest degradation and its associated fluxes.

4.2 Translating between Earth observation-based fluxes and NGHGIs

579 Our goal in translating GFW model results into a NGHGI reporting framework was to provide independent estimates of forest-

580 based GHG fluxes based on globally consistent, Earth observation-based forest flux data in the reporting categories that

581 national policymakers use. It was not to reproduce how countries classify their managed land, report their forest fluxes in

582 practice, or compare fluxes for individual countries. For example, we did not rely solely on the use of managed land polygons

583 for Case 1 countries to define managed forest; if our observations detected direct human activity in unmanaged polygons, we

584 assigned those fluxes as anthropogenic forest land fluxes or deforestation. Thus, although this translation makes the GFW

585 model more conceptually similar with NGHGIs in that the outputs are supposed to represent the same fluxes, they are still not

586 necessarily entirely comparable because we did not exactly reproduce what countries do in practice within their NGHGIs. It

587 demonstrates that the GFW model is sufficiently flexible to approximate the system boundaries of anthropogenic fluxes in the

588 IPCC reporting framework and that Earth observation models can be used to independently monitor anthropogenic GHG fluxes

589 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

590 NGHGIs and the GCB has been largely explained (Grassi et al. 2023) and translation between NGHGIs on the one hand and

591 bookkeeping models and DGVMs on the other is becoming routine (e.g., Schwingshackl et al. 2022); this work is the start of

592 a similar process for explaining the gap between NGHGIs and Earth observation-based models, primarily through reallocation

593 of emissions and removals to match NGHGIs' land use categories and filtering the results with maps of managed forest as a

594 proxy to delineate anthropogenic from non-anthropogenic fluxes.

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595 Although the conceptual alignment produces quantitatively similar annual average fluxes for the GFW model and NGHGIs
596 globally and for Non-Annex 1 countries, the trends from NGHGIs and the GFW model differ (Fig. 5). For Non-Annex 1
597 countries, where the trends in each data source are most evident, NGHGIs reported the forest land sink strengthening slightly
598 while deforestation emissions fluctuated but were generally steady. The GFW model, on the other hand, reported a weakening
599 sink in forest land and deforestation emissions that increased correspondingly. The tight association between the decreasing
600 forest land sink and increasing deforestation emissions in the GFW model is due to the use of average annual gross removals
601 over time (i.e. a constant value), with only gross emissions varying year to year. In NGHGIs, forest land and deforestation can
602 both change through time and are therefore not driven by the trajectory of just one flux. Quantitative similarity between the
603 GFW model and NGHGIs may be further improved when the GFW model's gross removals can vary through time as well
604 (Sect. 4.4). Moreover, for Non-Annex 1 countries, results from the GFW model and NGHGIs have converged for forest land
605 and deforestation since around 2010, with the two GFW model scenarios bracketing NGHGI fluxes from both reporting
606 categories after that year. This indicates that the GFW model, and the tree cover loss data that underlies its gross emissions,
607 were perhaps under-detecting loss as detected by NGHGIs in the early part of the time series.

608 Exploration of the differences between the GFW model and specific countries' NGHGIs is beyond the scope of this paper;
609 future work may include more detailed reclassification of the GFW model's fluxes and comparisons with specific regions or
610 countries. Further sub-setting results from our framework to differentiate anthropogenic and non-anthropogenic fluxes for
611 comparison with NGHGIs for individual regions, countries and other local-scale analyses is possible and encouraged. Indeed,
612 comparison of the GFW model and countries' inventories is a way to explore the complementarity and discrepancies between
613 Earth observation data and inventories, encourage transparency for both, and improve both approaches (Heinrich et al. 2023a).
614 For example, one advantage of the GFW model, which includes forest fluxes undifferentiated by human contribution, is that
615 it encompasses both anthropogenic and non-anthropogenic fluxes. When this translation exercise is conducted, GHG fluxes
616 from managed land can be put in the context of all land fluxes and compared with fluxes from unmanaged land. Because
617 NGHGIs are not required to estimate fluxes from unmanaged land (just report the area of unmanaged land), aggregation of
618 NGHGIs does not provide context for managed land fluxes with unmanaged land fluxes. In other words, the GFW model can
619 indicate the scale of non-anthropogenic fluxes that countries are not reporting in their NGHGIs (which are nevertheless affect
620 atmospheric CO_2 concentrations and global temperature), while NGHGIs are necessary for the GFW model to approximate
621 the anthropogenic fluxes that are being monitored by countries and the focus of the Paris Agreement. An alternative approach
622 for reconciling global models and NGHGIs would be for NGHGIs to report all land fluxes in the country, in both managed
623 and unmanaged land (Nabuurs et al. 2023), but adoption of this seems unlikely.

624 Future improvements to our flux reclassifications, which may improve regional or country-level comparisons, could include
625 customizing tree cover density thresholds that align more closely with countries' forest definitions to filter forest extent and
626 thus the associated fluxes on a country-by-country basis. Additionally, we used maps of primary forests and intact forest

627   landscapes from 2001 and 2000, respectively, to approximate the extent of unmanaged forests at the initial year of our model

628   framework. Further refinement to the GFW model's estimates of fluxes from managed lands could include recategorizing

629   forests as "managed" or "unmanaged" using updated primary/intact forest boundaries in different years to reflect changes to

630   countries' managed land area over time whenever known. Furthermore, for simplicity, we considered all forest removals as

631   forest land and did not differentiate the relatively small amount of removals from forest gain as "other land converted to forest",

632   which is a category that countries report in their NGHGIs. Another improvement would be to separate the emissions from

633   drainage of organic soils and the emissions from deforestation in the GFW model; in the current translation, deforestation

634   emissions and organic soil emissions are combined in both data sources. Separating them would further narrow the conceptual

635   similarity, which would matter most in countries with high emissions from organic soils. Finally, emissions from fires

636   occurring in unmanaged land could theoretically be differentiated into anthropogenic vs. non-anthropogenic using additional

637   geospatial data, rather than our simplified assumption that all fires in unmanaged forests are non-anthropogenic in origin.

638   While our geospatial, Earth observation-based framework permits estimation of fluxes for any geospatially defined forest and

639   the inclusion (or exclusion) of any area of interest, it cannot distinguish between managed versus unmanaged land without

640   relevant spatial data. Thus, the ability of the GFW model, and Earth observation models in general, to be translated into IPCC

641   categories largely depends on the transparency with which countries report on their managed lands. Three countries that

642   currently apply the managed land proxy (Canada, Brazil, and the United States) have publicly available managed land maps

643   (Ogle et al. 2018). For all remaining countries, the use and application of the managed land proxy was assumed based on the

644   available information from country reports. In the absence of this information, primary or intact forest have been used as proxy

645   for unmanaged forest. With sufficient transparency and flexibility in both the Earth observation-based products and NGHGIs,

646   the differences between them can be explored.

647   A crucial driver of forest disturbance, and thus emissions, in the GFW model is shifting agriculture. However, the comparison

648   between GFW and NGHGI is complicated by the fact that countries typically do not provide specific information on shifting

649   agriculture in their land representation; according to the IPCC guidelines it can be implicitly included either in forest or in

650   other land uses (e.g., cropland) (Grassi et al. 2023). Thus, we developed two scenarios for the treatment of fluxes from shifting

651   agriculture (Fig. 4). Hopefully, as countries begin to submit their Biennial Transparency Reports under the Paris Agreement,

652   their use of the managed land proxy, the treatment of shifting agriculture, and other exclusions from inventories will be

653   progressively clarified and translation between approaches will become more accurate. Although they are time-consuming to

654   implement, the goal should be for the kinds of Earth-observation based adjustments described by Heinrich et al. 2023a for

655   Brazil to be achievable for all countries. This will ultimately facilitate comparisons between global models such as the GFW

656   model and NGHGIs, provide national policymakers with timely geospatial data in their own reporting terms, and build

657   confidence in the magnitude and trends of land-based anthropogenic emissions and sinks (Grassi et al. 2023).

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, but the tree cover loss timeseries 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

690 as forests grow or climate changes. Thus, the GFW model does not incorporate growth-response curves or climate feedbacks,
691 unlike in Earth System Models.

4.4 Anticipated model developments

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

696 For activity data, anticipated model developments include:

697 1. Global forest change data: The model will use annual forest extent, loss, and gain maps for greater temporal detail
698   (similar to Potapov et al. 2019 or Turubanova et al. 2023) and improved representation of carbon dynamics. For
699   example, the year of tree cover gain will be known (at least approximately) and repeated forest disturbances in the
700   same location will be captured (unlike in Hansen et al. 2013), allowing the generation of annual time series of gross
701   emissions, gross removals, and net flux. This should further enhance comparability of flux trends with the GCB and
702   NGHGIs.

703 2. Drivers of forest loss: The model currently uses a global map of drivers of forest loss at 10-km resolution (Curtis et
704   al. 2018, updated to 2023) but research on mapping drivers of forest loss is advancing. An anticipated 1-km resolution
705   global map of drivers of forest loss will detect drivers that are not dominant at 10-km (and are therefore not mapped)
706   but are important at smaller scales, such as loss due to small-scale infrastructure and built-up areas amid loss due to
707   agricultural commodity expansion. Moreover, a separate driver class of forest loss due to natural disturbances would
708   further help with parsing natural and anthropogenic fluxes for translation into NGHGI reporting categories.

709 3. Delineation of organic soils and their drainage status: The GFW model currently compiles several different data
710   sources (Table 2), which have different definitions and resolutions, to map organic soil extent. The GFW model would
711   benefit from a globally consistent organic soil map based on comprehensive aggregation of soil samples and
712   standardized mapping methods. However, it is not just the extent of organic soils but their drainage that affects
713   emissions in the GFW model. Thus, we are exploring improved mapping of organic soil drainage using recent
714   improvements in delineating road networks (OSM 2010; Meijer et al. 2018; Engert et al. 2024), drainage canal
715   networks (Dadap et al. 2021), and land cover (Potapov et al. 2022). More comprehensive maps of organic soil extent
716   and drainage will improve where the GFW model reports these emissions, particularly affecting non-CO_2 GHG
717   emissions.

718 4. Improved initial forest age map: The GFW model currently classified forested pixels into primary forest, secondary
719   forest > 20 years, and secondary forest < 20 years old in 2000 using a few simple rules (described in Harris et al.

720 2021). However, a forest age map such as Besnard et al. 2021 could be used to refine the assignment of starting age

721 categories—particularly for secondary forests—or to determine where forest is along age-growth curves.

722 5. Extent of planted forests and trees: The model currently uses SDPT v2.0 (Richter et al. 2024) but plans are underway

723 for SDPT 3.0, which will improve differentiation between natural and artificial stands in the United States and

724 Canada, along with other improvements for delineating planted tree extent in other countries.

725 For emission and removal factors, anticipated model developments include:

726 1. Improved spatial and temporal resolution of forest carbon removals: The dominant role of removal factor uncertainties

727 in the uncertainty analysis highlights the need to further improve understanding of spatial and temporal variation in

728 forest carbon removals. Combining plot-level biomass estimates with spaceborne observations to produce static

729 biomass maps is well established (e.g., Saatchi et al. 2011, Santoro et al. 2021) and mapping biomass change is being

730 explored (Xu et al. 2021) but these do not provide spatiotemporally variable removal factors. An ecology-based, yet

731 still spatial, way to map removal factors could combine tree-level information collected in field plots with machine

732 learning methods to map forest population structure through time, including variables that influence biomass change

733 like upgrowth, mortality and recruitment for different forest types (Ma et al. 2020). Such an approach can generate

734 spatial and temporal predictions of how biomass changes across space and time that can be validated with forest plot

735 data. In conjunction with a time series of tree cover gain (in activity data list above), this would result in fully temporal

736 gross removals. Alternatively, growth curves for natural regeneration of forests could be developed, using methods

737 similar to Cook-Patton et al. 2020.

738 2. Improved maps of soil carbon dynamics: The GFW model currently uses a benchmark map of soil organic carbon

739 density in mineral soil in 2000 and assumes loss of specific fractions of carbon under certain types of tree cover loss,

740 following a Tier 1 approach from IPCC 2019. However, a timeseries of soil organic carbon density in mineral soil

741 would support more realistic mapping of SOC dynamics.

742 Additionally, opportunities remain to compare GFW model emissions and removals with NGHGIs, bookkeeping models, and

743 regional or local data (e.g., Araza et al. 2023, Heinrich et al. 2023b). Such work would further our understanding of the

744 complementary roles of Earth observation-based forest carbon models and other approaches to forest flux monitoring.

745 **5 Data and code availability**

746 Gross emissions, gross removals, and net flux are available for download as 10x10 degree geotifs in 0.00025x0.00025-degree

747 resolution. Gross emissions files (Gibbs et al. 2024a) are at https://doi.org/10.7910/DVN/LNPSGP/ Gross removals files

748 (Gibbs et al. 2024b) are at https://doi.org/10.7910/DVN/V2ISRH. Net flux files (Gibbs et al. 2024c) are at

749 https://doi.org/10.7910/DVN/TVZVBI. Data are also available as assets on Google Earth Engine at

750 https://code.earthengine.google.com/ae55707e335894d7be515386195390d2. Code is available at
751 https://github.com/wri/carbon-budget.

6 Conclusion

753 The updated Earth observation-based GFW forest carbon flux framework continues to show a substantial net sink for CO_2 in
754 forests globally, while also reporting sizeable gross emissions over half as large as gross removals since 2000. This highlights
755 ongoing opportunities to protect the forest carbon sink across a broad area and also reduce emissions from forest loss, especially
756 in hotspots of emissions that are discernable with our geospatial framework. The revised uncertainty analysis—with its
757 dramatic reduction in uncertainty in gross removals—demonstrates the importance of refining forest carbon sequestration rate
758 estimates. The flexibility of the model supports analyses at a range of spatial scales, while its operational nature means it can
759 incorporate new and existing Earth observation products and provide timely maps and data. Our translation of the GFW
760 model's fluxes into the reporting framework that NGHGIs use provides another lens through which to look at country-level,
761 land-based climate mitigation and is a resource for national policymakers interested in timely, spatial data on land fluxes. It
762 also demonstrates the two approaches' ability to improve, assess, and potentially confirm each other. Ultimately, confidence
763 and transparency are needed in assessments of progress towards the Paris Agreement, and Earth observation-based forest
764 carbon models are another tool to build consensus.

Author contributions

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

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1036 **Appendix A**

1037 **Table A1. Comparison of forest carbon fluxes in Annex 1 countries, Non-Annex 1 countries, and globally between the GFW flux**
1038 **model and national greenhouse gas inventories (NGHGIs).** Ranges in reported GFW values here come from two different scenarios: one
1039 scenario where emissions from shifting agriculture in secondary forests is included in forest land, while the other scenario includes all
1040 emissions from shifting agriculture in deforestation.

	Net flux in forest land (Gt CO$_2$ yr^{-1})		Deforestation emissions (Gt CO$_2$e yr^{-1})		Net anthropogenic forest flux (Gt CO$_2$e yr^{-1})		Non-anthropogenic forest flux (Gt CO$_2$e 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

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