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Global maps of twenty-first century forest carbon fluxes

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Managing forests for climate change mitigation requires action by diverse stakeholders undertaking different activities with overlapping objectives and spatial impacts. To date, several forest carbon monitoring systems have been developed for different regions using various data, methods and assumptions, making it difficult to evaluate mitigation performance consistently across scales. Here, we integrate ground and Earth observation data to map annual forest-related greenhouse gas emissions and removals globally at a spatial resolution of 30 m over the years 2001–2019. We estimate that global forests were a net carbon sink of $-7.6 \pm 49 \text{ GtCO}_2\text{e yr}^{-1}$, reflecting a balance between gross carbon removals ($-15.6 \pm 49 \text{ GtCO}_2\text{e yr}^{-1}$) and gross emissions from deforestation and other disturbances ($8.1 \pm 2.5 \text{ GtCO}_2\text{e yr}^{-1}$). The geospatial monitoring framework introduced here supports climate policy development by promoting alignment and transparency in setting priorities and tracking collective progress towards forest-specific climate mitigation goals with both local detail and global consistency.

Climate change must be addressed by various actors including scientists, policymakers, companies, investors and civil society, all of whom operate under different mandates and capabilities. Both IPCC reports^{1,2} and the Paris Agreement³ recognize that climate change mitigation goals cannot be achieved without a substantial contribution from forests but monitoring the extent to which forests impact atmospheric greenhouse gas (GHG) concentrations is challenging. Opposing fluxes (emissions from sources (+) and removals by sinks (-)) occur simultaneously within regions on the basis of where and when disturbance and management take place, interannual variability can be high and land-use patterns are more dynamic and operate on finer spatiotemporal scales than reflected in most global models⁴. Furthermore, ability to distinguish anthropogenic from non-anthropogenic effects is limited on the basis of direct observation² and most estimation methods offer few details about where, when and why forest fluxes occur. Yet understanding the magnitude, drivers and spatial distribution of carbon fluxes across the world's forests, and how they can be managed both to reduce emissions and enhance removals, is increasingly important for climate policy and the various actors developing nature-based solutions⁵.

Current estimates of terrestrial GHG fluxes vary with respect to scope, definitions, assumptions and level of transparency and completeness. At the global scale, the net annual carbon dioxide (CO₂) flux from anthropogenic land-use and land-cover change—driven mainly by tropical deforestation—is estimated in IPCC reports^{1,2} and the Global Carbon Project⁶ by a bookkeeping model^{7,8} or by dynamic global vegetation models⁶. The remaining

non-anthropogenic sink of atmospheric carbon on land—predominantly forests⁹—is then inferred as the residual of the other terms of the global carbon budget¹. Another approach compiles national GHG inventories (GHGIs), which reflect methodologies developed by the IPCC and agreed to under the United Nations Framework Convention on Climate Change^{10,11}. The quality, methodological complexity and sources of data used by each country vary, as do the completeness and frequency of reporting. These approaches produce dissimilar global net forest fluxes; GHGI estimates compiled from country reports are 4.3 GtCO₂ yr⁻¹ lower than global estimates from models summarized in IPCC reports—a discrepancy larger than the total annual emissions of India, the world's third highest emitter¹². A substantial part of this discrepancy (about 3.2 GtCO₂ yr⁻¹) can be explained by conceptual differences in what is counted in the anthropogenic forest sink. Beyond this large disparity in global estimates, data and methodological mismatches also exist across project, subnational and national forest GHG measurement systems, leading to complications around integrating smaller-scale activities into larger national or subnational monitoring programmes¹³ and around the potential international transfer of forest-related emission reductions versus those achieved as part of a country's own nationally determined contribution¹⁴. In sum, the complexity and lack of spatial detail in GHG measurement systems contributes to confusion about the role forests play in climate mitigation targets and discourages the transformational action and ambition needed in the forest sector to achieve global climate goals.

Here, we introduce a transparent, independent and spatially explicit global system for monitoring the collective impact of

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forest-related climate policies implemented by diverse actors across multiple scales. We complement existing global forest carbon flux estimation approaches of large area vegetation models and aggregation of national inventories with a third approach that capitalizes on recent advances in Earth observation. Using recently revised IPCC guidelines as a methodological framework^{10,11}, we separately map GHG emissions (sources) and carbon dioxide removals (sinks) from global forest lands at 30-m resolution between 2001 and 2019 (Methods). Areas of forest extent, loss and gain from the Global Forest Change product of Hansen et al.¹⁵ form the basis of the activity data. By co-locating activity data with spatially explicit emission and removal factors developed from integrating ground and Earth observation monitoring data on land use and management type, forest type, forest age class, fire history and biomass and soil carbon stocks, we separately map gross annual carbon removals occurring within natural, seminatural and planted forests and gross annual emissions arising from five dominant drivers of forest disturbance. We then map the difference between gross emissions (+) and gross removals (−) as the net annual forest-related GHG flux, which may be positive or negative in an area depending on the balance of gross fluxes. Tracking gross emissions and removals separately, rather than solely the net balance between the two, underscores the dual role of forests as sources and sinks in the global carbon cycle and facilitates more complete and transparent accounting of the individual pathways involved in forest-based mitigation (reducing emissions and increasing removals).

Global distribution of forest emissions and removals

Between 2001 and 2019, deforestation and other satellite-observed forest disturbances resulted in global gross GHG emissions of $8.1 \pm 2.5 \text{ GtCO}_2\text{e yr}^{-1}$ (mean \pm s.d.). Carbon dioxide (CO_2) was the dominant GHG; methane (CH_4) and nitrous oxide (N_2O) emissions from stand-replacing forest fires and drainage of organic soils in deforested areas accounted for 1.1% of gross emissions ($0.088 \text{ GtCO}_2\text{e yr}^{-1}$). Over the same period, gross carbon removals by forest ecosystems were $-15.6 \pm 49 \text{ GtCO}_2\text{e yr}^{-1}$. Taken together, the balance of these opposing fluxes (gross emissions and gross removals) yields a global net GHG forest sink of $-7.6 \pm 49 \text{ GtCO}_2\text{e yr}^{-1}$ (Table 1 and Fig. 1). The large uncertainties in global gross removals and net flux are almost entirely due to extremely high uncertainty in removal factors from the IPCC Guidelines¹¹ applied to old secondary temperate forests outside the United States and Europe (Supplementary Table 1).

Tropical and subtropical forests contributed the most to global gross forest fluxes, accounting for 78% of gross emissions ($6.3 \pm 2.4 \text{ GtCO}_2\text{e yr}^{-1}$) and 55% of gross removals ($-8.6 \pm 7.6 \text{ GtCO}_2\text{e yr}^{-1}$) (Table 1). While these forests removed more atmospheric carbon than temperate and boreal forests on a gross basis (-8.6 versus -4.4 and $-2.5 \text{ GtCO}_2\text{e yr}^{-1}$, respectively), tropical and subtropical forests contributed just 30% to the global net carbon sink; about two-thirds of the global net sink was in temperate (47%) and boreal (21%) forests, resulting from substantially lower gross emissions there than in the subtropics and tropics (0.87 and 0.88 versus $6.3 \text{ GtCO}_2\text{e yr}^{-1}$, respectively).

Just six large forested countries (Brazil, Canada, China, Democratic Republic of the Congo, Russia and the United States) accounted for 51% of global gross emissions, 56% of global gross removals and 60% of net flux. Forests in nearly all countries were net carbon negative, that is, gross carbon removals from established and regrowing forests exceeded gross emissions from land-use change and other forest disturbances. The main exceptions were in Indonesia, Malaysia, Cambodia and Laos, where annual gross emissions across these countries ($1.36 \text{ GtCO}_2\text{e yr}^{-1}$), including peat drainage and burning ($0.14 \text{ GtCO}_2\text{e yr}^{-1}$), exceeded gross removals ($-0.83 \text{ GtCO}_2\text{e yr}^{-1}$) (Fig. 2). Globally, 72% of gross removals were concentrated in older (>20 yr) secondary natural and seminatural

forests, 12% in tropical primary forests, 10% in plantations, 3.5% in young (<20 yr) forest regrowth, 1.3% in mangroves and 0.34% in boreal and temperate intact forest landscapes (Table 1).

Fluxes for specific localities and drivers of forest change

Our analysis enables consistent evaluation of forest GHG dynamics across scales and in custom geographies beyond national or climate domain boundaries (Fig. 1). For example, $\sim 27\%$ of the global net forest GHG sink occurred within protected areas¹⁶. Forests in the Brazilian Amazon were a net carbon source of $0.22 \text{ GtCO}_2\text{e yr}^{-1}$ between 2001 and 2019, whereas forests across the larger Amazon River basin—encompassing 514 Mha of forests across nine countries—were a net carbon sink of $-0.10 \text{ GtCO}_2\text{e yr}^{-1}$. Although smaller in extent than the Amazon, the net sink in forests of Africa's Congo River basin (298 Mha) was approximately six times stronger ($-0.61 \text{ GtCO}_2\text{e yr}^{-1}$), reflecting nearly identical gross removals (-1.1 versus $-1.2 \text{ GtCO}_2\text{e yr}^{-1}$) but gross emissions that were half those of the Amazon basin (0.53 versus $1.1 \text{ GtCO}_2\text{e yr}^{-1}$).

From overlaying forest GHG flux maps in Fig. 1 with a global map of dominant drivers of forest disturbance¹⁷, we estimate that commodity-driven deforestation was the largest source of gross forest-related emissions between 2001 and 2019 ($2.8 \text{ GtCO}_2\text{e yr}^{-1}$) and occurred primarily in the rainforests of South America and Southeast Asia. Forests in shifting agriculture landscapes, a dominant land use in the tropics characterized by cycles of small-scale forest clearing of both primary and secondary forests followed by secondary regrowth, contributed another $2.1 \text{ GtCO}_2\text{e yr}^{-1}$ to gross emissions and $-3.3 \text{ GtCO}_2\text{e yr}^{-1}$ to gross removals, leading to a net sink in these areas of $-1.2 \text{ GtCO}_2\text{e yr}^{-1}$. Gross emissions from stand-replacing forest fires, occurring primarily in temperate and boreal forests, averaged $0.69 \text{ GtCO}_2\text{e yr}^{-1}$. Forestry-dominated landscapes, comprised of both plantations and natural and seminatural forests, were a net sink of $-3.3 \text{ GtCO}_2\text{e yr}^{-1}$ between 2001 and 2019. This reflects $2.4 \text{ GtCO}_2\text{e yr}^{-1}$ of gross emissions from harvest offset by $-5.5 \text{ GtCO}_2\text{e yr}^{-1}$ of gross removals from forest management and regeneration and $-0.16 \text{ GtCO}_2\text{e yr}^{-1}$ of increased carbon storage in harvested wood products.

A flexible data integration framework

The IPCC Guidelines used as the overarching methodological framework in this analysis^{10,11} provide three tiers of methods, parameters and data sources for GHG flux estimation, where progression from Tier 1 to Tier 3 generally results in more accurate and precise estimates at the expense of more analytical complexity and larger data requirements. For forests, Tier 3 estimates are characterized by the incorporation of repeated, country-specific measurements over time but the land-use definitions and the spatial scale of data sources chosen can impact the resulting estimates. Therefore, in addition to estimating uncertainty in GHG estimates within geographies for which information was available to do so (climate domains), we also conducted sensitivity analyses to demonstrate how estimates change as data inputs and model assumptions are varied within our spatial data integration framework (Supplementary Information). At the global scale, GHG flux estimates were relatively insensitive to changes in model assumptions; estimates for most pixels changed less than 15% in either direction and sources stayed sources while sinks stayed sinks.

However, estimates were more affected by changes in data sources, particularly at local scales. For example, replacing the global 30-m biomass map developed in this study as the basis of emission factors (Extended Data Fig. 1) with a coarser (1-km) resolution biomass map produced by Saatchi et al.¹⁸ for the tropics produced 12% lower gross GHG emissions there than our original estimate. Replacing the 30-m annual tree cover loss data from Hansen et al.¹⁵ in the Brazilian Amazon with annual forest loss data from Brazil's national forest monitoring system¹⁹, which

Table 1 | Forest-related GHG fluxes by climate domain and forest type

Climate domain	Forest type	Forest extent 2000 (Mha)	GtCO ₂ e yr ⁻¹ , 2001–2019					
			Gross emissions	Percentage of global total	Gross removals	Percentage of global total	Net GHG flux	Percentage of global total ^d
Boreal	Primary ^a	38	0.26	3.2	−0.044	0.28	0.22	
	Old secondary (>20 yr)	1,030	0.60	7.4	−2.4	15	−1.8	
	Young secondary (≤20 yr)	22	0.015	0.19	−0.037	0.24	−0.022	
	Plantations/tree crops ^b	0.21	0.000056	0.00070	−0.0027	0.017	−0.0027	
Total boreal		1,090	0.88 ± 0.42	11	−2.5 ± 0.96	16	−1.6 ± 1.1	21
Temperate	Primary ^a	2.3	0.036	0.45	−0.0092	0.059	0.027	
	Old secondary (>20 yr)	560	0.71	8.8	−4.2	27	−3.5	
	Young secondary (≤20 yr)	16	0.049	0.60	−0.039	0.25	0.0092	
	Plantations/tree crops ^b	12	0.071	0.88	−0.14	0.92	−0.073	
Total temperate		590	0.87 ± 0.60	11	−4.4 ± 48	28	−3.6 ± 48	47
Subtropical	Primary ^a	3.6	0.0062	0.076	−0.0058	0.037	0.00035	
	Old secondary (>20 yr)	270	0.46	5.7	−0.84	5.4	−0.38	
	Young secondary (≤20 yr)	13	0.11	1.3	−0.067	0.43	0.040	
	Plantations/tree crops ^c	54	0.40	5.0	−0.71	4.6	−0.31	
	Mangroves	0.070	0.000066	0.00082	−0.0040	0.026	−0.0040	
Total subtropical		340	1.0 ± 0.59	12	−1.6 ± 0.56	10	−0.65 ± 0.81	8.6
Tropical	Primary ^a	1,010	1.8	22	−1.9	12	−0.12	
	Old secondary (>20 yr)	880	1.9	23	−3.8	24	−1.9	
	Young secondary (≤20 yr)	47	0.76	9.5	−0.40	2.5	0.37	
	Plantations/tree crops ^c	47	0.89	11	−0.73	4.7	0.16	
	Mangroves	7.2	0.010	0.12	−0.16	1.0	−0.15	
Total tropical		1,990	5.3 ± 2.4	66	−7.0 ± 7.6	45	−1.7 ± 8.0	22
Global	Primary	1,060	2.1	26	−2.0	13	0.13	
	Old secondary (>20 yr)	2,750	3.7	45	−11	72	−7.7	
	Young secondary (≤20 yr)	99	0.9	12	−0.54	3.5	0.39	
	Plantations/tree crops	113	1.4	17	−1.6	10	−0.23	
	Mangroves	8.7	0.012	0.14	−0.20	1.3	−0.19	
Total global		4,029	8.1 ± 2.5	100	−16 ± 49	100	−7.6 ± 49	100

Average annual gross GHG emissions, gross GHG removals and net GHG fluxes across global forest lands between 2001 and 2019. Estimates reflect forest ecosystem fluxes only; harvested wood products are excluded. Uncertainties are expressed as s.d. Large uncertainties in net flux estimates should be interpreted with caution; s.d. are very large relative to the estimates in part because net flux estimates reflect the sum of negative (removals) and positive (emissions) terms, complicating the combination of their error terms. ^aThe extent of primary forests was delineated differently for tropical and extratropical regions (Methods). ^bFluxes occurring within seminatural managed forests are reported in the relevant secondary forest category (old or young). ^cFluxes reported in the plantation/tree crop category include those associated with conversion of natural forests to plantations or tree crops (for example, oil palm) over the 2001–2019 analysis period. ^dCalculating percentages of net flux by forest type is complicated by the mixture of sources and sinks among forest types, and is thus omitted.

excludes deforestation events smaller than 6.25 ha, reduced average gross emissions there from 1.1 to 0.74 GtCO₂e yr⁻¹. This difference arises from increased detection of emissions from small forest clearings. Both examples highlight the value of our spatially detailed approach in capturing more changes and larger fluxes occurring at small scales where many human-induced forest changes are occurring. In the United States, replacing Tier 3 removal factors estimated specifically for US forest types and age classes from repeated inventory measurements with generalized Tier 1 defaults from the updated IPCC Guidelines¹¹ led to a 38% stronger net carbon sink there than the original estimate. (See Supplementary Table 2 and Extended Data Figs. 2–8 for additional examples.) These analyses quantitatively and spatially demonstrate tradeoffs between globally consistent analyses and locally derived values that are difficult to aggregate globally and may not be available or comparable across regions. The flexible spatial data integration framework introduced here enhances science-policy coordination by providing a more

systematic, structured, transparent and verifiable system for exploring differences in data, assumptions and resulting estimates than what has been available previously.

Forest fluxes in the global carbon budget

Our results are not directly comparable to other global estimates because other estimates typically reflect all terrestrial fluxes (versus forests only), report only net fluxes (versus gross and net fluxes), include only CO₂ (versus all relevant GHGs) and make assumptions to partition between anthropogenic and non-anthropogenic net fluxes^{2,12}. While the spatial, observation-based framework introduced here permits estimation of fluxes for any forest definition and the inclusion (or exclusion) of any geographic area of interest, it cannot distinguish between anthropogenic versus non-anthropogenic effects or between managed versus unmanaged land until the requisite spatial data become available to differentiate them²⁰. When considering only CO₂ fluxes to improve comparability with the

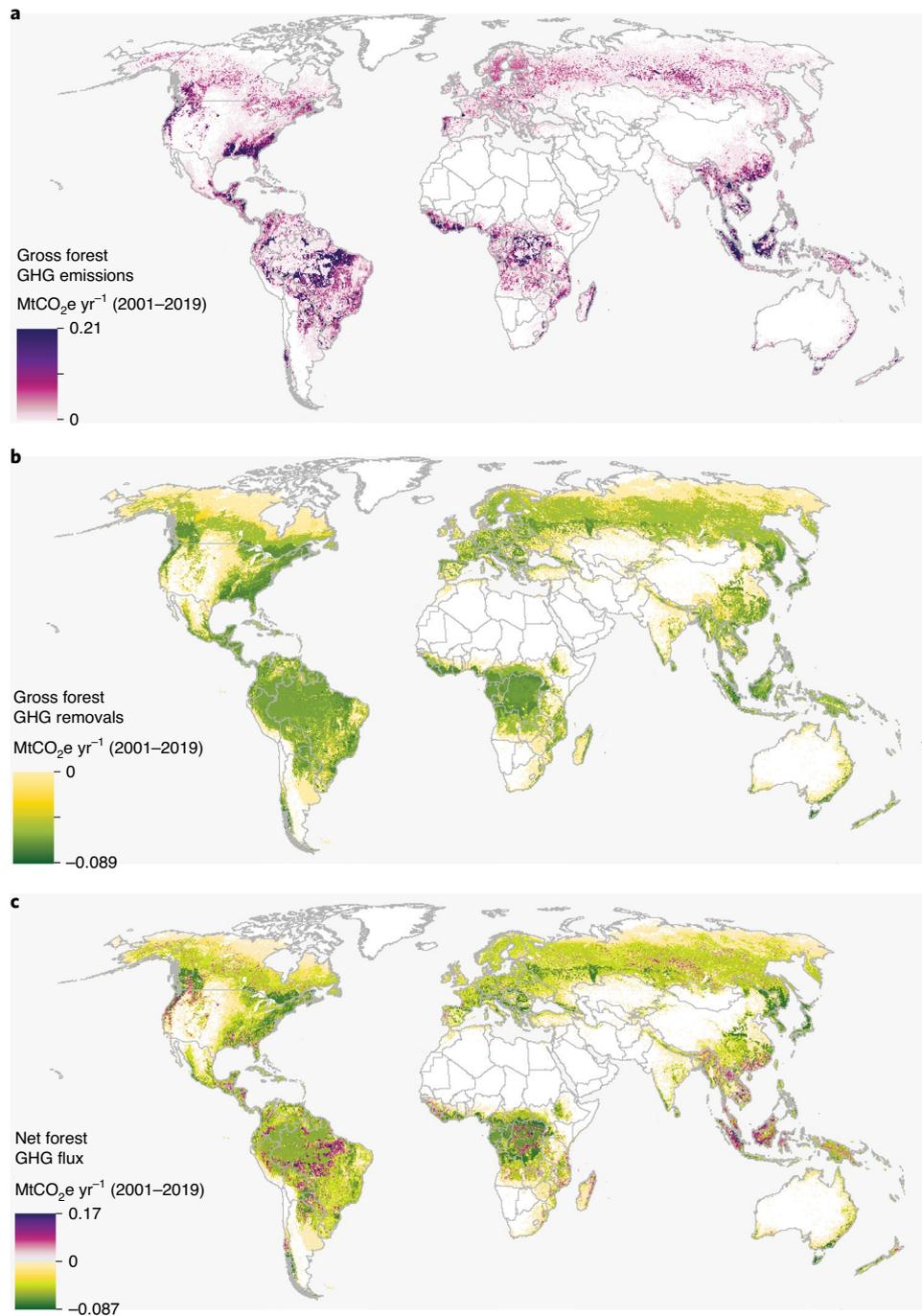


Fig. 1 | Forest-related GHG fluxes (annual average, 2001–2019). **a**, Gross annual GHG emissions. **b**, Gross annual GHG removals. **c**, Net annual GHG flux. For display purposes, maps have been resampled from the 30-m observation scale to a 0.04° geographic grid. Values in the legend reflect the average annual GHG flux from all forest dynamics occurring within a grid cell, including emissions from all observed disturbances and removals from both forest regrowth after disturbance as well as removals occurring in undisturbed forests.

Global Carbon Budget, we estimate a larger net CO_2 sink by forest ecosystems ($-7.8 \text{ GtCO}_2 \text{ yr}^{-1}$) than its estimate of $-5.2 \text{ GtCO}_2 \text{ yr}^{-1}$ for all terrestrial fluxes over the same time period⁶. One potential reason for this difference is that our model underestimates gross forest-related emissions due to the exclusion of forest disturbances that go undetected and unquantified in the medium resolution satellite observations that underpin our analysis. Gross emissions from tropical forest degradation have been estimated as $2.1 \text{ GtCO}_2 \text{ e yr}^{-1}$, with selective logging, fuelwood harvest and non-stand-replacing

fires accounting for 53, 30 and 17% of the total, respectively²¹. Adding this (non-spatial) estimate of gross degradation emissions to our satellite-based gross carbon emission and removal estimates occurring within forest ecosystems, as well as $-0.16 \text{ GtCO}_2 \text{ yr}^{-1}$ of net removals in harvested wood products, yields a revised net forest-atmosphere CO_2 flux of $-5.8 \text{ GtCO}_2 \text{ yr}^{-1}$ (Table 2). Taken together, these estimates of gross removals ($-15.6 \text{ GtCO}_2 \text{ yr}^{-1}$) and gross emissions related to forests (including degradation: $10 \text{ GtCO}_2 \text{ yr}^{-1}$) appear to nearly balance the global carbon budget

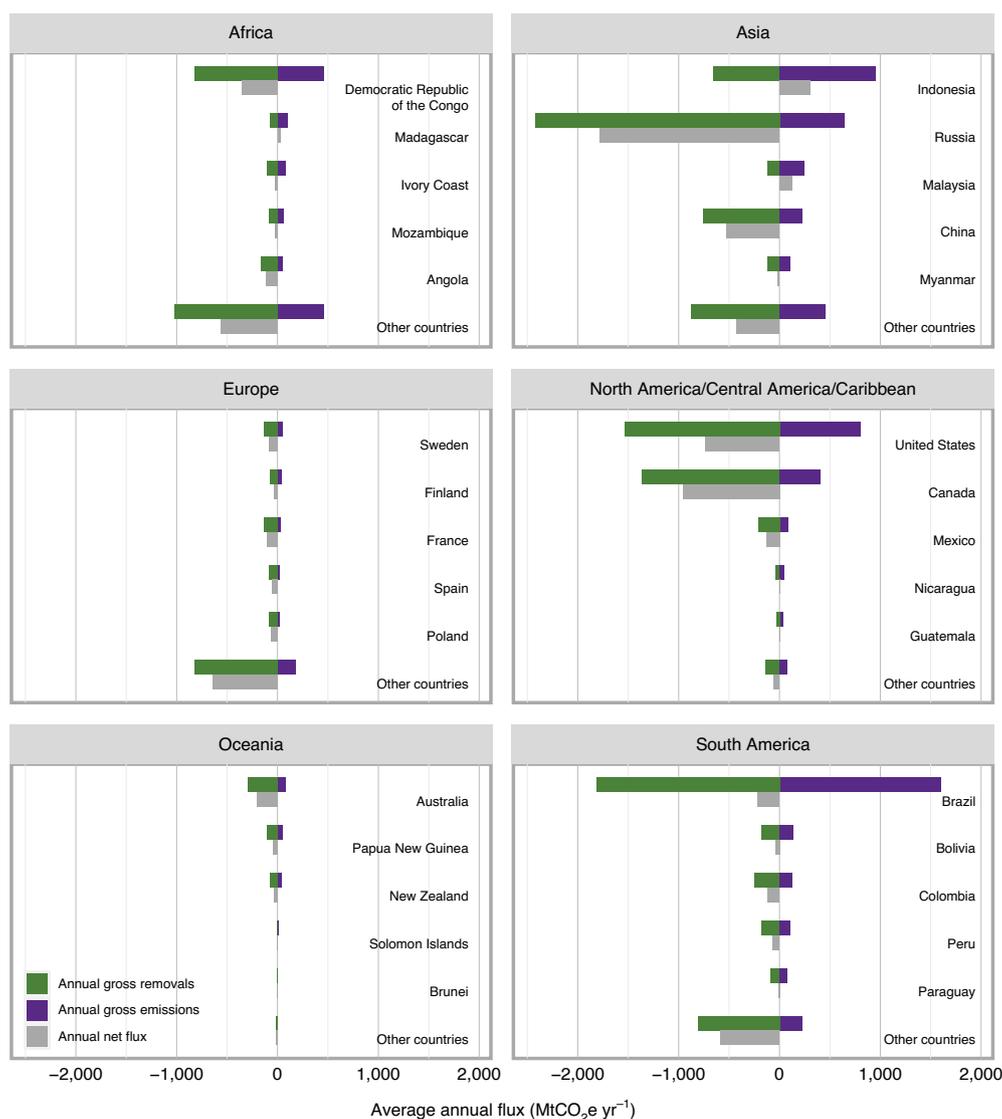


Fig. 2 | Gross and net GHG fluxes from forests by region (annual average, 2001–2019). Net forest-related fluxes (grey bars) are shown with their two component gross fluxes: gross emissions from land-use change and other forest disturbances (purple) and gross removals occurring in undisturbed forests as well as removals from forest regrowth after disturbance (green). The top five countries per region are ranked high to low on the basis of gross emissions, with all other countries in the region grouped into ‘other countries’.

(Table 2) but other important fluxes are omitted from our analysis such as those occurring within grasslands, semi-arid savannas and shrublands²² (due to the 30% per 5 m of tree cover definition used in our analysis), non-stand-replacing fires²³, degradation outside the tropics and other terrestrial fluxes not previously included in any global budget to date²⁴. We include Table 2 to highlight how our gross estimates of forest-related fluxes fit within the context of the global carbon budget but our research is geared towards highlighting forest emission and removal hotspots for policy-relevant applications and stakeholders (Fig. 1), not towards producing a comprehensive and precise accounting of the full terrestrial carbon budget.

Limitations and future improvements

All forest monitoring systems reflect a balance between data availability, scale of applicability, measurement costs, reducing uncertainties and other constraints. Given the urgency of addressing climate change, the time and costs required to develop monitoring systems that reduce uncertainties as far as practicable²⁵ must be balanced

against the potential benefits of publicly accessible, operational and fit-for-purpose systems that provide enough spatial detail to incentivize real, near-term and sustained investment in nature-based climate solutions on the ground. In this study, we combined publicly available data into a global monitoring framework that generates consistent information on forest carbon fluxes cost-effectively over large spatial scales. However, this approach encounters limitations that should be addressed as research progresses.

First, the global forest change data used as the basis of activity data in our analysis are spatially detailed but contain temporal inconsistencies. While the forest loss product is updated annually through 2019, gain has not been updated past 2012 and represents a cumulative total (2000–2012). Therefore, although gross emissions can be estimated annually (Extended Data Fig. 9), estimating annual trends in gross removals and net flux is limited by a lack of a consistent time series on forest regrowth. Globally, GHG flux estimates were relatively insensitive to this limitation; we estimate that expansion of forest extent observed after 2000 accounted for less than 5% of global gross carbon removals, with the vast majority occurring

Table 2 | Comparison of results from this study to the Global Carbon Project, 2001–2018

Global carbon budget, 2001–2018 (GtCO ₂ yr ⁻¹)			
Global Carbon Project			This study
Sources			
Fossil fuel and cement	32.0	Fossil fuel and cement	32.0
Land-use change (net, anthropogenic) ^a	5.3	Forests (gross, all observed disturbances) ^b	7.9
		Forests (gross, unobserved emission sources) ^c	2.1
Total sources	37.3		42.0
Sinks			
Atmosphere	16.9	Atmosphere	16.9
Ocean	8.7	Ocean	8.7
Terrestrial (net, non-anthropogenic) ^d	10.5	Forests (gross, all forests) ^e	15.6
		Harvested wood products	0.16
Total sinks	36.1		41.4
Land (net, all land)	-5.2	Forests (net, all forests) ^f	-5.8
Budget imbalance ^g	1.2		0.6

Estimates from the Global Carbon Project (GCP)²⁸ and this study are not directly comparable due to differences in scope (all land versus forests, respectively), data, methodologies and reporting structure. In GCP reporting, land-use change emissions (sources) reflect the net balance between anthropogenic emissions (+) and removals (-), thus the net emission estimate is lower than gross emissions reported in this study. Similarly, gross removals reported in this study reflect removals across all forest lands, including removals implicit (but unreported) in the net land-use change estimate of GCP. ^aEstimates only net direct anthropogenic effects, including deforestation, afforestation/reforestation and wood harvest. Gross fluxes higher but not reported. ^bGross emissions from all forest disturbances (anthropogenic and non-anthropogenic) observed from Landsat data. Estimate includes CO₂ only for comparability with GCP; non-CO₂ emissions are 0.086 GtCO₂e yr⁻¹. ^cGross emissions from forest degradation in 74 developing countries covering 2.2 billion hectares of forest, from Pearson et al.²¹. ^dIn IPCC's Fifth Assessment Report¹, calculated as the residual of all other terms in the carbon budget. ^eGross removals from all forest processes (direct, indirect and natural). ^fCalculated as the net balance between gross forest ecosystem emissions and removals (7.9 + 2.1 - 15.6 GtCO₂ yr⁻¹) plus an additional net removal of -0.16 GtCO₂ yr⁻¹ in harvested wood products. ^gBudget imbalance is the difference between total sources and total sinks.

instead in forests established before 2000. However, accurate monitoring of the timing of recent regrowth becomes more important in local contexts where rapid forest loss/gain dynamics are occurring, such as in plantations with short rotation cycles and other dynamic areas dominated by intensive forestry or short-fallow shifting cultivation systems (Extended Data Fig. 5). Temporal inconsistencies are also present within the global loss product; one algorithm covers years 2001–2010 and another covers 2011–2019, with later years of loss likely to be more sensitive to changes related to small-scale agriculture, fires and other forms of forest degradation. For these reasons, we report only long-term averages and not annual trends in forest GHG fluxes. A forthcoming 'version 2' global tree cover loss product and an improved global gain product, already piloted for the lower Mekong region of Southeast Asia²⁶, will improve temporal consistency. Incorporating these improvements into the forest GHG flux model will more accurately capture interannual variability in emissions and removals over time and will thus provide a consistent basis for more temporally detailed monitoring of the long-term net impact of forests on atmospheric GHGs²⁷.

Second, information is currently lacking to develop globally consistent and spatially detailed maps of forest carbon removals. In our analysis, uncertainty in gross removals is substantially higher than uncertainty in gross emissions, driven primarily by high uncertainty in removal factors for established forests in temperate regions (Table 1 and Supplementary Table 1). Through the integration of

ground and Earth observation data, several biomass and soil carbon maps have been developed that inform spatially explicit emission factors. However, accurate and precise estimation of forest carbon removal factors requires information derived from long-term forest inventories applied consistently and repeatedly through time across different forest types and age classes. For many of the world's forests, this information does not exist²⁸. Many developing countries have not completed their first forest inventory, let alone repeated inventories. Efforts to combine georeferenced plot networks with other spatially explicit data inputs to create maps over large scales of forest carbon accumulation rates over time, similar to what has been done to develop biomass density maps at a single point in time, have begun but are still in their infancy²⁹. We therefore applied removal factors using a stratification approach, where each forest pixel is assigned a removal factor on the basis of its geographic region, forest type and age class (Methods). Removal factors reflect both ecological forest dynamics (tree growth, mortality and recruitment through natural regeneration) and indirect effects (long-term increases in atmospheric CO₂ concentrations and temperature, nutrient fertilization). Going forward, new satellite missions such as GEDI, ICESAT-2 and BIOMASS will provide repeated measurements of forest height and biomass over time that should improve understanding of spatial variation in rates of carbon removal across heterogeneous forest landscapes.

The global forest carbon monitoring framework introduced here, and the main improvements identified above, allow for efficient prioritization and evaluation of how data updates and improvements influence GHG flux estimates and their uncertainties. As satellite- and ground-based forest monitoring improve, so too will the associated forest GHG flux estimates.

Conclusions

Our analysis reinforces the need to reduce gross emissions from tropical deforestation as a climate change mitigation strategy, while also highlighting the substantial but often underappreciated contribution of intact primary and older secondary forests to carbon dioxide removals. Quantifying gross emissions and removals separately and consistently across all forest lands—and producing maps in addition to tabular statistics—improves transparency in the accounting of factors and geographies contributing to the global net forest GHG flux. It also provides a framework to integrate new and improved data sources over time. Governments interested in spatially prioritizing implementation and tracking of national and subnational forest mitigation targets can increasingly make use of such data. Non-government actors, such as companies aiming to reduce emissions from deforestation associated with commodity supply chains and emerging market mechanisms considering the inclusion of forests for carbon offset programs, could benefit from a globally consistent and spatially explicit forest monitoring system developed using the same internationally accepted methods as national governments use but based on independent observations and with GHG estimates that can be linked to individual actions and generated at scales relevant to diverse climate-related policies, programmes and stakeholders.

The goals of the Paris Agreement—primarily, net zero anthropogenic emissions in the second half of this century—create an imperative to track forest-related emissions and removals transparently and at scales that link more closely to mitigation activities on the ground. As the capacity of national governments to collect, process and analyse data continues to improve, the global forest carbon monitoring framework introduced here can help to enhance transparency, inform forest-related climate policy and implementation initiatives, underpin independent technical assessments, reconcile differences between national reports and scientific studies, and provide a more consistent and comparable basis for tracking progress at local scales and for assessing atmospheric

impacts of global forest change under the Paris Agreement's forthcoming Global Stocktake³⁰.

Online content

Any methods, additional references, Nature Research reporting summaries, source data, extended data, supplementary information, acknowledgements, peer review information; details of author contributions and competing interests; and statements of data and code availability are available at <https://doi.org/10.1038/s41558-020-00976-6>.

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Methods

Study design and scope. We mapped gross and net GHG emissions by sources and removals by sinks from global forest lands by synthesizing information collected from more than 637,000 ground plots, 707,561 waveform lidar observations and other satellite data into a spatial forest carbon monitoring framework. The analysis covers 2001 to 2019 but can be extended to include later years as data are updated. To the extent possible, we adhered to IPCC Guidelines developed for the agriculture, forestry and other land use (AFOLU) sector^{10,11}. In the context of IPCC land-use categories, our analysis covers only forest-related transitions (forest to non-forest, non-forest to forest and forest remaining forest). We applied the IPCC gain-loss method (versus the stock-difference method¹⁰), in which forest carbon (C) stocks in five ecosystem pools were estimated for a base year (2000) after which changes in C stocks were estimated by considering both annual C losses from land-use change and disturbance (conventionally represented by a + sign) as well as annual C gains from forest regrowth (represented by a – sign). We included harvested wood products as a sixth (human-created) carbon pool. We also included methane (CH₄) and nitrous oxide (N₂O) emissions from stand-replacement forest fires and drainage of organic soils associated with a loss of tree cover. We summarized GHG fluxes across all relevant gases and reported in units of CO₂ equivalents (CO₂e) using 100-yr Global Warming Potentials (without climate feedbacks) from the IPCC Fifth Assessment Report¹.

We set all data inputs to a common resolution of 0.00025° × 0.00025° to match the resolution of Landsat-based tree cover change data of Hansen et al.¹⁵. Gross emissions and removals were modelled at this common resolution across approximately 90 billion individual pixels of global forest cover (defined below). We resampled all input layers to this resolution so that outputs can be flexibly aggregated to larger scales. Extended Data Fig. 10 summarizes the overall conceptual approach and Supplementary Table 3 provides a list of data inputs.

Forest definition and extent. Initially, we defined forest extent in the year 2000 similarly to Hansen et al.¹⁵, that is, any 30-m Landsat pixel that met a tree canopy threshold of at least 30% with trees taller than 5 m in height. This initial definition included natural and seminatural forests, plantations and agricultural tree crops such as oil palm and agroforestry systems where minimum height and cover thresholds were met. On the basis of available data, we made four modifications to the original tree cover map to refine our global map of forest extent:

1. We included pixels of tree cover gain since 2000 in addition to tree cover already present in the year 2000.
2. We included only tree cover pixels that also had a corresponding value in the aboveground biomass density map (0.031% of tree cover pixels lacked a biomass value).
3. We excluded all areas of tree cover falling within oil palm plantation boundaries mapped for the year 2000 in Indonesia and Malaysia^{31–34}.
4. We replaced tree cover extent from Hansen et al.¹⁵ with mangrove forest extent using data from Giri et al.³⁵; in areas of geographic overlap, mangroves had priority.

Forest aboveground live biomass density in 2000. We created a year 2000 map of aboveground live biomass density (AGB, in Mg ha⁻¹) at 30-m resolution by combining two maps: one developed specifically for mangroves³⁶ and the other developed to cover all woody vegetation globally (Supplementary Data 1). In areas of geographic overlap, the mangrove biomass map had priority. The basic approach is the same as that used to map tropical biomass at 500-m (ref. ³⁷) and 30-m (ref. ³⁸) resolution; published height–biomass equations were applied to estimate biomass over specific regions and forest types around the world (Extended Data Fig. 1a). These equations, developed by linking observations from airborne or spaceborne lidar to 20,347 ground-measured biomass plots, were applied to estimate aboveground biomass density from spaceborne lidar observations across 707,561 locations globally. To create a continuous biomass map (Extended Data Fig. 1b), separate random forest models were trained for each of six biogeographic realms using predictor variables of Landsat imagery (bands 3, 4, 5 and 7), normalized difference vegetation index (NDVI), normalized difference infrared index (NDII), mean percentage tree cover, mean elevation, mean slope and monthly mean precipitation, temperature and bioclimatic data. Additional details are provided in Supplementary Data 1.

Forest ecosystem carbon pools in 2000. From the 30-m global AGB map, we mapped belowground live biomass density (BGB) using a forest root-to-shoot ratio³⁹ with mangrove-specific ratios based on defaults provided in Table 4.5 of the 2013 IPCC Wetlands Supplement¹⁰. AGB and BGB values were converted to C density values using a biomass-to-carbon ratio of 0.45 for mangroves⁴⁰ and 0.47 for all other forest types^{10,11}. From the final 30-m AGB map we estimated dead wood and litter biomass densities per pixel as constant fractions of AGB using a lookup table based on global ecological zone, elevation and precipitation regime⁴¹ (Supplementary Table 4). Dead wood and litter biomass densities were converted to C densities using IPCC conversion factors¹⁰.

Soil organic carbon density in the top 30 cm of mineral soils was mapped using SoilGrids250 (v.2.0)⁴² after resampling from its original spatial resolution of 250 m

to match the common 30-m resolution of our analysis. For mangrove forests, we used a 30-m soil carbon map developed specifically for mangroves⁴³. We delineated locations of organic (peat) soils using maps summarized in Supplementary Table 3.

We used these five forest carbon pool maps as the basis for estimating emission factors associated with various forest disturbances (see below).

Activity data. Activity data were defined using the global forest change product of Hansen et al.¹⁵ with loss updated annually on Global Forest Watch. In the model, all pixels defined as forest were classified into one of four categories: (1) loss only; (2) gain only; (3) both loss and gain; or (4) no change over the period 2001–2019. Loss is defined by Hansen et al. as a stand-replacement disturbance and includes all disturbances (natural and anthropogenic) observable in Landsat imagery. Gain is defined as a non-forest to forest change, which includes tree cover gain observed after harvest and other disturbance. The loss product is annual, while the gain product represents a cumulative total (2000–2012). Loss and gain can co-occur on pixels undergoing forest management or other forms of disturbance and regrowth. Lack of annually updated gain data is addressed through the sensitivity analysis (Extended Data Fig. 5). Due to a lack of information about tree cover gain after 2012, we assumed no additional areas of gain from 2012 to 2019. Areas of no change reflect forest areas established before 2000 that showed no observable disturbance in Landsat imagery between 2000 and 2019.

Emission factors. We assigned emission factors to tree cover loss pixels following an IPCC land-use classification framework, on the basis of whether each pixel maintained its land use or was converted to a new use over the analysis period. Since forest may remain in the same use despite a temporary loss of tree cover, we used the global 10-km map of Curtis et al.¹⁷ (updated through 2019) to attribute tree cover loss to one of five dominant drivers; these influence the C pools affected (Supplementary Table 5) and thus the emission factors assigned to each individual loss pixel. Supplementary Table 6 summarizes emission factors by forest type within each climate domain.

Commodity-driven deforestation and shifting agriculture. The initial change in C stocks was estimated as a full loss of C in aboveground, belowground, dead wood and litter pools. In addition to CO₂ emissions resulting from a loss of C stocks, we used IPCC equation 2.27 (ref. ¹⁰) and a 1-km global burned area map⁴⁴ to calculate CH₄ and N₂O emissions in loss pixels that overlapped with areas that burned the same year or the year before (to account for lag effects between fire occurrence and observed tree cover loss). For deforestation on mineral soils, soil C loss was estimated using IPCC equation 2.25 (ref. ¹⁰); default soil stock change factors vary by ecological zone and were assigned spatially using ecozone boundaries⁴⁵. Per IPCC guidelines, 1/20th of the total soil C stock change was apportioned annually from the year of loss through the last year of the analysis period (2019) but assigned to the year of observed tree cover loss. Due to lack of information in the driver attribution map¹⁷ about the specific land use established after forest clearing, we assumed for the purposes of soil emission accounting that all deforested land on mineral soils for commodity-driven deforestation was converted to annual cropland with full tillage and medium inputs. A different factor was used to estimate loss of soil C on mineral soils (Table 5.10 in the IPCC Guidelines¹⁰) in areas of shifting agriculture, which were assumed to represent transient land-use conversions to cropland under shortened fallow, where vegetation recovery is not attained before re-clearing. Soil emissions were not estimated for areas of loss on mineral soils that overlapped with forest and wood fibre plantations, even if they fell within the broader commodity-driven deforestation or shifting agriculture classes, consistent with the assumption that loss of tree cover within tree plantations follows the forestry assumptions listed in Supplementary Table 5 (see emissions from Forestry below). For loss on organic soils that overlapped with tropical plantations and tree crops planted since 2000, GHG emissions associated with drainage were estimated using CO₂ and CH₄ emission factors provided in the IPCC Wetlands Supplement¹⁰. Like emissions from mineral soils, emissions from peat drainage were assumed to continue in each year after loss up through the last year of the analysis period (2019) but were assigned to the year of observed tree cover loss. Emissions (CO₂, CH₄ and N₂O) from peat burning were also calculated on the basis of methods provided in the IPCC Wetlands Supplement¹⁰ where a loss pixel overlapped with areas burned the same year, or the year before, the loss event (on the basis of global burned area data).

Urbanization. The same assumptions and calculations were used for calculating gross emissions from urbanization as for commodity-driven deforestation and shifting agriculture, except a different factor was used to estimate the loss of soil C on mineral soils. We assumed that forest land converted to settlement was paved over and applied the IPCC default assumption¹¹ that 20% of the soil C relative to the previous land use was lost as a result of disturbance, removal or relocation.

Forestry. Emission factors for loss attributed to forestry were estimated as the loss of C in live biomass only, following assumptions outlined in Supplementary Table 5 that there is no net change to the dead organic matter or soil C pools in the case of mineral soils. Emissions from peat drainage and burning associated with forestry activities, as well as non-CO₂ emissions in the case of forest fires, were included in

the same way as for deforestation and shifting agriculture above. Emission factors for loss pixels within the ‘zero or minor loss’ category of the driver attribution map also followed assumptions for forestry (Supplementary Table 5).

Wildfire. Within 10-km grid cells of the drivers map labelled wildfire, wildfire emission factors were applied only for 30-m pixels where loss occurred in the year of, or year after, a fire event in the 1-km burned area map. In these cases, we used IPCC equation 2.27 (ref. 10) to estimate both CO₂ and non-CO₂ emissions from forest fire. The AGB map determined the mass of fuel available for combustion and a lookup table (Table 2.6 of the IPCC Guidelines¹⁰) provided default combustion and emission factors that were applied on the basis of forest type (primary versus secondary). For boreal and temperate forests, combustion factors were applied on the basis of the assumption of a land-clearing fire, given that forest loss is defined in Hansen et al.¹⁵ as a stand-replacement disturbance. In cases where organic soils overlapped with burned areas, emissions from peat burning (CO₂, CH₄ and N₂O) were estimated following guidance in the IPCC Wetlands Supplement⁴⁰. Forestry emission factors, rather than wildfire factors, were applied where loss did not overlap with a fire event in the 1-km burned area map.

Removal factors. We developed removal factors spatially by linking information about each pixel’s geographic region, ecological zone, forest type and age class to corresponding growth rates on the basis of best available information. Supplementary Table 6 summarizes removal factors by forest type in each climate domain. In areas of geographic overlap, the priority of assigning removal factors to a given pixel reflects the order of data sources listed below. Removal factors include accumulation in live biomass only and reflect the net increase, accounting for both productivity and mortality. We assumed no change to the dead organic matter and soil organic carbon pools, consistent with the IPCC Tier 1 assumption of no net change to non-biomass pools in forest land remaining forest land. The number of years of carbon accumulation was assigned as 19 yr for undisturbed forest, 6 yr for areas of new tree cover gain and one less than the year in which tree cover loss occurred for loss-only forest.

Mangroves. We applied mangrove-specific growth rates and root-to-shoot ratios from IPCC Tables 4.4 and 4.5 of the Wetlands Supplement⁴⁰, respectively.

Europe. We assigned removal factors spatially according to a map of dominant tree species developed from 260,000 national inventory plot locations⁴⁶. For each species, we estimated mean annual increment (MAI) values from Table 4.11 of the updated IPCC Guidelines¹¹, FAO Planted Forest Assessment⁴⁷ and national inventories⁴⁸ (Supplementary Table 3). These were converted to aboveground biomass growth rates using species-specific biomass conversion and expansion factors and belowground biomass increment was added on the basis of a root-to-shoot ratio³⁹.

Plantations and tree crops. Outside Europe, we assigned removal factors for plantations and tree crops using a variety of published data sources⁴⁹. For common plantation species, we used MAI and biomass conversion and expansion factors summarized in the updated IPCC Guidelines¹¹ to estimate aboveground biomass increment and added belowground biomass increment on the basis of a root-to-shoot ratio³⁹. Rates in plantations were assigned on the basis of mapped species when known or, when unknown, the most common mix of plantation species grown in the region. Removal factors for tree crops such as oil palm and rubber as well as various types of agroforestry systems were estimated for areas mapped as such on the basis of regionally specific values derived from the published literature and from Tables 5.1 and 5.3 of the updated IPCC Guidelines¹¹. All removal factors used for plantations and tree crops, along with data sources and assumptions applied, are provided in the companion spatial attribute file associated with the global compilation of planted tree maps used in this analysis⁴⁹.

United States. We developed removal factors for three age classes (0–20, 20–100 and >100 yr) for forest types across 11 geographic regions using methods broadly similar to those of Smith et al.⁵⁰, except that we included more forest types in each region, as well as more recent and comprehensive data from the US Forest Inventory and Analysis database. Removal factors were developed from approximately 130,000 inventory plot locations. Pixels were assigned removal factors on the basis of dominant forest type⁵¹, age class⁵² and geographic inventory region.

Young secondary forests. Outside the United States and Europe, areas of tree cover gain that fell outside boundaries of mangroves³⁵ and planted trees⁴⁹ were assumed to be secondary natural forest regrowth <20 years old. We assigned natural forest regrowth removal factors to these areas using the 1-km map of Cook-Patton et al.²⁹.

Primary forests. We used removal factors by ecological zone and continent from IPCC Table 4.9 of the 2019 IPCC Refinement¹¹ and assigned them spatially between 30°N and 30°S within a tropical primary humid forest map⁵³. Outside 30°N and 30°S, we used a map of intact forest landscapes⁵⁴ as a proxy for primary forests, which is likely to be highly conservative due to the relatively large extent

criterion applied but represents the best available information by which to spatially delineate primary from old secondary forests in boreal and temperate regions.

Old secondary forests. We assigned removal factors from IPCC Table 4.9 (>20 yr) to all forest areas that fell outside the types identified above. Given no observed disturbance occurred in these areas since the year 2000, we assumed they were secondary natural forests at least 20 years old.

Harvested wood products. We used statistics reported in FAOSTAT and methods outlined in the 2019 Refinement¹¹ to estimate emissions and/or removals arising from harvested wood products. Losses of harvested wood products in use were assumed to result in CO₂ emissions to the atmosphere, with no explicit representation of the subsequent retention of disposed wood in solid waste disposal sites (SWDS) and eventual CO₂ emissions from SWDS. Calculations rely on statistics reported by countries on production, import and export volumes for three aggregate semifinished wood product commodity classes: sawnwood, wood-based panels and paper and paperboard.

Uncertainty analysis. We estimated uncertainty in GHG flux estimates globally and at the scale of climate domains by combining uncertainties in the activity data and emission/removal factors following a Taylor series statistical approach as in Roman-Cuesta et al.⁵⁵ and Carter et al.⁵⁶. This approach underlies the IPCC Approach 1 (simple error propagation)¹⁰ and produces similar results but reflect exact calculations of variances and s.d., whereas IPCC Approach 1 is an approximated approach that yields 95% confidence intervals.

Uncertainties of all major components of the flux model were included (activity data, affected C pools of the emission/removal factors, combustion and emission factor uncertainties for fire-related emissions). Errors were assumed to be statistically independent (uncorrelated), normally distributed and without bias. Supplementary Table 1 shows the contribution of each uncertainty component for domain and global gross emissions, removals and net flux, reported as the percentage reduction in output variances as each of the uncertainty components were assumed to have no variance. Variance of the net GHG flux was reduced the most when removing variance of the removal factor for temperate forests older than 20 yr. Variances are likely to be lower when estimated across smaller geographic regions. Estimation of uncertainty is currently limited to the global and biome scales based on available data for estimating uncertainty in the activity data.

Reporting Summary. Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability

Geospatial data generated from the current study are publicly available on Global Forest Watch’s Open Data Portal (<http://data.globalforestwatch.org/>) and from the corresponding author upon request. Summary geospatial statistics are available from the corresponding author upon request. All data inputs used in the current study are publicly available or were obtained by the corresponding author.

Code availability

To ensure full reproducibility and transparency of our research, we provide all of the scripts used in our analysis. Codes used for this study are permanently and publicly available on GitHub (<https://github.com/wri/carbon-budget>).

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Author contributions

N.L.H. was involved in conceptualization, data curation, formal analysis, funding acquisition, investigation, methodology, project administration, visualization and writing. D.A.G. contributed to data curation, formal analysis, investigation, methodology, software, validation, visualization and writing. A.B., R.A.B., R.R.C., M.F., L.F., M.C.H., R.A.H., P.V.P., C.M.S., D.R.S., S.S.S. and S.A.T. contributed to data curation, formal analysis, methodology and writing. M.H. contributed to data curation, visualization and writing. S.deB. and A.T. contributed to formal analysis and methodology.

Competing interests

The authors declare no competing interests.

Additional information

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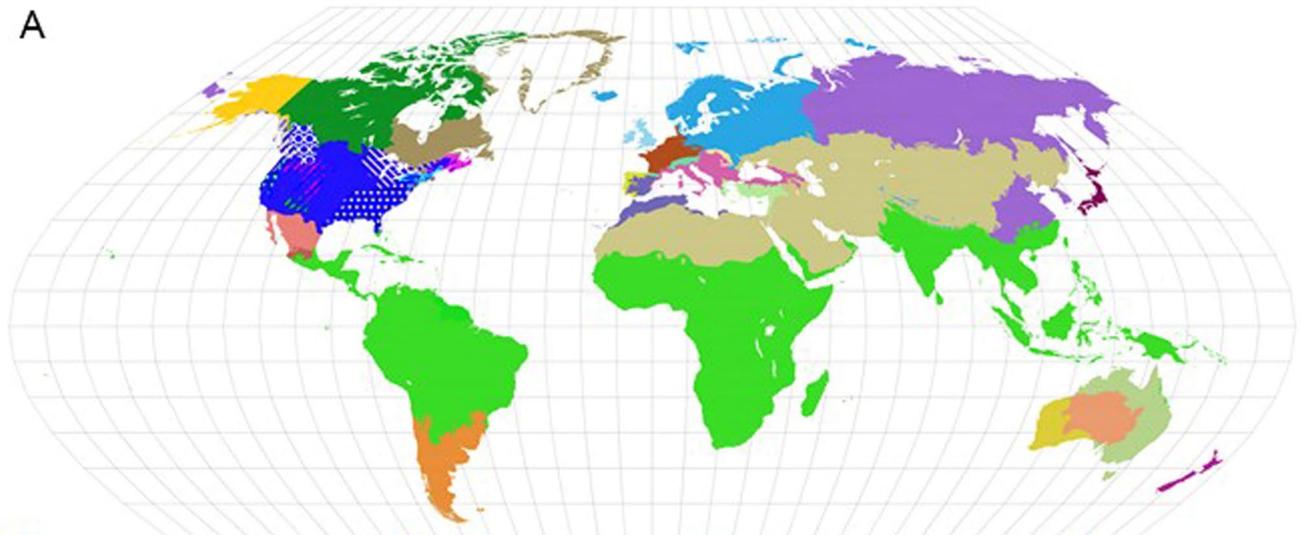
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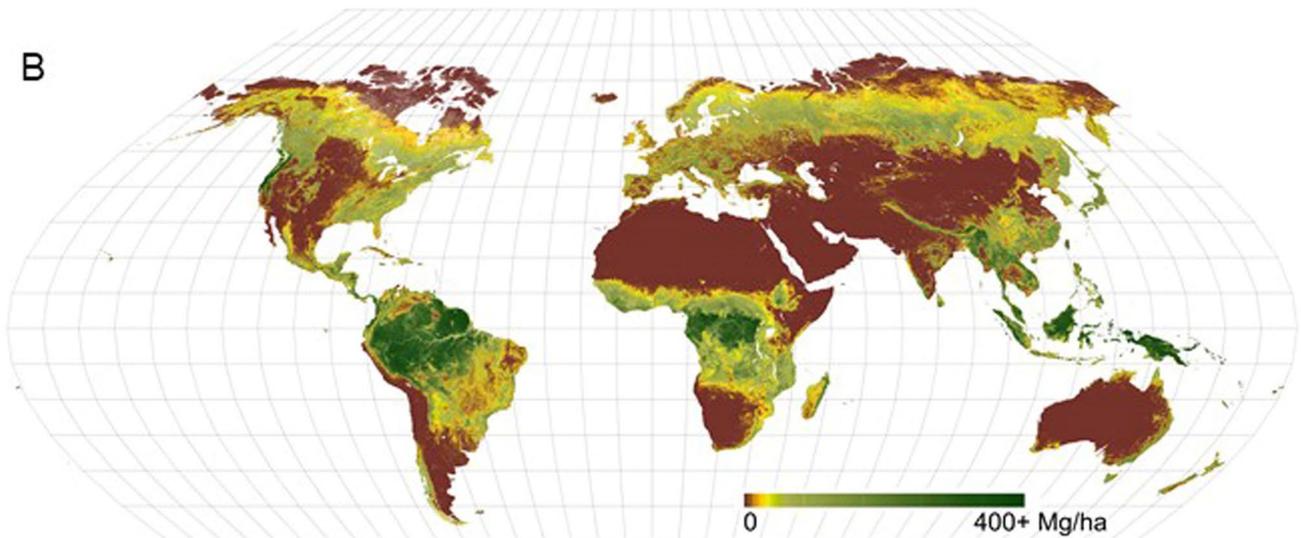
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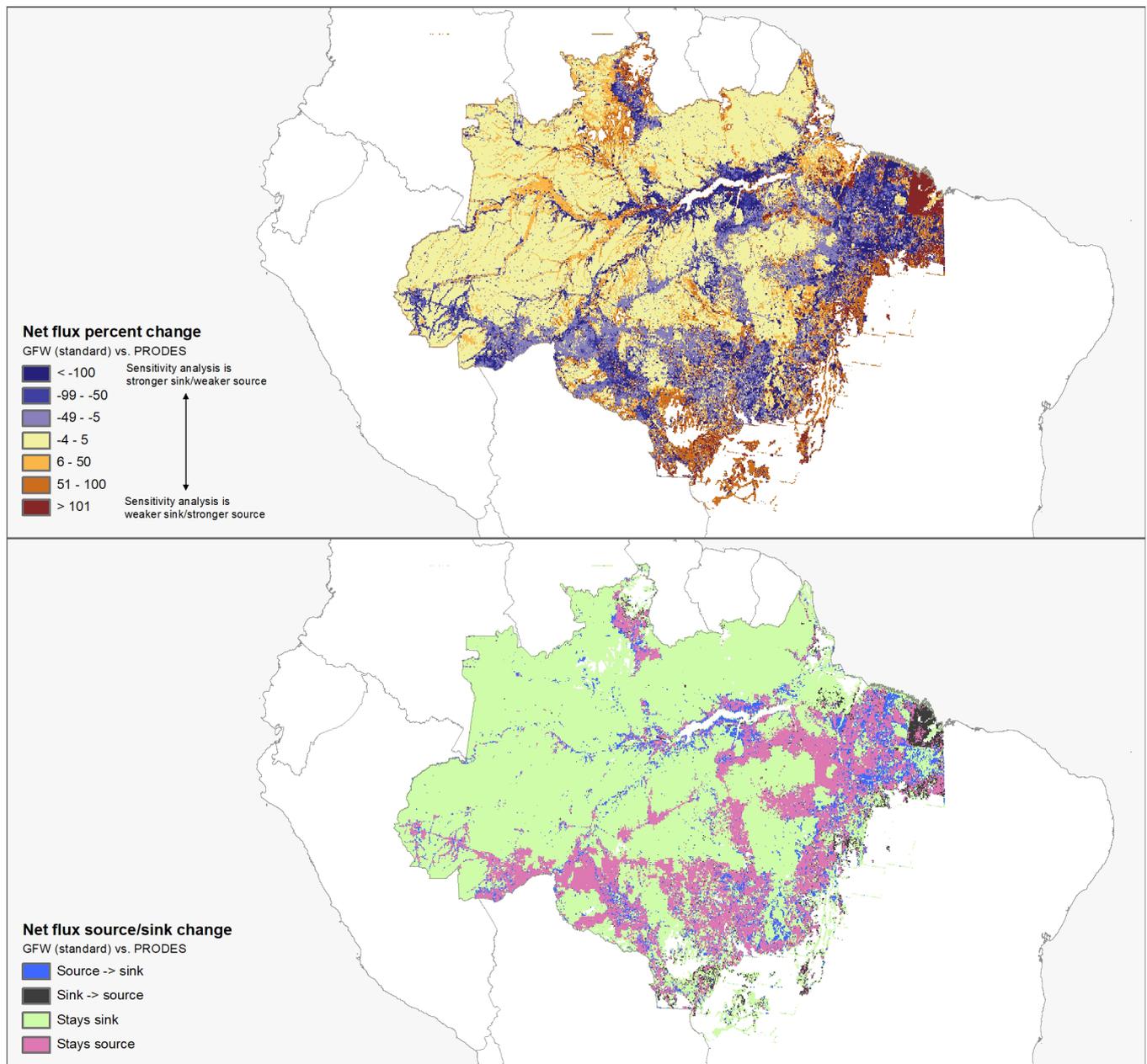


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| ■ Baccini et al. (2012) Pan-tropical | ■ Anderson et al. (2006) | ■ Alberti et al. (2013) | ■ Beets et al. (2011) |
| ■ Neigh et al. (2013) Alaska | ■ Duncanson et al. (2010) | ■ Brovkina et al. (2015) | ■ González-Roglich and Swenson (2016) |
| ■ Neigh et al. (2013) Canada east | ■ Hudak et al. (2012) | ■ Gonzalez-Ferreiro et al. (2013) | ■ Lucas et al. (2008) |
| ■ Neigh et al. (2013) Canada west | ■ Hyde et al. (2007) | ■ Patenaude et al. (2004) | ■ Suganuma et al. (2006) |
| ■ Nelson et al. (2017) CONUS | ■ Lim et al. (2003) | ■ Shang and Chazette (2014) | ■ Wang et al. (2015) |
| ■ Neigh et al. (2013) Eurasia east | ■ Lu et al. (2012) | ■ Simonson et al. (2016) | |
| ■ Neigh et al. (2013) Eurasia west | ■ Popescu et al. (2012) | ■ Takagi et al. (2015) | |
| ■ Nelson et al. (2017) Mexico north | ■ Skowronski et al. (2007) | ■ WHRC (unpublished) | |
| ■ Nelson et al. (2017) Mexico south | ■ Sun et al. (2011) | ■ Yavaşlı (2016) | |
| ■ Wang et al. (2013) Africa/Eurasia | ■ Tsui et al. (2012) | | |

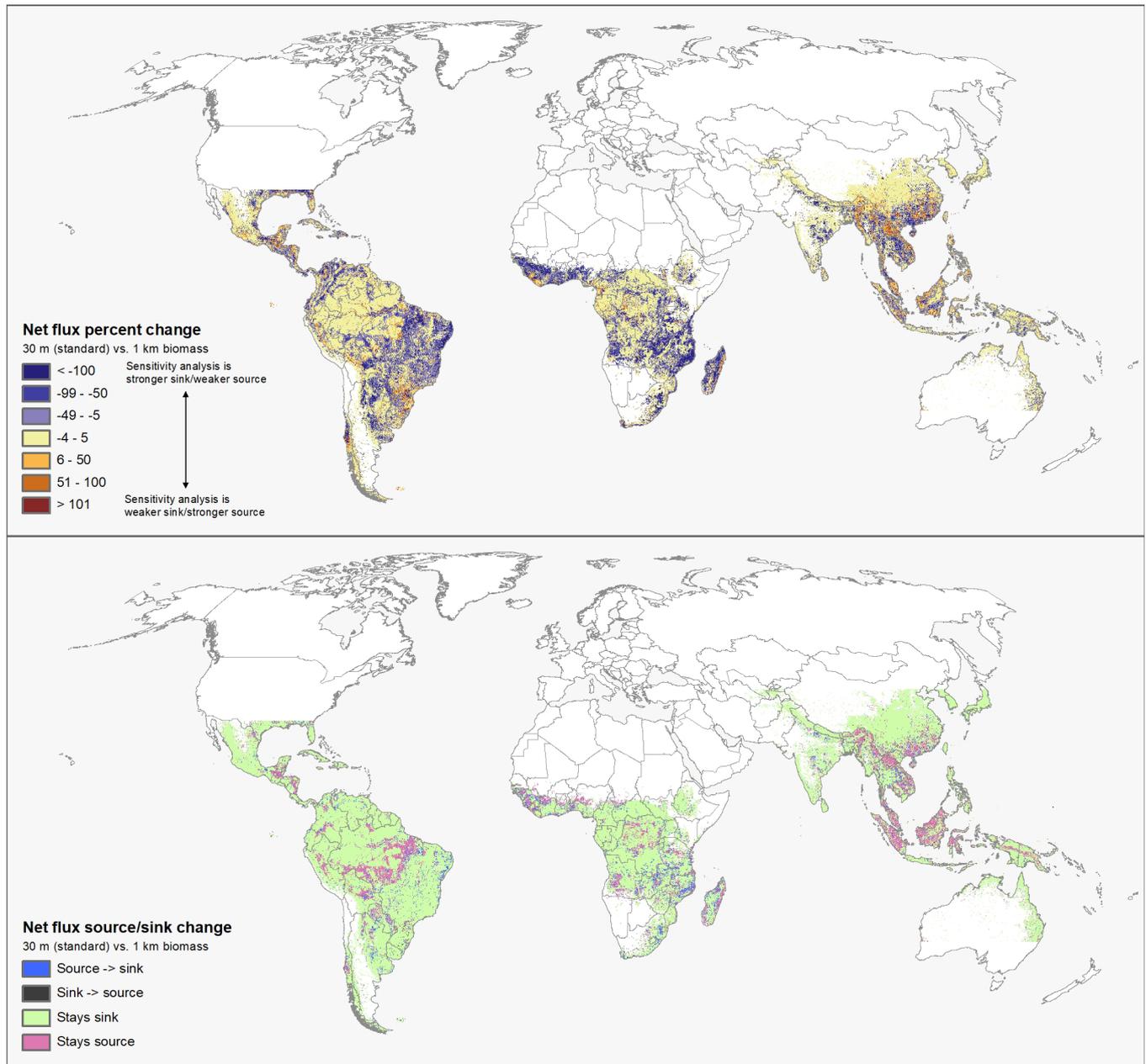
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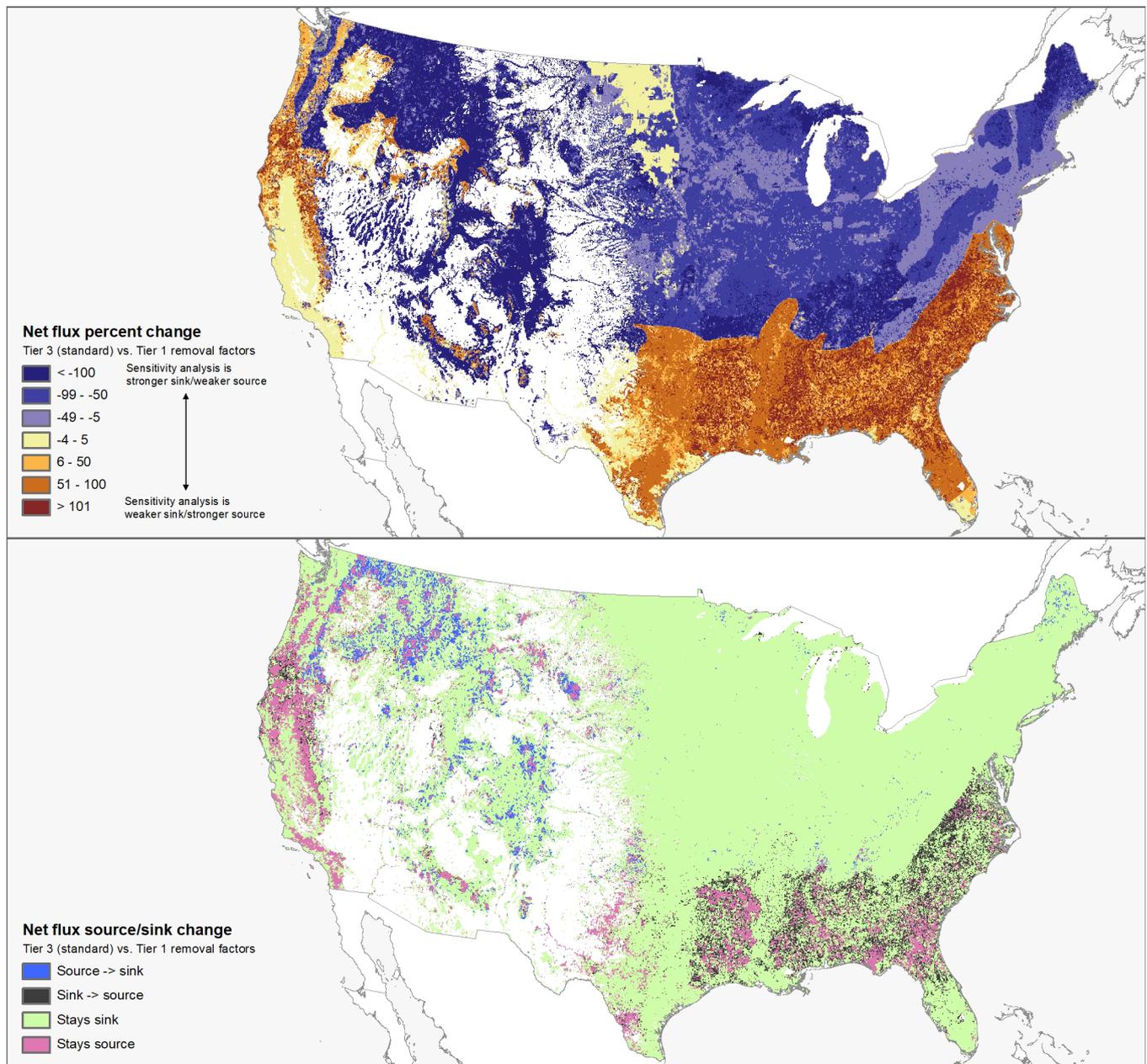
Extended Data Fig. 1 | Aboveground live woody biomass density in the year 2000. **a**, Subsets of ecoregions over which different height-biomass equations were applied. Patterned shading indicates equations that were only applied to conifer GLAS shots within the specified ecoregion. **b**, Global 30-m map of aboveground live woody biomass density in the year 2000.



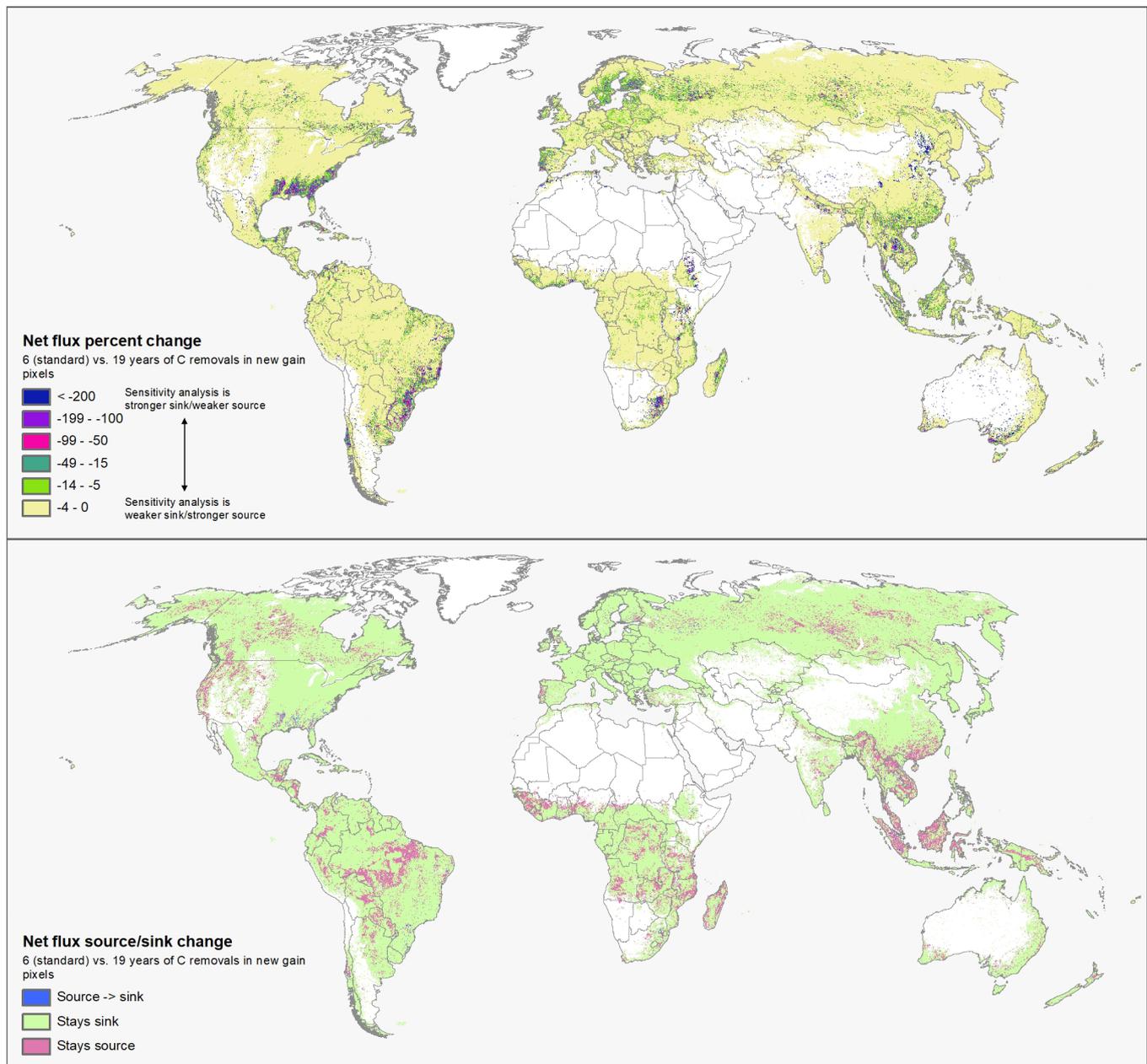
Extended Data Fig. 2 | Results of sensitivity analysis when the source of tree cover loss data used in the forest GHG flux model is changed from the 30-m tree cover loss product of Hansen et al.¹⁵ in the standard model to PRODES, Brazil's 250-m forest loss monitoring product for the Brazilian Amazon¹⁹, in the alternative model. Top panel: Percent change in net GHG flux between standard model and sensitivity analysis model; Bottom panel: Delineation of areas that remain a net GHG source or sink in the sensitivity analysis model vs. those that switch from being a net source or sink to a net sink or source as a result of the changes applied. For display purposes, maps have been resampled from the 30-m observation scale to a 0.04-degree geographic grid.



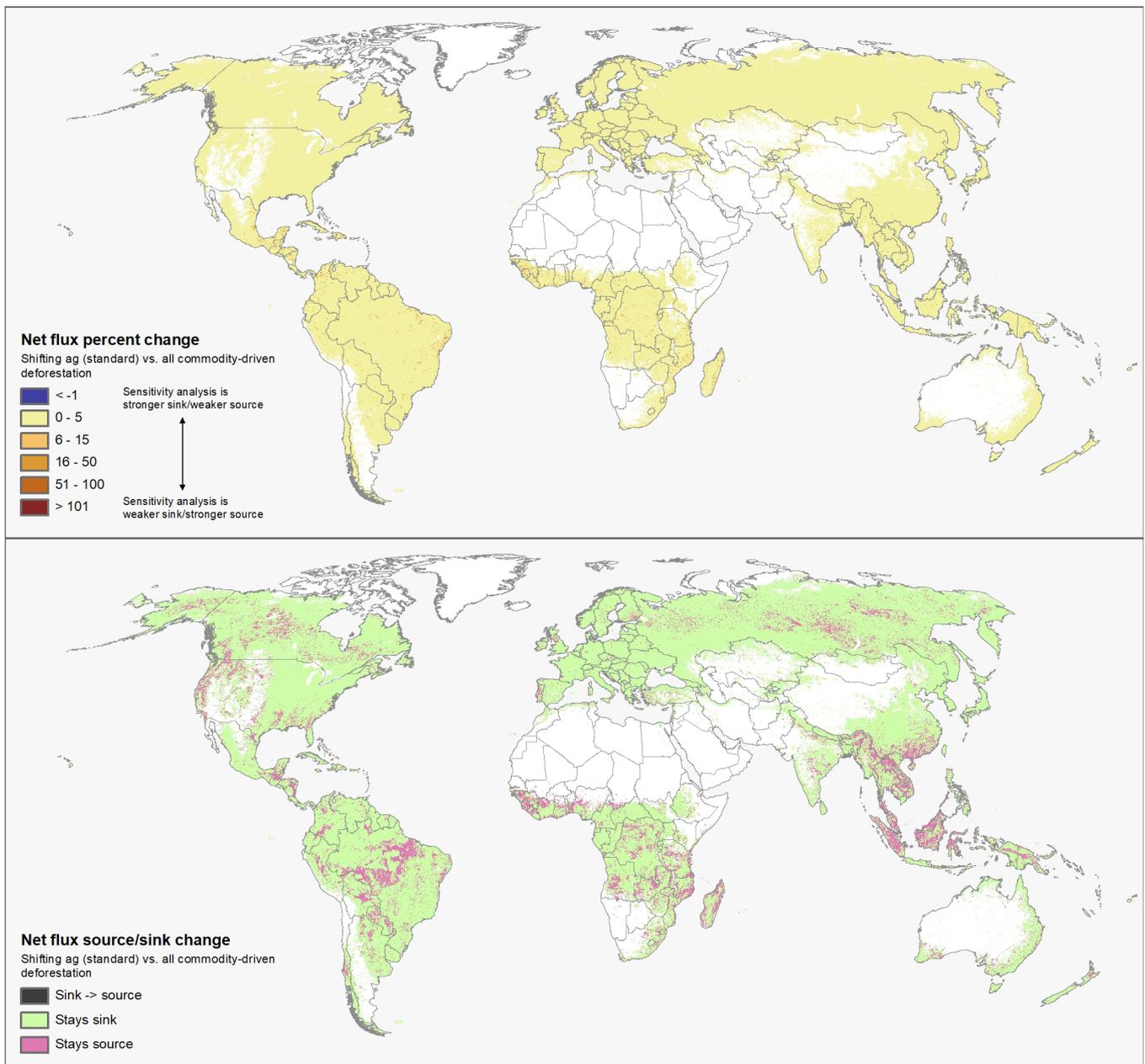
Extended Data Fig. 3 | Results of sensitivity analysis when the source of biomass data used in the forest GHG flux model is changed from a 30-m global AGB map in the standard model to a 1-km tropical AGB map in the alternative model. Top panel: Percent change in net GHG flux between standard model and sensitivity analysis model; Bottom panel: Delineation of areas that remain a net GHG source or sink in the sensitivity analysis model vs. those that switch from being a net source or sink to a net sink or source as a result of the changes applied. For display purposes, maps have been resampled from the 30-m observation scale to a 0.04-degree geographic grid.



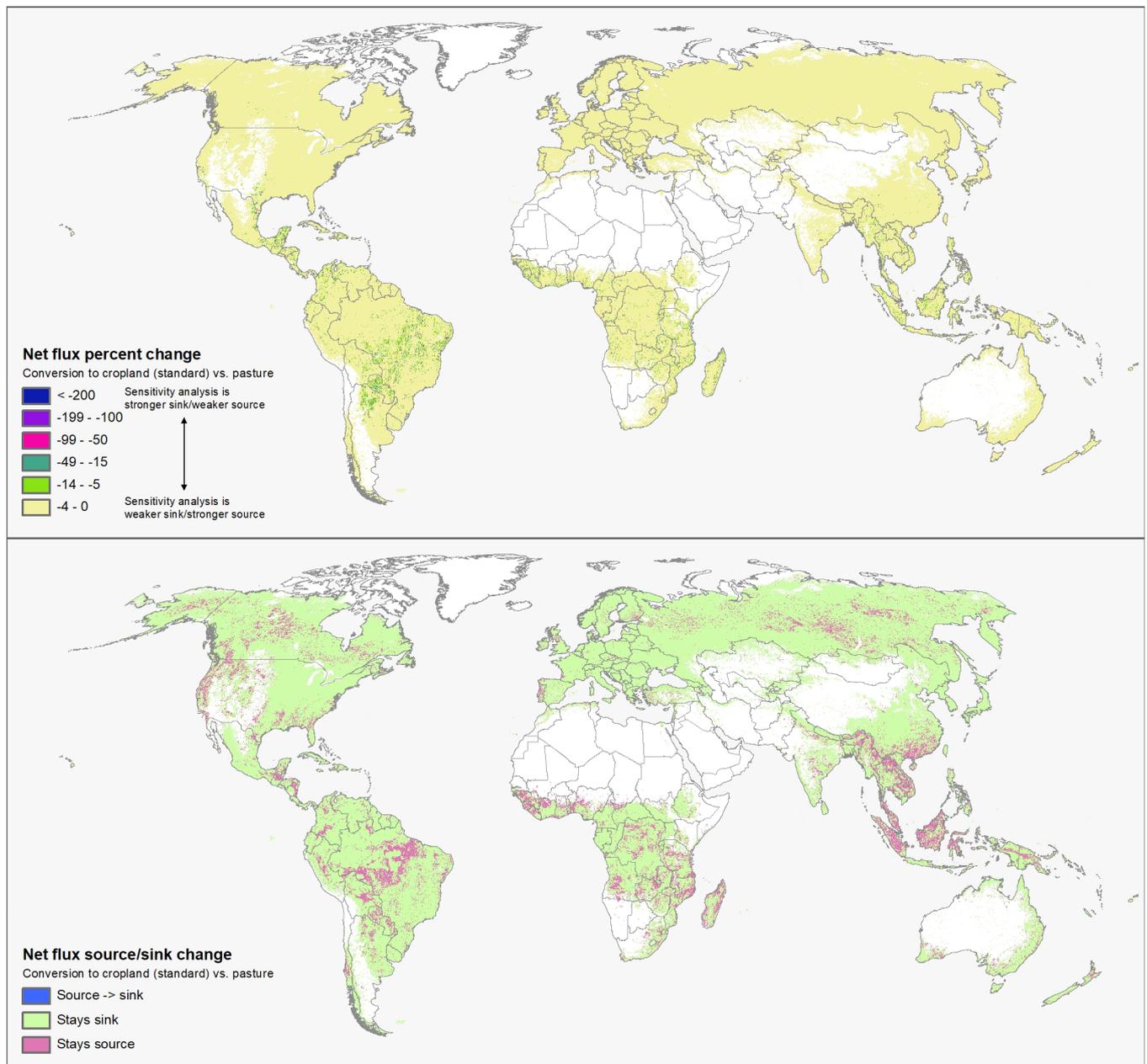
Extended Data Fig. 4 | Results of sensitivity analysis when rates of AGB accumulation derived from inventory data for different forest types of the United States in the standard model are replaced by IPCC Tier 1 default rates in the alternative model. Top panel: change in net GHG flux between standard model and sensitivity analysis model; Bottom panel: Delineation of areas that remain a net GHG source or sink in the sensitivity analysis model vs. those that switch from being a net source or sink to a net sink or source as a result of the changes applied. For display purposes, maps have been resampled from the 30-m observation scale to a 0.04-degree geographic grid.



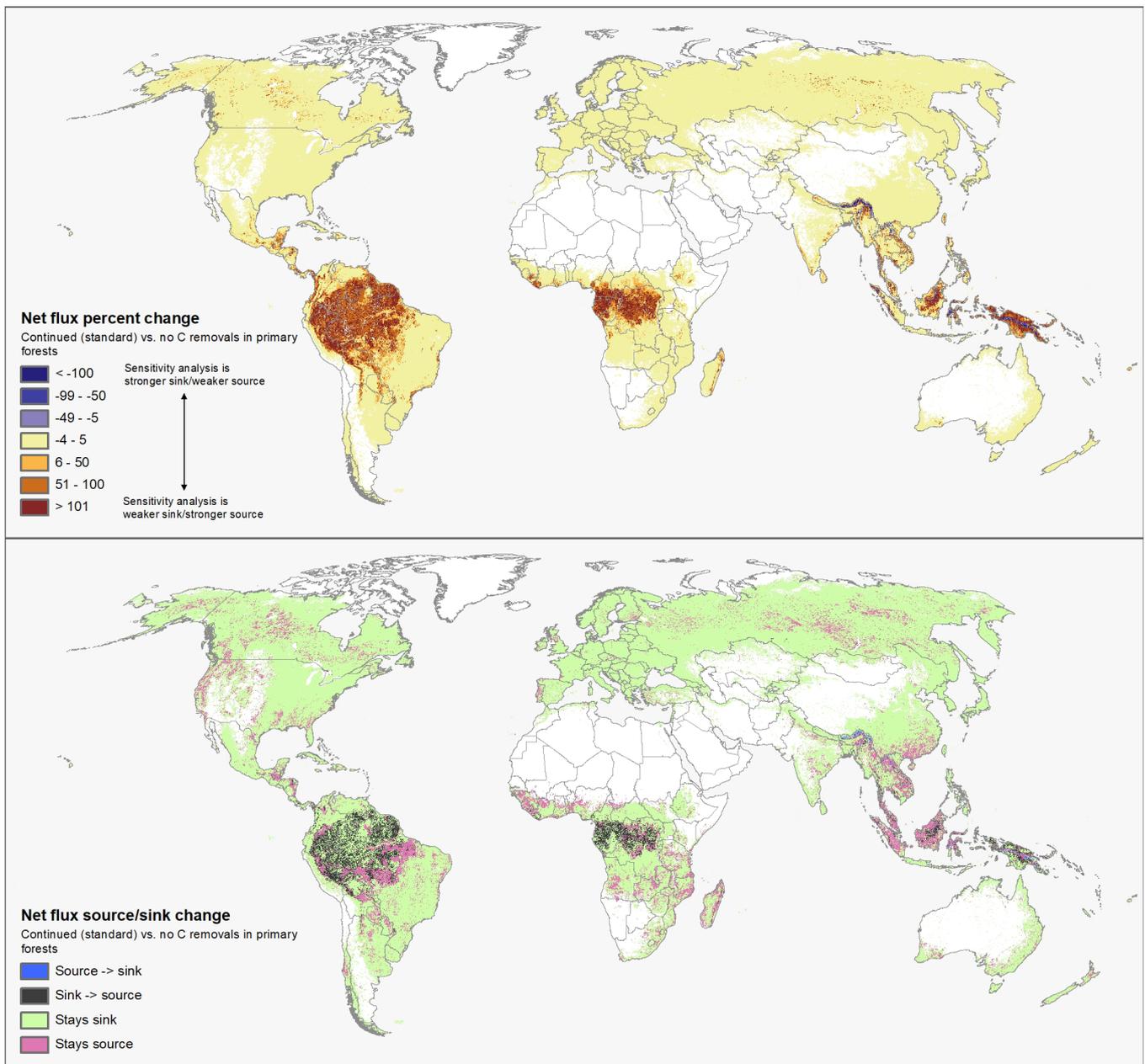
Extended Data Fig. 5 | Results of sensitivity analysis when the number of years of growth in the GHG flux model is assumed to be 19 in the alternative model vs. 6 in the standard model for pixels of tree cover gain since the year 2000. Top panel: Percent change in net GHG flux between standard model and sensitivity analysis model; Bottom panel: Delineation of areas that remain a net GHG source or sink in the sensitivity analysis model vs. those that switch from being a net source or sink to a net sink or source as a result of the changes applied. For display purposes, maps have been resampled from the 30-m observation scale to a 0.04-degree geographic grid.



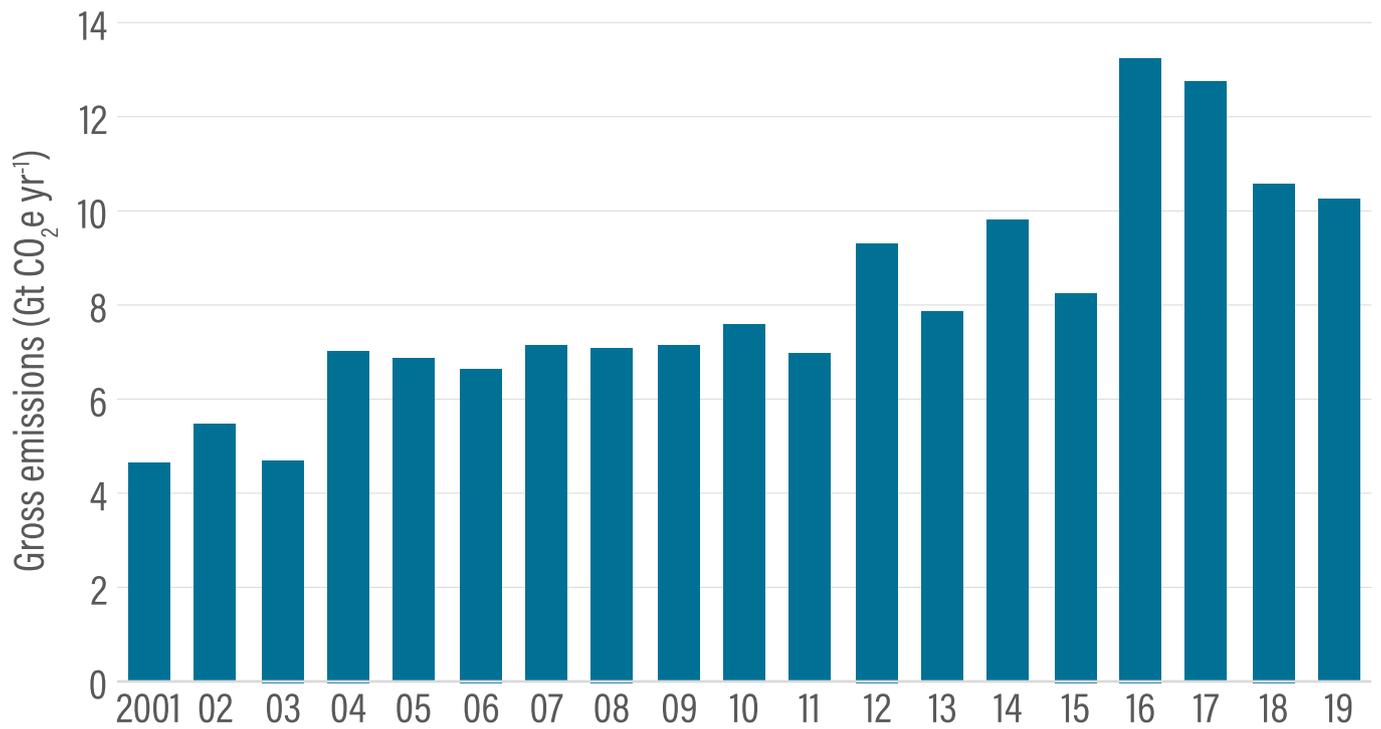
Extended Data Fig. 6 | Results of sensitivity analysis when tree cover loss in the GHG flux model is attributed to commodity-driven deforestation in the alternative model vs. shifting agriculture in the standard model. Top panel: Percent change in net GHG flux between standard model and sensitivity analysis model; Bottom panel: Delineation of areas that remain a net GHG source or sink in the sensitivity analysis model vs. those that switch from being a net source or sink to a net sink or source as a result of the changes applied. For display purposes, maps have been resampled from the 30-m observation scale to a 0.04-degree geographic grid.



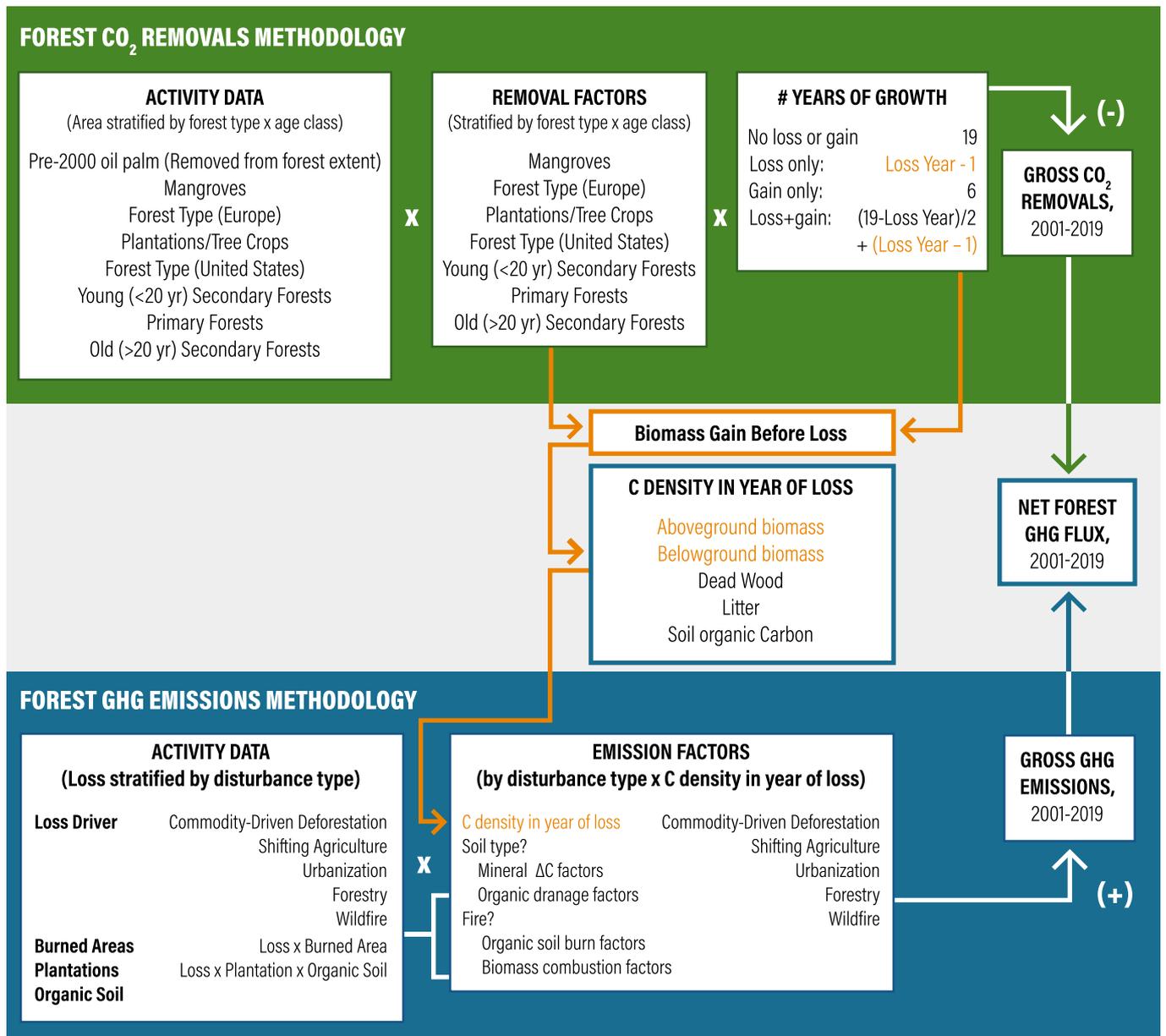
Extended Data Fig. 7 | Results of sensitivity analysis when the post- deforestation land-use assumption in the GHG flux model is changed from cropland in the standard model to grassland in the alternative model. Top panel: Percent change in net GHG flux between standard model and sensitivity analysis model; Bottom panel: Delineation of areas that remain a net GHG source or sink in the sensitivity analysis model vs. those that switch from being a net source or sink to a net sink or source as a result of the changes applied. For display purposes, maps have been resampled from the 30-m observation scale to a 0.04-degree geographic grid.



Extended Data Fig. 8 | Results of sensitivity analysis when assumptions about carbon uptake in primary forests and intact forest landscapes are changed to zero carbon uptake in the alternative model vs. positive carbon uptake in the standard model. Top panel: Percent change in net GHG flux between standard model and sensitivity analysis model; Bottom panel: Delineation of areas that remain a net GHG source or sink in the sensitivity analysis model vs. those that switch from being a net source or sink to a net sink or source as a result of the changes applied. For display purposes, maps have been resampled from the 30-m observation scale to a 0.04-degree geographic grid.



Extended Data Fig. 9 | Gross forest-related emissions, 2001-2019. Emissions reflect all stand-replacement disturbances (natural and anthropogenic) observable in Landsat imagery.



Extended Data Fig. 10 | Conceptual framework for modelling forest-related GHG fluxes. For each 30-m pixel included in the model, gross forest-related emissions and removals are estimated as the product of activity data and emission/removal factors. Net forest GHG flux is the sum of gross fluxes. Text and arrows in orange are portions of the removals methodology that are passed into the emissions methodology.

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Geospatial data generated from the current study will be made publicly available on Global Forest Watch's Open Data Portal (<http://data.globalforestwatch.org/>) and from the corresponding author upon request. Summary geospatial statistics will be available from the Global Forest Watch dashboards and a publicly accessible API, as well as from the corresponding author upon request. All data analyzed as part of the current study are either publicly available or were obtained by the corresponding author upon request.

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Study description	The study design is structured as a geographic information system (GIS) model and is based on a synthesis of spatially explicit data sources to map gross and net greenhouse gas emissions and removals from global forest lands at 30-m resolution between 2001 and 2019.
Research sample	Results of this study are not based on a statistical sampling design but on published wall-to-wall maps of global tree cover and tree cover change generated by Hansen et al. (2013) as well as other published geospatial data sets. The study area includes all global land except Antarctica and some small oceanic and Arctic islands. Table S3 documents the dozens of data sources we combined for this analysis. The model includes greenhouse gases CO ₂ , CH ₄ , and N ₂ O, and six carbon pools.
Sampling strategy	Results of this study are not based on a statistical sampling design, although quantification of uncertainty in this study is based in part on results from a probability-based stratified random sample of 1,500 blocks (120x120 m) to validate map-based estimates of global forest change. Three sub-strata were created per biome: no change, loss and gain. The sample allocation for each biome was 150 blocks for no change, 90 for change and 60 for gain (1,500 blocks total). For more information, refer to Hansen et al. (2013).
Data collection	Results of this study are based on a synthesis of published datasets, not on original data collection. The datasets are combined using existing frameworks for calculating GHG emissions and removals (IPCC guidelines for national GHG inventory reporting).
Timing and spatial scale	The time period of analysis covers 2001 to 2019. The starting and ending years were determined by the ranges of key data sources available during model development. The spatial scale of this study's results is 30-m resolution with full coverage of all continental land.
Data exclusions	No data were excluded from this analysis.
Reproducibility	The reproducibility of this study's results is facilitated by providing all model code used in a public repository (GitHub). Various data sources used as inputs into the study are publicly accessible and freely available.
Randomization	This is not relevant to our study because results are not based on a statistical sampling design.
Blinding	This is not relevant to our study because results are not generated based on a statistical sampling design.
Did the study involve field work?	<input type="checkbox"/> Yes <input checked="" type="checkbox"/> No

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