

Spatial accounting of greenhouse gas emissions and removals across global land

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Spatial accounting of greenhouse gas emissions and removals across global land

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Abstract

Global assessments quantify the net exchange of greenhouse gases (GHGs) between land and the atmosphere but lack a high-resolution, observation-based representation of underlying gross emissions and removals^{1–3}. Here, we integrate satellite-based data with GHG inventory methods to generate annual estimates of gross GHG emissions, gross carbon removals and net GHG fluxes from vegetation and soil across global land at 30-m resolution from 2016 to 2024. The monitored land processes, which exclude agricultural methane and nitrous oxide emissions, were a net sink of -3.6 ± 4.1 Gt CO₂e yr⁻¹, comprised of 20.2 ± 2.6 Gt CO₂e yr⁻¹ gross emissions and -23.8 ± 3.1 Gt CO₂ yr⁻¹ gross removals; the relative contributions of vegetation and soil varied across landscapes. Gross emissions were spatially concentrated, with half of global emissions occurring in 4.5% of emitting land, while half of global removals occurred across 19% of land with removals. Our approach complements global carbon budgets^{1,4} and inventory-based reporting systems^{5–7} by resolving the geography of emissions and removals within a consistent geospatial framework, enabling more targeted emissions reductions, sustained carbon removals, and transparent tracking of progress across scales.

Main

To achieve net zero emissions by 2050, humanity must rapidly reduce greenhouse gas (GHG) emissions from fossil fuels while strengthening mitigation from the land sector². Recent global assessments estimate that terrestrial ecosystems contribute roughly one-quarter of net anthropogenic GHG emissions while simultaneously removing approximately one-third of anthropogenic carbon dioxide (CO₂) emissions from the atmosphere through carbon uptake^{1,2}. Limiting warming to 1.5 °C or 2 °C therefore requires both substantial reductions in emissions from land-use change, as well as the maintenance and potential enhancement of the land carbon sink⁸. This reliance on land-based mitigation is reflected in climate commitments worldwide^{2,9,10}; nearly all countries include land as a climate mitigation option in the most recent round of Nationally Determined Contributions (NDCs)¹¹. Collectively, NDCs aim to increase the land net carbon sink by 1.5 Gt CO₂e yr⁻¹ to 4.2 Gt CO₂e yr⁻¹ by 2030, with roughly one-third of that coming from increased land removals¹².

Yet understanding the role of land in climate mitigation is challenging because GHG emissions and carbon removals occur simultaneously across heterogeneous landscapes and arise from multiple processes operating across different spatial and temporal scales¹³. Estimates of net GHG fluxes— inclusive of CO₂, methane (CH₄) and nitrous oxide (N₂O) and typically reported at national, regional, or global scales— combine the effects of land use, land management, natural disturbances, and broader environmental change, complicating attribution along the continuum from natural to anthropogenic drivers⁵. Moreover, attribution of fluxes to human activities cannot be determined solely from observations^{14,15}. Nevertheless, climate action relies on data that supports comparing mitigation opportunities across landscapes, tracking different components of the land GHG balance through time, and the identification of the processes driving emissions and removals.

Despite advances in monitoring land cover and biomass from space at high resolution over large areas^{16,17}, translation of these observations into integrated and actionable estimates of land-related GHG emissions and removals remains limited. Existing approaches (e.g., ^{18–20}) tend to focus on individual components of the land GHG balance, e.g., specific gases, carbon pools, regions, or land uses, making it difficult to obtain a consistent and comprehensive picture of emissions and removals across scales and through time. Here, we present an annual spatial assessment of GHG dynamics across global land from 2016 to 2024 at approximately 30-m resolution. Combining satellite-based land cover change data with a spatially explicit implementation of the IPCC Guidelines for National Greenhouse Gas Inventories^{8,21,22} for vegetation, organic soil²³ and mineral soil (0–30 cm depth, derived from ²⁴), we present a globally consistent framework for quantifying gross

emissions (+), gross removals (-), and net fluxes of CO₂, CH₄ and N₂O across terrestrial ecosystems and land uses, excluding CH₄ and N₂O emissions from agricultural land management (Extended Data Fig. 1). This integration of geospatial monitoring data and inventory-based GHG accounting provides a more complete picture of the magnitude, composition, and geographic distribution of terrestrial GHG dynamics, strengthening the empirical basis for efforts across spatial scales to reduce terrestrial GHG emissions and maintain and enhance carbon sinks.

Large opposing fluxes shape the global land sink

On average, global land emitted 20.2 ± 2.6 Gt CO₂e yr⁻¹ and removed -23.8 ± 3.1 Gt CO₂ yr⁻¹ between 2016-2024, resulting in a net GHG sink of -3.6 ± 4.1 Gt CO₂e yr⁻¹ (Fig. 1). Gross emissions (Fig. 1a) occurred in areas with deforestation, forest management, disturbed organic soil, and other natural and anthropogenic disturbances; gross removals (Fig. 1b) were distributed broadly across treed landscapes (-17.2 Gt CO₂ yr⁻¹), with removals by non-tree vegetation widespread but smaller in magnitude (-1.2 Gt CO₂ yr⁻¹). The resulting map of net fluxes (Fig 1c) emerges from these opposing processes, producing a heterogeneous distribution of GHG sources and sinks across regions and biomes. Together, these results indicate that the relatively modest global land sink reflects the net outcome of much larger gross emissions and removals occurring simultaneously across terrestrial ecosystems.

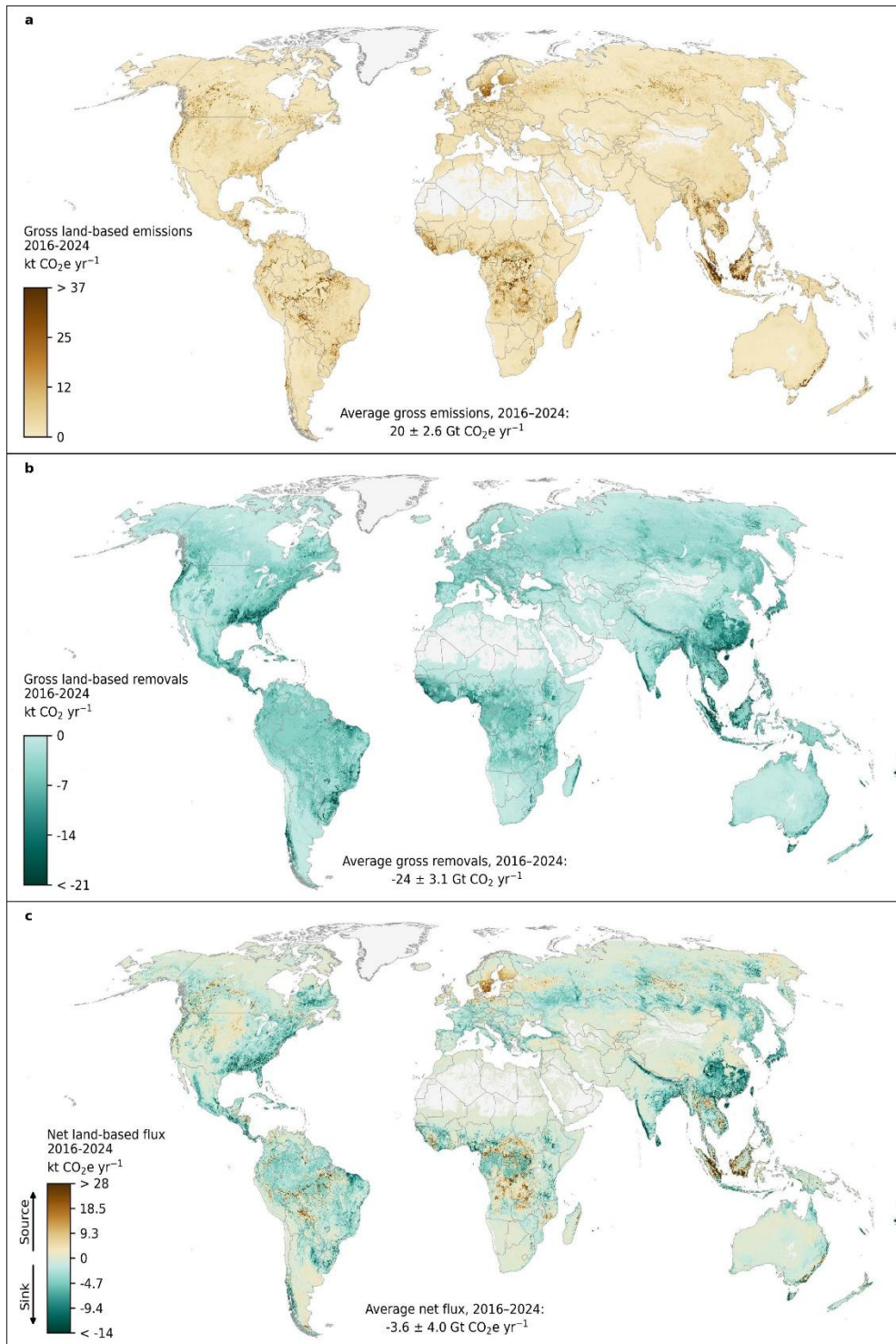


Figure 1. Spatial distribution of greenhouse gas (GHG) emissions, carbon removals, and net GHG fluxes across global land, 2016-2024. (a) Gross GHG emissions. (b) Gross carbon removals. (c) Net GHG flux, the difference between gross emissions (a) and removals (b). Values were aggregated from the original resolution of 30-m to approximately 4-km for global visualization. Minimum and maximum values in legends (and associated color saturation) represent the 0.5 and 99.5 percentiles of aggregated pixels with fluxes; all pixels with emissions higher than the maximum or removals lower than the minimum are represented by the same colors. Uncertainties represent ± 1 standard deviation.

Distribution of emissions and removals across spatial scales

To further characterize the large-scale geographic patterns of GHG fluxes (Fig. 1), we quantified the spatial distribution of emissions and removals using flux distribution curves that relate cumulative gross emissions and removals to their respective cumulative land areas. Globally, emissions were more spatially concentrated than removals. Between 2016 and 2024, half (10 Gt CO₂e yr⁻¹) of annual average GHG emissions originated from just 4.5% (260 Mha) of the global land surface with emissions, whereas half (-12 Gt CO₂ yr⁻¹) of average annual CO₂ removals originated from 19% (1310 Mha) of the land surface with removals (Fig. 2). The contrast was still pronounced at higher cumulative shares: 80% of global emissions originated from just 21% of emitting land, while 80% of global removals were distributed across 48% of land with removals.

The global asymmetry between emissions and removals is reflected in the shapes of the flux distribution curves (Fig. 2a, Gini coefficients 0.74 vs. 0.48, respectively); complementary maps of cumulative contribution classes (Fig. 2b-d) illustrate the distinct geographic patterns underlying these distributions. The highest emitting areas globally (Fig. 2d) were concentrated in ecosystems with high vegetation and soil carbon density, reflecting both recent land-use change, particularly tropical forest ecosystems (e.g., Democratic Republic of the Congo, Brazil), and areas with organic soil that continue to emit following historical drainage (e.g., Indonesia, southern Scandinavia). By comparison, areas contributing to global removals were more evenly distributed (Fig. 2c), reflecting more diffuse carbon uptake across forests of eastern North America, Europe, China, and west Africa, among others. Together, these geographic distributions reflect the combined influence of long-term climatic and ecological conditions, which determine where carbon can be stored and accumulated, and land management, including harvest, disturbance, afforestation/reforestation, and regrowth, which continue to shape contemporary patterns of emissions and removals²⁵. Areas contributing disproportionately to both emissions and removals (Fig. 2b) were concentrated in dynamic landscapes such as the southeastern United States, central Africa, eastern China, and Indonesia, characterized by active disturbance and regrowth cycles, whereas carbon uptake through vegetation persistence and recovery occurred alongside emissions associated with land-use change, disturbance, and management (including shifting cultivation). These results indicate that many of the regions that are most important for sustaining terrestrial carbon uptake are also major contributors to emissions, highlighting the challenge of simultaneously protecting existing carbon stocks while promoting continued atmospheric carbon sequestration through vegetation growth and recovery.

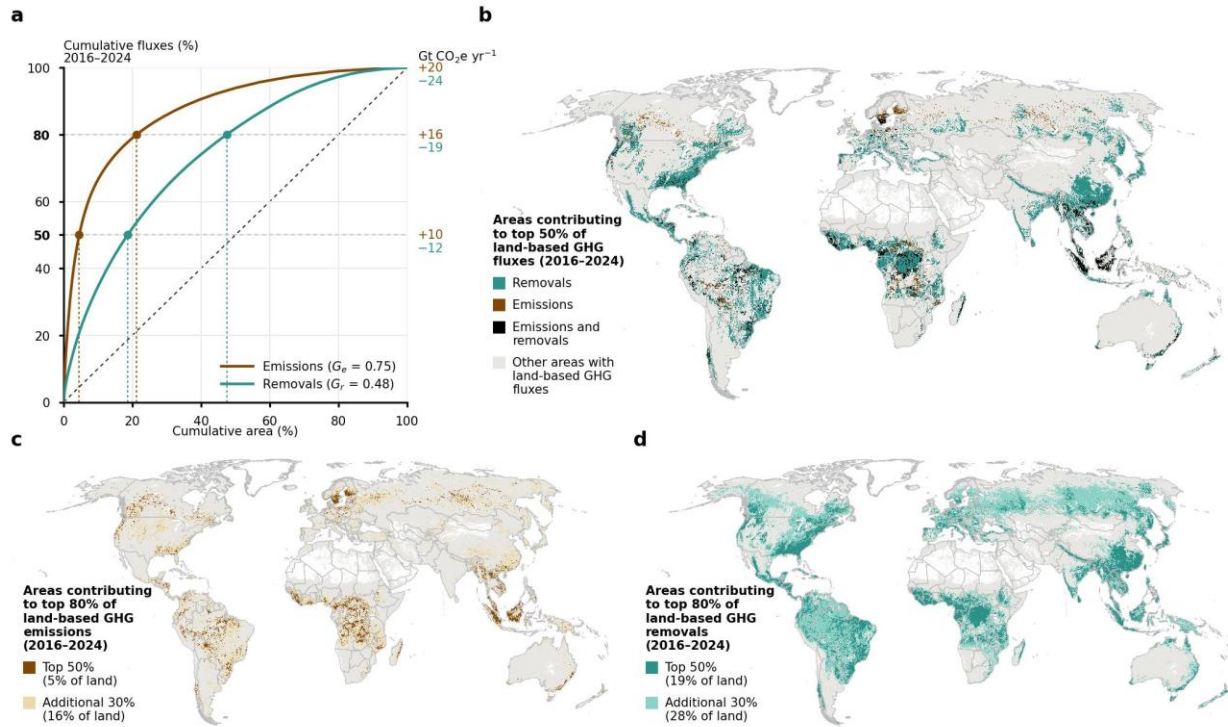


Figure 2. Contrasting spatial distributions of global terrestrial greenhouse gas emissions and removals. (a) Global distribution curves relating cumulative shares of average annual gross emissions and removals (2016-2024) to cumulative land area with emissions and removals, respectively. The curves show the cumulative land area with ranked emissions or removals required to account for a given share of that flux. G_e and G_r are the Gini coefficients for gross emissions and gross removals, respectively. (b) Spatial distribution of areas contributing to the first 50% of global emissions and removals. Black areas contribute to the first 50% of both emissions and removals. (c) Areas contributing to 50% and 80% of global removals; (d) Areas contributing to 50% and 80% of global emissions. In (c) and (d), darker shading identifies locations accounting for the first 50% of global emissions or removals, while lighter shading identifies areas contributing the next 30% (50-80% cumulative contribution). The distribution curves in (a) are based on fluxes at 30-m resolution, while the maps in (b-d) are based on 4-km aggregations of emissions and removals, and therefore areas shown in the maps do not correspond exactly to the areas with the highest fluxes in the curves.

Although emissions are more spatially concentrated than removals at the global scale (Fig. 2), local landscapes exhibit a range of spatial configurations (Fig. 3), shaped by environmental conditions and their unique histories of disturbance, management, and recovery. For example, in Oregon (United States), forest management resulted in localized carbon loss associated with harvests occurring since 2015 embedded within broadly distributed carbon removals from post-harvest forest regrowth across multiple stand-age cohorts (Fig. 3, first column). In Pará (Brazil), emissions associated with deforestation and forest degradation declined over the study period; ongoing carbon removals in adjacent Indigenous-controlled or protected forest areas increasingly outweighed emissions such that the landscape shifted to a weak net sink by the end of the timeseries (Fig. 3, second column). In Quebec (Canada), a 2023 spike in emissions driven by extensive wildfires illustrates how episodic disturbances can shift landscapes from sink to temporary source (Fig. 3, third column). In Central Kalimantan (Indonesia), high emissions and removals

occur simultaneously within a heavily managed tropical ecosystem situated on high-carbon organic soil that have been extensively drained and burned (Fig. 3, fourth column). Together, these illustrative examples provide insights into the processes and locations underlying global terrestrial GHG dynamics that are not apparent from regional or national statistics alone. Furthermore, they highlight that similar net GHG flux outcomes can arise from fundamentally different combinations and magnitudes of gross emissions and removals from both vegetation and soil components across space and time.

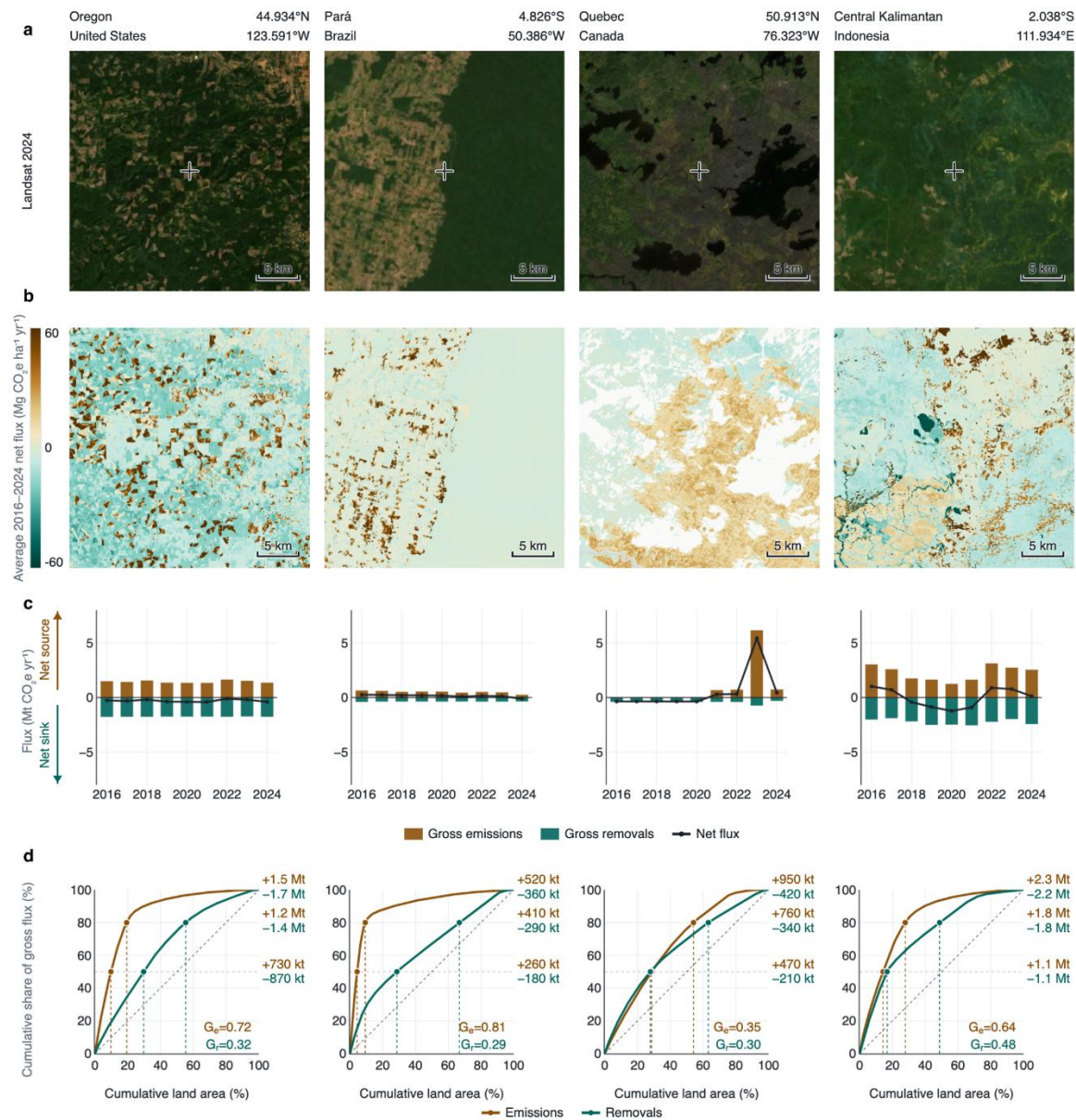


Figure 3. Contrasting spatial configurations of terrestrial greenhouse gas (GHG) fluxes across representative landscapes. (a) Landsat satellite imagery (composite for 2024) showing four illustrative landscapes characterized by distinct patterns of land use, disturbance, and ecosystem dynamics: managed forests in Oregon (United States); an

active forest frontier (left) abutting a protected area for the Parakanā Indigenous people in Para (Brazil); temperate forests with fires in 2023 in Quebec (Canada); and peatlands in Central Kalimantan (Kalimantan Tengah, Indonesia). Coordinates represent the center of the imagery. (b) Mean annual net GHG fluxes during 2016-2024 at 30-m resolution. In the second map (Brazil), the widespread green indicates forest with uniform net sink over this period. (c) Time series of annual gross emissions, gross removals, and resulting net fluxes for each landscape during 2016-2024. (d) Flux distribution curves relating cumulative shares of gross emissions and removals to cumulative land area, ranked by emissions and/or removals magnitude (as in Fig. 2). G_e and G_r are the Gini coefficients for gross emissions and gross removals, respectively. Gross emissions and removals are shown in brown and teal, respectively, at 50%, 80%, and 100% of the distribution curves.

Composition of terrestrial GHG fluxes

Vegetation contributed 54% of gross emissions and 77% of gross removals globally between 2016 and 2024 (Fig. 4a), with the remainder arising from organic and mineral soil. Drainage and burning of high-carbon organic soil represented an ongoing source of emissions ($2.6 \pm 1.9 \text{ Gt CO}_2\text{e yr}^{-1}$), while carbon stock changes in mineral soil contributed net emissions of $1.3 \pm 2.7 \text{ Gt CO}_2\text{ yr}^{-1}$, which together negate nearly half the global net carbon sink from vegetation ($-7.4 \pm 3.0 \text{ Gt CO}_2\text{e yr}^{-1}$). Removals were steady across years (Fig. 4b), driven by the largely stable global forest area that dominates removals. Emissions were highest in 2020 and 2024, associated with the catastrophic “Black Summer” bushfire season in Australia²⁶ and fires in Canada²⁷, respectively. However, the low interannual variability in global emissions and removals belies the range of emissions and removals trajectories found at smaller scales, in which landscape-scale processes have a proportionately higher impact (Fig. 3).

The relative contributions of land-sector GHG flux components of vegetation, organic soil, and mineral soil varied across climate domains (Fig. 4c). The subtropics/tropics were most dynamic and contributed the majority of gross emissions and removals (61% for emissions and 60% for removals), driven by large areas of relatively faster-growing forest and expanding human activity²⁷. Despite extensive tropical land-use change this century²⁸, the tropics and subtropics provided the majority of the net sink ($-2.1 \text{ Gt CO}_2\text{e yr}^{-1}$) between 2016 and 2024. Temperate and boreal lands were slight net sinks of -0.86 and $-0.66 \text{ Gt CO}_2\text{e yr}^{-1}$, respectively. Temperate and boreal regions had proportionately smaller vegetation fluxes, with soil contributing a larger share of total GHG fluxes compared to the tropics and subtropics.

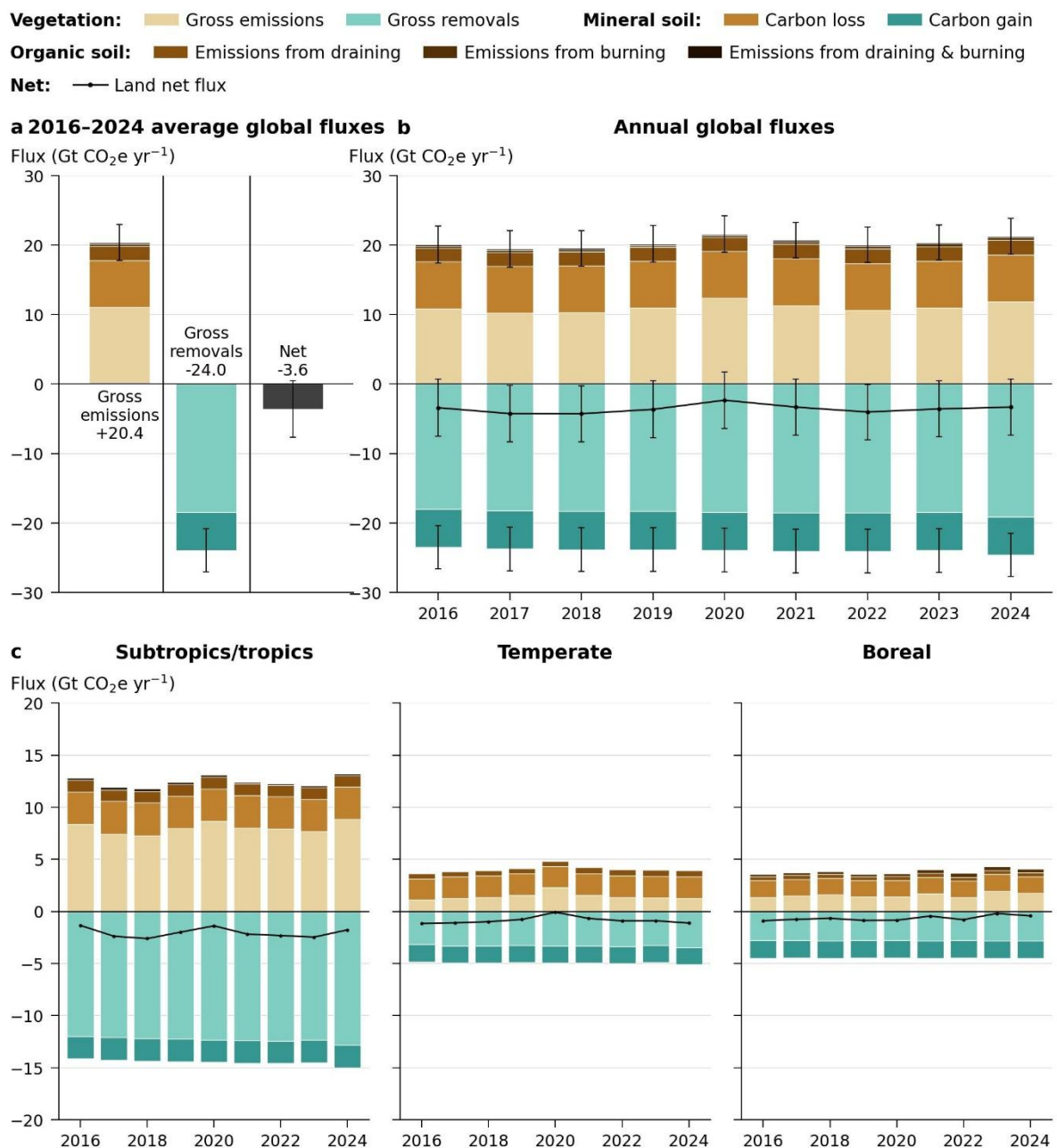


Figure 4. Contributions of vegetation, organic soil, and mineral soil components to terrestrial greenhouse gas fluxes globally and across biomes, 2016–2024. (a) Average annual gross and net fluxes by component. Annual gross emissions, gross removals, and net fluxes from vegetation, organic soil, and mineral soil (b) globally and (c) for subtropical/tropical, temperate, and boreal biomes. Vegetation fluxes are separated into gross emissions and gross removals, organic soil contributes only emissions, and mineral soil is separated into emissions from loss and removals from gain. Notes for all panels: Fluxes include CO₂, CH₄, and N₂O expressed as CO₂ equivalents. Uncertainty is ± 1 standard deviation and is only available for global totals due to limitations in input data. Uncertainty for all components for which it was calculated are included in Table 1; only uncertainty for total gross emissions, gross removals, and net flux are shown here for clarity.

Global results are further disaggregated in Table 1, showing the composition of GHG fluxes across component (trees, other vegetation, soils, harvested wood products), GHG, and flux

category. CO₂ was the dominant gas for emissions; CH₄ and N₂O emissions combined contributed 3.4% of total emissions, arising from both biomass burning and drainage and burning of organic soil. Despite occupying large areas of the terrestrial surface, non-tree vegetation accounted for a small share of gross emissions and removals globally (6.5 and 4.6%, respectively) compared with tree-dominated areas, underscoring the dominant role of trees in terrestrial GHG dynamics. However, non-tree vegetation can represent an important component of local GHG dynamics in treeless ecosystems.

Fluxes were substantial in both directions for land that maintained tree cover. Among tree-associated gross emissions, emissions from partial disturbance accounted for 27% (3.0 Gt CO₂e yr⁻¹) of total tree-related emissions, indicating that forest degradation and other non-stand-replacing disturbances are an important source of emissions beyond those arising from deforestation and other forms of complete tree cover loss, as suggested for the tropics²⁹, the Amazon³⁰, and the Congo basin³¹. Globally, carbon removals by undisturbed tree cover undisturbed was more than an order of magnitude larger than removals during the first five years of tree cover growth (-16 vs. -0.96 Gt CO₂e yr⁻¹, respectively). This result highlights that, while afforestation and reforestation remain an important strategy for expanding future carbon sinks, global removals are dominated by carbon uptake in tree cover that was already established prior to the study period, maintained cover, and accumulated carbon throughout it.

The relative contribution of vegetation and soil to the GHG balance varied regionally. Emissions from vegetation dominated in forested regions, emissions from disturbance of organic soil dominated in relatively limited areas such as Indonesia and parts of Scandinavia, and loss of carbon in mineral soil dominated in low-vegetation and arid climates (Extended Data Fig. 2). Emissions from organic soil (2.6 Gt CO₂e yr⁻¹) were twice as high as net carbon losses from mineral soil (1.3 Gt CO₂e yr⁻¹), despite occupying only 8.8% of the terrestrial surface²³, reflecting the high GHG emissions intensity of drained and fire-affected organic soil. National, regional, and compositional breakdowns further reveal geographic variation in the structure of global emissions and removals (Extended Data Figs. 3-4).

Table 1. Global land-related greenhouse gas (GHG) fluxes and their major components, 2016-2024. Average annual gross emissions, gross removals, and net fluxes disaggregated by component, class, flux category, and GHG. Uncertainty represents ± 1 standard deviation. Class refers to the major vegetation and soil categories used to partition fluxes. Vegetation is divided into tree-dominated and non-tree vegetation classes and includes aboveground and belowground biomass (roots), dead wood, and litter carbon pools. Soil is divided into organic and mineral soil classes. Trees: include natural tree cover, tree crops, planted trees, and trees in other land covers. New trees: up to the 5 years of growth after tree cover reached ≥ 5 m. Undisturbed trees: trees with no disturbance detected (i.e., no substantial height loss or fire). Tree loss: disturbance caused tree height to fall below 5 m. Partially disturbed trees: trees with fire detected, or height decrease of ≥ 5 m over one or more years. Other vegetation: row crops and vegetation < 5 m tall. Organic soil²³: soil with high carbon content, with emissions from drainage/extraction, burning, or both. Mineral soil (derived from ²⁴, 0-30 cm

245 depth): other, lower carbon content soils. Harvested wood products (HWP): sum of national-level estimates of net change
 246 in HWP⁸ for 2015-2023, the last year with available data. All other values in this article do not include HWP unless stated.

Component	Class	Flux Category	Flux (Gt CO ₂ e yr ⁻¹)					
			Net flux	Gross removals	Gross emissions			
					All gases	CO ₂	CH ₄	N ₂ O
Vegetation	Trees	New trees	-0.96	-0.96	N/A	N/A	N/A	N/A
		Undisturbed trees	-16	-16	N/A	N/A	N/A	N/A
		Tree loss	7.5	N/A	7.5	7.47	0.040	0.017
		Partially disturbed trees with fire	1.7	N/A	1.7	1.5	0.17	0.054
		Partially disturbed trees without fire	1.3	N/A	1.3	1.3	N/A	N/A
		Total	-6.7	-17.2	10.5	10.3	0.21	0.070
	Other vegetation	With fire	0.073	-0.0018	0.075	0.0032	0.042	0.030
		Without fire	-0.76	-1.2	0.43	0.43	N/A	N/A
		Total	-0.69	-1.2	0.51	0.43	0.042	0.030
	All vegetation	Total	-7.4 ± 3.0	-18 ± 2.8	11 ± 1.0	10.7	0.25	0.10
Soil	Organic soil	Drained	2.0	N/A	2.0	1.8	0.087	0.15
		Burned	0.33	N/A	0.33	0.28	0.052	N/A
		Drained and burned	0.20	N/A	0.20	0.16	0.039	0.0017
		Total	2.6 ± 1.9	N/A	2.6 ± 1.9	2.2	0.18	0.15
	Mineral soil	N/A	1.3 ± 2.7	-5.5 ± 1.3	6.7 ± 1.4	6.7	N/A	N/A
	All soil	Total	3.8	-5.5	9.3	9.0	0.18	0.15
Land without harvested wood products	All components	Total	-3.6 ± 4.0	-24 ± 3.1	20.4 ± 2.6	19.7	0.43	0.25
Harvested wood products	N/A	Total	-0.29	N/A	N/A	N/A	N/A	N/A
Land with harvested wood products	All components	Total	-3.9	-24	20.4	19.7	0.4	0.3

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248 Comparison with other global estimates

249 To evaluate our results against independent assessments of land's role in the global carbon
 250 cycle, we compared our net CO₂ flux estimates with those reported by the Global Carbon
 251 Budget 2025 (GCB 2025)¹. GCB 2025 estimates a net atmosphere-to-land carbon sink of
 252 approximately -2.6 to -5.1 Gt CO₂ yr⁻¹ during 2015-2024, depending on the methodology
 253 used, whereas our spatially explicit framework estimates a net atmosphere-to-land carbon
 254 sink of -4.5 Gt CO₂ yr⁻¹ for approximately the same period (2016-2024) (Fig. 5a). The
 255 alignment of our global estimate with the suite of independent GCB 2025 constraints

indicates that our results are broadly consistent with the current understanding of the global carbon cycle.

While GCB 2025 does not explicitly estimate gross emissions and removals, it partitions land fluxes into net land-use change emissions (E_{luc}) and the net natural land carbon sink (S_{land}). After reclassifying our estimates to approximate these categories (and major E_{luc} subcomponents (Methods and Supplementary Text 5)), our proxy estimates of average annual E_{luc} and S_{land} were $3.4 \text{ Gt CO}_2 \text{ yr}^{-1}$ smaller than those reported by GCB 2025 due to lower estimates from this framework in several sub-categories (Fig. 5b). One potential reason our E_{luc} estimate is lower is that GCB 2025 E_{luc} includes legacy emissions, such as substantial ones from the early 2000s, which are not captured under our committed emissions approach. Agreement was stronger for net emissions from permanent deforestation and net removals from forest regrowth, which together account for the majority of the gross land-use change flux. A directional difference between estimates of wood harvest and forest management reflects differences in how managed forests, harvested wood products and post-harvest regrowth are represented within bookkeeping and inventory-based accounting frameworks.

Although our average annual net atmosphere-to-land sink, E_{luc} , and S_{land} estimates show varying levels of agreement with the GCB 2025, our framework is not designed to model the same interannual variability in fluxes as the S_{land} component of the GCB. Our gross removals are estimated using removal factors derived from long-term changes in carbon stocks that implicitly reflect the average influence of environmental conditions over the periods from which they were derived, but they do not vary annually in response to climate or other environmental change, resulting in comparatively stable removal estimates through time. In contrast, removals in the S_{land} component in GCB 2025, estimated via process-based vegetation models, respond annually to climate variability and other environmental conditions³².

Our estimates are broadly consistent with other recent global carbon assessments. A synthesis of atmospheric inversions and long-term carbon stock changes³³ estimated terrestrial carbon accumulation at $-2.9 \pm 2.6 \text{ Gt CO}_2 \text{ yr}^{-1}$ for 2000-2019, while our analogous estimate is $-4.5 \text{ Gt CO}_2 \text{ yr}^{-1}$. A synthesis of in-situ forest data¹⁸ estimated the net forest carbon sink at $-5.1 \pm 2.3 \text{ Gt CO}_2 \text{ yr}^{-1}$, while our analogous estimate is $-4.7 \text{ Gt CO}_2 \text{ yr}^{-1}$. However, our estimates of global fire-related emissions ($2.1 \text{ Gt CO}_2 \text{e yr}^{-1}$) are well below the Global Fire Emissions Database 5³⁴ ($12.5 \text{ Gt CO}_2 \text{ yr}^{-1}$), with most of the difference coming from grassland systems. This discrepancy should be interpreted in the context of the large differences among current global fire emission products arising from contrasting burned

area datasets, fire detection approaches, fuel consumption assumptions, and treatment of small fires, especially in savanna and grassland ecosystems³⁵.

While differences among studies are expected due to varying definitions, system boundaries and treatment of individual processes^{5,15}, the goal of such comparisons is to assess broad consistency in land-atmosphere fluxes and identify complementarities between approaches. The overall agreement across multiple independent lines of evidence suggests that our estimates capture the magnitude of contemporary land-atmosphere GHG exchange. By resolving the spatial distribution, component composition, and temporal dynamics of emissions and removals within a single, internally consistent framework, our approach provides an additional line of evidence for evaluating terrestrial GHG dynamics.

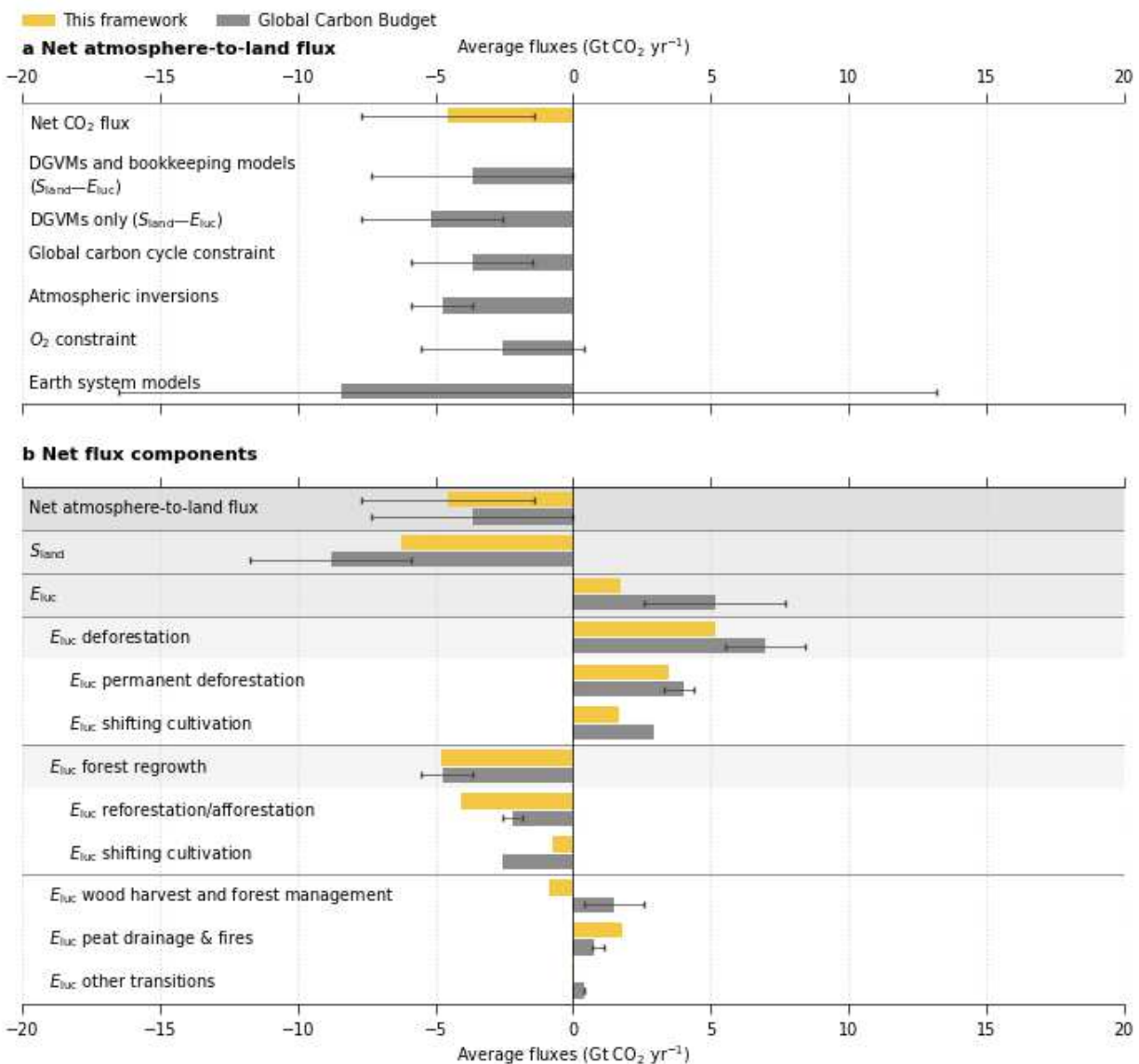


Figure 5. Comparison of carbon flux estimates from this study to the Global Carbon Budget 2025¹ (GCB 2025). (a) Comparison of net atmosphere-to-land CO₂ fluxes between this study and estimates reported by GCB 2025. The atmosphere-to-land net CO₂ flux in this framework is vegetation net flux + organic soil emissions + mineral soil net flux + net change in harvested wood products. This net flux does not match the net flux in Table 1 because this one includes CO₂ only, whereas Table 1 includes all greenhouse gases. (b) Comparison of major carbon cycle components after translating the spatially explicit estimates from this study into categories analogous to those reported by GCB 2025. Net atmosphere-to-land flux is partitioned into the residual terrestrial sink (S_{land}) and net land-use change emissions (E_{luc}), with further disaggregation of E_{luc} , as denoted by indentation. The translation of gross fluxes from this framework into S_{land} , E_{luc} , and its subcomponents is described in the Methods (“Comparison with the Global Carbon Budget”). E_{luc} from other transitions from this framework is too small to appear on the graph (0.027 Gt CO₂ yr⁻¹). Notes for both panels: Error bars indicate uncertainty ranges reported by the respective approaches (± 1 standard deviation for this study). Comparisons are based on CO₂ fluxes only and exclude methane (CH₄) and nitrous oxide (N₂O) emissions to maintain consistency with the carbon cycle accounting framework used by GCB 2025. GCB 2025 values have been converted from C to CO₂ by multiplying by 44/12 for consistency with this study. Negative values indicate net transfer of CO₂ from the atmosphere to land (removals), whereas positive values indicate net transfer of carbon from land to the atmosphere (emissions).

Inventory-consistent attribution of GHG fluxes

Collectively, national GHG inventories submitted by countries to the United Nations Framework Convention on Climate Change (UNFCCC) report a net land sink of -3.9 Gt CO₂ yr⁻¹ over 2016-2023 (the most recent year available in³⁶, as documented in³⁷). These estimates are not directly comparable to outputs from our monitoring framework because national GHG inventories report GHG fluxes occurring only on land that is considered managed, defined using country-specific methods and land-use categories^{38,39}. Using a simple global approximation of managed land (“Inventory-consistent attribution” section of Methods), our estimated net CO₂ flux was -2.9 Gt CO₂ yr⁻¹, a 1.0 Gt CO₂ yr⁻¹ smaller sink than the combined national GHG inventory estimate. Application of country-specific managed land proxies could help close this gap^{40,41}.

To facilitate further comparison with land use-based GHG reporting frameworks, such as corporate and national GHG inventories, we reaggregated our land cover-based estimates of net GHG fluxes into IPCC land-use reporting categories: Forest Land, Cropland, Grassland, Wetlands, Settlements and Other Land (“Inventory-consistent attribution” section of Methods). We estimated global emissions of 2.4 Gt CO₂e yr⁻¹ from land-use change, of which 2.1 Gt CO₂e yr⁻¹ (87%) was from deforestation (Supplementary Table 10). The remaining 0.3 Gt CO₂e yr⁻¹ came from all non-Forest Land transitions. Fluxes within land remaining in the same land-use category were substantially larger than those associated with land use changes, indicating how they are nevertheless highly dynamic in terms of GHG fluxes. Forest Land represented a net sink of -4.2 Gt CO₂e yr⁻¹, comprising large gross emissions and removals (6.4 Gt CO₂e yr⁻¹ and -11 Gt CO₂ yr⁻¹, respectively) from forest management, shifting cultivation and ecosystem recovery and growth, including responses to environmental change (e.g., CO₂ fertilization). Settlements were a net sink of -0.9 Gt CO₂e yr⁻¹, indicating the substantial carbon removals due to trees in built-up and developed landscapes.

The distinction between land cover and land use is particularly important for tree-dominated landscapes, where changes in tree cover do not necessarily imply changes in land use. For example, forest harvest may produce emissions from loss of tree cover while remaining temporarily unstocked within Forest Land, whereas oil palm plantations and agroforestry systems such as cocoa and coffee may be mapped biophysically as tree cover but are reported as Cropland land use under IPCC inventory guidelines. This distinction is evident in our estimated $-1.8 \text{ Gt CO}_2\text{e yr}^{-1}$ gross removals in Cropland.

Organizing net GHG flux estimates within a land-use transition matrix provides a transparent representation of the activities and land conversions underlying emissions and removals, distinguishing fluxes associated with land remaining in the same use from those associated with land converted to other uses. By translating our results in accordance with inventory land use reporting categories, we begin to establish a link between globally consistent, spatially explicit monitoring and national GHG inventories, enabling transparent comparison with nationally reported estimates and providing an independent benchmark where inventory data may be unavailable, infrequently updated, or methodologically variable. Detailed reconciliation with individual national GHG inventories is beyond the scope of the current analysis, but further work could be undertaken, as in

^{40,41}.

Discussion

The net terrestrial GHG balance quantified by this framework ($-3.6 \pm 4.1 \text{ Gt CO}_2\text{e yr}^{-1}$) emerges from the interaction of large gross emissions ($20.2 \pm 2.6 \text{ Gt CO}_2\text{e yr}^{-1}$) and removals ($-23.8 \pm 3.1 \text{ Gt CO}_2 \text{ yr}^{-1}$) that differ in their spatial distribution, composition, and temporal dynamics. Emissions were concentrated within relatively small areas associated with disturbance and land-use change and typically occur as pulsed releases of carbon, whereas removals arose from gradual vegetation growth and soil carbon accumulation taking place across broader areas of Earth's land surface. This implies that reducing land-sector emissions and maintaining and/or enhancing carbon sinks are related but distinct challenges⁴². Emission reduction activities can be targeted toward a relatively small fraction of emitting areas, whereas maintaining and enhancing carbon removals on land depends on sustaining ecological processes operating across much larger and more diffuse areas that require coordinated land management. Understanding both dimensions simultaneously is therefore essential for interpreting the role of land in climate mitigation and designing more effective policy interventions across local, national and international levels^{43,44}.

Because the GHG monitoring framework introduced here is spatially explicit and globally consistent, results can be aggregated to a wide range of reporting units, including countries, jurisdictions, river basins, protected areas, Indigenous territories, and corporate sourcing regions. For example, across their global mapped extents, protected areas and Indigenous lands were net sinks of -0.3 and -1.0 Gt CO₂e yr⁻¹ (9% and 28% of the global net land sink, respectively), while the Amazon River basin was effectively neutral (-0.0016 Gt CO₂e yr⁻¹), the Congo River basin was a net source (0.60 Gt CO₂e yr⁻¹), and the Mekong River basin was also effectively neutral (0.014 Gt CO₂e yr⁻¹) (additional values in Supplementary Table 11). These examples illustrate how a common global geospatial GHG accounting framework can support comparisons across scales and diverse user communities— from national GHG inventory compilers to conservation organizations and corporate reporting systems— while maintaining comparability with internationally recognized GHG accounting approaches^{6,8}.

Nonetheless, several limitations should be considered when interpreting results from this study. To achieve global consistency, annual updates, and complete spatial coverage, our monitoring framework relies on a combination of Earth observation products and geospatial datasets that vary in their spatial resolution and level of detail. As a globally consistent monitoring system, the framework is designed to provide comparable estimates across regions rather than to reproduce locally calibrated assessments or national GHG inventories, which may incorporate data at higher spatial and/or temporal resolution, country-specific emission and removal factors, or reporting conventions tailored to local circumstances. Differences between global and locally derived estimates are therefore expected and provide opportunities to identify data gaps, methodological differences, and priorities for future improvement^{37,40,41}. Additional uncertainty arises from limitations in satellite-based detection of disturbance and regrowth, the representation and attribution of partial forest loss, assumptions regarding vegetation growth rates, and the use of generalized emission and removal factors for some management practices and ecosystem types (e.g., primary forests, non-tree vegetation).

Our sensitivity analysis indicates that vegetation flux estimates are sensitive to assumptions surrounding emissions from partially disturbed tree cover, removal factors, and starting carbon densities (Supplementary Table 12). Average annual emissions from partially disturbed tree cover ranged from 9.9 to 12.2 Gt CO₂e yr⁻¹, depending on the range of emission factors applied (standard model emissions: 11 Gt CO₂e yr⁻¹). This sensitivity highlights the importance of developing more spatially explicit emission factors for partial disturbance (e.g., ^{45,46}). The use of alternative growth curves for tropical secondary forests⁴⁷ reduced global carbon removals from -9.0 to -6.6 Gt CO₂ yr⁻¹ and changed the tropics from a net sink of -2.3 Gt CO₂ yr⁻¹ to effectively neutral (-0.083 Gt CO₂ yr⁻¹), demonstrating the

sensitivity of large-scale removal estimates to how forest regrowth is characterized and quantified. Using an alternative starting aboveground biomass map of the same spatial resolution⁴⁸ (Yang et al. under review) reduced gross emissions from 11 (standard model) to 9.4 Gt CO₂ yr⁻¹, reflecting well-documented variation among and disagreement between AGB density maps⁴⁹ and demonstrating the influence of starting biomass assumptions on subsequent GHG flux estimates.

Furthermore, the vegetation, organic soil, and mineral soil components of our analysis are estimated independently using observation-based approaches and are not dynamically coupled; interactions between vegetation and soil carbon pools are represented through observed changes in each component rather than simulated through ecosystem process models. Similarly, carbon stock changes in harvested wood products are derived from national harvest statistics following IPCC methods, whereas changes in ecosystem carbon stocks are derived from geospatially located harvest events, so biomass transfers into the harvested wood product pool are not internally reconciled with observation-based forest biomass losses in our spatial accounting framework. This design prioritizes consistency with observations and transparency of component estimates but may not capture all interactions and feedbacks among carbon pools represented in process-oriented modeling approaches.

The framework presented here is designed to be updated and evolve as additional data become available, and continued annual updates will enable progressively longer time series and improved assessment of long-term trends. Because emissions and removals are estimated within a consistent spatial accounting framework, advances in Earth observation and carbon modeling can be incorporated without fundamentally changing the underlying methodology. Continued improvements in monitoring disturbance and regrowth dynamics, together with improved information synthesized from expanded and repeated national forest inventories⁵⁰, are likely to reduce uncertainty and improve attribution of emissions and removals through time. Greater public availability of ground-sourced carbon data would further strengthen global assessments by enabling a larger number of locally collected observations to inform spatially explicit emission and removal factors⁵¹, improving the accuracy, transparency, and comparability of land-sector GHG estimates while helping to reconcile monitoring systems developed across local, national, and global scales.

Conclusion

Land-related GHG fluxes are typically represented as aggregate estimates in carbon budgets and climate assessments, yet such summaries mask a heterogeneous Earth

system in which emissions and removals arise from different processes, occur in different places, and operate over different timescales. Resolving net GHG fluxes into their constituent emissions and removals reveals the underlying geographic distribution of terrestrial GHG dynamics from vegetation and soil and provides a framework for linking local land use decisions to global climate outcomes. As countries, companies and conservation practitioners rely on land-based mitigation to meet climate goals⁵², and as demand for transparent and geographically explicit climate information grows, recent advances in Earth observation, data synthesis, artificial intelligence and planetary-scale computing make it increasingly possible to monitor GHG dynamics continuously across landscapes rather than relying primarily on nationally or regionally aggregated statistics^{19,47}. While localized assessments remain essential for understanding site-specific processes and validating broader estimates, the spatially explicit monitoring framework introduced here offers a complementary capability by generating consistent, wall-to-wall GHG flux estimates. Integrating spatially explicit monitoring with inventory-based GHG accounting can help bridge local observations and global assessments, offering a pathway toward more transparent understanding of global land GHG dynamics while maintaining compatibility with existing reporting systems used to track progress toward climate goals.

Methods

Overview and scope

We developed a spatially explicit, global monitoring framework to estimate gross greenhouse gas (GHG) emissions (+), gross carbon removals (-), and net fluxes [difference between emissions (+) and removals (-)] for land between 2016 and 2024 at 0.00025° x 0.00025° resolution (referred to as 30-m below). The framework estimates annual fluxes from vegetation, organic soil²³, and mineral soil (0-30 cm depth, derived from ²⁴) for the three major GHGs associated with land use, land-use change and forestry (LULUCF): carbon dioxide (CO₂), methane (CH₄), and nitrous oxide (N₂O). It integrates globally consistent Earth observation geospatial datasets with the LULUCF components of the Agriculture, Forestry, and Other Land Use (AFOLU) methods from the Intergovernmental Panel on Climate Change (IPCC) Guidelines for National Greenhouse Gas Inventories ^{8,21,22} (Supplementary Table 1). The framework includes non-CO₂ emissions from biomass burning associated with vegetation and soil disturbance including drained and/or burned organic soil. It does not include natural wetland and inland-water CH₄ emissions or soil N₂O emissions, nor non-CO₂ emissions from agricultural management (e.g., enteric fermentation, rice cultivation, fertilizer application, etc.), which arise from distinct production processes and require different data and estimation methods. Agricultural

management emissions represent an important and complementary component of AFOLU GHG accounting that can be integrated with this framework as spatially explicit datasets mature (e.g., ^{53,54}).

Designed to be as comprehensive as possible, this framework expands the previous forest-focused analyses of ^{41,55} to cover vegetation and soil carbon dynamics across all land covers and land uses. It encompasses all major land-uses defined by the IPCC (Forest Land, Cropland, Grassland, Wetlands, Settlements, and Other Land), all major ecosystem carbon pools (aboveground biomass (AGB), belowground biomass (BGB), dead wood, litter, soil organic carbon (SOC)), and all major GHGs. We focus on spatially explicit monitoring of ecosystem vegetation and soil carbon dynamics, including non-CO₂ emissions associated with biomass burning and drainage and burning of organic soil, but also combine national harvest statistics⁵⁶ with IPCC Tier 1 production approach methods⁸ to estimate annual CO₂ emissions and removals arising from harvested wood products (HWP) in use for completeness, calculated from the sum of net carbon stock changes in defined HWP product commodity classes including both transfers into HWPs and loss from HWP decay. The temporal scope is constrained by the availability of globally consistent annual maps of land cover and tree height; although shorter than the multi-decadal records commonly used to assess long-term changes in the terrestrial carbon sink, 2016-2024 is the longest interval currently available for temporally consistent and observation-based monitoring of global land cover and vegetation dynamics at high spatial resolution (~30-m). The framework was designed to provide a globally consistent and inventory-compatible representation of terrestrial GHG dynamics while retaining the spatial detail necessary to flexibly aggregate results to a range of geographic units.

Vegetation fluxes were estimated using a gain-loss approach⁸ in which emissions associated with vegetation loss and disturbance and carbon removals associated with vegetation growth were quantified separately. Mineral soil carbon changes were estimated using a stock-change approach based on spatially explicit SOC density maps ²⁴. Emissions from organic soil were estimated using satellite-based observations of the extent of drained and burned organic soil combined with IPCC Tier 1 emission factors²³. Together, these three components provide a unified representation of land-sector GHG dynamics across the terrestrial surface. The integration of these components is depicted in Extended Data Fig. 1. All outputs were generated at 30-m resolution, matching the resolution of the underlying Landsat inputs. Inputs to the framework at coarser resolution were resampled to the resolution of activity data⁴⁷. Outputs from the framework are listed in Supplementary Table 13.

Consistent representation of land

The framework represents land using spatially explicit, wall-to-wall maps, in which individual land units (here, approximately 170 billion 30-m pixels globally) are tracked through time, consistent with IPCC Approach 3 for land representation⁸. Land classification was based on two globally consistent annual datasets for 2015–2024: (1) vegetation height (5 m to ≥ 25 m, in 1-m increments) and (2) a hierarchical land-cover/land-use (LC/LU) composite comprising built-up land, annual crops⁵⁷, trees, short vegetation, bare ground, water, and snow/ice¹⁶. Within the LC/LU composite, tree extent is masked by crop and built-up classes, although trees within these classes remain represented in the standalone vegetation height product. These datasets were used to classify land and identify transitions between land states (Supplementary Table 4).

The vegetation height and LC/LU composite products were derived from globally consistent Landsat Analysis Ready Data processed by the Global Land Analysis and Discovery Lab (GLAD-ARD)⁵⁸, generated from all available Landsat Collection 2 scenes acquired between 2015 and 2024 across virtually all land between 75 °N and 56 °S. Small islands, Arctic islands, and Greenland are excluded from the GLAD-ARD extent due to the absence of high-quality data and/or a short growing season¹⁶. GLAD-ARD is available online without restrictions (<https://registry.opendata.aws/glad-landsat-ard/>). Mangrove-specific data were used to distinguish mangrove ecosystems from other tree-dominated land⁵⁹.

For vegetation flux estimation, land was classified into the following land covers: trees (height ≥ 5 m), built-up, crops, short vegetation (vegetation cover $\geq 20\%$ and height < 5 m), bare ground (vegetation cover $< 20\%$ and height < 5 m), water and snow/ice. To improve representation of carbon dynamics, these classes were further stratified using information on vegetation height, ecosystem type, management and disturbance history into eight classes: mangroves, planted trees, trees in other land covers (crop and built-up), primary forest, secondary forest, crops, short vegetation, and non-vegetated land (water, bare ground, snow/ice, built-up without trees) (Supplementary Text 1, Supplementary Table 2). Land cover classifications were applied consistently across all years of the 2016-2024 time series, enabling tracking of land cover states and transitions through time and ensuring that changes in land state reflect biophysical land cover changes rather than methodological artifacts caused by changes in the classification method. These land cover classes and their changes form the basis for activity data and assigning emission and removal factors for vegetation (see below). For organic and mineral soil, land was grouped into organic and mineral soil types^{23,24} and classified *post-hoc* according to the LC/LU composite.

Starting carbon pools

Initial carbon densities were assigned to all land pixels in 2015 for vegetation and mineral soil carbon pools using globally consistent and spatially explicit biomass, dead organic matter, and soil carbon datasets representative of conditions in 2015 (Supplementary Table 3, left panel of Extended Data Fig. 1). The framework initializes carbon pools from these observed 2015 conditions rather than making assumptions about a theoretical equilibrium or reference state. Carbon pools for trees included aboveground live woody biomass^{17,60}, belowground biomass^{22,61}, and dead wood and litter^{21,22}. For non-tree vegetation pixels, we applied IPCC default carbon densities, applying climate-stratified aboveground carbon default values for annual crops and aboveground and belowground carbon default values for short vegetation⁸. We assumed that non-vegetated land had no biomass or dead organic matter carbon.

The organic soil component does not require initialization or temporal updating of the soil carbon pool; emissions (also 30-m resolution) were estimated using an IPCC approach whereby emissions are calculated by combining data on the extent of drainage, extraction and fire with relevant emission factors, rather than estimating changes in carbon stocks as for mineral soil²³. Mineral soil carbon (0-30 cm depth) was represented using spatially explicit (30-m) estimates of soil organic carbon density and excludes bare rock and shifting sands²⁴. Further information on initial soil carbon density is provided in Supplementary Text 2.

Activity data

Activity data representing changes in land over time (in hectares), including land cover change, disturbance, and persistence, were derived by applying deterministic decision trees to multiple annual Earth observation datasets across consecutive time intervals, in which each 30-m pixel of land was assigned to a unique activity stratum for each time interval (Supplementary Table 4). For vegetation, activity data represented annual losses, gains, and maintenance of tree cover, crops, and short vegetation, as well as disturbance events including fire and partial reductions in tree height (Supplementary Tables 4 and 5, left panel of Extended Data Fig. 1). For trees, loss was defined as a reduction in vegetation height to below 5 m and assigned to the year in which that threshold was crossed, while gain was defined as an increase in vegetation height to ≥ 5 meters and assigned to the year in which it crossed that threshold. Partial disturbances were identified where vegetation remained taller than 5 meters but experienced fire or a reduction in height ≥ 5 m over one or more years. Transitions that did not involve vegetation were grouped separately, as they do not generate vegetation CO₂ fluxes (although they may have soil carbon changes, which are calculated separately from vegetation). Organic soil activity data reflected drainage and

fire²³. Mineral soil carbon fluxes were estimated directly from changes in mapped soil carbon stocks²⁴ and therefore did not require separate activity data. Further information on the generation of activity data is provided in Supplementary Text 3.

Emission and removal factors

For vegetation, we define emission factors as the quantity of CO₂ or CO₂-equivalent released per unit area following an episodic loss or disturbance of vegetation (Mg CO₂e ha⁻¹), and removal factors as the annual rate of CO₂ uptake per unit area associated with vegetation growth or establishment (Mg CO₂ ha⁻¹ yr⁻¹). For organic soil, we define emission factors as the quantity of CO₂ or CO₂-equivalent released annually and continuously following soil drainage (Mg CO₂e ha⁻¹ yr⁻¹), or episodically in the case of fire (Mg CO₂e ha⁻¹)²³. For mineral soil, no emission or removal factors are used because carbon losses and gains were directly calculated from stock-changes between consecutive time periods; pixels with SOC loss contributed to gross soil carbon losses, while pixels with SOC gain contributed to gross soil carbon gains. Emission and removal factors are summarized in the center panel of Extended Data Fig. 1, with further information on their generation in Supplementary Text 4.

Collectively, emission and removal factors capture rapid emissions associated with abrupt vegetation loss (using the committed emissions approach, consistent with IPCC Tier 1 assumptions⁸) and disturbance of organic soil, comparatively slower responses from vegetation growth and recovery, and even slower changes in mineral SOC. Whereas bookkeeping approaches simulate legacy soil carbon responses to past land-use changes⁶², our mineral soil estimates are derived from a spatially explicit model of SOC density informed by observations²⁴. Consequently, legacy soil carbon stock changes associated with disturbances that occurred prior to the analysis period are inherently reflected in the modeled changes in soil carbon density and the resulting soil carbon stock change estimates.

For vegetation, emission factors were derived from carbon densities in biomass and dead organic matter pools at the time of loss or disturbance. Complete vegetation loss resulted in emissions of all the carbon stored within affected pools (Supplementary Table 6), whereas partial disturbances were assigned fractional emissions based on disturbance type^{63,64} (Supplementary Table 7). Non-CO₂ emissions associated with biomass burning were estimated using IPCC combustion and emission factors⁸.

Vegetation removal factors represent carbon accumulation from vegetation growth and were assigned by vegetation subtype using a combination of IPCC defaults and spatially explicit datasets (Supplementary Table 8), including separate removal factors for

mangroves, planted trees, naturally regenerating forests, primary forests, and trees in other land covers (i.e., in crops and built-up). For naturally regenerating forests, removal factors varied with forest age up to 100 years to represent changing carbon accumulation rates as stands mature⁶⁵. Removal factors were applied annually to persistent tree cover and in the year of establishment for new vegetation classes; following IPCC guidance, new vegetation associated with crops and short vegetation were assumed to reach vegetation carbon equilibrium within one year and did not have removals in subsequent years⁸.

Synthesis of component GHG fluxes

Vegetation and organic soil GHG fluxes were calculated by assigning emission and removal factors (the latter for vegetation only) to activity data each year (center panel of Extended Data Fig. 1, Supplementary Table 4). This resulted in maps of gross emissions and removals and their difference (net flux) by carbon pool and GHG for each time interval (right panel of Extended Data Fig. 1). For the vegetation model, the output carbon densities from one year were the input carbon densities for the next year, while primary forest extent, oil palm extent, forest age, and disturbance history of each pixel were also updated and carried forward to the next year. Mineral SOC changes were calculated as the difference between consecutive blocks of SOC density.

Under this framework, gross emissions from land include GHG emissions from vegetation, GHG emissions from disturbed organic soil, and loss of SOC in mineral soil, while gross removals include carbon removals by vegetation and gain of SOC mineral soil. Outputs were generated as cloud-optimized geospatial datasets in GeoTIFF and Zarr formats (Supplementary Table 13) and subsequently aggregated to countries and other reporting units using geodesic area-weighted zonal statistics. Country statistics reported here use country boundaries from Global Administrative Areas (GADM) database v4.1 (<https://gadm.org/index.html>).

Emissions and removals distribution curves

To characterize the spatial distribution of emissions and removals across land, we constructed flux distribution curves relating cumulative GHG fluxes to cumulative land areas. Curves were constructed separately for emitting and removing land, excluding pixels with no emissions or removals, respectively; including areas with no emissions or removals would artificially sharpen the curves and reduce their interpretability for identifying where emissions and removals occur. Pixels were ranked in descending order of their emissions and removals, cumulative fractions of total flux and land area were calculated, and cumulative percentages of global flux were plotted against cumulative percentages of land area. Curves that rise steeply indicate that a large fraction of total emissions or removals

originate from a relatively small area, whereas curves closer to the 1:1 line indicate more even spatial distribution. To quantify the spatial distribution of emissions and removals, we calculated Gini coefficients for each flux distribution curve, which range from 0 (uniformly distributed across all land with emissions or removals) to 1 (all emissions or removals occur within a single pixel), with higher values indicating greater spatial concentration of emissions or removals.

Fluxes from the distribution curves at global scale (Fig. 2) are very close approximations of the global fluxes reported elsewhere in this study due to some minor computational simplifications necessary to rank all ~170 billion land flux pixels. While we report distribution curves for the global land surface, the method is scale-independent and can be applied to any user-defined geography (e.g., Fig. 3), providing a consistent method for characterizing the geographic distribution of emissions and removals across scales.

Comparison with the Global Carbon Budget

To facilitate comparison with independent estimates of land's role in the global carbon cycle, we translated our spatially explicit flux estimates into categories analogous to those reported by the Global Carbon Budget 2025¹ (GCB 2025). For these comparisons, we used only CO₂ fluxes, excluding CH₄ and N₂O emissions, to align with the carbon cycle accounting scope of the GCB. As a first check of our framework's consistency with the global carbon cycle, we calculated the net atmosphere-to-land flux for 2016-2024 as the balance between gross CO₂ emissions and gross CO₂ removals across vegetation, organic soil, and mineral soil and compared the result with corresponding GCB 2025 estimates of net atmosphere-to-land flux derived from bookkeeping models, dynamic global vegetation models, atmospheric inversions, oxygen constraints, and other approaches.

We also reclassified our gross CO₂ emissions and removals into net land-use change emissions (E_{luc}) and the natural land carbon sink (S_{land}) following, as closely as possible, the accounting used in GCB 2025 (Supplementary Table 9). Direct anthropogenic fluxes associated with land-use change and management, including deforestation, forest regrowth, reforestation, shifting cultivation, organic soil emissions, and forest harvest were assigned to E_{luc} , whereas remaining net carbon uptake was assigned to S_{land} . We performed additional disaggregation to approximate the major E_{luc} subcomponents reported by the GCB. Because GCB 2025 and this monitoring framework differ in system boundaries, definitions, and underlying methodologies, these comparisons are intended to assess broad, global consistency in the magnitude and partitioning of land-atmosphere carbon

fluxes rather than to assess exact agreement or explore regional differences. Further information on comparison with GCB 2025 is provided in Supplementary Text 5.

Inventory-consistent attribution

Many GHG accounting and reporting frameworks (e.g., national GHG inventories⁸, the GHG Protocol Land Sector and Removals Standard for corporate GHG inventories⁶, jurisdictional REDD+⁶⁶) differ conceptually from the fluxes reported by this framework in two ways: 1) they generally report anthropogenic fluxes occurring on managed land as opposed to fluxes on all land, and 2) they report emissions and removals based on land use change rather than land cover change⁸. Although full reconciliation with such reporting frameworks was beyond the scope of this study, we explored two first-order approaches to address these differences. Neither approach changes the GHG emissions or removals calculations described above; they are simply a first attempt to cast those fluxes into existing reporting conventions.

To approximate fluxes for managed lands only, we derived a simple spatial approximation of managed lands by excluding primary forest extent in 2015 (as defined in section “Consistent representation of land”), following an approach similar to⁶⁷. This approximation does not incorporate country-specific managed land areas or distinguish managed vs. unmanaged grassland, so all grassland was effectively treated as managed³⁸. Future improvements include approximating managed land using national definitions and mapped boundaries for the few countries for which they are available (e.g.,³⁷).

Within managed land, we then attributed land cover-based fluxes into IPCC land use reporting categories. This attribution is necessary because the satellite observations used for our estimates detect changes in biophysical characteristics of the land surface in contrast to land use, which reflects the human activities and management objectives associated with that land⁶⁸. Broadly speaking, we assigned annual land uses using prior land use, tree cover disturbance history, ancillary geospatial datasets, and the complete annual land cover observation time series (2015-2024) to distinguish persistent land use change from temporary changes in land cover. This distinction is particularly important in tree-dominated landscapes, where changes in tree cover do not necessarily imply changes in land use, e.g., tree cover loss may be due to harvest or natural disturbance as opposed to deforestation. Our land use time series was applied to fluxes from vegetation, organic soil, and mineral soil, integrating them under a single classification framework. Further information is provided in Supplementary Text 6.

Reporting gross and net fluxes in terms of land-use transitions improves conceptual similarity with land-use-based reporting systems such as national GHG inventories,

although additional analysis is needed to fully translate outputs from this framework into the same terms as national GHG inventories⁴¹. While this approach should not be interpreted as an estimate of fluxes under any specific reporting or accounting framework, it is intended to provide an initial demonstration of how the monitoring framework introduced in this study could be adapted to facilitate better comparability with land-use-based and anthropogenic-focused GHG accounting and reporting frameworks.

Uncertainty and sensitivity analyses

We estimated uncertainty for fluxes from vegetation, organic soil, and mineral soil and propagated them to derive uncertainty bounds for gross and net land GHG fluxes at the global scale. The analysis incorporated uncertainty associated with initial carbon stocks, activity data, emission factors, removal factors, and soil flux estimates. It is limited to the global scale because some key uncertainty inputs are only available globally, such as vegetation change. Component uncertainties were combined using standard variance propagation approaches⁸. Due to the complexity of the global rule-based framework, uncertainty was estimated using deterministic variance propagation (following⁴⁷) rather than stochastic Monte Carlo simulation. Thus, uncertainties should be interpreted as estimates based on the range of deterministic analyses evaluated⁶⁹. Although the activity data do not have pixel-level uncertainty estimates, the overall classification uncertainty is incorporated into the uncertainty propagation and therefore contributes to the reported uncertainty estimates. Uncertainty around the net flux estimate is larger relative to the uncertainties for gross fluxes because net flux uncertainty combines two uncertainties that counteract each other (larger uncertainty, smaller flux). This is particularly relevant in the mineral soil net change uncertainty calculation, where the uncertainty is twice as large as the net change estimate. Further information is provided in Supplementary Text 7.

While our uncertainty analysis provides a single, global, non-spatial bound for fluxes, several important sources of uncertainty could not be incorporated into the formal uncertainty framework (as described in Supplementary Text 7). Therefore, we also performed complementary sensitivity analyses to evaluate the influence of key model assumptions and input datasets. Sensitivity analyses included exploration of alternative representations of starting 2015 vegetation biomass (by replacing¹⁷ with an alternative global map of AGB for 2015⁴⁸), alteration of emission factors associated with partial tree height reductions for fire and non-fire disturbances (by testing higher vs. lower emission fractions), and alteration of forest regrowth rates (by replacing the 1 km gridded removal factor map for regrowing natural forests with an alternative 1x1° gridded regrowth product from⁴⁷). Sensitivity analysis for activity data was not possible because of a lack of

alternative annual global harmonized vegetation height and land cover maps for 2015-2024. Together, the uncertainty and sensitivity analyses provide a range of plausible values for estimated terrestrial GHG fluxes. Further information is provided in Supplementary Text 7.

Data Availability

The geospatial datasets generated in this study, including gross emissions, gross removals and net fluxes for vegetation, organic soil, and mineral soil, will be made publicly available upon publication through [XX] at [DOI]. Derived tabular results used in the main figures and tables, including global, biome, regional and country-level summaries, will also be provided. Input datasets used in the analysis are publicly available from the sources cited in the Methods and Supplementary Tables. Any remaining data required to reproduce the analyses are available from the corresponding author upon request.

Code availability

All code is available at https://github.com/wri/AFOLU_GHG_flux_model.

The modeling framework was implemented in Python using open-source geospatial and scientific computing libraries and executed using a cloud-native geospatial processing workflow designed for global-scale analyses at approximately 30-m resolution. Global-scale processing was parallelized using the Python Dask library, with distributed clusters managed through Coiled and deployed on Amazon Web Services. Vegetation, organic soil, and mineral soil components were processed separately across 1° x 1° tiles that intersected the Global Administrative Areas (GADM) database v4.1 (<https://gadm.org/index.html>).

Tiles for each framework component were processed in parallel and subsequently integrated into a common framework for analysis and reporting. The vegetation model used 200 workers with 32GB of RAM per worker and took ~15 hours (~2700 CPU hours). The mineral soil model used 200 workers with 8 GB of RAM per worker and took ~5 hours (850 CPU hours). The organic soil model used 150 workers with 32 GB of RAM per worker and took 4.5 hours (~680 CPU hours). Post-processing, creating derivative outputs, and calculating zonal statistics involved more than 8,800 CPU hours, for more than 13,000 CPU hours total.

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Author contributions

DG, MR, and NH designed the research. DG and MR executed the research with contributions from EG, AS, and NH. DG and JT designed the computing infrastructure. DG, MR, AS, EG, NH, PP, MH, MI, and TH contributed to data acquisition. OS, DG, and NH contributed to data visualization. DG, YX, PC, MI, and TH designed the uncertainty analysis. DG, MR, NH, CS, and OS contributed to interpretation of the results, with additional support from EG. DG and NH drafted the paper, with further support from MR, and all authors contributed to revising and improving the text.

979 **Competing interests**

980 Authors declare no competing interests.

981

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Supplementary Text

[Note: keeping supplementary text references as (author, date) for clarity for now]

Supplementary Text 1. Land stratification for assignment of emission and removal factors

Beyond the classes of the land cover/land use (LC/LU) composite (Potapov et al. 2022), we stratified land into more homogeneous units designed to be more uniform in GHG dynamics, consistent with IPCC recommendations for improving emissions and removals estimation (IPCC 2019). We classified all land pixels in the starting year (2015), and every year thereafter based on both ecologically- and management-relevant characteristics using the hierarchy shown in Supplementary Table 2). There were eight classes for vegetation and two classes for soil.

Annual mangrove extent (class 1) was delineated using Global Mangrove Watch v3 (GMW v3, Bunting et al. 2022), which provides annual global maps of mangrove extent for 2015-2020. To reduce mangrove loss and gain instances that do not represent real changes, we smoothed isolated single-year mangrove extent omissions and detections within the annual time series. First, pixels that were classified as non-mangrove in a single year were reassigned to mangrove if mangrove extent was observed in both the prior and following year. Any remaining single-year mangrove observations were removed if mangrove extent was absent in both adjacent years. Under this system, the first and last years of the observation period were not modified. This approach assumes that mangrove loss occurs in the latest year and mangrove gain in the earliest year consistent with observations. Mangrove extent observed in 2020 was assumed to persist through the remainder of the analysis period, as annual GMW v3 observations were only available through 2020. Mangrove extent was not modified by the LC/LU composite (Potapov et al. 2022).

Planted trees (class 2), including plantations and tree crops, were identified using global and regional maps (Richter et al. 2024, Descals et al. 2024, Austin et al. 2017, Gaveau et al. 2014, Miettinen et al. 2016, Gunarso et al. 2013). Oil palm was treated separately where annual establishment information was available; the planting-year attribute from Descals et al. (2024) was used to infer loss of non-planted tree cover in the year before plantation establishment. Because maps of globally consistent establishment dates are unavailable for most other planted tree systems, tree cover for all other planted tree extents were assumed to have been planted before the start of the modeling period.

Trees occurring within crop and built-up classes in the LC/LU composite were retained as a distinct category (class 3) using the standalone vegetation height product. This allowed

tree cover within some other land cover classes to be represented as a unique stratum in the vegetation model (akin to “trees outside forests” and called “trees in other land covers” below). Analogous identification of trees within short vegetation was not possible from the input datasets because trees took priority over short vegetation; trees occurring within Grassland land use were instead identified using the subsequent translation from land cover to land use (Supplementary Text 6).

The remaining natural (non-planted) tree cover was divided into primary (class 4) and secondary (class 5) forest classes. Primary forests were defined as the union of humid tropical forests (Turubanova et al. 2018) that experienced no mapped tree cover loss between 2001 and 2014 (Hansen et al. 2013), intact forest landscapes outside the tropics (Potapov et al. 2017), and forests older than 100 years (Besnard et al. 2021, age cutoff per Crippa et al. 2025). Stand age in 2015 was estimated from the ensemble mean age in 2010 according to Global Age Mapping Integration (GAMI) v3.0 by adding 5 years. We used nearest neighbor extrapolation to assign ages to tree cover that was outside the extent of GAMI v3.0 to ensure that all tree cover in the vegetation model had a starting age. Remaining tree cover, including all tree cover up to 100 years of age, was classified as secondary forest (Besnard et al. 2021; Crippa et al. 2025).

Non-tree vegetation was represented by annual crops (class 6) and short vegetation (class 7). Annual crops were not further stratified because the LC/LU composite contains a single annual crop class. This class follows the definition of Khan et al. (2026), encompassing land used to grow annual and perennial herbaceous crops for food, forage, or biofuel while excluding woody perennial crops (which should be included in Richter et al. 2024), tall non-woody perennial crops (such as bananas), permanent pastures, and shifting cultivation. Additional information is provided in Khan et al. 2026. Short vegetation was stratified by IPCC climate zone following IPCC 2019 and 4th Corrigenda (IPCC 2023) to support assignment of climate-specific carbon stock and removal factors.

Non-vegetated land (water, bare ground, snow/ice, built-up without trees; class 8) was not further stratified because it does not contribute vegetation carbon fluxes under the assumptions used here.

For reporting purposes, the classes listed above can be aggregated into three broader vegetated classes: trees (1-5), crops (6), and short vegetation (7), plus non-vegetated land (8) (Supplementary Table 2). The finer stratification was retained within the vegetation modeling framework to better represent variation in carbon stocks, emissions, and removals across vegetation types and management systems.

Soils were stratified independently of vegetation because organic and mineral soils are treated separately within IPCC inventory methods (IPCC 2013, IPCC 2019). Land was classified as either organic or mineral soil for the full model period. Organic soil (class A), including peat and other organic soils, was delineated following Glen et al. (in press). In brief, organic soil was defined on the basis of soil properties rather than vegetation type or peatland status and were derived from an ensemble probability layer developed by Hengl et al. (2026) that combined soil taxonomy and peat-depth information. Climate domain-specific thresholds were then applied to generate a binary organic soil extent (Glen et al. in press). Mineral soil (class B) were defined as the soil domain of Hengl et al. (2026) excluding bare rock and shifting sands, which contain negligible organic carbon stocks, and organic soil extent (class A). This stratification enabled mineral soil stock changes and organic soil emissions to be estimated separately while avoiding double-counting and remaining integrated within a unified terrestrial GHG accounting framework.

Supplementary Text 2. Starting carbon pools

We assigned initial year 2015 carbon densities to each land pixel for aboveground carbon (AGC), belowground carbon (BGC), dead organic matter (DOM) carbon, and soil organic carbon (SOC) (Supplementary Table 3).

For tree cover, initial AGB was based on the European Space Agency Climate Change Initiative biomass map v6.0 for 2015 (100-m resolution) (Santoro et al. 2024, Santoro and Cartus 2025). To account for inconsistencies between mapped biomass and disturbance history, we adjusted AGB in pixels with evidence of prior or recurring disturbances. In pixels where tree cover loss occurred between 2001 and 2014 (Hansen et al. 2013), we set AGB to 0 Mg ha⁻¹ in the year of loss and simulated regrowth using removal factors corresponding to the starting tree cover type (e.g., planted trees, natural tree cover) for half of the years until the model start year (2015) (removal factors described in Supplementary Text 4). Similarly, we set AGB to 0 Mg ha⁻¹ in pixels with recurring (two or more) losses after 2015 on the assumption that such pixels likely also had loss before 2015, and therefore had an unrealistically high initial biomass value assigned from the AGB map. We converted AGB to AGC using 0.47 for non-mangrove tree cover (IPCC 2019) and 0.45 for mangroves (IPCC 2013, Table 4.2).

We mapped initial BGC densities for all non-mangrove tree cover using a global root-to-shoot ratio map (Huang et al. 2021). We mapped initial DOM carbon densities using IPCC default relationships based on elevation, precipitation, and climate domain (IPCC 2006) for planted forest and natural tree cover but assumed 0 Mg C ha⁻¹ for these pools for trees in

1088 other land covers and tree crops (IPCC 2006, IPCC 2019). Initial belowground BGC and
 1089 DOM carbon for mangroves were calculated using IPCC 2013 (Table 4.5 and Tables 4.2, 4.3,
 1090 and 4.7, respectively)

1091 We used IPCC default carbon densities for non-tree vegetation, applying a global AGC
 1092 default value (with no belowground carbon) for crops and climate-stratified IPCC grassland
 1093 defaults for both AGC and BGC in short vegetation (IPCC 2019). For short vegetation, we
 1094 scaled AGC and BGC density in IPCC 2019 by the fractional cover of short vegetation
 1095 (Potapov et al. 2022). We assumed that non-vegetated land had no biomass or DOM
 1096 carbon.

1097 Soil organic carbon in Hengl et al. 2026 (30-m resolution) is mapped as the average of 5-
 1098 year blocks (2001-2005, 2005-2010, 2010-2015, 2015-2020). We used the 2010-2015 block
 1099 (0-30 cm depth) for the initial (2015) SOC density for mineral soil. We converted soil carbon
 1100 density from volumetric density (kg m^{-3}) to areal density (Mg ha^{-1} for the top 30 centimeters
 1101 of soil) by multiplying by 3. Carbon density was not assigned for organic soil because IPCC
 1102 guidelines for organic soil emissions are not based on SOC density (IPCC 2013).

1103

1104 **Supplementary Text 3. Activity data generation**

1105 For vegetation and organic soil, activity data were derived from transitions among the land
 1106 cover classes and additional geospatial datasets by applying a set of deterministic
 1107 decision trees across consecutive intervals which assigned each 30-m pixel of land to a
 1108 unique activity stratum for each time interval. The resulting classification system contained
 1109 more than 90 classes for vegetation and over 140 classes for organic soil. Vegetation
 1110 activity data were generated annually from the annual vegetation height and land
 1111 cover/land-use composites, whereas organic soil activity data followed the reporting
 1112 intervals of Glen et al. (in press), consisting of approximately 5-year periods with a final
 1113 four-year interval (2021-2024). Mineral soil SOC did not have activity data because those
 1114 fluxes were calculated using the stock-change approach rather than the gain-loss
 1115 approach. The full implementation of the vegetation and organic soil activity data
 1116 classification trees are available at https://github.com/wri/AFOLU_GHG_flux_model.

1117 Vegetation activity data were structured around three broad categories of vegetation
 1118 represented in the framework (trees, crops, short vegetation, plus non-vegetated)
 1119 (Supplementary Table 2) and three corresponding activity states (gain, loss, maintained)
 1120 (Supplementary Table 4). For consecutive years, vegetation gain represented conversion
 1121 from any class to a vegetated class, loss represented conversion from any vegetated class
 1122 to a non-vegetated one, and maintained meant that the vegetation class remained the

1123 same. This structure is analogous to the IPCC land-use transition matrix, in which land
1124 either enters a land-use category, leaves it, or remains within it. However, in this
1125 framework, activity data are defined in terms of land-cover change rather than land-use
1126 change. Transitions that did not involve any vegetation type were grouped separately, as
1127 they do not generate vegetation CO₂ fluxes under Tier 1 assumptions (IPCC 2019).
1128 However, they may have soil carbon changes, which are calculated separately from
1129 vegetation.

1130 For trees, loss occurred in the year that height decreased below 5 m, while gain occurred
1131 the year height increased to ≥ 5 m. The gain, loss, and maintained categories for trees were
1132 further stratified according to vegetation subtype using the land subtypes/subclasses
1133 defined in Supplementary Text 1, as well as additional geospatial information including
1134 disturbance drivers and fire occurrence. We further subdivided trees remaining trees into
1135 undisturbed and disturbed, based on ≥ 5 m reductions in vegetation height over 1 or more
1136 years or presence of fire, to capture partial vegetation loss. For example, partial height
1137 disturbances over one or multiple years could be: height of 20 m in 2015 to 15 m in 2016, or
1138 from 20 m in 2019 to 18 m in 2020, to 14 m in 2021. The cutoff of ≥ 5 m height reduction is
1139 based on the uncertainty in height and change detection in Potapov et al. 2022; it attempts
1140 to balance the detection of meaningful height losses against fluctuations in canopy height
1141 unassociated with biomass loss.

1142 We overlaid a burned area dataset (MODIS Collection 6, Giglio et al. 2018) for all loss and
1143 maintained classes, and assigned pixels as burned for a year wherever fire was detected.
1144 Age increased by 1 year in maintained trees unless there was a ≥ 5 m height loss, in which
1145 case age was reset to 0 years. Primary forests were reclassified as secondary forests and
1146 their age reset to 0 years upon ≥ 5 m height loss. Resetting age to 0 years resulted in the
1147 assignment of forest removal factors for the youngest age class rather than primary forest
1148 removal factors in subsequent years (section “Emission and removal factors”).

1149 Mangroves were treated separately from other tree cover classes using smoothed
1150 mangrove extent from the GMW v3 time series (available 2015-2020) (Bunting et al. 2022),
1151 as described in Supplementary Text 1. Mangrove extent took precedence over other land
1152 cover inputs of land cover and vegetation height datasets, i.e., pixels identified as
1153 mangrove in any year were consistently treated as mangrove and did not use alternative
1154 land cover or vegetation height activity data inputs. Because vegetation height was not
1155 used for mangrove areas, disturbance within mangrove areas was not separately classified
1156 based on structural change. Because GMW v3 ends in 2020, we assumed that all mangrove
1157 extent in 2020 continued through the end of the modeling period, while areas that had

previously had mangroves but did not in 2020 continued to lack mangroves through the end of the modeling period.

Additional activity data rules were applied for transitions between short vegetation and bare ground to reduce noise in the LC/LU composite (Supplementary Table 5). Rather than emissions occurring if the LC/LU composite changed from short vegetation to bare ground and removals occurring if the LC/LU composite changed from bare ground to short vegetation, the transition had to be confirmed in the same year by a height transition from ≥ 2 m to < 2 m for short vegetation loss and from < 2 m to ≥ 2 m for short vegetation height gain using annual, global maps of vegetation height outside forests at 30-m resolution (Hunter et al. 2025). In Australia, for example, where the bare ground-short vegetation confusion was particularly widespread, this additional rule substantially reduced fluctuations in annual gross emissions and removals from short vegetation that were not associated with actual dieback and regrowth of woody biomass.

For organic soil, activity data was generated with a fixed, deterministic decision tree that assigns each organic soil pixel to a single disturbance/land-use stratum per interval, preventing double counting (Glen et al. in press). Drainage was inferred from observable proxies: proximity (≤ 500 m) to mapped canals, ditches, or roads; crop and built-up classes (Potapov et al. 2022); mapped plantations (Richter et al. 2024); and mapped peat or organic-soil extraction areas. Burning was identified by intersecting annual burned area (Giglio et al. 2018) with the organic soil mask. Crop and built-up extents were applied per 5-year interval, whereas linear infrastructure, plantations, coastal masks, and extraction areas were treated as temporally static. Disturbed extent was then routed to an IPCC Tier 1 emission factor stratum defined by climate zone and land use category, with coastal mangrove and tidal marsh pixels routed to coastal factors. Fire emissions were added to drainage emissions in burned years rather than replacing them, and pre-2001 (legacy) drainage was not masked because drained organic soil can continue emitting for decades. Further details are outlined in Glen et al. (in press).

Supplementary Text 4. Emission/Removal factors

For vegetation and organic soil, we assigned emission and/or removal factors to all pixels for all intervals based on their activity data stratum (Supplementary Text 3), resulting in pixel-level estimation of gross emissions and/or removals for each interval.

For vegetation, loss or disturbance resulted in CO₂ emissions in the year of occurrence (committed or instantaneous oxidation approach) (IPCC 2019), while gain resulted in CO₂ removals in the year of detection (Supplementary Tables 6-8). Maintenance of undisturbed

trees also resulted in CO₂ removals each year, whereas short vegetation and crops were assumed to reach carbon equilibrium in the year of gain and therefore did not accumulate additional carbon over time (IPCC 2006, IPCC 2019). As a simplifying assumption, the only situation in which emissions and removals could occur in the same year was when tree cover was converted to short vegetation or crops (gross emissions from loss of tree cover, gross removals from gain of short vegetation or crops). In this framework, tree cover remaining tree cover never had both emissions and removals in the same year.

For mineral soil (0-30 cm depth), we calculated the gross gain, gross loss, and net change in SOC as the pixel-wise difference between consecutive density blocks. Each pixel had either gross gain (-) or gross loss (+), but pixels over an area collectively had a mixture of gross gain and gross loss, with the net change being the difference. The loss, gain and net differences were annualized by dividing by block length (5 years). Only the difference between the 2015-2020 and 2010-2015 density blocks was used because it aligned best with the years covered by the vegetation model.

Assigning emission factors

Vegetation emission factors were based on carbon densities in biomass and DOM in the year of loss or disturbance. Complete vegetation loss was assumed to result in full emissions of the relevant carbon pools as CO₂ (Supplementary Table 6), while partial disturbance (applicable to trees only) resulted in fractional emissions that depended on disturbance type, driver, and the presence of fire (Supplementary Table 7). In tropical and subtropical ecozones (FAO 2012), the fraction emitted for partial disturbance of tree cover was based on Heinrich et al. 2026, applied spatially by continent and driver of tree cover loss (Sims et al. 2025). Outside the tropics, the fraction emitted was adapted from Lu et al. 2022, using basal area disturbance fraction and moderated solely by the driver of tree cover loss (Sims et al. 2025). Where fire was detected, IPCC default combustion fractions and emission factors (IPCC 2019, Tables 2.5 and 2.6) were used according to climate zone (IPCC 2023). Collectively, these approaches resulted in Tier 1 emission factors applied to crops and short vegetation and Tier 2 emission factors applied to tree cover using spatially explicit maps of tree biomass and disturbance drivers.

For vegetation, non-CO₂ (CH₄, N₂O) emissions were calculated separately. Non-CO₂ emissions arise from fires (biomass burning). The fuel load was carbon density (converted to biomass; see Supplementary Text 2 for biomass-carbon conversion details) in the relevant carbon pools in the year of fire. Combustion factors (IPCC 2019) depended on climate domain and driver of tree cover loss (Sims et al. 2025). Emission factors were assigned based on climate domain (IPCC 2019, Tables 2.5 and 2.6).

One additional situation in which emissions occurred was the year before oil palm planting was detected (Descals et al. 2024). In such cases, the framework assumed full loss of the existing tree cover (with associated emissions), followed by gain of oil palm the following year (with associated removal factor).

As with vegetation, we assigned emission factors for the disturbance of organic soil — drainage (including peat extraction) and fire—based on each pixel's classification by the organic soil activity data decision tree (Supplementary Text 3), enabling pixel-level estimation of gross emissions for each time interval (Glen et al. in press). Tier 1 factors came from the IPCC Wetlands Supplement (IPCC 2013): inland factors from Chapter 2 (Tables 2.1–2.7) and drained coastal mangrove and tidal-marsh factors from Chapter 4 (Table 4.13). For drained soils these comprise on-site CO₂, off-site CO₂ via dissolved organic carbon export, CH₄ from the land surface and drainage ditches, and direct N₂O; peat-fire CO₂ and CH₄ are added in burned years. We used Glen et al. (in press) organic soil emissions from 2016-2020 with vegetation fluxes for 2016-2020 and organic soil emissions from 2021-2024 with vegetation fluxes for 2021-2024.

For vegetation and soil, non-CO₂ emissions were converted to CO₂e using 100-year global warming potentials (IPCC 2023). Non-CO₂ emissions were added to CO₂ emissions to calculate gross emissions in CO₂-equivalents.

Assigning removal factors

Vegetation removal factors represent carbon accumulation through vegetation growth and were assigned by vegetation subtype (corresponding to classes in Supplementary Table 2) using a combination of IPCC defaults and spatially explicit datasets (Supplementary Table 8):

1. Mangroves: IPCC Wetlands Supplement (IPCC 2013, Table 4.4), stratified into three broad regions of tropical wet, tropical dry, and subtropical based on the ecozone (FAO 2012).
2. Planted trees (planted forests and tree crops): From the Spatial Database of Planted Trees v2 (Richter et al. 2024), in which each planted tree polygon has an associated removal factor. For oil palm (Descals et al. 2024, Austin et al. 2017, Gaveau et al. 2014, Miettinen et al. 2016, Gunarso et al. 2013, Richter et al. 2024) we used the IPCC default removal factor (IPCC 2019, 2.4 Mg C ha⁻¹ yr⁻¹).
3. Trees in other land covers: We used the IPCC 2019 default rate (2.8 Mg C ha⁻¹ yr⁻¹), assuming that the entire pixel had tree cover. This is likely an over-estimate of canopy cover in certain environments (e.g., street trees) but data is not available to consistently globally resolve the fraction of each Landsat-resolution pixel covered by trees from 2015 onwards.

4. Primary forests: IPCC 2019 rates (Table 4.9), stratified by continent and ecozone (FAO 2012).
5. Secondary forests: Wall-to-wall map from Robinson et al. 2025 for naturally regenerating forests for up to 100 years of regrowth. Rates were binned in 5-year intervals for the first 20 years of regrowth (1-5 years, 6-10, 11-15, 16-20 years) and binned in 20-year intervals thereafter (21-40, 41-60, 61-80, 81-100 years).
6. Crops: One-time removals when crop gain occurred (IPCC 2019 Cropland Section 5.3.1.2). No removals were applied in years of crops remaining crops, following the IPCC guideline that carbon equilibrium is achieved in the first year of crop growth.
7. Short vegetation: IPCC default (IPCC 2006, Table 6.4), stratified by climate zone (IPCC 2023), and adjusted for fractional cover of vegetation (Potapov et al. 2022). No removals were applied in years of short vegetation remaining short vegetation, following the IPCC guideline that carbon equilibrium is achieved in the first year (IPCC 2019).
8. Non-vegetated: No removal factor.

Supplementary Text 5. Comparison with the Global Carbon Budget

We performed a comparison of our results to the Global Carbon Budget in two stages.

First, we compared our combined net vegetation, organic soil emissions, and net mineral soil CO₂ fluxes (2016-2024 average) to the estimates of the net atmosphere-to-land flux in the Global Carbon Budget 2025 (GCB 2025, Friedlingstein et al. 2026). GCB 2025 estimates the net atmosphere-to-land flux from several methods: 1) the sum of land use change fluxes (E_{luc}) and the land sink (S_{land} , counted as negative values); 2) as the residual from fossil fuel emissions, atmospheric CO₂ growth, and the ocean sink; 3) from atmospheric inversion models; 4) constrained by O₂ concentrations; and 5) from Earth System Models.

Second, further comparison between GCB 2025 and our framework required addressing conceptual differences. Our framework reports gross emissions and removals, while the GCB reports fluxes from net land-use change emissions (E_{luc}) and the natural terrestrial carbon sink (S_{land}). The major conceptual difference between how fluxes are reported in this framework and the GCB is that this framework does not differentiate between natural and anthropogenic fluxes and aggregates all human and natural activities by default, while E_{luc} and S_{land} account for anthropogenic and natural fluxes, respectively. Thus, we “translated” (IPCC 2024) our gross fluxes from vegetation and soil to the definitions of E_{luc} and S_{land} based on contextual geospatial data that reclassifies gross fluxes based on human activity, limiting our results to CO₂ only.

1299 We reclassified gross emissions and removals using the vegetation type (tree cover vs.
1300 short vegetation) and annual primary forest extent from our framework, as well as the 1km
1301 dominant driver of tree cover loss for 2001-2024 (Sims et al. 2025) (Supplementary Table 9).
1302 We classified the drivers of loss as predominantly anthropogenic (hard commodities,
1303 logging, permanent agriculture, settlements & infrastructure, and shifting cultivation) or
1304 predominantly natural (wildfire, natural disturbances, and areas with no driver assigned).
1305 S_{land} was comprised of the net flux in natural drivers for all vegetation types and associated
1306 mineral soil. Additionally, removals occurring before primary forest loss in areas with
1307 anthropogenic drivers were classified as S_{land} , whereas removals from any forest regrowth
1308 after loss were classified as E_{luc} .

1309 E_{luc} was comprised of all other fluxes: net flux in areas with human-caused drivers of loss
1310 for all vegetation, except in primary forest where only emissions were included. E_{luc} also
1311 included associated SOC changes in mineral soil, as well as all CO_2 emissions from
1312 organic soil. We further classified our fluxes into the E_{luc} categories used by GCB 2025:
1313 deforestation (including permanent deforestation and shifting cultivation), regrowth
1314 (including re/afforestation and shifting cultivation), other transitions, wood harvest, and
1315 organic soil emissions. Although differences in CO_2 fluxes remain between our framework
1316 and GCB 2025, the use of vegetation type, a primary forest mask, and driver of tree cover
1317 loss demonstrates a way forward for translation of Earth observation-based gross
1318 emissions and removals into E_{luc} and S_{land} .

1319

1320 Supplementary Text 6. Reconciliation of land cover with land use

1321 GHG fluxes were calculated using biophysical data, like the LC/LU composites, but to
1322 reassign those fluxes to IPCC land uses (Forest Land, Grassland, Cropland, Settlement,
1323 Wetland, Other Land), we used a rule-based approach informed by the complete annual
1324 LC/LU composite time series (2015-2024, Potapov et al. 2022), ancillary geospatial
1325 datasets and disturbance history. To assign land use annually for 2015-2024, there were
1326 two broad steps: 1) determine initial land use where possible using information prior to
1327 2015, and 2) assign subsequent annual land use during the time series using land cover
1328 dynamics from the full observation period combined with contextual geospatial data.
1329 Annual land-use change was the difference between consecutive years of land use.

1330 While these default assignments provided a first order correspondence between land cover
1331 and land use, land cover alone is insufficient to determine land use. Of particular concern
1332 for reporting GHG fluxes, areas with trees may represent either Forest Land or Cropland
1333 (e.g., oil palm plantations), and temporary reductions in tree cover do not necessarily

indicate loss of Forest Land but may represent temporarily unstocked forest. Consequently, additional contextual information was incorporated to identify land use more consistently with IPCC definitions. Below, tree cover loss from Hansen et al. 2013 is referred to as TCL and is used to provide context for loss (including back to 2001), while tree loss refers to height decreasing below 5 m from 2015-2024, per Potapov et al. 2022 (see “Activity data” in Methods).

Land use assignment prior to the start of the LC/LU composite time series

Ancillary datasets were used to identify land use prior to the start of the annual land cover time series (2015). Areas were initially classified as Cropland if crop establishment had occurred by 2015. This includes plantations in Indonesia and Malaysia (Austin et al. 2017, Gaveau et al. 2014, Miettinen et al. 2016, Gunarso et al. 2013), oil palm extent combined with oil palm establishment year by 2015 (Descals et al. 2024), other tree crop extent (Richter et al. 2024), and areas with TCL by 2015 where the driver of loss was permanent agriculture (Sims et al. 2025). For areas with TCL attributed to permanent agriculture, pixels overlapping a global map of cultivated grasslands (Parente et al. 2024) were assigned to Grassland rather than Cropland because they are more consistent with managed pasture or rangeland systems under IPCC land use definitions.

Areas were classified as Forest Land prior to 2015 if they overlapped with planted forests (Richter et al. 2024), mangroves (Bunting et al. 2022), or areas with TCL by 2015 (Hansen et al. 2013) affected by temporary forest disturbances. These temporary disturbances, including logging, wildfire, natural disturbance, or shifting cultivation (Sims et al. 2025), were assumed to represent temporarily unstocked forest and were classified as Forest Land. Consistent with IPCC guidelines, temporary reductions in tree cover resulting from these processes were not interpreted as land use change. This treatment was particularly important for shifting cultivation systems. Areas undergoing repeated cycles of forest clearing, short term cultivation, and subsequent regeneration were classified as Forest Land remaining Forest Land unless evidence indicated permanent conversion to Grassland, Cropland, or Settlements. Classification of shifting cultivation as Forest Land is consistent with IPCC guidelines and previous IPCC translation implementation, although there is divergence among countries and ambiguity in their treatment of shifting cultivation (Gibbs et al. 2025).

Default translation from LC/LU composites land cover to IPCC land use

For areas where land use prior to 2015 could not be determined, the annual LC/LU composite classes provided the initial basis for assigning land cover to land use. Built-up land was assigned to Settlements, crops to Cropland, trees to Forest Land, short

vegetation (with at least 20% vegetation cover) to Grassland, open surface water to Wetlands, and bare ground (defined as short vegetation with less than 20% vegetation cover) or snow/ice classes to Other Land. To maintain conceptual similarity with national GHG inventories, we used the composite of primary forest and intact forest landscapes by 2015 (Supplementary Text 1) as a proxy for starting unmanaged land and thus did not include fluxes from them in this analysis unless there was evidence of conversion.

Conversion to Settlements

Conversion to Settlements was identified from the built-up class in the LC/LU composites. In that dataset, once a pixel has been classified as built-up it cannot change and thus its land use in all subsequent years was assigned to Settlements. In many locations, conversion to Settlements occurs following an intermediate period of bare ground or short vegetation after tree loss. In these cases, the year of land use change was assigned to the year of tree loss rather than to the first year classified as built-up to coincide with the associated carbon emissions from tree loss.

Conversion to Cropland

Conversion to Cropland during the time series was identified using three contextual datasets, applied in the following order: 1) annual crop classes in the LC/LU composites, 2) oil palm planting year (Descals et al. 2024), or 3) loss of trees (as identified by the LC/LU composite and defined in Supplementary Text 3) in pixels with TCL due to permanent agriculture (Sims et al. 2025).

The annual crop class in the LC/LU composite was first used to identify Cropland conversion. For pixels not classified as Cropland in the LC/LU composite, Cropland establishment was inferred where oil palm planting (Descals et al. 2024) occurred during the observation period. Finally, conversion to Cropland was identified in areas with tree loss coinciding with TCL due to permanent agriculture occurring outside of the cultivated grassland extent. Pixels with tree loss and TCL attributed to permanent agriculture that coincided with cultivated grassland extent (Parente et al. 2024) were instead classified as Grassland, consistent with the IPCC treatment of managed pasture and rangelands.

Conversion to Cropland was assigned to the earliest evidence of land use change. If trees were present before Cropland establishment and were followed by an intermediate land cover class, such as short vegetation or bare ground, the transition was assigned to the first year of tree loss. Otherwise, the transition year was assigned to the first year in which Cropland was identified.

Land use prior to Cropland was classified as Forest Land if trees were present before Cropland establishment or if TCL occurred within the five years preceding Cropland

1404 establishment, including before the start of the time series. Otherwise, the pre-conversion
1405 land use was assumed to be Grassland. Once a pixel was classified as Cropland, all
1406 subsequent years were assigned to Cropland unless there was subsequent conversion to
1407 Settlements.

1408 Conversion among Forest Land, Grassland, Wetlands, and Other Land

1409 Land use changes among the remaining four land uses were determined using all years of
1410 the LC/LU composite. Because temporary fluctuations in land cover are common,
1411 particularly in disturbed forests, seasonally inundated wetlands, and sparsely vegetated
1412 landscapes, land use changes were assigned only when supported by persistent evidence.

1413 For trajectories containing both trees and non-tree land cover, conversion from Forest Land
1414 was recognized only when trees were followed by at least three consecutive years of
1415 Grassland, Wetland, or Other Land, with no sustained return to trees before the end of the
1416 model. Trajectories that failed to meet this criterion of sustained change were classified as
1417 Forest Land throughout the time series. Albeit imprecise, this rule was included to
1418 distinguish permanent land use change from temporary disturbances and harvesting.

1419 Transitions between Grassland and Other Land were treated similarly. A transition was only
1420 assigned when both the initial and final states persisted for at least three consecutive years
1421 and the trajectory contained a single directional transition. Otherwise, the pixel was
1422 assigned to the dominant land use across the full time series.

1423 Conversion between Wetlands and all other land use was recognized only when persistent
1424 terrestrial cover was followed by persistent open water cover, or vice versa. Mixed time
1425 series containing repeated oscillation between terrestrial and aquatic classes were
1426 generally classified as Wetlands because they likely reflected natural hydrological
1427 variability rather than land use change. It is worth noting that, while land use classification
1428 for Wetlands may be particularly subjective and noisy, the GHG fluxes associated with this
1429 specific classification are minimal (Supplementary Table 10).

1430 When multiple landcover states occurred within a pixel and no persistent state could be
1431 identified, land use was assigned according to a higher priority land use combined with
1432 dominant state across the observation period. In cases where evidence was insufficient to
1433 distinguish among categories, ties were resolved using the following IPCC land use
1434 hierarchy: Forest Land > Grassland > Wetlands > Other Land (IPCC 2019). Consequently, in
1435 highly mixed time series, Forest Land was favored over Grassland, Grassland over
1436 Wetlands, and Wetlands over Other Land. This conservative approach minimizes land use
1437 changes arising from classification uncertainty or short-term fluctuations in land cover and

1438 emphasizes persistent changes in land management consistent with IPCC reporting
1439 guidance.

1440 This translation framework enables fluxes from our global GHG framework to be attributed
1441 consistently to IPCC land use categories and transitions. Although this translation does not
1442 alter our framework's underlying flux estimates, it distinguishes permanent land use
1443 change from temporary changes in land cover like forest harvest, natural disturbance, and
1444 shifting cultivation. As a result, fluxes can be reported in a manner consistent with land
1445 use-based accounting while retaining the spatial and temporal specificity of the underlying
1446 flux data.

1447

1448 Supplementary Text 7. Uncertainty and sensitivity analysis

1449 We quantified uncertainty separately for the vegetation, organic soil, and mineral soil
1450 components and propagated these component uncertainties by summing their variances.
1451 Because uncertainty information for several key inputs is only available as global summary
1452 statistics rather than spatially explicit estimates, uncertainty was evaluated only for
1453 globally aggregated fluxes. The specific approach to uncertainty calculation for each
1454 component is described below.

1455 Vegetation uncertainty

1456 Our uncertainty approach follows the approach of Xu et al. 2026. We quantified uncertainty
1457 associated with three major components of the vegetation model: activity data (tree cover
1458 loss, gain and maintained, and fire), initial carbon densities, and emission and removal
1459 factors. We did not include uncertainty around the driver of tree cover loss (Sims et al.
1460 2025) because this affected emission factors only in partially disturbed tree cover and
1461 could not be easily integrated into the uncertainty approach we used. We did not include
1462 uncertainty for fluxes from short vegetation and crops because these contribute only a
1463 small proportion (6.5% for removals and 4.6% for emissions) of global vegetation fluxes
1464 (Table 1). Consequently, uncertainty calculations as outlined here should be considered to
1465 result in a minimum, indicative estimate, rather than a comprehensive quantification of all
1466 sources of uncertainty.

1467 To calculate annual uncertainty in vegetation fluxes, we stratified tree fluxes into five
1468 dominant strata: tree loss (tree converted to non-tree), trees disturbed with fire only, trees
1469 disturbed with ≥ 5 m height loss, tree gain (non-tree converted to tree), and undisturbed
1470 trees. These strata were selected because they dominate global vegetation fluxes and
1471 because we could assemble the key elements of the uncertainty analysis for them. We
1472 calculated the following uncertainty components for each stratum. For each stratum and

component, we estimated a minimum and maximum value, from which we calculated standard error using a general approach $SE = (\max - \min) / (2 * Z_{score})$, where $Z_{score} = 1.96$, assuming that these bounds approximate a 95% confidence interval.

Activity data: For each stratum, we used the omission and commission errors (OE and CE) and the mapped areas to estimate the minimum and maximum plausible bounds for each year, respectively. Omission and commission errors for tree loss, tree gain, and undisturbed trees from Potapov et al. 2022. Errors for trees disturbed with fire came from Giglio et al. 2018. Errors for trees disturbed with height loss came from Hansen et al. 2013. Minimum plausible area was $area_reported * (1 - OE)$; maximum plausible area was $area_reported / (1 - CE)$.

Carbon densities: We calculated the average carbon densities ($Mg\ C\ ha^{-1}$) in each emissions stratum for each year of the model (2016-2024); removals strata did not include carbon density uncertainty because carbon densities are not used to calculate removals. The minimum plausible density for each stratum and year was $C_density / (1 + dens_stdev)$. The maximum plausible density for each stratum and year was $C_density * (1 + dens_stdev)$. We set $dens_stdev$ to 0.9 (i.e. standard deviation for density was 50% of the value) (adapted from Santoro et al. 2024). We did not explicitly include uncertainty in BGC or DOM carbon in the uncertainty analysis because of the variable way in which it is treated under different strata but chose a conservative carbon density uncertainty ratio to account for this additional level of uncertainty in carbon densities in other pools. Reducing this ratio to 0.5 (the mean in Santoro et al. 2024) did not significantly impact uncertainties for vegetation fluxes.

Emission and removal factors: The uncertainties for emission and removal factors for the five strata came from a variety of sources. For tree gain, removal factor uncertainty came from Robinson et al. 2025 (1-5 year removal factors), using the area-weighted average of tree cover gain extent by country. For undisturbed trees, removal factor uncertainty came from Robinson et al. 2025 (maximum uncertainty from the 20-year age bins for removal factor up to 100 years old, again weighted by undisturbed tree cover area in countries). For tree loss, emission factor uncertainty came from Heinrich et al. 2026. For trees disturbed with fire, emission factor uncertainty came from IPCC 2019 (Table 2.6). For trees disturbed with ≥ 5 m height loss, emission factor uncertainty came from Heinrich et al. 2026.

For each emissions stratum and year, we calculated the standard error for area, carbon density, and emission factor, and for each removals stratum we calculated the standard error for area and removal factor, then summed these standard errors using the root sum-of-squares to get the total standard error for that year and stratum. We used root sum-of-

1508 squares on emission stratum standard errors each year to get total emissions variance per
1509 year, and likewise for removals strata.

1510 The analysis relies on three general assumptions. First, we assumed that uncertainty is
1511 independent between years, as opposed to propagating from one year to the next. This was
1512 necessary given the complex, ruled-based framework. Second, we assumed independence
1513 of uncertainties for all inputs (Harris et al. 2021, Xu et al. 2026). Third, we assumed that the
1514 standard error for activity data could be calculated from the theoretical minimum and
1515 maximum areas if they are treated as 95% confidence intervals.

1516 Organic soil uncertainty

1517 Uncertainty in the organic-soil component was characterized by propagating the full
1518 plausible ranges of its two dominant inputs—organic-soil activity data and Tier-1 emission
1519 factors—rather than by formal probabilistic error propagation. For activity data we used the
1520 validation-based lower and higher area bounds of the mapped organic soil extent
1521 (spanning the classification-threshold range and independent global extent products)
1522 together with the range of drainage-distance assumptions; for emission factors we used
1523 the high and low bounds of the IPCC Wetlands Supplement Tier-1 factors. Jointly varying
1524 these inputs provide a plausible uncertainty envelope around the central estimate. Full
1525 methods, scenario definitions, and validation are given in Glen et al. (in press).

1526 Mineral soil uncertainty

1527 Uncertainty for average annual carbon losses, gains, and net change in mineral soil used
1528 $0.001 \times 0.001^\circ$ (120-m resolution) maps of the 16th and 84th percentile of probability of soil
1529 carbon density (p16 and p84, respectively) for the two density blocks used (2010-2015 and
1530 2015-2020). We masked 120-m pixels by 30-m mineral soil extent, where any 120-m pixel
1531 with any mineral soil in it was included in the analysis. For each pixel in the two density
1532 blocks, we calculated the asymmetric uncertainty (difference between mean estimate and
1533 p16 and between mean estimate and p84). Then we calculated a low end uncertainty value
1534 for loss, gain, and change pixels by taking the root sum-of-squares of the lower uncertainty
1535 of the later time block and the upper uncertainty of the earlier time block. We calculated a
1536 high end uncertainty value by taking the root sum-of-squares of the upper uncertainty of
1537 the later time block and lower uncertainty of the earlier time block. This resulted in 120-m
1538 resolution pixel-level maps of uncertainty in mineral soil for areas with loss, gain, and full
1539 extent (including pixels with no net change).

1540 To be conservative in our inclusion of the effect of spatial correlation on mineral soil carbon
1541 change uncertainty, we assumed full spatial correlation of uncertainties for all pixels in
1542 each $1 \times 1^\circ$ processing unit, and thus linearly summed their uncertainties, rather than using

the root sum-of-squares. However, we then assumed full independence of uncertainties across 1x1° processing units and summed those using root sum-of-squares to get global standard error for gross loss, gross gain, and net change. If information on the distances over which mineral soil carbon change is spatially correlated were available, we would use that instead of assuming correlation over 1x1° processing units.

Sensitivity analysis

We conducted sensitivity analyses for three key assumptions and datasets for which there were alternatives for the vegetation model. Glen et al. (in press) describes the sensitivity analysis for the organic soil emissions model.

Starting carbon pools: To evaluate the sensitivity of our flux outputs to the initial AGC density, we replaced the standard starting AGB dataset with the global 2015 AGB map of Yang et al. (under review) , which has a 100-m spatial resolution, like the ESA CCI biomass dataset. AGB was converted to AGC using the using the same biomass-to-carbon conversion factor applied in the standard model. All subsequent components of the vegetation model, including carbon pool initialization, disturbance emissions, and removals, were identical to the standard model.

Emission factors for partial disturbances: We increased and decreased emission factors for partial disturbance of trees by 1 standard deviation for both fire and non-fire disturbances. For fire disturbances, we used the uncertainties for G_{ef} and C_f in IPCC 2019. For non-fire disturbances, we used the uncertainties for the tropics reported by Heinrich et al. 2026 and used analogous uncertainties for the non-tropics from Lu et al. 2022. Collectively, these two analyses provide a plausible range of emissions from partial (non-stand-replacing) disturbances in trees.

Removal factors for naturally generating trees: We replaced removal factors from Robinson et al. 2025 for naturally regenerating secondary forest with removal factors from “other degradation” curves from Xu et al. 2026. Xu et al. 2026 parameterized Chapman-Richards curves at 1x1° resolution for most of the tropics. We used the same age bins for removal factors from Xu et al. 2026 as we did for Robinson et al. 2025. We ran this analysis only for the areas where Xu et al. 2026 parameterized Chapman-Richards curves.

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Supplementary tables

Supplementary Table 1. Data sources for vegetation and soil carbon fluxes in this framework

Model component	Source
Vegetation, land cover, and land stratification	
Tree height	Potapov et al. 2022
Land cover/land use composite	Potapov et al. 2022
Mangrove extent	Bunting et al. 2022
Tropical humid primary forest extent	Turubanova et al. 2018
Intact forest landscapes (boreal/temperate)	Potapov et al. 2017
Forest age	Besnard et al. 2021 (Global Age Mapping Integration v3.0)
Tree cover loss (for pre-2015 disturbances)	Hansen et al. 2013
Tree height in non-forest (for confirming short vegetation-bare ground transitions)	Hunter et al. 2025
Planted tree extent (plantations and tree crops)	Richter et al. 2024 (Spatial Database of Planted Trees v2.0)
Organic soil extent	Glen et al. in press
Mineral soil extent	Hengl et al. 2026, with organic soil masked per Glen et al. in press
Oil palm extent	Austin et al. 2017 (Indonesia), Gaveau et al. 2014 (Borneo), Miettinen et al. 2016 (Sumatra, Borneo), Gunarso et al. 2013 (peninsular Malaysia), Richter et al. 2024 (elsewhere)
Oil palm planting year	Descals et al. 2024
Cultivated grassland extent (for land use classification only)	Parente et al. 2024
Starting carbon density (2015)	

Aboveground live woody biomass density	Santoro et al. 2024, Santoro and Cartus 2025 (European Space Agency Climate Change Initiative biomass map v6.0)
Belowground biomass density ratio	Huang et al. 2021, IPCC 2013, Mokany et al. 2006
Soil organic carbon density and change (0-30 cm)	Hengl et al. 2026
Ecological zone (for deadwood and litter)	FAO 2012
Climate zone	IPCC 2023
Elevation (for deadwood and litter)	Farr et al. 2007
Mean annual precipitation (for deadwood and litter)	Fick and Hijmans 2017
Alternative starting carbon density (for sensitivity analysis)	Yang et al. under review
Emission factors	
Drivers of forest loss	Sims et al. 2025
Emission factors for partial height loss (tropics)	Heinrich et al. 2026
Emission factors for partial height loss (non-tropics)	Lu et al. 2022
Ecozone	FAO 2012
Fires (vegetation)	Giglio et al. 2018
Fire combustion and emission factors (vegetation)	IPCC 2019
Organic soil emission	Glen et al. in press
Removal factors	
Ecological zone	FAO 2012
Mangrove removal factors	IPCC 2013
Planted tree removal factors	Richter et al. 2024 (Spatial Database of Planted Trees v2.0)
Secondary forest removal factors	Robinson et al. 2025

Primary forest removal factors	IPCC 2019
Short vegetation removal factors	IPCC 2019
Crop removal factor	IPCC 2019
Trees in other land cover removal factor	IPCC 2019
Alternative removal factors for natural forests (sensitivity analysis)	Xu et al. 2026
Harvested wood products (country only)	
Production, import and export statistics of sawnwood, wood-based panels and paper & paperboard	FAOSTAT (2001–2023)

Supplementary Table 2. Land stratification hierarchy for vegetation (1-8) and soil (A-B), in descending priority. These strata are described in Supplementary Text 1.

Framework component	Stratum number	Class name	Broad class	Data source
Vegetation	1	Mangrove	Trees	Bunting et al. 2022
Vegetation	2	Planted trees (planted forests and tree crops)	Trees	Descals et al. 2024, Austin et al. 2017, Gaveau et al. 2014, Miettinen et al. 2016, Gunarso et al. 2013, Richter et al. 2024
Vegetation	3	Trees in other land covers	Trees	Potapov et al. 2022
Vegetation	4	Primary forest and other old tree cover	Trees	Potapov et al. 2022, with starting composite primary forest as defined in this framework
Vegetation	5	Secondary forest	Trees	Potapov et al. 2022
Vegetation	6	Crops	Crops	Khan et al. 2026
Vegetation	7	Short vegetation	Short vegetation	Potapov et al. 2022
Vegetation	8	Non-vegetated land (water, bare ground, snow/ice, built-up without trees)	Non-vegetated	Potapov et al. 2022
Soil	A	Organic soil	Soil	Glen et al. in press
Soil	B	Mineral soil	Soil	Hengl et al. 2026

Supplementary Table 3. Data sources for initial carbon pools (2015) by vegetation type. Strata are the same as in Supplementary Table 2 and are described in Supplementary Text 1.

Land cover stratum or vegetation type (class from Supplementary Table 2)	Carbon pools				
	Aboveground carbon	Belowground carbon	Carbon in dead wood	Carbon in litter	Soil organic carbon in mineral soil
Mangrove (1)	ESA CCI v6 for 2015, adjusted for pre-2015 TCL or repeat 2015-2024 tree loss	AGC * mangrove R:S (IPCC 2013, varies by ecozone)	AGC * mangrove DOM ratio (IPCC 2013, varies by ecozone)	AGC * DOM ratio (IPCC 2013, varies by ecozone)	Hengl et al. 2026 for 2010-2015 block, 0-30 cm depth, masked by Glen et al. in press
Tree cover- planted forest (excludes tree crops) (2)	ESA CCI v6 for 2015, adjusted for pre-2015 TCL or repeat 2015-2024 tree loss	AGC * R:S (Huang et al. 2021, global gridded product)	AGC * forest DOM ratio (IPCC 2006, varies by climate)	AGC * forest DOM ratio (IPCC 2006, varies by climate)	Hengl et al. 2026 for 2010-2015 block, 0-30 cm depth, masked by Glen et al. in press
Tree cover- tree crops (2)	ESA CCI v6 for 2015, adjusted for pre-2015 TCL or repeat 2015-2024 tree loss	AGC * 0.26 (Mokany et al. 2016, global value)	0 Mg C ha ⁻¹	0 Mg C ha ⁻¹	Hengl et al. 2026 for 2010-2015 block, 0-30 cm depth, masked by Glen et al. in press
Tree cover- trees in other land covers (3)	ESA CCI v6 for 2015, adjusted for pre-2015 TCL or repeat 2015-2024 tree loss	AGC * R:S (Huang et al. 2021, global gridded product)	0 Mg C ha ⁻¹	0 Mg C ha ⁻¹	Hengl et al. 2026 for 2010-2015 block, 0-30 cm depth, masked by Glen et al. in press
Tree cover- natural (4 and 5)	ESA CCI v6 for 2015, adjusted for pre-2015 TCL or repeat 2015-2024 tree loss	AGC * R:S (Huang et al. 2021, global gridded product)	AGC * forest DOM ratio (IPCC 2006, varies by climate zone)	AGC * forest DOM ratio (IPCC 2006, varies by climate zone)	Hengl et al. 2026 for 2010-2015 block, 0-30 cm depth, masked by Glen et al. in press
Crops (6)	IPCC 2019 default (global value of 4.7 Mg C ha ⁻¹)	0 Mg C ha ⁻¹	0 Mg C ha ⁻¹	0 Mg C ha ⁻¹	Hengl et al. 2026 for 2010-2015 block, 0-30 cm depth, masked by Glen et al. in press
Short vegetation (7)	IPCC 2006 Table 6.4 “Peak aboveground biomass”, adjusted by fractional cover (varies by ecozone)	IPCC 2006 Table 6.4 “Total” – “Peak aboveground biomass”, adjusted by fractional cover (varies by ecozone)	0 Mg C ha ⁻¹	0 Mg C ha ⁻¹	Hengl et al. 2026 for 2010-2015 block, 0-30 cm depth, masked by Glen et al. in press
Non-vegetated land (water, bare ground,	0 Mg C ha ⁻¹	0 Mg C ha ⁻¹	0 Mg C ha ⁻¹	0 Mg C ha ⁻¹	Hengl et al. 2026 for 2010-2015 block, 0-30 cm depth, masked by Glen et al. in press

snow/ice, built-up without trees) (8)					
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Notes: ESA CCI v6: European Space Agency Climate Change Initiative biomass product v6 (Santoro et al. 2024). TCL: tree cover loss (Hansen et al. 2013). AGC: aboveground carbon. R:S: root-to-shoot ratio. DOM: dead organic matter. Tree loss refers to loss as reported in Potapov et al. 2022. Adjustment in aboveground carbon for pre-2015 TCL or repeat 2015-2024 tree loss is described in Supplementary Text 2.

Supplementary Table 4. Activity data for vegetation model. Color indicates the direction(s) of GHG fluxes, as indicated in the legend.

		Ending land cover (year t)					
		Mangroves	Trees (≥ 5 m)	Built-up (no trees)	Crops (no trees)	Short vegetation	Non-vegetated
Previous land cover (year t-1)	Mangroves	Mangrove remaining mangrove	Mangrove loss	Mangrove loss	Mangrove loss	Mangrove loss	Mangrove loss
	Trees (≥ 5 m)	Mangrove gain	Trees remaining trees (emissions if disturbed: fire or height decreases ≥ 5 m)	Tree loss	Tree loss (emissions) and crop gain (removals)	Tree loss (emissions) and short vegetation gain (removals)	Tree loss
	Built-up (no trees)	N/A	N/A	Non-vegetated transition	N/A	N/A	N/A
	Crops (no trees)	Mangrove gain	Tree gain	Crop loss	Crops remaining crops (non-CO ₂ emissions if fire)	Crop loss (emissions) and short vegetation gain (removals)	Crop loss
	Short vegetation	Mangrove gain	Tree gain	Short vegetation loss	Crop gain	Short vegetation remaining short vegetation (non-CO ₂ emissions if fire)	Short vegetation loss
	Non-vegetated	Mangrove gain	Tree gain	Non-vegetated transition	Crop gain	Short vegetation gain	Non-vegetated transition

Gross removals only

Gross emissions only

Multiple fluxes possible

No flux

Notes: Land covers are in descending order of priority. Mangroves: Bunting et al. 2022. Trees: Potapov et al. 2022 stand-alone tree height map, includes trees in other land covers (i.e. trees in built-up and crops). Built-up, crops, short vegetation, and non-vegetated (water, bare ground, snow/ice; built-up without trees): Potapov et al. 2022 composite LC/LU maps. In the LC/LU composite maps, built-up is never converted to any other class (i.e. permanent class) and is therefore designated N/A.

Supplementary Table 5. Rules for activity data for short vegetation <-> bare ground transitions

Starting land cover (year t-1)	Ending land cover (year t)					
	Composite LC/LU class	Tree height (m)	Short vegetation		Bare ground	
			<2	≥2	<2	≥2
	Short vegetation	<2	Short veg->short veg (E _{fire})	Short veg->short veg (E _{fire})	Bare gr.->bare gr. (no flux)	Short veg->short veg (E _{fire})
		≥2	Short veg->short veg (E _{fire})	Short veg->short veg (E _{fire})	Short veg->bare gr. (E _{fire} , E _{non-fire})	Short veg->short veg (E _{fire})
	Bare ground	<2	Bare gr.->bare gr. (no flux)	Bare gr.->short veg (removals)	Bare gr.->bare gr. (no flux)	Bare gr.->bare gr. (no flux)
		≥2	Bare gr.->bare gr. (no flux)	Bare gr.->short veg (removals)	Bare gr.->bare gr. (no flux)	Bare gr.->bare gr. (no flux)

Notes: Short veg=short vegetation; bare gr.=bare ground. Tree height is from Hunter et al. 2025. Composite LC/LU (including short vegetation and bare ground) is from Potapov et al. 2022. Change in height from Hunter et al. 2025 and in LC/LU composite must occur in the same year. Asynchronous changes are not considered, e.g., height change the year before or after LC/LU composite change. However, this approach can cause inconsistency between fluxes and carbon stocks, e.g., 2016 will have carbon density if short vegetation->short vegetation, but then if 2017 is bare ground->bare ground, there will be no carbon density without any emissions (i.e. carbon stock change but no flux). Testing indicates that the difference is generally minimal.

Supplementary Table 6. Emission factors for vegetation for full tree cover loss by carbon pool, with and without fire, as fractions of carbon density in year of loss

Land cover transition	Tree type	Ending land cover (year t)	Driver of loss	With fire				Without fire			
				AGC	BGC	Deadwood	Litter	AGC	BGC	Deadwood	Litter
Oil palm converted to anything else	Oil palm	Any	Any	Y (full; CO ₂ and non-CO ₂)	Y (full; CO ₂ and non-CO ₂)	N	N	Y (full)	Y (full)	N	N
Non-oil palm tree crops converted to crops	Non-oil palm tree crops	Crops	Any	Y (full; CO ₂ and non-CO ₂)	Y (full; CO ₂ and non-CO ₂)	N	N	Y (full)	Y (full)	N	N
Non-oil palm planted forest converted to crops	Non-tree crop planted forest	Crops	Any	Y (full; CO ₂ and non-CO ₂)	Y (full; CO ₂ and non-CO ₂)	Y (non-CO ₂ only)	Y (non-CO ₂ only)	Y (full)	Y (full)	Y (full)	Y (full)
Non-oil palm tree crops converted to short vegetation	Non-oil palm tree crops	Short vegetation	Any	Y (full; CO ₂ and non-CO ₂)	Y (full; CO ₂ and non-CO ₂)	N	N	Y (full)	Y (full)	N	N
Non-oil palm planted forest converted to short vegetation	Non-oil palm planted forest	Short vegetation	Any	Y (full; CO ₂ and non-CO ₂)	Y (full; CO ₂ and non-CO ₂)	Y (non-CO ₂ only)	Y (non-CO ₂ only)	Y (full)	Y (full)	N	N
Non-oil palm tree crops converted to built-up	Non-oil palm tree crops	Built-up	Any	Y (full; CO ₂ and non-CO ₂)	Y (full; CO ₂ and non-CO ₂)	N	N	Y (full)	Y (full)	N	N
Non-oil palm planted forest converted to settlement	Non-oil palm planted forest	Built-up	Any	Y (full; CO ₂ and non-CO ₂)	Y (full; CO ₂ and non-CO ₂)	Y (non-CO ₂ only)	Y (non-CO ₂ only)	Y (full)	Y (full)	Y (full)	Y (full)
Non-oil palm tree crops converted to anything else	Non-oil palm tree crops	Everything else (e.g., water/ice/snow)	Any	Y (full; CO ₂ and non-CO ₂)	Y (full; CO ₂ and non-CO ₂)	N	N	Y (full)	Y (full)	N	N
Non-oil palm planted forest converted to anything else	Non-oil palm planted forest	Everything else (e.g., water/ice/snow)	Any	Y (full; CO ₂ and non-CO ₂)	Y (full; CO ₂ and non-CO ₂)	Y (non-CO ₂ only)	Y (non-CO ₂ only)	Y (full)	Y (full)	N	N
Natural tree cover converted to crops	Natural tree cover	Crops	Any	Y (full; CO ₂ and non-CO ₂)	Y (full; CO ₂ and non-CO ₂)	Y (full ⁸ CO ₂ and non-CO ₂)	Y (full; CO ₂ and non-CO ₂)	Y (full)	Y (full)	Y (full)	Y (full)
Natural tree cover converted to short vegetation with	Natural tree cover	Short vegetation	Permanent. Ag, Hard Commodities,	Y (full; CO ₂ and non-CO ₂)	Y (full; CO ₂ and non-CO ₂)	Y (full; CO ₂ and non-CO ₂)	Y (full; CO ₂ and non-CO ₂)	Y (full)	Y (full)	Y (full)	Y (full)

disturbance that emits all non-soil carbon pools			Shifting Agriculture, or Settlements								
Natural tree cover converted to short vegetation with disturbance that emits biomass carbon pools only	Natural tree cover	Short vegetation	Forest management, wildfire, natural disturbances, unlabeled	Y (full; CO ₂ and non-CO ₂)	N	Y (non-CO ₂ only)	Y (non-CO ₂ only)	Y (full)	Y (full)	N	N
Natural tree cover converted to built-up	Natural forest	Built-up	Any	Y (full; CO ₂ and non-CO ₂)	Y (full; CO ₂ and non-CO ₂)	Y (full; CO ₂ and non-CO ₂)	Y (full; CO ₂ and non-CO ₂)	Y (full)	Y (full)	Y (full)	Y (full)
Natural tree cover converted to anything else	Natural tree cover	Everything else (e.g., water/ice/snow)	Any	Y (full; CO ₂ only)	Y (full; CO ₂ only)	N/A	N/A	Y (full)	Y (full)	N	N
Trees in other land covers converted to anything else	Trees in other land covers	Any	Any	Y (full; CO ₂ and non-CO ₂)	N	N	N	Y (full)	Y (full)	N	N

Notes: Driver of loss is from Sims et al. 2025 (1-km resolution). Fire is from Giglio et al. 2018. AGC=aboveground carbon. BGC=belowground carbon. Full=all carbon in specified pool lost. N=No carbon in specified pool lost. Mineral soil carbon is not included here because emissions from it are not based on land cover and vegetation changes.

Supplementary Table 7. Emission factors for tree cover with ≥ 5 m height reductions by carbon pool, with and without fire, as fractions of carbon density in year of disturbance

Driver of loss	Climate domain	With fire				Without fire			
		AGC	BGC	Deadwood	Litter	AGC	BGC	Deadwood	Litter
Permanent agriculture	Non-tropical	IPCC 2019 Table 2.6 (range: 15-55%)	0%	0%	0%	70%	0%	0%	0%
	Tropical/sub-tropical	IPCC 2019 Table 2.6 (range: 15-62%)	0%	0%	0%	87/87/83%	0%	0%	0%
Hard commodities	Non-tropical	IPCC 2019 Table 2.6 (range: 15-55%)	0%	0%	0%	76%	0%	0%	0%
	Tropical/sub-tropical.	IPCC 2019 Table 2.6 (range: 15-62%)	0%	0%	0%	87/87/83%	0%	0%	0%
Shifting cultivation	Non-tropical	IPCC 2019 Table 2.6 (range: 15-55%)	0%	0%	0%	64%	0%	0%	0%
	Tropical/sub-tropical	IPCC 2019 Table 2.6 (range: 15-62%)	0%	0%	0%	87/87/83%	0%	0%	0%
Logging	Non-tropical	IPCC 2019 Table 2.6 (range: 15-55%)	0%	0%	0%	79%	0%	0%	0%
	Tropical/sub-tropical	IPCC 2019 Table 2.6 (range: 15-62%)	0%	0%	0%	23/23/42%	0%	0%	0%
Wildfire	Non-tropical	IPCC 2019 Table 2.6 (range: 15-55%)	0%	0%	0%	73%	0%	0%	0%
	Tropical/sub-tropical	IPCC 2019 Table 2.6 (range: 15-62%)	0%	0%	0%	23/23/42%	0%	0%	0%
Settlements & infrastructure	Non-tropical	IPCC 2019 Table 2.6 (range: 15-55%)	0%	0%	0%	67%	0%	0%	0%
	Tropical/sub-tropical	IPCC 2019 Table 2.6 (range: 15-62%)	0%	0%	0%	87/87/83%	0%	0%	0%
Natural disturbance	Non-tropical	IPCC 2019 Table 2.6 (range: 15-55%)	0%	0%	0%	58%	0%	0%	0%
	Tropical/sub-tropical	IPCC 2019 Table 2.6 (range: 15-62%)	0%	0%	0%	34/34/34%	0%	0%	0%

Notes: Driver of loss is from Sims et al. 2025 (1-km resolution). Fire is from Giglio et al. 2018. Climate domain is per FAO 2012. AGC=aboveground carbon. BGC=belowground carbon. Non-tropical values are adapted from Lu et al. 2022. Subtropical and tropical values are from Heinrich et al. 2026.

Supplementary Table 8. Removal factors by vegetation type and carbon pool. Strata are the same as in Supplementary Table 2 and are described in Supplementary Text 1.

Vegetation type (class from Supplementary Table 2)	Disturbance history	Aboveground carbon	Belowground carbon	Deadwood	Litter
Mangrove (1) ^a	N/A	IPCC 2013 (Table 4.4)	IPCC 2013 (Table 4.4)	IPCC 2013 (Table 4.4)	IPCC 2013 (Table 4.4)
Planted trees (planted forest and tree crops) (2) ^{b, c}	N/A	Richter et al. 2024, IPCC 2019 (Table 5.3) for oil palm	Richter et al. 2024, Mokany et al. 2016	N/A	N/A
Trees in other land covers (3) ^d	N/A	IPCC 2019 (Section 8.2.1.2)	Huang et al. 2021	N/A	N/A
Primary forest (4) ^e	N/A	IPCC 2019 (Table 4.9)	IPCC 2019 (Table 4.9)	IPCC 2019 (Table 4.9)	IPCC 2019 (Table 4.9)
Secondary forest (5) ^f	Always tree cover	Robinson et al. 2025	Robinson et al. 2025	N/A ^g	N/A ^g
Secondary forest (5) ^f	Non-tree cover at some previous point	Robinson et al. 2025	Robinson et al. 2025	Robinson et al. 2025 ^g	Robinson et al. 2025 ^g
Crops (6) ^h	N/A	IPCC 2019 (Section 5.3.1.2, Table 5.9)	N/A	N/A	N/A
Short vegetation (7) ⁱ	N/A	IPCC 2006 (Table 6.4)	IPCC 2006 (Table 6.4)	N/A	N/A
Non-vegetated (water, bare ground, snow/ice, built-up without trees) (8)	N/A	N/A	N/A	N/A	N/A

Notes:

^a Mangrove: IPCC mangrove Tier 1 removal factor (IPCC 2013), varies by climate domain and precipitation regime

^b Planted trees: Polygon-specific removal factor from Spatial Database of Planted Trees v2.0 (Richter et al. 2024). SDPT v2 removal factors include aboveground and belowground carbon but not deadwood or litter.

^c Oil palm: IPCC Tier 1 removal factor (2.4 Mg C ha⁻¹ yr⁻¹) (IPCC 2019 Refinement Cropland Table 5.3) (belowground carbon based on default non-mangrove R:S from Mokany et al. 2016 (0.26))

^d Trees in other land covers: IPCC 2019 trees outside forests Tier 1 removal factor (2.8 Mg C ha⁻¹ yr⁻¹) (IPCC 2019 Settlements Section 8.2.1.2)

^e Primary forest: IPCC primary forest Tier 1 removal factor (IPCC 2019, Table 4.9), varies by ecozone and continent

^f Age-specific secondary forest: Age-specific rate from Robinson et al. 2025, using 5-year age bin for forests 0-20 years old and 20-year bins for 21-100 years old

^g Deadwood and litter removals in natural forest only in forest regrowing after full forest loss. No deadwood and litter removals in forest until it is regrowing; dead organic matter assumed to be in equilibrium otherwise.

^h Annual cropland gain: IPCC 2019 Tier 1 annual cropland aboveground carbon stock (4.7 Mg C ha⁻¹) (IPCC 2019 5.3.1.2, Table 5.9).

ⁱ Short vegetation gain: IPCC Tier 1 total biomass stocks in grassland (IPCC 2006 (no 2019 update), Table 6.4): Uses “Peak above-ground biomass” column for AGB and “Total” – “Peak” for BGB, varies by climate zone

Supplementary Table 9. Translation of gross emissions and removals from this framework into Global Carbon Budget 2025 (GCB 2025, Friedlingstein et al. 2026) reporting categories of land-use net flux (E_{luc}) and the land sink (S_{land}) and the main subcomponents of E_{luc}

Framework component	Tree loss driver type	Primary forest	S_{land}	$E_{all\ luc}$	E_{luc} deforestation	E_{luc} regrowth	E_{luc} other transitions	E_{luc} wood harvest
Not trees	Human-induced	N/A	-	Net flux	-	-	LCL net flux	-
Not trees	Natural	N/A	Net flux	-	-	-	-	-
Trees	Human-not logging	No	-	Net flux	Gross emissions	Gross emissions	-	-
Trees	Human-not logging	Yes	Gross removals	Gross emissions	Gross emissions	-	-	-
Trees	Human-logging	No	-	Net flux	-	-	-	Net flux
Trees	Human-logging	Yes	Gross removals	Gross emissions	-	-	-	Gross emissions
Trees	Natural	No	Net flux	-	-	-	-	-
Trees	Natural	Yes	Net flux	-	-	-	-	-
Organic soil	N/A	N/A	-	All	-	-	-	-
Mineral soil	Human-not logging	N/A	-	Net flux	Net flux	-	-	-
Mineral soil	Human-logging	N/A	-	Net flux	-	-	-	Net flux
Mineral soil	Natural	N/A	Net flux	-	-	-	-	-
Harvested wood products	N/A	N/A	-	All	-	-	-	All

Notes:

Text in the E_{luc} and S_{land} columns denotes the flux categories from this framework (gross emissions, gross removals, net flux) that are included in the corresponding GCB 2025 reporting categories. “-” means that no fluxes from this framework are included in that GCB 2025 category.

Drivers of tree cover loss are from Sims et al. 2025 (1-km global gridded product):

- Human-induced tree cover loss drivers: hard commodities, logging, permanent agriculture, settlements & infrastructure, shifting cultivation
- Natural tree cover loss drivers: wildfire, natural disturbance, unassigned

Primary forest means that the area was primary forest until the year of disturbance/loss, as opposed to an initial primary forest loss mask. The result of this is that “primary forest” means that areas get reclassified from primary forest to not primary forest after disturbance and any subsequent removals from regrowth are not classified as primary forest removals. Primary forest is defined in Supplementary Text 1.

Supplementary Table 10. Translation of terrestrial greenhouse gas monitoring framework into land-use change matrix (average annual fluxes, 2016-2024). a) Net flux. b) Gross emissions. c) Gross removals. NA: no flux for this change. 0.00: negligible value. Forest Land is divided into unmanaged and managed components, as defined in Supplementary Text 6. Diagonal elements (shaded) represent emissions and removals occurring within stable land uses (e.g., Forest Land remaining Forest Land), whereas off-diagonal elements represent fluxes associated with land use changes. Fluxes are attributed annually according to the land use in each year of the time series. Emissions and removals occurring before land use change are attributed to the initial land use (diagonal element), fluxes occurring during the year of transition are attributed to the corresponding land-use transition (off-diagonal element), and fluxes occurring after the transition are attributed to the final land use (diagonal element). For example, for land converted from Forest Land to Cropland, fluxes prior to conversion are reported as Forest Land remaining Forest Land, fluxes in the year of conversion are reported as Forest Land to Cropland, and subsequent fluxes are reported as Cropland remaining Cropland.

a. Net flux

Net Flux (Mt CO ₂ e yr ⁻¹)		Ending land use (year t)						
		Forest Land (Unmanaged)	Forest Land (Managed)	Grassland	Cropland	Wetlands	Settlement	Other Land
Starting land use (year t-1)	Forest Land (Unmanaged)	-1,600	NA	170	820	3.8	71	0.00
	Forest Land (Managed)	NA	-4,200	220	450	1.9	75	0.22
	Grassland	NA	0.00	900	-24	1.5	16	1.6
	Cropland	NA	NA	NA	260	NA	100	NA
	Wetlands	NA	0.00	0.00	-1.1	-37	0.11	0.00
	Settlements	NA	NA	NA	NA	NA	-900	NA
	Other Land	NA	0.00	-0.51	-8.5	0.040	0.16	87

b. Gross emissions

Emissions (Mt CO ₂ e yr ⁻¹)		Ending land use (year t)						
		Forest Land (Unmanaged)	Forest Land (Managed)	Grassland	Cropland	Wetlands	Settlement	Other Land
Starting land use (year t-1)	Forest Land (Unmanaged)	5,200	NA	190	880	3.9	87	0.00
	Forest Land (Managed)	NA	6,400	270	550	1.9	150	0.22
	Grassland	NA	0.00	2,900	170	1.8	21	2.6
	Cropland	NA	NA	NA	2,070	NA	110	NA

	Wetlands	NA	0.00	0.00	0.072	170	0.15	0.00
	Settlements	NA	NA	NA	NA	NA	1000	NA
	Other Land	NA	0.00	1.2	0.082	0.053	0.19	190

c. Gross removals

Removals (Mt CO ₂ yr ⁻¹)		Ending land use (year t)						
		Forest Land (Unmanaged)	Forest Land (Managed)	Grassland	Cropland	Wetlands	Settlement	Other Land
Starting land use (year t-1)	Forest Land (Unmanaged)	-6,800	NA	-17	-59	-0.079	-15	0.00
	Forest Land (Managed)	NA	-10,600	-58	-96	-0.077	-74	0.00
	Grassland	NA	0.00	-2,050	-200	-0.21	-4.0	-1.0
	Cropland	NA	NA	NA	-1,800	NA	-8.1	NA
	Wetlands	NA	0.00	0.00	-1.2	-210	-0.044	0.00
	Settlements	NA	NA	NA	NA	NA	-1,900	NA
	Other Land	NA	0.00	-1.7	-8.6	-0.013	-0.031	-100

Supplementary Table 11. Additional average annual (2016-2024) gross emissions, gross removals, and net flux from vegetation and soil for areas referenced in the article

Boundary	Reference/source	Gross emissions (Gt CO ₂ e yr ⁻¹)			Gross removals (Gt CO ₂ yr ⁻¹)			Net flux (Gt CO ₂ e yr ⁻¹)		
		Vegetation	Soil	Total	Vegetation	Soil	Total	Vegetation	Soil	Total
Protected areas	World Database of Protected Areas, categories Ia, Ib, II	0.47	0.41	0.88	-0.90	-0.28	-1.18	-0.43	0.12	-0.30
Indigenous lands	Landmark	3.4	2.3	5.7	-5.0	-1.7	-6.7	-1.6	0.6	-1.0
Amazon River Basin	MapBox	1.1	0.3	1.4	-1.2	-0.2	-1.4	-0.1	0.1	-0.0016
Congo River Basin	MapBox	1.4	0.1	1.5	-0.8	-0.1	-0.9	0.6	0.0	0.6
Mekong River Basin	MapBox	0.23	0.067	0.30	-0.25	-0.036	-0.29	-0.017	0.031	0.014
Primary forest and other old forest	This paper (Supplementary Text 1)	4.7	3.2	7.9	-6.2	-1.8	-8.0	-1.5	1.4	-0.09

Supplementary Table 12. Average annual gross and net fluxes from vegetation from the sensitivity analysis. Sensitivity analysis scenarios are described in Supplementary Text 7. The extent of the sensitivity analysis using alternative removal factors is limited to part of the tropics and is thus compared to standard fluxes over a comparable extent. Negative Δ indicates stronger sinks or weaker sources; positive Δ indicates weaker sinks or stronger sources.

Extent	Variant	Net flux (Gt CO ₂ e yr ⁻¹)		Gross removals (Gt CO ₂ yr ⁻¹)		Gross emissions (Gt CO ₂ e yr ⁻¹)	
		Value	Δ from Standard	Value	Δ from Standard	Value	Δ from Standard
Global	Standard	-7.4	NA	-18.4	NA	11	NA
	Low emission factors from partial disturbance	-8.6	-1.2	-18.4	0	9.9	-1.1
	High emission factors from partial disturbance	-6.3	1.1	-18.4	0	12.2	1.2
	Change of starting biomass map	-9.0	-1.6	-18.4	0	9.4	-1.6
Xu et al. 2026 regrowth curve extent	Standard	-2.3	NA	-9.0	NA	6.7	NA
	Change of removal factors	-0.083	2.2	-6.6	2.4	6.5	-0.20

Supplementary Table 13. Framework outputs, including geospatial formats. AGC: aboveground carbon. BGC: belowground carbon. Zarr is a multi-dimensional geospatial data format. Geospatial outputs are at 0.00025x0.00025° resolution (~30m). Per-ha means that values (numeric only) are Mg ha⁻¹; per-pixel means that values have been adjusted by the geodesic pixel area and represent the value for that specific pixel area. Non-numeric outputs are neither per-ha nor per-pixel. Vegetation outputs are annual, mineral soil outputs are in 5- or 10-year blocks, organic soil outputs are in 5-year blocks, “all land” outputs are annual, and land use outputs are annual.

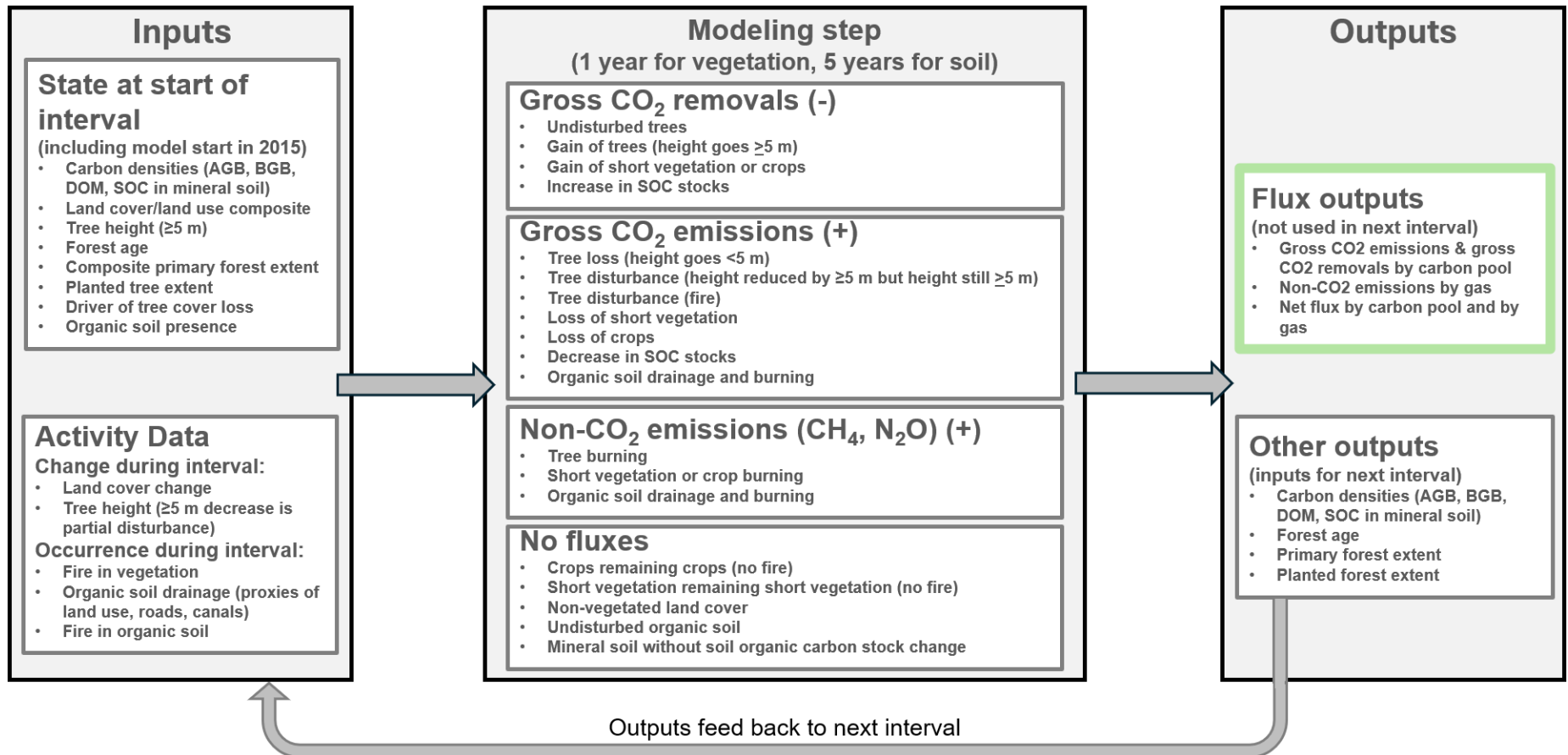
Number	Framework component	Name	Unit	Description	Zarr	1x1° geotif (per-ha)	10x10° geotif (per-ha and per-pixel if numeric)	Frequency
1	Vegetation	Vegetation gross emissions, AGC only (CO ₂ only)	Mg CO ₂ ha ⁻¹ yr ⁻¹		Y	Y	N	Annual (2016-24)
2	Vegetation	Vegetation gross emissions, BGC only (CO ₂ only)	Mg CO ₂ ha ⁻¹ yr ⁻¹		Y	Y	N	Annual (2016-24)
3	Vegetation	Vegetation gross emissions, deadwood only (CO ₂ only)	Mg CO ₂ ha ⁻¹ yr ⁻¹		Y	Y	N	Annual (2016-24)
4	Vegetation	Vegetation gross emissions, litter only (CO ₂ only)	Mg CO ₂ ha ⁻¹ yr ⁻¹		Y	Y	N	Annual (2016-24)
5	Vegetation	Vegetation gross emissions, all carbon pools (CO ₂ only)	Mg CO ₂ ha ⁻¹ yr ⁻¹	Sum of rows 1-4	Y	Y	Y	Annual (2016-24)
6	Vegetation	Vegetation gross emissions, CH ₄	Mg CO ₂ e ha ⁻¹ yr ⁻¹		Y	Y	N	Annual (2016-24)
7	Vegetation	Vegetation gross emissions, N ₂ O	Mg CO ₂ e ha ⁻¹ yr ⁻¹		Y	Y	N	Annual (2016-24)
8	Vegetation	Vegetation gross emissions, all non-CO ₂	Mg CO ₂ e ha ⁻¹ yr ⁻¹	Sum of 6-7	Y	Y	Y	Annual (2016-24)
9	Vegetation	Vegetation gross emissions, all carbon pools, all GHGs	Mg CO ₂ e ha ⁻¹ yr ⁻¹	Sum of rows 5 and 8	Y	Y	Y	Annual (2016-24)
10	Vegetation	Vegetation gross removals, AGC only	Mg CO ₂ ha ⁻¹ yr ⁻¹		Y	Y	N	Annual (2016-24)
11	Vegetation	Vegetation gross removals, BGC only	Mg CO ₂ ha ⁻¹ yr ⁻¹		Y	Y	N	Annual (2016-24)
12	Vegetation	Vegetation gross removals, deadwood only	Mg CO ₂ ha ⁻¹ yr ⁻¹		Y	Y	N	Annual (2016-24)
13	Vegetation	Vegetation gross removals, litter only	Mg CO ₂ ha ⁻¹ yr ⁻¹		Y	Y	N	Annual (2016-24)
14	Vegetation	Vegetation gross removals, all carbon pools	Mg CO ₂ ha ⁻¹ yr ⁻¹	Sum of rows 10-13	Y	Y	Y	Annual (2016-24)

15	Vegetation	Vegetation net flux, AGC only (CO ₂ only)	Mg CO ₂ ha ⁻¹ yr ⁻¹		Y	Y	Y	Annual (2016-24)
16	Vegetation	Vegetation net flux, BGC only (CO ₂ only)	Mg CO ₂ ha ⁻¹ yr ⁻¹		Y	Y	Y	Annual (2016-24)
17	Vegetation	Vegetation net flux, deadwood only (CO ₂ only)	Mg CO ₂ ha ⁻¹ yr ⁻¹		Y	Y	Y	Annual (2016-24)
18	Vegetation	Vegetation net flux, litter only (CO ₂ only)	Mg CO ₂ ha ⁻¹ yr ⁻¹		Y	Y	Y	Annual (2016-24)
19	Vegetation	Vegetation net flux, all carbon pools (CO ₂ only)	Mg CO ₂ ha ⁻¹ yr ⁻¹	Sum of rows 5 and 14	Y	Y	Y	Annual (2016-24)
20	Vegetation	Vegetation net flux, all carbon pools, all GHGs	Mg CO ₂ e ha ⁻¹ yr ⁻¹	Sum of rows 9 and 14	Y	Y	Y	Annual (2016-24)
21	Vegetation	AGC density	Mg C ha ⁻¹		Y	Y	N	Annual (2016-24)
22	Vegetation	BGC density	Mg C ha ⁻¹		Y	Y	N	Annual (2016-24)
23	Vegetation	Deadwood carbon density	Mg C ha ⁻¹		Y	Y	N	Annual (2016-24)
24	Vegetation	Litter carbon density	Mg C ha ⁻¹		Y	Y	N	Annual (2016-24)
25	Vegetation	Non-soil carbon density	Mg C ha ⁻¹	Sum of rows 21-24	Y	Y	Y	Annual (2016-24)
26	Vegetation	Land state	Categorical	Annual classification of land into activity data strata	Y	Y	Y	Annual (2016-24)
27	Vegetation	AGC emission factor	Fraction	Fraction of aboveground carbon emitted upon disturbance	Y	Y	N	Annual (2016-24)
28	Vegetation	AGC removal factor	Mg C ha ⁻¹ yr ⁻¹		Y	Y	N	Annual (2016-24)
29	Vegetation	Presence of composite primary forest at end of each year	Binary		Y	Y	N	Annual (2016-24)
30	Vegetation	Tree cover age at end of year	Years		Y	Y	N	Annual (2016-24)
31	Vegetation	Gain year count during year	Years	0 or 1 years	N	Y	N	Annual (2016-24)
32	Vegetation	Maximum height since last time not tree cover	Meters	Used for tracking disturbanes with partial height loss	N	Y	N	Annual (2016-24)
33	Vegetation	Most recent year not tree cover	Year	Used for tracking forest age and disturbance history	N	Y	N	Annual (2016-24)
34	Vegetation	Partial or full disturbance in current year	Binary	Used for tracking disturbanes with partial height loss	N	Y	N	Annual (2016-24)
35	Vegetation	Partial or full disturbance in previous years	Binary	Used for tracking disturbanes with partial height loss	N	Y	N	Annual (2016-24)

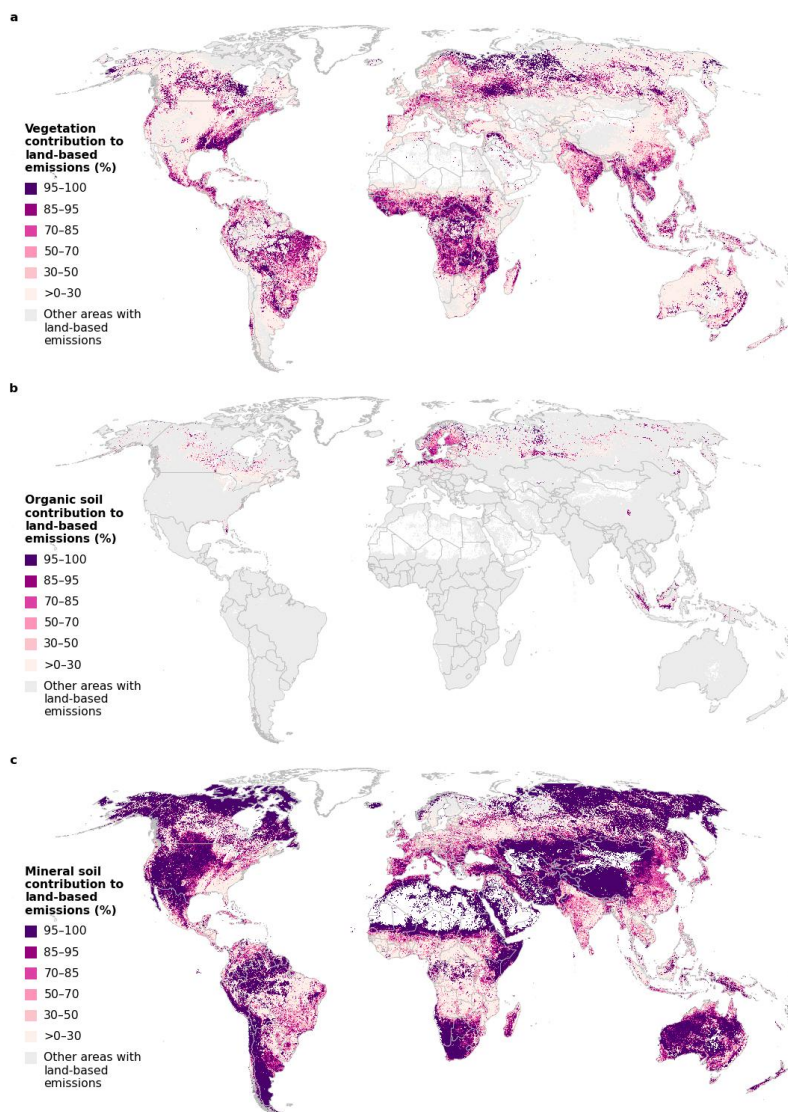
36	Vegetation	Burned in current year	Binary	Used for classifying disturbances and assigning emission factors	N	Y	N	Annual (2016-24)
37	Mineral soil	Soil organic carbon gross loss in mineral soil, 0-30 cm depth	Mg CO ₂ ha ⁻¹ yr ⁻¹	Loss is positive and gain is negative for consistency with vegetation and organic soil fluxes.	Y	Y	Y	Represents change between 2010-2015 and 2015-2020
38	Mineral soil	Soil organic carbon gross gain in mineral soil, 0-30 cm depth	Mg CO ₂ ha ⁻¹ yr ⁻¹	Loss is positive and gain is negative for consistency with vegetation and organic soil fluxes.	Y	Y	Y	Represents change between 2010-2015 and 2015-2020
39	Mineral soil	Soil organic carbon net change in mineral soil, 0-30 cm depth	Mg CO ₂ ha ⁻¹ yr ⁻¹	Loss is positive and gain is negative for consistency with vegetation and organic soil fluxes. Sum of rows 37 and 38.	Y	Y	Y	Represents change between 2010-2015 and 2015-2020
40	Mineral soil	Soil organic carbon density in mineral soil, 0-30 cm depth	Mg C ha ⁻¹		Y	Y	Y	5-year blocks (2010-15, 2015-20)
41	Mineral soil	Soil organic carbon gross loss in full soil extent, 0-30 cm depth	Mg CO ₂ ha ⁻¹ yr ⁻¹	Loss is positive and gain is negative for consistency with vegetation and organic soil fluxes.	Y	Y	Y	Represents change between 2010-2015 and 2015-2020
42	Mineral soil	Soil organic carbon gross gain in full soil extent, 0-30 cm depth	Mg CO ₂ ha ⁻¹ yr ⁻¹	Loss is positive and gain is negative for consistency with vegetation and organic soil fluxes.	Y	Y	Y	Represents change between 2010-2015 and 2015-2020
43	Mineral soil	Soil organic carbon net change in full soil extent, 0-30 cm depth	Mg CO ₂ ha ⁻¹ yr ⁻¹	Loss is positive and gain is negative for consistency with vegetation and organic soil fluxes. Sum of rows 41 and 42.	Y	Y	Y	Represents change between 2010-2015 and 2015-2020
44	Mineral soil	Soil organic carbon density in full soil extent, 0-30 cm depth	Mg C ha ⁻¹		Y	Y	Y	5-year blocks (2010-15, 2015-20)
45	Organic soil	Gross CO ₂ emissions from drained organic soil (on-site)	Mg CO ₂ e ha ⁻¹ yr ⁻¹		Y	Y	N	5-year intervals
46	Organic soil	Gross N ₂ O emissions from drained organic soil	Mg CO ₂ e ha ⁻¹ yr ⁻¹		Y	Y	N	5-year intervals

47	Organic soil	Gross CH ₄ emissions from drained organic-soil land surface	Mg CO ₂ e ha ⁻¹ yr ⁻¹		Y	Y	N	5-year intervals
48	Organic soil	Gross CH ₄ emissions from drainage ditches on organic soil	Mg CO ₂ e ha ⁻¹ yr ⁻¹		Y	Y	N	5-year intervals
49	Organic soil	Gross off-site (DOC) CO ₂ emissions from drained organic soil	Mg CO ₂ e ha ⁻¹ yr ⁻¹		Y	Y	N	5-year intervals
50	Organic soil	Gross total drainage GHG emissions, all GHGs	Mg CO ₂ e ha ⁻¹ yr ⁻¹	Sum of rows 45-49	Y	Y	Y	5-year intervals
51	Organic soil	Gross CO ₂ emissions from fire on organic soil	Mg CO ₂ e ha ⁻¹ yr ⁻¹		Y	Y	N	5-year intervals
52	Organic soil	Gross CO emissions from fire on organic soil	Mg CO ha ⁻¹ yr ⁻¹		Y	Y	N	5-year intervals
53	Organic soil	Gross CH ₄ emissions from fire on organic soil	Mg CO ₂ e ha ⁻¹ yr ⁻¹		Y	Y	N	5-year intervals
54	Organic soil	Gross total fire GHG emissions, all GHGs	Mg CO ₂ e ha ⁻¹ yr ⁻¹	Sum of rows 51-53	Y	Y	Y	5-year intervals
55	Organic soil	Gross emissions from drainage and fire	Mg CO ₂ e ha ⁻¹ yr ⁻¹	Sum of rows 50 and 54	N	Y	N	5-year intervals
56	All land	Gross emissions from organic and mineral soil	Mg CO ₂ e ha ⁻¹ yr ⁻¹	Sum of rows 37 and 55. Tabular output only.	N	N	N	Annual (2016-24)
57	All land	Gross emissions, all carbon pools, all GHGs	Mg CO ₂ e ha ⁻¹ yr ⁻¹	Sum of rows 9, 37, and 55	Y	Y	Y	Annual (2016-24)
58	All land	Gross removals, all carbon pools	Mg CO ₂ ha ⁻¹ yr ⁻¹	Sum of rows 14 and 38	Y	Y	Y	Annual (2016-24)
59	All land	Net flux, all carbon pools, all GHGs	Mg CO ₂ e ha ⁻¹ yr ⁻¹	Sum of rows 57 and 58	Y	Y	Y	Annual (2016-24)
60	Land use	Land use	Categorical	Annual land use	Y	Y	Y	Annual (2015-24)
61	Land use	Land use change	Categorical	Land use change between consecutive years	Y	Y	Y	Annual (2016-24)
62	Land use	Land use summary	Categorical	Summary of all land use changes over the observation period with 2015 representing the initial land use and 2024 representing the final land use	Y	Y	Y	Summary for 2015-24

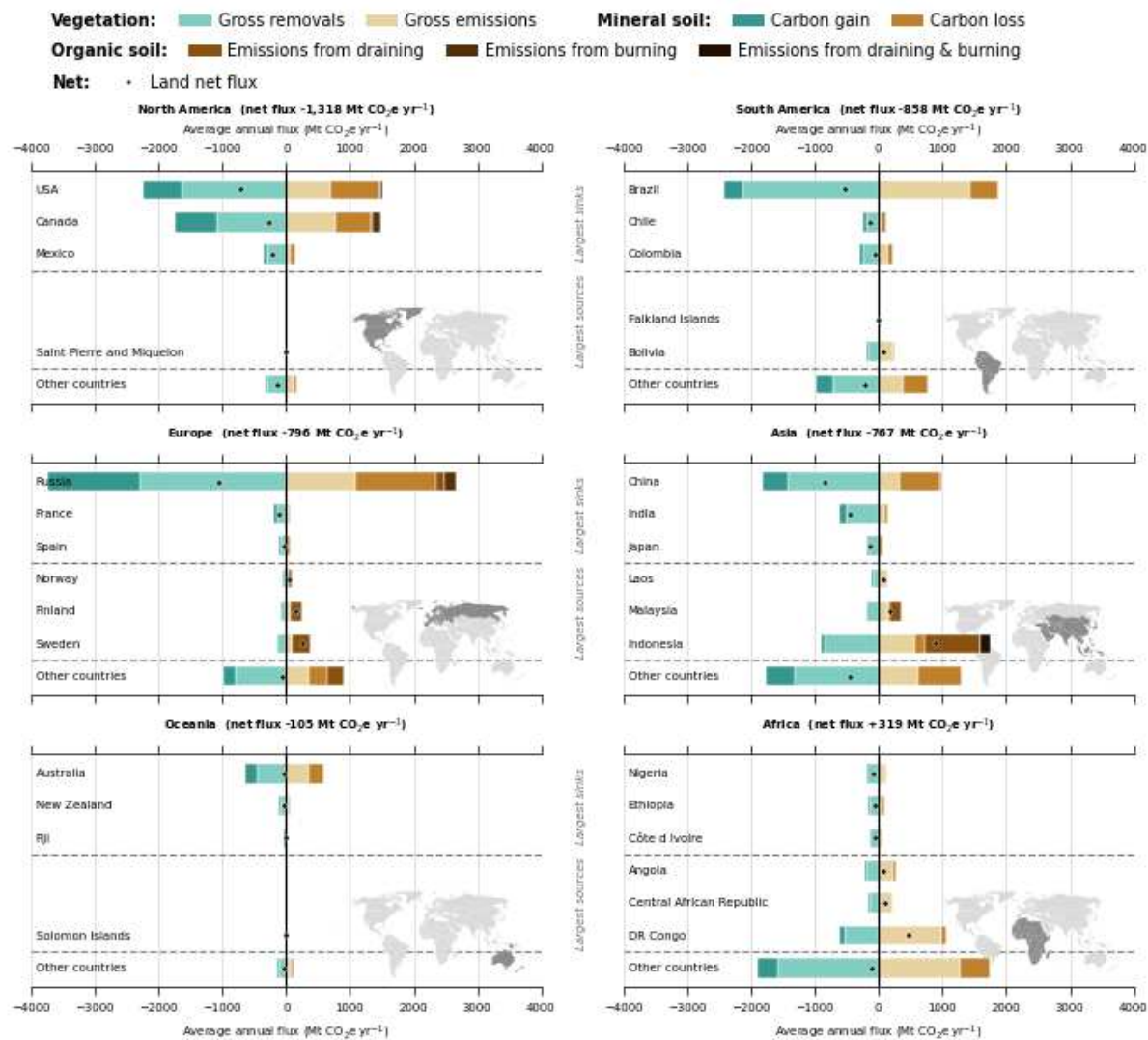
Extended data



Extended Data Figure 1. GHG flux framework overview, showing its iterative nature. “Other outputs” are used as inputs for the next interval, while flux outputs (the outputs of primary interest) are not used for the next interval. AGB: aboveground biomass; BGB: belowground biomass; DOM: dead organic matter (deadwood and litter); SOC: soil organic carbon.



Extended Data Figure 2. Contribution of framework components to average annual gross emissions (2016-2024), aggregated to ~4x4 km. a) Fraction from vegetation gross emissions. b) Fraction from organic soil gross emissions. c) Fraction from mineral soil carbon loss (0-30 cm).



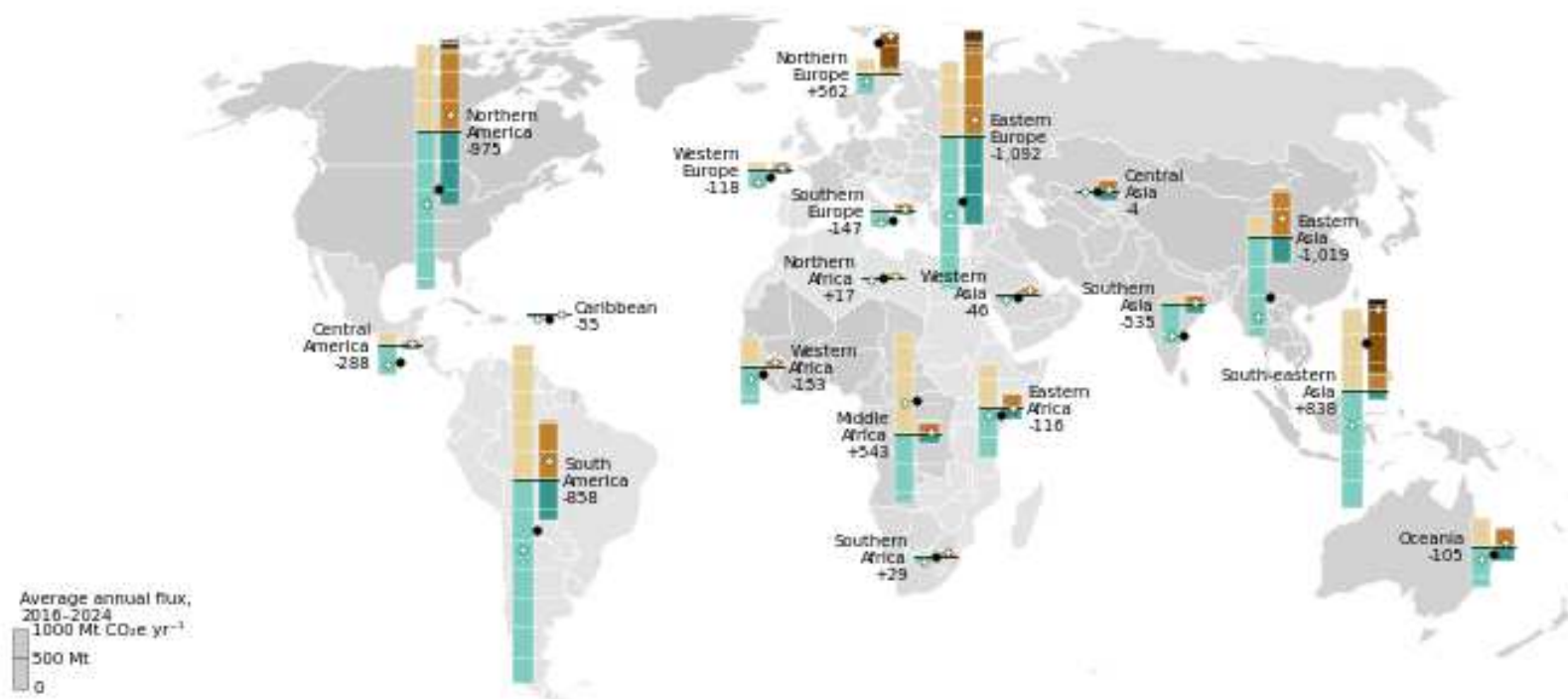
Extended Data Figure 3. The three countries with the largest average annual net sinks and sources (2016-2024) by UN Geoscheme region. Some regions with minimal fluxes have been combined. Countries are ranked in order from largest net sink to largest net source; dashed lines separate net sink countries, net source countries and the sum of all other countries. Panels with less than three countries shown as sources or sinks have only that number of countries with net fluxes in that direction. Panels are organized in order from region with largest net sink to region with largest net source.

Vegetation: ■ Gross removals ■ Gross emissions ○ Vegetation net flux

Soils: ■ Mineral soil gain ■ Mineral soil loss ■ Emissions from draining organic soils

■ Emissions from burning organic soils ■ Emissions from draining & burning organic soils ○ Soil net flux

Net: ● LULUCF net flux



Extended Data Figure 4. Average annual terrestrial net flux (2016-2024) and its components by UN Geoscheme region. Some regions with minimal fluxes have been combined. For each region, the left bars show vegetation fluxes and the right bars show soil fluxes. The black dot between vegetation and soil bars depicts the net land flux.