

Net carbon losses in Central African forests revealed by high-resolution biomass change maps

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Dense humid forests in Central Africa hold vast biomass carbon stocks but are increasingly affected by small-scale disturbances that are difficult to detect with current satellite observations. Here, we generate 10 m canopy height maps for 2019–2022 using deep learning with spaceborne lidar and Sentinel-1/–2 imagery, and derive aboveground biomass changes at 30 m resolution. The maps reveal widespread small disturbance patches, 87% smaller than 1 ha. These account for 48% of biomass carbon gains in regrowing forests and 37% of carbon losses from deforestation. We estimate a net forest carbon loss of -58 ± 14 Tg C yr⁻¹, with gross losses of -126 ± 21 Tg C yr⁻¹ partially offset by gains of 68 ± 10 Tg C yr⁻¹. The Democratic Republic of the Congo emerges as a net carbon source (-46 ± 11 Tg C yr⁻¹), representing 79% of the regional loss, primarily due to degradation, despite having the largest carbon gains in young secondary forests. Our remote-sensing estimates of national carbon budgets are broadly consistent with country-level inventories and bookkeeping model estimates, paving the way for spatially explicit and transparent carbon monitoring.

Central African forests play a vital role in the global carbon cycle, storing approximately 10% of the world's forest biomass carbon^{1–3}. Although intact forests have historically acted as a major carbon sink⁴, recent studies suggest that this sink is weakening, tending toward carbon neutrality or even becoming a net source^{5–7}. Disturbances from

deforestation, degradation (canopy disturbances that reduce biomass without converting forest to non-forest⁸), and fragmentation are increasingly affecting these forests^{9,10}. At the same time, carbon gains arise from sustainable forestry, restoration, plantations, and forest regrowth following clearing events from shifting cultivation and

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changes of environmental factors like rainfall, yet these gains remain difficult to detect and quantify using satellite observations. Legal protections have been put in place through the designation of protected areas and certified forest concessions, but the effectiveness of these measures remains uncertain^{11,12}. While previous studies have explored the types and drivers of forest disturbances in Central Africa^{13–15}, the associated carbon losses and gains remain poorly quantified¹⁶, limiting our understanding of the region's carbon balance¹⁷.

The main approaches to estimate the carbon balance of African forests in previous carbon budget assessments relied on National greenhouse gas inventories (NGHGs), bookkeeping models, and dynamic global vegetation models (DGVMs)^{18–20}. NGHGs provide nationally consistent estimates defining the UNFCCC reporting, while bookkeeping models track carbon fluxes associated only with land-use transitions¹⁹. Both approaches are generally not spatially explicit, limiting their verification on the ground. DGVMs simulate large-scale vegetation dynamics and climate–carbon interactions, but they have unconstrained parameters in Africa and oversimplify disturbances, for example, neglecting forest degradation. Building on these approaches, recent synthesis efforts such as the RECCAP2²¹ analysis by Ernst et al.²², although important uncertainties remain, particularly in resolving disturbance processes.

Advances in satellite remote sensing have improved the monitoring of forest carbon dynamics. Harris et al.²³ developed a spatially explicit framework to estimate forest carbon fluxes using fixed forest growth rates and Landsat-derived tree cover loss. Gibbs et al.²⁴ subsequently updated this framework with improved model inputs, emission and removal factors, uncertainty analysis, and extended temporal coverage, showing that Central African forests remained a net carbon sink ($-210 \text{ MtCO}_2\text{e year}^{-1}$). But they ignored biomass loss and regrowth from degradation events, which are crucial in Central African forests^{8,25}. Direct mapping of biomass carbon stock change from satellite observations can complement inventories and models based on growth rates by providing direct spatially explicit observations of forest carbon changes^{8,26,27}. However, these approaches are also subject to uncertainties from sensor noise, errors in height–biomass allometric relationships, limited sensitivity to understory changes, and potential biases when the same algorithms are applied across structurally diverse forest types^{28,29}. Despite these limitations, maps of stock changes offer a valuable opportunity to resolve the spatial distribution, size, and type of disturbance events^{30,31}, which are often not captured by existing approaches. Existing biomass change maps relying on coarse-resolution satellites (500 m to 25 km) have shown inconsistent estimates of carbon sources and sinks across tropical regions^{3,32,33}. A recent study has explored higher-resolution approaches (for example, at $\sim 100 \text{ m}$ resolution)⁶, but did not resolve sub-hectare disturbance processes. As a result, previous studies had limited ability to detect small-scale disturbances, especially those smaller than 1 ha, and to robustly quantify their contribution to regional carbon losses and gains^{34–38}. This truncated representation of disturbance size, type, and spatial distribution limits our ability to quantify forest carbon dynamics^{34,39}. This knowledge gap is particularly critical in Central African forests, where disturbances are small, spatially complex, and shaped by a combination of natural dynamics and human activities^{27,40,41}.

To address these challenges, we generated annual maps of canopy height (CH) at 10 m resolution across Central African forests²⁹. To do so, a deep learning model was trained to predict maximum CH measured by the GEDI spaceborne LiDAR^{42,43} from Sentinel-1 radar and Sentinel-2 multispectral imagery, enabling spatially continuous estimation of CH (“Methods”, Supplementary Fig. 7). These 10-m CH estimates were then aggregated to 30 m and converted to aboveground carbon (AGC) using field inventory data and allometric relationships from ref. 29. The 30 m resolution

matches the spatial scale of available field plots, knowing that large tropical tree crowns often extend over 20 m⁴⁴. First, we validated the CH and AGC change estimates for the period 2019–2022 using different reference datasets (Supplementary Notes 5–7). We then analyzed carbon losses and gains across different sizes of disturbances to address the following questions: Do the small-scale disturbances revealed by our high-resolution maps represent real disturbance events that were overlooked by existing Landsat/Sentinel-1-based datasets^{8,26,27}? How do these small disturbances contribute to carbon losses and gains associated with degradation, deforestation, and regrowth? Finally, we extended the approach to non-dense forest systems such as dry deciduous woodlands (often referred to as Miombo in Africa) to obtain national budgets. This extension is based on the key methodological assumption that our height–biomass relationships calibrated for dense forests hold for more sparsely distributed woodlands, which may introduce additional uncertainty in woodlands north and south of the Congo Basin. To address this, as we lack field data in woodlands, we assessed the robustness of our biomass estimates against independent satellite-based biomass products (Supplementary Note 12). We also incorporated belowground carbon estimates to assess the carbon balance of protected areas, forest concessions, and countries, and discuss the implications for national carbon accounting, in comparison with inventories and bookkeeping land use change carbon models^{19,20}.

Results

Evaluation of canopy height changes

To quantify CH changes from 2019 to 2022 from the raw height maps²⁹ provided by our deep learning model trained on GEDI and Sentinel satellite data, we applied a multi-step filtering and validation procedure to minimize noise and eliminate implausible structural changes, due to uncertainties caused by instrumental, atmospheric, and processing artifacts^{27,28} (Supplementary Fig. 7 and Supplementary Note 4).

The predicted height changes were evaluated against independent airborne LiDAR (ALS) campaigns at the only site with repeat acquisitions. Validation was primarily conducted at 30 m resolution due to scale compatibility with ALS data and consistency with biomass change data used in subsequent analyses, $R^2 = 0.53$ and $\text{MAE} = 3.19 \text{ m}$ (Supplementary Fig. 12). Agreement at 10 m was lower ($R^2 = 0.22$, $\text{MAE} = 3.70 \text{ m}$) than at 30 m due to increased fine-scale heterogeneity and unresolved sub-pixel canopy gaps relative to ALS data, although MAE remained comparable across resolutions. Aggregation to 30 m improves the agreement through spatial smoothing, whereas the 10 m product preserves fine-scale canopy disturbances. Comparisons with changes from GEDI discrete footprint samples (RH100) showed weak agreement at 30 m but improved when aggregated to 10 m ($R^2 = 0.23$, $\text{MAE} = 4.35 \text{ m}$) (Supplementary Fig. 15). This reflects several factors, including scale mismatch, sparse GEDI footprint sampling with no revisit in time, and geolocation uncertainty⁴⁵, as well as the difficulty of detecting small height changes at fine spatial scales. Using the RH95 or RH98 height metrics slightly improves agreement but does not change the overall pattern (Supplementary Fig. 16), indicating that discrepancies are largely independent of the choice of height metric. These results highlight that validation at very small spatial scales remains limited, and the maps are primarily interpreted in terms of aggregated spatial patterns rather than individual pixels. Nevertheless, our continuous maps of height change showed a spatial distribution of gains and losses that was consistent with the discrete individual GEDI footprints (Supplementary Fig. 17).

The sign of our height change also matches the Tropical Moist Forests (TMF) disturbance data⁸ with a negative sign indicating height loss for deforestation and degradation events and a positive sign for

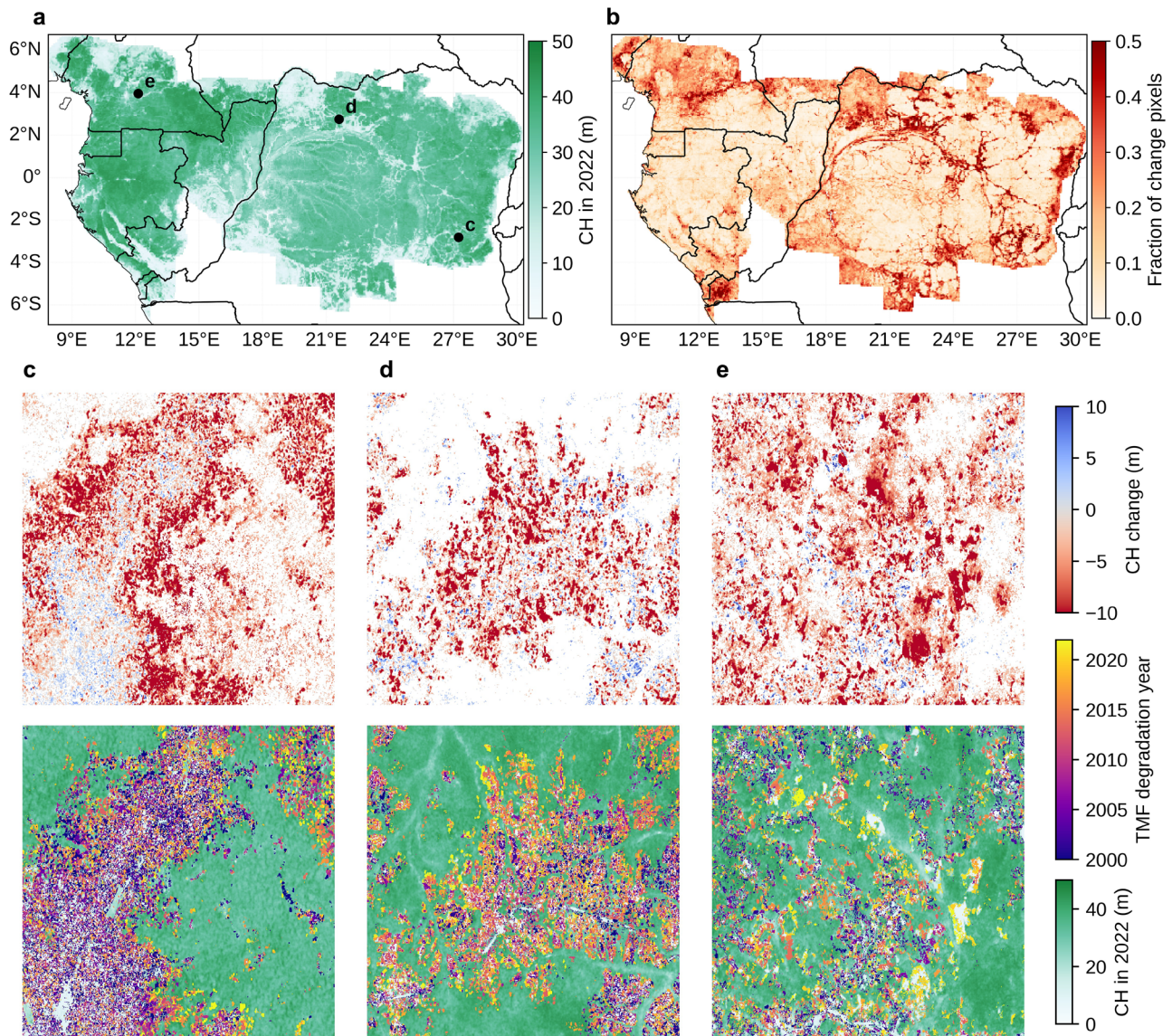


Fig. 1 | Canopy height and its change in Central African forests. **a** Spatial distribution of mean canopy height (CH) in 2022, aggregated to 5-km grid cells for visualization. The locations of three illustrative regions are marked with black points. **b** Spatial distribution of the fraction of pixels exhibiting canopy height change (Δ CH) between 2019 and 2022, aggregated to 5-km grid cells for visualization. **c–e** Maps of Δ CH (top row) with Tropical Moist Forests (TMF) degradation years overlaid, at 30 m resolution for three 30 km $\times$ 30 km illustrative regions. These regions are located in areas of high disturbance density and represent typical disturbance patterns dominated by shifting and permanent agriculture, the

primary drivers of forest change in dense tropical forests of Central Africa¹³. To clearly show CH gains and losses, we limited the displayed Δ CH range to -10 to 10 m; this range includes pixels with changes exceeding 10 m. Noise pixels were masked through a multi-step filtering procedure designed to exclude no-change pixels and spurious change signals. This filtering is based on change consistency rather than spatial location and is therefore not expected to introduce systematic spatial bias. Forest degradation is shown in the bottom panel based on TMF data. Degradation is encoded by the year of first occurrence (colorbar), enabling differentiation between recent and older degradation events.

regrowth events (Supplementary Figs. 18 and 19), and further distinguishes protection status and types (Supplementary Figs. 20 and 21). Finally, we conducted an independent validation using high-resolution (5 m) PlanetScope imagery with a stratified sampling design⁴⁶ across patch sizes and change types (Supplementary Fig. 22 and Supplementary Note 6). This analysis indicated that the user's accuracy (UA) was 84% for loss and 77% for gain across the 0–100 ha range (area-weighted), and 79% and 69%, respectively, for small disturbances (<1 ha) (Supplementary Table 1). Omission and commission errors were -6% and -5% , respectively, when evaluated relative to the full landscape, corresponding to undetected changes within no-change areas and false detections in stable forests. Further comparison showed that only 26–78% of the independently validated small CH loss patches overlapped with TMF disturbances, depending on the

minimum patch-overlap criterion applied (10–50% of the CH loss patch area; Supplementary Table 2).

High-resolution maps of height change reveal more small disturbances

The CH map is shown in Fig. 1a, and the fraction of pixels with height change in Fig. 1b. Large height losses are observed across the Democratic Republic of the Congo (DRC) and southern Cameroon, whereas height gains are found in Gabon and Equatorial Guinea (Supplementary Fig. 19). Zooming over three small regions in Fig. 1c–e shows that the patterns of our height change have a good visual agreement with the TMF disturbances. Quantitative analysis confirms that 80% of the areas where we detect large height losses (>20 m) match TMF events at 30 m resolution (Supplementary Fig. 18), indicating consistency for

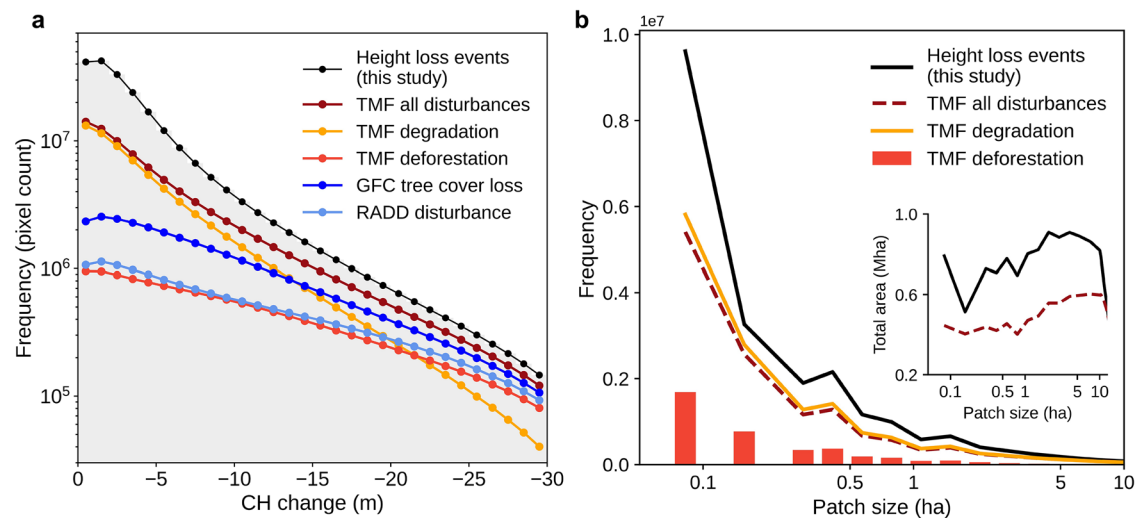


Fig. 2 | Predicted canopy height loss compared against previous disturbance datasets. **a** Frequency distribution of canopy height (CH) loss ($\Delta\text{CH} < 0$) at 30 m resolution across varying change bins and its corresponding reference disturbance datasets between 2019 and 2022. The disturbance datasets include the Tropical Moist Forests (TMF), Global Forest Change (GFC) tree cover loss map, and radar-based deforestation alerts (RADD). Pixel counts were calculated within each 1 m CH change bin. TMF disturbances include both degradation and deforestation pixels during this period. **b** Comparison of frequency distributions between TMF disturbances and CH loss (30 m) across different patch sizes. The inset shows the total

disturbed area (Mha) across patch size classes for CH loss and TMF disturbances, with lines smoothed for visualization using a 3-point moving average. Patch sizes were grouped into 51 logarithmically spaced bins ranging from 0.01 to 100,000 ha. For clarity, only the overlapping patch-size bins represented in both the height-loss and TMF datasets are displayed. Due to the wide range of patch sizes (0.09 to 10,000 ha) and the concentration of differences in smaller patches (<10 ha), a logarithmic scale was used to better visualize variation that would be obscured on a linear scale, with most differences occurring below -10 ha.

large disturbances. The main difference arises for small CH losses (<10 m), where our CH loss estimates identify 65% more affected area than is captured by the TMF deforestation and degradation products within the same disturbed regions. Independent visual validation using high-resolution PlanetScope imagery confirmed that $\sim 72\%$ of these small height losses represent real canopy disturbances (Supplementary Table 3). The contributions of different height change classes to the affected area and AGC change are summarized in Supplementary Table 4, highlighting the substantial contribution of small height losses. Further, the credibility of the small height gains and losses is indirectly supported by consistent canopy cover changes, relationships with road distance, and agreement with published local small-disturbance datasets^{38,47} (Supplementary Note 7 and Supplementary Figs. 24–28).

The TMF product is not the only one to underestimate small disturbances in Central Africa. We also found a 90% larger area affected by height loss in our product than in the Global Forest Change (GFC) tree-cover map²⁶ and the radar-based deforestation alerts (RADD)²⁷ (Fig. 2a). Here, independent visual validation using high-resolution PlanetScope imagery showed that GFC and RADD captured less than 53% and 26%, respectively, of validated CH loss patches less than 1 ha in area (Supplementary Table 2), indicating limited sensitivity of existing products to partial canopy loss and small-scale degradation^{48–50}.

In our maps, $\sim 87\%$ of patches exhibiting CH decrease from 2019 to 2022 fall within the smallest height-loss size class (<1 ha; Fig. 2b). Among the ~ 10 million 0.09 ha (single-pixel) CH loss patches identified in our maps, 56% coincide with disturbances recorded in the TMF dataset. The remaining differences may reflect either additional small disturbances not captured by TMF³⁷ or uncertainties in our detection of small changes. Those small loss patches not captured in previous datasets are prevalent in persistently cloudy regions such as the northern Congo Basin (Supplementary Fig. 19), where disturbances are associated with logging³⁷ and clearings from shifting cultivation¹⁴. Notably, the native 10 m CH-change maps reveal substantially more

small disturbance patches than the aggregated 30 m maps (Supplementary Fig. 23).

Size-dependence patterns of biomass gains and losses

To better understand how disturbance size influences biomass carbon change, we classified each canopy height change event into six distinct gain and loss categories. Since our map captures more disturbance events than TMF (Fig. 2), we developed a framework (see “Methods”) to extend the TMF classification to all the events detected in our study. For each contiguous disturbance patch, we then calculated its size⁵¹. All patches classified as deforestation events show a strong decrease of biomass density between 2019 and 2022, as expected (Fig. 3a). Degradation events show a smaller decrease in biomass density than deforestation events (Fig. 3c), with substantial variability across patches, particularly at small sizes, likely reflecting a mixture of partial canopy loss, recovery, and heterogeneous disturbance processes, and resulting in a wide dispersion. The size distribution of deforestation and degradation events is dominated by small patches (mean = 0.9 ha; median = 0.18 ha), indicating a strongly right-skewed distribution, with very rare large-scale clearings (maximum size 10,000 ha) and many small clearings. Relative to the initial biomass density in 2019, the fraction of biomass lost after deforestation increases with patch size. Biomass loss is even higher when excluding edge pixels, reaching up to $\sim 89\%$, suggesting that patch edge effects dilute the biomass loss signal because edge pixels contain cut and intact trees (Supplementary Note 8 and Supplementary Fig. 29). In contrast, degradation events result in a smaller fraction of initial biomass density being lost (1–34%). For each size category, we calculated the total biomass loss by multiplying the area of each event by its corresponding biomass loss density. The key finding is that degradation patches of approximately 1.5–10 ha and deforestation patches of approximately 1.5 ha contribute the largest share of total biomass loss in the study region, although uncertainty remains due to limitations in disturbance detection and classification (Supplementary Table 5). Altogether, small deforestation clearings of less than 1 ha contribute 37% of the total basin-scale biomass loss from deforestation (~ 8.6 Tg C year⁻¹, Fig. 3f) while the largest

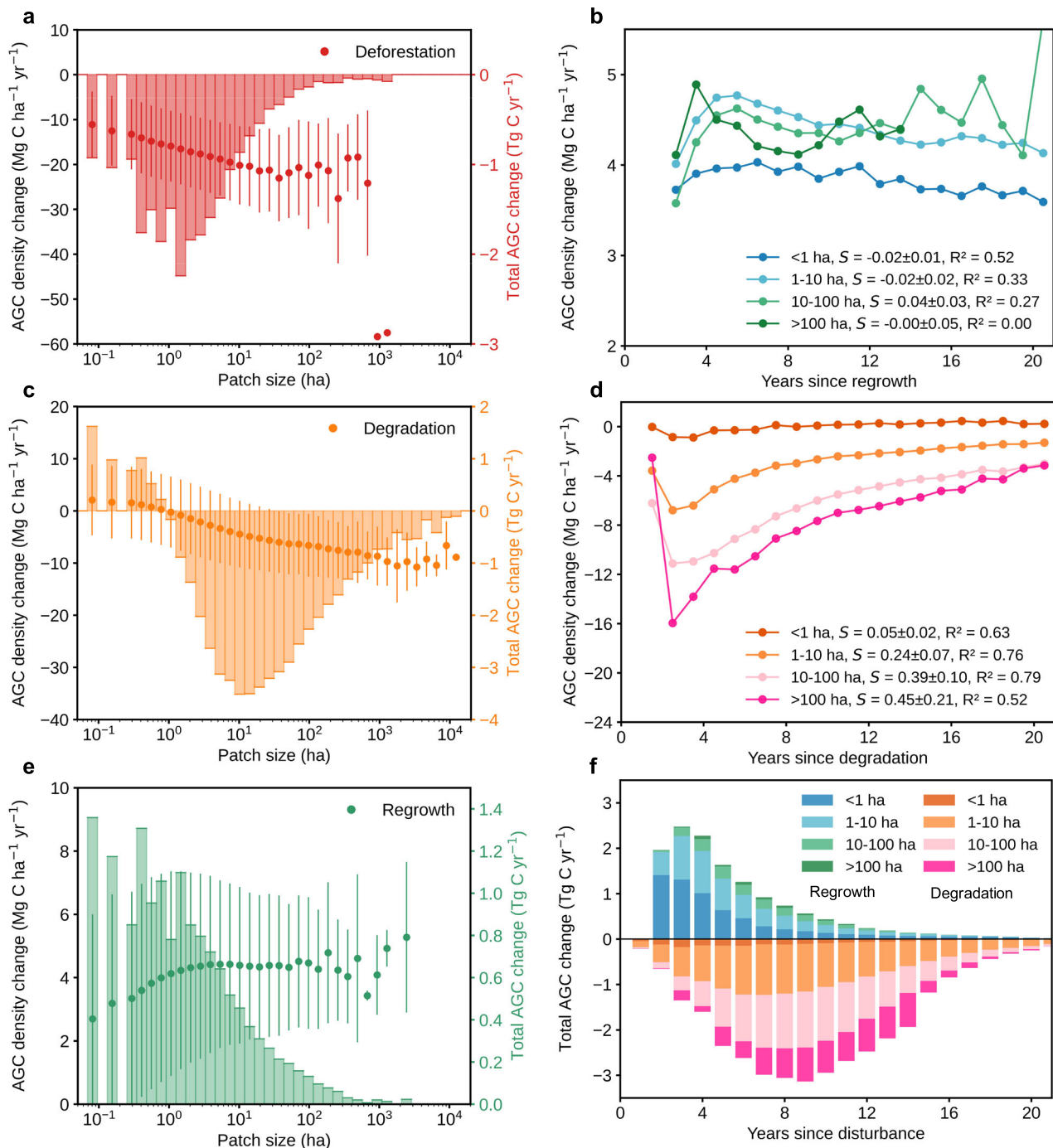


Fig. 3 | Aboveground carbon (AGC) changes across varying patch sizes and years in Central African forests. AGC density changes from deforestation (a), forest degradation (c), and forest regrowth (e) across different patch sizes. For each patch size bin, the mean value $\pm$ standard deviation is shown. The large standard deviations indicate considerable within-class variability. The bars on the secondary (right) y-axis represent the total AGC change for each patch size category. Patch sizes were derived from canopy height change maps for each disturbance class. Mean AGC density changes across patch sizes over regrowth years after

deforestation (b) and degradation years (d). The slope (S), along with its 95% confidence interval and the coefficient of determination (R^2), is reported for each regression. **f** Total AGC changes across patch sizes over disturbance (degradation and regrowth) years. AGC changes from different patch sizes are stacked, with regrowth values shown above the x-axis and degradation values shown below. Long-term records of continuous degradation and regrowth disturbances, persisting for up to 21 years before our observations, were derived from the Tropical Moist Forests dataset.

clearings above 100 ha contribute only 2%. In contrast, small degradation patches where forests are regrowing contribute mainly to basin-scale gains.

Then, we analyzed biomass changes in patches of regrowing forests that had previously been deforested but showed recovery several years later. The size distribution of these regrowth patches peaks at

0.1–1 ha, with the largest patches exceeding 1000 ha (Supplementary Fig. 30). Within those regrowth patches, we found that biomass density increases over time and shows a clear dependence on patch size, with a higher carbon gain rates in patches of less than 10 ha and a more gradual increase in larger patches (Fig. 3e). The biomass gains observed in regrowth patches of less than 1 ha are linked to post-

disturbance recovery processes such as post-fire regeneration, small-scale afforestation, regrowth following fallow cycles in slash-and-burn systems (Supplementary Fig. 32), and recovery from road-related disturbances (Supplementary Fig. 33). In contrast, the biomass gains in larger regrowth patches reflect organized afforestation or plantations. Overall, small regrowth patches (<1 ha) contribute 48% to the basin-scale biomass regrowth gain ($-7.0 \text{ Tg C year}^{-1}$) while large patches (>100 ha) only contribute 3%.

Because gains or losses of AGC observed during 2019–2022 often reflect the legacy dynamics of past disturbance events, we analyzed AGC gain and loss rates associated with former disturbance events detected by TMF prior to our observation period (Supplementary Fig. 34). For regrowing forests, high AGC growth rates are sustained for two years after regrowth is detected, followed by declining growth rates thereafter (Fig. 3b). This temporal dynamics of growth rates is however sensitive to TMF legacy data, as early-period TMF estimates may be biased toward easier to detect larger and long duration (>1 year) disturbances due to limited Landsat data availability in the early 2000s. Nevertheless, Fig. 3f shows that small patches (<1 ha) of regrowth in young secondary forests exhibit substantial AGC gains and play a dominant role in basin-scale carbon gains. In contrast, forests that experienced degradation in the past show a large initial loss of AGC density that attenuates over time. Based on this space-for-time substitution approach that assumes no secular trends in degradation severity, recovery conditions, or climate over the past two decades, we found no clear evidence of a return to a carbon gain regime in the first ~20 years after degradation (Fig. 3d). This result is consistent with recent GEDI-based analyses showing saturation in young regrowth and persistent losses in degraded forests¹⁰.

Canopy height and biomass changes at the biome scale and per forest management type

Scaling up to the entire Central African forest biome (Fig. 4a), our data show a small net AGC loss of $-58.3 \pm 13.5 \text{ Tg C year}^{-1}$ (see uncertainty estimates in “Methods”, Supplementary Note 10). This net loss is the sum of gross gains of $67.8 \pm 10.0 \text{ Tg C year}^{-1}$ and gross losses of $-126.1 \pm 20.6 \text{ Tg C year}^{-1}$ (Fig. 4b). With a total AGC stock of 24.3 Pg C (8.65% relative uncertainty) in 2019, the turnover rate associated with disturbance-driven losses was $0.52 \pm 0.10\% \text{ year}^{-1}$. The reported uncertainty was obtained by first-order propagation of the uncertainties in AGC loss (16.34% relative uncertainty) and the 2019 AGC stock, resulting in an overall relative uncertainty of 18.49% for the turnover-rate estimate (Supplementary Note 11). In terms of forest area affected, a fraction of 5.5% of the forest area shows a net AGC gain, and 9% a net loss. Two-thirds of the gross losses are attributed to degradation ($-80.4 \pm 11.5 \text{ Tg C year}^{-1}$) while the rest is due to deforestation ($-23.3 \pm 6.6 \text{ Tg C year}^{-1}$). The regrowth of secondary forests after deforestation accounts for 21.4% of the gross AGC gain ($14.5 \pm 2.6 \text{ Tg C year}^{-1}$). The AGC budget of so-called ‘other forests’, classified as apparently undisturbed in TMF but not exempt from AGC gains and losses, is close to neutral and not distinguishable from zero within uncertainty (Supplementary Table 6), although these forests exhibit substantial localized gross gains and losses. Their loss and gain fluxes in ‘other forests’ likely reflect a combination of real features (gaps, natural disturbances, human disturbances missed by TMF) and uncertainties in our disturbance classification and CH change data.

Protected forest areas and forestry concessions together represent 34% (73.5 Mha) of the total dense forest area. In protected areas, we assess a net biomass carbon loss of $-3.8 \pm 1.4 \text{ Tg C year}^{-1}$ (mean rate = $-0.09 \pm 2.40 \text{ Mg C ha}^{-1} \text{ year}^{-1}$), substantially lower than that observed in non-protected areas ($-0.31 \pm 3.55 \text{ Mg C ha}^{-1} \text{ year}^{-1}$). In concessions, we found a net loss of $-5.4 \pm 1.6 \text{ Tg C year}^{-1}$ (mean rate = $-0.15 \pm 2.88 \text{ Mg C ha}^{-1} \text{ year}^{-1}$) (Fig. 4c–f and Supplementary Table 7). Overall, 59% of the protected areas and concessions experienced AGC losses during our study period. Importantly, the difference

in AGC loss between different forest concessions ($n = 268$) is smaller than between protected areas ($n = 180$) (Fig. 4e). Concessions tend to experience more gross AGC losses from degradation and deforestation, whereas protected areas have more regrowth gains from secondary forests. Notably, 57% and 50% of the gross AGC losses from all the protected areas and concessions in our study area, respectively, occurred in the DRC, the country with the largest forest area in the region.

The mean loss rate of biomass per unit forest area is ~67% larger in concessions than in protected areas (Supplementary Table 7). Concessions and protected areas differ in environmental and socio-economic contexts, including accessibility, forest types, surrounding land use, and disturbance history (Supplementary Note 9). Therefore, this comparison does not imply a causal attribution to protection status or effectiveness alone. We found that many protected areas exhibit biomass losses³² near their boundaries where deforestation pressures occur (Supplementary Fig. 37). National parks and wildlife sanctuaries tend to have a higher AGC and greater carbon gains (Supplementary Fig. 38), while some long-established protected areas have larger carbon losses, suggesting a loosened effectiveness of conservation measures³³. Interestingly, protected areas have a smaller mean AGC density ($127 \pm 47 \text{ Mg C ha}^{-1}$) than concessions ($144 \pm 44 \text{ Mg C ha}^{-1}$) (Supplementary Fig. 39). However, this difference is modest relative to the uncertainty in AGC estimates and is accompanied by substantial overlap between distributions, indicating that the two land-use types are only weakly separable in terms of obvious influence on mean biomass density. This pattern may partly reflect non-random spatial placement of protected areas, which may include lower-biomass ecosystems due to non-carbon-centric choices for deciding a protection status (cultural value, animal and plant diversity). It may also be influenced by differences in management regimes, for example, where logging in concessions is relatively low-intensity or in more fertile forests, and allows trees to retain or recover biomass¹². In contrast, some protected areas were already degraded prior to their designation, which could contribute to their lower current AGC levels.

National carbon budgets

We finally estimate country-level carbon budgets after extending our method to non-dense forests, and including belowground biomass carbon (BGC)³⁴ changes (Supplementary Note 12 and Supplementary Figs. 40–42). Our national budgets derived from satellite data are split into gains (post-degradation, secondary regrowth, and other forests) and losses (degradation, deforestation, and other forests), and compared with national inventories and bookkeeping model results in Fig. 5. Our definition of loss and gain is different from national inventories which primarily separate ‘forest remaining forest’ and ‘land converted to another land use type’ from deforestation and afforestation. National inventories report carbon stock changes only within managed lands, but all African countries shown in Fig. 5 classify their entire forest area as managed, hence the comparison with our study covering all forests is valid. Bookkeeping models provide only the carbon fluxes from land use change, generally without spatially explicit data, and their results are presented for information.

Net biomass carbon changes at the country scale (Fig. 5a) show broadly consistent magnitudes with national inventories²⁰ harmonized by Grassi et al.¹⁹ in Gabon and Equatorial Guinea, which have relatively small and stable forest sectors, with differences of 1 and 0.2 Tg C year^{-1} , and of 5 Tg C year^{-1} in Cameroon, where there is more deforestation. Differences between our estimates and Grassi et al. are larger in large countries such as DRC that dominate the regional carbon budget. In the DRC, our estimate indicates a smaller net carbon loss than the inventory (Supplementary Table 8). This discrepancy may reflect differences between the harmonized inventory framework¹⁹ and our satellite-based biomass change estimates, particularly in the partitioning of gross carbon losses and gains, as well as uncertainties in our

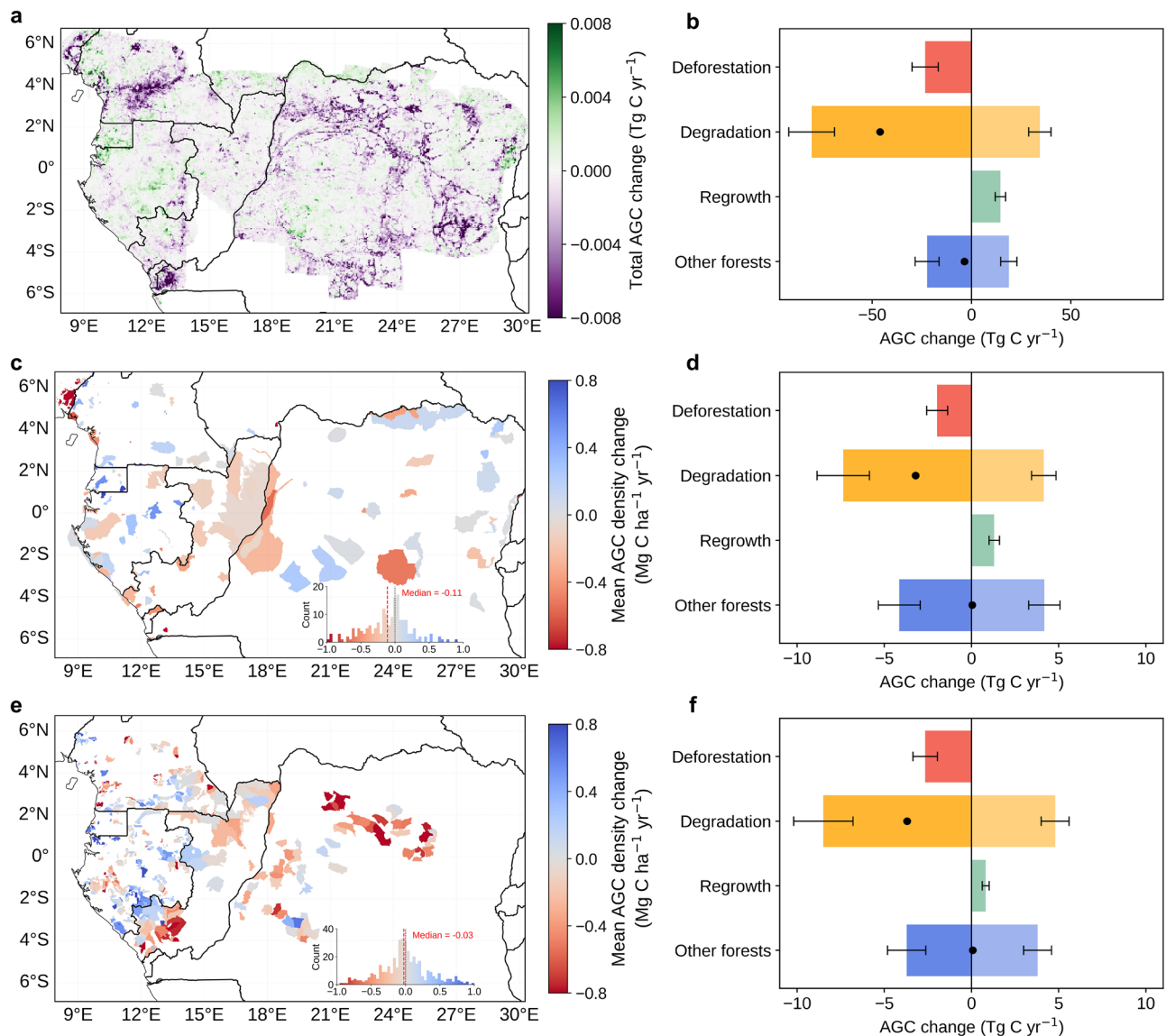


Fig. 4 | Aboveground carbon change across different land use types in Central African forests. **a** Spatial distribution of total aboveground carbon (AGC) change in each 5 × 5 km grid cell. Spatial distribution of mean AGC density change in each protected area (**c**) and forest concession (**e**). Insets show distributions of mean AGC density change, where each value corresponds to an individual area. Black dashed lines indicate no change, and red dashed lines show medians. Spatial distribution of the total AGC change for each protected area and forest concession is presented in Supplementary Fig. 36. Only officially designated protected areas and allocated forest concessions were included in the analysis. Total AGC gain and loss were

assessed for secondary, degraded, and deforested areas in Tropical Moist Forests (TMF) disturbance data, and ‘other forests’ which are classified as undisturbed forest in TMF but nevertheless show small AGC gains and losses in the whole Central Africa forests (**b**), protected areas (**d**), and forest concession areas (**f**). Error bars indicate the estimated uncertainty for each class. The black dot represents the net carbon change associated with degraded and other forests. Change classes were determined based on canopy height change and TMF disturbance data from 2019 to 2022.

estimates, including possible underestimation of biomass losses in low-canopy non-dense forests. In the DRC, our net biomass carbon change is the sum of a gain of 78.1 ± 13.0 and a loss of -168.3 ± 29.3 Tg C year⁻¹ (Fig. 5b, c), which is comparable to 74.1 ± 14.0 and -197.1 ± 35.1 Tg C year⁻¹ from the bookkeeping models¹⁸ (Supplementary Table 8). Similar levels of agreement were observed in Equatorial Guinea. In contrast, our estimates of gross gains and losses in Gabon and Congo are larger than bookkeeping models⁵⁵. This may be due to the high spatial resolution of our data, which allows us to better detect gains and losses at the scale of individual patches, whereas bookkeeping models use an arbitrary national fraction of ‘shifting cultivation’ areas as a proxy of degradation and calculate harvest removal as a bulk without spatial details. Since our dataset includes natural disturbances which are not captured in bookkeeping models,

the fair agreement between our approach and bookkeeping models suggests that most disturbances in the region are from anthropogenic land use activities in Fig. 5. Further comparison with DGVM models and the statistical division of the Food and Agricultural Organization of the United Nations (FAOSTAT)^{20,56} is given in the Supplementary Note 13 but they are not discussed in detail since DGVMs do not simulate fine-scale land use change and degradation and FAOSTAT assumed a growth rate of zero for forest remaining forest in some countries⁵⁷.

Despite a fair agreement with our net biomass carbon changes, national inventories¹⁹ tend to report larger gross carbon gains (Fig. 5b). This overestimation could be from the use of Tier 1 IPCC methods⁵⁸ in inventories, which are based on default values of intact forest growth rates applied uniformly across all forest types. To evaluate this assumption, we calculated the average forest carbon growth rate from

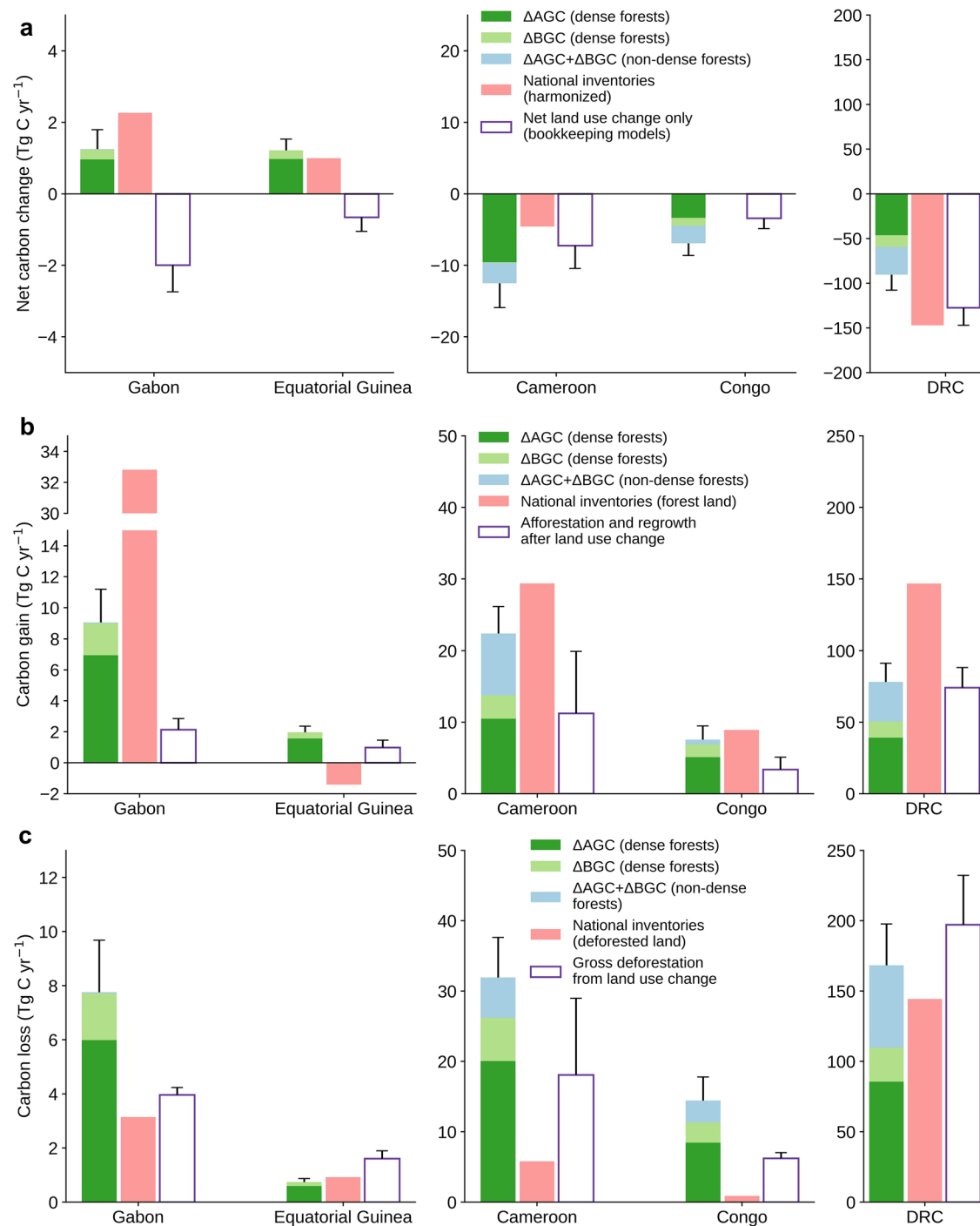


Fig. 5 | Comparison of national biomass carbon change and land-use carbon flux estimates in Central African forests. **a** Comparison of net carbon change from biomass carbon and Land Use, Land-Use Change and Forestry (LULUCF) estimates based on bookkeeping models and harmonized national inventories²⁰. Original CO_2 fluxes were converted into carbon fluxes based on their molar mass ratio. National inventories of net carbon change were harmonized to address the managed land issue and align with model definitions^{19,20}; however, such estimates were unavailable for the Congo. The estimated biomass carbon change (this study) includes aboveground carbon (AGC) change (ΔAGC) and belowground carbon (BGC) change (ΔBGC) estimated from AGC using country-level ratios of belowground biomass (BGB) to aboveground biomass (AGB)⁵⁴. In the context of LULUCF

averaged from three bookkeeping models (BKs; BLUE, OSCAR, and HN), deforestation generally represents a carbon source, whereas forest land usually acts as a carbon sink, although a few cases for forest land may indicate the opposite. The error bars for ΔAGC and ΔBGC represent estimated uncertainty, while those for bookkeeping models indicate the standard deviation across models. **b** Comparison of carbon gains from biomass carbon change and LULUCF estimates for forest land based on bookkeeping models and national inventories¹⁹. The large carbon flux from forest land reported in the national inventories database for Gabon was visualized using a broken y-axis. **c** Comparison of carbon losses from biomass carbon change and LULUCF estimates for deforested land based on bookkeeping models and national inventories¹⁹.

our maps and found that our growth rates over intact (undisturbed) forests were close to zero or even negative (Supplementary Table 9), lower than the refined IPCC default values⁵⁹. This result suggests that the gross carbon gains reported in national inventories may be overestimated by more than 50% in Gabon, Cameroon, and the DRC (Fig. 5b). At face value, this difference may also reflect methodological limitations in our satellite-based height change estimates, including potential regression-to-the-mean effects in deep-learning models and saturation of satellite data in very high biomass forests that may attenuate height gains in old-growth forests.

National inventories also report lower gross carbon losses than our estimates (Fig. 5c). This difference partly reflects methodological differences between the two approaches. National inventories primarily report emissions associated with deforestation and do not explicitly report human-induced degradation losses, whereas biomass losses in our study include both deforestation and forest degradation, as well as natural disturbance processes. By explicitly separating carbon gains and losses, our approach provides a complementary perspective on the dynamics of all disturbances and associated biomass carbon changes.

Discussion

Our high-resolution maps of forest carbon change provide detailed insights into fine-scale carbon dynamics in Central African forests and can help inform or complement national inventories by linking carbon changes to local processes such as small-scale clearing and regrowth. Our estimates of gross carbon losses (2019–2022) from degradation and deforestation are broadly comparable to previous coarse-resolution estimates based on L-band vegetation optical depth data for 2010–2019⁶⁰ (Supplementary Table 11), although the comparison should be interpreted with caution due to differences in the analyzed time periods and the coarse spatial resolution (25 km) of the L-band data, which does not allow detection of individual disturbances. Interestingly, our patch-scale AGC recovery rates from regrowing forests are broadly consistent with recent remote-sensing estimates of Amazonian forest growth⁶¹ and with global modeled estimates of tropical forest recovery, including those reported for African forests⁶², but exceed the refined IPCC guidelines 2006 default growth rates⁵⁹. We also find high relative recovery rates in the first three years of regrowth after degradation or temporary deforestation, followed by regrowth. This highlights the important contribution of young regrowth forests in Central Africa (1–8 years old; Fig. 3), which exhibit faster biomass accumulation during early succession than older secondary forests⁶². Some of these areas may include a small proportion of agroforestry systems (e.g., shaded cacao plantations) that are difficult to distinguish from natural regrowth. Based on the Spatial Database of Planted Trees⁶³, these systems account for ~3% of our total AGC gain within regrowth forests and do not substantially affect regional biomass recovery estimates.

We did not explicitly attribute the drivers of biomass change to fire, windthrow, plantation expansion, or afforestation⁶⁴, due to the short time window covered by our maps and the lack of detailed and spatially explicit ancillary data. This constrains the analysis of long-term disturbance signals. Comparisons with long-term datasets like TMF can provide context, but temporal inconsistencies, especially in areas of small degradation or regrowth events⁴⁸, limit their reliability for interpreting our maps of carbon changes. Our approach integrates annual height composites, strict detection thresholds, and external forest loss datasets to improve the robustness of change detection. Visual validation indicates that most detected loss patches correspond to real canopy disturbances, although ~16% do not represent true loss signals based on expert interpretation (Supplementary Table 1). A key next step will be to distinguish natural disturbances (e.g., storms, droughts, fires) from anthropogenic drivers (e.g., logging, land-use conversion)⁶⁵, which is essential for carbon reporting, mitigation

tracking, and evaluation of bookkeeping models¹⁹. Ongoing efforts to extend the dataset through 2024 and before, along with improved reference data, will support trend detection and the development of fully classified, high-resolution maps of forest carbon dynamics.

Reducing regional biases on biomass estimation related to forest type, disturbance severity, and recovery dynamics requires more extensive field inventory data⁴². Furthermore, our height mapping primarily reflects top-of-canopy structure and does not probe understory trees, which can be preferentially cut by fuelwood collection, selective logging of small trees, agro-forestry practices, low-intensity fires, or die from drought⁶⁶. Because such disturbances often occur without substantially altering top canopy height, their contribution to biomass loss may be underestimated in our analysis. In particular, small-scale and sub-canopy disturbances that do not produce detectable height reductions may not be captured, contributing to uncertainty in biomass loss estimates. More broadly, uncertainties in canopy height change estimation itself, arising from detection limits, temporal sampling, and signal variability, further complicate the interpretation of both loss and gain.

Future work should expand field inventories and leverage higher-resolution satellite data and deep learning-based models able to map full vertical waveforms from GEDI⁶⁷. Recent missions such as BIOMASS, whose P-band radar is sensitive to large stems and will provide forest vertical tomography, together with NISAR, help reduce uncertainties associated with height-to-biomass conversion and improve monitoring of biomass dynamics. Our results suggest that Central African forests acted as a net carbon source during 2019–2022, broadly consistent with previous studies reporting a weakening or reversal of the forest carbon sink^{5,6}. However, substantial spatial variability remains, and some regions, particularly Gabon and Equatorial Guinea, may still function as carbon sinks (Fig. 5). Our findings highlight the urgent need for fine-scale monitoring and investment strategies that jointly prioritize carbon and biodiversity, especially in under-monitored regions¹⁷.

Methods

Annual canopy height and biomass mapping

To derive CH change in Central African forests, we produced annual 10-m CH maps (FORMS-Africa V1)²⁹ using a deep learning U-Net model trained with Sentinel-1 Synthetic Aperture Radar, Sentinel-2 L2A optical imagery, and GEDI L2A RH100 measurements⁶⁸. Sentinel-1 GRD data (VH polarization) were preprocessed using radiometric terrain calibration⁶⁹, orthorectification, and border noise removal. For each tile and year, a temporal stack of Sentinel-1 images acquired during the dry season (June–October) was generated, from which the ten images with the lowest mean backscatter were selected and averaged to reduce radar noise and moisture effects. Sentinel-2 predictors included bands B2, B3, B4, B8, and B11 (resampled to 10 m). Images were filtered using the ESA cloud mask, and the three least cloudy observations during the dry season were selected to build annual composites. All Sentinel-1 and Sentinel-2 inputs were normalized to the range [0, 1]. The training dataset was constructed from 600 tiles (20 × 20 km) distributed across African dense forests. Tiles were randomly divided into training (80%), validation (10%), and testing (10%) subsets. The U-Net model was trained to perform pixel-wise regression of CH from Sentinel-1/2 imagery, using a weighted mean absolute error (MAE) loss⁷⁰ to balance the contribution of different CH classes. Annual CH inference was then performed across the entire region, producing yearly CH maps from 2019 to 2023. The maps show overall good agreement with GEDI RH100 observations and ALS-derived CH maps, respectively. Further details of the model architecture, training procedure, and preprocessing are provided in Supplementary Note 1.

Following our recently published study²⁹, the annual CH maps were aggregated to 30 m resolution and then combined with 1 km wood density (WD)^{71,72} maps to derive AGB (Mg ha⁻¹) at 30 m grids

using the empirical relationship in that study:

$$\text{AGB} = 6.5981 \times (\text{CH} \times \text{WD})^{1.2670} \quad (1)$$

Although biomass–height scaling relationships are theoretically expected to be non-linear, we evaluated several alternative formulations, including machine-learning approaches²⁹. While some models achieved higher predictive accuracy of biomass on validation samples, they produced spatial artifacts and unstable temporal patterns when applied to wall-to-wall mapping at 30 m resolution. To ensure spatial coherence and temporal consistency across annual maps, we therefore adopted this simpler height-based formulation. The WD map was resampled from 1 km to 30 m for AGB estimation. Although this resampling does not introduce fine-scale variation in WD, including WD helps mitigate biomass saturation effects when converting CH to AGB. In practice, most spatial and temporal variability in AGB is driven by CH, while WD acts primarily as a regional modifier. Because the WD dataset did not fully cover all forest pixels in either 2019 or 2022, missing values were filled using the nearest available WD value. These filled pixels occur primarily in disturbed areas and low-density forest regions and account for only 1.5% of all pixels. The AGB model was calibrated using more than 400 field observations of AGB from African dense forests and showed moderate agreement with available field inventory data, with an R^2 of 0.40 and a relative error of 32.6%. This validation statistic reflects scale mismatch and representativeness of the available field inventory plot validation dataset and should not be interpreted as the variance explained across the entire mapped domain. Field plots are sparse across Central Africa and are disproportionately located in high-biomass forests, which affects the validation statistics. Then, we converted AGB to carbon, assuming that AGC (in Mg C ha^{-1}) is 45.6% of AGB, which lies within the commonly reported range of carbon fractions for tropical woody biomass^{73,74}.

Following the definition used in the GLAD tree height product⁷⁵, we defined forest pixels as those with $\text{CH} \geq 5$ m. This is similar to the FAO FRA forest definition⁷⁷, but does not consider the tree cover or patch size criteria. This height threshold may include some tree-based agricultural systems (e.g., shaded cacao agroforestry), although their influence on regional biomass estimates is expected to be limited in the dense forest regions analyzed here. The AGB model selected in this study was specifically calibrated for African dense forests. To enable country-level carbon accounting, we applied the same CH–AGB relationships to non-dense forest systems. This represents an important assumption, as structural differences in canopy architecture, species composition, and disturbance regimes may affect the transferability of these relationships (Supplementary Note 1). However, our previous ALS-based evaluation²⁹ included a wide range of forest structures, including relatively short forests in wet regions that are not classified as dense forests, and showed generally consistent performance across these conditions. Due to the limited availability of field inventory data for non-dense forests, a direct recalibration of the model was not feasible. Instead, we evaluated the robustness of the resulting AGB estimates through comparison with the ESA-CCI AGB product as an independent satellite-based dataset. The two datasets showed broadly consistent spatial patterns (Supplementary Note 12 and Supplementary Figs. 40–42), supporting the large-scale applicability of the approach while acknowledging potential uncertainties at local scales.

Reference data for CH change validation

To evaluate the predicted maps of CH change, we used different reference datasets, including ALS CH, GEDI RH100, and published disturbance datasets (Supplementary Notes 2 and 3).

We used the available repeated ALS scans from 2015 and 2023²⁹ over the Yangambi Biosphere Reserve, DRC (Lat: 24.26583°–24.55838°; Lon: 0.77435°–0.85176°), obtained from the network of canopy observatories (www.CanObs.net). We compared the estimated CH

changes against ALS-derived changes at spatial resolutions of 10 m, 20 m, and 30 m. The original ALS CH maps, generated at 2 m resolution, were aggregated to coarser grids by extracting the maximum value within each cell, representing the upper canopy envelope. Although this approach does not fully reproduce the GEDI waveform-derived RH100 metric, it provides a practical approximation of top-of-canopy height in the absence of waveform information. To enhance the quality of the ALS CH maps, we excluded edge pixels that were adjacent to invalid values within a 3×3 pixel window. Because ALS observations were only available for 2015 and 2023, we estimated CH changes comparable to the 2019–2022 observation period using temporal interpolation. Pixels with height loss occurring outside the comparison window were excluded to reduce temporal mismatch. CH gains and losses were then identified using a 0.5 m threshold⁶¹ to match the sensitivity of the satellite-derived CH maps. These steps improve the consistency of the comparison by reducing temporal mismatches between ALS and satellite observations (Supplementary Figs. 13 and 14). We also acknowledge that this comparison is subject to limitations, including temporal mismatches, the need for interpolation and sample filtering, and limited spatial representativeness. To assess the potential effects of temporal interpolation and sample filtering, we conducted sensitivity analyses (Supplementary Note 5).

We also compared our CH change maps to changes directly obtained from GEDI footprint data. We filtered GEDI footprints to retain high-quality, high-sensitivity L2A RH100 observations (V2), following quality control criteria established in previous studies^{76,77}. We compared CH change over grid cells of various sizes (from 2019 to 2022) containing multiple GEDI footprints by averaging the data of all GEDI footprints in each grid cell. It is important to note that GEDI geolocation uncertainty and sensor- and atmosphere-related effects⁷⁸ in Sentinel-2 images introduce uncertainty in matching GEDI and CH changes at the 30 m pixel scale. To improve the robustness of the comparison, we therefore aggregated CH change maps to coarser spatial resolutions (from 100 m up to 100 km) (Supplementary Note 3). Because the CH model is trained on GEDI RH100 observations, this comparison is not fully independent. It is therefore intended primarily as a consistency check of large-scale RH100 change patterns rather than as an independent validation.

Furthermore, we compared CH change with several disturbance datasets, which are independent from GEDI data, including TMF⁸, GFC²⁶, RADD²⁷ (Supplementary Note 2). These datasets provide independent satellite-based references for disturbance patterns, although they are not used here as formal validation because each product is based on different methods and has its own detection uncertainties. The GFC dataset, derived from time-series Landsat imagery, was used to identify forest loss pixels within Central African forests based on the loss-year layer. The RADD alerts, generated from Sentinel-1 data, were used to extract high-confidence disturbance pixels (value = 3) over the same period at 10 m resolution. The TMF dataset (v2023) provides annual 30 m disturbance maps, from which we derived deforestation, degradation, and regrowth (secondary forests growing after deforestation) from the annual change collection. Note that the TMF product uses a dedicated methodology tailored to Tropical Moist Forest dynamics, combining spectral decision rules with single-date image classification across the full Landsat archive⁸, which enables the detection of short-duration disturbances and consequently identifies more disturbance events than GFC and RADD.

To assess the reliability of mapped CH changes, we conducted an independent validation using high-resolution monthly PlanetScope imagery (5 m) (Supplementary Note 6). We adopted a stratified random sampling design following commonly used good practices for land-change accuracy assessment⁴⁶, based on patch-size classes (0–1, 1–5, 5–10, and 10–100 ha) and change type (gain and loss). Samples were randomly selected across the study region, and only locations with sufficiently cloud-free PlanetScope imagery in both 2019 and

2022 were retained for interpretation. We visually interpreted whether sampled patches exhibited canopy structural decrease or increase consistent with the mapped CH change direction. Interpretation was based on comparisons between monthly PlanetScope imagery from 2019 and 2022, together with the mapped CH change layer, including changes in canopy cover, shadowing, canopy openings, and vegetation recovery signals. We included a total of 422 validated loss patches and 498 validated gain patches. Small disturbance patches, which are particularly difficult to identify because of subtle canopy structural changes, were independently interpreted by both an experienced forest remote sensing expert and a trained analyst following the same interpretation protocol. Interpretation consistency across the same validation samples reached 94%. Larger disturbance patches (1–100 ha) were interpreted by the trained analyst using the same protocol. Finally, we derived user's accuracy for each size class as well as area-weighted accuracy⁴⁶ to account for the disproportionate contribution of large patches to total mapped area change (Supplementary Table 1). In addition, omission errors were assessed using randomly sampled 2-ha reference patches selected from undisturbed forest areas. These reference areas were visually confirmed as stable forest using PlanetScope imagery together with independent disturbance datasets. To further evaluate the reliability of CH loss detections across different loss magnitudes, we conducted an additional visual assessment using randomly sampled 1-ha and 5-ha image chips extracted from the mapped CH change layer (Supplementary Table 3). These image-chip sizes refer to the area of the sampled image subsets rather than the size of individual CH loss patches, because CH changes cannot be reliably interpreted at the individual-pixel level using optical imagery alone. Image chips were stratified according to their mean estimated CH-loss magnitude ($-10 \leq \Delta CH < 0$ m, $-20 \leq \Delta CH < -10$ m and $\Delta CH < -20$ m) (Supplementary Fig. 43). Monthly PlanetScope imagery acquired in 2019 and 2022 was visually interpreted to determine whether canopy loss was present within each sampled image chip. This assessment was designed to quantify the reliability of CH loss detection (true and false detections) across different loss-magnitude classes, rather than to validate the quantitative accuracy of the estimated CH loss values, which cannot be independently assessed by visual interpretation alone. Furthermore, we validated and characterized small CH changes against multiple reference datasets, such as canopy cover, road map⁷⁹, and local disturbance data⁴⁷ (Supplementary Note 7).

CH change processing

Satellite-derived CH change estimates are subject to uncertainties caused by sensor noise, atmospheric effects, and environmental variability, which may introduce spurious signals in CH change detection. To reduce these artifacts while minimizing the risk of excluding genuine disturbances, we applied a multi-constraint filtering framework that combines spatiotemporal consistency of canopy height changes with independent disturbance information. In this study, we focused on CH change between 2019 and 2022, using CH in 2023 as a reference to infer the overall trend.

- (1) To identify and filter out isolated noise pixels, we constructed a 3D data cube of CH changes voxels across 3 years and applied a 26-connectivity method⁸⁰ to detect spatiotemporally coherent clusters of change: $\Delta CH_{2021-2019}$, $\Delta CH_{2022-2019}$, and $\Delta CH_{2023-2019}$. Similar connectivity analysis methods have been widely used to identify forest disturbances and fragmentation patterns^{51,81}. We retained only the $\Delta CH_{2022-2019}$ layer, treating a pixel as reliable if it was part of a 3D-connected cluster; isolated voxels were considered noise and removed. We then applied a temporal consistency check: if the sign of change in $\Delta CH_{2022-2019}$ was opposite to both $\Delta CH_{2021-2019}$ and $\Delta CH_{2023-2019}$, the pixel was excluded. Although the three layers share the same 2019 baseline, they are influenced by noise in

that baseline. The additional temporal consistency check can reduce such effects by removing pixels whose change direction in 2022 is inconsistent with both neighboring years, thereby filtering out isolated or inconsistent fluctuations.

- (2) To identify and filter out noise in CH gain ($\Delta CH > 0$), we applied a Mann–Kendall trend test^{82–84} to assess the temporal trend of ΔCH from 2019 to 2022. Because the available time series is short, this test mainly identifies pixels with gradual and consistent canopy height increases, and pixels with an S-statistic < 6 were excluded. This filtering may remove some abrupt regrowth events (e.g., rapid post-disturbance vegetation recovery). To reduce this risk, pixels classified as regrowth in the TMF dataset were re-evaluated and retained when the disturbance signal was consistent with the CH gain trend. TMF information was therefore used only to reduce potential omission of real regrowth signals rather than to introduce new detections.
- (3) To reduce the noise of the remaining valid CH loss pixels, we collocated the annual-mean Sentinel-1 descending images with the pixels exhibiting valid CH changes. Pixels showing very low variability in the Sentinel-1 VV signal ($|CV| \leq 5\%$) between 2019 and 2022 were excluded, as these are likely associated with false structural canopy changes. This threshold was selected empirically based on model uncertainty, as height loss within this range is generally small (< 5 m) and subject to higher relative uncertainty. The threshold is therefore intended to reduce noise from low-magnitude and uncertain changes rather than to define a sharp physical transition.
- (4) The last step is to use annual canopy cover change (ΔCC) data from 2019 to 2022, trained using the GEDI canopy cover dataset (Supplementary Note 2) as a reference. Following previous studies^{85,86}, forest pixels with valid CH change after the previous steps but with $|\Delta CC| \leq 2\%$ were considered weak or uncertain disturbances. In this step, pixels were removed only when ΔCC and ΔCH showed inconsistent change directions, such that disturbances with coherent ΔCH signals were retained even when ΔCC was small. TMF disturbance classifications were further used to reduce omission when both datasets indicated consistent change. However, some low-intensity disturbances associated with minimal ΔCC may still be missed.

To avoid excluding real disturbances during the threshold-based filtering steps, the TMF disturbance data⁸ was only used in steps (2)–(4) to re-evaluate the pixels for which our CH change and TMF disturbance trends were consistent. TMF pixels classified as disturbed were not automatically retained; instead, they were kept only when their disturbance signal matched our CH change trends. Further, we evaluated the sensitivity of our results to key parameter choices in the CH change processing, including trend detection, Sentinel-1 filtering, and canopy cover filtering (Supplementary Table 12). The resulting variability in AGC gain, loss, net change, and associated area (Supplementary Tables 13 and 14) was propagated as part of the structural uncertainty in the uncertainty framework. Details of the sensitivity analysis are provided in Supplementary Note 4.5. To assess the impact of filtering processes, we summarized the change in CH-loss pixels after each step (Supplementary Table 15). The results show that the filtering primarily excluded pixels with CH change < 10 m (17.3%–85.7%), while only 0.2%–2.3% of pixels were removed when CH loss exceeded 20 m. After CH change processing, we re-evaluated the performance of the CH change estimates and compared them to the original, unprocessed results (Supplementary Note 5).

CH change classification

To attribute CH changes to disturbance types, we developed a classification framework that categorizes CH changes into six classes, including other loss, deforestation, degradation loss, regrowth,

degradation gain, and other gain. This classification is based on height changes derived from satellite observations rather than land-use definitions used in national inventories. We classified forest degradation as small CH reductions and deforestation as large losses, based on CH change estimates. Regrowth classification relies on TMF due to the short time span of our dataset. This specific classification extends the TMF classification to our dataset since TMF detects less disturbances than our CH change map. Our approach classifies disturbance types based on structural changes and may therefore not fully align with TMF labels, particularly for shifting cultivation and disturbances occurring within the last 3–5 years of the time series. Limited historical depth can make it difficult to distinguish permanent from non-permanent disturbances, while TMF relies on the duration and recurrence of spectral change sequences. These methodological differences may lead to reclassification between degradation and deforestation.

- (1) Other forests: pixels identified as undisturbed forests in the TMF dataset were classified as “other forests” in our map if $|\Delta\text{CH}| \leq 5\text{ m}^{87}$, representing 30.1% of all change pixels. TMF-undisturbed pixels with large ΔCH values in our maps were reclassified into other disturbance types using the criteria below.
- (2) Deforestation and degradation ($\Delta\text{CH} < 0$): although deforestation implies the removal of forest canopy, it is difficult to observe CH values close to 0 m using satellite data at 10–30 m resolution due to overestimation of short vegetation and mixed pixels. Following definitions used in ALS-based canopy gap studies⁸⁷, we defined deforestation as pixels with $\Delta\text{CH} \leq -5\text{ m}$ and a final CH below 10 m in 2022, while remaining loss pixels were classified as degraded forests. Although these thresholds were initially informed from other tropical regions, our analysis combining TMF classifications and CH change shows that the separation between degradation and deforestation is more clear using these thresholds (Supplementary Fig. 44). Our ΔCH threshold is consistent with previous studies showing that severe canopy loss is associated with mean height reductions of 5 m or more^{88,89}. This CH-based definition does not fully overlap with TMF classifications. TMF deforestation represents persistent forest-cover disruption detected from long-term Landsat observations (>900 days)⁸, which serves as a proxy for deforestation processes, whereas our CH-based framework emphasizes the structural change. Consequently, some TMF-deforestation pixels retained relatively high post-disturbance CH or experienced rapid recovery, making them structurally more consistent with partial canopy disturbance than complete canopy removal in our framework. These pixels were therefore classified as degraded forests in the CH-based analysis (Supplementary Table 16).
- (3) Regrowth and degradation ($\Delta\text{CH} > 0$): to classify CH gains, we used the TMF dataset as an auxiliary reference. TMF labels pixels as regrowth, degraded, or “uncertain” (12.7%), the latter representing pixels classified as undisturbed or outside the TMF disturbance categories. For these uncertain pixels, we trained an XGBoost⁹⁰ classifier using TMF-labeled degraded and regrowth pixels as training samples. The input features included CH values from 2019 to 2023, $\Delta\text{CH}_{2023-2019}$, $\Delta\text{CH}_{2023-2022}$, $\Delta\text{CH}_{2022-2019}$, and $\Delta\text{CC}_{2022-2019}$. The model was then used to assign uncertain pixels to either degraded or regrowth classes. Because the model is trained on TMF-derived labels, it does not provide an independent classification but is used to assign TMF “uncertain” pixels to regrowth or degradation categories based on canopy height features. This step extends the TMF disturbance classification to pixels lacking a definitive label. The model shows good agreement with TMF-defined classes (overall accuracy = 0.87), reflecting consistency with the TMF labeling scheme rather than independent classification

accuracy. Class-specific F1-scores are 0.86 for regrowth and 0.88 for degradation, and are used to characterize classification uncertainty in subsequent analyses.

Characterization of disturbance patterns

To characterize disturbance patterns, we identified contiguous clusters of disturbed pixels using an 8-connected component labeling algorithm applied to CH change maps. Annual CH maps were first generated at 10 m resolution and subsequently aggregated to 30 m by averaging, from which AGC maps were derived. To ensure spatial consistency with AGC estimates, patch delineation was primarily based on CH change maps derived from annual 30 m CH data. Disturbed pixels were defined as valid CH changes following the multi-step filtering procedure described above. Each connected cluster was labeled as a patch, and patch size was calculated based on the number of connected pixels (0.09 ha per pixel at 30 m resolution). To assess sensitivity to spatial resolution, we compared this approach with patch delineation based on native 10 m resolution CH change maps (Supplementary Fig. 23). In addition, we evaluated an alternative approach in which 10 m CH change maps were first aggregated to 30 m prior to patch identification. This approach produced CH change distributions consistent with those from our primary 30 m-based method, but missed some small disturbance patches that are not represented in the 30 m AGC change maps. In contrast, using native 10 m CH change maps results in a substantially larger number of small disturbance patches due to increased sensitivity to fine-scale variability, with the number of small patches differing by orders of magnitude compared to the 30 m-based analysis. Finally, we quantified both patch counts and their contributions to total AGC change across different bins of CH loss and gain, as well as across disturbance types defined above. Uncertainty associated with disturbance classification was explicitly propagated into the AGC change estimates for each class.

To explore potential drivers of disturbance patterns, we assessed the distance from patch pixels to the nearest mapped road. Road mapping (Supplementary Fig. 33) was derived from 5-m Planet imagery⁷⁹, and road fraction was calculated as the ratio of road pixels to total pixels within 30-m grids. Because optical imagery may miss small logging trails or canopy-covered roads, this dataset primarily captures visible roads and should be interpreted as a proxy for accessibility rather than a complete representation of all forest access routes. We note that our map of roads based on 5 m Planet data is the best available to date for the whole region, and it is consistent across all the tropics.

To quantify how patch size influences subsequent AGC change following past disturbances, we collocated disturbance information from the TMF dataset with AGC change observed during our study period (2019–2022), and jointly evaluated AGC change as a function of patch size and disturbance age, enabling comparisons of patch-size effects under comparable recovery stages. Because biomass recovery depends both on disturbance size and time since disturbance, the TMF disturbance year was used to evaluate disturbance age when interpreting these relationships. Our results focus on disturbances occurring during the 20 years preceding the observation period (2000–2019), as reliable Landsat-based disturbance monitoring in Central Africa generally begins around 2000⁸. Disturbances prior to this period may still influence current biomass dynamics, but cannot be consistently detected using available satellite records. For completeness, results including the full TMF disturbance record (1990–2022) are provided in Supplementary Fig. 45. We conducted an additional sensitivity analysis excluding pixels classified as afforestation in the TMF Transition Map (v2023), which captures the sequential dynamics of forest change from the beginning of the monitoring period through 2023. The resulting AGC change estimates are presented in Supplementary Fig. 46 and show highly consistent patterns, indicating that afforestation has a minimal impact on our results.

Uncertainty in AGC change estimates

Uncertainty in AGC change was quantified by explicitly accounting for three sources: (1) biomass uncertainty arising from allometric modeling and measurement errors (σ_{bio}); (2) classification uncertainty associated with disturbance attribution and detection accuracy (σ_{bio}); and (3) uncertainty related to the choice of a CH change processing scheme (σ_{scheme}), including trend detection, Sentinel-1 filtering, and canopy cover filtering. Independent validation using stratified sampling further quantified the accuracy of CH change detection across different patch sizes. However, this source of uncertainty was not treated as a separate component because it had already been incorporated into the classification uncertainty framework. We quantified σ_{bio} , σ_{bio} , and σ_{scheme} separately using dedicated simulation and error propagation approaches, and combined these components under the assumption of independence to obtain a tractable estimate of total uncertainty. Full methodological details of uncertainty formulation, parameterization, and propagation are provided in Supplementary Note 10 and Supplementary Fig. 35. The resulting total relative uncertainties are 23.2%, 16.3%, and 14.7% for net AGC change, gross AGC loss, and AGC gain in Central African forests, respectively (Supplementary Table 6).

AGC change in protected and concession areas

To evaluate the effectiveness of conservation and land-use policies in Central Africa, we quantified total AGC change (carbon budget) and AGC density change within protected areas and forest concessions. Protected area boundaries were obtained from the World Database on Protected Areas (WDPA)⁹¹, and forest concession boundaries were sourced from Global Forest Watch (<https://data.globalforestwatch.org/>). For the analysis, we only considered officially designated protected areas and allocated forest concessions. We examined whether significant differences exist in AGC density and its change across protected, concession, and other land types. Since these areas were established in different years, we also analyzed AGC change as a function of time since designation (Supplementary Fig. 38). Additionally, we compared AGC changes across different types of protected areas, such as National Parks, Biosphere reserve, Ramsar site, and Wildlife reserve.

Comparisons of AGC budget with inventories and bookkeeping models, country reports

In this section, we estimated forest biomass carbon budgets in Gabon, Equatorial Guinea, Cameroon, Congo, and DRC by combining AGC in dense and non-dense forests with BGC derived from country-level BGB/AGB ratios⁵⁴ (Supplementary Note 12). Country-level carbon budgets were compared to national inventory reports harmonized by refs. 19,20, the average of three bookkeeping models used in the global carbon budget of the year 2022 (GCB2022)¹⁸, and additionally to DGVMs from TRENDY V8, V11⁹² of GCB2022¹⁸, and FAOSTAT^{20,56}. These datasets provide annual net carbon change data for 2019–2021. Bookkeeping models BLUE⁹³, OSCAR⁹⁴, and Houghton and Nassikas⁹⁵ are driven by expanding areas of agricultural land from FAOSTAT downscaled into annual maps by the LUH2 model⁹⁶ for BLUE and OSCAR, and by reconstructed forest and agricultural areas at the national scale for Houghton and Nassikas and OSCAR. We used the average of the simulations with both forcings from OSCAR. The bookkeeping models report carbon gains from afforestation, post-harvest regrowth, and shifting cultivation regrowth, and carbon losses from all land use transitions (dominated by deforestation), harvest removals, and shifting cultivation clearings. Harvest and shifting cultivation activities are not spatially explicit. National inventory data are from the harmonized database of Grassi et al. corrected¹⁹ to account for differences in the definition of managed land and for clerical errors, and uses additional REDD+ submissions and nationally determined contributions in addition to the original UNFCCC national reports^{19,20}.

The FAOSTAT emissions database estimates forest-sector carbon changes separately for ‘forest remaining forest’ and ‘forest converted to other land uses’. It combines activity data from national FRA reports (and FAO-analyzed geospatial datasets) with IPCC 2006 emission factors, resorting to country-specific factors where available.

Data availability

The tropical moist forests (TMF) data used in this study are available at <https://forobs.jrc.ec.europa.eu/TMF>. The tree cover loss data from Global Forest Change (GFC) are available at <https://glad.earthengine.app/view/global-forest-change>. The RADD Forest Disturbance Alert data are available at <https://gee-community-catalog.org/projects/radd/>. Forest concession boundaries are available from Global Forest Watch (<https://data.globalforestwatch.org/>). Sentinel-1 SAR, Sentinel-2 optical imagery, and GEDI canopy cover and canopy height data used in this study are available through the Google Earth Engine platform. PlanetScope images are available via Planet Labs at <https://www.planet.com/products/> upon acquiring a license agreement. The canopy height and biomass change maps generated in this study, together with the original data underlying the main figures, are publicly available in Code Ocean (<https://doi.org/10.24433/CO.8030647.v1>)⁹⁷. Additional data supporting the findings of this study are provided in the Supplementary Information.

Code availability

The code used to reproduce the main figures in the manuscript is publicly available in Code Ocean (<https://doi.org/10.24433/CO.8030647.v1>)⁹⁷.

References

1. Saatchi, S. S. et al. Benchmark map of forest carbon stocks in tropical regions across three continents. *Proc. Natl. Acad. Sci. USA* **108**, 9899–9904 (2011).
2. Pan, Y. et al. The enduring world forest carbon sink. *Nature* **631**, 563–569 (2024).
3. Baccini, A. et al. Tropical forests are a net carbon source based on aboveground measurements of gain and loss. *Science* **358**, 230–234 (2017).
4. Lewis, S. L. et al. Increasing carbon storage in intact African tropical forests. *Nature* **457**, 1003–1006 (2009).
5. Hubau, W. et al. Asynchronous carbon sink saturation in African and Amazonian tropical forests. *Nature* **579**, 80–87 <https://doi.org/10.1038/s41586-020-2035-0> (2020).
6. Rodríguez-Veiga, P. et al. Loss of tropical moist broadleaf forest has turned Africa's forests from a carbon sink into a source. *Sci. Rep.* **15**, 41744 (2025).
7. Sagang, L. B. et al. Managed rainforests support higher carbon density and sequestration in the Congo Basin. *Nat. Commun.* <https://doi.org/10.1038/s41467-026-72399-4> (2026).
8. Vancutsem, C. et al. Long-term (1990–2019) monitoring of forest cover changes in the humid tropics. *Sci. Adv.* **7**, eabe1603 (2021).
9. Zhuravleva, I. et al. Satellite-based primary forest degradation assessment in the Democratic Republic of the Congo, 2000–2010. *Environ. Res. Lett.* **8**, 024034 (2013).
10. Bourgoin, C. et al. Human degradation of tropical moist forests is greater than previously estimated. *Nature* **631**, 570–576 <https://doi.org/10.1038/s41586-024-07629-0> (2024).
11. Butsic, V., Baumann, M., Shortland, A., Walker, S. & Kuemmerle, T. Conservation and conflict in the Democratic Republic of Congo: the impacts of warfare, mining, and protected areas on deforestation. *Biol. Conserv.* **191**, 266–273 <https://doi.org/10.1016/j.biocon.2015.06.037> (2015).
12. Poulsen, J. R. et al. Old growth Afrotropical forests critical for maintaining forest carbon. *Glob. Ecol. Biogeogr.* **29**, 1785–1798 (2020).

13. Sims, M. J. et al. Global drivers of forest loss at 1 km resolution. *Environ. Res. Lett.* (2024).
14. Shapiro, A. et al. Small scale agriculture continues to drive deforestation and degradation in fragmented forests in the Congo Basin (2015–2020). *Land Use Policy* **134**, 106922 <https://doi.org/10.1016/j.landusepol.2023.106922> (2023).
15. Masolele, R. N. et al. Mapping the diversity of land uses following deforestation across Africa. *Sci. Rep.* **14**, 1681 <https://doi.org/10.1038/s41598-024-52138-9> (2024).
16. Mitchard, E. T. A. The tropical forest carbon cycle and climate change. *Nature* **559**, 527–534 <https://doi.org/10.1038/s41586-018-0300-2> (2018).
17. White, L. J. et al. Congo Basin rainforest—invest US \$150 million in science. *Nature* **598**, 411–414 (2021).
18. Friedlingstein, P. et al. Global carbon budget 2022. *Earth Syst. Sci. Data* **14**, 4811–4900 (2022).
19. Grassi, G. et al. Harmonising the land-use flux estimates of global models and national inventories for 2000–2020. *Earth Syst. Sci. Data* **15**, 1093–1114 (2023).
20. Obermeier, W. A. et al. Country-level estimates of gross and net carbon fluxes from land use, land-use change and forestry. *Earth Syst. Sci. Data* **16**, 605–645 (2024).
21. Ciais, P. et al. Definitions and methods to estimate regional land carbon fluxes for the second phase of the REgional Carbon Cycle Assessment and Processes Project (RECCAP-2). *Geosci. Model Dev. Discuss.* **2020**, 1–46 (2020).
22. Ernst, Y. et al. The African regional greenhouse gases budget (2010–2019). *Glob. Biogeochem. Cycles* **38**, e2023GB008016 (2024).
23. Harris, N. L. et al. Global maps of twenty-first century forest carbon fluxes. *Nat. Clim. Change* **11**, 234–240 (2021).
24. Gibbs, D. A. et al. Revised and updated geospatial monitoring of 21st century forest carbon fluxes. *Earth Syst. Sci. Data* **17**, 1217–1243 (2025).
25. Heinrich, V. H. et al. The carbon sink of secondary and degraded humid tropical forests. *Nature* **615**, 436–442 (2023).
26. Hansen, M. C. et al. High-resolution global maps of 21st-century forest cover change. *Science* **342**, 850–853 (2013).
27. Reiche, J. et al. Forest disturbance alerts for the Congo Basin using Sentinel-1. *Environ. Res. Lett.* **16**, 024005 (2021).
28. Bossy, T. et al. State of the art and for remote sensing monitoring of carbon dynamics in African tropical forests. *Front. Remote Sens.* **6**, 1532280 (2025).
29. Wan, L. et al. Satellite-based mapping of annual canopy height and aboveground biomass in African dense forests. *Front. Remote Sens.* **6**, 1724950 (2025).
30. Brandt, M. et al. High-resolution sensors and deep learning models for tree resource monitoring. *Nat. Rev. Electr. Eng.* **2**, 13–26 (2025).
31. Arévalo, P., Baccini, A., Woodcock, C. E., Olofsson, P. & Walker, W. S. Continuous mapping of aboveground biomass using Landsat time series. *Remote Sens. Environ.* **288**, 113483 (2023).
32. Xu, L. et al. Changes in global terrestrial live biomass over the 21st century. *Sci. Adv.* **7**, eabe9829 <https://doi.org/10.1126/sciadv.abe9829> (2021).
33. Yang, H. et al. Global increase in biomass carbon stock dominated by growth of northern young forests over past decade. *Nat. Geosci.* **16**, 886–892 <https://doi.org/10.1038/s41561-023-01274-4> (2023).
34. Espírito-Santo, F. D. B. et al. Size and frequency of natural forest disturbances and the Amazon forest carbon balance. *Nat. Commun.* **5**, 3434 <https://doi.org/10.1038/ncomms4434> (2014).
35. Ryan, C. M. et al. Quantifying small-scale deforestation and forest degradation in African woodlands using radar imagery. *Glob. Change Biol.* **18**, 243–257 (2012).
36. Kalamandeen, M. et al. Pervasive rise of small-scale deforestation in Amazonia. *Sci. Rep.* **8**, 1600 <https://doi.org/10.1038/s41598-018-19358-2> (2018).
37. Dupuis, C., Fayolle, A., Bastin, J.-F., Latte, N. & Lejeune, P. Monitoring selective logging intensities in central Africa with sentinel-1: a canopy disturbance experiment. *Remote Sens. Environ.* **298**, 113828 (2023).
38. Welsink, A.-J. et al. Monitoring fine-scale natural and logging-related tropical forest degradation using Sentinel-1. *Remote Sens. Environ.* **328**, 114878 (2025).
39. Holcomb, A., Burns, P., Keshav, S. & Coomes, D. A. Repeat GEDI footprints measure the effects of tropical forest disturbances. *Remote Sens. Environ.* **308**, 114174 <https://doi.org/10.1016/j.rse.2024.114174> (2024).
40. Mugabowindekwe, M. et al. Nation-wide mapping of tree-level aboveground carbon stocks in Rwanda. *Nat. Clim. Change* **13**, 91–97 (2023).
41. Kleinschroth, F., Laporte, N., Laurance, W. F., Goetz, S. J. & Ghazoul, J. Road expansion and persistence in forests of the Congo Basin. *Nat. Sustain.* **2**, 628–634 (2019).
42. Duncanson, L. et al. Aboveground biomass density models for NASA's Global Ecosystem Dynamics Investigation (GEDI) lidar mission. *Remote Sens. Environ.* **270**, 112845 <https://doi.org/10.1016/j.rse.2021.112845> (2022).
43. Dubayah, R. et al. The Global Ecosystem Dynamics Investigation: high-resolution laser ranging of the Earth's forests and topography. *Sci. Remote Sens.* **1**, 100002 <https://doi.org/10.1016/j.srs.2020.100002> (2020).
44. Jucker, T. et al. Tallo: a global tree allometry and crown architecture database. *Glob. Change Biol.* **28**, 5254–5268 (2022).
45. Fayad, I. et al. Hy-TeC: a hybrid vision transformer model for high-resolution and large-scale mapping of canopy height. *Remote Sens. Environ.* **302**, 113945 (2024).
46. Olofsson, P. et al. Good practices for estimating area and assessing accuracy of land change. *Remote Sens. Environ.* **148**, 42–57 (2014).
47. Dupuis, C. et al. Scaling up the assessment of logging's impact on forest structure in Central Africa using field and UAV data. *Environ. Res. Lett.* **20**, 014018 (2024).
48. Doyle, E. et al. Evaluating GEDI for quantifying forest structure across a gradient of degradation in Amazonian rainforests. *Environ. Res. Lett.* **20** <https://doi.org/10.1088/1748-9326/adc752> (2025).
49. Dalagnol, R. et al. Mapping tropical forest degradation with deep learning and Planet NICFI data. *Remote Sens. Environ.* **298**, 113798 <https://doi.org/10.1016/j.rse.2023.113798> (2023).
50. Slagter, B. et al. Monitoring direct drivers of small-scale tropical forest disturbance in near real-time with Sentinel-1 and-2 data. *Remote Sens. Environ.* **295**, 113655 (2023).
51. Senf, C. & Seidl, R. Mapping the forest disturbance regimes of Europe. *Nat. Sustain.* **4**, 63–70 (2021).
52. McNicol, I. M. et al. Protected areas reduce deforestation and degradation and enhance woody growth across African woodlands. *Commun. Earth Environ.* **4**, 392 <https://doi.org/10.1038/s43247-023-01053-4> (2023).
53. Watson, J. E., Dudley, N., Segan, D. B. & Hockings, M. The performance and potential of protected areas. *Nature* **515**, 67–73 (2014).
54. Spawn, S. A., Sullivan, C. C., Lark, T. J. & Gibbs, H. K. Harmonized global maps of above and belowground biomass carbon density in the year 2010. *Sci. Data* **7**, 112 (2020).
55. Friedlingstein, P. et al. Global carbon budget 2021. *Earth Syst. Sci. Data* **14**, 1917–2005 (2022).
56. Tubiello, F. N. et al. Carbon emissions and removals from forests: new estimates, 1990–2020. *Earth Syst. Sci. Data* **13**, 1681–1691 (2021).
57. FAO. *Global Forest Resources Assessment 2020: Main Report* (FAO, 2020).

58. Eggleston, H., Buendia, L., Miwa, K., Ngara, T. & Tanabe, K. 2006 IPCC guidelines for national greenhouse gas inventories. (2006).
59. Requena Suarez, D. et al. Estimating aboveground net biomass change for tropical and subtropical forests: refinement of IPCC default rates using forest plot data. *Glob. Change Biol.* **25**, 3609–3624 (2019).
60. Zhao, Z. et al. Central African biomass carbon losses and gains during 2010–2019. *One Earth* **7**, 506–519 (2024).
61. Csillik, O. et al. A large net carbon loss attributed to anthropogenic and natural disturbances in the Amazon Arc of Deforestation. *Proc. Natl. Acad. Sci. USA* **121**, e2310157121 <https://doi.org/10.1073/pnas.2310157121> (2024).
62. Cook-Patton, S. C. et al. Mapping carbon accumulation potential from global natural forest regrowth. *Nature* **585**, 545–550 (2020).
63. Richter, J. et al. *Spatial Database of Planted Trees (SDPT Version 2.1)* (World Resources Institute, 2024).
64. Csillik, O. et al. A large net carbon loss attributed to anthropogenic and natural disturbances in the Amazon Arc of Deforestation. *Proc. Natl. Acad. Sci. USA* **121**, e2310157121 (2024).
65. Ross, C. W. et al. Woody-biomass projections and drivers of change in sub-Saharan Africa. *Nat. Clim. Change* **11**, 449–455 (2021).
66. Liu, M., Trugman, A. T., Peñuelas, J. & Anderegg, W. R. Climate-driven disturbances amplify forest drought sensitivity. *Nat. Clim. Change* **14**, 746–752 (2024).
67. Fayad, I. et al. DUNIA: Pixel-sized embeddings via cross-modal alignment for Earth observation applications. *arXiv* <https://doi.org/10.48550/arXiv.2502.17066> (2025).
68. Dubayah, R. et al. GEDI L2A elevation and height metrics data global footprint level V002. *NASA EOSDIS Land Processes DAAC* (2020).
69. Small, D. Flattening gamma: radiometric terrain correction for SAR imagery. *IEEE Trans. Geosci. Remote Sens.* **49**, 3081–3093 (2011).
70. Lang, N., Jetz, W., Schindler, K. & Wegner, J. D. A high-resolution canopy height model of the Earth. *Nat. Ecol. Evol.* **7**, 1778–1789 (2023).
71. Fischer, F. J. et al. A global map of wood density. *bioRxiv* <https://doi.org/10.1101/2025.08.25.671920> (2025).
72. Fischer, F. J. et al. Beyond species means-the intraspecific contribution to global wood density variation. *bioRxiv* <https://doi.org/10.1101/2025.08.25.671896> (2025).
73. Martin, A. R., Doraisami, M. & Thomas, S. C. Global patterns in wood carbon concentration across the world's trees and forests. *Nat. Geosci.* **11**, 915–920 (2018).
74. Cuni-Sanchez, A. et al. High aboveground carbon stock of African tropical montane forests. *Nature* **596**, 536–542 (2021).
75. Potapov, P. et al. The global 2000–2020 land cover and land use change dataset derived from the Landsat archive: first results. *Front. Remote Sens.* **3**, 856903 (2022).
76. de Conto, T., Armston, J. & Dubayah, R. Characterizing the structural complexity of the Earth's forests with spaceborne lidar. *Nat. Commun.* **15**, 8116 (2024).
77. Burns, P., Hakkenberg, C. R. & Goetz, S. J. Multi-resolution gridded maps of vegetation structure from GEDI. *Sci. Data* **11**, 881 (2024).
78. Tang, H. et al. Evaluating and mitigating the impact of systematic geolocation error on canopy height measurement performance of GEDI. *Remote Sens. Environ.* **291**, 113571 (2023).
79. L. Shidong, et al. Road-induced fragmentation endangers half of the global tropical tree cover. In preparation (2025).
80. Zscheischler, J. et al. Extreme events in gross primary production: a characterization across continents. *Biogeosciences* **11**, 2909–2924 (2014).
81. Grantham, H. S. et al. Anthropogenic modification of forests means only 40% of remaining forests have high ecosystem integrity. *Nat. Commun.* **11**, 5978. <https://doi.org/10.1038/s41467-020-19493-3> (2020).
82. Mann, H. B. Nonparametric tests against trend. *Econometrica* **245–259** (1945).
83. Kendall, M. G. Rank correlation methods. (1948).
84. Gilbert, R. O. *Statistical Methods for Environmental Pollution Monitoring* (John Wiley & Sons, 1987).
85. Su, Y. et al. Asymmetric influence of forest cover gain and loss on land surface temperature. *Nat. Clim. Change* **13**, 823–831 (2023).
86. Alkama, R. & Cescatti, A. Biophysical climate impacts of recent changes in global forest cover. *Science* **351**, 600–604 (2016).
87. Jackson, T. D. et al. Tall Bornean forests experience higher canopy disturbance rates than those in the eastern Amazon or Guiana shield. *Glob. Change Biol.* **30**, e17493 (2024).
88. Dubayah, R. O. et al. Estimation of tropical forest height and biomass dynamics using lidar remote sensing at La Selva, Costa Rica. *J. Geophys. Res. Biogeosci.* **115** (2010).
89. Favrichon, S. et al. Monitoring changes of forest height in California. *Front. Remote Sens.* **5**, 1459524 (2025).
90. Chen, T. & Guestrin, C. In *Proc. 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. 785–794.
91. UNEP-WCMC, I. *Protected Planet: The World Database on Protected Areas (WDPA) and World Database on Other Effective Area-based Conservation Measures (WD-OECM)* (UNEP-WCMC and IUCN, 2025).
92. Le Quéré, C. et al. Global carbon budget 2013. *Earth Syst. Sci. Data* **6**, 235–263 <https://doi.org/10.5194/essd-6-235-2014> (2014).
93. Hansis, E., Davis, S. J. & Pongratz, J. Relevance of methodological choices for accounting of land use change carbon fluxes. *Glob. Biogeochem. Cycles* **29**, 1230–1246 (2015).
94. Gasser, T. et al. Historical CO₂ emissions from land use and land cover change and their uncertainty. *Biogeosciences* **17**, 4075–4101 (2020).
95. Houghton, R. A. & Nassikas, A. A. Negative emissions from stopping deforestation and forest degradation, globally. *Glob. Change Biol.* **24**, 350–359 (2018).
96. Hurtt, G. C. et al. Harmonization of global land-use change and management for the period 850–2100 (LUH2) for CMIP6. *Geosci. Model Dev. Discuss.* **2020**, 1–65 (2020).
97. Wan, L., Ciaia, P. & de Truchis, A. Net carbon losses in Central African forests revealed by high-resolution biomass change maps [Source Code]. <https://doi.org/10.24433/CO.8030647.v1> (2026).

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Author contributions

L.W. and P.C. conceived the paper and prepared the initial draft. L.W., P.C., and A.T. developed and validated the data products. M.B., J.C., C.B., J.-F.B., S.L., L.B.S., A.V.L., T.B., and P.P. provided relevant reference datasets for model validation and analysis. L.W., P.C., Y.X., M.B., J.C., C.B., J.-P.W., J.-F.B., W.L., Y.R., S.L., D.P., I.F., and P.P. contributed to the interpretation of the results. All authors contributed to reviewing and editing the manuscript.

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Competing interests

The authors declare no competing interests.

Additional information

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