

Supplementary Information for:

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

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This Supplementary Information includes:

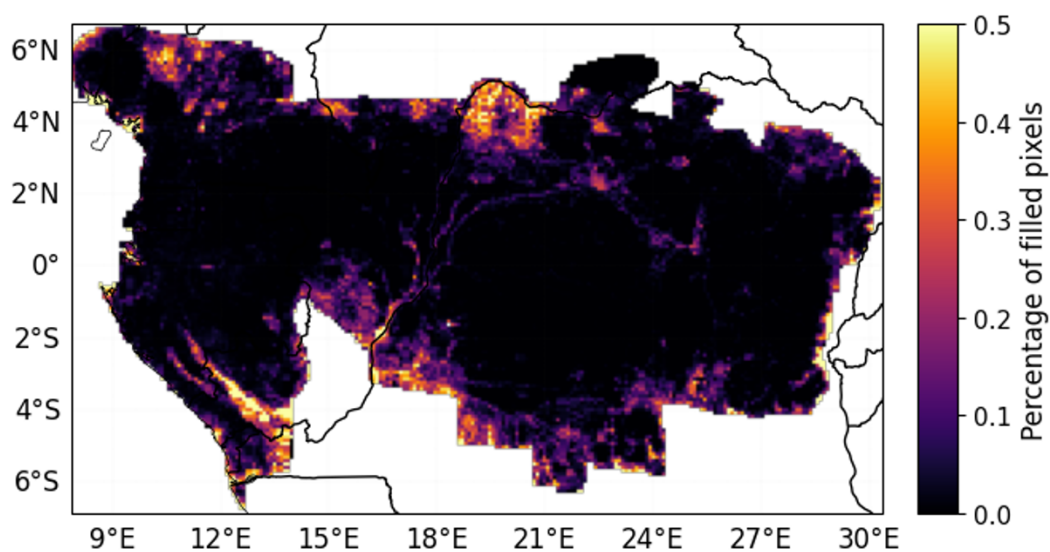
Supplementary Figures 1–46

Supplementary Tables 1–16

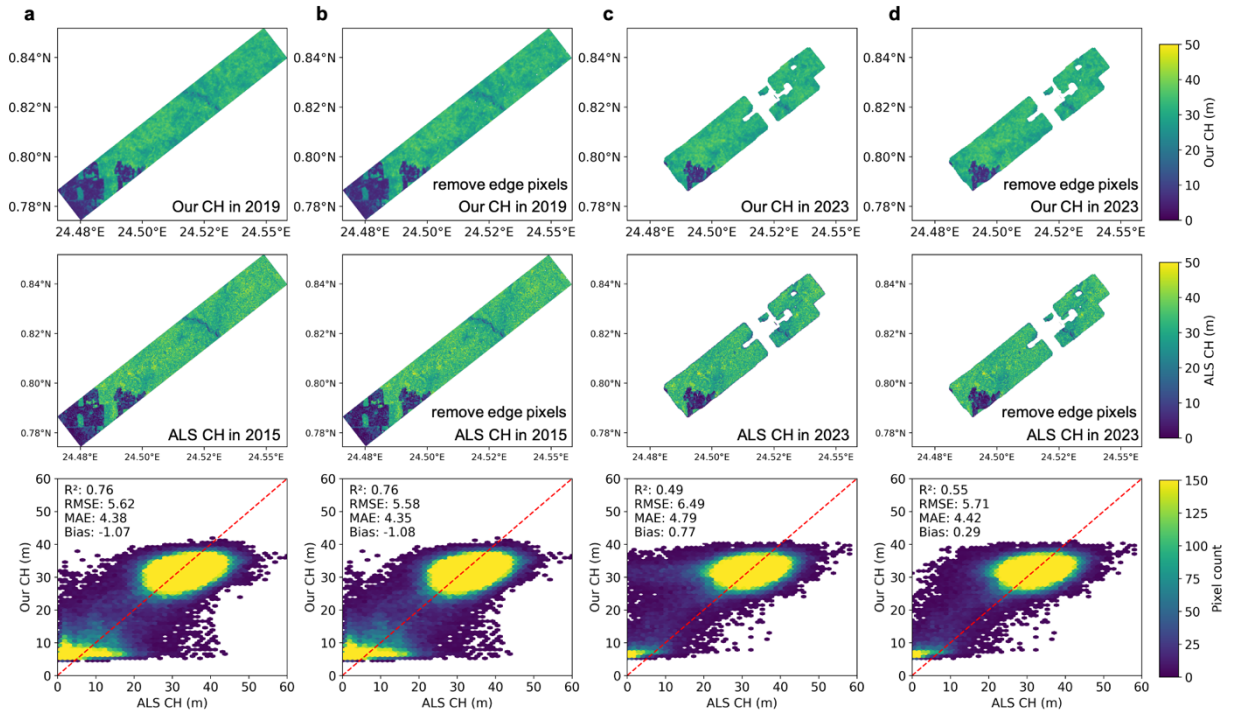
Supplementary Notes 1–13

Supplementary References

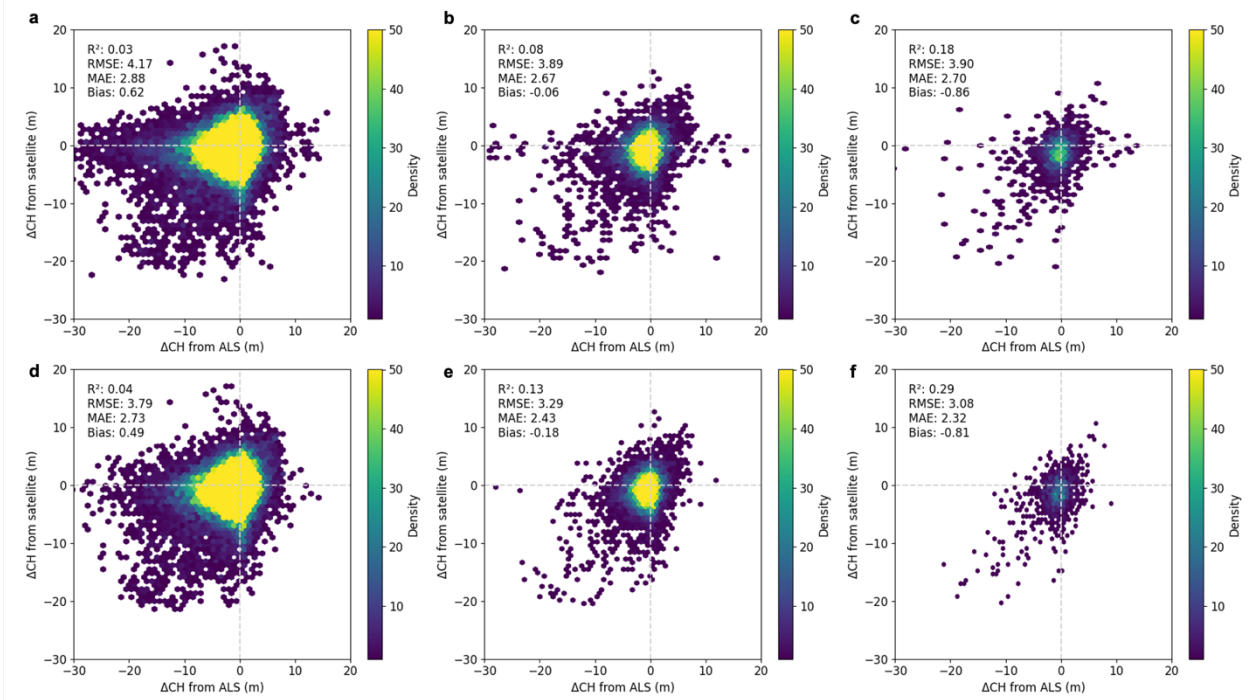
Supplementary Figures



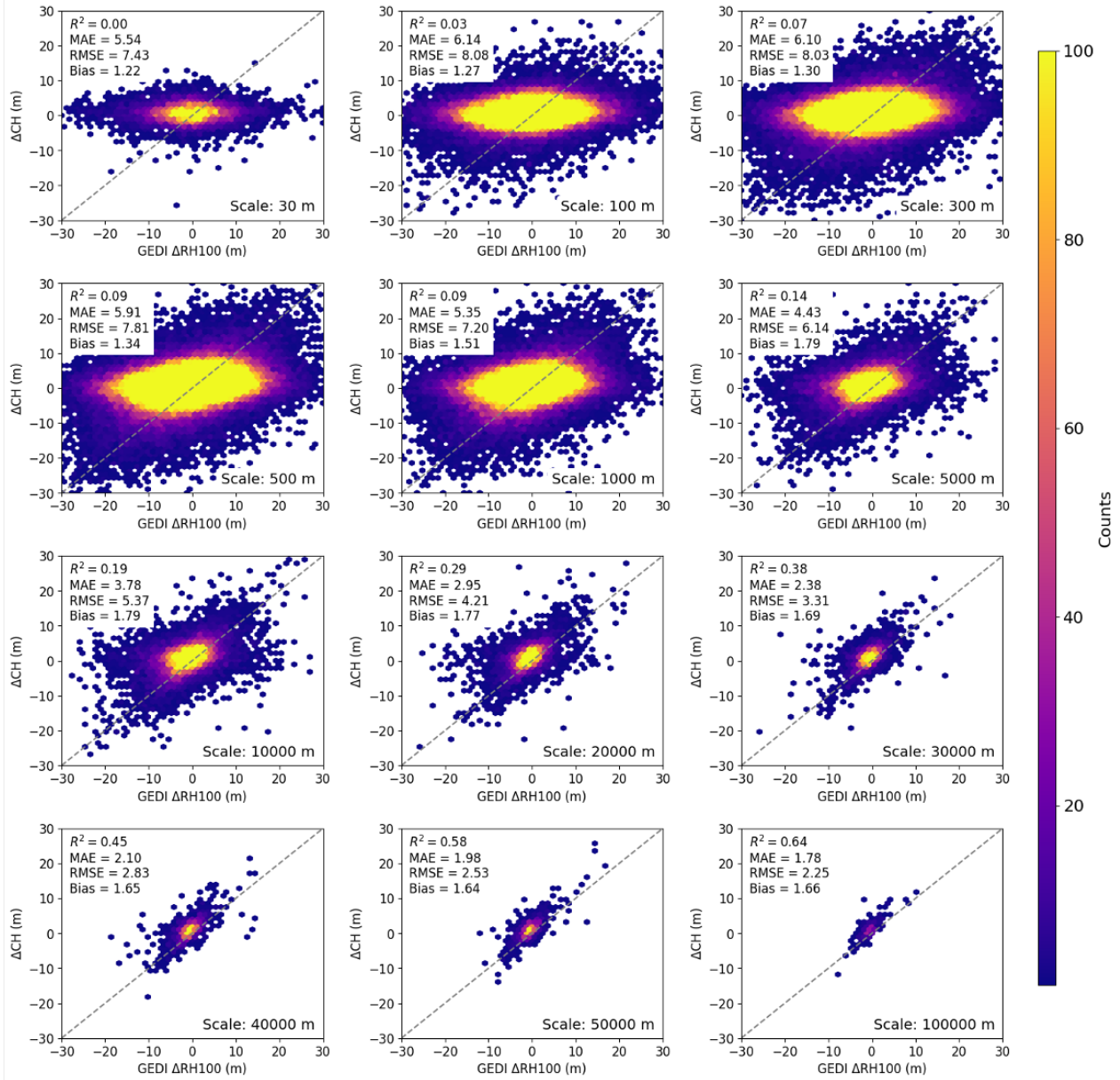
Supplementary Fig. 1: Spatial distribution and proportion of pixels requiring wood density gap filling (10 km resolution). These gap-filled pixels are limited in extent and spatially clustered, occurring primarily in disturbed areas and low-density forest regions, where the original ~1 km wood density (WD) data do not capture valid values. Pixels filled using the nearest available WD value account for only 1.5% of all pixels.



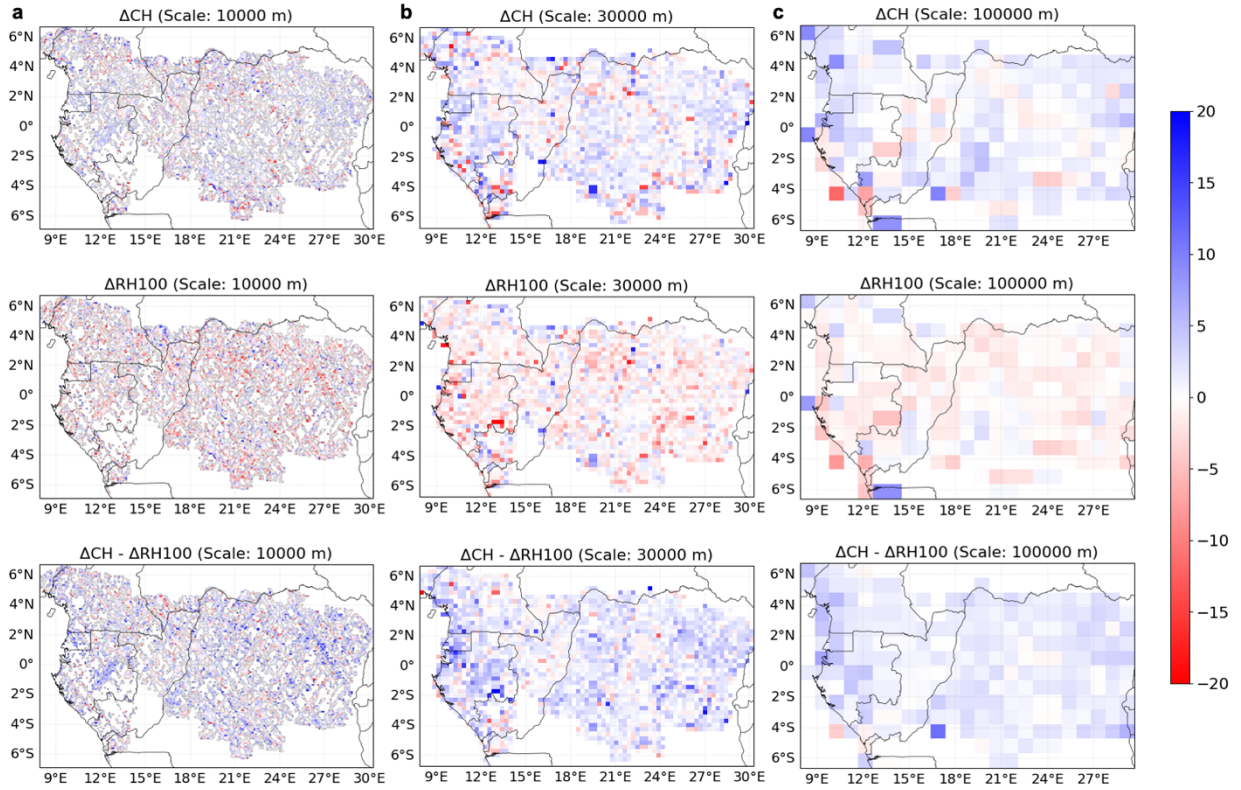
Supplementary Fig. 2: Comparison of canopy height (CH) maps derived from airborne LiDAR (ALS) and satellite (in this study) observations. a, c, The original ALS and satellite-derived CH maps at 10 m resolution. b, d, Processed ALS and satellite-derived CH maps by removing edge pixels at 10 m resolution.



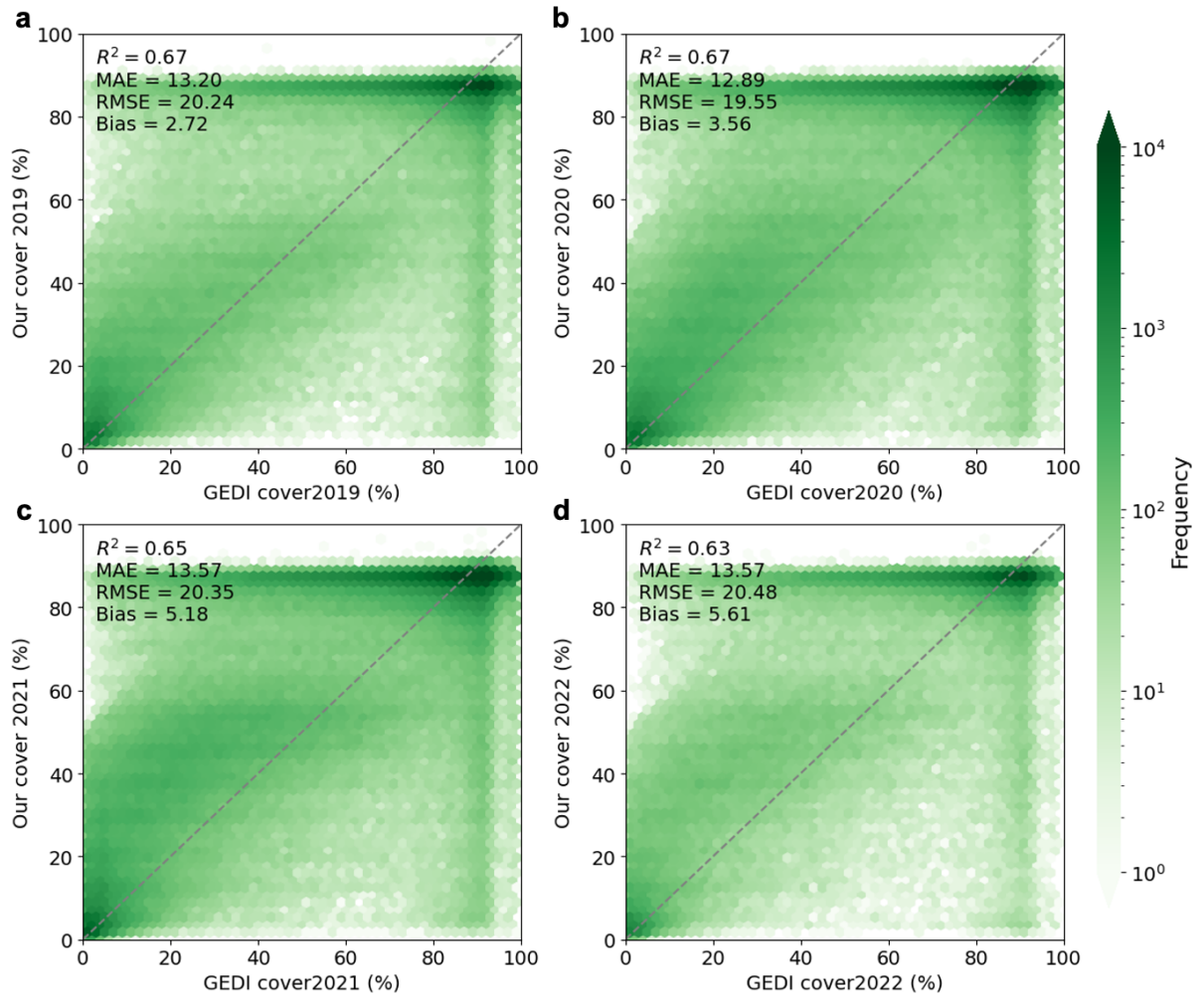
Supplementary Fig. 3: Validation of satellite-derived original canopy height changes using airborne LiDAR data. **a–c**, Comparisons of canopy height change (ΔCH) between satellite and airborne LiDAR (ALS) data at spatial resolutions of 10 m (**a**), 20 m (**b**), and 30 m (**c**), including all pixels. **d–f**, Same comparisons as in **a–c**, but with edge pixels excluded. Note that the satellite-derived canopy height changes (ΔCH) were not processed.



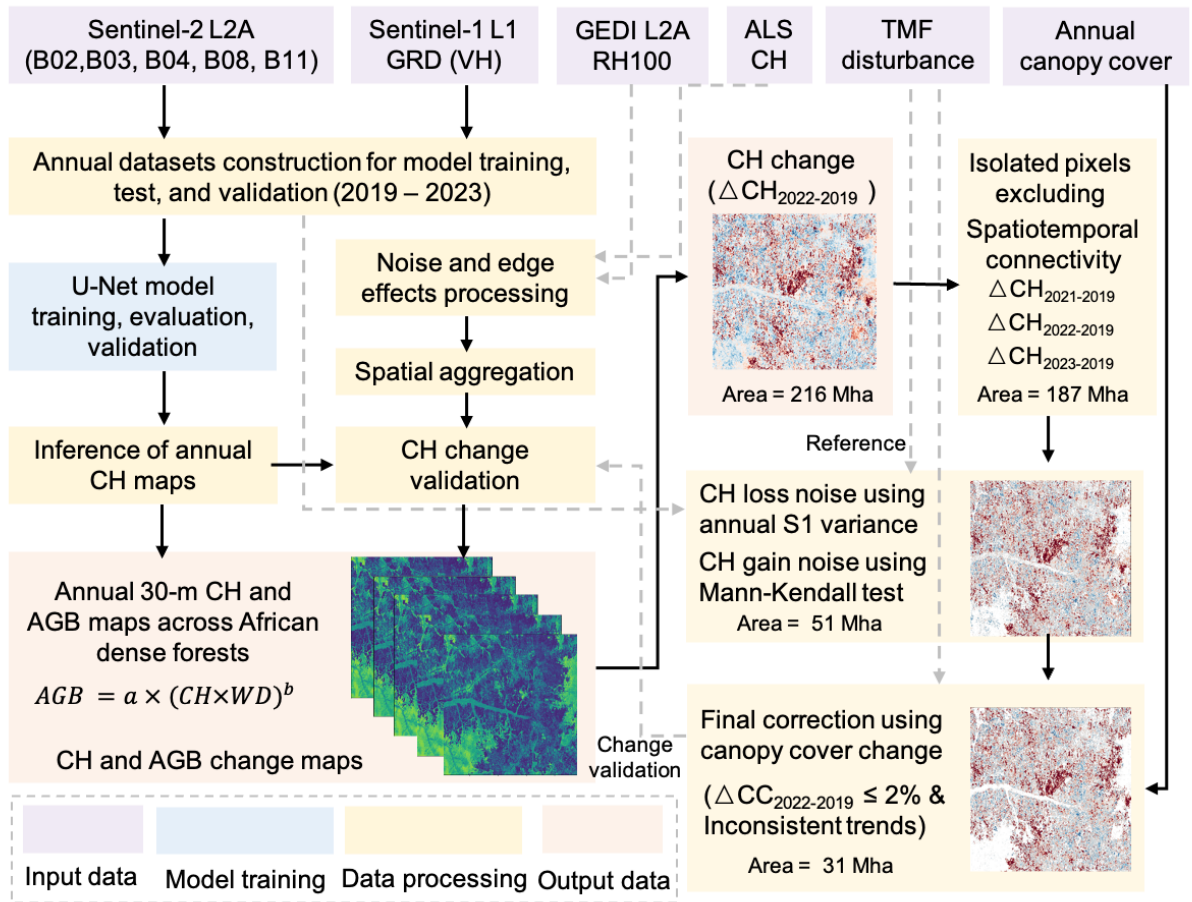
Supplementary Fig. 4: Comparison of satellite-derived original canopy height changes and GEDI RH100 change at different scales. CH change ($\Delta CH_{2022-2019}$) and GEDI RH100 change ($\Delta RH100_{2022-2019}$) were calculated as the difference between the 2022 and 2019 data. We aggregated the 30-m data to coarser resolutions for more robust comparisons. Note that the satellite-derived canopy height changes ($\Delta CH_{2022-2019}$) were not processed.



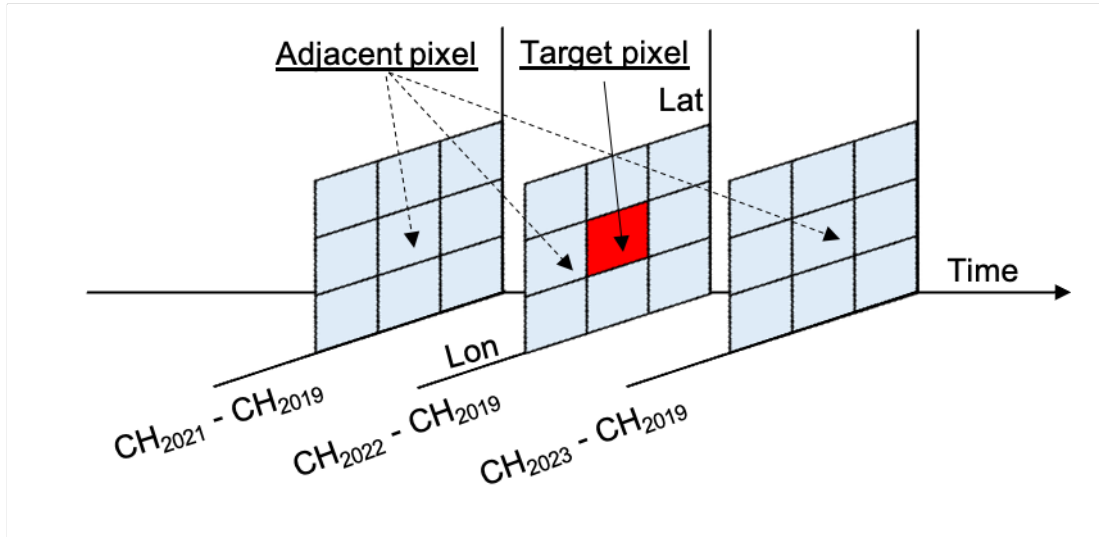
Supplementary Fig. 5: Comparison of satellite-derived original canopy height changes and GEDI RH100 change maps and their difference at three scales. CH change (ΔCH) and GEDI RH100 change (ΔRH100) were calculated as the difference between the 2022 and 2019 data. We aggregated the 30-m data to coarser resolutions (**a**, 10000 m; **b**, 30000 m; **c**, 100000 m) for more robust comparisons. Note that the satellite-derived canopy height changes (ΔCH) were not processed.



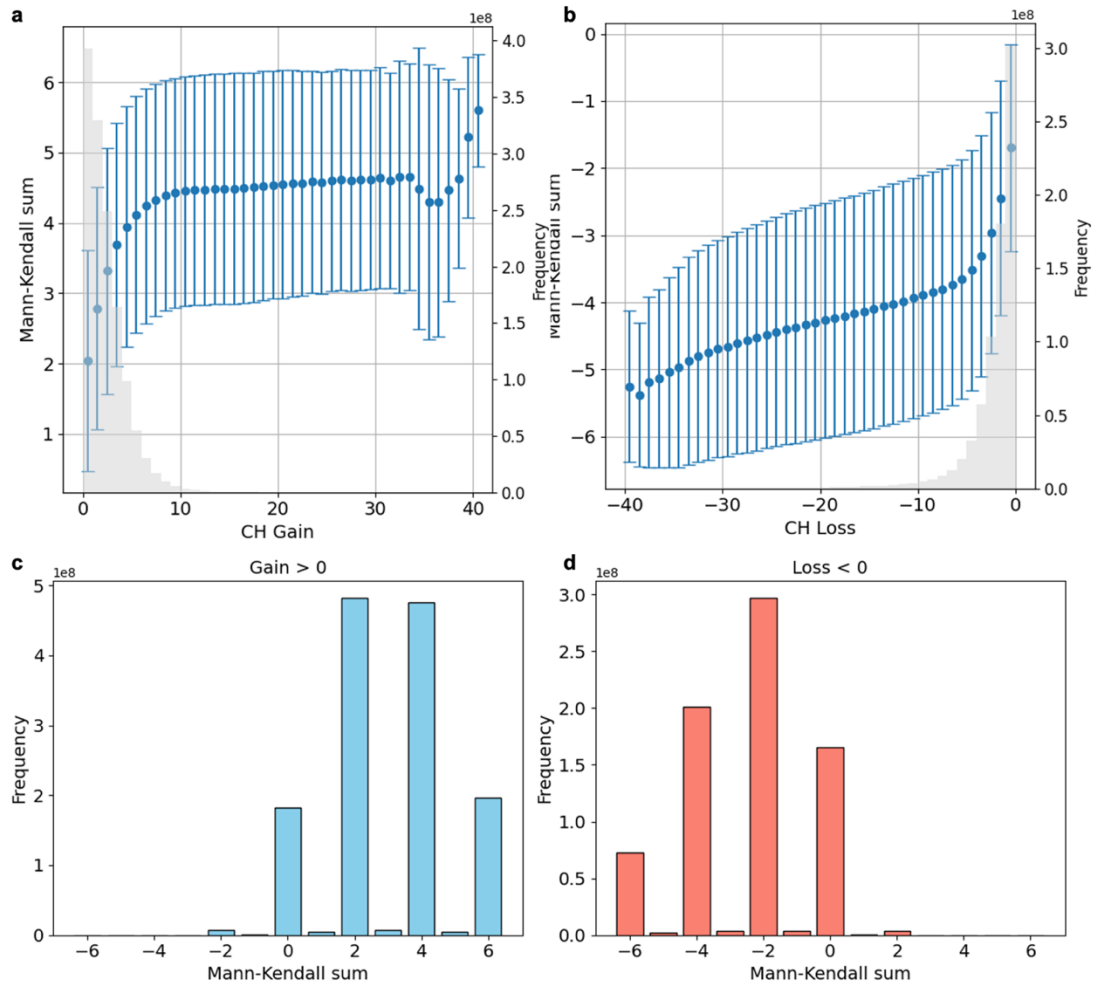
Supplementary Fig. 6: Evaluation of annual canopy cover maps using independent GEDI canopy cover data. **a–d**, All comparisons were conducted from 2019 to 2022. The GEDI cover data is derived from the GEDI Level 2B Canopy Cover and Vertical Profile Metrics product (GEDI02_B).



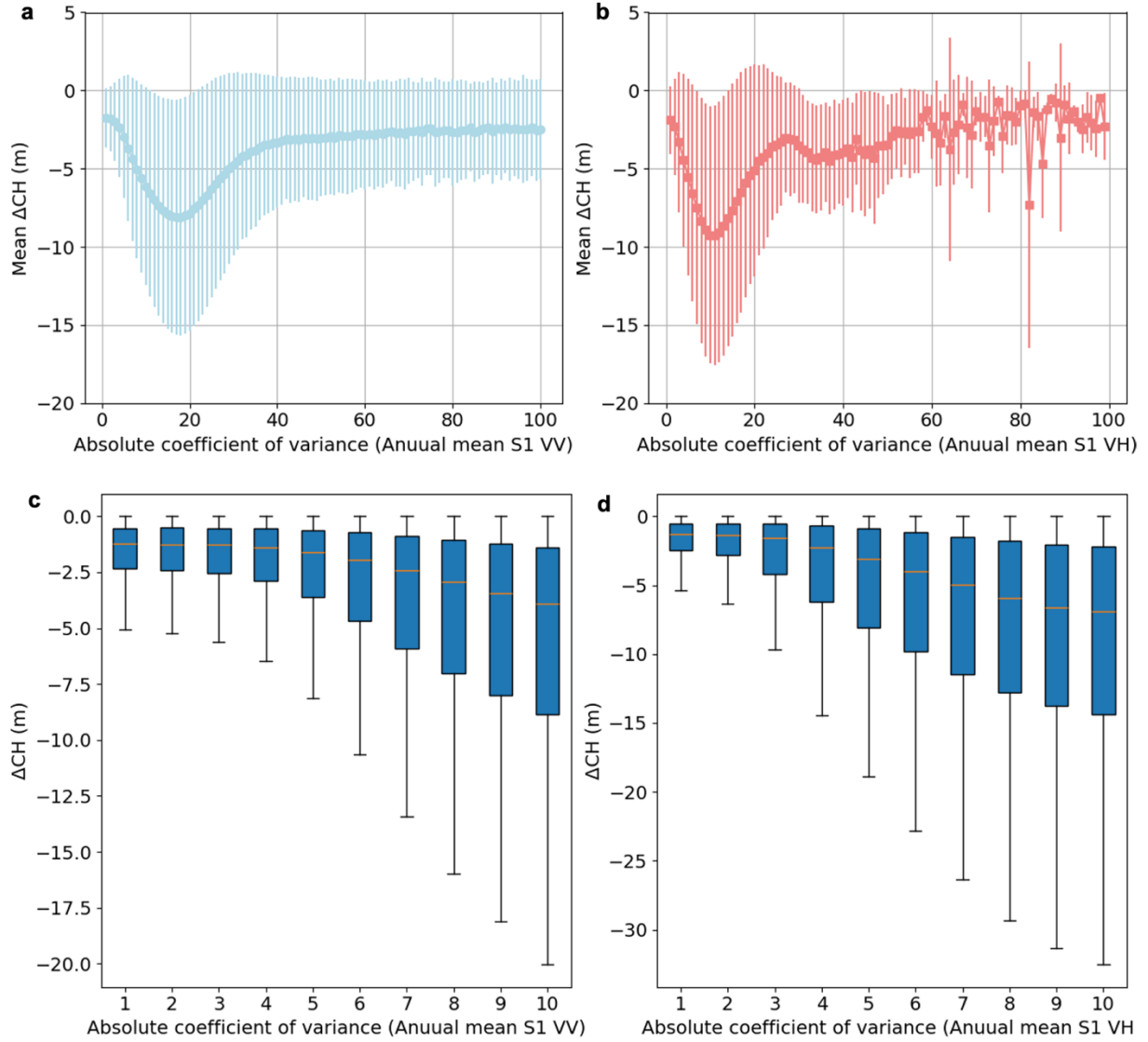
Supplementary Fig. 7: Framework for canopy height and change map processing. The framework includes the following key steps: (1) generation of annual canopy height (CH) and aboveground biomass (AGB) maps; (2) derivation of the initial CH change (ΔCH) map; (3) refinement of CH change by removing isolated pixels, identifying genuine CH gain and loss, and applying corrections based on canopy cover change (ΔCC); (4) comparison and validation of the initial and refined CH change maps; (5) production of the final CH and AGB change maps. The approximate total valid area (Mha) for each of the four CH change processing steps is presented.



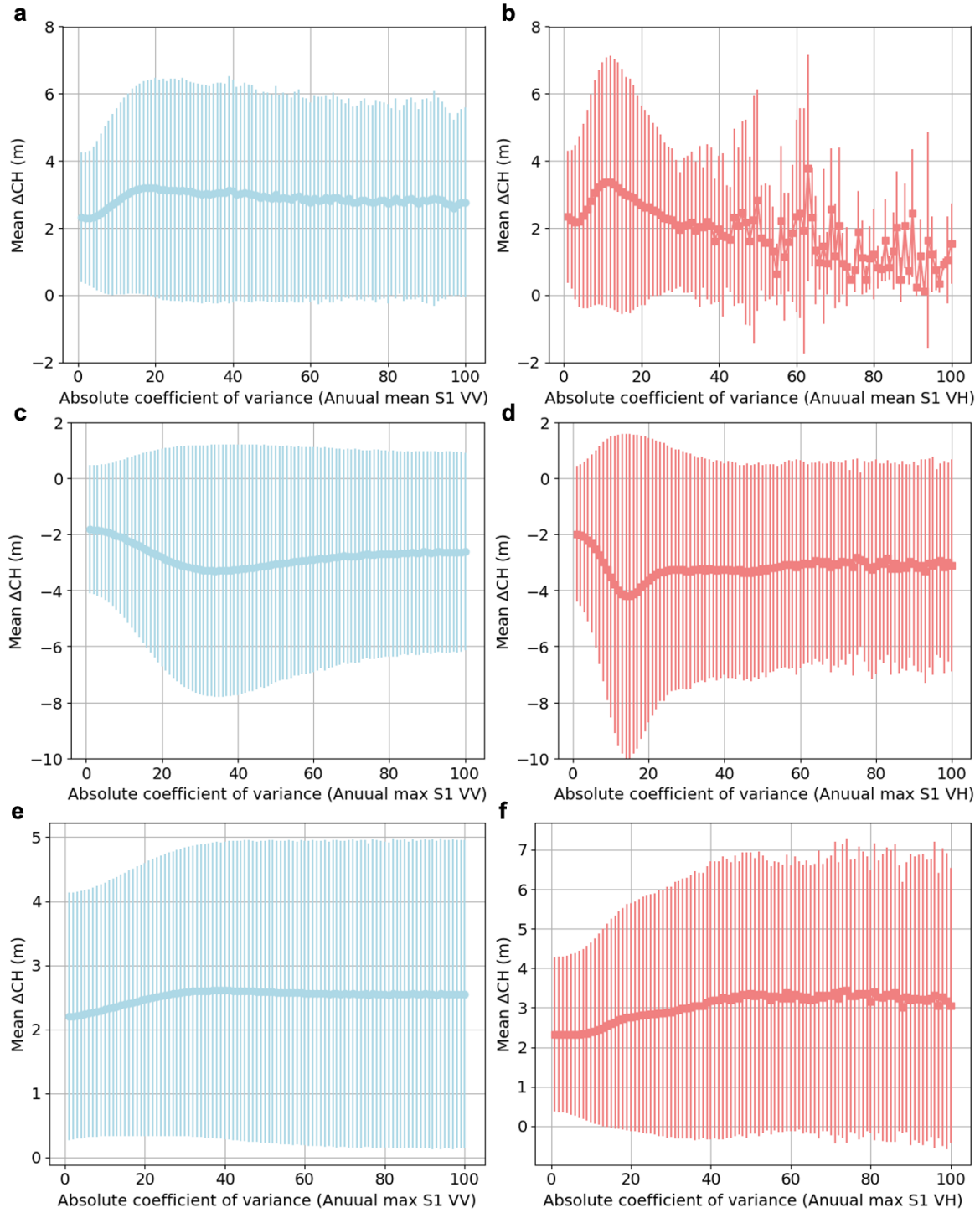
Supplementary Fig. 8: Visualization of spatiotemporal connectivity for a target pixel in a 3D data cube. Elements are connected if they share at least one common corner. This connectivity indicates that adjacent pixels exhibit the same canopy height (CH) change trend and may form a disturbance event.



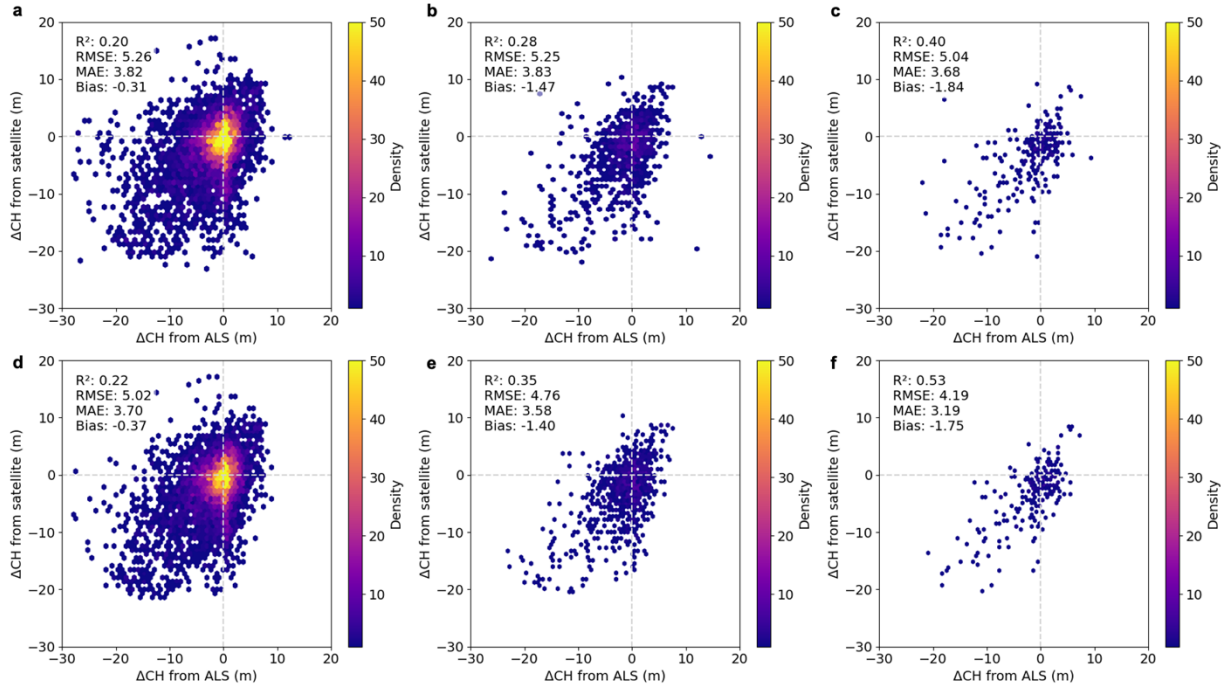
Supplementary Fig. 9: Statistics of the Mann-Kendall sum across different bins of canopy height (CH) loss and gain. a, b, Distribution of the Mann-Kendall sum across CH gain (a) and loss (b) bins, with a bin width of 1 meter. **c, d,** Frequency distribution of the Mann-Kendall sum for CH gain (c) and loss (d), respectively.



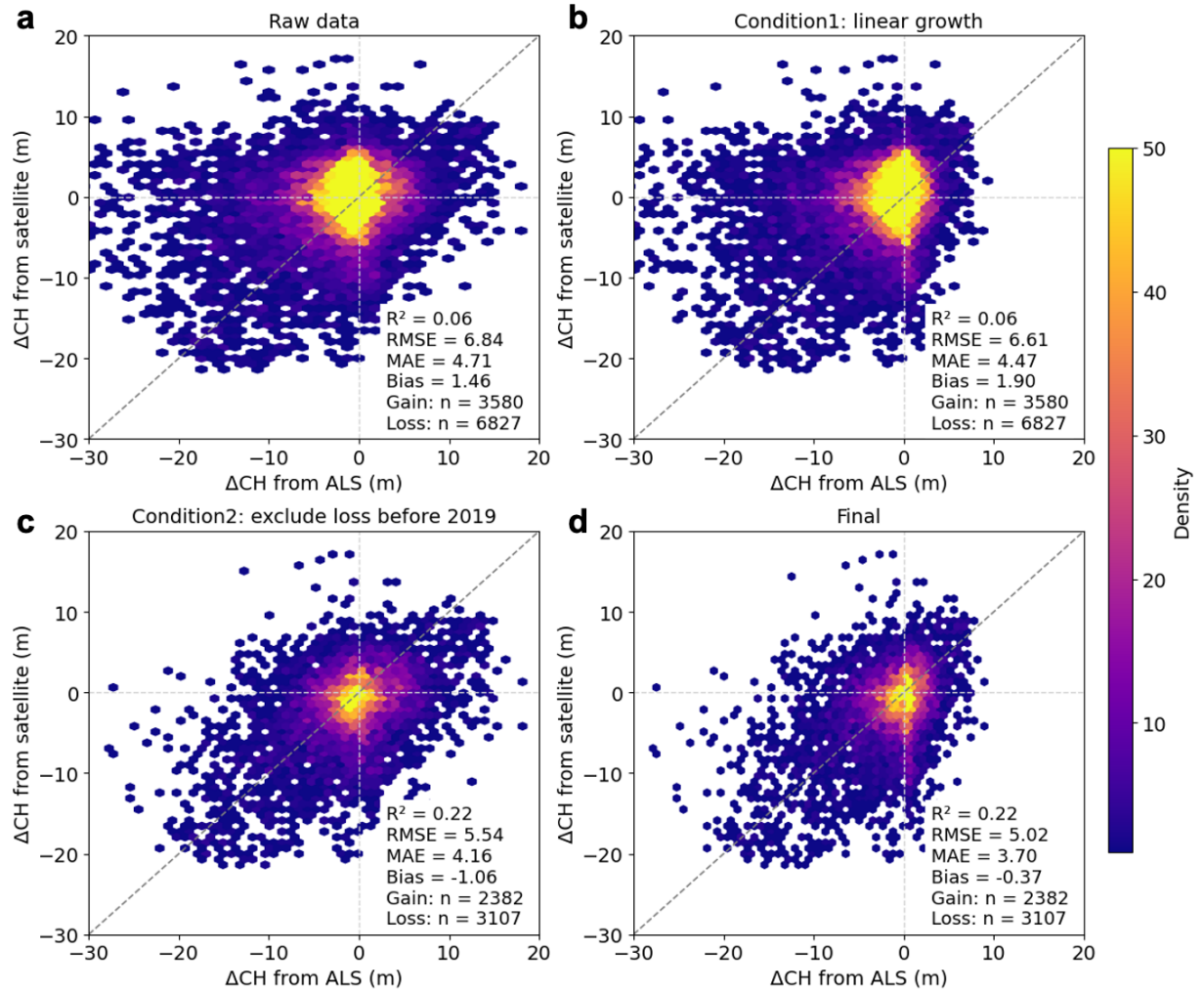
Supplementary Fig. 10: Canopy height loss across the absolute coefficient of variation in Sentinel-1 data. **a, b,** Mean canopy height loss ($\Delta\text{CH} < 0$) across varying the absolute coefficient of variation ($|\text{CV}|$) of Sentinel-1 VV (**a**) and VH (**b**) bands. The $|\text{CV}|$ range is set to 1–100 to show the overall trend. The $|\text{CV}|$ of VV and VH is calculated using annual mean Sentinel-1 images from 2019 to 2022. **c, d,** Distribution of ΔCH across varying $|\text{CV}|$ of Sentinel-1 VV (**c**) and VH (**d**) bands. The $|\text{CV}|$ range is set to 1–10 for a clearer distribution of ΔCH .



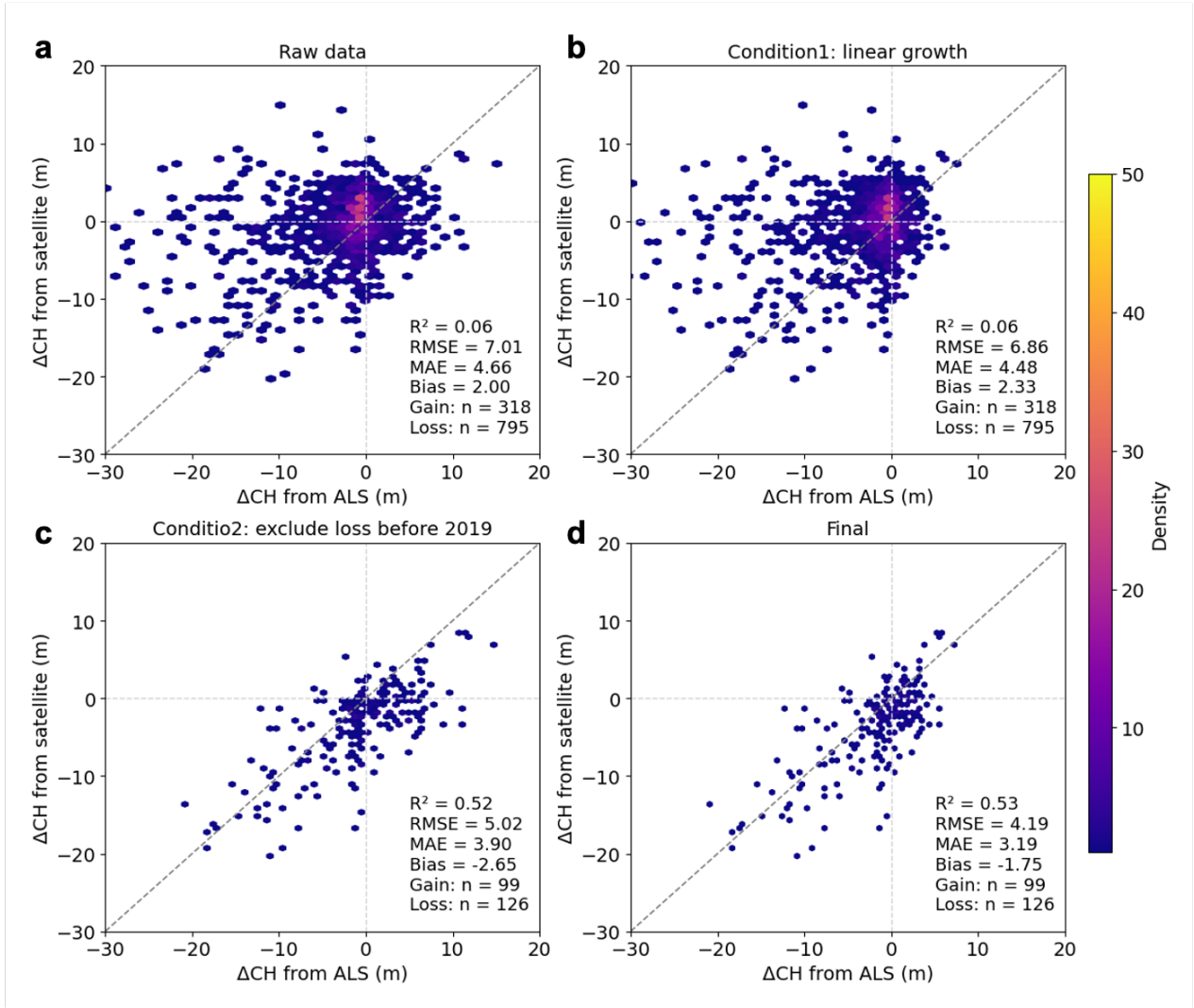
Supplementary Fig. 11: Mean canopy height (CH) change across bins of the absolute coefficient of variance ($|CV|$) in Sentinel-1 VV and VH bands. **a, b, Positive CH change ($\Delta CH > 0$), with $|CV|$ of VV and VH calculated from annual mean Sentinel-1 images (2019–2022). **c, d**, Negative CH change ($\Delta CH < 0$), with $|CV|$ of VV and VH calculated from annual maximum Sentinel-1 images (2019–2022). **e, f**, Positive CH change ($\Delta CH > 0$), with $|CV|$ of VV and VH calculated from annual maximum Sentinel-1 images (2019–2022).**



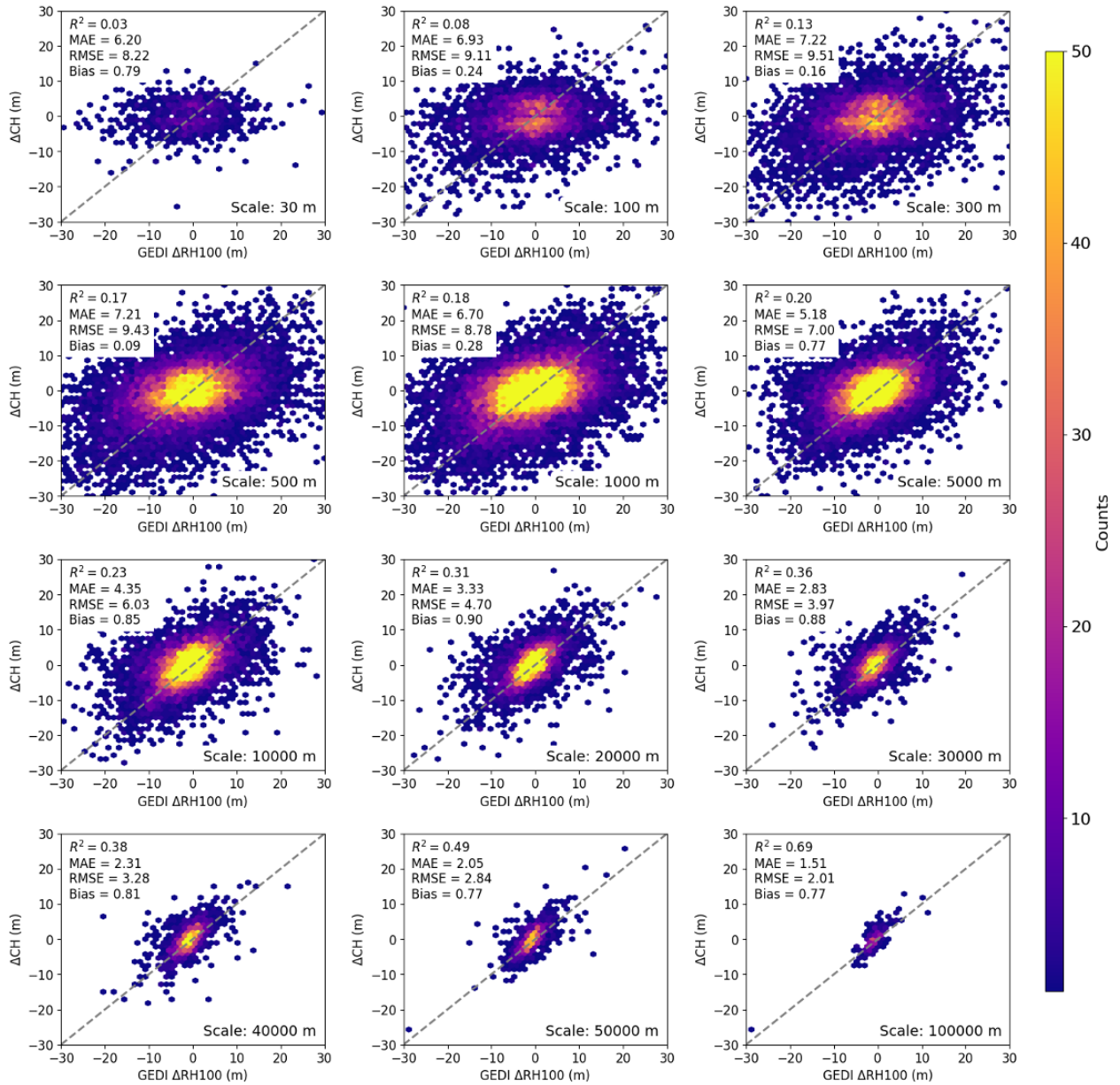
Supplementary Fig. 12: Comparison of processed canopy height change from satellite and airborne LiDAR data. **a–c**, Comparisons of canopy height change (ΔCH) between satellite and airborne LiDAR (ALS) data at spatial resolutions of 10 m (**a**), 20 m (**b**), and 30 m (**c**), including all pixels. **d–f**, Same comparisons as in **a–c**, but with edge pixels excluded. CH change was processed to exclude isolated and noise pixels. Satellite-derived CH change (ΔCH) was processed using a multi-step filtering and validation procedure to reduce noise and remove implausible structural changes.



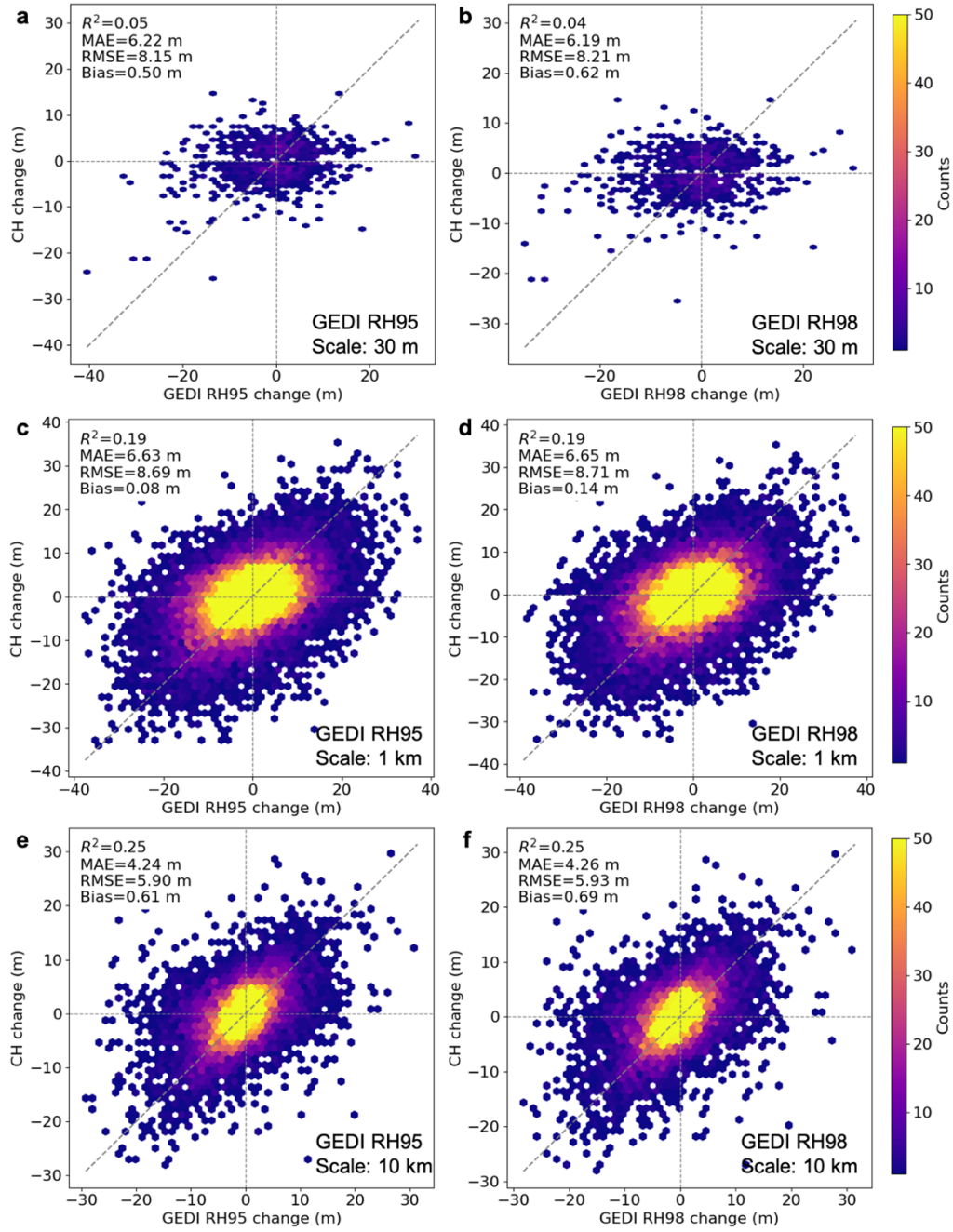
Supplementary Fig. 13: Comparison of satellite-derived and ALS canopy height change at 10 m resolution under different processing conditions. **a**, Comparison between processed satellite-derived canopy height (CH) change and original ALS observations. Satellite-derived CH change was processed using a multi-step filtering and validation procedure to reduce noise and remove implausible structural changes. **b**, Linear interpolation applied to ALS data for pixels with height gain to account for temporal mismatch. **c**, Pixels with pre-2019 height loss excluded from the ALS reference dataset. **d**, Final comparison after applying all processing steps. The number (n) of gain and loss pixels are derived from the ALS CH change data. The linear interpolation of growth pixels results in only a slight improvement, whereas the largest gain in agreement arises from excluding pixels with height loss occurring outside the 2019–2022 study period. This indicates that temporal mismatch in disturbance timing, rather than assumptions on growth dynamics, is the primary source of discrepancy in the raw comparison.



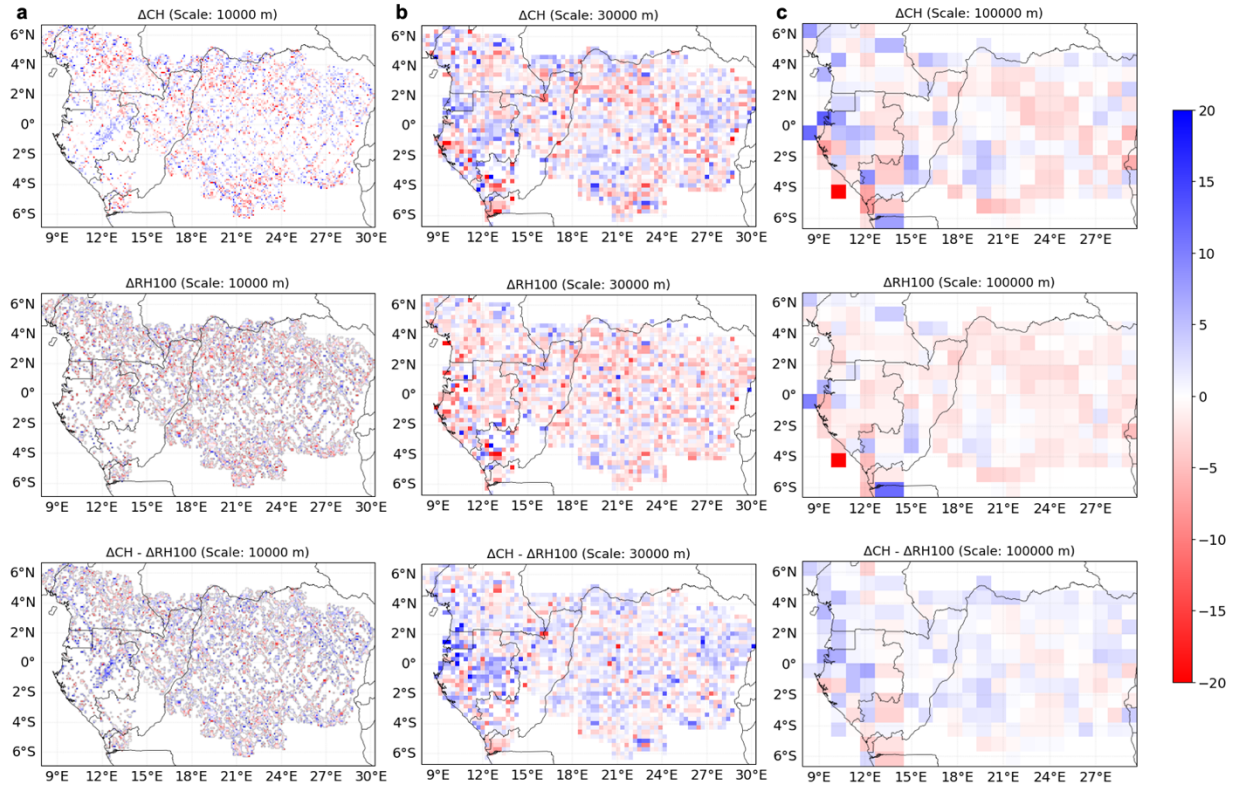
Supplementary Fig. 14: Comparison of satellite-derived and ALS canopy height change at 30 m resolution under different processing conditions. **a**, Comparison between processed satellite-derived canopy height (CH) change and original ALS observations. Satellite-derived CH change was processed using a multi-step filtering and validation procedure to reduce noise and remove implausible structural changes. **b**, Linear interpolation applied to ALS data for pixels with height gain to account for temporal mismatch. **c**, Pixels with pre-2019 height loss excluded from the ALS reference dataset. **d**, Final comparison after applying all processing steps. The number (n) of gain and loss pixels are derived from the ALS CH change data. The linear interpolation of growth pixels results in only a slight improvement, whereas the largest gain in agreement arises from excluding pixels with height loss occurring outside the 2019–2022 study period. This indicates that temporal mismatch in disturbance timing, rather than assumptions on growth dynamics, is the primary source of discrepancy in the raw comparison.



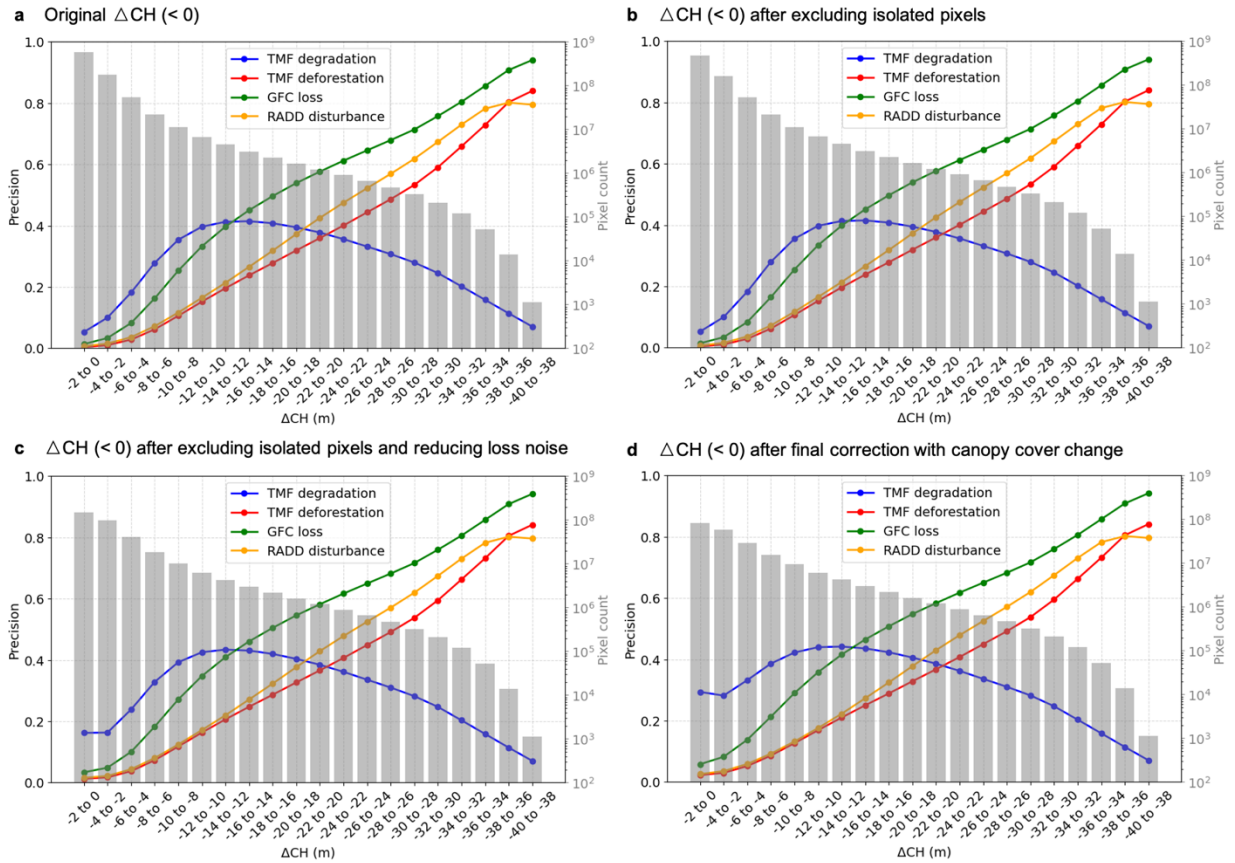
Supplementary Fig. 15: Comparison of processed canopy height (CH) change from satellite and GEDI RH100 change at different scales. Satellite-derived CH change was processed using a multi-step filtering and validation procedure to reduce noise and remove implausible structural changes. CH change ($\Delta CH_{2022-2019}$) and GEDI RH100 change ($\Delta RH100_{2022-2019}$) were calculated as the difference between the 2022 and 2019 data. We aggregated the 30-m data to coarser resolutions for more robust comparisons. CH change was processed to exclude isolated and noise pixels.



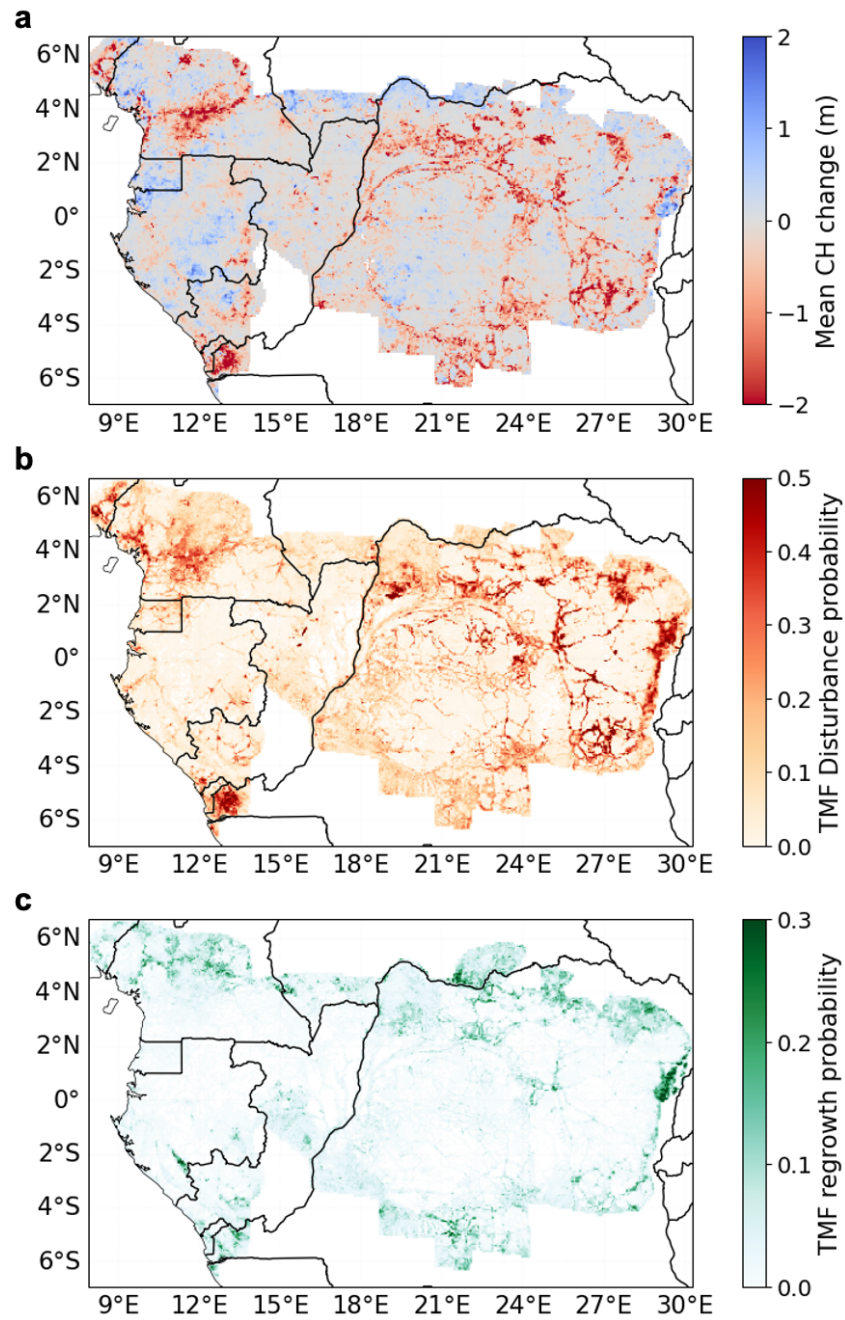
Supplementary Fig. 16: Comparison of processed canopy height (CH) change from satellite with GEDI RH95 and RH98 changes across spatial scales. a–f, Comparison of CH change and GEDI RH95 (a, c, e) and RH98 (b, d, f) at 30 m resolution (a, b), 1 km resolution (c, d), and 10 km resolution (e, f). Satellite-derived CH change was processed using a multi-step filtering and validation procedure to reduce noise and remove implausible structural changes. CH change and GEDI RH metrics were derived from differences between 2019 and 2022 observations. Satellite CH change was filtered to remove noise and implausible values, and aggregated from 30 m to 1 km and 10 km for robust comparisons.



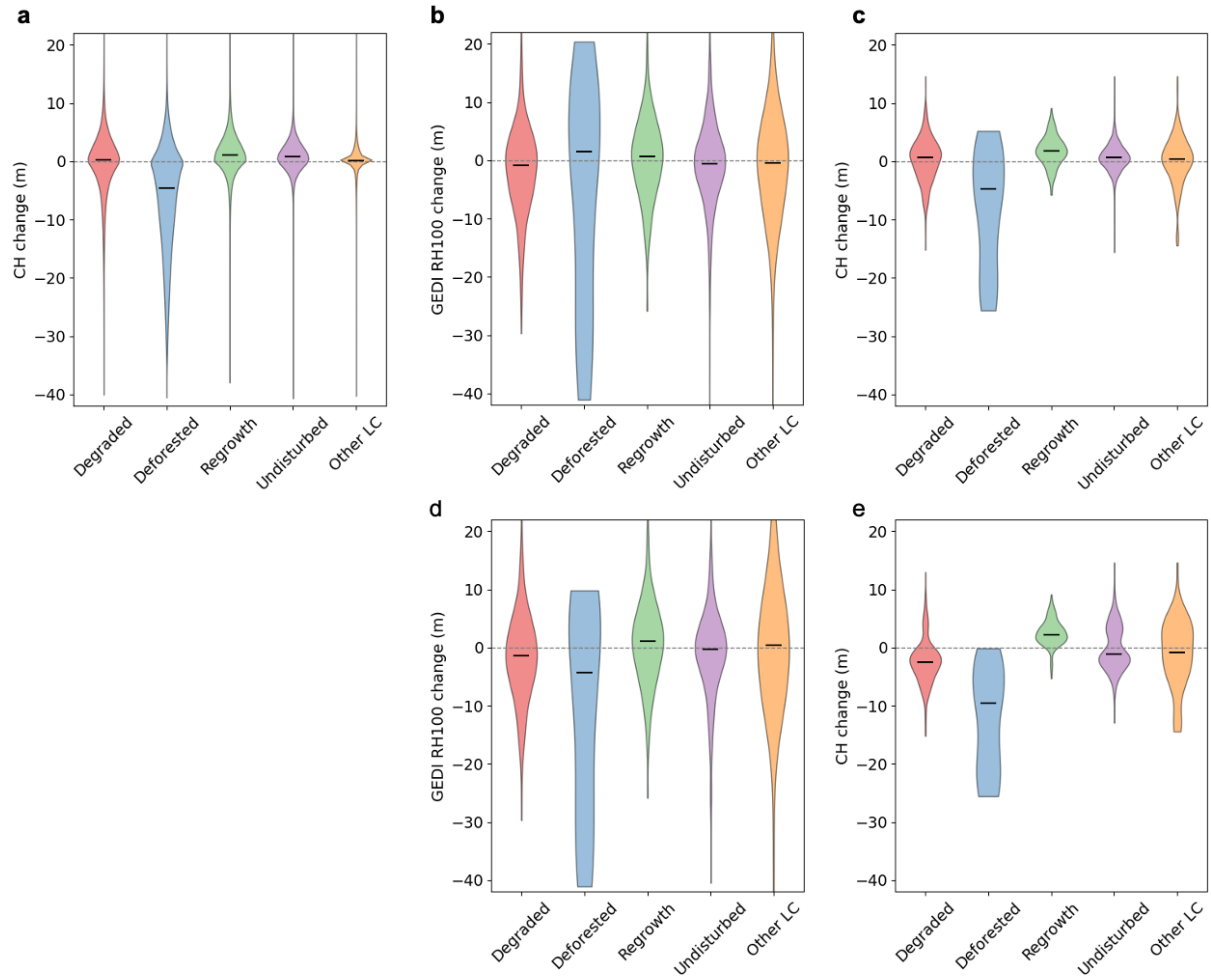
Supplementary Fig. 17: Comparison of processed CH change from satellite and GEDI RH100 change maps and their difference at three scales after a multi-step filtering and validation procedure. CH change (ΔCH) and GEDI RH100 change (ΔRH100) were calculated as the difference between the 2022 and 2019 data. We aggregated the 30-m data to coarser resolutions (**a**, 10000 m; **b**, 30000 m; **c**, 100000 m) for more robust comparisons. CH change was processed to exclude isolated and noise pixels.



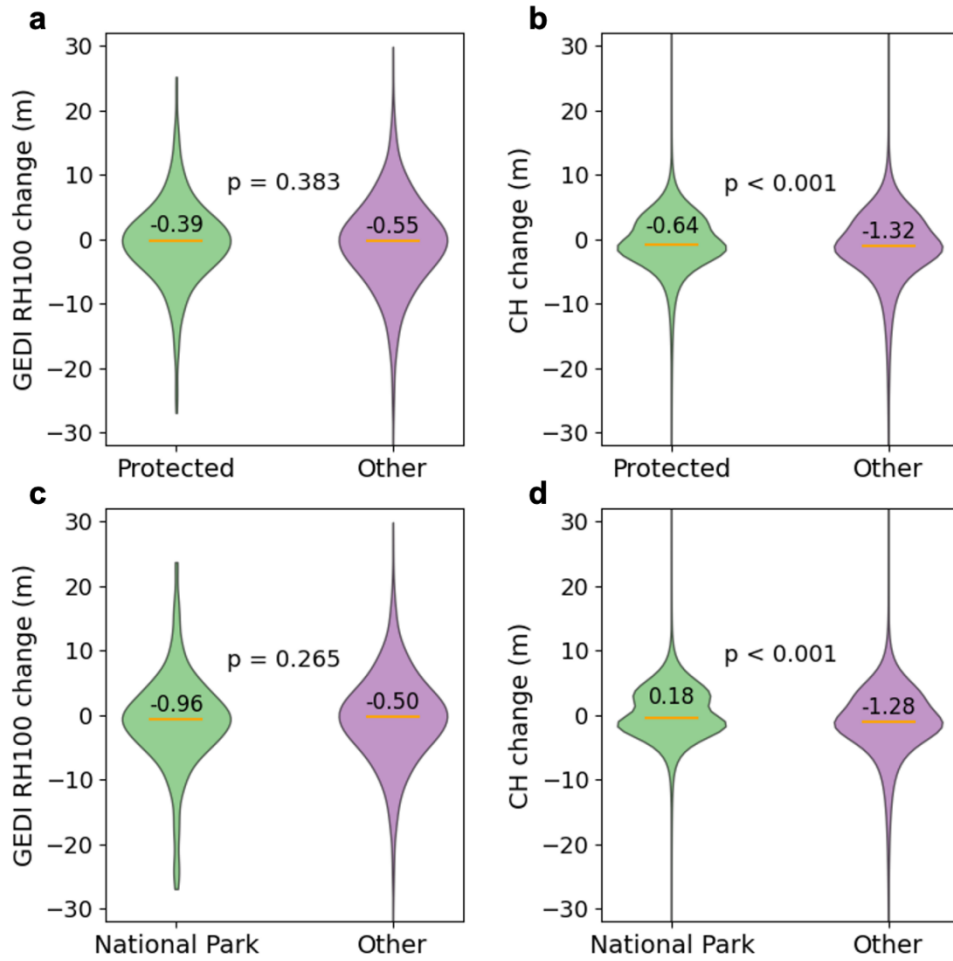
Supplementary Fig. 18: Precision of CH loss estimates before and after processing, evaluated against various disturbance datasets. a–d, Comparisons for original $\Delta CH (< 0)$ (a), $\Delta CH (< 0)$ after excluding isolated pixels (b), $\Delta CH (< 0)$ after excluding isolated pixels and reducing loss-related noise (c), and $\Delta CH (< 0)$ after final correction with canopy cover change (d). The disturbance datasets include TMF degradation, TMF deforestation, GFC loss, and RADD disturbance.



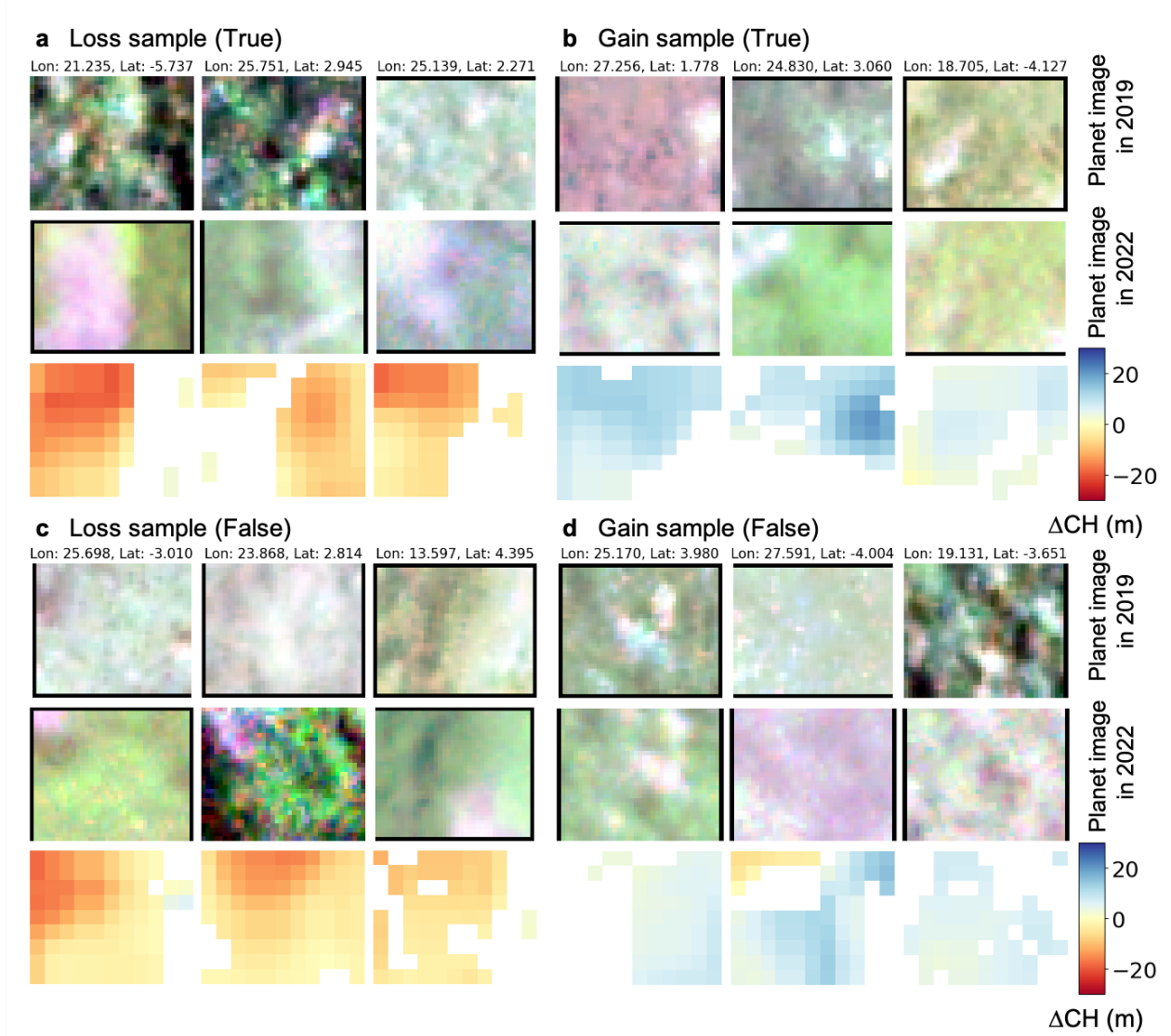
Supplementary Fig. 19: Maps of canopy height change and TMF forest disturbance and regrowth probability in Central African forests (2019–2022). **a**, Spatial distribution of mean canopy height change (ΔCH) from 2019 to 2022, aggregated to 5-km grid cells for visualization. Height change was averaged across all pixels, including both change and non-change pixels, within each grid cell. **b**, **c**, Spatial distributions of disturbance (including degradation and deforestation) and regrowth probability within 5-km grid cells, derived from the Tropical Moist Forests (TMF) dataset.



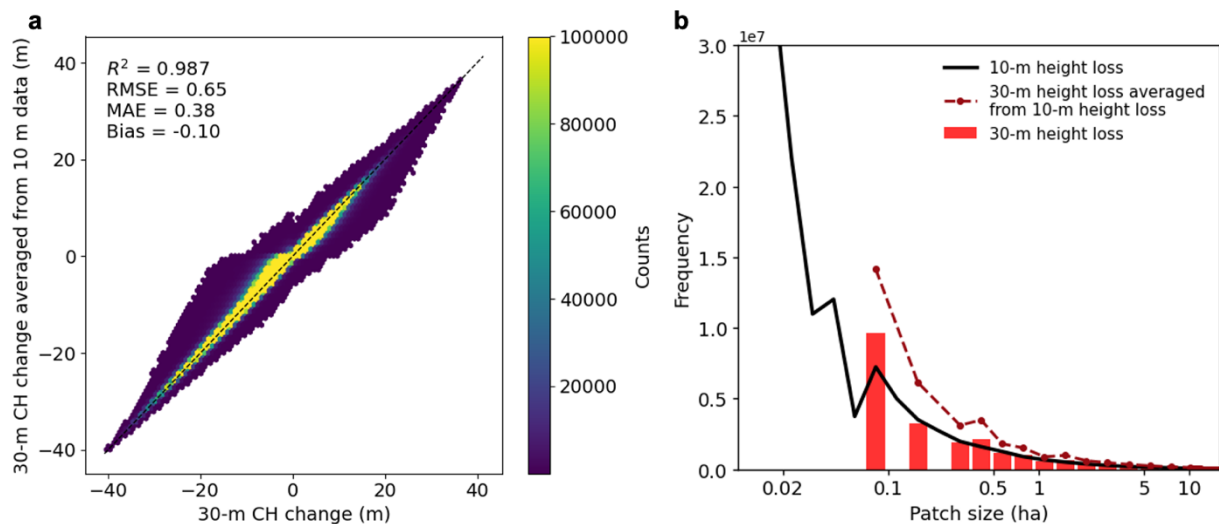
Supplementary Fig. 20: Comparison of distribution of CH change and GEDI RH100 change across disturbance classes. Disturbance classes, representing degraded, deforested, regrowth, undisturbed forests, and other land cover (LC), were derived from Tropical Moist Forests (TMF) data at 30 m resolution from 2019 to 2022. **a–c**, Comparison of CH change (ΔCH) and GEDI RH100 change (ΔRH100) before CH data processing: all ΔCH data (**a**), repeated GEDI RH100 measurements from 2019 and 2022 (**b**), and matched ΔCH and ΔRH100 data (**c**). **d–e**, Comparison of ΔCH and ΔRH100 after CH data processing: repeated GEDI RH100 from 2019 and 2022 (**d**), and matched ΔCH and ΔRH100 data (**e**). Both ΔCH and ΔRH100 represent the difference between 2022 and 2019 values. The black line within each box represents the median. The large variation in CH change within the degraded class may be due to differences in the timing of TMF degradation, where negative values reflect recent disturbances and positive values indicate recovery from older degradation events.



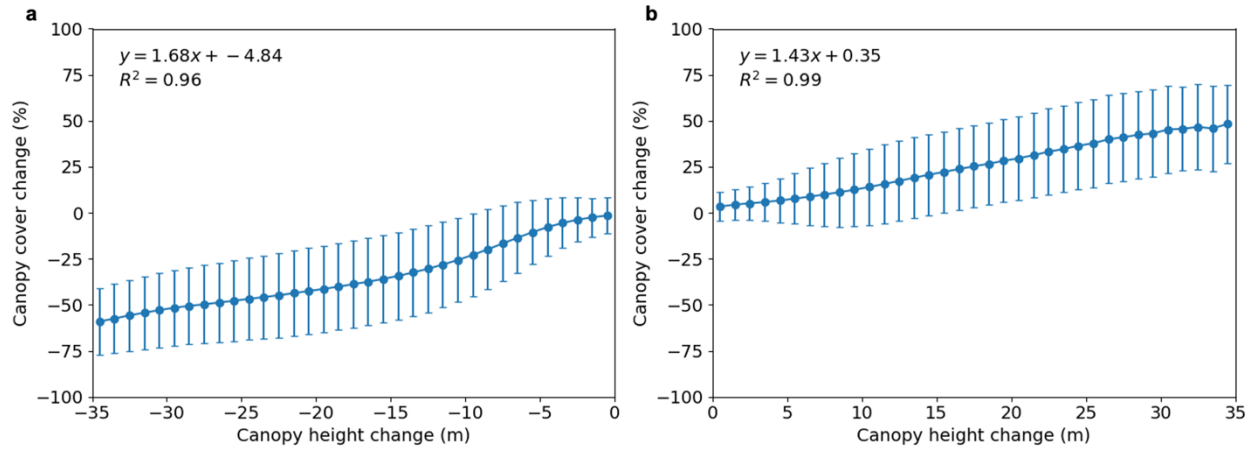
Supplementary Fig. 21: Comparison of the distribution of processed CH change and GEDI RH100 change between protected and other areas. a, c, Comparison of GEDI RH100 change (Δ RH100) in protected areas (a) and National Parks (c) against other areas. b, d, Comparison of CH change (Δ CH) in protected areas (b) and National Parks (d) against other areas. Both Δ CH and Δ RH100 represent the difference between 2022 and 2019 values. The orange line within each box represents the mean, with the mean value displayed. The significance level (p value) between two groups is also shown.



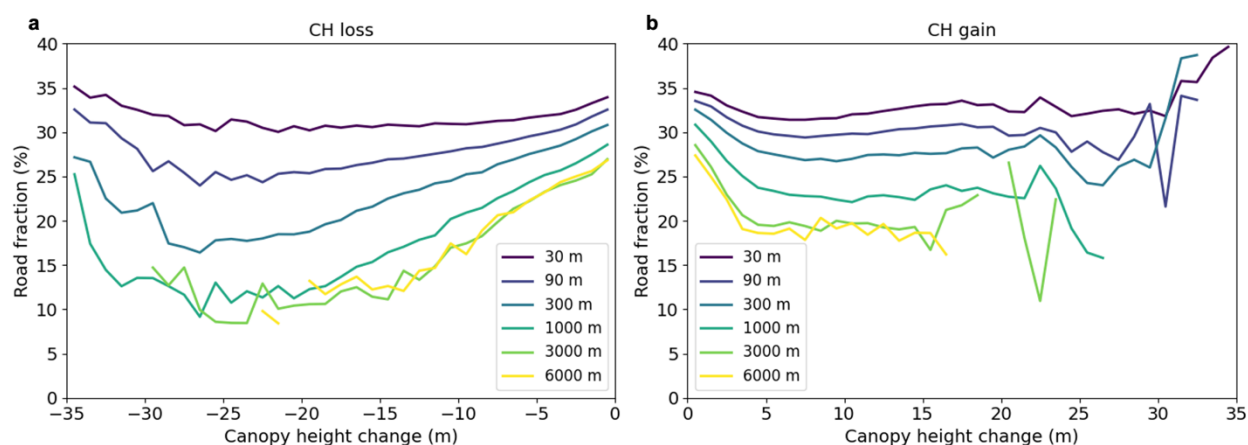
Supplementary Fig. 22: Visual comparison of canopy height (CH) change patches with PlanetScope imagery (2019–2022). **a, b**, True CH loss (**a**) and gain (**b**) examples, respectively, validated against PlanetScope imagery and exhibiting consistent change signals between 2019 and 2022. **c, d**, False CH loss (**c**) and gain (**d**) examples, respectively, where the estimated CH changes are not supported by corresponding changes in the imagery. Each panel represents a spatial extent of ≤ 1 ha. Only patches ≤ 1 ha are presented, as small disturbances exhibit the highest uncertainty in CH change detection. Latitude and longitude coordinates of the center of each sample patch are shown above the corresponding column.



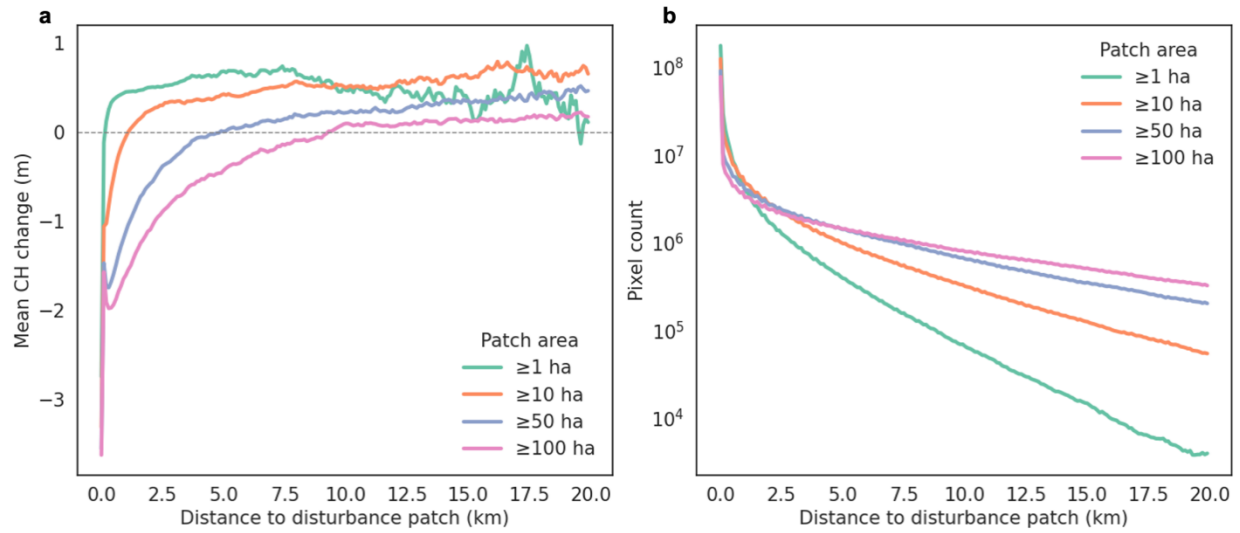
Supplementary Fig. 23: Consistency of canopy height change estimates and scale-dependent differences in disturbance patch size. (a) Comparison between two approaches for deriving 30 m canopy height (CH) change : (i) aggregation of annual 10 m CH maps to 30 m followed by CH change detection (30-m CH change used in this study, consistent with 30-m AGC change), and (ii) direct aggregation of 10 m CH change maps to 30 m. The two approaches show high agreement across the full range of CH change values. (b) Patch size distributions of CH loss derived from native 10 m CH change maps and from two 30 m CH loss products. While the two 30 m approaches yield broadly consistent patterns, the 30 m CH change derived from aggregated 10 m CH change maps captures more small disturbance patches than that derived from 30 m CH data, reflecting the higher sensitivity of the 10 m observations. However, these additional small disturbances are not resolved in the 30 m AGC change maps, resulting in a mismatch between disturbance detection and carbon change estimates at finer scales.



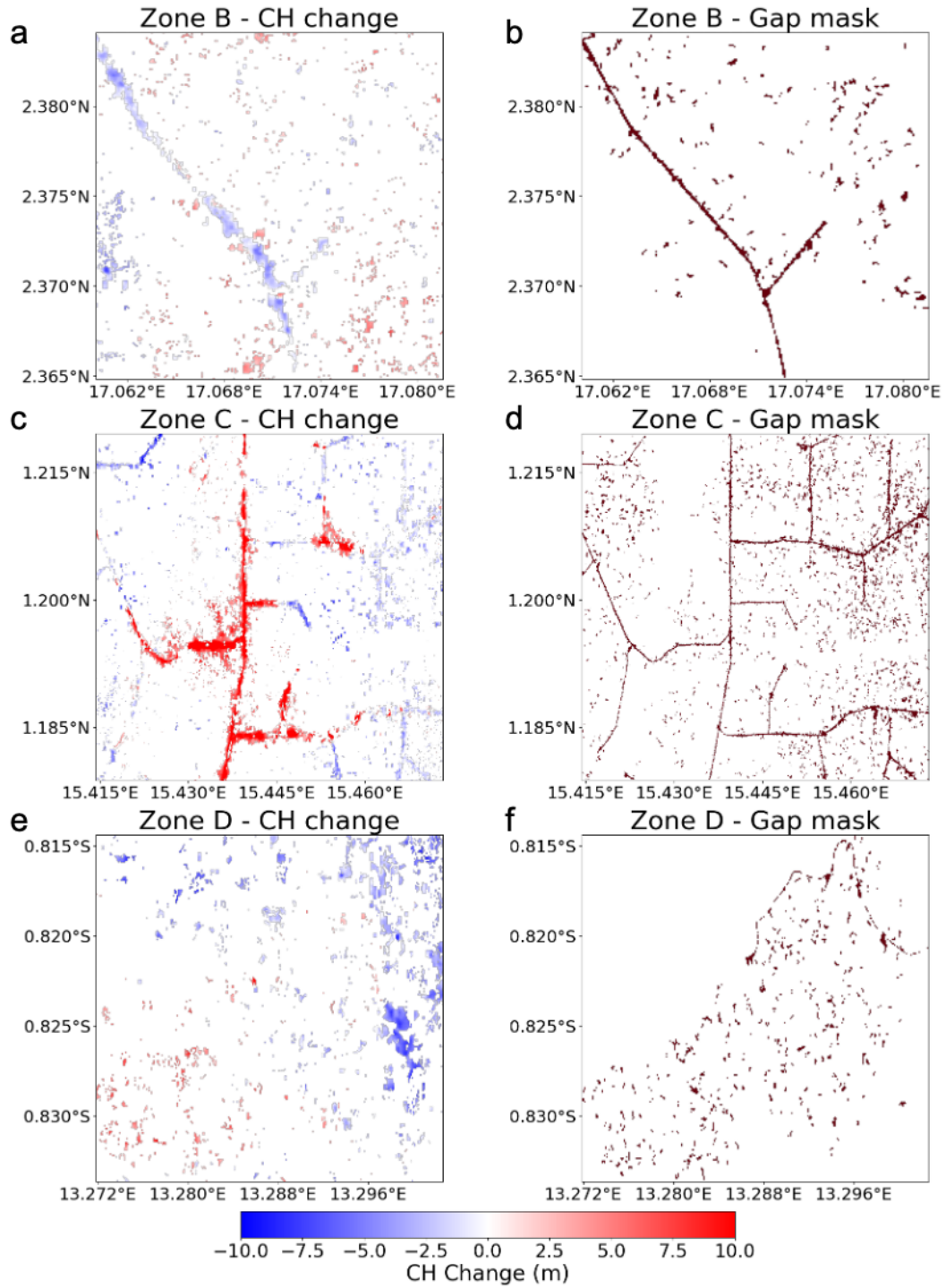
Supplementary Fig. 24: Comparison of canopy height and canopy cover changes from 2019 to 2022 across Central African forests. a, Relationship between canopy height loss and canopy cover loss. Canopy height change is grouped into 1-meter bins, with the mean and standard deviation shown for each bin. A linear regression line and the corresponding correlation coefficient are also provided. **b,** Relationship between canopy height gain and canopy cover gain. As with canopy height, canopy cover change was derived using a U-Net model trained on GEDI cover data.



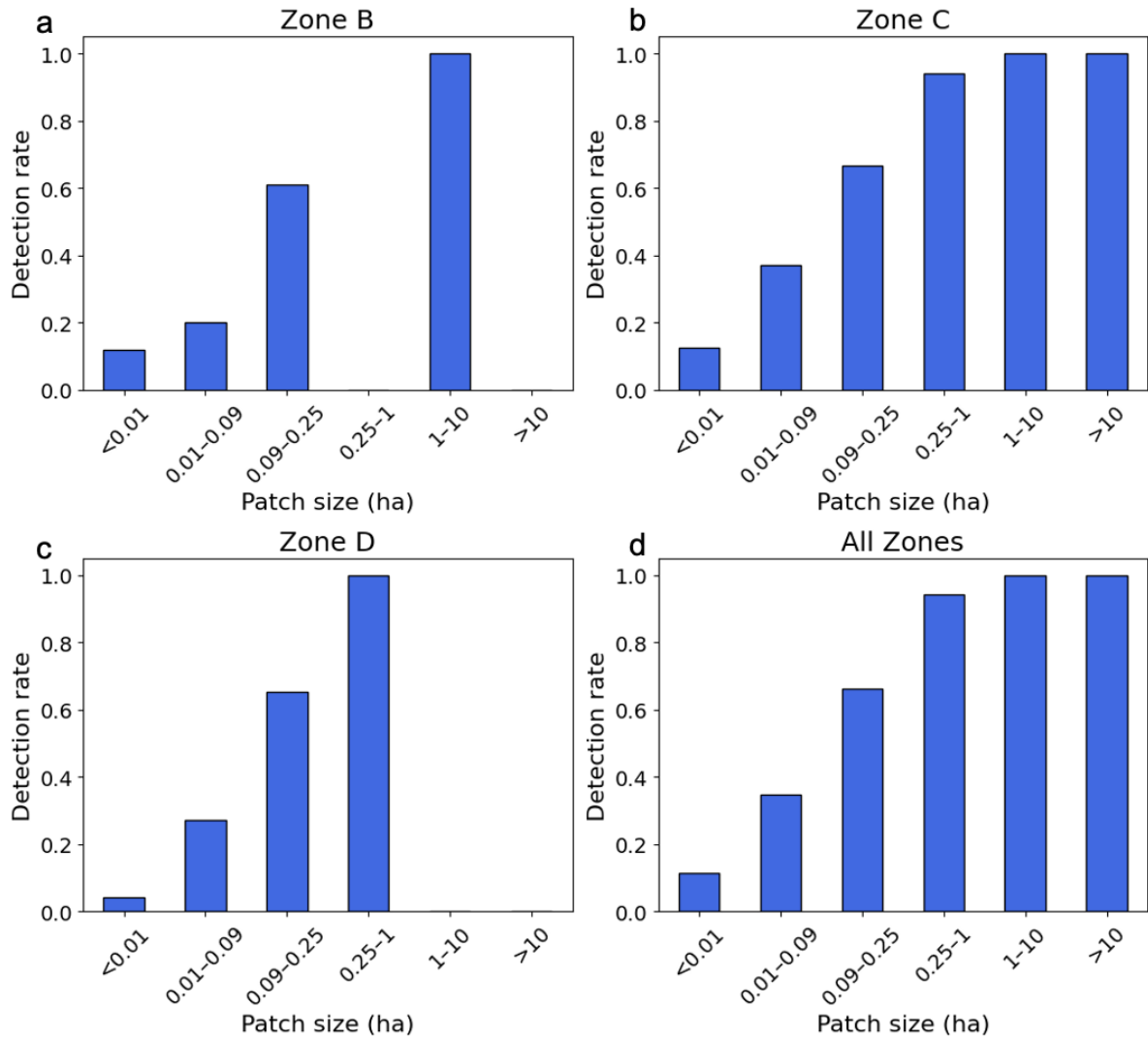
Supplementary Fig. 25: Relationship between road fraction and canopy height change at different pixel sizes (2019–2022) across Central African forests. **a**, Relationship between canopy height loss and road fraction (%) at pixel sizes of 30 m, 90 m, 300 m, 1000 m, 3000 m, and 6000 m. Road fraction is defined as the percentage of road pixels relative to the total number of pixels within each aggregation unit, based on a 5-meter resolution road map. The mean road fraction was calculated within each 1-meter bin of canopy height change. **b**, Relationship between canopy height gain and road fraction at the same set of pixel sizes.



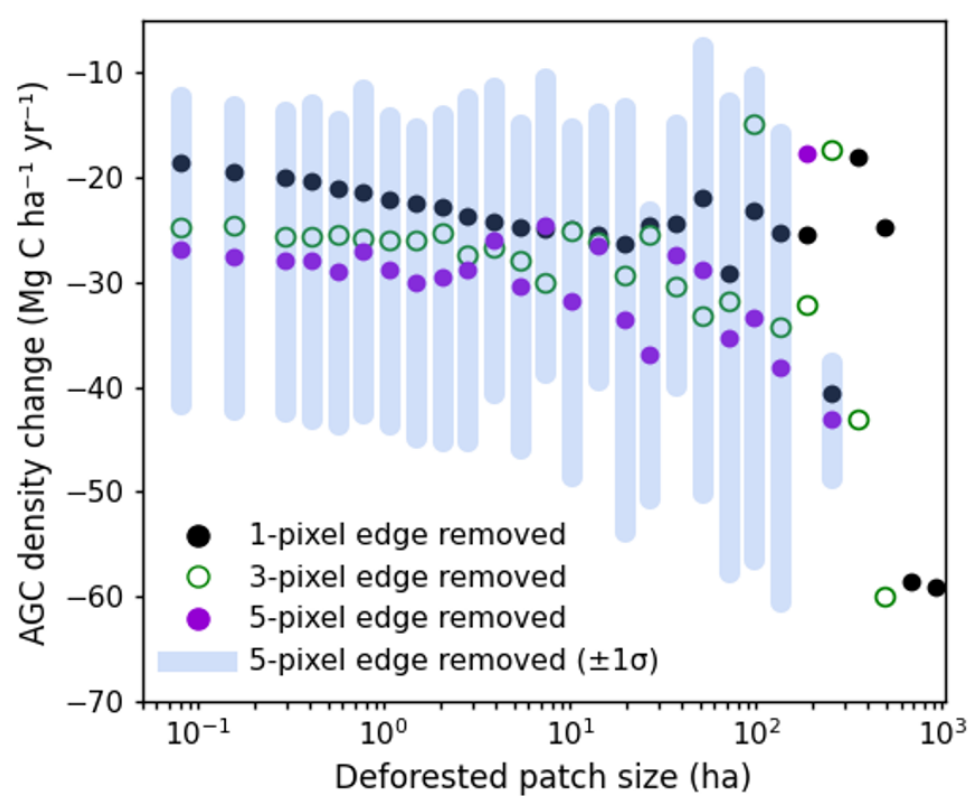
Supplementary Fig. 26: Canopy height change across varying distances to large disturbance patches. Disturbance patches were identified using degradation and deforestation events detected by TMF data from 2015 to 2022. **a**, Mean canopy height change as a function of distance to disturbance patches larger than 1 ha, 10 ha, 50 ha, and 100 ha. **b**, Distribution of the number of CH change samples as a function of distance to disturbance patches above the same size thresholds.



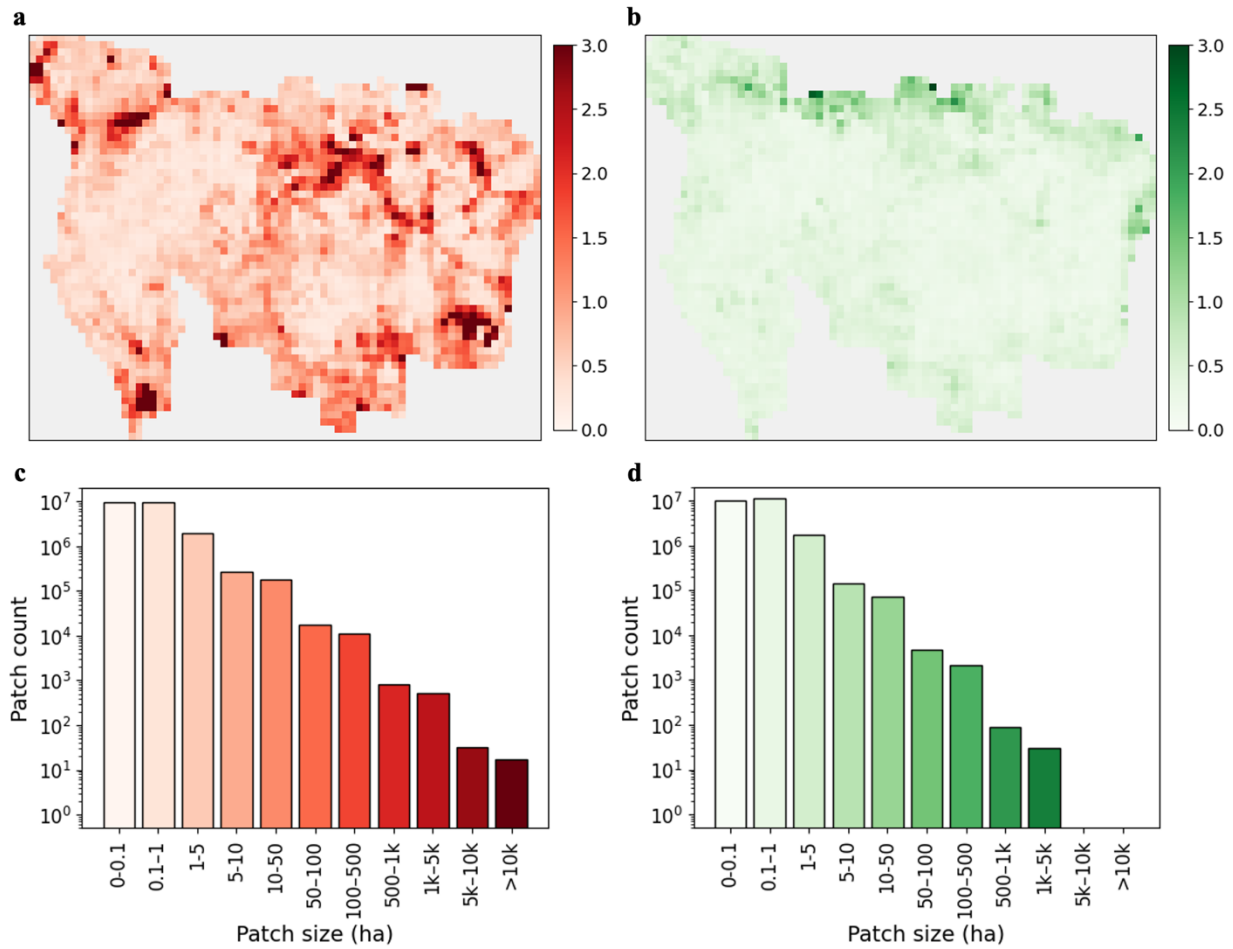
Supplementary Fig. 27. Mapping of our CH change (2019–2022) and UAV-derived canopy gaps in the Congo Basin. a–f, Comparisons of spatial distributions of CH changes and canopy gaps within Zone C and D. The canopy gaps were collected from repeated UAV flights: Zone B (Jun 2018 – Jan 2019), Zone C (Feb 2019 – Sep 2019) and Zone D (Jun 2019 – Sep 2020), at 10 cm resolution ¹.



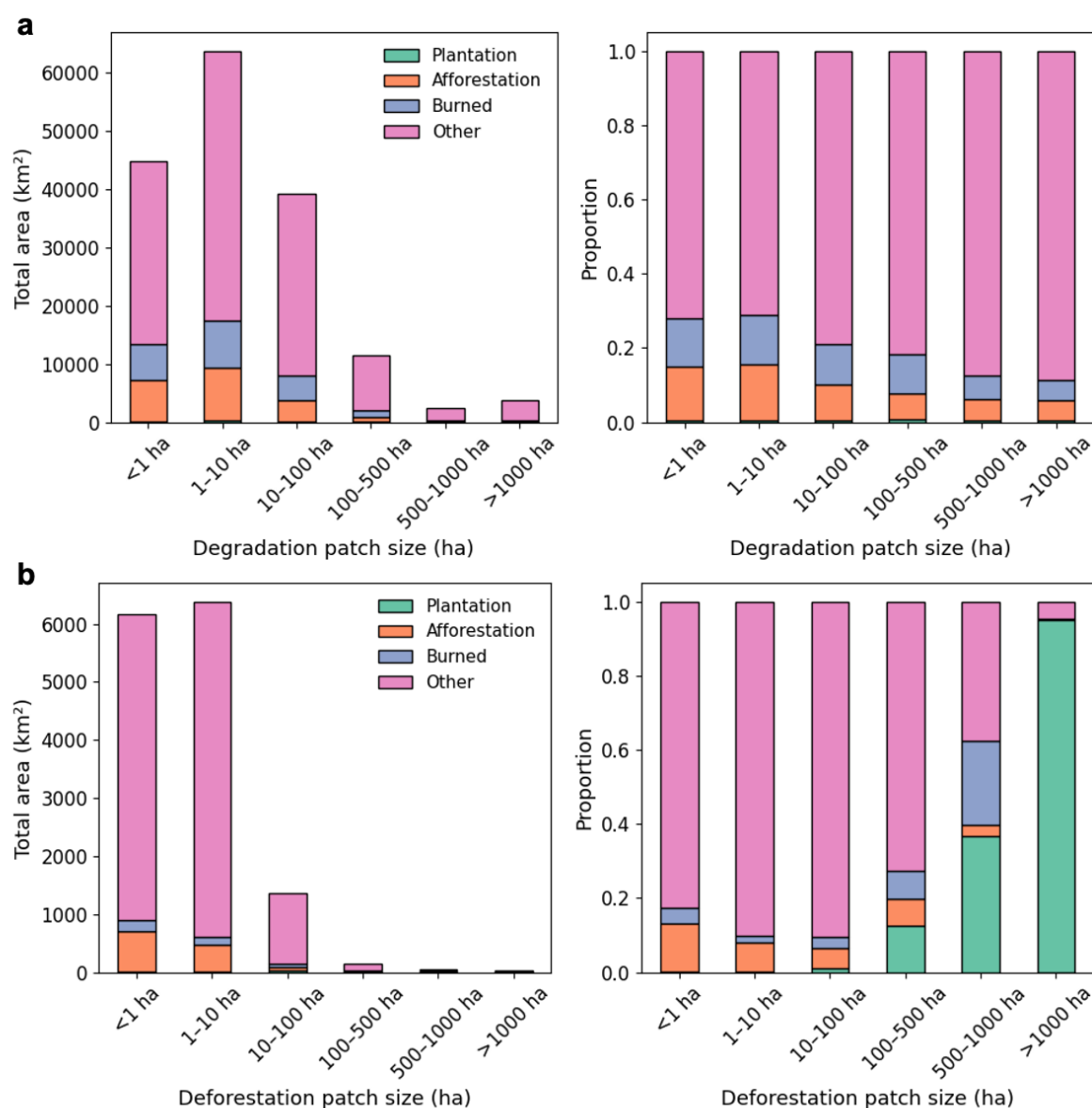
Supplementary Fig. 28: Comparisons of detected small disturbances using our CH change (2019–2022) and UAV-derived canopy gaps at two sites in the Congo Basin. a–d, Detection rate of our CH change in canopy gaps across different patch sizes in Zone B, Zone C, Zone D, and all zones combined. The canopy gaps were collected from repeated UAV flights: Zone B (Jun 2018 – Jan 2019), Zone C (Feb 2019 – Sep 2019) and Zone D (Jun 2019 – Sep 2020), at 10 cm resolution ¹.



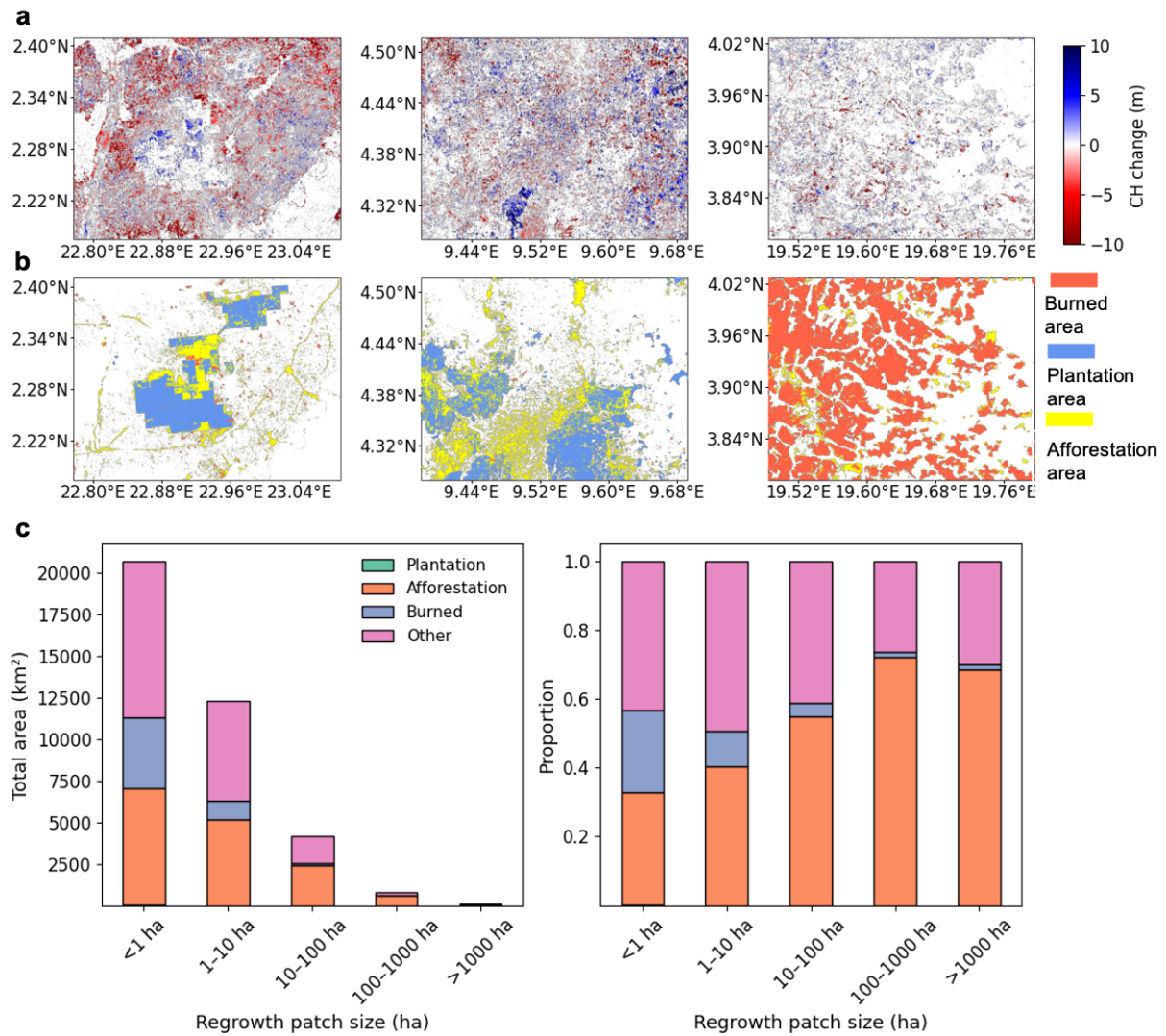
Supplementary Fig. 29: Aboveground carbon (AGC) density changes from forest deforestation across different patch sizes, with edge pixels excluded. '1-pixel edge removed' indicates that the outermost 1-pixel-wide boundary was excluded; similarly for 3-pixel and 5-pixel removals.



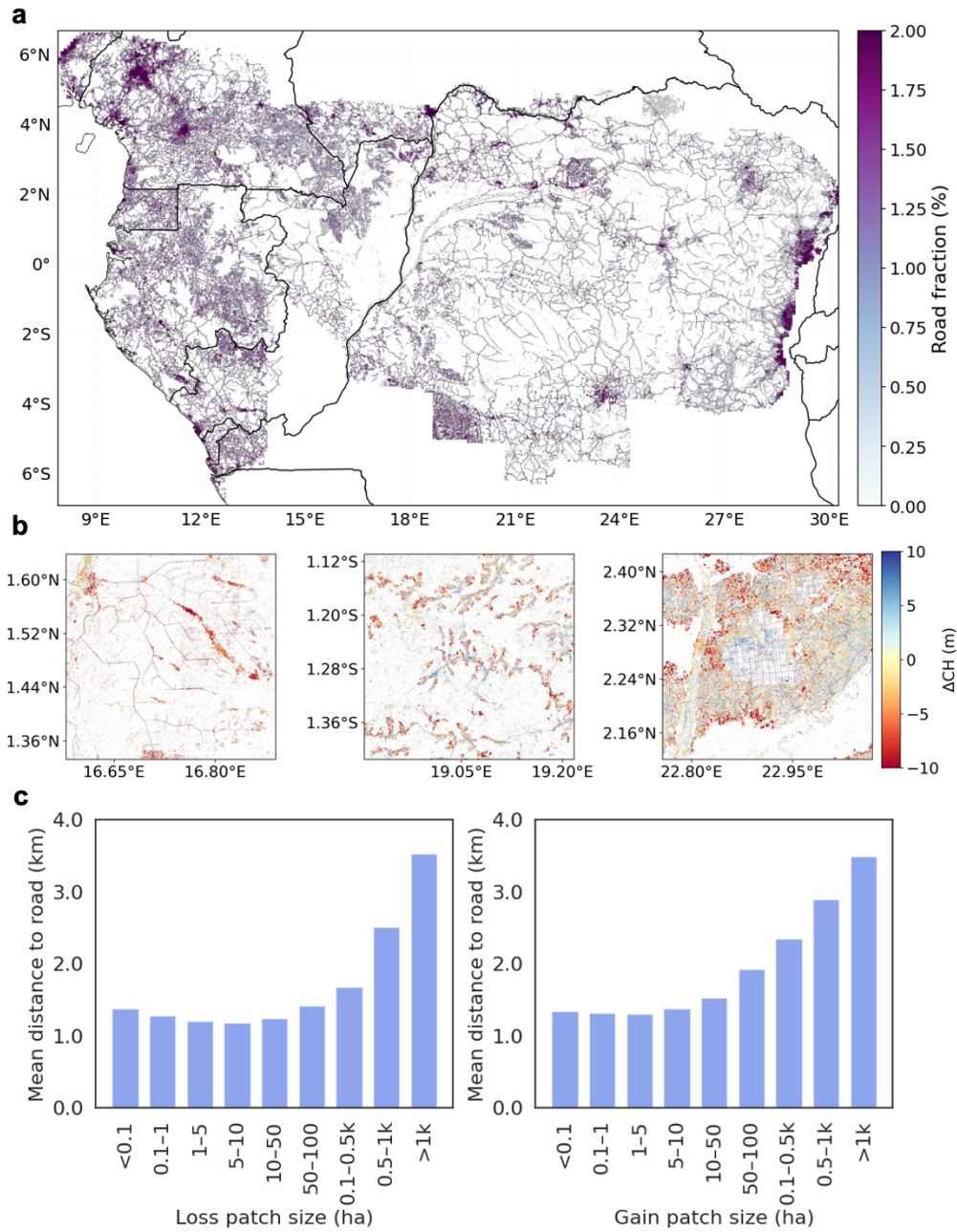
Supplementary Fig. 30: Canopy height change patch size across Central African forests. a, b, Maps of average patch size (0–3 ha) for canopy height loss (**a**) and gain (**b**) within 30-km grids. Patch sizes were derived from 30-m canopy height change maps from 2019 to 2022. **c, d,** Frequency distribution of canopy height loss (**c**) and gain (**d**) patch size across different patch size ranges at 30-m resolution. Patch size was represented using the area at each patch.



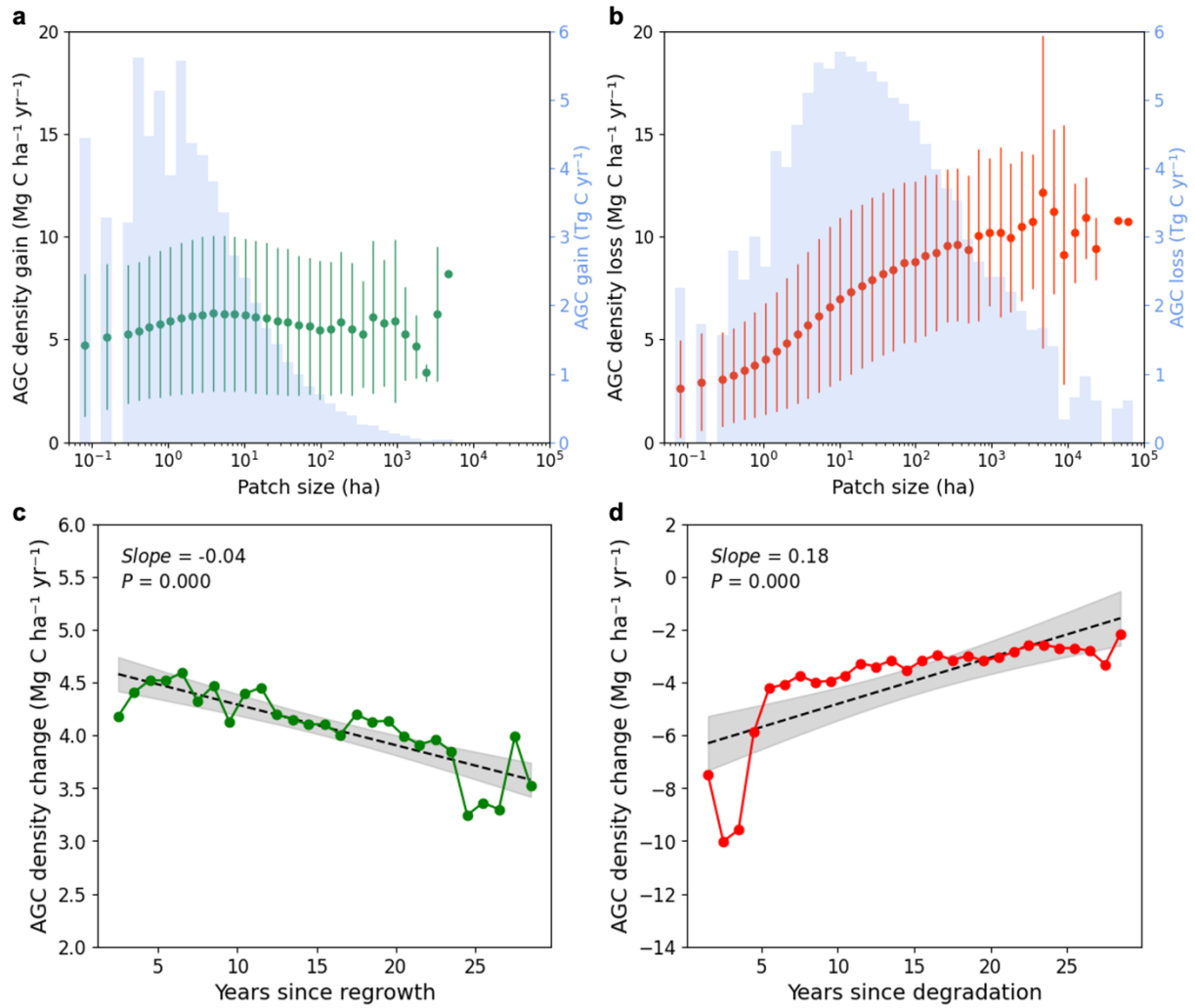
Supplementary Fig. 31: Distribution of afforestation, plantation, burned, and other (uncertain) areas by disturbance patch size class. a, Distribution of total area and the proportions of afforestation, plantation, burned, and other pixels across degradation patch size classes. **b,** Distribution of total area and the proportions of afforestation, plantation, burned, and other pixels across deforestation patch size classes. The plantation and afforestation maps are extracted from the TMF map², and the burned area map (2014–2018) is derived from the 30-m Global Annual Burned Area Maps (GABAM)³.



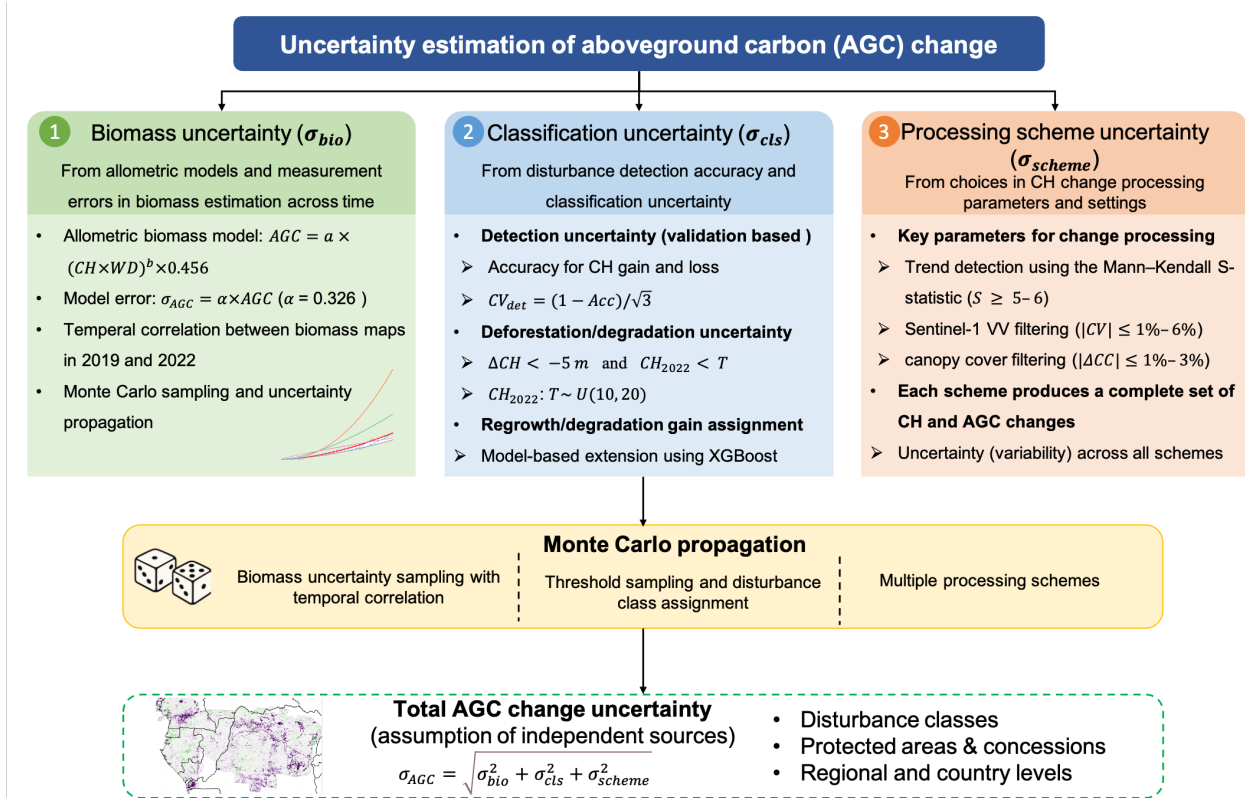
Supplementary Fig. 32: Distribution of afforestation, plantation, burned, and other (uncertain) areas by regrowth patch size class. a, b, Canopy height change (ΔCH) and the corresponding afforestation, plantation, and burned maps at 30 m resolution for three representative regions. The plantation and afforestation maps are extracted from the TMF map², and the burned area map (2014–2018) is derived from the 30 m Global Annual Burned Area Maps (GABAM)³. c, Distribution of total area and the proportions of afforestation, plantation, burned, and other pixels across regrowth patch size classes.



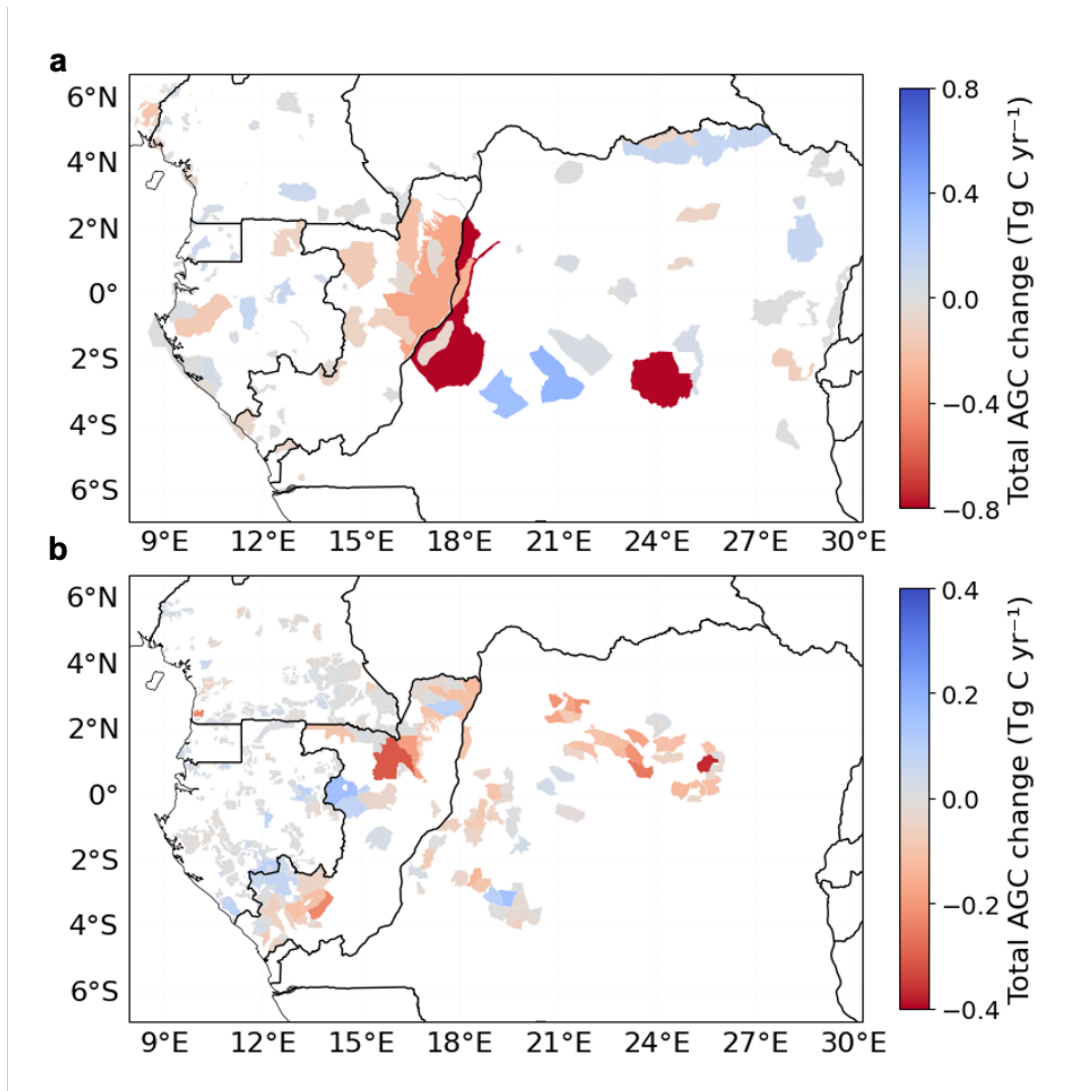
Supplementary Fig. 33: Road fraction and its relation to canopy height change patch size across Central African forests. **a**, Map of average road fraction within 6-km grid cells. Road fraction was calculated as the ratio of road pixels to total pixels at 30-m resolution from high resolution road mapping ⁴, then aggregated to 6-km resolution. **b**, Road lines (purple) overlaid with canopy height change at 30-m resolution for three representative regions. **c**, Average distance from CH change pixels to the nearest road, grouped by patch size. Distances were calculated based on the road fraction threshold (e.g., >0.1).



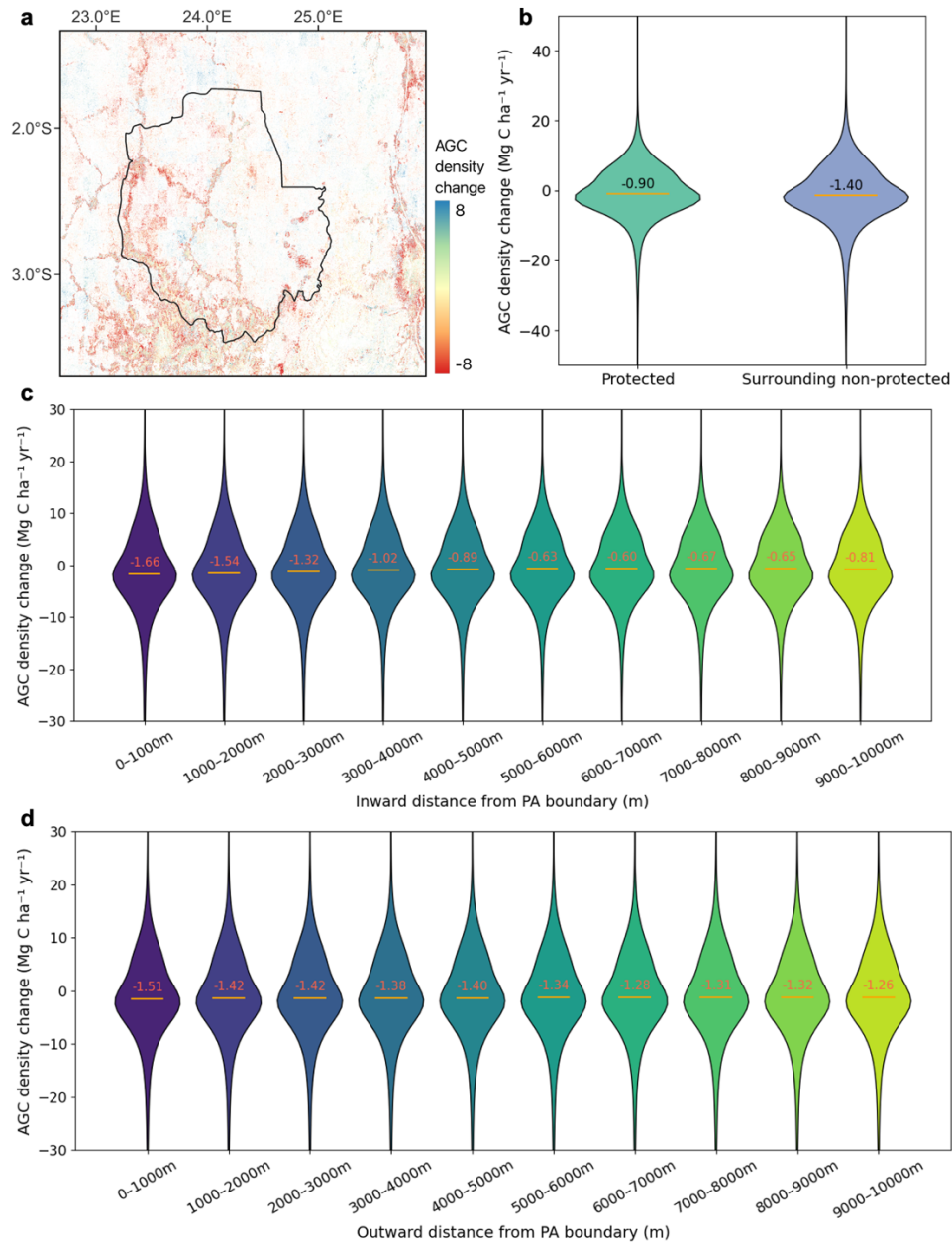
Supplementary Fig. 34: Aboveground carbon (AGC) changes across varying patch sizes and disturbance periods. **a, b**, Aboveground carbon (AGC) density gain (**a**) and loss (**b**) across different patch sizes. Patch sizes were derived from canopy height gain and loss maps, respectively. For each patch size bin, the mean AGC change $\pm$ standard deviation is shown. The bars in light blue indicate the total AGC loss or gain within each patch size category. **c, d**, Mean AGC density changes across different regrowth (**c**) and degradation (**d**) years. Long-term degradation and regrowth dynamics were derived from the TMF dataset. Linear regression was used to model the relationship between mean AGC change and time/duration, with the slope and p -value indicated. Shaded areas represent the 95% confidence intervals of the fitted models.



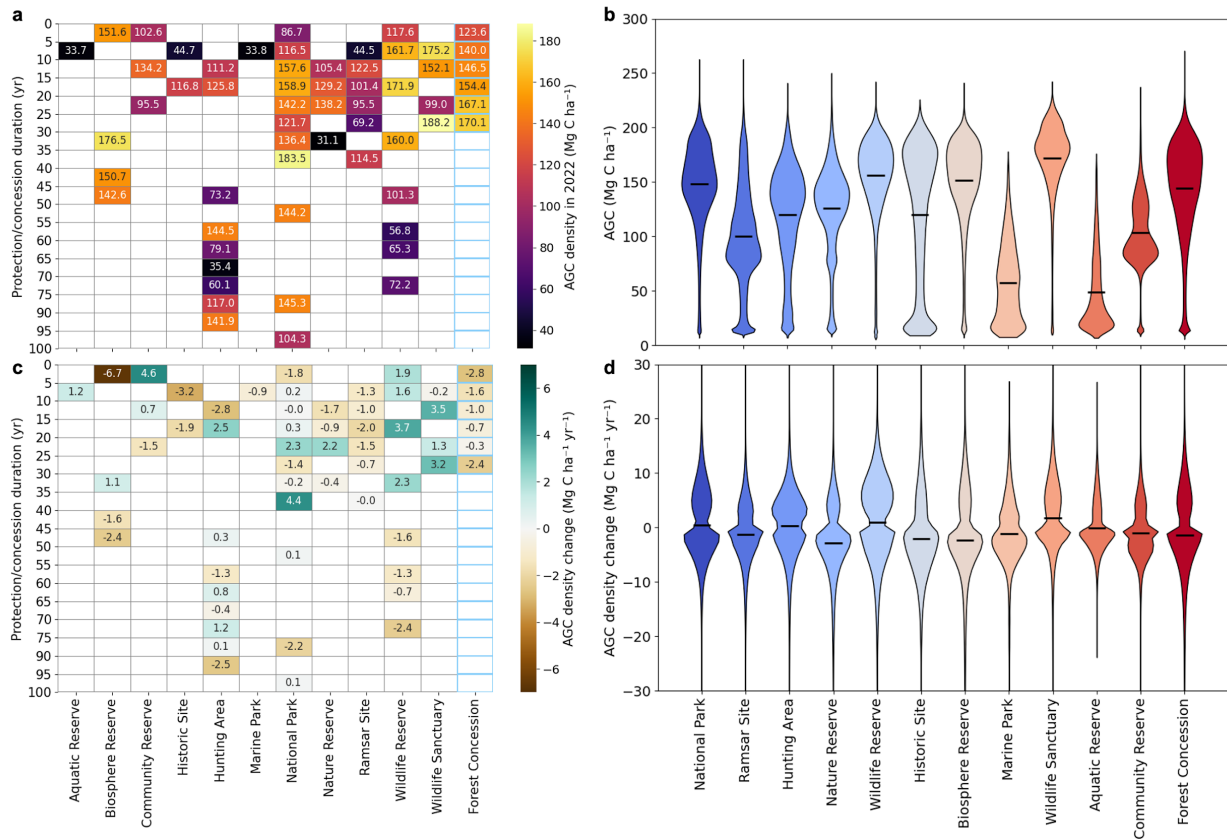
Supplementary Fig. 35: Framework for uncertainty estimation and propagation of aboveground carbon (AGC) change. The framework integrates three major sources of uncertainty in AGC change estimation: uncertainty of AGC change by explicitly accounting for three sources: (1) biomass uncertainty arising from allometric modelling and measurement errors (σ_{bio}); (2) classification uncertainty associated with disturbance attribution and detection accuracy (σ_{cls}); 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. These uncertainty sources were propagated through Monte Carlo simulations and combined assuming independence among sources to estimate total uncertainty in AGC gain, loss, and net change across disturbance classes, protected areas, concessions, and regional and country scales. AGC: aboveground carbon; CH: canopy height; ΔCH : canopy height change; ΔCC : canopy cover change; CV: coefficient of variation; Acc: detection accuracy; σ : standard deviation; WD: wood density; TMF: Tropical Moist Forest; VV: Sentinel-1 VV polarization backscatter.



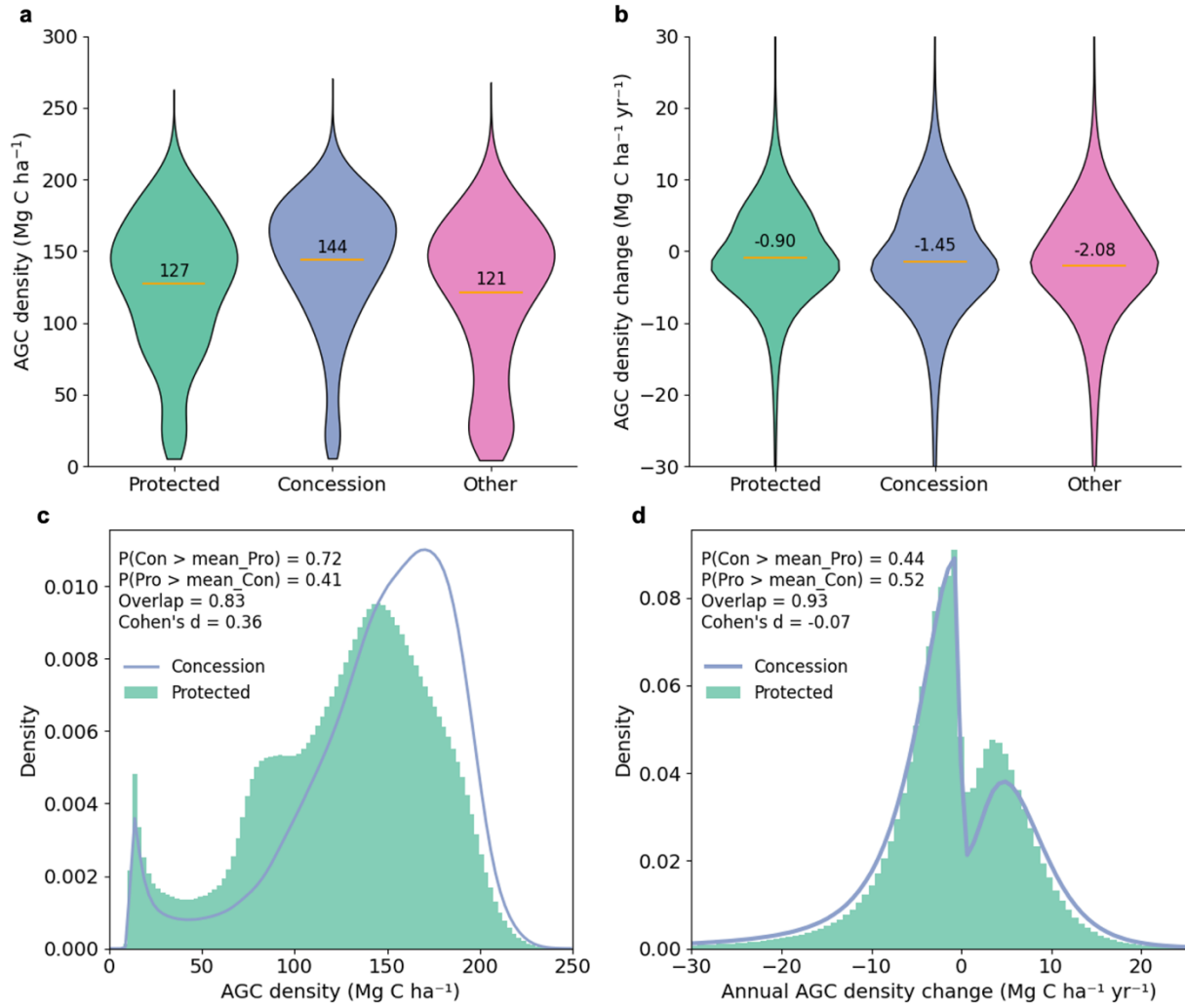
Supplementary Fig. 36: Mapping of aboveground carbon (AGC) change within protected areas and forest concessions in Central African forests. a, b, Spatial distribution of total AGC change (Tg C yr⁻¹) across individual protected areas (a) and forest concessions (b). Only officially designated protected areas and allocated forest concessions were included. Total AGC change was calculated for each individual area.



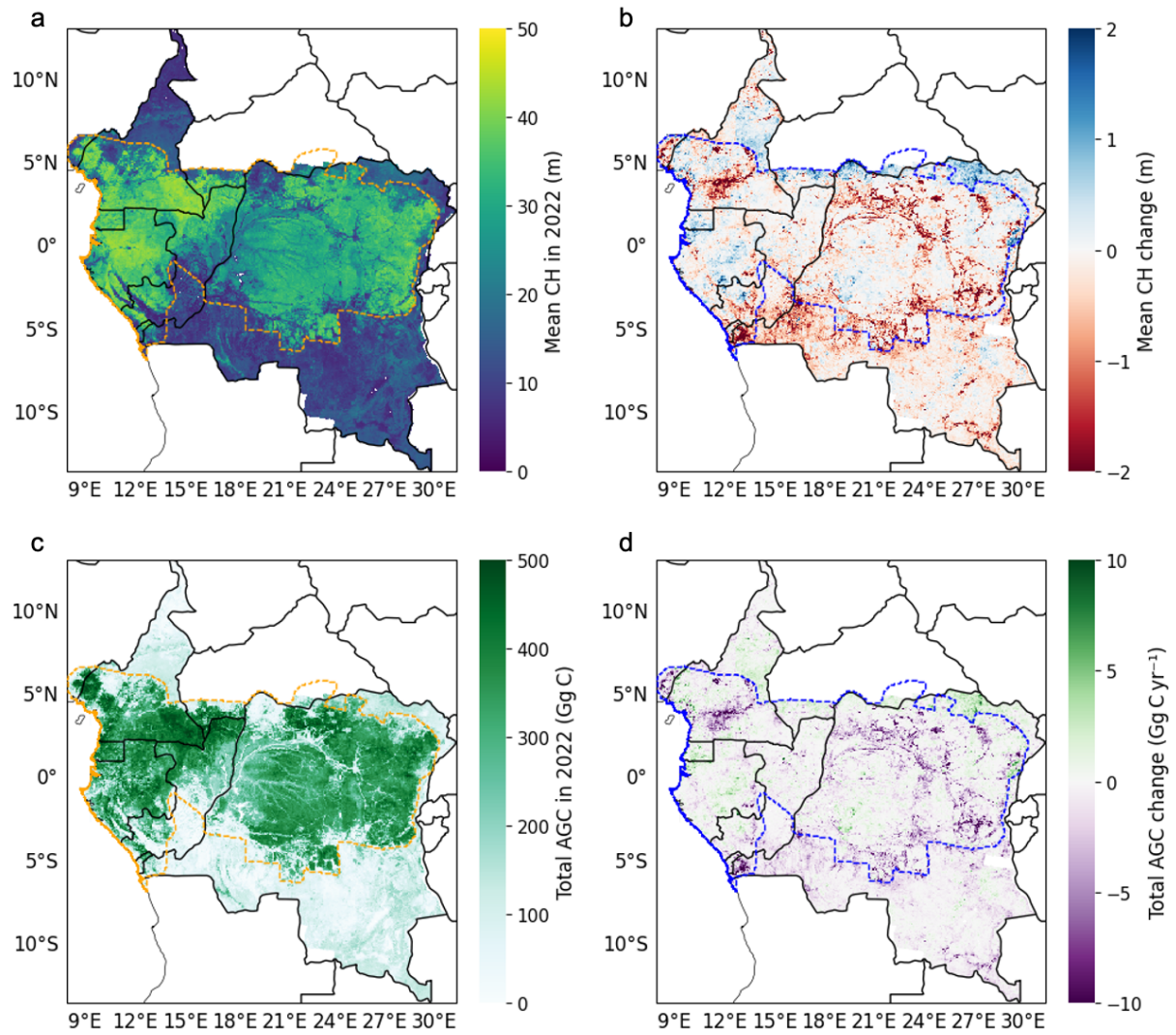
Supplementary Fig. 37: Comparisons of aboveground carbon density change within protected areas and their surroundings in Central African forests. **a**, Example of aboveground carbon (AGC) density change within a protected area (PA), with the PA boundary marked in black. **b**, Comparison of AGC density change within PAs and in surrounding areas (up to 3 km from the PA boundary). The orange line in each boxplot represents the mean, with corresponding values labeled. Differences between all group pairs are statistically significant ($p < 0.01$). **c**, Distribution of AGC density change across varying inward distances (0–10,000 m, at 1,000 m intervals) from the PA boundary. **d**, Distribution of AGC density change across varying outward distances (0–10,000 m, at 1,000 m intervals) from the PA boundary.



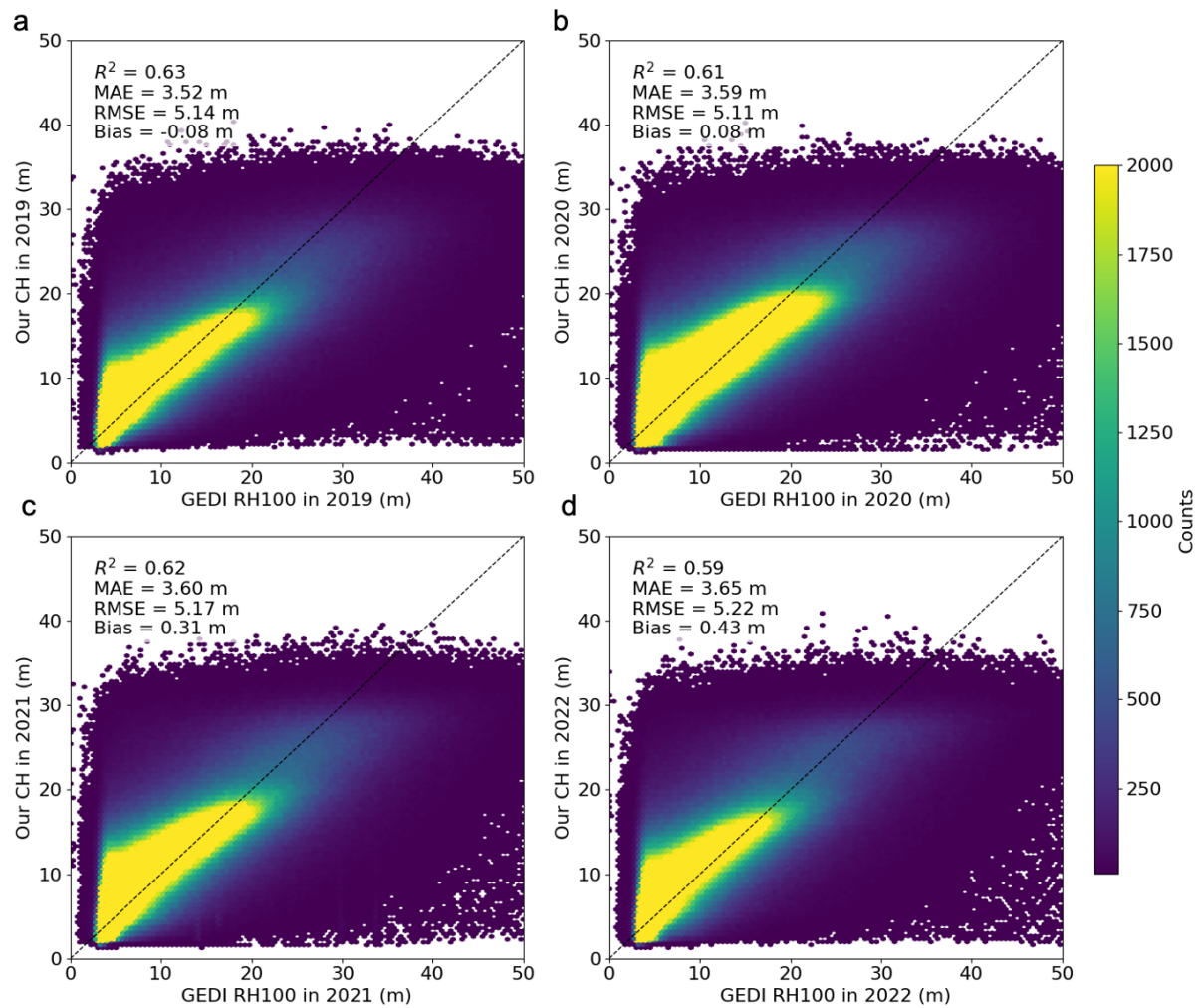
Supplementary Fig. 38: Aboveground carbon density and its change across protected and forest concession areas in Central African forests. a, c, Mean aboveground carbon (AGC) density in 2022 (a) and AGC density change between 2019 and 2022 (c) across forest concessions and different categories of protected areas, grouped by years since designation. Only officially designated protected areas and allocated forest concessions were included in the analysis. Areas lacking valid information on the year of establishment (≤ 2022) were excluded. To ensure statistical robustness, at least three areas of each type were required within each duration category to calculate mean values. b, d, Distributions of AGC density in 2022 (b) and AGC density change (d) for forest concessions and protected area categories. The black line within each box indicates the mean value.



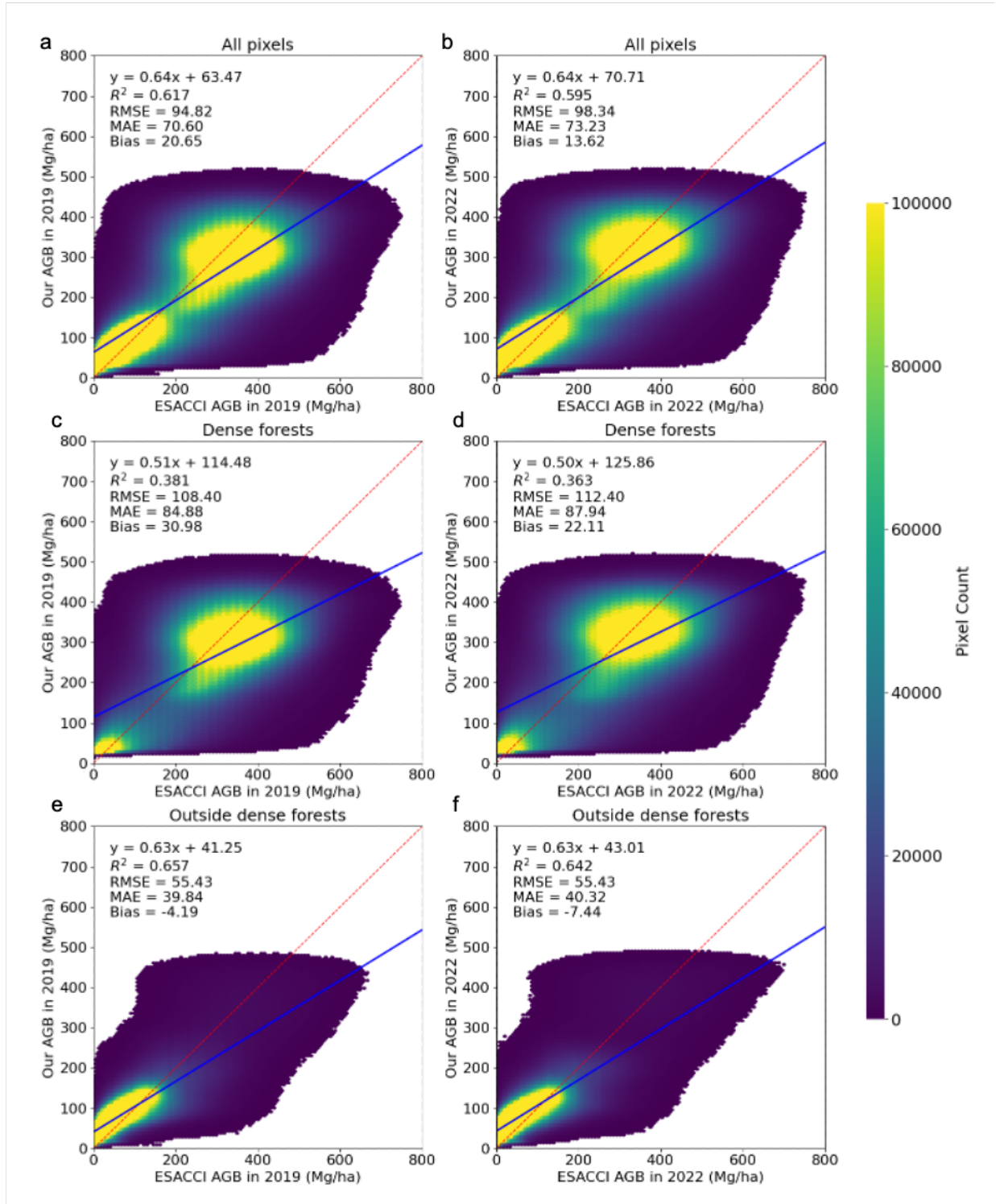
Supplementary Fig. 39: Comparisons of aboveground carbon density and its change across protected areas and forest concessions in Central African dense forests. **a**, Distribution of aboveground carbon (AGC) density in 2022 within protected areas, forest concessions, and other types. **b**, Distribution of AGC density change for all changed pixels from 2019 to 2022 within the same land categories. The orange line in each box represents the mean, with corresponding values labeled. Differences between all pairs of groups are statistically significant (p -value < 0.01). **c**, Distribution of AGC density in protected areas and concessions, showing substantial overlap between the two distributions (overlap coefficient = 0.83; Cohen's $d = 0.36$). The proportion (P) of concession pixels (Con) exceeding the mean AGC of protected areas (mean_Pro) is 0.72, while 0.41 of protected pixels exceed the concession mean. **d**, Distribution of AGC density change in protected areas and concessions, showing near-complete overlap (overlap coefficient = 0.93; Cohen's $d = -0.07$). The probabilities are close to 0.5 in both directions (0.44 and 0.53), indicating that carbon change dynamics are indistinguishable between land management types.



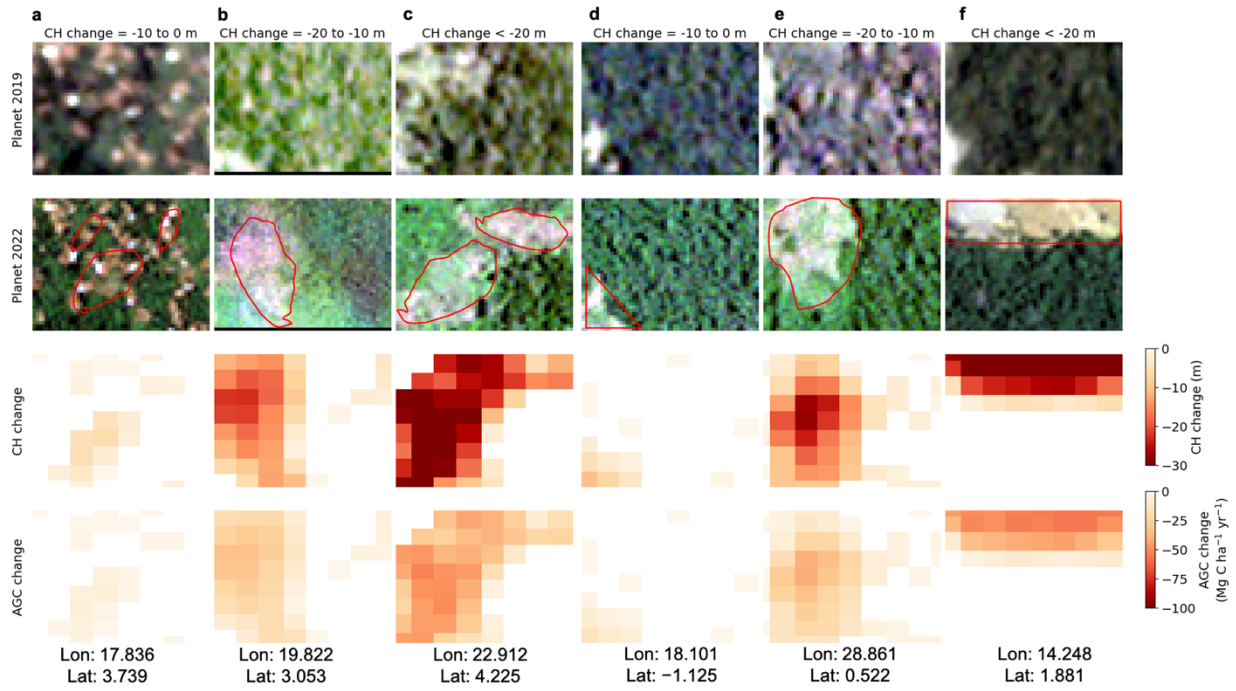
Supplementary Fig. 40: Maps of canopy height (CH), aboveground carbon (AGC), and their changes in five African countries. a, b, Mean CH in 2022 (**a**) and CH change from 2019 to 2022 (**b**), aggregated to 5-km grid cells for visualization. The height change was averaged from all change and non-change pixels within each 5-km grid cell. **c, d,** Total AGC in 2022 (**c**) and AGC change from 2019 to 2022 (**d**), aggregated to 5-km grid cells for visualization. The yellow and blue lines indicate the boundaries of the dense forest map.



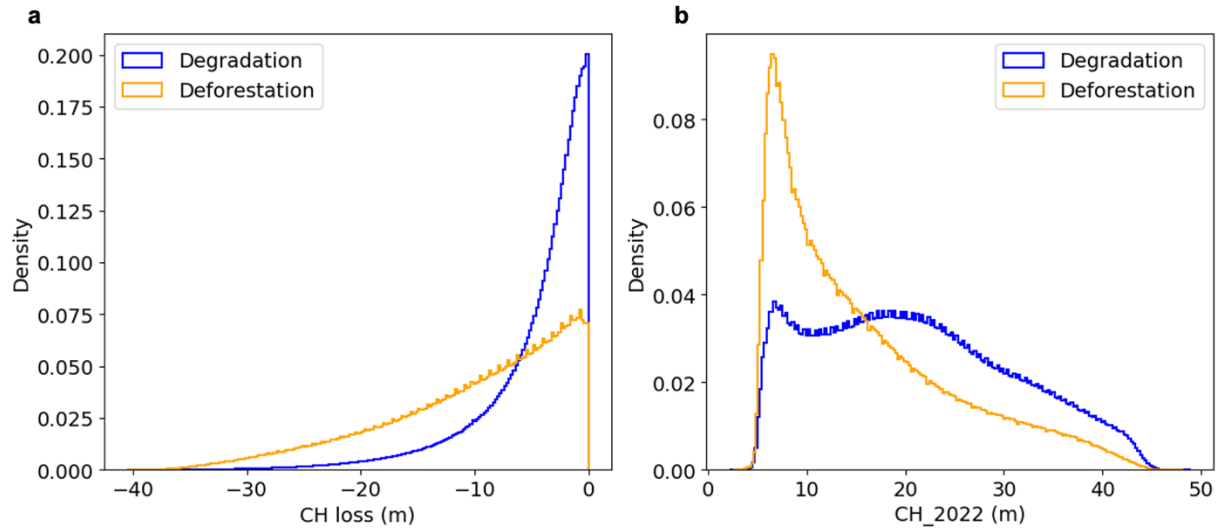
Supplementary Fig. 41: Validation of estimated annual canopy height in the non-dense forests of Central Africa against independent GEDI RH100 data. a–d, Comparisons between our CH estimates and GEDI RH100 for the years 2019–2022 in non-dense forests.



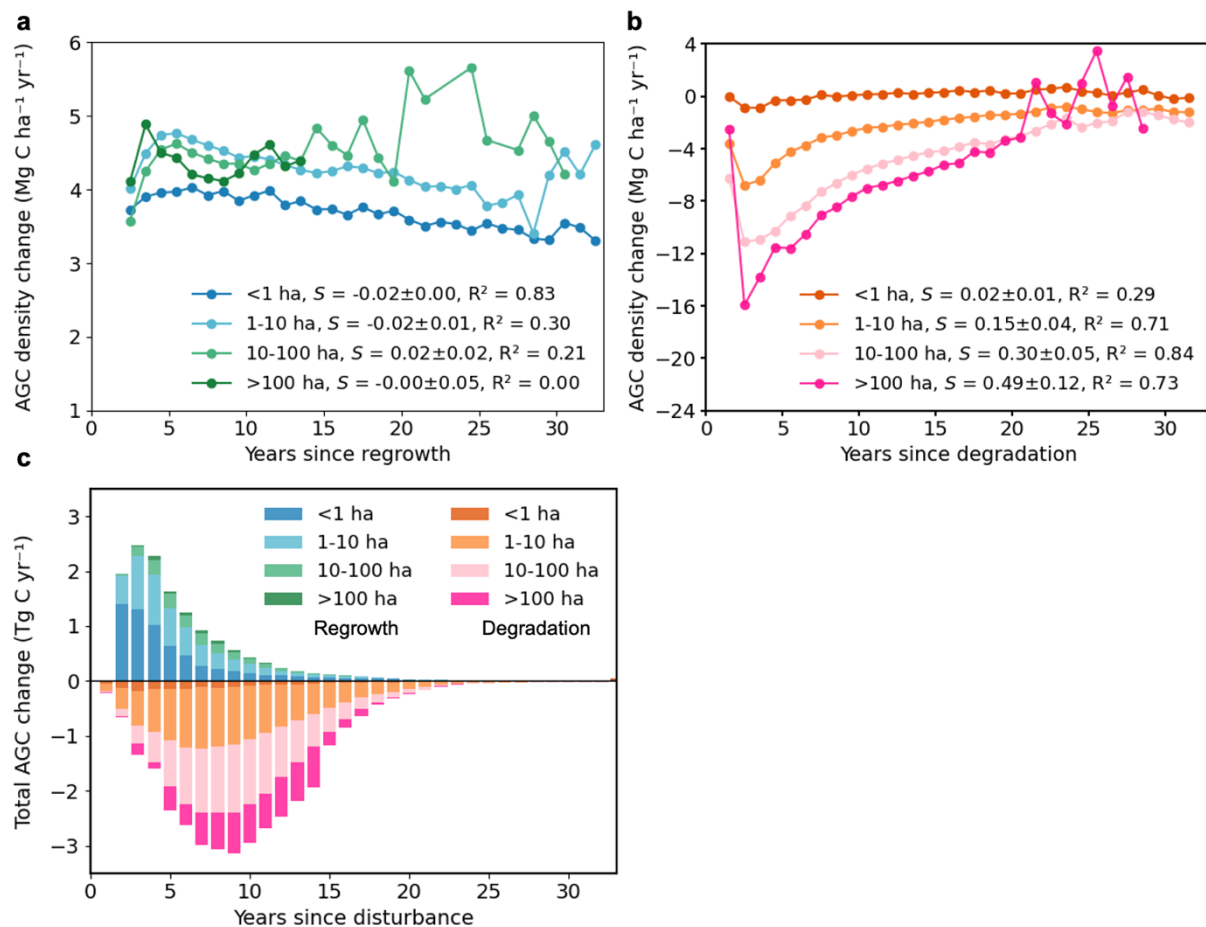
Supplementary Fig. 42: Validation of our estimated aboveground biomass (AGB) using ESA CCI AGB in Central African forests. a–f, Comparisons between our AGB estimates and ESA CCI AGB for 2019 and 2022 across all pixels (a, b), dense forests (c, d), and non-dense forests (e, f) in Central Africa. All comparisons are made at 100-m resolution. The regions of dense and non-dense forests are shown in **Supplementary Fig. 40**.



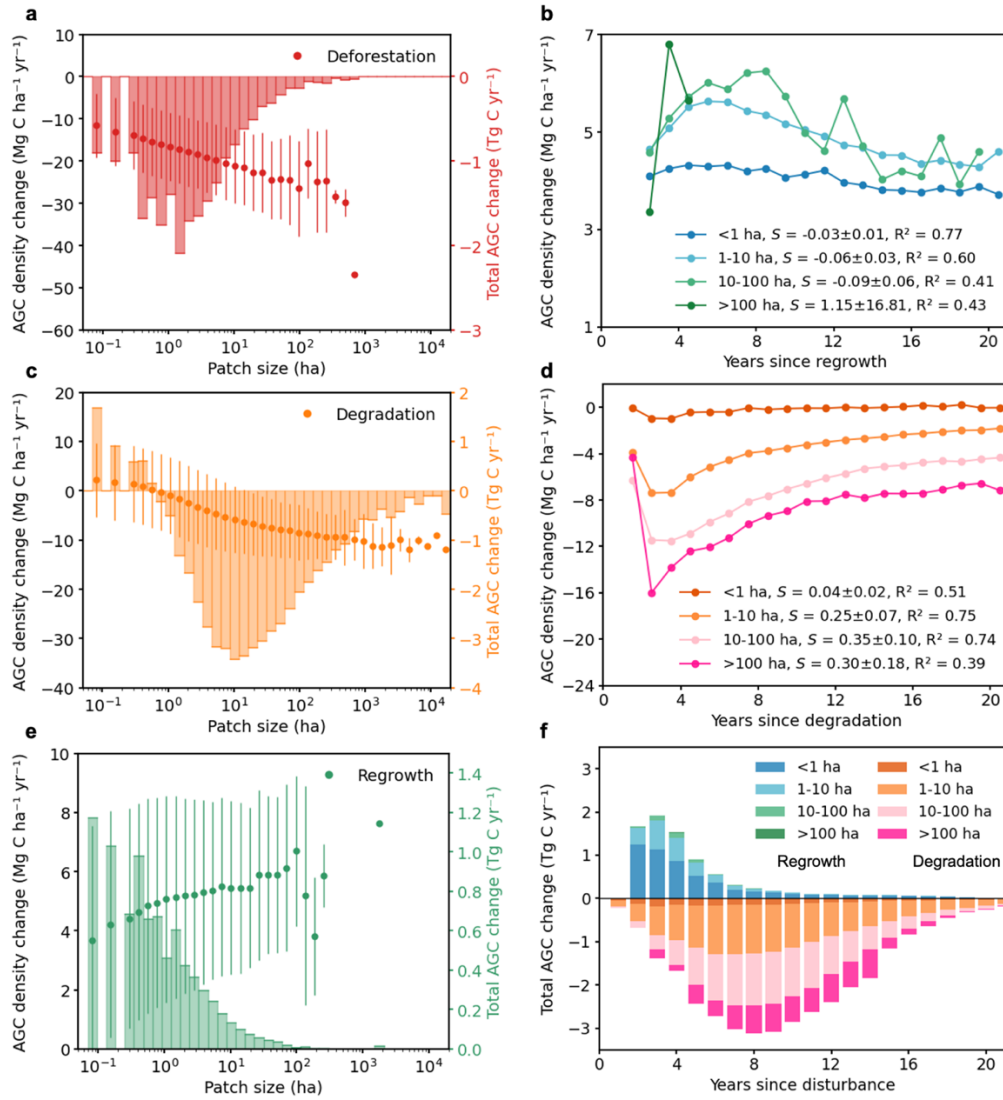
Supplementary Fig. 43. Examples of canopy height (CH) loss and corresponding aboveground carbon (AGC) change across different CH loss magnitude classes. Representative examples of CH-loss detections are shown for three CH loss magnitude classes ($-10 \leq \Delta\text{CH} < 0$ m, $-20 \leq \Delta\text{CH} < -10$ m and $\Delta\text{CH} < -20$ m), with two examples for each class (**a–f**). For each example, the top two rows show 5-m PlanetScope imagery acquired in 2019 and 2022, respectively, followed by the corresponding 30-m CH change map and AGC change map (2019–2022). The latitude and longitude of the center of each image chip are provided below each example. Red outlines delineate the regions that exhibit visible changes between the 2019 and 2022 PlanetScope images. These examples illustrate how visually identifiable canopy disturbances correspond to increasing canopy-height loss and associated AGC loss across the three CH loss magnitude classes.



Supplementary Fig. 44: Distribution of canopy height (CH) loss and CH in 2022 in areas of Tropical Moist Forests (TMF) degradation and deforestation. a, CH loss in pixels classified as TMF degradation and deforestation between 2019 and 2022, after processing. **b,** CH in 2022 in pixels classified as TMF degradation and deforestation between 2019 and 2022, after processing.



Supplementary Fig. 45: Aboveground carbon density changes across disturbance duration at varying patch sizes. **a**, **b**, Aboveground carbon (AGC) density changes across patch sizes over time since regrowth following deforestation (**a**) and degradation (**b**), showing mean values and associated trend lines (slope). **c**, Total AGC changes across patch sizes over time since regrowth after deforestation and degradation. AGC changes from different patch sizes are stacked, with regrowth values shown above the x-axis and degradation values shown below. Patch sizes were defined based on canopy height degradation and regrowth. Long-term records of continuous degradation and regrowth disturbances were derived from the Tropical Moist Forests dataset.



Supplementary Fig. 46: Aboveground carbon (AGC) changes across varying patch sizes and years in Central African forests after excluding afforestation. **a, c, e**, 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 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. **b, d**, AGC density changes across patch sizes over regrowth years after deforestation (**b**) and degradation years (**d**). Mean values and their trends (slope) are presented. **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. We excluded afforestation pixels identified from the Transition Map sub-types.

Supplementary Tables:

Supplementary Table 1: Visual validation of canopy height (CH) loss and gain detections, and estimation of false detection rates using visually confirmed stable forest areas from 5-m Planet imagery. Area (%) represents the proportion of each patch size class relative to the total mapped area of 0–100 ha patches. “No-change (CH-based)” refers to pixels where the CH-based method detected no CH change. “Reference stable forest” refers to pixels interpreted as having no detectable disturbance based on 5-m Planet imagery. “No-change” and “Reference stable forest” cover a much larger area than change patches

Patch size	Type	Area (%)	Sample size	TP	FP	UA
0–1 ha	Loss	29.48%	176	139	35	78.98%
1–5 ha	Loss	27.52%	71	57	14	80.28%
5–10 ha	Loss	11.98%	79	67	12	84.81%
10–100 ha	Loss	31.02%	96	89	8	92.70%
Area-weighted user’s accuracy (UA) for loss (0–100 ha)						84.29%
0–1 ha	Gain	45.63%	169	117	52	69.23%
1–5 ha	Gain	30.94%	113	92	21	81.42%
5–10 ha	Gain	8.79%	112	93	19	83.04%
10–100 ha	Gain	14.64%	104	91	13	87.50%
Area-weighted user’s accuracy (UA) for gain (0–100 ha)						76.89%
Type		/	Sample size	TN	FN	False omission rate (predicted no-change)
No-change (CH-based)		/	101	95	6	5.94%
Type		/	Sample size	Detected as change (%) (false positive rate)		
Reference stable forest (Planet imagery)		/	102	4.90%		

Note: Pixels with CH change (loss or gain) are treated as the positive class, and no-change pixels as the negative class. TP (true positives) and FP (false positives) refer to correctly and incorrectly detected change pixels, respectively. FN (false negatives) represent reference change pixels that are incorrectly classified as no change, while TN (true negatives) represent correctly identified no-change pixels. User’s accuracy (UA) is defined as $TP/(TP + FP)$. For reference stable forest pixels, the proportion detected as change corresponds to the false positive rate.

Supplementary Table 2: Percentage of independently validated canopy height (CH) loss patches detected by existing forest disturbance products under different minimum overlap thresholds. For each overlap threshold, percentages indicate the proportion of independently validated CH-loss patches for which the disturbed area mapped by RADD, GFC or TMF covered at least the specified percentage (10–50%) of the total CH loss patch area. CH-loss patches were grouped into four patch-size classes (0–1 ha, 1–5 ha, 5–10 ha, and 10–100 ha). These CH-loss patches were visually validated using high-resolution PlanetScope imagery. RADD overlap was defined as pixels with RADD alerts = 3 (high confidence), GFC overlap as pixels with Global Forest Change forest loss, and TMF overlap as Tropical Moist Forest disturbance pixels classified as degradation or deforestation. Lower thresholds indicate partial spatial agreement, whereas higher thresholds represent increasingly strong spatial correspondence between CH loss patches and existing disturbance products.

Patch size	Dataset	CH loss patch overlap (%)				
		>10%	>20%	>30%	>40%	>50%
0–1 ha	RADD	25.6	16.5	10.8	8.0	5.7
	GFC	53.4	40.3	30.1	22.7	13.1
	TMF	77.8	64.2	54.0	40.9	26.1
1–5 ha	RADD	14.1	5.6	1.4	0.0	0.0
	GFC	26.8	5.6	1.4	0.0	0.0
	TMF	70.4	56.3	32.4	21.1	8.5
5–10 ha	RADD	17.7	5.1	2.5	1.3	0.0
	GFC	53.2	20.3	5.1	0.0	0.0
	TMF	76.0	60.8	46.8	24.1	10.1
10–100 ha	RADD	17.7	6.3	2.1	1.0	1.0
	GFC	59.4	26.0	5.2	2.1	1.0
	TMF	86.5	71.9	54.2	28.1	13.5

Supplementary Table 3: Visual validation of canopy-height (CH) loss detections stratified by mean CH loss magnitude using randomly sampled 1-ha and 5-ha image chips interpreted from 5-m Planet imagery. The 1-ha and 5-ha categories refer to the size of randomly sampled image chips extracted from the CH change map rather than the size of individual CH loss patches. Image chips were stratified according to the mean estimated CH loss within each chip. Visual interpretation using 5-m Planet imagery was used only to determine whether canopy loss was present (true positive) or absent (false positive); it does not provide an independent assessment of the quantitative accuracy of CH loss magnitude estimates.

Random image-chip size	CH loss magnitude (m)	Sample number	TP	FP	UA
1 ha	$-10 \leq \Delta CH < 0$	95	68	27	71.58%
	$-20 \leq \Delta CH < -10$	98	80	18	81.63%
	$\Delta CH < -20$	117	100	17	85.47%
5 ha	$-10 \leq \Delta CH < 0$	92	74	18	80.43%
	$-20 \leq \Delta CH < -10$	105	88	17	83.81%
	$\Delta CH < -20$	108	94	14	87.04%

Supplementary Table 4. Contributions of disturbance patch-size classes and canopy-height (CH) change classes to affected area and aboveground carbon (AGC) change associated with mapped forest loss and gain. Area is expressed in Mha and AGC change in Tg C yr⁻¹. Percentages for forest loss and forest gain were calculated separately relative to the total affected area and total AGC change within the corresponding loss or gain category. Values are rounded to one decimal place

Type	Patch size (ha)	Area (Mha)	Area (%)	AGC change (Tg C yr ⁻¹)	AGC change (%)
Loss	0–1 ha	4.5	23.2	–14.6	11.6
	1–5 ha	4.2	21.7	–21.2	16.8
	5–10 ha	1.8	9.4	–12.0	9.5
	10–100 ha	4.8	24.5	–37.8	30.0
	>100 ha	4.1	21.1	–40.5	32.1
Gain	0–1 ha	5.2	43.7	27.6	40.7
	1–5 ha	3.5	29.7	21.4	31.6
	5–10 ha	1.0	8.4	6.2	9.2
	10–100 ha	1.7	14.0	9.8	14.5
	>100 ha	0.5	4.2	2.8	4.1
	CH change (Δ CH, m)	Area (Mha)	Area (%)	AGC change (Tg C yr ⁻¹)	AGC change (%)
Loss	$-10 \leq \Delta\text{CH} < 0$	17.5	90.3	–80.9	64.2
	$-20 \leq \Delta\text{CH} < -10$	1.5	7.9	–31.7	25.2
	$\Delta\text{CH} < -20$	0.4	1.8	–13.4	10.6
Gain	$0 < \Delta\text{CH} \leq 10$	11.4	97.0	60.7	89.5
	$\Delta\text{CH} > 10$	0.3	3.0	7.1	10.4

Supplementary Table 5: Patch-size classes with the largest contribution to AGC loss under different canopy-height thresholds. We compared results for deforestation loss and two degradation definitions: (i) TMF-based gain combined with canopy height threshold–defined loss, and (ii) TMF with XGBoost-based gain extension combined with canopy height threshold–defined loss. The reported patch size represents the size class with the largest contribution to AGC loss.

CH_{2022} threshold (m)	Deforestation based on CH-based threshold		Degradation based on CH-based threshold (loss) and TMF (gain)		Degradation based on CH-based threshold (loss) and XGBoost extension of TMF (gain)	
	Patch-size class with the largest AGC loss (ha)	AGC loss (Tg C yr ⁻¹)	Patch-size class with the largest AGC loss (ha)	AGC loss (Tg C yr ⁻¹)	Patch-size class with the largest AGC loss (ha)	AGC loss (Tg C yr ⁻¹)
10	1.5 ha	-2.2	5.4	-4.5	10.2	-3.5
11	1.5 ha	-2.6	5.4	-4.4	10.2	-3.4
12	1.5 ha	-2.9	5.4	-4.3	10.2	-3.2
13	1.5 ha	-3.3	5.4	-4.2	10.2	-3.0
14	1.5 ha	-3.5	5.4	-4.0	10.2	-2.8
15	1.5 ha	-3.8	5.4	-3.8	10.2	-2.6
16	1.5 ha	-4.0	5.4	-3.7	5.4	-2.4
17	1.5 ha	-4.2	5.4	-3.5	5.4	-2.2
18	1.5 ha	-4.3	3.9	-3.3	5.4	-2.1
19	1.5 ha	-4.5	3.9	-3.2	5.4	-1.9
20	1.5 ha	-4.6	1.5	-3.0	5.4	-1.7

Supplementary Table 6: Summary of aboveground carbon and corresponding area changes in Central African dense forests. Disturbance types were identified using canopy height (CH) change data, multiple reference datasets, and a machine learning–based classification of CH change, which differs from the Tropical Moist Forests (TMF) disturbance map. The units for aboveground carbon (AGC) and area changes are Tg C yr⁻¹ and Mha, respectively. Uncertainty in AGC change estimation arises from three sources: biomass change estimation, disturbance classification, and CH change processing. Uncertainty in area change estimation is derived from the latter two components.

		All		Protected area		Concessions	
		AGC	Area	AGC	Area	AGC	Area
Loss	Other	-22.4 ± 6.0	5.8 ± 2.0	-4.1 ± 1.2	1.1 ± 0.4	-3.7 ± 1.1	1.0 ± 0.4
	Deforestation	-23.3 ± 6.6	1.4 ± 0.4	-2.0 ± 0.6	0.1 ± 0.0	-2.7 ± 0.7	0.2 ± 0.1
	Degradation	-80.4 ± 11.5	12.2 ± 1.5	-7.4 ± 1.5	1.3 ± 0.2	-8.5 ± 1.7	1.2 ± 0.1
	Total	-126.1 ± 20.6	19.4 ± 3.2	-13.5 ± 2.4	2.5 ± 0.5	-14.9 ± 2.7	2.4 ± 0.5
Gain	Other	18.8 ± 4.1	3.6 ± 0.7	4.2 ± 0.9	0.8 ± 0.2	3.8 ± 0.8	0.7 ± 0.1
	Degradation	34.4 ± 5.6	4.4 ± 0.6	4.1 ± 0.7	0.5 ± 0.1	4.8 ± 0.8	0.5 ± 0.1
	Regrowth	14.5 ± 2.6	3.8 ± 0.5	1.3 ± 0.3	0.4 ± 0.1	0.8 ± 0.2	0.2 ± 0.0
	Total	67.8 ± 10.0	11.8 ± 1.1	9.6 ± 1.5	1.7 ± 0.2	9.4 ± 1.5	1.4 ± 0.2
Net AGC (All change area)		-58.3 ± 13.5	31.2 ± 3.6	-3.8 ± 1.4	4.2 ± 0.6	-5.4 ± 1.6	3.8 ± 0.6

Supplementary Table 7: Summary of aboveground carbon (AGC) changes in dense forests of Central Africa and across individual countries. The total forest area was quantified based on canopy height (≥ 5 m) in 2022. Note that overlaps exist between protected areas and forest concessions; therefore, a combined category is also reported to account for these overlapping regions. We calculated the mean AGC density change using both changed and unchanged pixels.

The loss and gain fractions represent the percentage of pixels experiencing AGC loss or gain relative to the total number of pixels.

	Total area (Mha)	Total AGC change (Tg C yr ⁻¹)	Mean AGC density change (std; Mg C ha ⁻¹ yr ⁻¹)	Loss fraction	Gain fraction
Central Africa dense forest					
All area	216.0	-58.3	-0.27 ± 3.36	9.0%	5.5%
Combined protected & concession areas	73.5	-8.7	-0.12 ± 2.62	6.2%	3.9%
Protected	41.6	-3.8	-0.09 ± 2.40	6.0%	4.1%
Concession	36.7	-5.4	-0.15 ± 2.88	6.5%	3.8%
Cameroon dense forest					
All area	27.6	-9.6	-0.35 ± 3.97	10.5%	6.2%
Combined protected & concession areas	9.3	-0.4	-0.04 ± 2.51	5.0%	3.3%
Protected	3.1	0.1	0.04 ± 2.12	4.5%	4.2%
Concession	6.2	-0.5	-0.09 ± 2.68	5.3%	2.8%
DRC dense forest					
All area	129.0	-46.4	-0.36 ± 3.50	9.8%	5.5%
Combined protected & concession areas	31.2	-6.2	-0.20 ± 2.86	7.1%	4.3%
Protected	21.3	-2.3	-0.11 ± 2.56	6.4%	4.6%
Concession	12.4	-4.0	-0.33 ± 3.39	8.3%	4.4%
Congo dense forest					
All area	25.3	-3.4	-0.13 ± 2.30	7.0%	3.8%
Combined protected & concession areas	21.5	-2.6	-0.12 ± 2.27	6.3%	3.5%
Protected	11.0	-1.3	-0.12 ± 1.84	6.0%	3.3%
Concession	12.3	-1.7	-0.13 ± 2.60	6.6%	3.6%
Gabon dense forest					
All area	21.7	1.0	0.04 ± 2.57	4.9%	3.8%
Combined protected & concession areas	9.5	0.9	0.10 ± 2.33	3.8%	3.6%
Protected	4.4	0.2	0.03 ± 2.30	4.3%	3.4%
Concession	5.4	0.7	0.13 ± 2.33	3.4%	3.6%
Equatorial Guinea dense forest					
All area	2.3	1.0	0.42 ± 3.43	3.7%	6.9%
Combined protected & concession areas	0.7	0.3	0.42 ± 2.97	2.8%	6.7%
Protected	0.4	0.2	0.50 ± 2.69	2.0%	7.3%
Concession	0.3	0.1	0.33 ± 3.40	4.0%	5.9%

Supplementary Table 8: Comparison of aboveground carbon change and land-use carbon flux estimates in Central African forests. Carbon gains and losses (Tg C yr^{-1}) from bookkeeping models (BKs) and national inventories (NGHGI DB) are derived from Land Use, Land-Use Change and Forestry (LULUCF) estimates for forest and deforest land, respectively⁵. Net carbon changes from BKs, dynamic global vegetation models (DGVMs), NGHGI DB, and the statistical division of the Food and Agricultural Organization of the United Nations (FAOSTAT) are derived from Land Use, Land-Use Change and Forestry (LULUCF) estimates⁶, which include the carbon change from organic soils and other land uses. The results for BKs are based on the averaged from three BKs (BLUE, OSCAR, and HN). The results for DGVMs are based on the average of simulations from three versions of the TRENDY model ensemble. FAOSTAT^{6,7} and NGHGI DB correspond to national greenhouse gas inventory databases derived from country reports and geospatial analyses. The net carbon change from NGHGI DB was harmonized for the managed land issue to align more closely with model definitions⁶. The error for ΔAGC represents estimated uncertainty, while those for BKs and DGVMs indicate the standard deviation across models. Based on our AGC

		ΔAGC (dense forests)	ΔAGC + ΔBGC (dense forests)	$\Delta\text{AGC} + \Delta\text{BGC}$ (country: dense, non-dense forests)	BKs ⁵	BKs ⁶	DGVMs ⁶	NGHGI DB ⁵	FAOS TAT ^{6,7}	Harmonized NGHGI. DB ⁶
Cameroon	Gain	10.5 ± 1.7	13.8 ± 2.6	22.4 ± 3.8	11.2 ± 8.7			29.4		
	Loss	-20.0 ± 3.9	-26.2 ± 5.4	-31.9 ± 5.7	-18.1 ± 10.9			-5.8		
	Net	-9.6 ± 2.8	-12.5 ± 3.3	-9.6 ± 3.4	-7.1 ± 3.0	-7.2 ± 3.2	-16.2 ± 7.4	20.9	-9.2	-4.6
DRC	Gain	39.1 ± 6.0	50.5 ± 10.1	78.1 ± 13.0	74.1 ± 14.0			146.7		
	Loss	-85.5 ± 15.7	-109.7 ± 23.3	-168.3 ± 29.3	-197.1 ± 35.1			-144.3		
	Net	-46.4 ± 10.8	-59.5 ± 14.3	-90.5 ± 17.3	-126.6 ± 21.2	-127.4 ± 19.7	-63.6 ± 21.0	2.4	-164.0	-147.1
Congo	Gain	5.1 ± 0.9	6.9 ± 1.9	7.6 ± 1.9	3.4 ± 1.7			8.9		
	Loss	-8.5 ± 1.8	-11.3 ± 3.3	-14.4 ± 3.4	-6.2 ± 0.8			-0.9		
	Net	-3.4 ± 1.1	-4.5 ± 1.5	-6.9 ± 1.7	-3.1 ± 1.2	-3.4 ± 1.4	-7.4 ± 1.6	8.0	-2.9	
Gabon	Gain	6.9 ± 1.4	9.0 ± 2.1	9.0 ± 2.1	2.1 ± 0.7			32.8		
	Loss	-6.0 ± 1.3	-7.7 ± 1.9	-7.8 ± 1.9	-4.0 ± 0.3			-3.1		
	Net	1.0 ± 0.5	1.2 ± 0.5	1.3 ± 0.5	-1.9 ± 0.7	-2.0 ± 0.7	-3.1 ± 0.7	29.7	-1.8	2.3
Equatorial Guinea	Gain	1.6 ± 0.4	2.0 ± 0.4	2.0 ± 0.4	1.0 ± 0.5			-1.4		
	Loss	-0.6 ± 0.1	-0.7 ± 0.1	-0.7 ± 0.1	-1.6 ± 0.3			-0.9		
	Net	1.0 ± 0.3	1.2 ± 0.3	1.2 ± 0.3	-0.6 ± 0.4	-0.7 ± 0.4	-0.5 ± 0.1	-2.3	-1.1	1.0

Supplementary Table 9: Comparisons of forest carbon growth rates from the NGHGI database, IPCC defaults, and observed aboveground carbon change (Δ AGC) across different countries. The carbon sink reported in the national inventories (NGHGI) database refers to forest land, while forest area estimates are taken from national reports in the Global Forest Resources Assessment 2020 (FRA 2020). The NGHGI carbon growth rate is calculated as the ratio of the NGHGI-reported carbon sink to the corresponding forest area from FRA 2020. The mean Δ AGC was derived from all undisturbed forests identified by the TMF dataset, with unchanged pixels set to zero. The IPCC conversion factor is 0.47⁸.

	NGHGI DB carbon sink (Tg C yr ⁻¹)	FRA 2020 (Forest area, 1000 ha)	NGHGI DB mean forest carbon growth (Mg C ha ⁻¹ yr ⁻¹)	Mean Δ AGC (undisturbed forests; Mg C ha ⁻¹ yr ⁻¹)	IPCC default growth ⁹ (Mg C ha ⁻¹ yr ⁻¹)	Refined IPCC default growth ⁸ (Mg C ha ⁻¹ yr ⁻¹)
Gabon	29.4	23531	1.25	0.075	Tropical rainforest. 4.7 (≤ 20 y); 1.1–1.8 (> 20 y)	Tropical rainforest. 0.6 (Primary; undisturbed forests); 3.6 (Secondary $\leq$ 20 years); 1.6 (Secondary $>$ 20 years)
Equatorial Guinea	-1.4	2448	-0.57	0.400		
Cameroon	32.8	20340	1.61	-0.034		
Congo	8.9	21946	0.41	-0.028		
Democratic Republic of the Congo	146.7	126155	1.16	-0.014		

Supplementary Table 10: Summary of country-level average belowground-to-aboveground carbon (BGC/AGC) ratios in dense and non-dense forests. The BGC/AGC ratios are derived from Spawn et al. (2020) [10](#).

Country	Average BGC/AGC ratio	
	Dense forests	Non-dense forests
Cameroon	0.31	0.74
DRC	0.29	0.63
Congo	0.35	0.71
Gabon	0.29	0.80
Equatorial Guinea	0.25	0.26

Supplementary Table 11: Comparisons of our estimated aboveground carbon change with prior work. The relative recovery rates indicate the percentage AGC recovered relative to old-growth-forest values.

Our map (2019–2022, Central African forests)	Reference
–69.3 Tg C yr ^{–1} from all forest degradation and deforestation	–75.5 ± 10.4 Tg C yr ^{–1} from deforestation based on L-band vegetation optical depth data (2010–2019, Central Africa) ¹¹
AGC density loss rate per unit of disturbance area (–22.9 Mg C ha ^{–1})	GEDI-derived results for the Amazon (–23.1 Mg C ha ^{–1}) ¹²
AGC gain rates from regrowth (3.8 Mg C ha ^{–1} yr ^{–1})	LiDAR-derived growth (3.8 Mg C ha ^{–1} yr ^{–1}) reported in Amazon forests ¹³
Our retrieved AGC recovery rate across varying patch sizes (2.7–4.8 Mg C ha ^{–1} yr ^{–1})	Global modeled estimates in African tropical rainforests (4.55 Mg C ha ^{–1} yr ^{–1}) and moist forest (2.67 Mg C ha ^{–1} yr ^{–1}) ¹⁴ ; exceed refined IPCC defaults for aboveground net biomass change (ΔAGB) rates in African tropical rainforests (3.6 Mg C ha ^{–1} yr ^{–1}) and moist forests (1.4 Mg C ha ^{–1} yr ^{–1}) ⁸
Relative AGC recovery rates (2.0%–3.6% per year) over three years for regrowth forests in Africa (most young regrowth forests; 1–8 years old)	20-year recovery estimates (e.g., 2.3% ¹⁵ , 1.7% ¹⁶ , and 2.6% ¹⁴)

Supplementary Table 12: Sensitivity analyses of key parameter choices of the canopy height.

The table summarizes the main parameter settings used in the canopy height (CH) change detection framework and the corresponding sensitivity analyses. Trend detection refers to the Mann–Kendall trend threshold (S-statistic) used to identify consistent CH gain signals. Sentinel-1 filtering refers to the coefficient of variation (CV) threshold applied to Sentinel-1 VV backscatter to remove potentially noisy CH loss pixels. Canopy cover filtering refers to the canopy cover change threshold (ΔCC) used as a consistency constraint for weak disturbances. Sensitivity analyses were conducted by varying each parameter within plausible ranges while keeping the remaining processing steps unchanged.

Canopy height change processing	Description of change processing	key parameter choices	
		Parameter used in main analysis	Sensitivity analysis
trend detection	We applied a Mann–Kendall trend test to annual CH gain data from 2019 to 2022 to identify gradual and consistent canopy height increases, retaining only pixels with S-statistic (S) ≥ 6 to reduce noise and avoid false regrowth signals.	$S \geq 6$	$S \geq 6$; $S \geq 5$
Sentinel-1 filtering	Sentinel-1 filtering was applied to remove potentially false CH loss pixels exhibiting very low temporal variability in the Sentinel-1 VV signal ($ CV \leq 5\%$) between 2019 and 2022.	$ CV \leq 5\%$	$ CV \leq 1\% - 6\%$
Canopy cover filtering	We used annual canopy cover change ($ \Delta CC $) data as an additional reference to validate CH change, treating pixels with $ \Delta CC \leq 2\%$ as weak or uncertain disturbances and removing them only when ΔCC and ΔCH showed inconsistent change directions.	$ \Delta CC \leq 2\%$	$ \Delta CC \leq 1\% - 3\%$

Supplementary Table 13: Variability in estimated aboveground carbon (AGC) change across different canopy height change processing configurations. Different combinations of thresholding, filtering, and change detection parameters were tested to assess methodological uncertainty. The Mann–Kendall S-statistic was used to identify canopy height (CH) gain between 2019 and 2022, with a threshold of $S \geq 6$ to ensure consistent growth signals given the short time series; sensitivity to a relaxed threshold ($S \geq 5$) was assessed and incorporated into structural uncertainty. Variability in the Sentinel-1 VV signal was used to reduce noise in pixels classified as CH loss. Canopy cover change was further used as a consistency check to ensure that CH change trends aligned with canopy cover dynamics, focusing specifically on areas with small canopy cover changes. The bold values indicate the selected processing configurations.

Canopy cover change (ΔCC , %)	Variability in Sentinel-1 VV signal ($ CV $, %)	Mann-Kendall statistic for CH gain	AGC change ($Tg\ C\ yr^{-1}$)			AGC loss ($Tg\ C\ yr^{-1}$)			AGC gain ($Tg\ C\ yr^{-1}$)		
			Gain	Loss	Net	Other	Def	Deg	Reg	Deg	Other
$ \Delta CC \leq 1$	$ CV \leq 1$	$S \geq 5$	74.2	-155.2	-81.0	-42.8	-23.9	-88.5	17.2	34.9	22.2
	$ CV \leq 1$	$S \geq 6$	73.6	-155.2	-81.6	-42.8	-23.9	-88.5	17.1	34.6	21.8
	$ CV \leq 2$	$S \geq 5$	74.2	-144.7	-70.4	-34.7	-23.8	-86.2	17.2	34.9	22.2
	$ CV \leq 2$	$S \geq 6$	73.6	-144.7	-71.1	-34.7	-23.8	-86.2	17.1	34.6	21.8
	$ CV \leq 3$	$S \geq 5$	74.2	-137.8	-63.5	-29.9	-23.6	-84.3	17.2	34.9	22.2
	$ CV \leq 3$	$S \geq 6$	73.6	-137.8	-64.2	-29.9	-23.6	-84.3	17.1	34.6	21.8
	$ CV \leq 4$	$S \geq 5$	74.2	-133.9	-59.7	-27.5	-23.5	-82.9	17.2	34.9	22.2
	$ CV \leq 4$	$S \geq 6$	73.6	-133.9	-60.3	-27.5	-23.5	-82.9	17.1	34.6	21.8
	$ CV \leq 5$	$S \geq 5$	74.2	-131.7	-57.4	-26.5	-23.3	-81.9	17.2	34.9	22.2
	$ CV \leq 5$	$S \geq 6$	73.6	-131.7	-58.1	-26.5	-23.3	-81.9	17.1	34.6	21.8
	$ CV \leq 6$	$S \geq 5$	74.2	-129.9	-55.7	-25.9	-23.1	-80.9	17.2	34.9	22.2
	$ CV \leq 6$	$S \geq 6$	73.6	-129.9	-56.3	-25.9	-23.1	-80.9	17.1	34.6	21.8
$ \Delta CC \leq 2$	$ CV \leq 1$	$S \geq 5$	68.3	-146.4	-78.1	-35.9	-23.8	-86.7	14.6	34.6	19.1
	$ CV \leq 1$	$S \geq 6$	67.8	-146.4	-78.7	-35.9	-23.8	-86.7	14.5	34.4	18.8
	$ CV \leq 2$	$S \geq 5$	68.3	-137.5	-69.2	-29.2	-23.7	-84.5	14.6	34.6	19.1
	$ CV \leq 2$	$S \geq 6$	67.8	-137.5	-69.7	-29.2	-23.7	-84.5	14.5	34.4	18.8

	$ CV \leq 3$	$S \geq 5$	68.3	-131.5	-63.2	-25.2	-23.6	-82.7	14.6	34.6	19.1
	$ CV \leq 3$	$S \geq 6$	67.8	-131.5	-63.8	-25.2	-23.6	-82.7	14.5	34.4	18.8
	$ CV \leq 4$	$S \geq 5$	68.3	-128.1	-59.8	-23.3	-23.4	-81.4	14.6	34.6	19.1
	$ CV \leq 4$	$S \geq 6$	67.8	-128.1	-60.4	-23.3	-23.4	-81.4	14.5	34.4	18.8
	$ CV \leq 5$	$S \geq 5$	68.3	-126.1	-57.7	-22.4	-23.3	-80.4	14.6	34.6	19.1
	$CV \leq 5$	$S \geq 6$	67.8	-126.1	-58.3	-22.4	-23.3	-80.4	14.5	34.4	18.8
	$ CV \leq 6$	$S \geq 5$	68.3	-124.4	-56.1	-21.9	-23.1	-79.5	14.6	34.6	19.1
	$ CV \leq 6$	$S \geq 6$	67.8	-124.4	-56.7	-21.9	-23.1	-79.5	14.5	34.4	18.8
$ \Delta CC \leq 3$	$ CV \leq 1$	$S \geq 5$	66.3	-143.0	-76.7	-33.7	-23.8	-85.5	14.6	33.4	18.3
	$ CV \leq 1$	$S \geq 6$	65.7	-143.0	-77.3	-33.7	-23.8	-85.5	14.5	33.2	18.0
	$ CV \leq 2$	$S \geq 5$	66.3	-134.6	-68.3	-27.5	-23.7	-83.4	14.6	33.4	18.3
	$ CV \leq 2$	$S \geq 6$	65.7	-134.6	-68.9	-27.5	-23.7	-83.4	14.5	33.2	18.0
	$ CV \leq 3$	$S \geq 5$	66.3	-129.0	-62.7	-23.7	-23.5	-81.7	14.6	33.4	18.3
	$ CV \leq 3$	$S \geq 6$	65.7	-129.0	-63.3	-23.7	-23.5	-81.7	14.5	33.2	18.0
	$ CV \leq 4$	$S \geq 5$	66.3	-125.7	-59.4	-21.9	-23.4	-80.4	14.6	33.4	18.3
	$ CV \leq 4$	$S \geq 6$	65.7	-125.7	-60.0	-21.9	-23.4	-80.4	14.5	33.2	18.0
	$ CV \leq 5$	$S \geq 5$	66.3	-123.7	-57.5	-21.0	-23.2	-79.5	14.6	33.4	18.3
	$ CV \leq 5$	$S \geq 6$	65.7	-123.7	-58.0	-21.0	-23.2	-79.5	14.5	33.2	18.0
	$ CV \leq 6$	$S \geq 5$	66.3	-122.1	-55.9	-20.6	-23.1	-78.5	14.6	33.4	18.3
	$ CV \leq 6$	$S \geq 6$	65.7	-122.1	-56.4	-20.6	-23.1	-78.5	14.5	33.2	18.0

Supplementary Table 14: Variability in estimated aboveground carbon (AGC) change area across different canopy height change processing configurations. Different combinations of thresholding, filtering, and change detection parameters were tested to assess methodological uncertainty. The Mann–Kendall S-statistic was used to identify canopy height (CH) gain between 2019 and 2022, with a threshold of $S \geq 6$ to ensure consistent growth signals given the short time series; sensitivity to a relaxed threshold ($S \geq 5$) was assessed and incorporated into structural uncertainty. Variability in the Sentinel-1 VV signal was used to reduce noise in pixels classified as CH loss. Canopy cover change was further used as a consistency check to ensure that CH change trends aligned with canopy cover dynamics, focusing specifically on areas with small canopy cover changes. The bold values indicate the selected processing configurations.

Canopy cover change (ΔCC , %)	Variability in Sentinel-1 VV signal ($ CV $, %)	Mann-Kendall statistic for CH gain	AGC change area (Mha)			AGC loss area (Mha)			AGC gain area (Mha)		
			Gain	Loss	Net	Other	Def	Deg	Reg	Deg	Other
$ \Delta CC \leq 1$	$ CV \leq 1$	$S \geq 5$	12.8	30.0	42.7	14.2	1.5	14.3	4.1	4.4	4.2
	$ CV \leq 1$	$S \geq 6$	12.6	30.0	42.6	14.2	1.5	14.3	4.0	4.4	4.2
	$ CV \leq 2$	$S \geq 5$	12.8	25.7	38.4	10.6	1.5	13.6	4.1	4.4	4.2
	$ CV \leq 2$	$S \geq 6$	12.6	25.7	38.3	10.6	1.5	13.6	4.0	4.4	4.2
	$ CV \leq 3$	$S \geq 5$	12.8	22.9	35.7	8.4	1.4	13.1	4.1	4.4	4.2
	$ CV \leq 3$	$S \geq 6$	12.6	22.9	35.5	8.4	1.4	13.1	4.0	4.4	4.2
	$ CV \leq 4$	$S \geq 5$	12.8	21.5	34.3	7.4	1.4	12.7	4.1	4.4	4.2
	$ CV \leq 4$	$S \geq 6$	12.6	21.5	34.1	7.4	1.4	12.7	4.0	4.4	4.2
	$ CV \leq 5$	$S \geq 5$	12.8	20.8	33.5	6.9	1.4	12.4	4.1	4.4	4.2
	$ CV \leq 5$	$S \geq 6$	12.6	20.8	33.4	6.9	1.4	12.4	4.0	4.4	4.2
	$ CV \leq 6$	$S \geq 5$	12.8	20.2	32.9	6.7	1.4	12.1	4.1	4.4	4.2
	$ CV \leq 6$	$S \geq 6$	12.6	20.2	32.8	6.7	1.4	12.1	4.0	4.4	4.2
$ \Delta CC \leq 2$	$ CV \leq 1$	$S \geq 5$	11.9	27.2	39.2	11.8	1.5	14.0	3.8	4.4	3.7
	$ CV \leq 1$	$S \geq 6$	11.8	27.2	39.0	11.8	1.5	14.0	3.8	4.4	3.6
	$ CV \leq 2$	$S \geq 5$	11.9	23.6	35.6	8.8	1.5	13.4	3.8	4.4	3.7
	$ CV \leq 2$	$S \geq 6$	11.8	23.6	35.4	8.8	1.5	13.4	3.8	4.4	3.6
	$ CV \leq 3$	$S \geq 5$	11.9	21.3	33.3	7.1	1.4	12.8	3.8	4.4	3.7

	$ CV \leq 3$	$S \geq 6$	11.8	21.3	33.1	7.1	1.4	12.8	3.8	4.4	3.6
	$ CV \leq 4$	$S \geq 5$	11.9	20.1	32.0	6.2	1.4	12.5	3.8	4.4	3.7
	$ CV \leq 4$	$S \geq 6$	11.8	20.1	31.9	6.2	1.4	12.5	3.8	4.4	3.6
	$ CV \leq 5$	$S \geq 5$	11.9	19.4	31.4	5.8	1.4	12.2	3.8	4.4	3.7
	$CV \leq 5$	$S \geq 6$	11.8	19.4	31.2	5.8	1.4	12.2	3.8	4.4	3.6
	$ CV \leq 6$	$S \geq 5$	11.9	18.9	30.8	5.6	1.4	11.9	3.8	4.4	3.7
	$ CV \leq 6$	$S \geq 6$	11.8	18.9	30.7	5.6	1.4	11.9	3.8	4.4	3.6
$ \Delta CC \leq 3$	$ CV \leq 1$	$S \geq 5$	11.6	26.3	37.9	11.1	1.5	13.7	3.8	4.3	3.5
	$ CV \leq 1$	$S \geq 6$	11.5	26.3	37.8	11.1	1.5	13.7	3.8	4.2	3.5
	$ CV \leq 2$	$S \geq 5$	11.6	22.9	34.5	8.3	1.4	13.1	3.8	4.3	3.5
	$ CV \leq 2$	$S \geq 6$	11.5	22.9	34.4	8.3	1.4	13.1	3.8	4.2	3.5
	$ CV \leq 3$	$S \geq 5$	11.6	20.7	32.3	6.6	1.4	12.6	3.8	4.3	3.5
	$ CV \leq 3$	$S \geq 6$	11.5	20.7	32.2	6.6	1.4	12.6	3.8	4.2	3.5
	$ CV \leq 4$	$S \geq 5$	11.6	19.5	31.2	5.8	1.4	12.3	3.8	4.3	3.5
	$ CV \leq 4$	$S \geq 6$	11.5	19.5	31.0	5.8	1.4	12.3	3.8	4.2	3.5
	$ CV \leq 5$	$S \geq 5$	11.6	18.9	30.5	5.5	1.4	12.0	3.8	4.3	3.5
	$ CV \leq 5$	$S \geq 6$	11.5	18.9	30.4	5.5	1.4	12.0	3.8	4.2	3.5
	$ CV \leq 6$	$S \geq 5$	11.6	18.4	30.0	5.3	1.4	11.7	3.8	4.3	3.5
	$ CV \leq 6$	$S \geq 6$	11.5	18.4	29.9	5.3	1.4	11.7	3.8	4.2	3.5

Supplementary Table 15: Summary of changes in the number of original and processed CH-loss pixels. We applied a three-step procedure to filter out noisy CH-loss pixels: (1) the first step excluded isolated pixels; (2) the second step removed loss-related noise; and (3) the final correction, based on canopy cover change, identified pixels with consistent trends.

CH loss range	Original CH loss pixels	CH loss pixels after the first step (reduced pixel ratio relative to original)	CH loss pixels after the second step (reduced pixel ratio relative to original)	CH loss pixels after final processing (reduced pixel ratio relative to original)
(-2, 0]	584223643	467508777 (20.0%)	151266621 (74.1%)	83592769 (85.7%)
(-4, -2]	175709066	161942721 (7.8%)	98960462 (43.7%)	57330458 (67.4%)
(-6, -4]	55240562	52868200 (4.3%)	40457861 (26.8%)	29065552 (47.4%)
(-8, -6]	22060475	21485171 (2.6%)	18302287 (17.0%)	15563116 (29.5%)
(-10, -8]	11277466	11092082 (1.6%)	10030624 (11.1%)	9331473 (17.3%)
(-12, 10]	6809437	6737865 (1.1%)	6296655 (7.5%)	6089785 (10.6%)
(-14, -12]	4515669	4485046 (0.7%)	4271145 (5.4%)	4193457 (7.1%)
(-16, -14]	3148670	3134814 (0.4%)	3020882 (4.1%)	2986322 (5.2%)
(-18, -16]	2256362	2250146 (0.3%)	2186560 (3.1%)	2169374 (3.9%)
(-20, -18]	1648179	1645337 (0.2%)	1608801 (2.4%)	1599835 (2.9%)
(-22, 20]	1219535	1218223 (0.1%)	1196369 (1.9%)	1191773 (2.3%)
(-24, -22]	905833	905189 (0.1%)	891936 (1.5%)	889559 (1.8%)
(-26, -24]	666194	665884 (0.0%)	657939 (1.2%)	656763 (1.4%)
(-28, -26]	478097	477971 (0.0%)	473306 (1.0%)	472735 (1.1%)
(-30, -28]	329562	329509 (0.0%)	326713 (0.9%)	326457 (0.9%)
(-32, 30]	211184	211166 (0.0%)	209680 (0.7%)	209581 (0.8%)
(-34, -32]	119836	119832 (0.0%)	119099 (0.6%)	119073 (0.6%)
(-36, -34]	52933	52933 (0.0%)	52703 (0.4%)	52698 (0.4%)
(-38, -36]	14117	14117 (0.0%)	14078 (0.3%)	14078 (0.3%)
(-40, -38]	1113	1113 (0.0%)	1111 (0.2%)	1111 (0.2%)

Supplementary Table 16: Correspondence between TMF disturbance classes and canopy-height-based disturbance classes. Percentages represent the proportion of TMF disturbance pixels overlapping with canopy-height-based (CH-based) disturbance classes derived from canopy height change and post-disturbance canopy height. Overlap ratios were calculated as the number of overlapping pixels divided by the total number of pixels within each Tropical Moist Forest (TMF) disturbance class, including degradation and deforestation. Our definition of CH degradation and deforestation excludes a substantial fraction of TMF-deforestation pixels with relatively high post-disturbance canopy height (e.g., 15–45 m). Although uncertainties in satellite-derived CH estimates may affect low-height or subtle disturbances, they are unlikely to account for the consistently high residual CH observed in these pixels. Such residual CH data are therefore more consistent with partial canopy disturbance or structurally degraded forests than with complete canopy removal. This difference reflects the distinction between spectral disturbance products such as TMF and structure-based disturbance definitions derived from CH change. Consistent with this interpretation, nearly all TMF degradation pixels were classified as CH degradation in our framework, whereas only ~24% of TMF-deforestation pixels satisfied our structural deforestation criterion, with the majority being reclassified as CH degradation.

TMF disturbance class	Percentage of TMF disturbed pixels overlapped with CH deforestation	Percentage of TMF disturbed pixels overlapped with CH degradation	Outside CH degradation and deforestation
TMF degradation	6.3%	93.7%	0.0%
TMF deforestation	24.4%	75.5%	0.1%

Supplementary Notes:

Supplementary Note 1: Canopy height (CH) and biomass mapping

(1) Canopy height mapping using deep learning

Our deep learning model¹⁷ for CH estimation uses Sentinel-1 Synthetic Aperture Radar (SAR), Sentinel-2 L2A, and GEDI L2A RH100 data in African dense forests. We obtained Sentinel-1 SAR data from Level-1 Ground Range Detected (GRD) products based on the Interferometric Wide Swath (IW) mode, at a 10-m resolution. We extracted the mean annual value of the VH band from Sentinel-1 images. From Sentinel-2 images, we selected all 10-meter resolution wavebands (B2, B3, B4, B8) along with the 20-meter shortwave infrared band (B11), which was resampled to 10 meters using bilinear interpolation. We used the relative height metric RH100 from the GEDI L2A height product (V2) as the target CH data for model training¹⁸.

To retain high-quality Sentinel-1/-2 data, within each tile of size 20×20 km, firstly, we processed Sentinel-1 GRD products using radiometric terrain calibration¹⁹, orthorectification, and border noise removal. Secondly, we generated a temporal stack of Sentinel-1 imagery by selecting the 10 images captured during the main dry season (June to October) with the lowest mean backscatter, aiming to reduce the influence of residual rainfall or surface moisture. This selection improves the signal-to-noise ratio and enhances the contrast between vegetation and bare soil, ensuring more consistent and dry-condition observations for analysis. This approach also helps ensure temporal consistency across years when constructing multi-year composites. Thirdly, we calculated the temporal mean of the stack to reduce radar noise and scaled the resulting mean composite values between 0 and 1. The Sentinel-2 L2A data were filtered by selecting only images acquired during the driest months of the year, each tile being cropped to align with the grid of Sentinel-2 raw products. We utilized the cloud mask provided by the European Space Agency (ESA) to select the three least cloudy Sentinel-2 images. For products with identical cloud cover, we prioritized those with the lowest mean water vapor content, using the water vapor content sub-product delivered by ESA. This step effectively minimizes impacts from ‘heavy atmospheres’ with opaque clouds, cirrus, and haze. Finally, Sentinel-2 images were normalized to a range of 0 to 1 across all spectral bands. We constructed the sample data including Sentinel-1/-2 and GEDI data from 600 tiles of 20×20 km across the entire African dense forest region, which were evenly distributed across the study area and selected to maximize the number of GEDI orbits within each tile. For each tile and year, we first selected the three least cloudy Sentinel-2 images. This training dataset included a total of 8.5 million GEDI footprints after filtering.

We employed a U-Net model²⁰, a fully convolutional neural network (CNN), to perform a pixel-wise regression to predict canopy height from Sentinel-1/-2 imagery. We iteratively optimized the U-Net model's loss function by minimizing the difference between estimated and GEDI observed height data. Unlike conventional regression losses such as mean absolute error (MAE) or mean squared error (MSE), we chose to use a weighted version of the MAE, inspired by Lang et al. (2023)²¹, in order to balance the weight of each height class and more properly handle the tails of the height distributions (low and high trees). During training, tiles were randomly drawn according to their weights so that tiles with larger weights were drawn more often. Each training batch consisted of 20 input images (1 S1 + 5 S2) of size 256×256 pixels, incorporating preprocessed Sentinel-1/-2 images and corresponding GEDI labels. Based on the trained U-Net model, the entire African dense forest region was subdivided into numerous $10 \text{ km} \times 10 \text{ km}$ tiles for annual CH inference. The number of tiles from 2019 to 2021 was 23,871, but it decreased to 23,675 in 2022 and 2023 due to a lack of sufficient Sentinel-1 observations. This process was repeated for each year from 2019 to 2023, ultimately resulting in annual CH maps for this period. This study examines CH change between 2019 and 2022, with CH in 2023 used as a reference to infer the overall trend.

(2) Uncertainty in biomass mapping

Aboveground biomass (AGB) estimates are derived from a CH-based allometric model (coupled with wood density), calibrated using field inventory data from African dense forests¹⁷. While this approach enables consistent large-scale mapping, it introduces several sources of uncertainty that are important to consider. Biomass–height scaling relationships are generally expected to be non-linear from an ecological perspective. However, empirical relationships derived from remote sensing proxies may deviate from this expectation. In this study, the near-linear exponent likely reflects the use of GEDI RH100 as a top-of-canopy metric, which does not fully capture stand-level biomass variability in structurally complex forests. We evaluated several alternative formulations, including machine-learning approaches and more flexible allometric models in ref.¹⁷. While some of these approaches (such as machine learning) achieved higher predictive performance on validation samples, they introduced spatial artifacts and unstable temporal patterns when applied to wall-to-wall mapping at 30 m resolution. This reflects a trade-off between local predictive accuracy and large-scale spatial consistency. To ensure stable and interpretable biomass estimates across space and time, we therefore adopted a simpler height-based formulation.

The wood density (WD) dataset^{22,23} used in this study has a spatial resolution of approximately 1 km and was resampled to 30 m. As a result, fine-scale variation in WD is not captured, and most

of the spatial and temporal variability in AGB is driven by CH. WD primarily acts as a regional modifier, helping to reduce biomass saturation effects in high-biomass forests. The WD dataset does not fully cover all forest pixels due to gaps in the underlying species distribution data. Missing values were filled using the nearest available WD value. We quantified the fraction and spatial distribution of pixels requiring gap filling (**Supplementary Fig. 1**) and found that these gaps are limited and spatially clustered. These pixels occur primarily in disturbed areas and low-density forest regions, where the original ~1 km WD data do not capture valid values. Pixels filled using the nearest available WD value account for only 1.5% of all pixels. To assess the role of WD, our previous work ¹⁷ compared biomass estimates derived with and without WD. While WD influences regional biomass levels, the spatial patterns and temporal changes in AGB remain largely consistent, indicating that CH is the primary driver of biomass dynamics in this framework.

The AGB model based on the allometric relationship shows moderate agreement with available field data ($R^2 = 0.40$; relative error = 32.6%), reflecting scale mismatch and representativeness of the available field inventory 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. Because of the limited number of field plot samples, it was not possible to robustly evaluate the height–biomass relationship separately across forest types. Nevertheless, we have collected 400 plots data with all site PI being authors of our previous study, which is the largest dataset ever used for African biomass validation. Although this level of agreement implies some uncertainty at the pixel level, uncertainties are reduced when estimates are aggregated over larger spatial scales due to spatial averaging effects. Consequently, uncertainties in national-scale carbon budgets are lower than pixel-level errors and primarily reflect aggregated variability.

In addition, comparisons with external biomass products (e.g., ESA-CCI AGB) represent consistency checks between independent models rather than validation against ground observations. The AGB model was originally developed and 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. However, our previous ALS-based evaluation ¹⁷ 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, supporting the large-scale applicability of the approach while acknowledging potential uncertainties at local scales.

Supplementary Note 2: Reference disturbance datasets

GEDI footprint data are used to estimate our CH change maps from 2019 to 2022. We filtered GEDI footprints to retain high-quality, high-sensitivity L2A RH100 observations (V2), following quality control criteria established in previous studies ^{24,25}: (1) "degrade_flag" = 0 and "quality_flag" = 1; (2) "sensitivity" between 0.98 and 1; (3) "landsat_water_persistence" < 10 and "urban_proportion" ≤ 50; (4) "pft_mask" = 1, 2, 3, 4, 5, 6, or 11; (5) "rh100" > 5 and classified as trees in the ESA WorldCover V200 product; and (6) "leaf_off_flag" = 0. We then compared CH change over grid cells of various sizes containing multiple GEDI footprints. Due to the lack of sufficient repeated GEDI RH100 observations at the same locations, we estimated the average RH100 change between these two years by averaging all GEDI footprint data within each grid cell. It is important to note that GEDI footprints are subject to substantial geolocation uncertainty, and observations collected at different times of the year may reflect differences in phenology²⁶. Furthermore, the effective spatial resolution of Sentinel-2 data can be affected by the point spread function, adjacency effects, and incomplete atmospheric correction²⁷. These factors introduce considerable uncertainty when matching GEDI and CH changes data at the 30 m pixel scale.

Global Forest Change (GFC) datasets are the results from time-series analysis of Landsat images in characterizing global forest extent and change²⁸. The GFC data primarily include 4 bands related to tree cover change: (1) "treecover2000": Tree canopy cover for year 2000, defined as canopy closure for all vegetation taller than 5 m in height; (2) "loss": Forest loss during the study period, defined as a stand-replacement disturbance (a change from a forest to non-forest state); (3) "gain": Forest gain during the period 2000–2012, defined as the inverse of loss (a non-forest to forest change entirely within the study period); (4) "lossyear": Year of gross forest cover loss event during the study period. Encoded as either 0 (no loss) or else a value in the range 1–23, representing loss detected primarily in the year 2001–2023, respectively. In this study, we used the data from the "lossyear" band downloaded from GEE, and identified all loss pixels during 2019 and 2022.

RADD (Radar for Detecting Deforestation) alerts are triggered based on Sentinel-1 radar imagery, which provide the disturbance map in primary humid tropical forest at 10 m spatial scale and in near real-time with the temporal resolution of 6–12 days²⁹. Forest disturbance is defined as the complete or partial removal of tree cover within a 10 m Sentinel-1 pixel. Subsequent observations are used to iteratively update the forest disturbance probability, increase confidence

and confirm or reject the alert. Alerts are confirmed within a maximum 90-day period if the forest disturbance probability is above 97.5% (high confidence alerts). Unconfirmed alerts (low confidence alerts) are provided for forest disturbance probabilities above 85%. The date of the alert is set to the date of the image that first triggered the alert. We extracted all disturbance pixels with high (pixel value = 3) confidence during 2019–2022.

Tropical Moist Forests (TMF) maps are derived from the new dataset on forest cover change developed by the European Commission’s Joint Research Centre using 42 years of Landsat time series³⁰. TMF provides the wall-to-wall maps at 0.09 ha resolution (30 m), related to TMF extent and the related disturbances (deforestation and degradation), and post-deforestation recovery (or forest regrowth) over the period 1990–2023. We used the *Annual change collection* to identify the degradation and deforestation in Central African forests during 2019–2022. A degraded forest is a closed evergreen or semi-evergreen forest (covered by existing or regrowing trees) that has been temporarily disturbed during a period of maximum 2.5 years (900 days) and that started at the latest during the current year. It includes different types of degradation such as selective logging, fires, and unusual weather events. Deforestation refers to a change in land cover (from forest to non-forested land) when degradation refers to a temporary disturbance in a forest remaining forested such as selective logging, fires and unusual weather events (hurricanes, droughts, blowdown). We used the TMF annual change collection (v2023)³⁰ to extract degraded, deforested, regrowth, undisturbed forests, and other land cover classes. At the pantropical scale, the TMF forest change class (combining degradation and deforestation) has documented uncertainty estimates, with a commission error of 0.084 and an omission error of 0.181³¹. For deforestation, we only considered newly deforested pixels between 2019 and 2022. As the TMF product is designed for annual forest disturbance and recovery mapping, the regrowth class includes both secondary forests (following deforestation since 1990) and afforestation (at least three years of regrowth, as defined by classes 92–94 in the Transition Map sub-types). When relying solely on the annual change collection, afforestation and secondary forests cannot be distinguished.

The annual canopy cover maps for Central African forests were produced using a deep learning model similar to the CH model (**Supplementary Note 1**), integrating Sentinel-1, Sentinel-2, and GEDI canopy cover data. Consistent with the CH maps, we generated annual canopy cover maps at 10 m resolution. We evaluated the performance of canopy cover maps using independent GEDI canopy cover data. The results showed good consistency between the estimated canopy cover and GEDI observations from 2019 to 2022, with R^2 values of 0.63–0.67 and a bias of 2.7%–5.6% (**Supplementary Fig. 6**). Note that we used this dataset only as a reference for undisturbed forests (canopy cover change $\leq 2\%$) in order to exclude inconsistent CH change trends, and we employed

the TMF dataset as an additional reference to further reduce uncertainty (**Supplementary Note 4**). Therefore, the uncertainty in canopy cover data has only a minor impact on the processing of CH change.

Supplementary Note 3: Validation of original CH changes using ALS and GEDI data

Validation of satellite-derived CH changes (ΔCH) is limited by the scarcity of long-term, repeated field observations in Central Africa (2019–2022). To address this, we utilized the only available repeated ALS scans from 2015 and 2023 (Lat: 24.26583°–24.55838°; Lon: 0.77435°–0.85176°) in the Democratic Republic of the Congo (DRC), as shown in **Supplementary Fig. 2**. Although the observation period does not fully align with the timeline of the satellite-derived CH maps, we applied a processing approach to estimate CH changes from the ALS data for comparison: (1) For ALS CH gain between 2015 and 2023 ($\Delta\text{CH} > 0.5$ m), we assume a linear annual increase. Based on this assumption, the CH gain from 2019 to 2023 is estimated as half of the total ΔCH from 2015 to 2023. The threshold of ALS CH change was determined with reference to [Csillik, et al. ³²](#). (2) We exclude ALS CH pixels that exhibited a negative change ($\Delta\text{CH} < -0.5$ m) between 2015 and 2019. As shown in **Supplementary Fig. 3**, the ALS-derived ΔCH maps exhibit moderate agreement ($R^2 = 0.29$) with the original satellite-derived ΔCH at 30 m resolution, with a relatively small mean absolute error (MAE) of 2.32 m. The results also indicate that excluding edge effects improves the consistency between the two datasets.

We aggregated 30-m GEDI RH100 changes data to coarser resolutions for more robust comparisons (**Supplementary Fig. 4**). The results showed good agreement between ΔCH and ΔRH100 at resolutions coarser than 10 km, although low correlations were observed at finer resolutions ranging from 30 m to 5 km. This reduced agreement at fine spatial scales is mainly related to the sparse and uneven spatial sampling of GEDI footprints, geolocation uncertainties, and the fact that GEDI observations from different years do not sample exactly the same locations. In addition, seasonal differences in acquisition dates may introduce variability associated with phenology, which further increases noise in the interannual RH100 estimates. The MAE remained relatively stable at approximately 2 m when the resolution exceeded 40 km. Although the correlation between ΔCH and ΔRH100 was high at coarse resolutions, ΔCH generally showed more gains and fewer losses compared to ΔRH100 (**Supplementary Fig. 5**), resulting in a positive difference between the two. This difference may partly reflect uncertainties in both datasets, including potential regression-to-the-mean effects in the satellite-derived CH model and the limited temporal sampling of GEDI observations.

Supplementary Note 4: 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 (**Supplementary Fig. 7**). In this study, we focused on CH change between 2019 and 2022, using CH in 2023 as a reference to infer the overall trend. We primarily assessed the spatiotemporal consistency of CH changes by excluding isolated and noisy pixels lacking continuous change trends, and evaluated their agreement with other published disturbance datasets, including the TMF disturbance map and canopy cover change (**Supplementary Note 2**).

4.1. Excluding isolated pixels

Based on the target pixel from the CH change between 2022 and 2019 ($\Delta\text{CH}_{2022-2019}$), we constructed a 3D data cube to examine the spatiotemporal consistency of CH gain and loss (**Supplementary Fig. 8**). To determine whether two elements in the cube belong to the same disturbance or growth event, we considered different types of 3D connectivity^{33,34}. In a 3D grid, commonly used options include 6-, 18-, and 26-connectivity. Specifically, 26-connectivity treats all 26 neighboring voxels in a $3 \times 3 \times 3$ cube—including vertical, horizontal, and diagonal neighbors—as connected. We adopted 26-connectivity to identify connected regions of change, as it captures full spatiotemporal proximity across three-time layers ($\Delta\text{CH}_{2021-2019}$, $\Delta\text{CH}_{2022-2019}$, and $\Delta\text{CH}_{2023-2019}$). After computing the 3D connected components, we retained only the $\Delta\text{CH}_{2022-2019}$ layer for further analysis. This means that a pixel in 2022 is considered reliable if it is connected to at least one neighboring pixel (in space or time) showing a consistent gain or loss trend. Isolated pixels—those that form a one-voxel cluster in the 3D connected structure—are treated as noise and removed. To further ensure temporal consistency, we applied an additional filter: if the sign of $\Delta\text{CH}_{2022-2019}$ was opposite to both $\Delta\text{CH}_{2021-2019}$ and $\Delta\text{CH}_{2023-2019}$, the change was discarded as a likely anomaly. If at least one adjacent year showed the same trend, the change was retained. This combined spatiotemporal filtering strategy helps eliminate short-term fluctuations and isolated artifacts, improving the robustness of CH change detection.

4.2. Identifying CH gain noise using Mann-Kendall test

To identify noise of CH gain ($\Delta\text{CH} > 0$), we used Mann-Kendall test³⁵⁻³⁷ to calculate the trend of ΔCH as:

$$S = \sum_{k=2019}^{2021} \sum_{j=k+1}^{2022} \text{sign}(\text{CH}_j - \text{CH}_k) \quad (1)$$

$$\text{sign}(\text{CH}_j - \text{CH}_k) = \begin{cases} +1 & \text{if } \text{CH}_j - \text{CH}_k > 0 \text{ (gain)} \\ 0 & \text{if } \text{CH}_j - \text{CH}_k = 0 \text{ (no change)} \\ -1 & \text{if } \text{CH}_j - \text{CH}_k < 0 \text{ (loss)} \end{cases} \quad (2)$$

The relationship between the Mann-Kendall sum and CH change is illustrated in **Supplementary Fig. 9**. For forest growth, CH generally exhibited a continuous increase from 2019 to 2022. Therefore, the random differences between CH_j and CH_k is expected to be consistently positive, resulting in a Mann-Kendall sum (S) of 6. In contrast, for CH loss, it is often unclear which specific year experienced degradation or deforestation, and the reduction in CH may not follow a clear temporal trend. As a result, using S to exclude noise in CH loss is more challenging.

4.3. Identifying CH loss noise using Sentinel-1

To reduce noise of CH loss, we incorporated Sentinel-1 data, which is less affected by cloud cover and has potential for tracking forest disturbances^{29,38,39}, to monitor CH changes. Although Sentinel-2 is more directly related to forest dynamics, its availability is limited in Central African forests, which may affect the reliability of annual trends derived from Sentinel-2 observations. To identify the optimal approach, we compared the performance of the annual mean and maximum values of the VV and VH bands in capturing CH changes (**Supplementary Figs. 10, 11**).

The results showed that the coefficient of variance (CV) of the annual mean Sentinel-1 VV better reflected CH loss ($\Delta\text{CH} < 0$) than the CV of VH. Although ΔCH exhibited similar trends with increasing $|\text{CV}|$ of mean VV and VH, it showed greater variance, particularly at small $|\text{CV}|$ values of mean VH (**Supplementary Fig. 10**). Consequently, when using the same CV values (e.g., 1, 2, 3, 4, 5), VH may include larger ΔCH values exceeding 5 m. Based on the validation results shown in **Supplementary Figs. 3, 4**, the major uncertainty in ΔCH , as indicated by the MAE, is generally below 5 m across different spatial resolutions. Therefore, we applied a threshold of $|\text{CV}|$ ($|\text{CV}| \leq 5\%$) on the mean VV signal to exclude pixels with ΔCH values likely within the uncertainty range (< 5 m). The threshold is therefore intended to reduce noise from low-magnitude and uncertain changes rather than to define a sharp physical transition.

When $|\text{CV}|$ exceeds 5, some large ΔCH values may also be excluded, potentially removing true changes along with noise. Additionally, we attempted to use the maximum VV and VH signals to detect CH loss; however, this approach proved ineffective, capturing only minor variations (**Supplementary Fig. 10**). VV and VH also showed limited capacity to reflect CH gain, which may be due to the fact that natural increases in CH do not result in substantial changes in the structure of the top canopy.

As mentioned above, we filtered change noise through several processing steps: (1) for CH gain ($\Delta CH > 0$), we excluded pixels with a Mann-Kendall sum (S) < 6 . However, this approach only captured pixels exhibiting continuous growth, potentially missing some regrowth pixels during this period. To address this limitation, we retained pixels classified as regrowth during 2019–2022 in the TMF dataset ³⁰; (2) for CH loss ($\Delta CH < 0$), we excluded pixels with $|CV| \leq 5\%$ on the mean VV signal; To avoid excluding real changes, we retained pixels with a Mann-Kendall sum (S) ≤ -4 (**Supplementary Fig. 9**), as well as pixels classified as degraded or deforested in the TMF dataset ³⁰.

4.4. Final correction of CH changes using canopy cover change

To further exclude false CH change pixels, we used annual canopy cover change (ΔCC) data from 2019 to 2022 as a reference. Following previous studies ^{40,41}, forests with $|\Delta CC| \leq 2\%$ were considered undisturbed. We then examined CH change pixels within this threshold but retained those where ΔCC and ΔCH showed the same trend. Specifically: (1) For pixels with $0 \leq \Delta CC \leq 2\%$, those with $\Delta CH < 0$ were removed; (2) For pixels with $-2\% \leq \Delta CC < 0$, those with $\Delta CH > 0$ were removed. However, if the TMF dataset indicated a consistent trend (i.e., disturbance or regrowth aligned with CH loss or gain), these pixels were retained.

4.5. Sensitivity of key processing parameters

To assess the robustness of our CH change detection, we evaluated the sensitivity of our results to key parameter choices in the canopy height change processing. Sensitivity analyses of parameters of our change detection algorithm including trend detection, Sentinel-1 filtering, and canopy cover filtering as below (**Supplementary Table 12**):

(1) Trend detection: We applied a Mann–Kendall trend test ³⁵⁻³⁷ to assess the temporal trend of CH gain ($\Delta CH > 0$) using annual data from 2019 to 2022. Because the available time series is short, this test mainly identifies pixels with gradual and consistent canopy height increases. Only pixels with S-statistic (S) ≥ 6 were retained to ensure that detected increases represent consistent growth signals, as lower values are insufficient to robustly distinguish true regrowth from noise. Sensitivity analyses using alternative thresholds ($S \geq 5$) resulted in only minor differences in AGC and area estimates.

(2) Sentinel-1 filtering: To reduce 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. In addition, we evaluated the sensitivity of our estimated AGC loss and disturbed area to alternative Sentinel-1 variability thresholds ($|CV| \leq 1\%–6\%$).

(3) **Canopy cover filtering:** We used annual canopy cover change (ΔCC) data as an additional reference to validate CH change. Forest pixels with valid CH change (ΔCH) after the previous processing but with $|\Delta CC| \leq 2\%$ ^{40,41} were considered weak or uncertain disturbances. In this step, pixels were removed only when ΔCC and ΔCH showed inconsistent change trends, such that disturbances with consistent ΔCH signals were retained even when ΔCC was small. Furthermore, we evaluated the sensitivity of our estimated AGC loss and disturbed area to alternative $|\Delta CC|$ thresholds ($|\Delta CC| \leq 1\%–3\%$)

Across all tested configurations (**Supplementary Tables 13, 14**), variations in these parameters primarily affected estimates of net AGC change (up to 12.43%) and the corresponding area (up to 10.00%) as well as gross AGC gain (6.65%) and the corresponding area (15.58%). At the disturbance-class level, the largest sensitivity was observed for the “other loss” category, with AGC estimates varying by up to 21.80% and area by up to 31.51%, while other disturbance classes showed comparatively smaller variations. These results indicate that parameter choices mainly influence less constrained disturbance types, whereas overall AGC budgets remain relatively stable. The resulting variability was incorporated into the structural uncertainty of AGC and area change estimates.

Supplementary Note 5: Validation of processed CH changes using ALS, GEDI, and published disturbance datasets

To further demonstrate the improvement achieved by the proposed CH processing framework, we conducted a comprehensive comparison of CH change performance before and after processing. We compared the processed CH changes with airborne LiDAR (ALS) data. Compared to the original results shown in **Supplementary Figs. 3, 4**, the processed CH change exhibited significantly higher consistency (R^2) with ALS CH change (**Supplementary Fig. 12**). The improved agreement was partially attributed to the exclusion of noisy pixels with small changes.

Additionally, the processed CH change showed a clearer and more consistent spatial pattern with GEDI RH100 change (**Supplementary Figs. 15, 17**). In contrast, the original CH change map indicated widespread growth, whereas the GEDI RH100 change generally exhibited a decreasing trend. Although the estimation errors against the GEDI RH100 change data increased due to the removal of many noisy pixels with small changes, the spatial agreement between CH change and

GEDI RH100 change improved. These improvements in consistency further support the effectiveness and accuracy of the CH change noise filtering process.

We also observed obviously improved spatiotemporal consistencies with multiple reference disturbance datasets ²⁸⁻³⁰, particularly for TMF-identified degradation associated with CH losses (**Supplementary Figs. 18, 19**). A considerable number of pixels with small Δ CH loss (e.g., -4 to 0 m) were removed after excluding isolated pixels, although the precision against TMF degradation did not change significantly. After further reducing loss-related noise, additional small-loss pixels were removed, resulting in improved consistency against TMF degradation. After CH change processing, it is still clear that the developed CH change data could find more small loss pixels compared to other disturbance datasets. Moreover, compared to GEDI RH100 change, the processed CH change better distinguished disturbance types, including deforestation, degradation, and regrowth as well as among different land-use categories (**Supplementary Figs. 20, 21**).

The effects of temporal interpolation and sample filtering on the comparison between satellite-derived CH change (2019–2022) and ALS observations (2015–2023) were evaluated at both 10 m and 30 m resolutions (**Supplementary Figs. 13, 14**). We first evaluated the consistency between satellite-derived and ALS-derived CH maps at individual years (**Supplementary Fig. 2**). Our CH map in 2019 showed good agreement with ALS CH observations acquired in 2015 ($R^2 = 0.76$, MAE = 4.35 m, Bias = -1.08 m), with comparable performance between our CH map and ALS observations acquired in the same year 2023, although the correlation was lower ($R^2 = 0.55$, MAE = 4.42 m, Bias = 0.29 m). The shift in bias between the two comparisons likely reflects temporal mismatches between ALS acquisition dates and satellite observations, as forest growth and disturbance may occur between acquisition periods. Applying a linear interpolation to pixels with height gain (condition 1) resulted in only minor changes in agreement metrics, indicating that assumptions on growth dynamics have a limited influence on the comparison. In contrast, excluding pixels with ALS-detected height loss prior to the 2019–2022 study period (condition 2) led to a substantial improvement in agreement, increasing R^2 from 0.06 to 0.22 at 10 m resolution and to 0.52 at 30 m resolution, while also reducing error metrics at both spatial resolutions. This reflects the effect of temporal mismatch between the ALS acquisition (2015 and 2023) and our shorter study period, whereby disturbances occurring before our observation window introduce inconsistencies in the raw comparison. Removing these pixels reduces discrepancies associated with misaligned disturbance timing rather than altering the underlying distribution of canopy height change. Importantly, consistent patterns across 10 m and 30 m analyses indicate that the observed improvements are not driven by scale-dependent smoothing or selective bias, but by improved temporal alignment between datasets.

We also note that the ALS comparison is based on a small spatial extent and may not fully represent the balance of canopy height gain and loss across the broader region. Conversely, validation using GEDI data provides larger spatial coverage but is spatially sparse and subject to known uncertainties on GEDI footprints, including geolocation errors and sampling limitations. Importantly, the GEDI-based validation shows predominantly positive bias, in contrast to the negative bias observed in the ALS comparison. As such, neither dataset alone can fully constrain the regional bias in canopy height change. The contrasting bias patterns observed between ALS and GEDI further suggests that bias estimates are dataset-dependent, rather than indicative of a consistent directional error in the satellite-derived product.

Therefore, the current validation datasets do not provide sufficient evidence to robustly determine whether the net carbon change is systematically overestimated or underestimated at the regional scale. From a methodological perspective, our framework may tend to produce slightly conservative estimates of forest gain, suggesting that carbon gains could be underestimated, e.g. in mature forests. However, independent validation (**Supplementary Table 1**) indicates that both loss and gain estimates are subject to uncertainty, with relative uncertainties of approximately 16% and 23%, respectively. These uncertainties highlight that both components of the carbon budget remain imperfectly constrained, and further validation with expanded spatial and temporal coverage will be necessary to better quantify potential biases in net carbon change.

Supplementary Note 6. Estimation of processed CH changes using high-resolution PlanetScope imagery

To evaluate the reliability of detected CH changes, we performed a large stratified visual validation⁴² using high-resolution PlanetScope imagery. CH loss and gain patches derived from the CH change map (2019–2022) were grouped into four patch-size classes: 0–1 ha, 1–5 ha, 5–10 ha, and 10–100 ha. Patches larger than 100 ha were not included in this validation because disturbances at this scale are already captured with near-complete agreement by previously published disturbance datasets (**Fig. 2**). Within each patch-size class, we randomly sampled CH loss and CH gain patches and visually interpreted the corresponding PlanetScope images (5 m resolution) acquired in 2019 and 2022. For each sampled patch, we assigned a binary label (true or false) according to whether the mapped CH loss or gain was supported by visible canopy change in the imagery. For each patch-size class i , we calculated user's accuracy (UA) as:

$$UA_i = \frac{TP_i}{TP_i + FP_i} \quad (3)$$

where TP_i and FP_i are the numbers of true-positive and false-positive samples in size class i , respectively. To account for the unequal area contribution of different patch-size classes, we further calculated the area-weighted user's accuracy (UA_{area})⁴² for CH loss and gain across the 0–100 ha range as:

$$UA_{area} = \sum_i \omega_i \cdot UA_i \quad (4)$$

where ω_i is the proportional area contribution of patch-size class i . This weighting ensures that the overall accuracy reflects the relative contribution of each size class to the total mapped area of gain or loss. In addition to validating mapped gain and loss patches, we randomly sampled areas classified as no change in the CH change mapping. Based on these samples, we quantified the proportion of missed changes within pixels predicted as no change (false omission rate, F_o) as:

$$F_o = \frac{FN}{FN+TN} \quad (5)$$

where FN is the number of samples that were actually changed but classified as no change in the CH change mapping (missed disturbances), and TN is the number of samples correctly identified as no change. We also evaluated false detections within stable forests. We first identified undisturbed forest pixels from the TMF dataset and then visually interpreted a subset of these using PlanetScope imagery to confirm the absence of CH change between 2019 and 2022. These reference stable-forest samples were then compared against the CH change product to quantify the proportion that had nonetheless been mapped as change. This metric corresponds to the false positive rate (FPR), calculated as:

$$FRR = \frac{N_{stable,detected\ as\ change}}{N_{stable,total}} \quad (6)$$

where $N_{stable,total}$ is the total number of visually interpreted stable-forest samples and $N_{stable,detected\ as\ change}$ is the number of those samples incorrectly mapped as CH change. Together, this stratified validation framework provides a comprehensive assessment of CH change detection across patch sizes, change directions, and stable-background conditions, explicitly quantifying both omission errors (missed disturbances) and false positive detections (spurious change signals).

Supplementary Note 7. Further validation and characterization of small CH changes

(1) During CH change processing (Supplementary Note 4), we used canopy cover (CC) change data (2019–2022; 10 m), trained from GEDI L2A canopy cover data, as a reference to validate the CH change. As shown in **Supplementary Fig. 24**, small CH gains and losses consistently

correspond to small CC changes, with a very high correlation ($R^2 = 0.96\text{--}0.99$). This indicates that the small CH changes are reliable and not false positives.

- (2) We examined the relationship between CH change and road fraction extracted from the 5-m road map ⁴ across different pixel sizes (**Supplementary Fig. 25**). The results show that areas with small CH loss or gain tend to exhibit higher road density, especially at large grids (≥ 1 km). This spatial association suggests that subtle height changes are more likely to be linked to human disturbances or edge effects near roads. Notably, we also observed that some areas with large CH loss coincide with high road fractions, indicating that both subtle and severe disturbances can occur near road networks. Therefore, the elevated road fraction in low- and high-magnitude CH change areas supports the interpretation that these changes reflect real, human-associated forest degradation or regrowth processes.
- (3) To evaluate the spatial relationship between disturbance patch size and accessibility, we used a 5-meter resolution road map to analyze the distance between CH change patches and nearby roads. Specifically, we examined the mean distance to road across a range of loss and gain patch sizes (**Supplementary Fig. 33**). Our results reveal a clear pattern: smaller CH change patches (<10 ha) tend to occur closer to roads than larger ones, for both loss and gain events. In contrast, larger patches (>100 ha) are generally found farther from roads, with mean distances exceeding 2 km in some cases. These findings are consistent with established patterns of forest disturbance, where human activities typically initiate near roads and gradually expand outward. The observed spatial association between small CH change events and proximity to roads supports their credibility as realistic and plausible disturbance signals rather than noise.
- (4) To assess the spatial validity of newly detected CH changes, we analyzed their proximity to previously disturbed areas identified by TMF data from 2015 to 2022. As shown in **Supplementary Fig. 26**, the majority of canopy height loss occurs near large disturbance patches (≥ 1 ha), with both the magnitude of CH change and the density of affected pixels decreasing with distance. This indicates that most CH losses between 2019 and 2022 are spatially clustered around known degradation and deforestation fronts, rather than occurring randomly in intact forests. Such spatial patterns are consistent with typical disturbance expansion dynamics in tropical forests, where human activities often extend gradually from roads or previously cleared areas. This supports the reliability of our CH change detection, especially for small disturbances.
- (5) We evaluated CH change against independent small-scale disturbances derived from repeated UAV flights in the Congo Basin ¹. Three regions (B: Jun 2018 to Jan 2019; C: Feb 2019 to Sep 2019; D: June 2020 to September 2020) with repeated UAV surveys were selected for

comparison, while other datasets lacking repeated UAV observations were excluded. Note that the acquisition times of these datasets differ from that of our CH change data (2019–2022), which may result in considerable mismatches when detecting change pixels. Our CH change results showed a similar spatial pattern in Zone B and C but a significant difference in Zone D (**Supplementary Fig. 27**). Overall, when the disturbance size was greater than 0.09 ha (30-m pixel), our CH change data detected 60%–100% of the disturbances (**Supplementary Fig. 28**). For disturbance sizes between 0.01 ha and 0.09 ha, the detection accuracy was approximately 20%–40%, outperforming both the TMF and integrated RADD datasets ⁴³. The lower detection rates for very small disturbances (<0.01 ha) can be attributed to several factors: (1) the reference datasets represent gaps within a single year, whereas our CH change covers the period from 2019 to 2022; additionally, the UAV-derived canopy gaps have extremely high spatial resolution (10 cm), which is difficult to detect using 10-m satellite data; (2) canopy gaps do not always correspond to CH change, as small gaps may not result in measurable height loss.

Supplementary Note 8: AGC changes associated with different disturbance patches

The observed rate of biomass loss associated with deforestation events increases with patch size, reaching a loss rate of $-24 \text{ Mg C ha}^{-1} \text{ yr}^{-1}$, with two extreme clearing events of size ~ 1000 ha reaching $-58 \text{ Mg C ha}^{-1} \text{ yr}^{-1}$ (**Fig. 3**), primarily driven by plantation establishment and burned areas (**Supplementary Fig. 31**). Relative to the initial biomass density in 2019, the fraction of biomass lost after deforestation ranges between 58% and 89%. When excluding patch edge pixels (**Supplementary Fig. 29**), for example, a 1-pixel-wide boundary—we observed substantially increased losses from deforestation (-18 to $-59 \text{ Mg C ha}^{-1} \text{ yr}^{-1}$), with loss proportions ranging from 75% to 89% relative to the AGC in 2019. When removing a wider boundary (3 pixels), deforested patches showed even greater loss ratios.

The apparent positive AGC change in small degradation patches may partly reflect the heterogeneity of the TMF degradation class, which can include pixels of afforestation or regrowth. In small patches, these recovering pixels can outweigh the loss signal. In contrast, large degradation patches are dominated by more severe disturbances, where such recovery signals are less prevalent, leading to sustained AGC loss. Based on AGC changes from regrowth, degradation, and deforestation, small disturbance patches (<3 ha) show a net carbon gain, whereas medium-sized patches (10–100 ha) contribute the most to net carbon loss. Total AGC losses from degradation first increase until ≈ 9 years after degradation, and then decline (**Fig. 3f**). We also observe in this figure that medium-sized patches (1–100 ha) contribute more significantly to degradation-related carbon losses, indicating that they should be prioritized in mitigation strategies ⁴⁴.

Supplementary Note 9. Comparison of AGC density and changes in protected areas and concessions

We compared the distributions of AGC density and its change between protected areas and forest concessions across Central African dense forests to evaluate both baseline differences and their implications for carbon dynamics (**Fig. 4, Supplementary Table 7**). Protected areas exhibit a lower mean AGC density ($127 \pm 47 \text{ Mg C ha}^{-1}$) than concessions ($144 \pm 44 \text{ Mg C ha}^{-1}$) (**Supplementary Fig. 39**), corresponding to a difference of approximately 17 Mg C ha^{-1} (~13%). However, this difference is small relative to the uncertainty in the biomass estimates. The underlying allometric model has a relative RMSE = 32.6%, which substantially exceeds the observed difference. In addition, protected areas cover a larger extent (41.6 Mha) than forest concessions (36.7 Mha), resulting in very similar total AGC stocks (~5.3 Pg), further suggesting limited practical differences in baseline carbon storage. The slightly higher mean AGC density in concessions likely reflects, at least in part, the non-random spatial placement of protected areas, which may preferentially include lower-biomass ecosystems due to biodiversity or representativeness criteria. Overall, differences in AGC density between protected areas and concessions are modest and small relative to model uncertainty.

Distribution-based metrics further show strong overlap between land-use types (**Supplementary Fig. 39**). The overlap coefficient is 0.83, indicating that most of the distributions are shared. The probability that a concession pixel exceeds the mean AGC of protected areas is 0.72, while 41% of protected-area pixels exceed the concession mean. The effect size is small (Cohen's $d = 0.36$), confirming that the difference is modest relative to overall variability. Together, these results indicate that although concessions have a higher mean AGC density, the two distributions are only weakly separable in practice. In contrast to baseline AGC density, AGC density change shows near-complete overlap between protected areas and concessions. The overlap coefficient is 0.93, and the probabilities are close to symmetric (0.44 and 0.52), indicating that pixels from the two land-use types are indistinguishable in terms of carbon gain or loss. The effect size is effectively zero (Cohen's $d = -0.07$).

Protected areas and forest concessions also exhibit highly similar carbon dynamics. Total AGC change amounts to $-3.8 \pm 1.4 \text{ Tg C yr}^{-1}$ in protected areas and $-5.4 \pm 1.6 \text{ Tg C yr}^{-1}$ in concessions, while mean AGC density change is -0.09 and $-0.15 \text{ Mg C ha}^{-1} \text{ yr}^{-1}$, respectively. The proportion of pixels experiencing carbon loss is nearly identical (6.0% vs. 6.5%), as is the proportion of gain pixels (4.1% vs. 3.8%). These results indicate that both land-use types exhibit comparable rates of carbon loss and gain. Importantly, the observed difference in mean AGC

density has limited implications for carbon-budget assessments. A difference of 17 Mg C ha⁻¹ across the total concession area (36.7 Mha) corresponds to a stock difference of ~ 0.6 Pg C. However, given the large uncertainty in biomass estimates and the strong overlap between distributions, this difference cannot be robustly attributed to land-use effects and does not translate into measurable differences in annual carbon loss rates, which are the primary focus of this study.

Supplementary Note 10: Uncertainty propagation of aboveground carbon change

We quantified the uncertainty of AGC change by explicitly accounting for three sources (**Supplementary Fig. 35**): (1) biomass uncertainty arising from allometric modelling and measurement errors (σ_{bio}); (2) classification uncertainty associated with disturbance attribution and detection accuracy (σ_{cls}); 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. All uncertainties were expressed as standard deviations (σ) and coefficients of variation (CV). For any estimated quantity Y (here referred to AGC and area change), the coefficient of variation was defined as:

$$CV(Y) = \frac{\sigma(Y)}{|\mu(Y)|} \quad (7)$$

where $\mu(Y)$ is the mean estimate and $\sigma(Y)$ denotes its standard deviation. Because AGC and area estimates are affected by different processes, uncertainty propagation was performed using two distinct pathways. For AGC-related quantities, total uncertainty was computed assuming independence among sources:

$$\sigma_{AGC} = \sqrt{\sigma_{bio}^2 + \sigma_{cls,AGC}^2 + \sigma_{scheme,AGC}^2} \quad (8)$$

For area-based quantities, only classification and structural uncertainties were considered:

$$\sigma_{Area} = \sqrt{\sigma_{cls,Area}^2 + \sigma_{scheme,Area}^2} \quad (9)$$

Biomass uncertainty was not included in area estimates because it does not affect pixel classification or spatial extent.

(1) Biomass uncertainty

The AGC density was estimated using an allometric relationship between canopy height and biomass ¹⁷:

$$AGC = a \times (CH \times WD)^b \times 0.456 \quad (10)$$

where CH is canopy height, WD is wood density, and a and b are empirical coefficients derived from previously published biomass–height relationships. Biomass prediction uncertainty was

modeled as a heteroscedastic error proportional to biomass magnitude, based on the relative validation error of the biomass allometric model (32.6%, expressed as RMSE/mean):

$$\sigma_{AGC} = \alpha \times AGC \quad (11)$$

where $\alpha = 0.326$. This formulation allows uncertainty to vary spatially across forest types and structural conditions, rather than assuming a constant error. As this uncertainty is derived from independent validation against field plots, it reflects the aggregate prediction error of the biomass estimation framework, implicitly capturing uncertainties from field measurements and allometric models, without explicitly propagating individual components. Including an additional plot-level uncertainty term would therefore risk double counting these contributions. We further tested the inclusion of plot-level biomass uncertainty (8.3%) reported in previous studies ⁴⁵, and found that incorporating this additional component had a small impact on aggregated AGC estimates, indicating that model-level prediction error dominates the uncertainty budget at the spatial scale of this analysis.

To propagate uncertainty across time, we considered AGC at two time points (2019 and 2022), AGC_1 and AGC_2 , with associated standard deviations $\sigma_1 = \alpha AGC_1$ and $\sigma_2 = \alpha AGC_2$. To account for spatial autocorrelation in biomass estimation errors, we applied a mixed error structure combining a spatially coherent component and a pixel-level independent component to model the errors between time steps (2019 and 2022):

$$\varepsilon_1 = (\sqrt{\rho}z_s + \sqrt{1-\rho}z_1)\sigma_1 \quad (12)$$

$$\varepsilon_2 = (\sqrt{\rho}z_s + \sqrt{1-\rho}z_2)\sigma_2 \quad (13)$$

where $z_s \sim \mathcal{N}(0,1)$ is a shared Gaussian random term, $z_1, z_2 \sim \mathcal{N}(0,1)$ are independent Gaussian random terms. Under this formulation, ρ controls the strength of dependence between the perturbations applied to the two dates, such that $\rho = 0$ corresponds to fully independent errors and $\rho = 1$ corresponds to fully shared errors. In this study, $\rho = 0.8744$ was taken as the empirical correlation between the 2019 and 2022 AGC estimates and was used as a proxy for the intertemporal dependence of biomass estimation errors. Because the true correlation of the errors is not directly observable, this parameter should be interpreted as an empirical approximation rather than a direct estimate of error covariance. Its use provides a conservative representation of the fact that uncertainties at the two dates are expected to be strongly related, owing to shared input data, model structure, and spatial patterns in forest properties. Perturbed AGC values were computed as:

$$AGC'_1 = AGC_1 + \varepsilon_1, \quad AGC'_2 = AGC_2 + \varepsilon_2 \quad (14)$$

and the AGC change at the pixel level (p indicates pixels) was defined as:

$$\Delta AGC_p = AGC'_{2,p} - AGC'_{1,p} \quad (15)$$

For each Monte Carlo realization, AGC change (gain, loss, and net) was aggregated to obtain:

$$AGC_{gain} = \sum_{\Delta AGC_p > 0} \Delta AGC_p, \quad AGC_{loss} = \sum_{\Delta AGC_p < 0} \Delta AGC_p, \quad AGC_{net} = \sum_p \Delta AGC_p \quad (16)$$

The same aggregation was performed for each disturbance class c , yielding class-specific AGC change ($AGC_{gain,c}$, $AGC_{loss,c}$, and $AGC_{net,c}$). Biomass uncertainty (σ_{bio}) was quantified as the standard deviation of these quantities across Monte Carlo realizations.

(2) Classification uncertainty

To attribute CH changes to disturbance types, we developed a classification framework that categorizes CH changes into six classes: (1) other loss, (2) deforestation, (3) degradation loss, (4) regrowth, (5) degradation gain, and (6) other gain. This classification is derived from CH change magnitude and direction as well as the TMF disturbance types. Classification uncertainty arises from ambiguity in assigning pixels to disturbance classes and was quantified through three components: (1) detection uncertainty derived from independent validation data, (2) threshold sensitivity in degradation and deforestation loss, (3) Uncertainty associated with ex regrowth and degradation gain estimation. These components were combined to derive class-specific uncertainties, which were then propagated to AGC and area estimates.

Uncertainty for less constrained disturbance classes (“other loss” and “other gain”) was estimated using expert-based validation of small disturbance patches. Specifically, we analyzed patches smaller than 1 ha with mean $|\Delta CH| < 5$ m, which were used as proxies for other loss and gain classes characterized by subtle CH changes. For CH loss, 79% of patches were clearly confirmed. For CH gain, 69% of patches were confirmed. Based on these observations, classification uncertainty for “other loss” and “other gain” was represented as a bounded relative error. The upper bounds of uncertainty (u) were defined from the proportion of ambiguous and inconsistent cases, yielding $u = 0.21$ for other loss and $u = 0.31$ for other gain. Assuming a uniform distribution of relative error within these bounds, the corresponding coefficient of variation (CV) was approximated as:

$$CV_{det,other} = \frac{u}{\sqrt{3}} \quad (17)$$

For the remaining disturbance classes (deforestation, degradation loss, regrowth, degradation gain), detection accuracy was estimated using area-weighted validation across disturbance patches. Separate accuracies (Acc) were derived for gain and loss classes. Detection uncertainty was then computed by treating the classification error ($1 - Acc$) as a bounding interval rather than a standard deviation. By assuming a uniform distribution within these bounds, which is

a standard approach for Type B uncertainty evaluation⁴⁶, we derived a conservative estimate of the CV as:

$$CV_{det} = \frac{1-Acc}{\sqrt{3}} \quad (18)$$

This formulation provides a conservative estimate of uncertainty without imposing restrictive assumptions about error symmetry or normality. It reflects the combined effects of visual ambiguity and sampling limitations, ensuring that the propagated uncertainty in AGC and area estimates remains reliable even under non-normal error distributions.

The distinction between deforestation and degradation loss depends on CH thresholds. Deforestation was defined using a structural criterion based on canopy height dynamics, combining a minimum canopy height loss and a post-disturbance canopy height threshold:

$$\Delta CH < -5 \text{ m} \text{ and } CH_{2022} < T \quad (19)$$

where ΔCH represents canopy height change between 2019 and 2022, and CH_{2022} is the canopy height after disturbance. The threshold T is used to distinguish complete canopy removal from partial canopy disturbance. The criterion $\Delta CH \leq -5 \text{ m}$ is adopted from previous studies⁴⁷ and represents reliably detectable canopy height changes in satellite observations⁴⁸. This threshold is also consistent with previous studies showing that severe canopy loss is associated with mean height reductions of approximately 5 m or greater^{49,50}. The additional constraint on post-disturbance CH ($< 10 \text{ m}$) ensures the formation of new canopy gaps⁴⁷ and accounts for limitations in detecting low-height canopy structures, as residual vegetation, sub-pixel heterogeneity, and retrieval uncertainty may result in non-zero CH values even after substantial canopy removal at 30 m resolution. To account for uncertainty associated with the choice of CH threshold, we treated T as a stochastic parameter and propagated it within the Monte Carlo framework. Specifically, for each iteration, the threshold was randomly sampled from a uniform distribution:

$$T \sim U(10, 20) \quad (20)$$

This range encompasses plausible values for distinguishing complete canopy removal from partial disturbance and reflects uncertainty in the threshold definition across forest types and disturbance regimes. For each sampled threshold, pixels satisfying the above condition were classified as deforestation, while remaining pixels within the loss category were classified as degradation. This procedure propagates threshold sensitivity into class assignment (CV_{thr}), and consequently into aggregated estimates of AGC change and area:

$$CV_{thr}^{AGC} = \frac{\sigma(AGC_T)}{|\mu(AGC_T)|}, \quad CV_{thr}^{Area} = \frac{\sigma(Area_T)}{|\mu(Area_T)|} \quad (21)$$

Uncertainty in the extension estimation for regrowth and degradation gain (CV_{exc}) was modeled to account for ambiguity in disturbance classification in areas lacking direct reference

labels. The classification of CH gains was based on the TMF dataset, which distinguishes regrowth, degradation, and a category of “uncertain” pixels (~12.7%) that are not assigned to a specific disturbance type. To extend disturbance labels to these uncertain pixels, we trained an XGBoost classifier using TMF-labeled regrowth and degradation pixels as training samples. The trained model achieved an overall agreement of 0.87 with TMF labels, with precision, recall, and F1-scores of 0.95, 0.78, and 0.86 for regrowth, and 0.81, 0.96, and 0.88 for degradation, respectively. Uncertainty was represented through stochastic perturbation of class labels, reflecting the observed ambiguity and asymmetry in classification performance. For each Monte Carlo iteration, a proportion of pixels was randomly reassigned between regrowth and degradation gain:

$$p_{reg}, p_{deg} \sim U(0, u) \quad (22)$$

where $u_{reg} = 0.14$ and $u_{deg} = 0.12$. These upper bounds were selected to reflect the magnitude of classification ambiguity inferred from model performance and class-specific differences in precision and recall. This approach allows classification uncertainty to be propagated explicitly into estimates of AGC change AGC_p and area $Area_p$:

$$CV_{exc}^{AGC} = \frac{\sigma(AGC_p)}{|\mu(AGC_p)|}, \quad CV_{thr}^{Area} = \frac{\sigma(Area_p)}{|\mu(Area_p)|} \quad (23)$$

For each class c , total classification uncertainty was computed by combining relevant components. For deforestation and degradation loss classes, uncertainty includes detection uncertainty (CV_{det}) and threshold sensitivity (CV_{thr}) assuming independence among sources:

$$CV_c^{AGC} = \sqrt{(CV_{det})^2 + (CV_{thr}^{AGC})^2} \quad (24)$$

For regrowth and degradation gain classes, uncertainty includes detection uncertainty (CV_{det}) and internal class exchange errors (CV_{exc}), which are assumed to be independent:

$$CV_c^{AGC} = \sqrt{(CV_{det})^2 + (CV_{exc}^{AGC})^2} \quad (25)$$

For other loss and gain classes, uncertainty is derived from proxy-based detection uncertainty:

$$CV_c^{AGC} = CV_{det, other} \quad (26)$$

After class-level CVs were determined, the corresponding standard deviations (σ) were computed by scaling CV with the magnitude of AGC change. For area, uncertainty was assumed to follow a similar relative magnitude as AGC change for each class, as both quantities are derived from the same underlying classification. For disturbance types subject to sensitivity analyses (deforestation, degradation, and regrowth), uncertainty in area and AGC was evaluated separately through threshold variation and class reassignment. These analyses indicate that while differences between AGC and area uncertainty may arise, they are generally small. Therefore, a consistent CV-

based formulation was applied to both AGC and area, providing a parsimonious and internally consistent representation of classification uncertainty.

Class-level AGC uncertainty was propagated to aggregated quantities using a covariance-based approach. This was implemented because AGC uncertainties among classes are not independent, and class-level AGC changes can covary when aggregated. Let σ_{AGC} denote the vector of class-level AGC standard deviations:

$$\sigma_{AGC} = (\sigma_c^{AGC})^T, c = 1,2,3,4,5,6 \quad (27)$$

and let $\mathcal{R}$ denote the 6×6 correlation matrix estimated from bootstrap samples of class-level AGC changes. The covariance matrix was then constructed as:

$$\Sigma^{AGC} = \text{diag}(\sigma_{AGC}) \cdot \mathcal{R} \cdot \text{diag}(\sigma_{AGC}) \quad (28)$$

where $\text{diag}(\sigma_{AGC})$ is the diagonal matrix containing the six class-level standard deviations. Aggregated AGC quantities were then defined as sums over relevant class subsets. AGC gain included the three gain-side classes (regrowth, degradation gain, and other gain), AGC loss included the three loss-side classes (other loss, deforestation, and degradation loss), and net AGC change included all six classes. For area, class-level uncertainties were propagated using an independent approximation. This differs from the AGC case because no empirical covariance matrix was constructed for area, and area uncertainty was treated as class-wise independent in the implementation. Let σ_c^{Area} denote the class-level standard deviation of area for class c . For any aggregated area quantity defined over a class subset S (gain, loss, net), the classification-related variance was computed as the sum of class-level variances:

$$\sigma_S^{Area} = \sum_{c \in S} (\sigma_c^{Area})^2, S = (gain, loss, net) \quad (29)$$

In summary, class-level baseline AGC change (AGC_c) and area ($Area_c$) were first obtained directly from the classified raster. Threshold sensitivity was then quantified by recomputing deforestation and degradation-loss AGC and area under thresholds from 10 to 20 m. Internal class exchange was quantified by 200 Monte Carlo realizations of random reassignment between regrowth and degradation gain. These components were combined with validation-based detection uncertainty to derive final class-level CVs for AGC and area. Finally, class-level uncertainties were propagated to aggregated AGC and area summaries using a covariance-based approach for AGC and an independent approximation for area, respectively.

(3) uncertainty related to the choice of a CH change processing scheme

To account for methodological uncertainty associated with canopy height (CH) change detection, we constructed multiple alternative processing schemes by varying key parameters in the

detection pipeline, including trend detection, Sentinel-1 filtering, and canopy cover filtering (**Supplementary Table 12**). Specifically, we varied the Mann–Kendall trend S-statistic ($S \geq 5-6$) used to identify CH gain, the Sentinel-1 VV variability threshold (coefficient of variation, $|CV| \leq 1\%-6\%$) used to filter noise in CH loss pixels, and the canopy cover change threshold ($|\Delta CC| \leq 1\%-3\%$) used as a consistency constraint for weak disturbances. Each combination of parameters produced a distinct but internally consistent set of CH change, disturbance classification, and AGC change layers. For each processing scheme, AGC gain, loss, and net change, as well as the corresponding disturbed area, were computed independently. Structural uncertainty was then quantified as the variability across all schemes, expressed as a coefficient of variation (CV_{scheme}). The resulting variability was incorporated into the structural uncertainty of both AGC and area change estimates.

Overall, the total relative uncertainties in AGC gain, loss, and net change across Central African dense forests are 14.80%, 16.34%, and 23.22%, respectively, with disturbance classification representing the dominant source of uncertainty. Area-related uncertainties, arising from disturbance classification and CH change processing, are 9.47%, 6.60%, and 11.59%, respectively, and are generally smaller than biomass uncertainties. Using the same framework, we further quantified uncertainties within protected areas and forest concessions based on their spatial boundaries and extended the analysis to country-level estimates.

Supplementary Note 11. Uncertainty propagation for biomass carbon turnover rate

We quantified the annual biomass carbon turnover rate as the ratio between the mean annual AGC loss during 2019–2022 and the total AGC stock in 2019:

$$R = \frac{AGC_{loss}}{AGC_{2019}} \quad (30)$$

where R is the turnover rate⁵¹, AGC_{loss} is the mean annual AGC loss, and AGC_{2019} is the total AGC stock in 2019. AGC in 2019 was estimated from canopy height (CH) and wood density (WD) using a power-law model:

$$AGC = a \times (CH \times WD)^b \times 0.456 \quad (31)$$

Total AGC stock in 2019 was computed by summing AGC across all valid forest pixels:

$$AGC_{2019} = \sum_{p=1}^n AGC_p \quad (32)$$

where p represents pixels with $CH \geq 5$ m. Pixels with nodata values were excluded, and canopy height was converted from centimeters to meters prior to calculation. Pixel-level prediction uncertainty was represented as a proportional error with coefficient of variation $\alpha = 0.326$, derived from independent validation (relative RMSE = 32.6%)¹⁷. For each pixel:

$$\sigma_p = \alpha \times AGC_p \quad (33)$$

Uncertainty was propagated using Monte Carlo simulations. For each realization k , perturbed AGC values were generated as:

$$AGC_p^{(k)} = AGC_p + \varepsilon_p^{(k)} \quad (34)$$

where $\varepsilon_p^{(k)}$ represents a stochastic error term. Because spatial correlation in prediction errors is not directly observable, we evaluated uncertainty under a range of plausible correlation assumptions. Specifically, pixel-level perturbations were modeled as a combination of a spatially shared component and a pixel-specific component:

$$\varepsilon_p^{(k)} = (\sqrt{\rho} z_s^{(k)} + \sqrt{1-\rho} z_p^{(k)}) \sigma_p \quad (35)$$

where $z_s^{(k)} \sim \mathcal{N}(0,1)$ is a shared Gaussian variable, $z_p^{(k)} \sim \mathcal{N}(0,1)$ is an independent pixel-level term, and ρ controls the degree of spatial correlation. Because the true spatial correlation structure is unknown, we evaluated uncertainty across a range of plausible correlation assumptions ($\rho = 0.1, 0.3, 0.5, 0.7, 0.9$). For each Monte Carlo realization, total carbon stock was computed as:

$$AGC_{2019}^{(k)} = \sum_{p=1}^n AGC_p^{(k)} \quad (36)$$

The mean and standard deviation ($\sigma_{AGC_{2019}}$) across all realizations were used as the estimate and uncertainty. The uncertainty in total carbon stock depends on assumptions regarding spatial correlation in prediction errors. By evaluating a range of correlation scenarios, we provide a plausible envelope of uncertainty. The corresponding relative uncertainties for $\rho = 0.1, 0.3, 0.5, 0.7$, and 0.9 were 3.25%, 6.66%, 8.65%, 9.40%, and 11.13%, respectively. A correlation coefficient of $\rho = 0.5$ was adopted as the primary estimate, while additional values were used to assess sensitivity.

Uncertainty in AGC_{loss} ($\sigma_{AGC_{loss}}$) was estimated by explicitly accounting for three sources: (1) biomass uncertainty arising from allometric modelling and measurement errors (σ_{bio}); (2) classification uncertainty associated with disturbance attribution and detection accuracy (σ_{cls}); 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. Full details are provided in **Supplementary Note 10**. Uncertainty in the turnover rate (σ_R) was estimated using first-order error propagation:

$$\sigma_R = R \sqrt{\left(\frac{\sigma_{AGC_{loss}}}{AGC_{loss}}\right)^2 + \left(\frac{\sigma_{AGC_{2019}}}{AGC_{2019}}\right)^2} \quad (37)$$

where σ_R is the uncertainty of the turnover rate, $\sigma_{AGC_{loss}}$ is the uncertainty in annual carbon loss, and $\sigma_{AGC_{2019}}$ is the uncertainty in total carbon stock. This formulation assumes that uncertainties in

annual AGC change and baseline AGC stock are independent. Although both quantities are derived from related biomass products, their uncertainties arise from different components of the modeling framework, and the independence assumption provides an approximation for uncertainty propagation in ratio estimates. Finally, the results showed the total relative uncertainties of AGC_{loss} and AGC_{2019} are and 8.65%, respectively, resulting in an estimated relative uncertainty in the turnover rate of 18.49%, corresponding to an absolute uncertainty of approximately $\pm 0.10\% \text{ yr}^{-1}$ for the estimated turnover rate ($0.52\% \text{ yr}^{-1}$).

Supplementary Note 12: Country-scale biomass carbon change estimates

- (1) **Mapping of CH and AGB in non-dense forests:** To produce complete CH maps for each country (**Supplementary Fig. 40**), we applied the same method used in dense forests to train a deep learning model for CH mapping in non-dense forests, using Sentinel-1/-2 and GEDI RH100 data. The resulting CH maps performed well when validated against independent GEDI RH100 measurements from 2019 to 2022 ($R^2 = 0.59\text{--}0.63$; $MAE = 3.52\text{--}3.65 \text{ m}$; $bias = -0.08$ to 0.43 m) (**Supplementary Fig. 41**). Then, we applied the same AGB model to the CH map in non-dense forests. To assess the accuracy of AGB estimates in non-dense forests, field inventory data were not available; therefore, we used ESA CCI AGB as a reference. This represents an important assumption, as structural differences in canopy architecture, species composition, and disturbance regimes may affect the transferability of these relationships. We compared our estimated AGB with ESA CCI AGB in 2019 and 2022 across all forest pixels, including dense and non-dense forests. The comparison showed a close slope, although the intercept differed due to the varying AGB value ranges (**Supplementary Fig. 42**). In non-dense forests, our AGB estimates were highly consistent with ESA CCI AGB ($R^2 > 0.64$). These results suggest that the same allometric AGB model is applicable to both dense and non-dense forests, while acknowledging potential uncertainties at local scales.
- (2) **Estimation of country-level belowground carbon change (BGC) change:** Our remote sensing method produced estimates of aboveground carbon (AGC) change for each country. To derive complete carbon change estimates, we further estimated BGC change based on the corresponding AGC change, using country-specific BGB/AGB ratios¹⁰ (**Supplementary Table 10**). Given the substantial differences in BGB/AGB ratios between dense and non-dense forests, we first calculated the mean BGB/AGB ratios separately for dense and non-dense forests within each country. BGC change was then estimated by applying these ratios to the respective AGC changes in dense and non-dense forests. For the country-level carbon budget, we did not include soil carbon or non-forest fluxes, as they are comparatively small⁵² or even zero according to

national inventory datasets ⁵, relative to biomass carbon changes. Nevertheless, this approach has limitations. BGC was estimated using mean empirical ratios, although relatively stable across our study region ¹⁰, which may still introduce uncertainty due to local variation in root-to-shoot ratios.

Supplementary Note 13: Comparisons of national carbon budgets with DGVMs and FAO

Our national estimates of net (biomass) carbon stock change show reasonable agreement with outputs from dynamic global vegetation models (DGVMs) in countries such as Cameroon and Congo. However, in Gabon and Equatorial Guinea, the DGVM ensemble ⁶ (TRENDY v8, v11) simulates a net carbon loss, whereas our results indicate a net carbon gain during the same period (**Supplementary Table 8**). This divergence likely reflects key limitations of DGVMs, particularly their omission of forest regrowth processes and reliance on coarse, globally harmonized land-use change inputs⁵³ that may not capture regional dynamics accurately. In the DRC, both our estimates and the DGVM ensemble indicate net carbon loss, although our estimated loss is larger in magnitude. This partial agreement may be due to more extensive disturbance processes in the DRC, which are underestimated or not fully represented in DGVMs. Overall, these discrepancies highlight the importance of incorporating high-resolution disturbance and regrowth dynamics into global vegetation models for improved regional carbon assessments.

Our national estimates of net (biomass) carbon stock change show close agreement with the statistical division of the Food and Agricultural Organization of the United Nations (FAOSTAT) ⁷ in Congo, but discrepancies in the DRC and Cameroon. In the FAOSTAT dataset, a default net growth rate of zero is applied to "forest remaining forest", resulting in unchanged AGC densities for DRC and Cameroon between 1990 to 2020 ^{7,54}. This assumption fails to capture actual carbon dynamics, particularly in regions experiencing degradation and regrowth. Moreover, our results reveal that mature forests in these areas are not carbon neutral and many exhibit net carbon losses (**Supplementary Table 9**), likely due to small-scale degradation or climate-related stress not captured by Tier 1 default rates ⁹. These discrepancies underscore the limitations of applying uniform, static assumptions in national reporting frameworks, and highlight the added value of spatially explicit, observation-based assessments like ours for detecting nuanced carbon changes across forest types and regions.

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