

Carbon recovery potential of Afrotropical secondary forests

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Physical Sciences - Article

Keywords:

Posted Date: October 13th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10277995/v1>

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Additional Declarations: There is **NO** Competing Interest.

Carbon recovery potential of Afrotropical secondary forests

Running:

- *Afrotropical secondary forests regain substantial carbon but on variable timescales*
- *Early carbon gains are predictable, but long-term recovery is not in Afrotropical secondary forests*
- *Predictable near-term but uncertain long-term carbon recovery in Afrotropical secondary forests*

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Secondary forests are becoming an increasingly dominant component of tropical landscapes. They play a critical role in the global carbon cycle by removing atmospheric CO₂ during regrowth after disturbance. Yet, their capacity to sequester carbon and the time needed to recover carbon stocks comparable to those of nearby old-growth forests remain poorly understood – particularly in sub-Saharan Africa, where forest clearing for smallholder agriculture is accelerating. Here, using ground-based data from 983 secondary forest plots across 32 sites in 12 African countries, we show that natural regeneration delivers substantial aboveground carbon gains within the first two decades (11–109 Mg C ha⁻¹). These gains are substantially overestimated unless remnant biomass left on abandoned fields is accounted for. The median time to recover 90% of old-growth carbon stocks ranged from 36 to 92 years across sites, albeit with considerable uncertainty. Early carbon accumulation followed identifiable environmental gradients – increasing with precipitation, whereas the time needed to reach old-growth stocks decreased with the maximum climatic water deficit and remained poorly predicted. By combining field-derived biomass recovery trajectories with spatial environmental predictors, we map carbon recovery potential across Afrotropical secondary forests. Because full carbon recovery takes many decades – far longer than the timescales required to meet global climate targets by 2050 – secondary regrowth cannot reliably compensate for the loss of old-growth carbon, making the conservation of remaining old-growth forests essential.

Main text

Dynamics in African tropical forest landscapes

Tropical old-growth forests are being converted to other land uses at alarming rates¹, with dominant drivers differing across regions^{2,3}. In sub-Saharan Africa, forest loss is largely driven by diverse smallholder agricultural systems, ranging from shifting cultivation and subsequent forest regrowth to more permanent conversion for pasture and perennial cash crops such as cocoa, coffee, rubber, and cashew, linked to global markets^{2,4–6}. These pressures are expected to intensify substantially as Africa's population is projected to nearly triple by 2100, increasing demand for food, land, and agricultural commodities^{7–10}. Consequently, Afrotropical landscapes are becoming increasingly dominated by a heterogeneous mosaic of forest disturbance, regrowth, and permanent agricultural conversion^{10,11}. These processes are increasing the extent of secondary forests across the Afrotropics, making them an increasingly important component of regional and global carbon cycling and a major opportunity for ecosystem restoration^{12,13}. Quantifying their distribution, carbon stocks, and dynamics is therefore essential for understanding the future of Afrotropical forests.

Carbon uptake during the first decades after abandonment determines how quickly regrowth removes atmospheric CO₂, while recovery to old-growth carbon stocks depends on processes operating over much longer timescales. Together, these dynamics shape the near- and long-term CO₂ mitigation potential of natural regeneration and may thus guide the spatial and thematic prioritization of forest restoration efforts^{14–16}. Regional-scale recovery of aboveground carbon stocks during secondary succession has been studied in the Neotropics through chronosequences, where nearby forest patches of varying ages serve as a space-for-time substitution for temporal recovery dynamics¹⁷. Yet, no comparable large-scale, field-based analyses exist for the Afrotropics, which host the second-largest tropical forest on Earth. Although pantropical remote-sensing products provide broad-scale estimates of carbon recovery^{12,16,18}, they are rarely validated with African field data. Similarly, carbon accounting

estimates from the Intergovernmental Panel on Climate Change (IPCC) for forest regrowth rely on fixed, regionally uniform recovery values¹⁹. Consequently, the magnitude and spatial variability of carbon recovery in Afrotropical secondary forests remain poorly quantified, limiting assessments of their CO₂ mitigation potential.

Modeling regrowth trajectories

Drawing on an unprecedented field-based dataset of 983 forest inventory plots, spanning 32 site-level chronosequences in 12 sub-Saharan countries (Fig. 1), we quantify aboveground carbon (AGC) dynamics in Afrotropical secondary forests using three complementary metrics derived from recovery trajectories. Total aboveground carbon (AGC) stock after 20 years of succession (AGC₂₀) and the carbon accumulated during the first 20 years of recovery (CA₂₀) are absolute recovery metrics, while the time required to recover 90% of old-growth AGC stocks represents the relative recovery (t₉₀; Fig. 1). AGC₂₀ includes carbon retained in remnant trees at the onset of succession, whereas CA₂₀ excludes this legacy biomass, allowing explicit quantification of its contribution to carbon recovery. We then assess the extent to which these metrics can be predicted from climatic, edaphic, and landscape drivers. Finally, we translate these analyses into spatially explicit maps of Afrotropical carbon recovery potential and associated uncertainty that can inform national carbon accounting and restoration planning, while highlighting key knowledge gaps in AGC recovery across sub-Saharan Africa.

Plots spanned 1-60 years since the last clearing event (Extended Data Table 1) and covered broad climatic, edaphic, and landscape gradients (Extended Data Table 2). Aboveground biomass was quantified from tree inventories using established allometric relationships based on diameter, wood density, and tree height^{20,21}, and converted into carbon stocks. Plots affected by selective logging rather than complete deforestation were excluded to maximize standardization of the restoration process. Old-growth forest reference plots were included when available (Extended Data Table 1). The dataset included both mixed-species and, to a lesser extent, natural monodominant forest systems, as well as forest recolonizing savanna – although only 2 of the 32 sites fell into this latter category. We

simulated site-level AGC recovery trajectories using a hierarchical Bayesian framework based on a sigmoidal growth function^{22,23} (Fig. 1), explicitly incorporating uncertainties for stand age estimates and old-growth AGC reference levels. The key site-level recovery metrics derived from these trajectories – CA_{20} , AGC_{20} , and t_{90} – were regressed against environmental predictors while propagating uncertainty from the recovery trajectory simulations. Finally, we combined these relationships with spatial environmental layers to generate regional maps of short- and long-term carbon recovery potential.

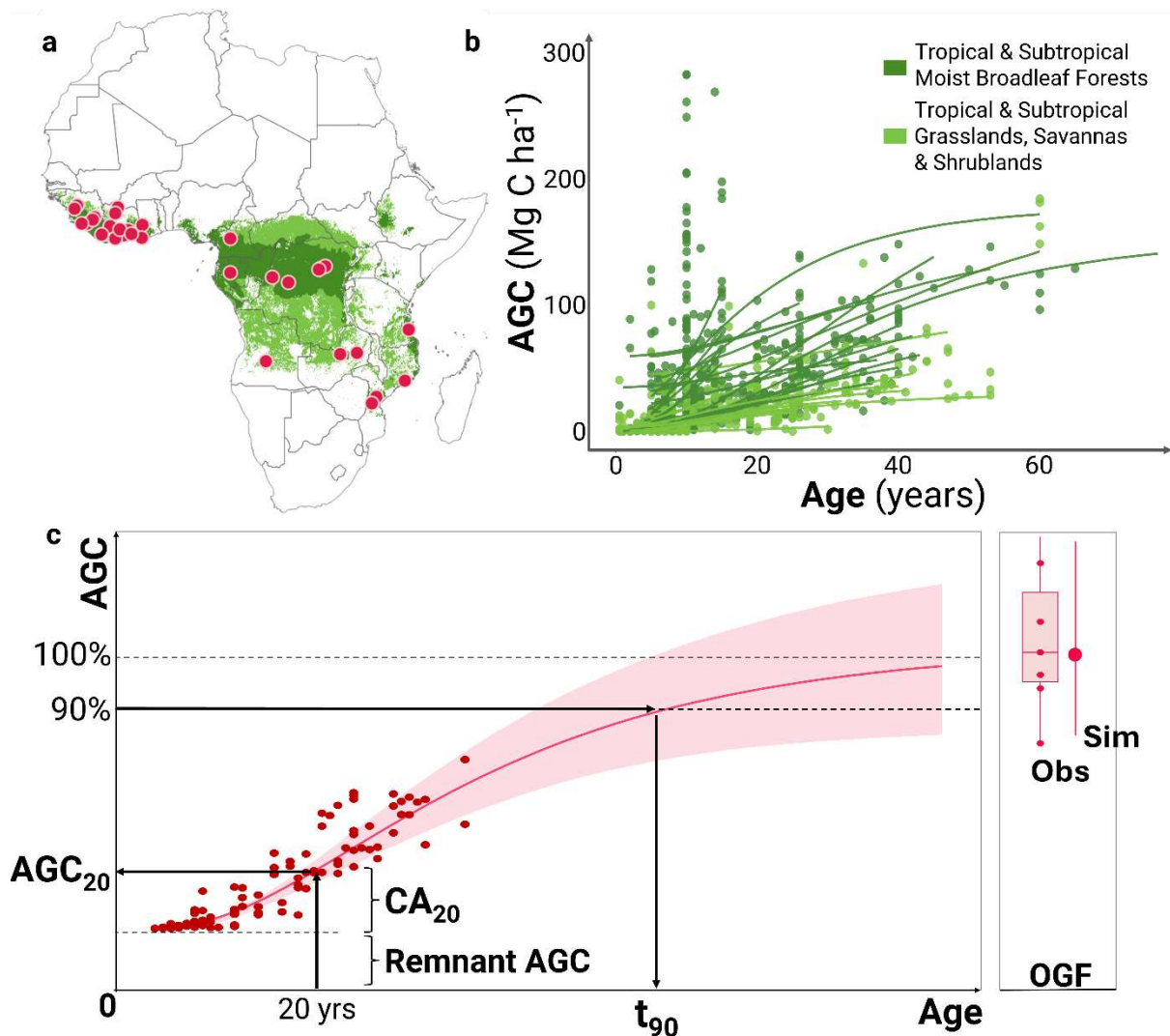


Figure 1 | Chronosequence approach underlying the cross-continental simulation of secondary forest regrowth trajectories, based on inventories of forests regrowing after clearing throughout sub-Saharan Africa. A trajectory was fit for each of the 32 sites (a, b), with nearby old-growth forest data

(‘OGF’; ‘Obs’) informing the simulation of the asymptotic value (‘Sim’; **c**). The uncertainty in the simulated curve is quantified using 90% credible intervals, shown as a colored band. Based on the trajectory, several emerging properties were calculated, such as the total AGC stock accumulated after 20 years of forest recovery (AGC_{20}), and the AGC accrual during the first 20 years (CA_{20}) – which is calculated as the difference between the AGC_{20} and the initial carbon stock in remnant trees – and the time to 90% recovery of the simulated asymptotic value (t_{90}). Green lines (b) show the 32 simulated AGC recovery trajectories fitted to field inventory data (dots). Colors indicate the two biomes represented in the dataset²⁴. The biome mask was combined with a 30% tree-cover threshold¹ and exclusion of oil palm plantations²⁵ to visually delineate the analysis extent. For clarity, axes (b) were truncated at 300 Mg C ha⁻¹ and 75 years (retaining 773 out of 777 plots). Map boundaries are approximate and do not imply any judgment on the legal status of territories.

t_{90} varied widely across Afrotropical secondary forests, ranging from 36 to 92 years, with an overall median of 59 years (Fig. 2; Extended Data Table 3). However, the uncertainty was substantial: in several sites, the 90% credible interval width exceeded a century. Also, CA_{20} and AGC_{20} showed large variation among sites, respectively ranging from 11 to 109 Mg C ha⁻¹ with a median of 24 Mg C ha⁻¹ and from 13 to 170 Mg C ha⁻¹ with an overall median of 40 Mg C ha⁻¹.

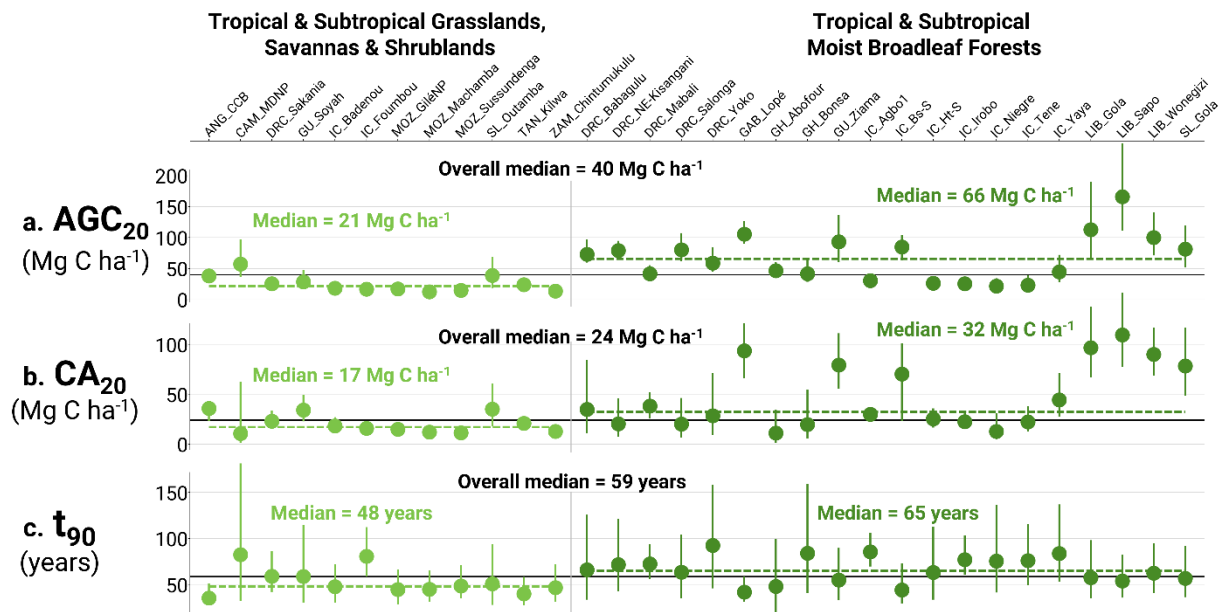


Figure 2 | Total aboveground carbon stocks at 20 years of succession (AGC₂₀; a), aboveground carbon
accrual during the first 20 years of succession (CA₂₀; b), and the time to 90% AGC recovery relative to
old-growth forest reference values (t₉₀; c) across the 32 sites. The results were split into the two
 biomes²⁴ represented in the dataset. The capital letters preceding site names indicate the
 corresponding country (ANG = Angola, CAM = Cameroon, IC = Côte d'Ivoire, DRC = Democratic Republic
 of the Congo, GAB = Gabon, GH = Ghana, GU = Republic of Guinea, LIB = Liberia, MOZ = Mozambique,
 SL = Sierra Leone, TAN = Tanzania, ZAM = Zambia; plot metadata is provided in Extended Data Table 1.
 Sites were ordered alphabetically within each biome class. Green dots indicate median values and error
 bars represent 90% credible intervals. Biome-specific medians are shown in dotted lines in the
 corresponding colors. The overall medians across all 32 sites are shown as black solid lines. Site-specific
 estimates are provided in Extended Data Table 3.

Environmental controls on carbon recovery

Bayesian linear regression models were developed to relate CA_{20} , AGC_{20} , and t_{90} to environmental predictors. To identify the environmental drivers of these recovery metrics, we applied projection predictive feature selection^{26–28} to an initial set of eight candidate predictors spanning *climatic*²⁹ (mean annual temperature [MAT], temperature seasonality, mean annual precipitation [MAP], the absolute value of the maximum cumulative water deficit [MCWD; i.e., how severely a region experiences drought over a year]); *landscape*^{1,25} (mean forest cover [MFC], contagion [a Shannon entropy-based index reflecting how clumped versus fragmented the surrounding forest is], distance to 30% forest cover); and *edaphic*³⁰ (soil pH) variables, revealing several consistent relationships. This approach yielded parsimonious models while avoiding collinearity and overfitting. MAP had positive effects on both CA_{20} and AGC_{20} (Fig. 3; Supplementary Information Fig. S1), with an additional positive effect from MFC on AGC_{20} . The t_{90} was negatively affected by the absolute value of MCWD. The retained predictors explained markedly different fractions of variance across recovery metrics (Fig. 3). The AGC_{20} was best predicted by the environmental predictor set ($R^2 = 0.68$), CA_{20} showed moderate predictability ($R^2 = 0.37$), and t_{90} was least predictable (Bayesian $R^2 = 0.12$). Spatial projections revealed regional patterns in recovery potential and their associated uncertainty (Fig. 3; Supplementary Information, Fig. S2). The tropical moist forest belt exhibited the highest short-term, absolute AGC recovery, a pattern that was more pronounced for AGC_{20} than for CA_{20} . However, this same region showed lower long-term, relative recovery rates, as indicated by higher t_{90} values. In contrast, more sparsely forested regions outside the tropical moist forest belt exhibited the opposite patterns.

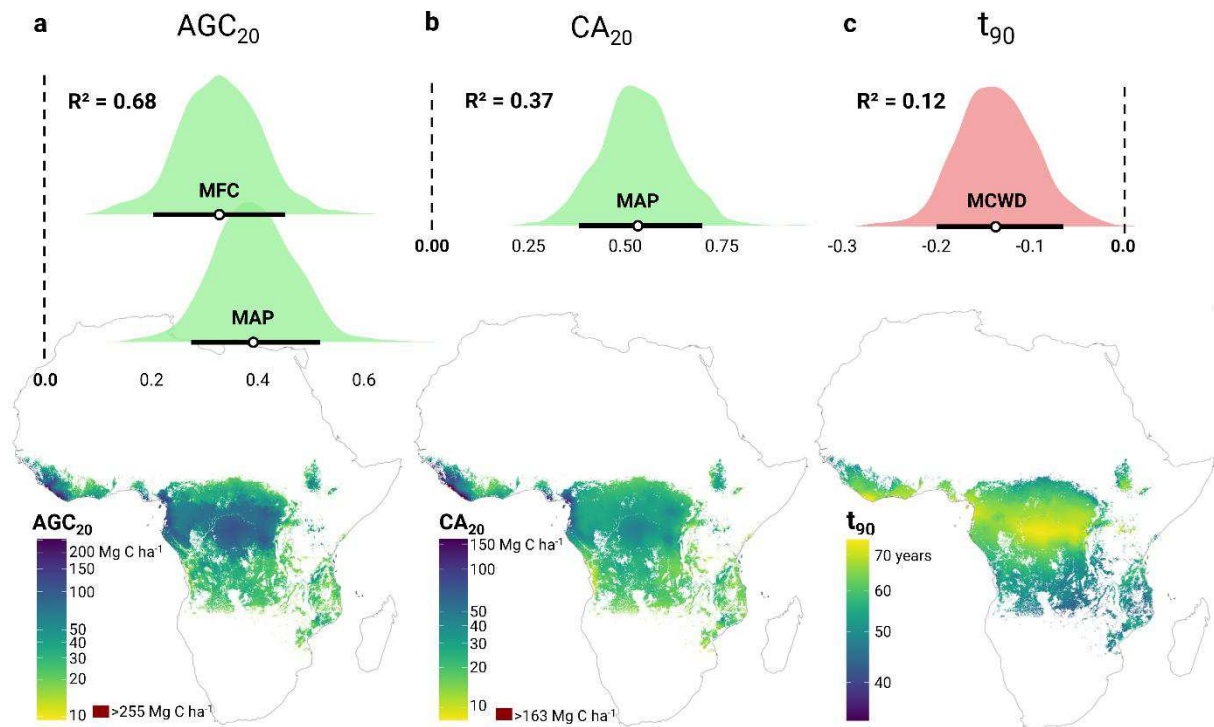


Figure 3 | Environmental effects on the total aboveground carbon stocks at 20 years of succession (AGC₂₀; a), the aboveground carbon accrual during the first 20 years of succession (CA₂₀; b), and the time to 90% recovery (t₉₀; c), with their spatial projections representing the potential values across the study region. Points indicate posterior median effect size and error bars denote 90% credible intervals. Abbreviations: ‘MCWD’ = absolute value of the maximum cumulative water deficit; ‘MAP’ = mean annual precipitation; ‘MFC’ = mean percentage forest cover. ‘R²’ represents the Bayesian R-squared³¹. Effect size posterior distributions with 90% credible intervals that do not overlap zero are shown in green (positive) or red (negative). Legend scales are log-transformed to resolve spatial variation among the predominant low-value pixels. Pixels exceeding the maximum median values for CA₂₀ and AGC₂₀ observed across the 32 sites by 50% are shown in dark red. The corresponding model uncertainty is quantified and visualized as the difference between the upper and lower 90% credible interval limits, divided by the corresponding median value (Supplementary Information Fig. S2). When interpreting the maps, caution is advised in regions where values were extrapolated beyond the calibration data range (Supplementary Information Fig. S3).

The early-stage recovery metrics showed high spatial variability. CA_{20} spanned a $\sim 100 \text{ Mg C ha}^{-1}$ range across sites (Fig. 2), with upper values comparable to reported carbon gains in tropical forests, including $60\text{--}80 \text{ Mg C ha}^{-1}$ over 20 years in the Neotropics^{17,32–34}. When remnant biomass is included (AGC_{20}), median values nearly double (40 for AGC_{20} vs. 24 Mg C ha^{-1} for CA_{20}), highlighting the strong influence of legacy carbon stocks on early recovery estimates. This likely contributes to the higher predictability of AGC_{20} relative to CA_{20} (Fig. 3). Caution is therefore warranted when interpreting early carbon recovery estimates from studies that do not distinguish remnant biomass from true biomass accrual, as this may lead to proper estimates of the carbon stock but inflated estimates of carbon sequestration rates. Positive effects of precipitation on both metrics are consistent with previous studies¹⁷. MFC was retained as a positive predictor of AGC_{20} but not CA_{20} , likely because AGC_{20} incorporates initial carbon stock at the start of succession. Consistent with this, MFC strongly predicted the alpha parameter of succession trajectories (Supplementary Information Fig. S4; $R^2 = 0.27$), indicating an effect on initial conditions rather than recovery rates. This pattern may reflect land-use practices in highly forested regions of sub-Saharan Africa, where large trees characteristic of high-MFC forests³⁵ are more difficult to remove during conversion.

The pronounced between-site variation in recovery times (t_{90}) spans decades to nearly a century. Together with the considerable within-site uncertainty (Fig. 2), this highlights the long and highly variable timescales required for full AGC recovery and the limited data density available for some sites. These prolonged trajectories are in line with century-scale biomass recovery reported for Central African forests^{36,37} and pantropical estimates exceeding 120 years³⁸. Our estimates are further consistent with site-level comparisons: we obtained a median t_{90} of 76 years across Côte d'Ivoire sites versus 63 years in a broader regional analysis³⁹ – with differences falling within our 90% credible intervals. At most sites, recovery times exceed typical restoration horizons of one to three decades^{40,41}, often spanning more than a human generation – underscoring the irreplaceable carbon value of remaining old-growth forests.

The negative effect of maximum cumulative water deficit on t_{90} is consistent with previously reported increases in relative recovery rates under more seasonally dry climates^{39,42}. Notably, t_{90} showed substantially lower predictability than CA_{20} and AGC_{20} (Fig. 3), with linear model predictions consistently underestimating trajectory-derived values (Extended Data Fig. 1). This low predictability extended to t_{50} (Supplementary Information Fig. S4), suggesting that limited predictive power reflects a broader constraint in addition to uncertainty near asymptotic biomass levels where data are mostly sparse. Parameter-level analyses of the Chapman-Richards model (Supplementary Information Fig. S4; Supplementary Information Table S1 for predicted values) further support this interpretation, with the lowest predictability in λ and δ (which govern recovery rates) and the highest for ω (associated with AGC levels).

Importantly, the lower predictability of t_{90} likely – at least partly – reflects ecological processes and historical contingencies not captured by the current predictor set. Land-use history can influence recovery through legacy effects on biomass, soils, and species composition^{43–45}, while differences in prior ecosystem states may lead to distinct successional pathways. Ecosystem history, fire legacies, species pools, and dispersal constraints may therefore strongly influence long-term carbon accumulation. Seed dispersal limitation can restrict recruitment⁴⁶, while local biotic interactions, including competition among regenerating individuals^{47,48} may alter growth rates. In some regions, understory vegetation can create additional feedbacks; for example, Marantaceae-dominated understories in Central Africa may slow biomass recovery by limiting tree recruitment and modifying competitive interactions⁴⁹. Together, these factors suggest that key controls on long-term recovery remain underrepresented in broad-scale datasets. Explicit consideration of ecosystem history, previous land cover, and local ecological feedbacks could therefore improve predictions of recovery trajectories. Remaining variation likely reflects differences in land-use history and disturbance legacies^{39,50,51}, resprouting dynamics that can temporarily elevate biomass beyond old-growth levels^{52–54}, and broader

social factors such as land-use intensity and duration⁵⁵. Expanding and standardizing plot-level metadata will therefore be critical for improving predictive accuracy^{33,50}.

Implications for carbon accounting and restoration policy

Our site-level estimates provide a robust bottom-up baseline for evaluating spatial predictions of carbon accumulation used in restoration planning and IPCC emission factor frameworks^{12,19}. The median CA₂₀ of 24 Mg C ha⁻¹ closely matches the previously reported benchmark of ~26 Mg C ha⁻¹ for African secondary forests¹⁹, while the upper range (up to 109 Mg C ha⁻¹) aligns with high-end estimates from the Neotropics^{17,32}. At the same time, the wide range observed across sites (11–109 Mg C ha⁻¹) highlights substantial spatial heterogeneity not captured by continental-scale averages (Extended Data Fig. 1). Applying fixed accrual rates to inherently non-linear recovery trajectories risks introducing systematic errors in carbon accounting and projections^{12,19,56}. In contrast, our Bayesian framework explicitly propagates uncertainty from parameter estimation to spatial prediction (Fig. 3; Supplementary Information Fig. S2), providing a more realistic representation of variability. Spatial carbon recovery products must therefore be grounded in field-based estimates with fully quantified uncertainties to reliably inform restoration policy and carbon accounting.

Finally, AGC stock recovery provides only a one-sided view of forest regrowth. It overlooks key processes, including soil fertility regeneration^{57–59} and biodiversity recovery^{60–64}, that underpin long-term ecosystem stability. Additionally, effective restoration strategies must balance carbon gains with legal and socio-economic dimensions (e.g., community acceptance and participation, equity and inclusion, cost-effectiveness, and livelihood impacts, etc.) to achieve sustainable outcomes^{65–69}. This calls for integrative frameworks that evaluate restoration outcomes beyond carbon metrics^{70–73}. Importantly, we explicitly recognize that restoration should avoid the afforestation of naturally open, non-forested ecosystems⁷⁴ (e.g., savannas and grasslands), and that our framework is intended to support context-appropriate interventions that safeguard these systems rather than promote their conversion.

323 Our dataset provides the most comprehensive field-based benchmark of Afrotropical carbon recovery
324 to date, yielding two key insights. First, already from the sole C point of view, conserving remaining old-
325 growth forests is indispensable: secondary forests require many decades to over a century to approach
326 comparable carbon stocks, well beyond typical restoration timelines. Critically, these long-term,
327 relative recovery horizons (t_{90}) are also the least predictable from broad environmental variables,
328 suggesting that key ecological processes remain inherently challenging to predict across large
329 environmental gradients. Second, carbon recovery shows a strongly non-linear trajectory and
330 substantial heterogeneity among sites. Differences in the magnitude and predictability of CA_{20} and
331 AGC_{20} indicate that estimates of recovery depend strongly on whether remnant biomass is included or
332 excluded, and this distinction substantially shapes inferred recovery patterns. The latter is particularly
333 important for remote sensing products, where aboveground carbon stocks determined at a single time
334 point are often used as a proxy for carbon accumulation, despite the strongly non-linear nature of
335 recovery trajectories. This practice can lead to systematic overestimation of sequestration potential,
336 especially during early succession.

337 Overall, while early carbon gains during regrowth of secondary forests can be substantial, recovery to
338 old-growth levels is highly variable and difficult to predict. Natural regeneration alone cannot offset
339 old-growth carbon stock losses within policy-relevant timescales, making their conservation essential.

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495

Methods

Forest inventory data and plot-level metrics

We compiled secondary forest census data from 983 plots spanning 32 sites across 12 African countries (Fig. 1; Extended Data Table 1), encompassing more than 100,000 individual tree records. Datasets were included in the study if they contained forest inventories along a chronosequence in sub-Saharan Africa (minimum 5 plots, covering several age classes). We excluded plots for which selective logging was noted instead of a clear-cut of the vegetation. The inventories consisted of tree identification (preferably to species level), accompanied by tree diameter at breast height (DBH; 1.30 m) measurements. The DBH cutoff across sites was standardized to 5 cm DBH when possible; however, measurements were only available for trees with DBH ≥ 10 cm for 14 of the 32 sites (Extended Data Table 1). We obtained age estimates (i.e., the time since disturbance) and land-use history information on the plots from detailed interviews with multiple local landowners. Plot age ranged between 1 and 60 years since disturbance. The included sites are distributed across sub-Saharan Africa (-12.5257 to 39.2972° longitude, -19.967 to 10.2928° latitude) and represent a wide range of climatic and environmental conditions, including substantial variation in mean annual precipitation (822 to 2,933 mm year⁻¹), mean annual temperature (19 to 28 °C), and mean forest cover within a 500 m radius (13 to 99%) (Extended Data Table 2). No African montane forests were represented in the dataset⁷⁵. Within the same site, we assumed similar environmental conditions during the recovery period, and there were no restrictions on the census year. Potential differences in successional dynamics among mixed-species natural monodominant forests were not explicitly assessed.

Endpoints of secondary succession were represented by nearby old-growth forest (OGF) plots per site when available (25 out of 32 sites), which were defined as ‘undisturbed’ according to local interviewees. Where no old-growth plots were available, the asymptotic end values of succession could still be estimated based on the informed priors and secondary forest likelihoods (Supplementary Information: Materials and Methods). Additionally, because the inclusion of palms (Arecaceae) was

inconsistent across datasets, all Arecaceae individuals were excluded prior to calculating plot-level aboveground carbon (AGC) stocks. Tree-level aboveground carbon (AGC) stocks were calculated from the DBH measurements using the *BIOMASS* R package (version 2.2.4)⁷⁶. First, all scientific tree names were evaluated and corrected using the Taxonomic Name Resolution Service via the *correctTaxo* function⁷⁷. Subsequently, wood density (WD; defined as oven-dry mass divided by fresh volume) was retrieved using the *getWoodDensity* function, which relies on a global wood density database^{78,79}. Tree heights were estimated from DBH measurements using established regional allometric relationships implemented via the *retrieveH* function, incorporating the corresponding plot coordinates^{20,21}. Finally, tree-level aboveground biomass (AGB) stocks were calculated from the obtained DBH, WD, and height using the *computeAGB* function²⁰. Aboveground biomass stocks were converted to AGC, assuming a wood carbon content of 45.6% for tropical angiosperms⁸⁰, after confirming the absence of coniferous species across the dataset. The tree-level AGC stocks were subsequently summed per plot and divided by the plot area for further analyses.

Bayesian modeling of AGC recovery

The recovery of AGC to the OGF reference state was simulated within a Bayesian framework using a sigmoidal function inspired by the Chapman-Richards growth model^{22,23}. The model contains two hierarchical levels: site-level parameter estimates (the base level) are evaluated on higher-level lognormal hyper distributions. Because age estimates of secondary forest plots derived from interviews with local informants are subject to substantial uncertainty due to inaccurate recall or misinterpretation, the true plot age was modeled as a latent variable drawn from a normal distribution with mean equal to the reported age and the standard deviation parameterized such that 90% of the probability mass is located within $\pm 20\%$ of the observed age. This formulation assumes a constant relative error in age estimates, such that the absolute uncertainty increases proportionally with reported age and is therefore explicitly incorporated into the model.

Because observed OGF values strongly influence the estimated recovery trajectory and asymptotic biomass, yet are typically based on fewer reference plots than secondary forest plots, we specified informative priors (Supplementary Methods) for the asymptotic value of the succession trajectory. These priors were derived from the upper 10th percentile of the European Space Agency Climate Change Initiative (ESA CCI) 2020 aboveground biomass map at its native 100 m resolution within 50 × 50 km² grid cells. To characterize the biomass distribution in each grid cell, we restricted the analysis to pixels classified as rainforest or seasonally dry forest using a reclassified version of the ESA Tropical Africa land-cover map, resampled to 100 m resolution using nearest-neighbor interpolation, and extracted the corresponding biomass quantiles.

OGF measurements entered a different likelihood term than secondary forest plots, allowing the asymptotic value to be evaluated against empirical OGF data, while the CCI-derived prior captured a broader regional estimated range of this parameter.

The following posterior calculations were executed for each iteration in the Bayesian sampling algorithm (implemented in Stan⁸¹), yielding probability distributions for all calculated variables. Forest AGC recovery trajectories were simulated for t going from 1 to 100 years using equation 1, which captures the typical sigmoidal shape of the recovery trajectory, including the inflection point and asymptotic phase.

$$\mu_{X,t} = \alpha_X + (\omega_X - \alpha_X) \cdot (1 - \exp(-\lambda_X \cdot t))^{\delta_X} \quad (1)$$

with $\mu_{X,t}$ [Mg C ha⁻¹] the AGC recovery at time t for a specific site X , α_X [Mg C ha⁻¹] the site-specific modeled starting AGC value of succession (i.e. the value for $\mu_{X,t}(t = 0)$, which accounts for the standing biomass due to remnant trees), ω_X [Mg C ha⁻¹] the site-specific modeled asymptotic value (i.e. the OGF AGC), λ_X [year⁻¹] the site-specific intrinsic recovery rate, and δ_X the instantaneous growth rate in the inflection point of the sigmoidal curve [dimensionless].

The time to recovery of a given percentage of the OGF reference AGC stock was calculated as the time at which the predicted AGC stock reached that percentage of the predicted asymptotic value. In the

following, only the time to 90% recovery (t_{90} ; equation 2) is discussed. Early successional aboveground carbon accrual during the first 20 years of succession (CA_{20} ; equation 4) was calculated as the difference between simulated total AGC at 20 years (AGC_{20} ; equation 3) and the site-specific simulated starting value α_X .

$$t_{90} = -\frac{1}{\lambda_X} \cdot \log \left(1 - \left(\frac{0.9 - \frac{\alpha_X}{\omega_X}}{1 - \frac{\alpha_X}{\omega_X}} \right)^{\frac{1}{\delta_X}} \right) \quad (2)$$

$$AGC_{20} = \alpha_X + (\omega_X - \alpha_X) \cdot (1 - \exp(-\lambda_X \cdot 20))^{\delta_X} \quad (3)$$

$$CA_{20} = AGC_{20} - \alpha_X \quad (4)$$

We note that estimates of t_{90} (but also t_{50}) are based on relatively few older plots, which likely reduces the precision of these estimates and represents an inherent limitation of the current dataset. However, the parameters λ and δ also capture relative rates of forest recovery and are informed by the greater density of observations from the first decades of succession. These parameters therefore provide additional context for assessing differences in relative recovery rates, rather than relying solely on the longer-term metrics t_{50} and t_{90} .

Model fitting was performed on the full dataset, including remnant trees. However, preliminary analyses for sites in Liberia, the Republic of Guinea, and Sierra Leone revealed unrealistically high CA_{20} values, driven by a near-zero estimated starting value. This artifact arose because large remnant trees were scarce in the youngest plots (ca. 5 years) but became increasingly abundant in older plots, causing an overestimation of early AGC accrual. Since remnant tree abundance should not systematically vary with stand age under comparable land-use histories — and detailed land-use histories were unavailable — we attributed this pattern to a bias in the estimated starting value of succession. Remnant trees were identified using a maximum diameter growth threshold of 5 cm yr⁻¹. For each tree, we compared its observed diameter with the maximum diameter increment possible since the onset of succession (i.e., 5 cm yr⁻¹ times the plot age). Individuals whose observed diameter exceeded this threshold were

classified as remnant trees and flagged; all others were retained as part of the regenerating cohort. Fast-growing pioneer species (notably *Musanga* and *Macaranga* spp.), which can attain such growth rates during regrowth, were excluded from this classification. We acknowledge that resprouts, which are common on abandoned agricultural fields, can also exceed the 5 cm yr⁻¹ growth threshold while representing genuine post-disturbance biomass accumulation. Their misclassification as remnants could therefore lead to an underestimation of AGB productivity during succession, but the extent of this bias cannot be assessed with the available data.

To avoid bias in model parameter estimation, the remnant filtering procedure was applied consistently across all plots and sites. For the affected sites (Liberia, the Republic of Guinea, and Sierra Leone), CA₂₀ estimates and associated environmental effect-size analyses were derived from the remnant-removed dataset; all other trajectory metrics and visualizations were derived from the full dataset. Consequently, the productivity estimates of CA₂₀ include the productivity in remnant trees at all sites except those noted above, providing a comprehensive estimate of early successional AGC accrual where appropriate.

To contextualize the dataset, sites were classified as either “Tropical and Subtropical Moist Broadleaf Forests” or “Tropical and Subtropical Grasslands, Savannas and Shrublands”²⁴, overlain with a 30% tree cover threshold^{1,25}. These broad categories are used solely to provide geographic context based on vegetation structure, not to assess the ecological status or restoration potential of grasslands or savannas⁷⁴. The Lopé site (Gabon), initially categorized in the second class, was reclassified as Tropical and Subtropical Moist Broadleaf Forest in line with the data authors’ description of it as Western Congo Basin moist lowland forest.

Environmental effects on parameter estimates and emergent properties

To identify which environmental conditions may predict secondary forest recovery, a structured Bayesian modeling workflow was applied to the three main recovery metrics derived from a preceding

Stan model (t_{90} , CA_{20} , and AGC_{20}). The analysis proceeded in two main stages: predictor selection followed by a final regression model with full uncertainty propagation.

Eight candidate predictors were assembled from three predictor domains. Climate was represented by mean annual temperature (MAT), temperature seasonality (TS; standard deviation of mean monthly temperatures), mean annual precipitation (MAP), and maximum cumulative water deficit (MCWD) – all derived from the WorldClim database, averaged over 1970–2000 at 30" resolution²⁹. Landscape structure was characterized within a 500 m buffer around each site using the mean forest cover^{1,25} (MFC), spatial contagion⁸² (CONT), and the shortest distance to the nearest pixel with at least 30% tree cover (D30) – a threshold chosen to remain applicable even in sparse woodland systems such as miombo. Finally, soil pH-H₂O of the upper 0–20 cm layer was included as a ‘master edaphic variable’⁸³, extracted from 30 m resolution maps³⁰, to partially account for soil-mediated variation in recovery rates despite the scarcity of local soil data across sites.

Given the sample size of 32 sites, reducing predictor redundancy and multicollinearity was essential to avoid overfitting in the regression models. Projection predictive variable selection^{26–28} was applied using the *projpred* package⁸⁴, a method that anchors submodel evaluation to the regularized predictions of a full reference model (containing all eight predictors) rather than refitting models repeatedly to observed outcomes – making it less prone to overfitting than classical stepwise approaches. Starting from the full set of eight predictors, the method sequentially builds submodels by adding one predictor at a time, at each step retaining whichever predictor best preserves the predictive utility of the full reference model.

The full reference model was first fitted using Bayesian linear regression in *brms*, with the per-site mean of log-transformed posterior samples of each metric as the response and its per-site standard deviation as a partial propagation of estimation uncertainty. Regularized horseshoe priors were placed on regression coefficients, with the sparsity parameter set to reflect a prior expectation of approximately four relevant predictors out of eight. Normal and exponential priors were used for the intercept and

residual standard deviation, respectively. Predictor selection was validated through 10-fold cross-validation, and only predictors appearing in all 10 folds were retained - providing strong confirmation that the selected subset is a stable, reproducible signal rather than an artifact of any particular data partition.

After identifying the response-specific predictor subsets, the regression models were re-run with full propagation of posterior uncertainty from the upstream Stan model. Rather than using point estimates for t_{90} , CA_{20} , and AGC_{20} , 500 random draws from each metric's posterior distribution were treated as uncertain observations of an underlying latent "true" value. This latent variable was modeled with a lognormal distribution, where the draw-level dispersion captured estimation uncertainty from the first model. The latent true value was itself modeled as lognormally distributed, with its median determined by a multiple linear regression on the retained environmental covariates. Effect sizes, the intercept, and dispersion parameters were assigned weakly informative priors – normal distributions for effect sizes and the intercept (with wider dispersion for the latter), and exponential priors for standard deviations. This nested lognormal structure cleanly separates two distinct sources of variation: the estimation uncertainty inherited from the trajectory model, and the genuine ecological signal attributable to environmental conditions – yielding effect size estimates that are truthful about both.

It should be noted that our environmental models assume linear relationships with the log-transformed response variables, a deliberate choice given the sample size. Recovery rates may, however, respond non-linearly to environmental gradients — for example, through threshold effects of water availability or interactions between climate and land-use legacies — which such models cannot capture. Part of the lower predictability of t_{90} relative to AGC_{20} may therefore partly reflect our assumption of linear responses to environmental variation.

Further details on the methodology and Bayesian modeling framework can be found in the Supplementary Information.

667 **Data availability**

668 Site metadata and environmental data are available in Extended Data Tables 1 and 2. Fitted regrowth
669 curve parameters and their uncertainty per site are given in Supplementary Information Table S1. Full
670 resolution figures and raster files (ca. 1 km²) will be made available via a Figshare repository as soon as
671 the final versions have been made after reviewers' comments.

672 *The authors suggest expanding this further with an interactive online app in which the results can be*
673 *easily visualized for locations outside of the current dataset.*

674 **Use of AI-assisted technologies in the writing process**

675 During the preparation of this work, the first author used Claude Sonnet 4.6 (Anthropic, claude.ai)
676 and GPT-5.3 (OpenAI, ChatGPT) in order to improve the readability and language of the manuscript.
677 After using this tool/service, the first author reviewed and edited the content as needed and takes
678 full responsibility for the content of the published article.

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Acknowledgments

V.V.D.V. acknowledges Tropenbos RDC and BOS+ for their support in establishing the chronosequence sites northeast of Kisangani, and extends sincere gratitude to the local communities of Barumbi-Tshopo, Bapondi, Bafwamogo, and those living around the Yoko and Babagulu reserves for their invaluable assistance in the field and for granting access to their forests and fallows. V.V.D.V. further acknowledges the ForestPlots.net and 2ndFOR networks for providing data from Gabon and Ghana, respectively. We also acknowledge the African Tropical Rainforest Observatory (AfriTRON), curated at ForestPlots.net, for maintaining long-term old-growth forest plots used in this study.

Funding sources

This study was made possible by the Special Research Fund of Ghent University, through the Methusalem mandate of Pascal Boeckx [BOF.MET.2021.0004.01]. M.B., D.L., J.L.M., and S.A.M. acknowledge the financial support of the European Research Council ERC Starting grant [FORECAT; 101114639]. S.L.L., F.M. and P.B. acknowledge funding from Schmidt Sciences' Virtual Institute for the Carbon Cycle [INT.DIV.2025.0036.01]. F.M. was supported by the Research Foundation – Flanders (FWO) as a Senior Postdoctoral Fellow and through an ERC runner-up project [1214723N and G0BHJ26N]. J.V.P. was supported by an FWO Junior Postdoctoral Fellowship [12A2L25N]. W.W.M.V. was supported by the FWO and the F.R.S.-FNRS through the Excellence of Science programme [EOS; O.0026.22]. M.N.S. was supported by USAID through the West Africa Biodiversity and Low Emission Development programme to the Reptile and Amphibian Program [RAP-SL], Sierra Leone. N.B., L.B.S. and P.C. acknowledge support from the Nachtigal Hydro Power Company, Conservation Mpem & Djim National Park, and MINFOF. S.L.M. was supported by FWO [1203025N]. W.H. and J.-R.M. acknowledge support from the Belgian Directorate-General for Development Cooperation and Humanitarian Aid [DGD; PilotMABplus], the Central African Forest Initiative [CAFI; CongoFor1.5], the Belgian Science Policy Office [BELSPO; FED-tWIN2019-prf-075-CongoFORCE and B2/223/P1/DAMOCO], and the Research Foundation – Flanders [FWO; G014123N COBARCHIVES and 3G0I3922 CANOPI]. J.-F.B., T.C. and T.M. acknowledge support from a start-up grant from the Francqui Foundation (Belgium) and the

723 Belgian Science Policy Office [BELSPO; AFROCARDS, STEREO4 SR/00/410, and CoForFunc, Biodiversa+
724 BioDivMon RT/24/CoForFunc]. F. Mai. acknowledges financial support from the German Federal
725 Ministry of Education and Research (BMBF) through The Future Okavango Project [01LL0912A]. S.D. is
726 a Research Fellow of the Fonds de la Recherche Scientifique (F.R.S.-FNRS). S.L.L. also acknowledges
727 funding from the Central African Forest Initiative (CAFI) project [CongoFor1.5]. L.P. was supported by
728 the European Research Council Advanced Grant PANTROP [834775].

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731 editing, Data analysis, Investigation, Data curation. **Pascal Boeckx, Marijn Bauters:** Conceptualization,
732 Methodology, Writing – review & editing, Investigation, Resources, Funding acquisition, Data curation,
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737 preparation. **Eben Broadbent, Frans Bongers, Iris Hordijk, Lourens Poorter, Masha van der Sande:**
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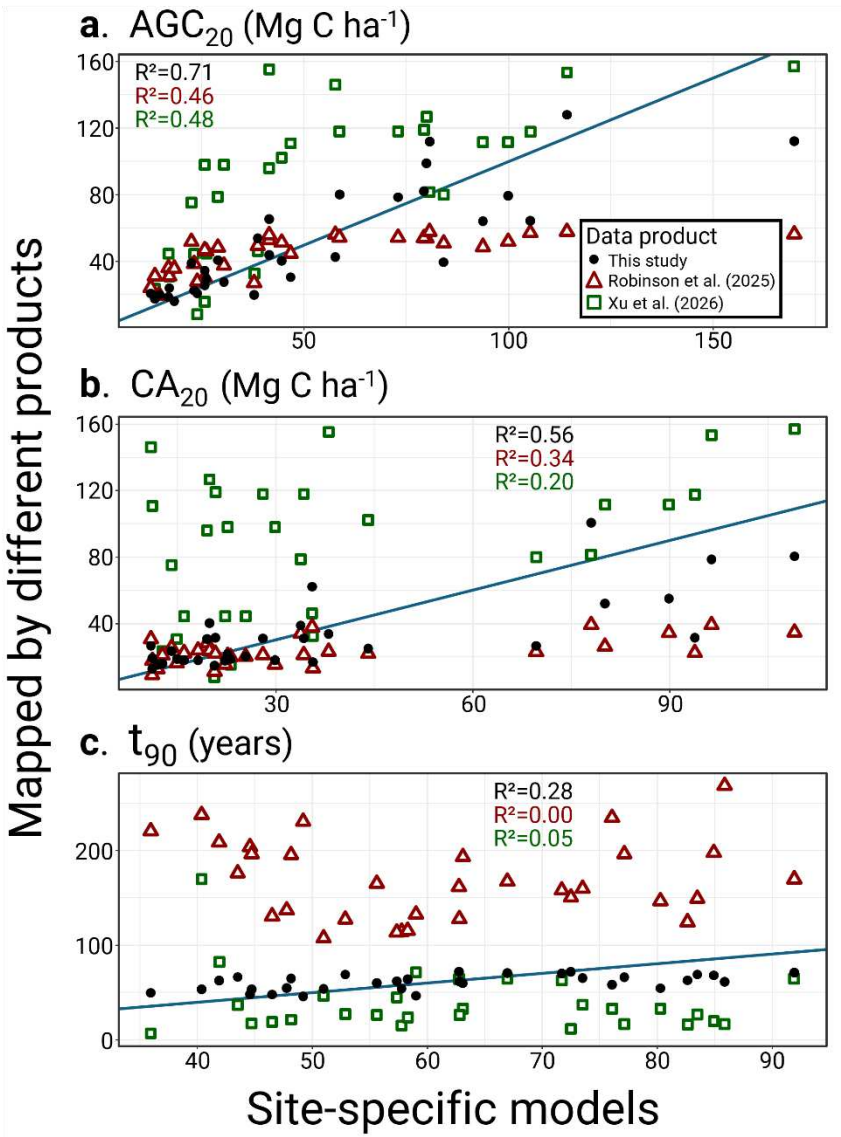
749 **Charles Sangne:** Data contribution, Writing – review & editing.

750 **Declaration of Competing Interest**

751 The authors declare not to have any known conflict of interest.

Additional information

Extended data



Extended Data Figure 1 | Spatial comparison of three recovery metrics between the current study and published pantropical data products. **a**, the total aboveground carbon stocks at 20 years of succession (AGC₂₀), **b**, the aboveground carbon accrual during the first 20 years of succession (CA₂₀), and **c**, the time to 90% AGC recovery relative to old-growth forest reference values (t₉₀). The mapped values (y-axis) refer to the point estimates extracted from the published, publicly available pantropical

761 reference maps^{16,18} and our prediction maps. 'Site-specific model' values (x-axis) refer to the estimates
762 inferred from the trajectory simulations. The blue lines indicate the 1:1 line. Differences reflect distinct
763 methodological approaches, spatial extents, and training datasets rather than deficiencies in either
764 product.

765 **Extended Data Table 1 | Metadata summary of the chronosequence sites included in the study.** Abbreviations: # SF = the number of secondary forest plots
766 at the site, # OGF = the number of old-growth forest reference plots, DBH = tree diameter at breast height (1.30 m). The final two columns indicate if tree
767 heights and/or remnant trees were identified in the field (y) or not (n).

Country	Site	Ages	# SF	# OGF	Plot area (ha)	Land use(s)	# clearing cycles	Inventory year	DBH cutoff	Tree heights measured?	Remnants indicated?
Angola	ANG_CCB	8-20	30	10	0.10	Slash-and-burn	1	2013	5	n	n
Cameroon	CAM_MDNP	5-47	10	32	0.16	Slash-and-burn	Unknown	2019-2020	10	y	n
Côte d'Ivoire	IC_Agbo1	1-40	89	16	0.20	Shifting cultivation, logged	Unknown	2016-2017	2.5	y	y
Côte d'Ivoire	IC_Badenou	1-41	16	5	0.20	Shifting cultivation and pasture	Unknown	2019	2.5	y	y
Côte d'Ivoire	IC_Bs-S	9-26	96	32	0.06	Shifting cultivation and pasture	Unknown	2023-2024	2.5	n	y
Côte d'Ivoire	IC_Foumbou	7-42	16	4	0.20	Shifting cultivation and pasture	Unknown	2019	2.5	y	y
Côte d'Ivoire	IC_Ht-S	2-40	16	4	0.20	Shifting cultivation and pasture	Unknown	2020	2.5	y	y
Côte d'Ivoire	IC_Irobo	2-40	16	4	0.20	Shifting cultivation and pasture	Unknown	2020	2.5	y	y
Côte d'Ivoire	IC_Niegre	4-36	16	4	0.20	Shifting cultivation and pasture	Unknown	2020	2.5	y	y
Côte d'Ivoire	IC_Tene	2-43	16	4	0.20	Shifting cultivation and pasture	Unknown	2019	2.5	y	y
Côte d'Ivoire	IC_Yaya	1-45	16	4	0.20	Shifting cultivation and pasture	Unknown	2019	2.5	y	y
DRC	DRC_Babagulu	8-30	18	3	0.25	Slash-and-burn	1-2	2024	5	y	n
DRC	DRC_NE-Kisangani	5-53	17	3	0.16	Slash-and-burn	1	2021-2022	10	n	y
DRC	DRC_Mabali	20-90	8	4	1.00	Savanna, Slash-and-burn	Unknown	2025	10	y	n
DRC	DRC_Yoko	5-20	12	3	0.16	Slash-and-burn	1	2018	10	y	n
DRC	DRC_Salonga	2-36	7	9	1.00	Slash-and-burn	4+	2008	10	n	n
DRC	DRC_Sakania	1-26	20	5	0.16	Recently abandoned, Slash-and-burn	Unknown	2024	5	y	n
Gabon	GAB_Lopé	5-60	8	24	0.08	Slash-and-burn	Unknown	2013	10	y	n
Ghana	GH_Abofour	0.5-37	10	2	0.13	Cocoa plantation/shifting cultivation	Varying	2020	1	n	y
Ghana	GH_Bonsa	5-42	11	2	0.13	Cocoa plantation/shifting cultivation	Varying	2021-2022	1	n	y
Liberia	LIB_Gola	5-15	20	0	0.10	Slash-and-burn	Unknown	2022	10	n	y
Liberia	LIB_Sapo	5-15	12	0	0.10	Slash-and-burn	Unknown	2023	10	n	y
Liberia	LIB_Wonegizi	5-15	20	0	0.10	Slash-and-burn	Unknown	2023	10	n	y
Mozambique	MOZ_GiléNatPark	5-33	36	20	0.03-0.08	Slash-and-burn	1-15	2015-2019	5	y	n
Mozambique	MOZ_Sussundenga	2-53	45	10	0.07-0.13	Slash-and-burn	Unknown	2023	5	n	n
Mozambique	MOZ_Machamba	2-25	28	14	0.13-0.25	Slash-and-burn	Unknown	2004-2005	5	y	n
Republic of Guinea	GU_Soyah	5-15	20	0	0.10	Slash-and-burn	Unknown	2022	10	n	y
Republic of Guinea	GU_Ziama	5-13	10	0	0.10	Slash-and-burn	Unknown	2023	10	n	y
Sierra Leone	SL_Gola	5-15	20	0	0.10	Slash-and-burn	Unknown	2022	10	n	y
Sierra Leone	SL_Outamba	5-13	20	0	0.10	Slash-and-burn	Unknown	2023	10	n	y
Tanzania	TAN_Kilwa	0-40	52	15	0.20-0.25	Active Field, slash-and-burn	Unknown	2011-2012	5	n	y
Zambia	ZAM_Chintumukulu	2-23	16	4	0.16	Agriculture - miscellaneous	Unknown	2021	3	y	n

770 **Extended Data Table 2 | Environmental data summary of the chronosequence sites included in the study.** Abbreviations: 'MAP' = annual precipitation (mm),
771 'MAT' = annual mean temperature (°C), 'PS' = precipitation seasonality, 'SR' = solar radiation ($\text{kJ m}^{-2} \text{day}^{-1}$), 'MCWD' = absolute value of the maximum cumulative
772 water deficit (mm), 'TS' = temperature seasonality, Al, Ca, K, Mg, P the Mehlich III-extractable soil contents of the respective chemical elements, 'clay' = the
773 percentage clay in the soil texture, 'eCEC' = effective cation exchange capacity ($\text{cmol}(+)/\text{kg}$), 'OC' and 'ON' = organic C and N (%), 'D30' = distance to the nearest
774 pixel with at least 30% tree cover, 'MFC' = mean forest cover in a 500 m-radius, 'FC30' = percentage of pixels in a 5 km radius that showed at least 30% tree
775 cover, 'CONT' = contagion.

Country	Site	MAP	MAT	PS	SR	MCWD	TS	Al	Ca	K	Mg	P	clay	eCEC	pH	OC	ON	D30	MFC	FC30	CONT
Angola	ANG_CCB	1,117	19.5	94	17,605	770	227	176	75	39	41	7.9	18	4.4	5.5	0.68	0.06	68	32	44	47
Cameroon	CAM_MDNP	1,585	24.5	71	14,706	333	90	58	272	61	85	7.3	32	12.5	5.4	1.34	0.15	3	61	86	39
Côte d'Ivoire	IC_Agbo1	1,187	26.7	61	17,100	381	112	84	552	71	103	4.7	20	8.2	5.6	1.11	0.24	1	52	96	54
Côte d'Ivoire	IC_Badenou	1,187	26.8	90	18,874	588	138	122	336	55	91	6.1	22	9.6	5.8	0.77	0.11	1,842	13	0	72
Côte d'Ivoire	IC_Bs-S	1,580	25.8	50	16,999	217	90	68	162	56	50	5.0	21	7.3	5.0	1.16	0.16	2	55	94	45
Côte d'Ivoire	IC_Foumbou	1,183	26.2	79	18,061	602	142	160	452	61	92	6.1	21	10.9	5.8	0.87	0.17	144	23	13	46
Côte d'Ivoire	IC_Ht-S	1,308	25.4	61	16,863	420	99	150	562	76	116	5.1	21	9.5	5.6	1.13	0.16	3	50	92	36
Côte d'Ivoire	IC_Irobo	1,376	26.5	71	17,542	232	105	78	271	67	75	6.2	18	6.8	5.3	1.09	0.21	1	58	96	46
Côte d'Ivoire	IC_Niegre	1,455	25.7	80	17,536	253	99	129	247	64	66	6.6	21	8.2	5.0	1.24	0.19	1	62	93	33
Côte d'Ivoire	IC_Tene	1,170	26.1	54	17,381	476	105	88	643	77	113	4.2	20	9.9	5.9	1.09	0.16	20	37	72	39
Côte d'Ivoire	IC_Yaya	1,517	26.4	62	17,049	177	114	78	229	62	58	6.6	20	6.3	5.0	1.26	0.18	0	62	99	45
DRC	DRC_Babagulu	1,744	24.6	30	15,149	112	52	77	161	46	34	8.2	32	11.1	4.7	1.08	0.12	0	96	100	65
DRC	DRC_NE-Kisangani	1,755	24.3	30	15,358	120	48	58	206	49	46	8.9	33	11.8	4.7	1.18	0.14	0	99	100	84
DRC	DRC_Mabali	1,829	25.2	29	15,318	76	55	86	163	39	36	9.8	29	14.0	4.7	1.24	0.13	58	76	60	75
DRC	DRC_Yoko	1,746	24.7	30	15,127	99	53	78	152	46	33	8.2	31	11.5	4.7	1.07	0.13	0	97	100	75
DRC	DRC_Salonga	2,001	24.8	29	14,688	70	49	63	105	41	20	9.3	29	11.1	4.6	1.15	0.12	0	99	99	65
DRC	DRC_Sakania	1,224	19.6	114	17,260	894	258	139	139	56	62	8.5	30	8.0	5.4	0.90	0.08	11	44	84	47
Gabon	GAB_Lopé	1,756	25.4	70	11,992	333	99	104	126	53	37	7.9	35	11.6	4.8	1.33	0.17	2	81	90	51
Ghana	GH_Abofour	1,255	24.8	59	16,037	269	116	176	642	86	152	5.6	24	9.8	5.6	1.16	0.19	2	55	93	43
Ghana	GH_Bonsa	1,729	26.1	57	15,981	149	104	108	263	61	62	6.4	21	6.7	4.7	1.33	0.23	0	57	95	45
Liberia	LIB_Gola	2,684	25.5	67	16,006	293	82	126	233	57	62	8.3	30	9.3	4.9	1.65	0.17	0	82	100	48
Liberia	LIB_Sapo	2,542	25.5	52	16,174	145	79	77	171	56	45	6.1	24	5.8	4.9	1.22	0.15	0	73	100	60
Liberia	LIB_Wonegizi	2,331	24.6	66	16,289	363	73	141	300	62	99	8.0	27	11.1	5.2	1.50	0.17	0	67	99	56
Mozambique	MOZ_GiléNatPark	1,229	25.0	79	17,903	635	246	127	487	83	114	7.9	19	8.5	5.9	0.79	0.09	51	38	64	41
Mozambique	MOZ_Sussundenga	822	24.1	97	18,290	921	283	47	425	111	121	10.0	24	10.5	5.8	0.82	0.10	6	48	82	49
Mozambique	MOZ_Machamba	1,011	24.6	92	17,703	834	278	54	628	119	197	10.3	23	11.3	5.9	0.95	0.11	21	41	80	35
Republic of Guinea	GU_Soyah	1,959	26.1	95	18,350	613	147	240	421	90	115	9.0	25	10.9	5.5	1.47	0.16	19	39	80	35
Republic of Guinea	GU_Ziama	2,270	24.0	72	16,635	416	78	151	317	73	83	8.3	30	11.3	5.4	1.46	0.17	1	56	97	60
Sierra Leone	SL_Gola	2,933	26.1	76	16,216	355	83	176	233	62	62	6.9	23	8.9	5.2	1.55	0.16	1	61	99	53
Sierra Leone	SL_Outamba	2,445	27.6	97	18,055	618	158	278	365	76	97	8.0	24	8.5	5.3	1.38	0.16	20	35	61	32
Tanzania	TAN_Kilwa	984	25.9	81	17,654	649	119	128	592	108	164	7.9	23	13.5	6.2	0.90	0.10	17	42	74	38
Zambia	ZAM_Chintumukulu	1,063	18.7	119	17,491	850	203	138	245	66	70	9.1	24	7.8	5.7	0.83	0.08	136	25	27	49

777 **Extended Data Table 3 | Simulated values of the time to 90% AGC recovery relative to old-growth forest reference values (t_{90}), aboveground carbon accrual**
778 **during the first 20 years of succession (CA_{20}), and total aboveground carbon stocks at 20 years of succession (AGC_{20}) across the 32 sites.** Abbreviations: 'MLE'
779 = maximum likelihood estimate in the joint posterior space; '5% Qt' and '95% Qt' = lower and upper bounds of the 90% credible interval, respectively. See the
780 Supplementary Materials and Methods section for model details. Note that the MLE and median of the regional posterior distributions frequently diverge, as
781 the joint posterior maximum does not necessarily coincide with the mode of any individual metric's marginal distribution.

Country	Site	t_{90} (years)				CA_{20} (Mg C ha ⁻¹)				AGC_{20} (Mg C ha ⁻¹)			
		MLE	Median	5% Qt	95% Qt	MLE	Median	5% Qt	95% Qt	MLE	Median	5% Qt	95% Qt
Angola	ANG_CCB	33.06	35.95	27.95	50.85	37.95	35.62	23.83	42.72	38.84	37.83	31.23	43.79
Cameroon	CAM_MDNP	157.62	82.66	32.50	179.03	1.86	10.94	1.20	63.98	52.95	57.65	35.46	98.39
Côte d'Ivoire	IC_Agbo1	90.74	85.87	69.61	106.49	30.76	29.85	26.07	34.38	31.24	30.41	26.67	34.96
Côte d'Ivoire	IC_Badenou	31.75	47.79	30.73	74.52	25.15	18.13	11.43	26.63	25.15	18.29	11.67	26.93
Côte d'Ivoire	IC_Bs-S	50.48	43.52	29.71	72.75	35.99	69.65	22.84	102.11	80.97	84.15	62.82	104.64
Côte d'Ivoire	IC_Foumbou	85.47	80.29	59.49	110.05	15.88	16.00	10.50	21.71	16.16	16.85	12.41	22.37
Côte d'Ivoire	IC_Ht-S	38.31	63.10	34.34	108.39	27.91	25.37	17.61	35.95	29.88	26.13	19.17	36.39
Côte d'Ivoire	IC_Irobo	53.33	77.15	60.34	99.57	29.80	22.65	15.64	31.52	33.22	25.71	19.40	33.86
Côte d'Ivoire	IC_Niegre	123.15	73.53	41.14	131.87	7.87	14.10	4.17	30.41	17.88	22.48	15.16	33.30
Côte d'Ivoire	IC_Tene	50.24	76.09	50.46	115.50	34.85	22.24	12.80	37.18	35.50	23.14	13.78	38.11
Côte d'Ivoire	IC_Yaya	68.36	84.93	53.56	141.00	42.70	44.07	27.70	70.93	43.26	44.54	28.43	71.50
DRC	DRC_Babagulu	38.59	66.97	34.93	126.93	111.19	34.23	10.75	81.25	111.43	72.99	58.41	94.59
DRC	DRC_NE-Kisangani	72.47	71.71	40.83	122.02	12.90	20.78	7.29	47.19	87.64	79.34	66.13	96.94
DRC	DRC_Mabali	72.08	72.50	56.59	92.65	38.27	38.01	25.62	51.54	38.39	41.47	31.27	54.75
DRC	DRC_Sakania	57.81	59.03	42.22	85.11	15.49	23.09	14.76	33.32	18.86	25.74	17.83	35.53
DRC	DRC_Salonga	73.98	62.77	34.48	104.94	9.75	19.87	5.98	48.71	80.70	79.96	62.77	108.58
DRC	DRC_Yoko	130.49	91.93	48.85	161.08	15.19	28.01	9.21	72.47	44.81	58.69	44.41	87.96
Gabon	GAB_Lopé	33.66	41.91	30.37	58.46	107.24	93.81	65.31	119.84	113.72	105.35	89.11	125.31
Ghana	GH_Abofour	67.30	48.16	19.07	101.45	10.67	11.18	1.53	33.29	47.77	46.75	36.39	61.78
Ghana	GH_Bonsa	86.48	83.50	42.50	162.25	20.25	19.49	5.05	55.36	30.43	41.47	29.30	65.52
Republic of Guinea	GU_Soyah	29.89	57.78	29.51	108.88	28.79	33.75	22.32	48.63	35.92	28.92	18.16	47.23
Republic of Guinea	GU_Ziama	63.00	55.62	32.82	94.36	52.97	80.14	56.67	112.13	88.46	93.77	62.26	137.54
Liberia	LIB_Gola	32.76	58.31	34.72	100.20	97.23	96.35	65.21	138.47	221.99	114.29	63.73	189.57
Liberia	LIB_Sapo	61.36	52.89	34.80	80.42	101.55	109.00	77.95	153.72	260.14	169.86	108.75	258.02
Liberia	LIB_Wonegizi	61.87	62.81	41.61	95.13	102.69	89.88	67.36	117.78	109.08	99.90	71.36	140.73
Mozambique	MOZ_GiléNatPark	38.50	44.73	29.34	67.77	19.77	14.90	8.45	21.20	21.91	17.05	12.61	22.38
Mozambique	MOZ_Machamba	37.87	44.59	31.42	63.64	13.99	11.95	8.35	15.94	14.96	12.51	9.20	16.36
Mozambique	MOZ_Sussundenga	39.21	49.22	35.69	70.30	11.48	11.15	8.27	14.35	15.63	14.68	12.43	17.16
Sierra Leone	SL_Gola	35.73	57.36	37.24	87.64	94.34	78.02	50.34	116.36	82.82	80.72	53.23	122.98
Sierra Leone	SL_Outamba	35.14	50.99	27.84	93.67	43.30	35.51	17.81	59.33	44.27	38.66	19.11	70.91
Tanzania	TAN_Kilwa	35.38	40.39	28.08	58.66	23.01	20.62	14.62	27.10	25.75	23.89	18.41	30.38
Zambia	ZAM_Chintumukulu	42.15	46.51	31.65	71.99	12.76	12.70	7.04	18.50	12.76	13.54	8.97	19.16

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