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Rapid tree carbon stock recovery in managed Amazonian forests

Ervan Rutishauser[1,2,*], Bruno Hérault[3,a], Christopher Baraloto[4,5], Lilian Blanc[2], Laurent Descroix[6], Eleneide Doff Sotta[7], Joice Ferreira[8], Milton Kanashiro[8], Lucas Mazzei[8], Marcus V.N. d'Oliveira[9], Luis C. de Oliveira[9], Marielos Peña-Claros[10,11], Francis E. Putz[12], Ademir R. Ruschel[8], Ken Rodney[13], Anand Roopsind[12,13], Alexander Shenkin[14], Katia E. da Silva[15], Cintia R. de Souza[15], Marisol Toledo[11], Edson Vidal[16], Thales A.P. West[12], Verginia Wortel[17], and Plinio Sist[2,a]

While around 20% of the Amazonian forest has been cleared for pastures and agriculture, one fourth of the remaining forest is dedicated to wood production [1]. Most of these production forests have been or will be selectively harvested for commercial timber, but recent studies show that even soon after logging, harvested stands retain much of their tree-biomass carbon and biodiversity [2,3]. Comparing species richness of various animal taxa among logged and unlogged forests across the tropics, Burivalova *et al.* [4] found that despite some variability among taxa, biodiversity loss was generally explained by logging intensity (the number of trees extracted). Here, we use a network of 79 permanent sample plots (376 ha total) located at 10 sites across the Amazon Basin [5] to assess the main drivers of time-to-recovery of post-logging tree carbon (Table S1). Recovery time is of direct relevance to policies governing management practices (i.e., allowable volumes cut and cutting cycle lengths), and indirectly to forest-based climate change mitigation interventions.

We found that the proportion of initial above-ground carbon stock lost (i.e., trees harvested and destroyed by logging operations) best predicted the time to recover initial carbon stocks. No other variables tested contributed substantially to the prediction of recovery time, despite the fact that the sampled plots span large geographic and environmental gradients across the entire Amazon Basin. These results reveal clear patterns that can clarify tradeoffs between short-term economics and long-term carbon storage/climate regulation for policy makers and forest managers.

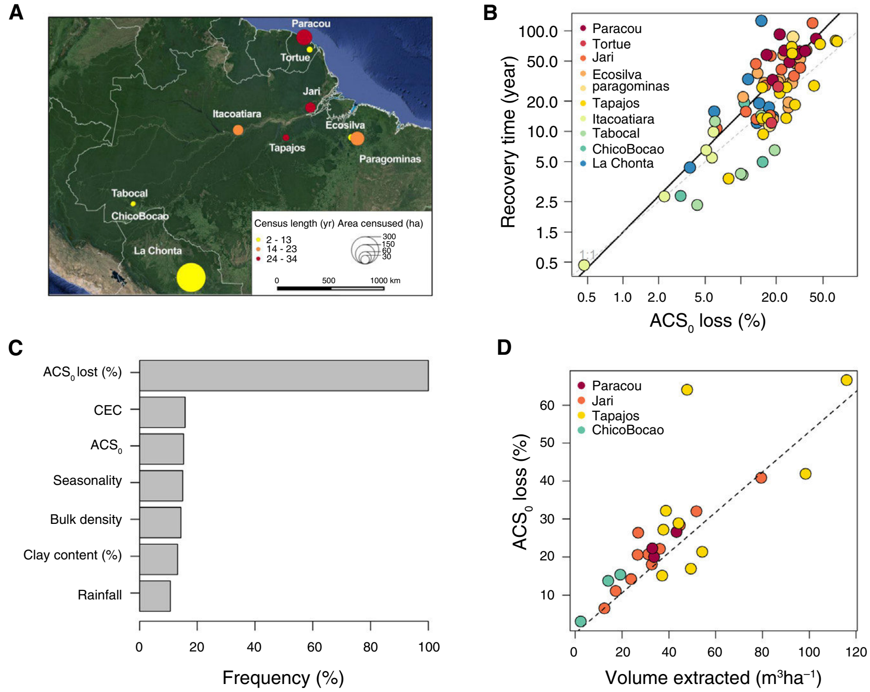

Figure 1. Assessing the main drivers of tree carbon recovery in managed forests in the Amazon Basin.
(A) Site locations, census length (color) and area censused (size). (B) Relationship between time of recovery and percentage of initial above ground carbon stocks lost (ACS_0 loss) due to selective timber harvests and damage-induced mortality at 10 sites across the Amazon Basin. OLS regression (solid) and 1:1 relationship (dashed) lines are shown. Sites are listed from northeast to southwest. (C) Frequency of selection of variables explaining t_{rec} (ACS_0 loss (%), initial ACS lost; bulk density, soil bulk density; ACS_0, initial ACS; CEC, cation exchange capacity; seasonality, coefficient of variation in monthly means of precipitation; clay content (%), percentage clay content in soil; rainfall, average annual rainfall). (D) Relationship between timber volume extracted (m^3/ha) and initial ACS lost (%) at four sites under RIL management ($y = 0.53*x$, $R^2 = 0.88$, $P < 10^{-6}$).

While the REDD+ international agreement on climate change explicitly recognizes the contributions of sustainable management of forests and enhancement of forest carbon stocks in developing countries, less than 5% of tropical forest area is under some form of recognized sustainable management [1]. As a consequence, unplanned and destructive timber harvests are estimated to contribute 25% as much carbon loss as deforestation in the Amazon Basin [6]. Additionally, poorly managed forests are more susceptible to other threats, such as conversion to croplands or fire [2]. To understand the impact of logging on the global carbon cycle, a major gap in our knowledge must be filled, notably the rate at which this emitted carbon is recaptured by post-logging forest recovery across managerial, spatial, and environmental gradients. It is speculated that time to recover initial above-ground carbon stocks (ACS) varies with logging intensity and harvesting methods, along with initial forest structure and abiotic conditions [6]. In the present study, we use plot data to assess the effects of several biophysical variables, such as ACS lost due to logging (ACS_{loss}), rainfall, and soil properties, on time to recover initial ACS (ACS_0), hereafter recovery time (t_{rec} in year). These plots represent a breadth of logging intensities, soils, rainfall regimes, and forest structure and dynamics (Figure 1A) [5]. While reduced-impact logging (RIL) techniques were implemented at most sites, 7 plots (7.7%) were conventionally logged. Due to limited numbers of plots conventionally logged, and because our definition of logging accounts for most direct logging damages, we have decided not to include this term in our models, but a separate analysis is presented. We applied a standardized protocol to estimate ACS of live trees with stem diameters at breast height (DBH) ≥ 20 cm before (1–4 years) and after (1–33 years) selective logging. The main explanatory variables for t_{rec} and recovery rates (r_{rec} in Mg C/year) were selected using linear mixed models, treating sites as random effects to reduce pseudo-replication (Supplemental Experimental Procedures).

The percentage of initial ACS lost (ACS_{loss}/ACS_0; Figure 1B) is the best predictor of t_{rec} with a significant interaction (goodness of fit, $R^2 = 0.994$); no other variables tested contributed significantly to the predictions (Figure 1C and Table S2). More practically, $t_{rec} = (100{*}ACS_{loss}/ACS_0)^{\theta}$, where $\theta = 1.106 \pm 0.022$. This result implies that losses of 10, 25 or 50% of pre-logging ACS would require 12, 43 or 75 years, respectively, to recover regardless of location in the Amazon region. In contrast, r_{rec} was more complex to predict, as it was positively correlated with initial ACS (i.e., forests with larger biomass stocks recover faster), but with a lower goodness of fit. Our r_{rec} estimates (0.04–2.96 Mg C ha^{-1} yr^{-1}, mean = 1.33 Mg C ha^{-1} yr^{-1}) sits at the lower bound of those reported in bookkeeping approaches (1.5–5.5 Mg C ha^{-1} yr^{-1} [7]). Although there is an apparent geographical uniformity of t_{rec} across the region, our results suggest that recovery rates correlate with the regional distribution of biomass stocks. We also expect that post-logging tree demography (growth, recruitment and mortality) will follow a similar pattern as that observed for structure and dynamics of unmanaged forests [8]. For instance, northeastern Amazonian forests with higher carbon stocks (initial ACS) are subjected to higher logging intensities, but tend to regenerate at faster rates than in the southwest.

Forest management regulations vary among Amazonian countries, but generally set minimum cutting cycles at 30–60 years, with harvests of 10–30 m^3 ha^{-1}. While these cutting cycles are generally insufficient to recover commercial timber stocks [9], such harvest intensities require 7 and 21 years, respectively, to recover their initial ACS, assuming ACS losses proportional to harvested timber volumes (Figure D) and linear biomass aggradation over time. Our results are likely to represent optimal recovery processes, given that plots that experienced negative r_{rec} over the study period were disregarded and most plots are located in well-managed areas. Accounting for further post-logging disturbances (e.g., fire or illegal logging), which many logged forests are experiencing [2,3], would undoubtedly extend the recovery times presented here. Nevertheless, these results reveal the overwhelming importance of logging intensity in the recovery capacity of Amazonian forests. If logging intensity is such a main driver of recovery rates in other tropical forests, such as Borneo, where high logging intensities can reach 150 m^3 ha^{-1}, often followed by other disturbances, there will likely be dramatic consequences for future carbon sequestration. Additionally, we propose our data-driven results to be used as cost-efficient estimates of post-logging carbon recovery instead of regional default values [7,10].

Globally, half of the remaining tropical forests (~400 million ha) is allocated for timber production [1] and there is growing evidence that these forests will play a crucial role in future timber supply and climate change mitigation [2,3,5]. However, forest managers and decision makers still lack the information and practical guidance to define sustainable harvest intensities or cutting rotations that at the same time ensure long-term timber harvest, maintenance of biodiversity and carbon stocks. Our results provide forest managers and policy makers with a new tool to make informed decisions, but also stress that forest management has to be effective on a regional scale where alternative management may coexist to maximize a compromise between timber production and preservation of essential environmental services.

SUPPLEMENTAL INFORMATION

Supplemental Information includes Supplemental Experimental Procedures, Supplemental Discussion, Supplemental References and two tables and can be found with this article online at http://dx.doi.org/10.1016/j.cub.2015.07.034.

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[1]CarboForExpert, Hermance, 1248, Switzerland. [2]UR BSEF, CIRAD, Montpellier, 34398, France. [3]UMR Ecofog, CIRAD, Kourou, 97310, France. [4]UMR Ecofog, Inra, Kourou, 97310, France. [5]International Center for Tropical Botany, Florida International University, Miami, Florida, 33199, USA. [6]ONF-Guyane, Cayenne, 97300, France. [7]EMBRAPA, Macapá, Amapá, 68903, Brazil. [8]EMBRAPA, Belém, Pará, 66095, Brazil. [9]EMBRAPA, Rio Branco, Acre, 69900, Brazil. [10]Forest Ecology and Forest Management Group, Wageningen University, Wageningen, 6700AA, the Netherlands. [11]Instituto Boliviano de Investigación Forestal, Santa Cruz de la Sierra, 10260, Bolivia. [12]Biology Department, University of Florida, Gainesville, Florida, FL 32611-8525, USA. [13]Iwokrama, Hight St, Georgetown, Guyana. [14]Environmental Change Institute, Oxford University Centre for the Environment, University of Oxford, Oxford, OX1 3QY, UK. [15]EMBRAPA, Manaus, Amazonas, 69011, Brazil. [16]Escola Superior de Agricultura Luiz de Queiroz, University of São Paulo, São Paulo, 01002, Brazil. [17]Biodiversity Department, CELOS, Paramaribo, Paramaribo, Suriname. [a]Co-senior authors.
*E-mail: er.rutishauser@gmail.com

Supplemental information

Rapid tree carbon stock recovery in Amazonian managed forests

Ervan Rutishauser, Bruno Hérault, Christopher Baraloto, Lilian Blanc, Laurent Descroix, Eleneide Doff Sotta, Joice Ferreira, Milton Kanashiro, Lucas Mazzei, Marcus V.N. d'Oliveira, Luis C. de Oliveira, Marielos Peña-Claros, Francis E. Putz, Ademir R. Ruschel, Ken Rodney, Anand Roopsind, Alexander Shenkin, Katia E. da Silva, Cintia R. de Souza, Marisol Toledo, Edson Vidal,Thales A.P. West, Verginia Wortel, and Plinio Sist

Inventory of Supplemental Information:
Tables S1 and S2
Experimental Procedures
Acknowledgements
Supplemental References

Due to limited space availability, we provide supplemental online information (OS), graphs and analysis at: http://tmfo.org/Data/CurrentBio.SI/TmFO.code.Amazon.html

Table S1: Information on ACS stocks over time and recovery rates for each of the 90 plots included in this study (provided as an Excel file). Eleven (11) plots (in italic) were discarded from the analysis

Table S2: Alternative models with ΔBIC < 5.

Model	ACS_0 lost (%)	ACS_0	bulk density	CEC	clay	rainfall	seasonality	BIC	delta	AIC	delta	df	logLik	weight
2	1.1064							248.9015	0	241.79	0	3.0000	-117.8966	0.1443
6	0.9978		0.2537					252.5302	3.629	243.05	1.48	4.0000	-117.5262	0.0688
66	1.0443						0.0032	252.6067	3.705	243.13	1.556	4.0000	-117.5644	0.0662
4	1.0332	0.0518						253.0193	4.118	243.54	1.969	4.0000	-117.7707	0.0539
18	1.1230				-0.0014			253.1164	4.215	243.64	2.066	4.0000	-117.8193	0.0513
34	1.1131					0.0000		253.2668	4.365	243.79	2.216	4.0000	-117.8945	0.0476
10	1.1038			0.0003				253.2670	4.366	243.79	2.217	4.0000	-117.8946	0.0476

Supplemental Experimental Procedure

1. Site selection and biometric data collection

Ten (10) sites spread across the Amazon Basin and the Guiana Shield were selected based on the following criteria: (i) located in tropical forests with a total area inventoried ≥ 1 ha; (ii) mean annual rainfall ≥ 1000 mm (Fig. S1); (iii) consistent and detailed information about logging treatments (e.g. number of stems harvested and correspondent biomass removal) and logging impacts (e.g. logging damages assessment); (iv) at least one pre-logging and (v) at least two post-logging censuses. As sites were generally established by different organizations, there is no standardized protocol for data collection among sites, but all sites comply with generally agreed standards [S1]. A general description of the sites can be found in [S2]. In all plots, trees ≥ 20 cm DBH (diameter at breast height) had their girth measured at 130 cm or above buttresses/deformations, and were tagged and identified to the lowest taxonomical level.

2. Data quality checking and biomass computation

To avoid bias due to discrepancies in data quality (e.g. difference in botanical identification or tree species wood density information), a standardized protocol was applied to each site. At first, botanical identification was checked to match the Global Wood Density Database (GWDD) classification [S3]. Tree species present in GWDD were assigned correspondent dry wood density (WD, $gr.cm^{-3}$). When only the genus was present, genus-average WD was assigned and for unidentified species and species not present in the GWDD, plot-average WD was attributed. In the absence of tree height measurements, tree above-ground biomass (AGB) was estimated using the generic allometric model developed by Chave et al. [S4] and including WD, DBH and a synthetic climatic index (E).

Above-ground carbon density (ACS) was obtained by multiplying tree biomass by 0.47 [S5]. ACS stock of each plot was further computed as the sum of ACS of live trees DBH ≥ 20 cm divided by the plot surface and expressed in Mg C ha^{-1}.

3. Definition of logging intensity and biomass recovery

The same definition of logging intensity was applied at all sites. Due to varying interval length (1 to 4 years) between pre- and post-logging censuses and application of silvicultural treatments (i.e. poisoning, girdling, understorey clearing) at three sites (Paracou, Tapajos and la Chonta), we estimated the minimum carbon stock (ACS_{min}, Fig. OS2) attained at last within 4 years after logging and computed the difference with initial carbon stock (ACS_0). This initial ACS drop off, referred to as ACS_{loss}, is due to both timber harvest and mortality of damaged trees (that can affect up to 46% of remaining trees [S6]). As residual mortality peaks within the first years preceding logging [S7-8], this approach allows most of logging-induced mortality to be accounted.

We found no evidence of deviation from linearity; therefore, we estimated the annualized ACS recovery rates (Mg C ha^{-1} yr^{-1}) per plot using linear models among all post-logging censuses spreading between t_{min} and t_{final} (Figure OS3).

Recovery time (t_{rec} in years) refers to the estimated time needed to recover initial ACS stock, given by dividing initial ACS loss by the average recovery rate.

4. Relationship between recovery times and recovery rates

While ACS recovery rates are related to the capacity of a given forest to recover from a disturbance, the recovery time t_{rec} accounts for both the recovery rate and the disturbance intensity (see above). The below demonstration reveals how both variables are mechanically related. By definition:

$$t_{rec} = \frac{|ACS_{loss}|}{ACS\ \widehat{recovery}\ rate}$$

From our results:

$$\log(t_{rec}) \propto \theta \times \log\left(\frac{|ACS_{loss}|}{ACS_0}\right)\ for\ \frac{|ACS_{loss}|}{ACS_0} \in [0.05, 0.5]$$

$$t_{rec} \propto \left(\frac{|ACS_{loss}|}{ACS_0}\right)^{\theta}$$

$$\frac{|ACS_{loss}|}{\widehat{recovery}\ rate} \propto \left(\frac{|ACS_{loss}|}{ACS_0}\right)^{\theta}$$

From our results, θ was found to be N (1.106, 0.022) close to 1, meaning that we are very close to

$$\widehat{recovery\ rate} \propto ACS_0$$

Mechanically, recovery rates could thus depend directly on initial ACS stocks. However, recovery rate relates to more complex mechanisms of forest productivity (i.e. growth, recruitment and mortality) and deserves a separate thorough analysis.

5. Explanatory variables

Several explanatory variables were calculated at each site: (1) average pre-logging ACS stock (ACS_0 in Mg C ha^{-1}); (2) Basal Area-weighted wood density (or community wood density, WD_{BA} in g.cm^{-3}); (3) stem density (ha^{-1}); (4) average annual rainfall (mm yr^{-1}) that arose from local weather stations; (5) rainfall seasonality (annual standard deviation) were extracted at each site using WorldClim data [S9] using highest resolution (30 arc-seconds or ~1 km). Due to lack of information at all sites, soil properties were extracted from the Harmonized World Soil raster at a resolution of 30 arc-seconds [S10]. Information on top soil (0-30 cm) quality was extracted at each site: texture, drainage, available water content (range), clay, silt and sand content (%), cation-exchange capacity (CEC, cmol/kg) and bulk density (kg/dm^3).

To test for possible circularity between the synthetic climatic index (E) used to compute ACS and the climatic explanatory variables, all analysis were recomputed with another generic allometric model [S11], based on local WD and DBH only. All pattern and variables significance remained unchanged (data not shown).

6. Plot selection and weighing

To ensure that observed biomass recovery was mainly related to logging and to avoid bias due to stochastic natural mortality (e.g. the 2005 drought and fires), we selected only plots (79 out of 90) with positive recovery rates (e.g. that gain biomass/carbon over the monitored period), as a detailed checking revealed that those 11 plots suffered from wildfires and droughts. As our sample plots and sites vary in both total area and length of time monitored for, the contribution of each site was weighted by the monitoring effort (number of censuses x plot size), as recommended by [S12]. Hence, sites with longer and larger monitoring (more prone to capture and depict forest recovery) are given more weight. To avoid artificial inflation of the variance of random effects, the sum of weights was set to 1. Table S1 provides information on initial and final ACS, ACS loss, recovery rate and recovery time for each plot (N=90).

7. Variable selections

Our main point was to understand generic drivers that led recovery time and recovery rate among all sites. We developed a linear mixed model (LMM, package *lme4* [S13]) in which recovery time and rate were tested over the different biometric response variables defined above. To account for the site effect, we introduced a random site effect. Indeed, most sites are constituted of several contiguous plots in which silviculture treatments (e.g. logging, girdling or understorey clearing) of varying intensities were applied. Such experimental design ensures a relative homogeneity in environmental conditions and forest structure, but might also induce pseudo-replication. Pseudo-replication occurs when multiple samples from a single treatment unit are analyzed, as if they were independent replicates and embed to distinguished the effect due to treatment from other sources of variation [S14]. To avoid this bias, a "site-effect" was introduced in the LMM and pre-logging forest structures were accounted for as explanatory variables in the analysis.

The best models are found through conducting an exhaustive screening and ranking using Bayesian Information Criterion (BIC) (package *lmerTest* [S15]). Instead of picking a single "best" model, we averaged the fits of a number of "good" models (model averaging) based on Bayesian Information Criterion (BIC) weights, thereby stressing prediction over precision [S16]. Very good fits were effectively found at each site (Figure OS3). To reduce residual heteroscedasticity, recovery time along with two explanatory variables (ACS logged and number of trees harvested) was log-transformed. Table S2 shows alternative models with ΔBIC < 4.

All analyses were carried out with R language and environment [S 17].

8. Assessing the effect of logging techniques

We ran a second analysis including logging techniques (conventional (CL) and reduced impact (RIL) logging), as a binary variable with an interaction with ACS loss. We found that logging techniques had a significant effect and improved predictions of t_{rec} (BIC = 244.26 vs. 248.9, OS). However, we highly doubt the validity of this result, as conventional (CL) logging was applied at only 2 sites (Paragominas and Tabocal), representing only 7.7% of all plots used in our study. Moreover, both techniques were implemented at Paragominas only, with marked difference in post-logging dynamics [S18]. Due to its size (24.5 ha), this site has a strong leverage in our analysis, leading to conclusions that have little ecological meaning and robustness.

While an increasing number of studies reveals the benefit of RIL techniques for preserving vital environmental services [S19–21], we believe that our dataset is not robust enough to efficiently test for such an effect. Our sites were implemented over the past 30 years, while the concept of RIL techniques emerged in the 90's.. However, we do not believe that such a simple dichotomy might reflect the differences in logging techniques, intensity and damages found among our sites. For this reason, we have adopted a broad definition of 'ACS loss' that account for both tree harvested and injured/killed and form a gradient of intensity *sensus largo*, at which RIL forms the lower bound. We think that this approach reflects better the diversity of logging types encountered in our dataset.

Supplemental Author Contributions

L.D., L.M., MdO, K.R., CdS., M.T., E.V, V.W. provided summary statistics at their sites. E.R. and B.R. formatted, checked and analysed the data. E.R., B.R. and P.S. wrote the manuscript. All authors equally contributed in elaborating the protocol and proof-reading the manuscript. All authors read and approved the final manuscript.

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