Old growth deforestation emissions

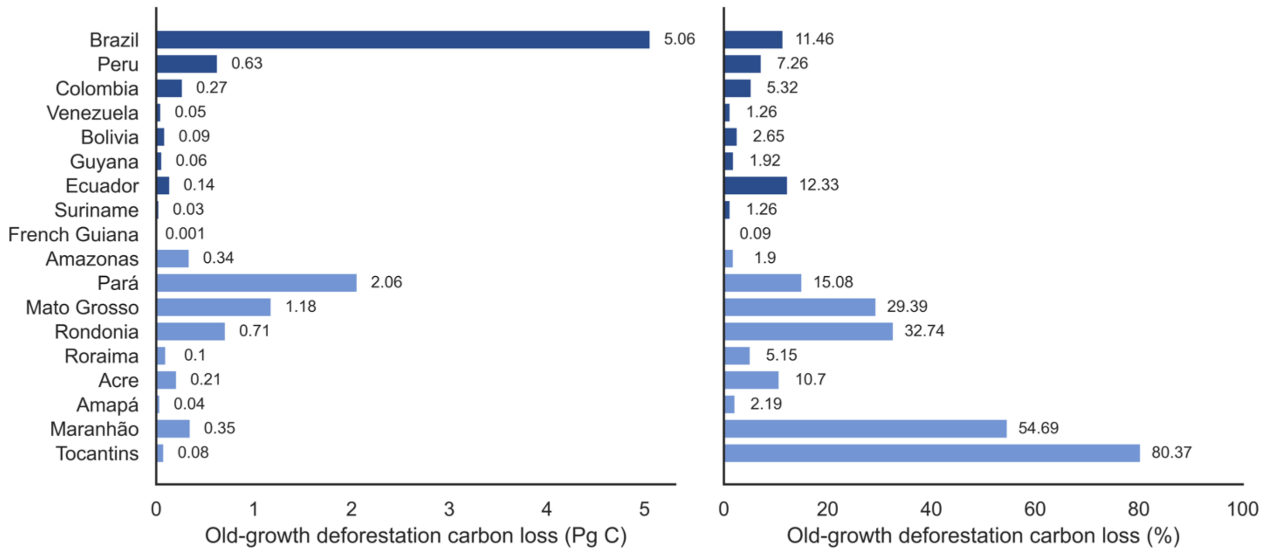

Figure S1: Carbon loss from old-growth deforestation in Amazonian countries and Brazilian States in Amazonian countries and Brazilian states in 2017

The (a) carbon lost from old-growth deforestation and (b) the proportion of original old-growth forest carbon stock lost to deforestation for Amazonian countries (dark) and Brazilian states (light) in 2017. Countries and states are ordered by the area of the Amazon they contain.

Secondary forest age and residence time

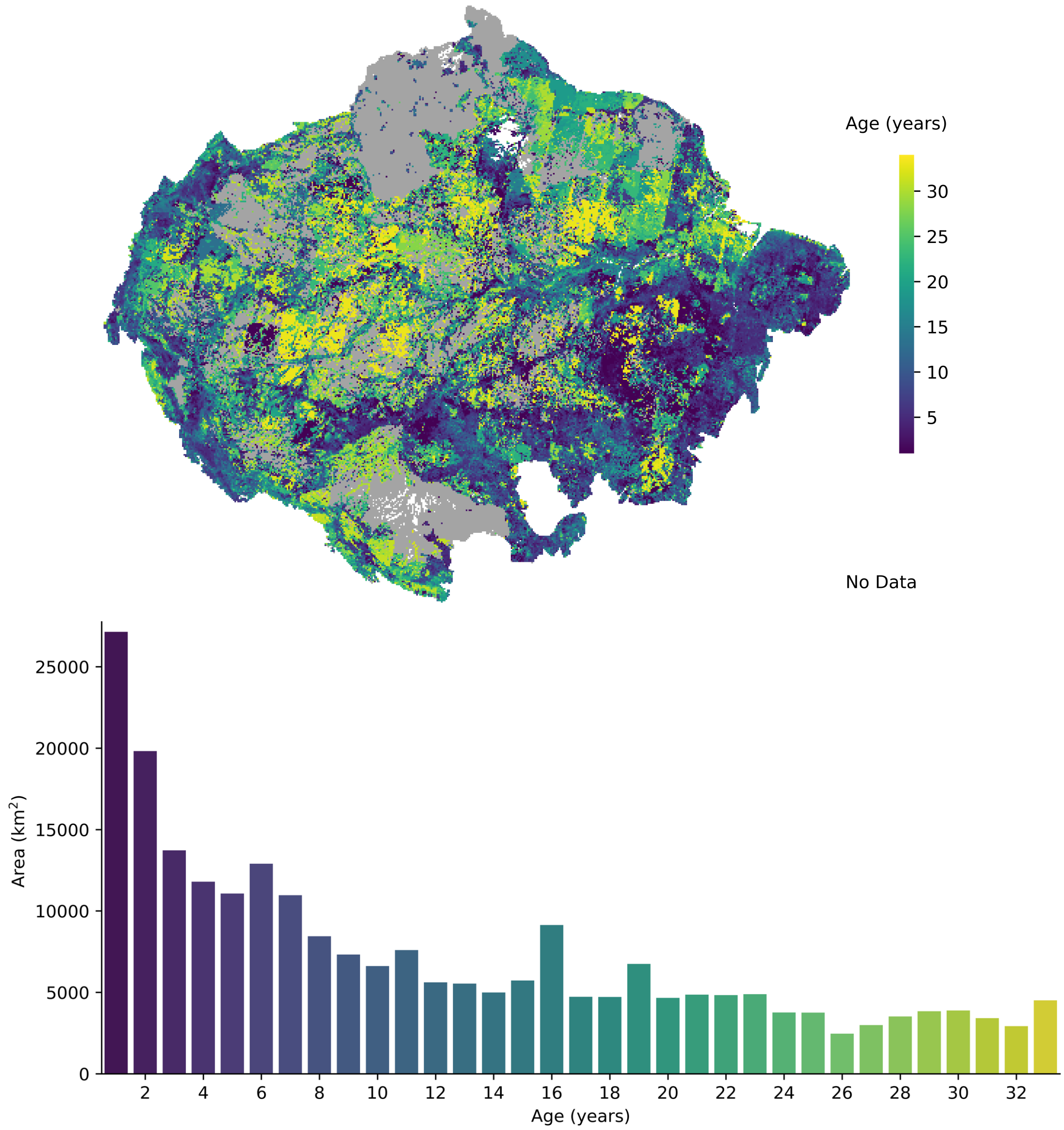

Figure S2: Secondary forest age in the Amazon Biome
(a) Spatial variation in median secondary forest age across the Amazon, plotted on an ~60km² grid. Cells which have experienced no deforestation are shown in grey and those where <1% of the cell is capable of supporting forest are omitted.
(b) The distribution in secondary forest age for all secondary forest in the Amazon.

Secondary forest age: The age distribution of secondary forest in the majority of Amazon countries is highly skewed towards young forests. Bolivia, Guyana and Suriname are the exceptions. Bolivia shows a largely bimodal distribution, with fewer mid-age forests than either young or old. While Guyana and Suriname, both exhibit a skew towards old forests and large spikes in 31-year-old and 18 to 22-year-old secondary forests respectively. While all Brazilian states show a skew toward younger secondary forest, Acre, Amapa and Tocantins all exhibit similar large spikes in 16-year-old secondary forest. Kruskal-Wallis tests indicated significant differences in the distribution of secondary forest age between countries and states (Kruskal–Wallis Chi square = 174.4, P<0.01, df = 16), but post-hoc Dunn's test reveal that Guyana and Suriname are the only political units with significantly different age distributions (Figure S2). The anomalous distributions of Guyana, Suriname and the three Brazilian States are likely due to these regions having persistently limited cloud-free Landsat image cover over much of the time series (see MapBiomas data availability layer).

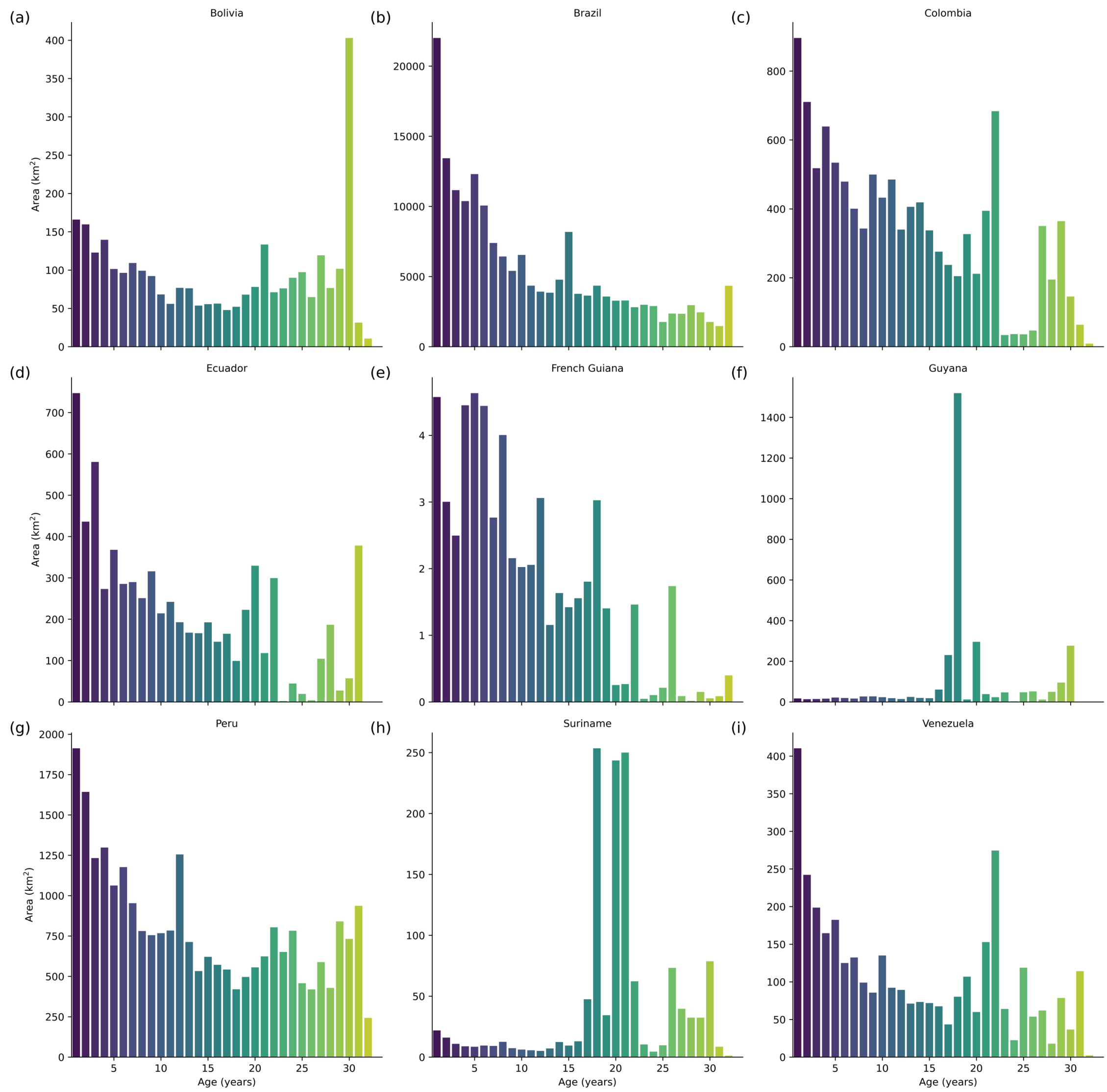

Figure S3: The age distribution of secondary forest in Amazonian countries
The distribution of secondary forest age in (a) Bolivia, (b) Brazil, (c) Colombia, (d) Ecuador, (e) French Guiana, (f) Guyana, (g) Peru, (h) Suriname and (i) Venezuela

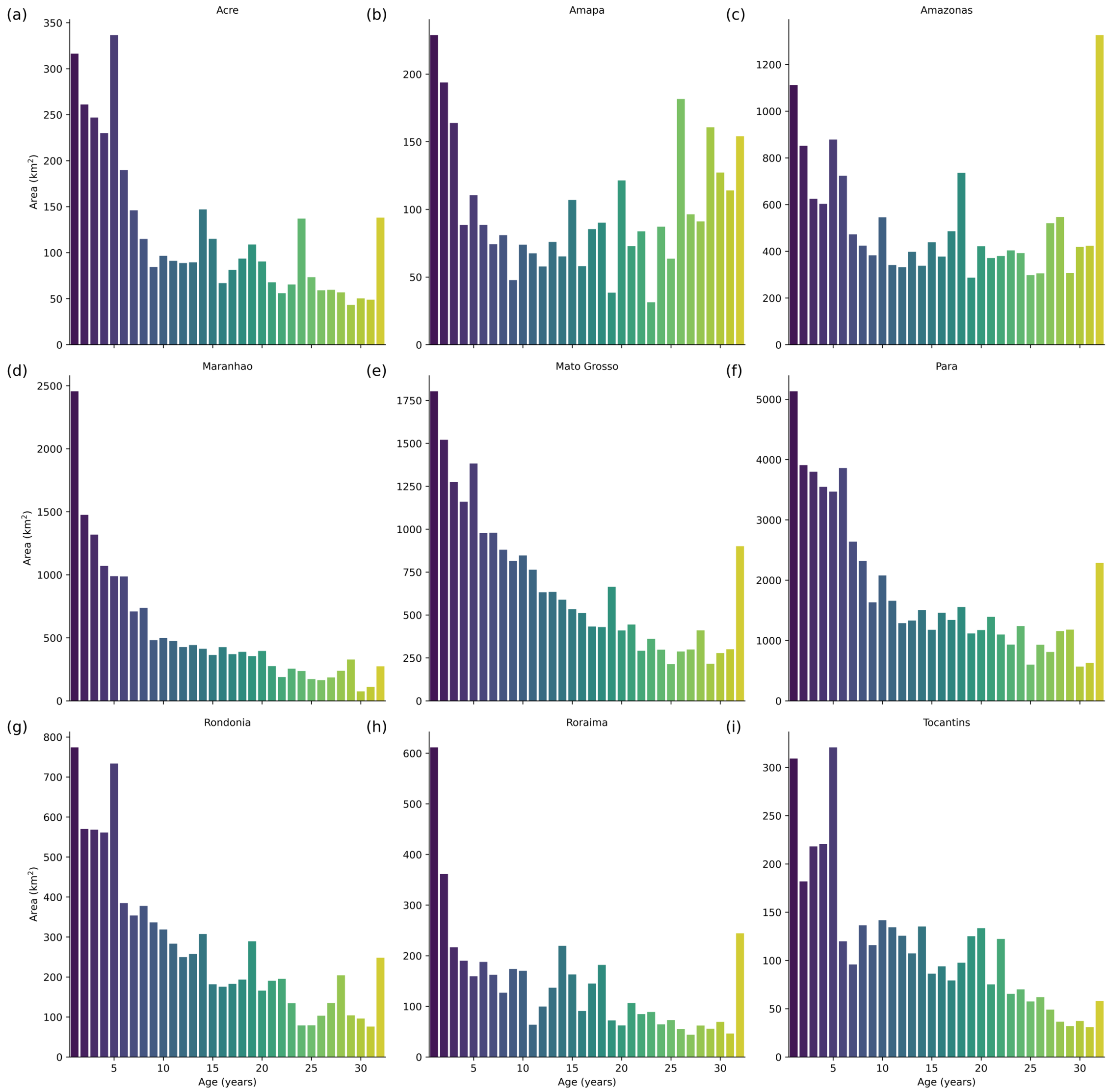

Figure S4: The age distribution of secondary forest in Brazilian States
The distribution of secondary forest age in (a) Acre, (b) Amapa, (c) Amazonas, (d) Maranhao, (e) Mato Grosso, (f) Para, (g) Rondonia, (h) Roraima and (i) Tocantins

Residency time: Across the Amazon, the majority (70.03%) of secondary forest cleared since 1997 was 5 years old or less at clearance and the median residency time was just 2 years. This skew towards the clearance of young forests is seen in every Amazonian country, with median residency time ranging from 2 years in Brazil and French Guiana, to 5 years in Ecuador and Suriname (Figure 6c). While Kruskal-Wallis tests indicated significant differences in the distribution of secondary forest age between countries and states (Kruskal–Wallis Chi square = 48.2, P<0.01, df = 16), post-hoc Dunn's test reveal that there are no significant differences between political units (Figure S3).

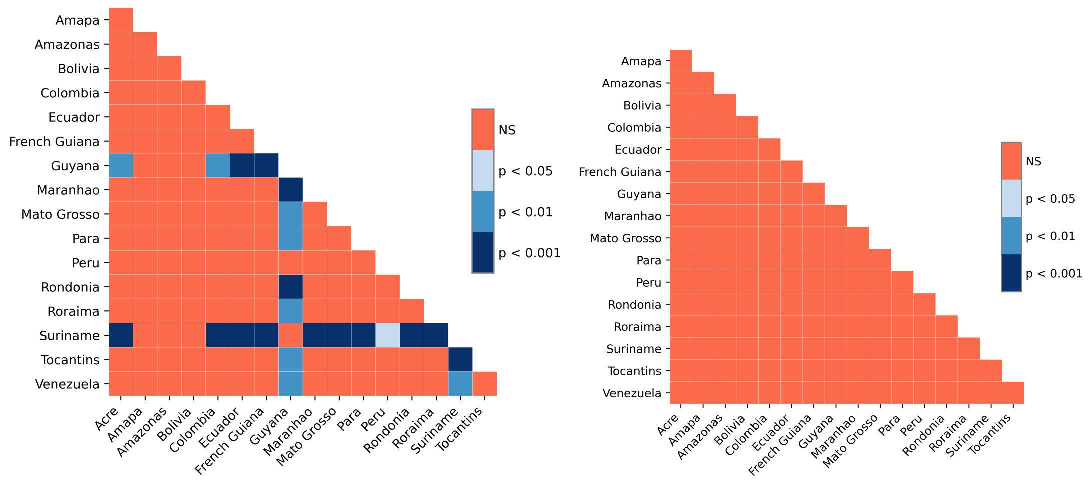

Figure S5: Differences in secondary forest age and residence time across political units in the Amazon.

The significance of post-hoc Dunn's test for differences in (a) secondary forest age and (b) secondary forest residence time between Amazonian countries and Brazilian states.

Temporal trends in deforestation and recovery

Table 1: Best-fit models (ΔAICc ≤ 2; in bold) for the temporal trends in changes in old-growth and secondary forest cover in the Amazon biome.

	M_i	AICc	Δ_iAICc	W_i	*P*
Area of old-growth deforestation	**NON-LINEAR (2)**	**116.77**	**0.00**	**0.98**	**–**
	LINEAR	126.94	10.17	0.01	0.99
	NON-LINEAR (3)	127.92	11.15	0.00	1.00
	NON-LINEAR (1)	130.03	13.26	0.00	1.00
	NULL	146.27	29.50	0.00	1.00
Area of secondary forest deforestation	**LINEAR**	**80.53**	**0.00**	**0.45**	**–**
	NON-LINEAR (1)	84.81	4.28	0.05	0.89
	NULL	85.62	5.08	0.04	0.93
	NON-LINEAR (2)	91.49	10.95	0.00	1.00
	NON-LINEAR (3)*	–	–	–	–
Area of new secondary forest	**NULL**	**98.28**	**0.00**	**0.38**	**–**
	LINEAR	98.72	0.45	0.30	0.56
	NON-LINEAR (1)	104.66	6.38	0.02	0.96
	NON-LINEAR (2)	112.70	14.42	0.00	1.00
	NON-LINEAR (3)	118.75	20.47	0.00	1.00
Net change in secondary forest area	**NULL**	**107.80**	**0.00**	**0.64**	**–**
	LINEAR	110.43	2.64	0.17	0.79
	NON-LINEAR (1)	115.90	8.10	0.01	0.98
	NON-LINEAR (2)	123.81	16.02	0.00	1.00
	NON-LINEAR (3)	133.18	25.39	0.00	1.00
Net change in forest cover	**LINEAR**	**137.24**	**0.00**	**0.22**	**–**
	NON-LINEAR (2)	135.51	-1.73	0.52	0.30
	NON-LINEAR (1)	140.33	3.09	0.05	0.82
	NON-LINEAR (3)	146.14	8.90	0.00	0.99
	NULL	149.67	12.43	0.00	1.00

M_i = model; Δ_i (AIC) = [AIC_i – min(AIC)]; w_i = the rounded Akaike weights; *P* = the normalised probability that the best-fit model is preferred to M_i; * = did not converge

Table 2: Best-fit models (delta AICc ≤ 2; in bold) for the temporal trends in changes in old-growth and secondary forest emissions in the Amazon biome.

	M_i	**AICc**	**Δ_iAICc**	**W_i**	***P***
Old-growth deforestation emissions	**NON-LINEAR (2)**	**256.15**	**0.00**	**0.73**	**–**
	NON-LINEAR (1)	260.03	3.87	0.11	0.87
	LINEAR	260.53	4.38	0.08	0.90
	NON-LINEAR (3)	264.01	7.86	0.01	0.98
	NULL	268.82	12.67	0.00	1.00
Secondary forest deforestation emissions	**NON-LINEAR (2)**	**125.02**	**0.00**	**0.81**	**–**
	NON-LINEAR (1)	127.95	2.93	0.19	0.81
	LINEAR	156.02	31.00	0.00	1.00
	NULL	180.61	55.59	0.00	1.00
	NON-LINEAR (3)*	–	–	–	–
Secondary forest carbon accumulation	**LINEAR**	**166.68**	**0.00**	**0.33**	**0.50**
	NON-LINEAR (1)	171.89	5.21	0.02	0.93
	NULL	204.44	37.75	0.00	1.00
	NON-LINEAR (2)*	–	–	–	–
	NON-LINEAR (3)*	–	–	–	–
Net secondary forest emissions	**LINEAR**	**164.29**	**0.00**	**0.26**	**–**
	NON-LINEAR (1)	164.80	0.51	0.20	0.56
	NON-LINEAR (2)	173.25	8.96	0.00	0.99
	NULL	180.76	16.47	0.00	1.00
	NON-LINEAR (3)*	–	–	–	–
Net emissions from changes in forest cover	**NON-LINEAR (2)**	**256.11**	**0.00**	**0.77**	**–**
	LINEAR	260.20	4.09	0.10	0.89
	NON-LINEAR (1)	260.64	4.53	0.08	0.91
	NON-LINEAR (3)	263.28	7.17	0.02	0.97
	NULL	271.23	15.12	0.00	1.00

M_i = model; Δ_i (AIC) = [AIC_i – min(AIC)]; w_i = the rounded Akaike weights; *P* = the normalised probability that the best-fit model is preferred to M_i; * = did not converge

Table 3: Best-fit models (delta AICc ≤ 2; in bold) for the relationship between deforestation and recovery across Amazonian countries

	M_i	AICc	Δ_iAICc	W_i	*P*
Forest Area	**LINEAR**	**143.69**	**0.00**	**0.38**	**–**
	NON-LINEAR (1)	144.95	1.27	0.20	0.65
	NULL	148.85	5.16	0.03	0.93
	NON-LINEAR (2)	154.90	11.22	0.00	1.00
Carbon Emissions	**NON-LINEAR (1)**	**104.02**	**0.00**	**0.96**	**–**
	LINEAR	111.22	7.21	0.03	0.97
	NON-LINEAR (2)	113.09	9.08	0.01	0.99
	NULL	116.15	12.14	0.00	1.00

M_i = model; Δ_i (AIC) = [AIC$_i$ – min(AIC)]; w_i = the rounded Akaike weights; *P* = the normalised probability that the best-fit model is preferred to M_i

Table 4: Best-fit models (delta AIC ≤ 2; in bold) for the relationship between deforestation and recovery across the Amazon biome.

	M_i	AIC	Δ_iAIC	W_i	*P*
Forest Area	**NON-LINEAR (2)**	**704100**	**0.00**	**1.00**	**–**
	NON-LINEAR (1)	704591	490.21	0.00	1.00
	LINEAR	711351	7250.95	0.00	1.00
	NULL	753395	49294.99	0.00	1.00
Carbon Emissions	**NON-LINEAR (2)**	**638038**	**0.00**	**1.00**	**–**
	NON-LINEAR (1)	638313	274.24	0.00	1.00
	LINEAR	641272	3233.39	0.00	1.00
	NULL	657814	19775.82	0.00	1.00

M_i = model; Δ_i (AIC) = [AIC$_i$ – min(AIC)]; w_i = the rounded Akaike weights; *P* = the normalised probability that the best-fit model is preferred to M_i

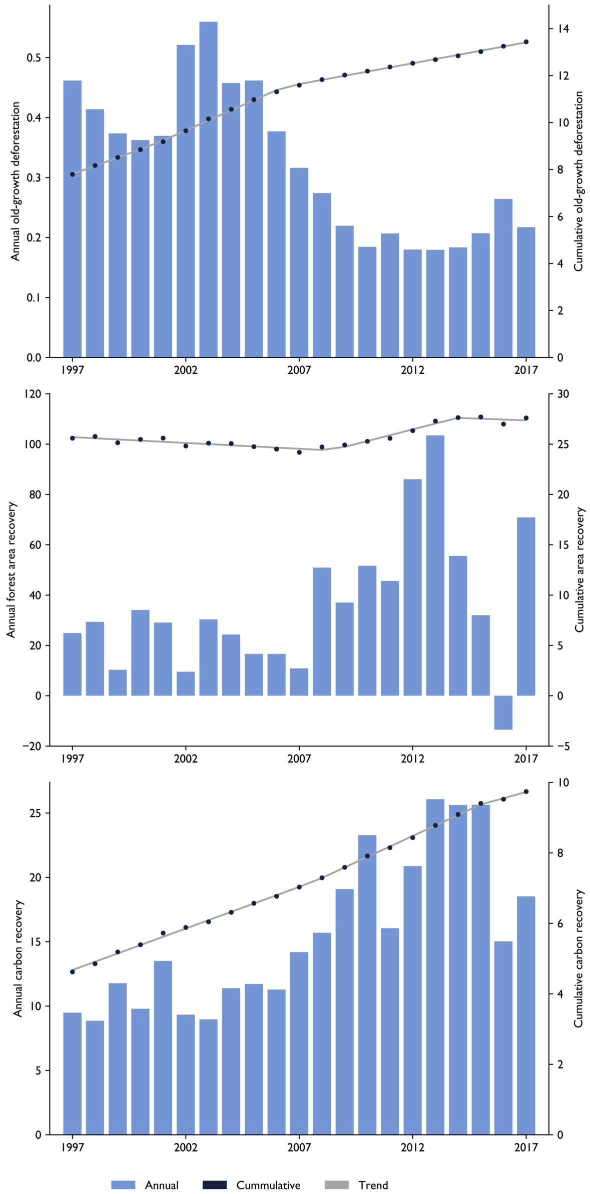

Figure S6: Temporal trends in old-growth deforestation and secondary forest recovery.

(a) Deforestation measured as the percentage of remaining old-growth forest cleared annually (bars) and the percentage of original old-growth forest cleared (points). The temporal trend in cumulative deforestation (line) is well-described by a broken-stick regression with two segments.

(b) Forest area recovery measured as the percentage of the area deforested each year offset by the net change in secondary forest extent that year (bars) and the percentage of the total deforested area offset by the total secondary forest extent (points). The temporal trend in forest area recovery (line) is well-described by a broken-stick regression with three segments.

(c) Carbon recovery measured as the percentage of annual old-growth deforestation emissions offset by the net carbon balance of secondary forest that year (bars) and the percentage of cumulative old-growth deforestation emissions offset by the total accumulated carbon for all secondary forest (points). The temporal trend in cumulative carbon recovery (line) is well-described by a broken-stick regression with two segments.

Data Processing

We opted to use the MapBiomas dataset over other alternatives due to its high-resolution (30 m), longer temporal series (1985–2018) and extensive validation process (MapBiomas, 2020). The geographic limit of MapBiomas Amazonía is defined by Red Amazónica de Información Socioambiental Georreferenciada (RAISG) and incorporates six biomes (Amazonia, Andes, Cerrado, Chaco-Chiquitano, Panantal, Tucumano-Boliviano). For this study we use the RAISG defined 'Amazonia' biome. This dataset is freely available to download: https://amazonia.mapbiomas.ord/downloads/. We conduct our analysis for 2017 as the MapBiomas filtering method (SI) means the land cover classification is likely to be more accurate than for 2018. We simplify the MapBiomas schema by reclassifying it into four broader classes: forest, pasture, cropland and other (Table S1).

Table S1: Reclassification of MapBiomas schema

MapBiomas ID	MapBiomas Classification	Reclassification
1	1. Forest	Old-growth Forest
2	1.1. Natural Forest	Old-growth Forest
3	1.1.1. Forest Formation	Old-growth Forest
4	1.1.2. Open Forest	Old-growth Forest
5	1.1.3. Mangrove	Old-growth Forest
6	1.1.4 Flooded Forest	Old-growth Forest
9	1.2. Forest Plantation	Cropland
10	2. Non-Forest Natural Formation	Other/Water
11	2.1. Wetland	Other/Water
12	2.2. Grassland Formation	Other/Water
13	2.4. Other Non-Forest Natural Formation	Other/Water
14	3. Agriculture	Cropland
15	3.1. Pasture	Pasture
16	3.1.1 Pasture in Natural Fields	Pasture
17	3.1.2 Other Pastures	Pasture
18	3.2. Agriculture	Cropland
19	3.2.1 Annual Perennial Use	Cropland
20	3.2.1 Semi-Perennial Use	Cropland
28	3.2.3 Mixed Crop	Cropland
21	3.3. Mosaic of Agriculture and Pasture	Cropland
22	4. Non-Vegetated Area	Other/Water
23	4.1. Beach and Dune	Other/Water
24	4.2. Urban Infrastructure	Other/Water
29	4.3. Rocky Outcrop	Other/Water
30	4.4. Mining	Other/Water
25	4.5. Other Non-Vegetated Area	Other/Water
26	5. Water	Other/Water
33	5.1. River, Lake and Ocean	Other/Water
31	5.2. Aquaculture	Other/Water
34	5.3 Glacier	Other/Water
27	6. Non-Observed	NA

Water Masking

Following reclassification, a temporal filter was applied to create a uniform water mask to be used across the time series. The land cover data were analysed in three-year increments such that if a pixel remained as water for a single year before returning to the previous year's land cover type, the middle year was reclassified to match the others. For example, if a pixel follows the trajectory Forest – Water – Forest it becomes Forest – Forest – Forest. MapBiomas applies similar rules during its classification process. We then applied the maximum extent of water across the time series.

Change Detection

Change detection was conducted at the pixel level to produce a comprehensive history of change for the entire Amazon Biome at 30-m resolution. Following reclassification, pixels were given the arbitrary value 0, 1, 4 or 9, representing water/other, cropland, pasture and old-growth forest, respectively. Transitions were calculated by subtracting the classification value of the current year from that of the same pixel in the previous year, generating a unique value for each possible transition (Table S2). MapBiomas does not separate secondary forest in its classification, thus, at this stage, secondary forest is introduced as an additional land cover class (4). Any pixel which transitions from 'non-forest' to 'forest' is marked by the algorithm as secondary forest. For the first year in the time series, we assuming all forest is old-growth forest.

Table S2: Possible land cover transitions

Transition Value	From	To
-9	Water/Other	Old-growth forest
-8	Cropland	Old-growth forest
-5	Pasture	Old-growth forest
-4	Water/Other	Pasture
-3	Cropland	Pasture
-1	Water/Other	Cropland
0	No Change	
1	Cropland	Water/Other
3	Pasture	Cropland
4	Pasture	Water/Other
5	Old-growth forest	Pasture
8	Old-growth forest	Cropland
9	Old-growth forest	Water/Other

Highly deforested landscapes in 1997

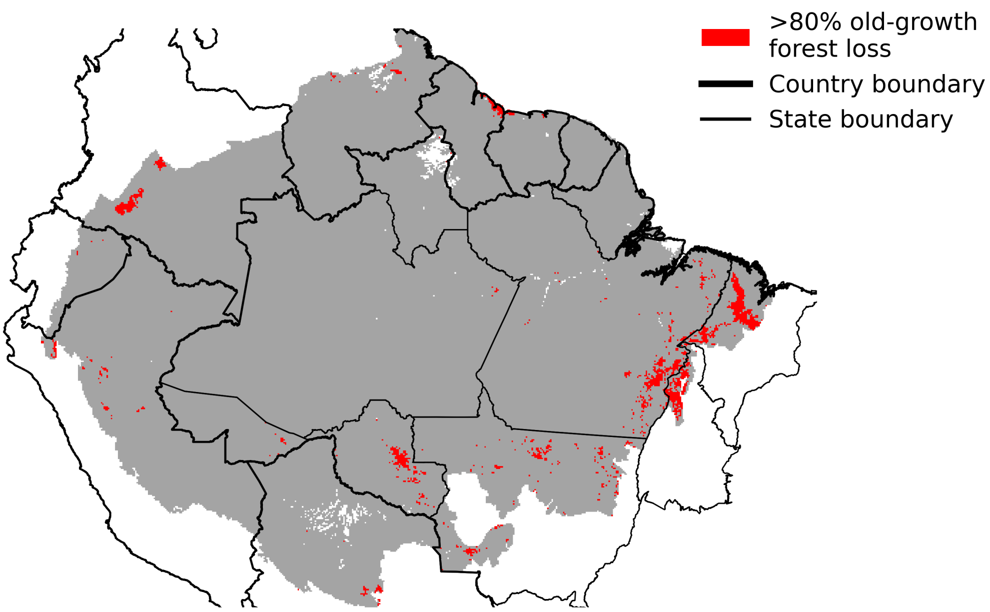

Figure S7: Highly deforested landscapes in the Amazon biome in 1997
The Amazon biome gridded at ~60km^2. Cells with ≥80% old-growth deforestation in 1997 are shown in red. The Amazon biome is shown in grey.