Old-growth forest loss and secondary forest recovery across Amazonian countries

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Title

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Abstract

There is growing recognition of the potential of large-scale restoration in the Amazon as a "nature-based solution" to climate change. However, our knowledge of forest loss and recovery beyond Brazil is limited, and carbon emissions and accumulation have not been estimated for the whole biome. Combining a 33-year land cover dataset with estimates of above-ground biomass and carbon sequestration rates, we evaluate forest loss and recovery across nine Amazonian countries and at a local scale. We also estimate the role of secondary forests in offsetting old-growth deforestation emissions and explore the temporal trends in forest loss and recovery. We find secondary forests across the biome to have offset just 9.7% of carbon emissions from old-growth deforestation, despite occupying 27.6% of deforested land. However, these numbers varied between countries ranging from 9.0% in Brazil to 23.8% in Guyana for carbon offsetting, and 24.8% in Brazil to 56.9% in Ecuador for forest area recovery. We reveal a strong, negative spatial relationship between old-growth forest loss and recovery by secondary forests, showing that regions with the greatest potential for large-scale restoration are also those that currently have the lowest recovery (e.g. Brazil dominates deforestation and emissions but has the lowest recovery). Our findings identify three important challenges for policy makers: (1) incentivising large-scale restoration in highly deforested regions, (2) protecting secondary forests without disadvantaging landowners who depend on farm-fallow systems, and (3) preventing further deforestation. Combatting all of these successfully is essential to ensuring that the Amazon biome achieves its potential in mitigating anthropogenic climate change.

Introduction

Deforestation is a major and ongoing threat, with an estimated 4.2 million km^2 of global forests cleared since 1990 (FAO and UNEP 2020). Across the world tropical deforestation represents around 8% of all anthropogenic emissions (Seymour and Busch 2016), and deforestation and land-use change combined contribute the majority of the carbon emissions of most tropical forest countries. However, tropical forests are fundamental to the world's climate crisis not only as a source of emissions, but also as a means for capturing atmospheric carbon. There is growing recognition of the potential of large-scale tropical forest restoration as a "nature-based solution" to climate change mitigation (UN 2019) and its importance for meeting the ambitious emissions targets of the Paris agreement (Grassi *et al* 2021).

The Amazon biome has been recognised by researchers and policymakers alike for its key role in future climate policy for two main reasons. First, the Amazon biome stores an estimated 86 Pg of carbon (Saatchi *et al* 2007), making it one of the world's largest carbon strongholds (Saatchi *et al* 2011) Unchecked, deforestation could convert much of this carbon stock into emissions, significantly accelerating climate change. The Brazilian Amazon has witnessed amongst the highest absolute rates of deforestation in the tropics, with a notable increase in recent years (PRODES 2020), placing Brazil in the top 10 emitters in the world (World Resources Institute 2021). Second, compared with other tropical regions, the Amazon could be ideal for forest restoration as it has low population densities (Cunningham and Beazley 2018), extensive areas of unproductive or unprofitable agricultural systems (Garrett *et al* 2017, 2021), and high carbon sequestration rates (Requena Suarez *et al* 2019). However, patterns of forest loss and recovery, and its impact on the carbon balance have not been estimated for the whole biome. Our understanding has previously focused on Brazil (e.g. Smith et al 2020), which only makes up 60% of the Amazon biome. The contribution of the other seven countries (Bolivia, Colombia, Ecuador, Guyana, Peru, Suriname, Venezuela) and the French overseas territory (French Guiana; henceforth included in the collective 'countries') is much less well understood. With recent studies showing increasing occurrences of deforestation hotspots outside Brazil (Kalamandeen *et al* 2018), the need to expand our knowledge beyond Brazil grows more critical. Furthermore, forest recovery also varies greatly over space and time (Smith *et al* 2020), making it crucial to understand where forests are already recovering and how this recovery differs both across political units and on finer spatial scales, so that active restoration efforts and novel policy incentives can be targeted effectively. Despite restoration offering a growing opportunity to mitigate anthropogenic emissions (Chazdon *et al* 2016, Matos *et al* 2020), to date, we are not aware of any analysis examining patterns of forest loss and recovery across Amazonia at both national and subnational level, which are the relevant scales for restoration projects.

Here, we combine a 33-year land-use dataset (i.e. MapBiomas Amazonia 2; 1985-2018) with estimates of above-ground biomass (AGB) (Avitabile *et al* 2016) and forest regrowth potential (Requena Suarez *et al* 2019) to evaluate the distribution of forest loss and recovery across the nine countries and nine Brazilian states that intersect the Amazon biome. We ask three questions. (1) What is the current (2017) extent of old-growth deforestation and forest recovery, and their associated impact on the Amazonian carbon balance? We estimate carbon emissions from forest loss and carbon accumulation from secondary forest growth (i.e. forest growing on previously deforested land) across the Amazon biome and its major political units. (2) What is the geographic relationship between old-growth deforestation and secondary forest recovery? We examine this at the country- and state-level, and then at a finer resolution using a ~60 km^2 grid. (3) How have the rates of old-growth deforestation and secondary forest recovery varied over the last two decades? We discuss our results in light of the challenges of avoiding further deforestation and encouraging large-scale forest restoration across Amazonia.

Results

Old-growth deforestation extent and carbon emissions

By 2017, we found 813,944 km^2 of old-growth forest (OG) in the Amazon biome had been cleared (Table 1). Brazil has seen the greatest loss in OG area both in absolute terms (689,451 km^2; **Figure 1**a) and proportional to its Amazonian extent (17.6%; **Figure 1**b). Two-thirds of Brazil's nine Amazonian states have an absolute area of deforestation exceeding that of any of the other countries (**Figure 1**a); the deforested area in Pará state alone is more than double that of all other countries combined (Pará: 262,869 km^2; other countries: 124,493 km^2; **Figure 1**a). By 2017, OG deforestation across the Amazon biome had resulted in the loss of 6.33 Pg C from AGB, emitting the equivalent of 23.22 Pg CO_2 (Table 1). Brazil contributed 79.9% of all OG deforestation emissions (5.06 Pg C;

Figure S1). Ecuador had the greatest percentage loss of carbon relative to its original OG above-ground carbon stock (12.3%), but this represents just 2.2% of total emissions. The Brazilian states of Pará, Mato Grosso and Rondônia exceed the emissions of any other individual Amazonian country (Table 1).

Secondary forest extent, age, residence time and carbon accumulation

In 2017, secondary forests (SF) covered 234,795 km^2 of land in the Amazon biome, accounting for approximately 4.1% of the total forest cover (Table 1). 76.8% of Amazonian SF was in Brazil (180,215 km^2; **Figure 1**c), with 10.9% in Peru (25,579 km^2; **Figure 1**c), and 4.7% in Colombia (11,055 km^2; **Figure 1**c). Making up 5.3%, 3.7% and 2.5% of each country's total forest cover respectively (Table 1). The majority (78.2%) of all SF was less then 20-years old and the median age was 8 years. Very young SF (≤ 5 years old) accounted for 35.9% of all cover. This skewed age distribution was apparent in the majority of countries (Figure S3). Guyana and Suriname were the only countries with significantly different age distributions with large spikes in 18 to 24-year-old SF (Dunn's post-hoc test: $P<0.05$; Figure S5), although this could be an artifact of poor temporal data availability in these countries (SI). As our time series began in 1985, the maximum detectable age of SF is 32 years. However, the skewed distribution of forest ages suggests that very little forest would have exceeded the maximum detectable age (Figure S2). Across the Amazon biome, during the period 1997-2017, the majority (70.0%) of SF cleared was 5-years old or less and the median residence time (from the start of SF regrowth to clearance) was just 2 years. There were no significant differences in the distribution of residence times across countries or states (SI). SF present in 2017 had accumulated 0.62±0.11 Pg C, equivalent to 2.26±0.41 Pg CO_2. SF deforestation has resulted in the loss of 38.9% (391.65±94.62 Tg C) of all carbon accumulated by SF between 1985 and 2017.

Spatial relationships between deforestation and recovery

In 2017, carbon accumulated in SF had offset less than 30% of OG deforestation emissions in every Amazonian country or Brazilian state we assessed (Table 1). Across the Amazon biome as a whole just 9.7±1.8% of emissions had been offset, despite 28.8% of deforested land being occupied by SF. Forest area recovery (defined here as the percentage of deforested land occupied by SF) varied across countries and Brazilian states. Brazil had the lowest forest area recovery (24.8%) of any Amazon country, while Ecuador and Amapá state had the greatest forest area recovery, with SF occupying 56.9% and 69.1% of deforested land, respectively (***Figure 2***a). Carbon recovery (defined here as the percentage of emissions from OG deforestation offset by carbon accumulation in SF) also varied greatly between countries, with the lowest in Brazil (7.7%) and the highest in Guyana (23.8%; ***Figure 2***c).

Across countries and states, there were significant negative relationships between deforestation and recovery, which followed linear or L shaped trends (***Figure 2***a,c; Table S3; see Methods). As such, countries or states with a high percentage loss of OG typically have a low forest area recovery, while those which have lost less OG have a higher forest area recovery (***Figure 2***a). For example, Ecuador, which was 12.7 % deforested in 2017, had the greatest forest area recovery (56.9%)**,** while Brazil, which was 17.6% deforested, had the lowest forest area recovery (24.8%; ***Figure 2***a). The extremes are more accentuated across Brazilian states: Tocantins had 82.9% OG deforestation and just 18.5% forest area recovery, while Amapá had 4.0% OG deforestation and 69.1% forest area recovery (***Figure 2***a). These spatial patterns of loss and recovery were even more pronounced for losses and gains of above-ground carbon stocks (***Figure 2***c).

These relationships between OG deforestation and SF recovery (and their resulting carbon balance) were also spatially linked at a local scale. The gridded analysis revealed strong negative, non-linear relationships that were well described by broken-stick regression with two breakpoints (***Figure 2***b,d; Table S4). Of the cells that had experienced some OG deforestation (>0.01% forest loss), the majority (62.8%) were characterised by low deforestation (<50% forest loss) with high forest area recovery (>50% forest loss), and just 1.1% of cells exhibit both high deforestation (>50%) and high forest area recovery (>50%; **Figure2**b; **Figure 3**c-d). These trends were even more pronounced for carbon, with high carbon recovery only ever occurring in grids with the smallest losses from OG deforestation (**Figure 2**d; **Figure 3**g-h). Mapping these data revealed clear patterns in the distribution of the percentage of both OG loss and SF recovery (**Figure 3**). As expected, the highest levels of OG deforestation were concentrated in the south and east, forming the well-characterised 'arc of deforestation' (**Figure 3**). This contrasted with the spatial patterns for SF, where recovery of extent and carbon stocks was highest in areas of low deforestation or low carbon losses (**Figure 3**e-f).

Temporal trends in deforestation and recovery

The annual trend in OG deforestation between 1997 and 2017 was best described by a broken-stick regression with three segments (Table S1); the most recent of which (2009-2017) showing an increase in the annual rate of deforestation from a low of 9,918 km^2 in 2013 to 11,899 km^2 in 2017 (**Figure 4**a). This reversed the previous trend in which annual OG loss declined by more than half from 29,806 km^2 in 2002.

We found no temporal trend in the area of new SF from 1997 to 2017, which was average 22,882±2,247 km^2 each year (mean±SD; **Figure 4**c). In contrast, the extent of SF deforestation has increased over time, from 15,775 km^2 in 1997 to 17,750 km^2 in 2017, and is well described by a linear trend (**Figure 4**c; Table S1). However, there was no temporal trend in net change in SF area (Table S1), which fluctuated between plus 10,263 km^2 and minus 1,961 km^2 with a mean of 5490 km^2.

OG deforestation emissions decreased from 0.82 Pg CO_2 in 2004, to a low of 0.40 Pg CO_2 in 2010, before increasing to 0.56 Pg CO_2 in 2017 (**Figure 4**b), best described by a broken-stick model with 2 segments (Table S2). Annual carbon accumulation from the expansion and growth of SF increased from 1997 to 2017 and is well described by a linear trend (Table S2). It was typically 2.42±0.3 times (mean±sd) the carbon emitted by SF deforestation each year (**Figure 4**d), which was best described by a broken stick model with two segments. SF net annual carbon accumulation increased linearly from 65.91 Tg CO_2 in 1997 to 103.91 Tg CO_2 in 2017 (**Figure 4**d,

Table S2). The trend in annual OG deforestation emissions offset by net annual secondary forest carbon accumulation (i.e. carbon recovery) was described by a broken stick regression with three segments (Table S2). It remained below 15% until 2007, then peaked at 26.1% in 2013 before declining again.

Discussion

We conduct the first comparison of forest loss and recovery across national and sub-national political boundaries in Amazonia, analysing its impact on the carbon balance and exploring recent temporal trends. We found that, across the biome, SF offset just 9.7% of carbon emissions from OG deforestation despite occupying 28.9% of deforested land. We also reveal a strong, negative spatial relationship between OG deforestation extent and recovery by SF, with high recovery unlikely where a greater percentage of OG has been cleared. Building upon recent work in the Brazilian Amazon (Smith *et al* 2020, Nunes *et al* 2020, Silva Junior *et al* 2020), we use the newly expanded MapBiomas land cover dataset to look beyond changes in Brazil and examine trends across the entire Amazon biome.

By providing measures of OG deforestation and SF recovery specific to each Amazonian country, our study reveals high variation across political boundaries. Some countries, such as Ecuador, demonstrate much higher levels of recovery than the Amazon biome as a whole, while in other countries and Brazilian states recovery is much lower. As expected, we find that Brazil is dominating Amazonian deforestation and emissions (85.4%; 79.9%), but its dominance also goes beyond that expected by the portion of the Amazon biome is contains. For example, Pará state alone has contributed more deforestation than that of all other Amazonian countries combined. Furthermore, Brazil has the lowest forest area recovery, with just 24.8% of deforested land occupied by SF, compared to 28.8% for the Amazon biome as a whole and a range of 28.8–56.9% amongst the other countries. These trends were even more marked when we analysed the percentage of carbon emissions resulting from OG deforestation offset by SF carbon accumulation. Despite growing awareness of deforestation in other Amazonian countries (Kalamandeen *et al* 2018), these findings make it clear that combating land-use change in Brazil remains fundamental to efforts to mitigate climate change. However, the Brazilian Amazon's high deforestation rates – including the recent uptick in deforestation that was not covered by the time series we analysed (PRODES 2020) – and its low percentage of restoration also suggest that there are major institutional and social barriers to change (Arima *et al* 2014). These are exacerbated by issues of governance, with the current Brazilian administration being accused of encouraging deforestation by weakening policies, undermining forest monitoring, cutting resources for environmental law enforcement (Barlow *et al* 2020, Vale *et al* 2021) and censoring scientific publications (Escobar 2021).

Our findings show that OG deforestation emissions are outstripping SF carbon accumulation across the Amazon biome, with less than a third of emissions offset in every country or state we assess and less than 10% for the biome as a whole. This confirms the need to prioritise halting deforestation and preserve remaining OG. However, it is widely accepted that in order to mitigate climate change reducing emissions is not enough, and that we must also recapture carbon from the atmosphere (Griscom *et al* 2017, Houghton *et al* 2015, Edenhofer *et al* 2014), with SF growth suggested as an efficient and cost-effective method to do so (Rogelj *et al* 2018, Lubowski and Rose 2020). Our analysis provides some important insights into the challenge of large-scale restoration.

First, the negative relationship between OG deforestation and forest area recovery highlights the importance of new policy interventions for enhancing SF in low OG cover landscapes. With this relationship even more evident at smaller scales, it is clear that policies must be targeted locally rather than nationally. Although secondary growth rates may be lower in these highly deforested regions that those proposed by Requena Suarez et al. (2019) (e.g. Elias et al., 2019; Heinrich et al., 2021), restoration also delivers other important benefits, such as regulating local temperatures and stream flows as well as providing habitat for a number of species (Lennox *et al* 2018).

Second, the young SF age and low carbon offsets found across the biome highlight the importance of addressing the high turnover rates and low residence times of SF (Jakovac *et al* 2017), which result in the loss of huge quantities of carbon annually (Wang *et al* 2020, Smith *et al* 2020, Tyukavina *et al* 2017). Implementing and enforcing policies to protect SF from deforestation could substantially increase their effectiveness as long-term carbon stores. For example, following the accumulation rates of Requena Suarez et al. (2019), preserving the 2017 extent of SF (234,795 km^2) would result in the accumulation of 3.3±0.5 Pg C by 2050. However, any such policy needs to be carefully implemented as the use of forests as fallows is crucial for the livelihoods of many Amazonian smallholders and traditional peoples (Porro *et al* 2015). Furthermore, the temporal consistency of the net increase in SF indicates that it is less sensitive to socio-economic events than OG deforestation, suggesting that instigating change may be difficult.

This study used three up-to-date resources to quantify forest cover dynamics and their resulting effects on carbon balance (Methods). Yet important uncertainties remain. First, while this study focuses on emissions from deforestation, it is important to note that forest degradation, which effects up to 17% of forest cover (Bullock *et al* 2020), is also resulting in huge losses of carbon from OG (Bullock and Woodcock 2021). As our biomass map was from the early 2000s, the carbon emissions from OG deforestation reported in this study may be over-estimated as some of the above-ground carbon will have already been lost to disturbance. Recent advances in assessing forest disturbance (e.g. Matricardi et al., 2020; Qin et al., 2021) are restricted to the Brazilian Amazon, but demonstrate the importance – and complexity (Silva et al. 2020) - of estimating it across decadal time-scales. Second, we used Requena Suarez et al. (2019) to estimate the SF carbon accumulation, but it is likely to over-estimate recovery in the more deforested and drier regions of the 'arc of deforestation' (e.g. Elias et al., 2019; Heinrich et al., 2021). As such, Brazil's contribution to carbon recovery may be over-estimated in our analysis, increasing its net contribution to carbon emissions.

Although our analysis shows a pan-Amazonian uptick in deforestation in recent years, it also helps highlight moments in space and time that can be used to guide more positive actions. For example, the huge reduction in Brazilian OG deforestation from an all-time high in 2004 to an all-time low in 2012 is a demonstration of what can be achieved with well-implemented policy (PRODES 2020, Boucher *et al* 2013, Saraiva *et al* 2020). Furthermore, although instigating change in Brazil will be key to restoration efforts within the Amazon biome, an understanding of what is enabling the other countries to achieve greater levels of recovery could also help guide policy interventions across the Amazon biome (Latawiec *et al* 2014). For example, the high levels of recovery in Ecuador and Amapá demonstrates that there are contexts where recovery is occurring, and there may be valuable lessons to be learned from previous and ongoing success. However, future research needs to go beyond mapping forest cover change and examine the socio-economic conditions which are key to restoration success (Rudel *et al* 2016, Aide *et al* 2013, Grau *et al* 2003). Finally, the strong negative patterns of recovery found consistently across geographic scales show that the regions with the greatest potential for large-scale restoration are also those that currently have the least amount of recovery. The new challenge facing policy makers is how to incentivise large-scale restoration in these regions in order to break the trend. Doing so successfully is essential to ensuring that the Amazon biome achieves its potential in mitigating anthropogenic climate change.

Methods

Old-growth and secondary forest extent

We use the MapBiomas Amazonía 2 dataset to assess deforestation and SF extent for the Amazon Biome (SI). We reclassify the MapBiomas schema into: forest, pasture, cropland and other, then use a change detection algorithm to produce annual maps of the extent of OG and SF cover across the Amazon biome (SI). Any pixel (900 m^2) classified as 'forest' in the first year of the time series (1985) was considered to be OG until it transitioned to 'non-forest'. Pixels that transitioned from 'non-forest' to 'forest' were classified as SF. As the MapBiomas time series begins in 1985, any SF that began growing before this date is included in our OG class (SI). Our method is based on the approach previously described by Smith et al (2020). All code is available here: [GIT HUB LINK].

Secondary forest age and residence time.

We measured SF age as the number of consecutive years a pixel was classified as SF in our annual maps of forest cover. Due to incomplete data coverage in some regions this should be considered a "minimum" age estimate rather than a precise measure (SI). We measured SF residence time as the age of SF at clearance. We conducted Kruskal-Wallis tests to determine if SF age or residence time (for SF cleared 1997 to 2017) differs between countries and Brazilian states. To avoid assigning significance to small effect sizes due to large samples, we used a sample size of 100. We repeated this process 10,000 times and recorded the mean p-value. Brazil as whole was excluded from the analysis in favour of its component states to avoid pseudo-replication. Where the Kruskal-

Wallis test was significant, we conducted Dunn's post-hoc tests to identify which pairs of countries or states had different distributions.

Calculating above-ground carbon

Old-growth forest: We calculated AGB in OG using the Avitabile et al. (2016) 1-km resolution pan-tropical AGB map, which we downscaled to match the 30-m resolution MapBiomas land cover data. For areas deforested before 2010, prior to the most recent dataset used by Avitabile et al. (2016), we interpolate AGB using the *KNNImputer* function from the Python package *sklearn*, which infills missing values with the mean of a pixel's twenty nearest neighbours. We converted AGB to carbon stock using the Intergovernmental Panel on Climate Change (IPCC) conversion factor of 0.47 g C (g biomass)$^{-1}$ (Eggleston *et al* 2006). For the purposes of this study, we assume above-ground carbon to be static as, although OG are accumulating carbon, it is at a very slow rate (~1 Mg ha^{-1} year^{-1}; Requena Suarez et al, 2019). Due to the complexity of mapping the intensity of disturbance in OG over large spatial scales, accounting for the impact of degradation on carbon stocks was beyond the scope of this study. Therefore, we may be over-estimating carbon emissions from deforestation. Below-ground carbon is estimated to contribute an additional 25% to tropical forest carbon stocks (Luyssaert *et al* 2007), but its assessment was also beyond the scope of this study.

Secondary forest: We estimate SF AGB using our maps of SF age in conjunction with the Requena Suarez et al. (2019) biomass accumulation rates for old (>20 years) and young (<20 years) SF. We converted AGB values to carbon stock as above (conversion factor: 0.47). Carbon accumulation rates can vary greatly in response to local climatic, environmental and disturbance factors (Elias *et al* 2019, Poorter *et al* 2016), but to date analyses calculating local scale accumulation rates have been limited to the Brazilian Amazon (Heinrich *et al* 2021). As our study encompasses the entire Amazon biome, we opted to use the baseline carbon accumulation rates calculated by (Requena Suarez *et al* 2019) for the FAO Ecozones (FAO 2012). Four ecozones intersect our study area: tropical rainforest (~61.7%), tropical moist forest (~25.6%), tropical montane forest (~11.7%) and tropical dry forest (~1.0%).

Deforestation extent and emissions

Using the change in forest cover captured by our analysis of MapBiomas, we calculated the annual extent OG and of SF deforestation and the associated carbon emissions. For each forest type, we applied an exponential decay of 0.49 to our estimate of the pixel's above-ground carbon in order to extend emissions from a deforestation event over several years, as is seen in long-term assessments of AGB loss on deforested land (e.g. Berenguer et al., 2014). Above-ground carbon was converted to carbon dioxide equivalent using the conversion factor 3.67. For pixels classified as cropland or pasture in the first year of our time series (1985), we calculate emissions as if the pixels were cleared in 1984. While this means that some of the pixels are assumed to have been cleared more recently than they were, the impact of this on our estimates of OG deforestation emissions is negligible as, by the most recent year of our anaylsis (2017), more than 99.99% of the carbon they contained is accounted for. We report variation in SF emissions using the 95% confidence interval of estimates of Requena Suarez et al. (2019).

Relationship between deforestation and recovery

Political scale: We use the term *forest area recovery* to mean the percentage of the total area of OG deforestation occupied by SF, and the term *carbon recovery* to mean the percentage of total OG deforestation emissions offset by carbon accumulated in SF. We use Akaike information criterion (AIC) model selection to find best-fit models (mac Nally *et al* 2018) for the relationships between the percentage of OG deforestation (relative to original OG extent; see above) and forest area recovery, and between the percentage of OG carbon emissions (relative to original carbon stock; see above) and SF carbon recovery. We conducted this analysis across political units, comparing the AIC score of five difference models: null, linear and broken-stick (up to three break points). This analysis was conducted using the *stats* (R Core Team 2021) and *segmented* (Muggeo 2017) R-packages. The assumptions of the models were checked by graphical analysis (Quinn and Keough 2002)

Local scale: We repeated the above analysis at a local scale by dividing the Amazon biome into a regular grid of ~58.9 km^2 cells (65,536 pixels; pixel size: 0.0009 km^2; size determined by computational efficiency). Cells with >99% of pixels classified as 'other' (i.e. where less than 1% of the cell area is capable of being forest) were excluded from the grid level analysis. Cells with ≤0.1% deforestation were considered to have experienced no deforestation and were excluded from the analysis.

Temporal trend analysis

To explore how OG deforestation, SF extent and their associated carbon emissions have changed over time, we used the AIC model selection method described above using AICc; a small-sample-size corrected version of AIC. We conduct this analysis between 1997 and 2017 to avoid assigning significance to 'trends' that are an artifact of SF older than 33-years being included in our OG class.

Figures

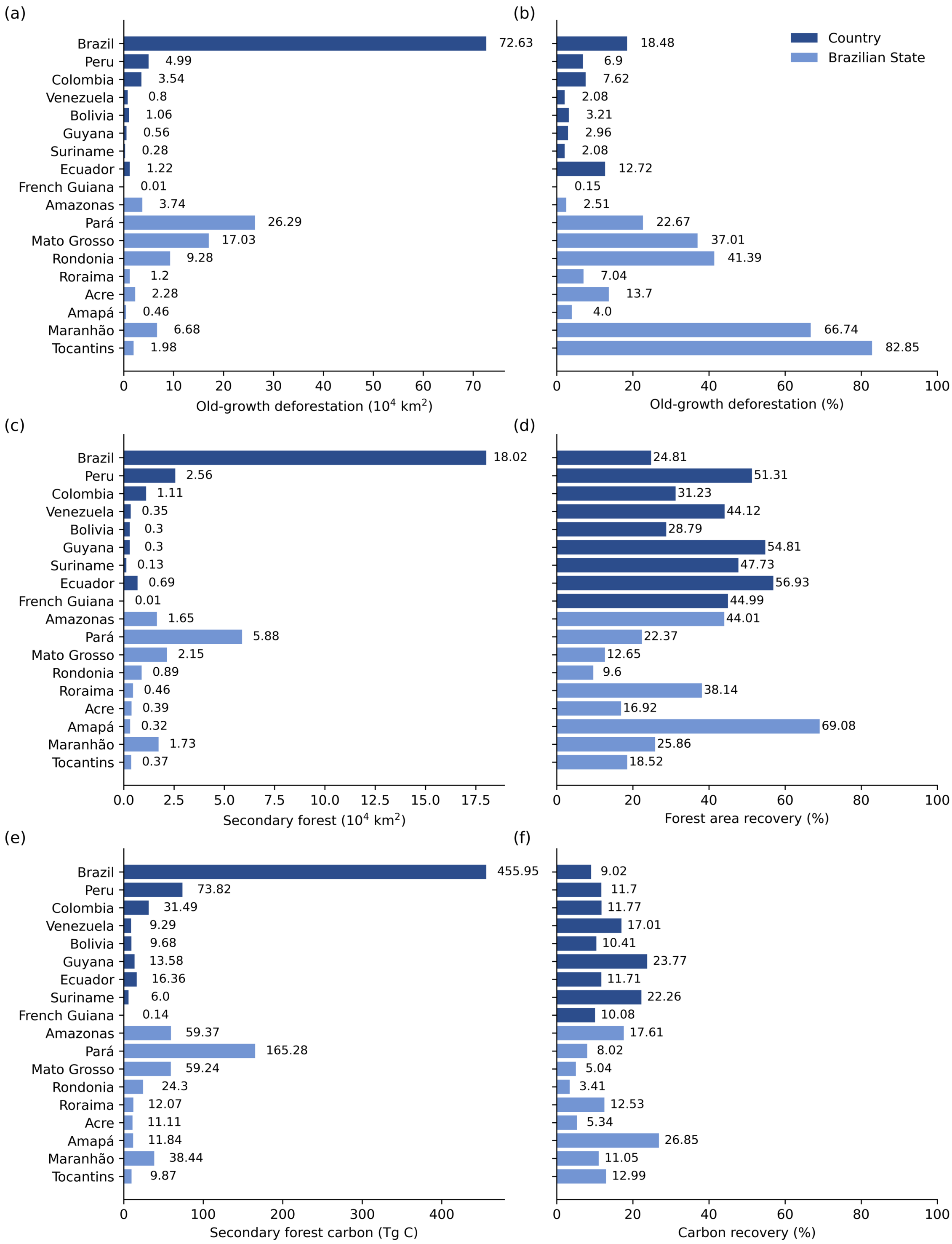

Figure 1: Old-growth deforestation, secondary forest extent and secondary forest carbon recovery in Amazonian countries and Brazilian states in 2017

The (a) area of old-growth deforestation, (c) area of secondary forests, and (e) secondary forest carbon stock for Amazonian countries (dark) and Brazilian states (light) in 2017. Proportional values (right) are measured as (b) the percentage of original old-growth forest extent which has been deforestation, (d) the percentage of deforested land occupied by secondary forest, and (f) the percentage of old-growth deforestation emissions offset by carbon sequestration in secondary forests. Countries and states are ordered by the area of the Amazon they contain.

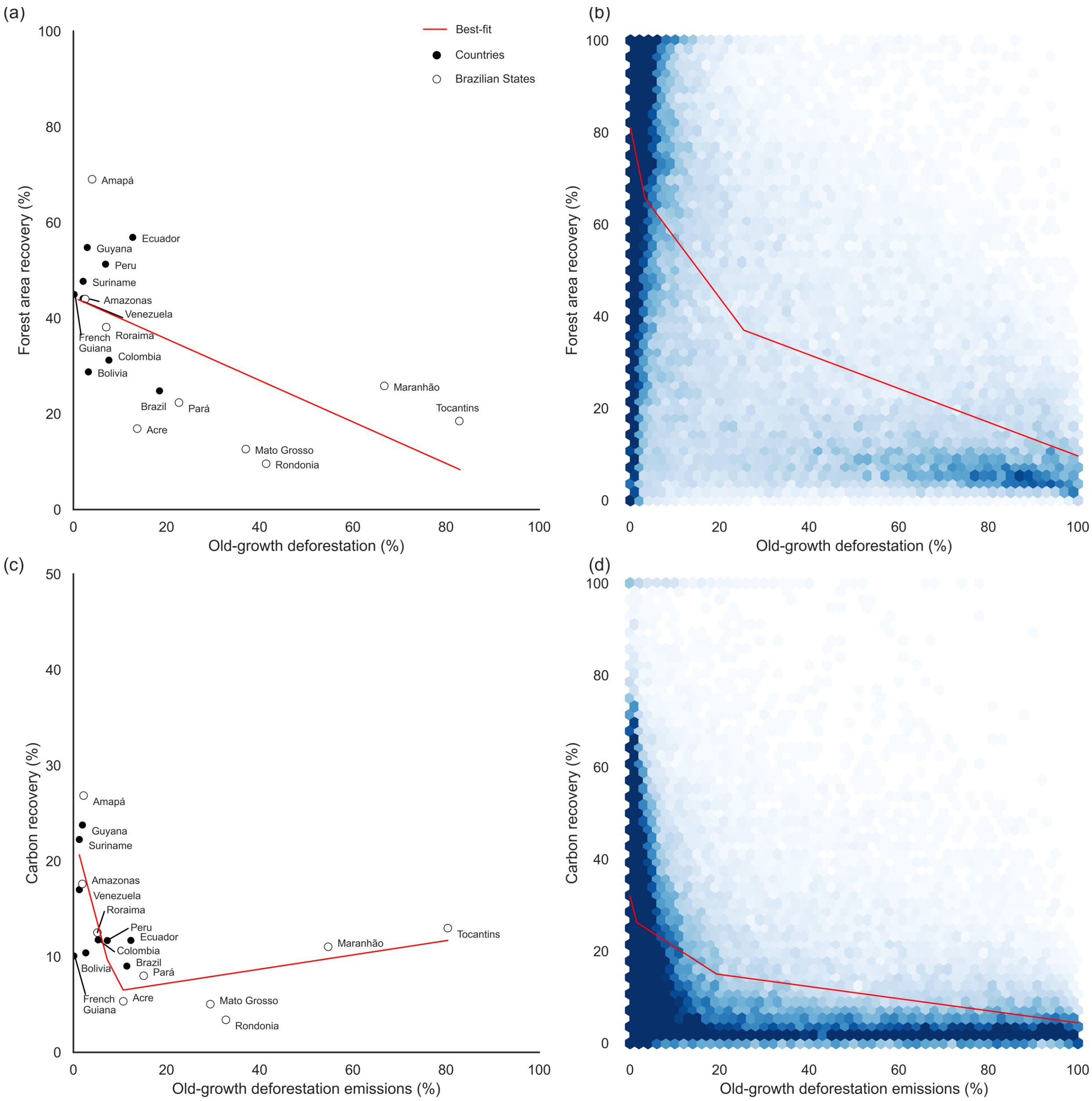

Figure 2: ***Proportional recovery of secondary forest recovery in the Amazon biome in 2017.***
The relationship between secondary forest recovery, measured as the percentage of cleared land occupied by secondary forest and deforestation as a percentage of total land within the Amazon basin (a, b). The relationship between emissions offset by secondary forest carbon accumulation and deforestation emissions as a percentage of original above-ground carbon (c, d). For (a, c) Amazonian countries (•) and Brazilian states (o); and (b, d) the Amazon basin gridded at ~60km². The best-fit models (where AICc ≥ 2) are shown in red: generalised linear model for panel a; and broken stick for panels b, c, d. Brazil was excluded from the calculation of the best-fit models for panels a and c in favour of its component states.

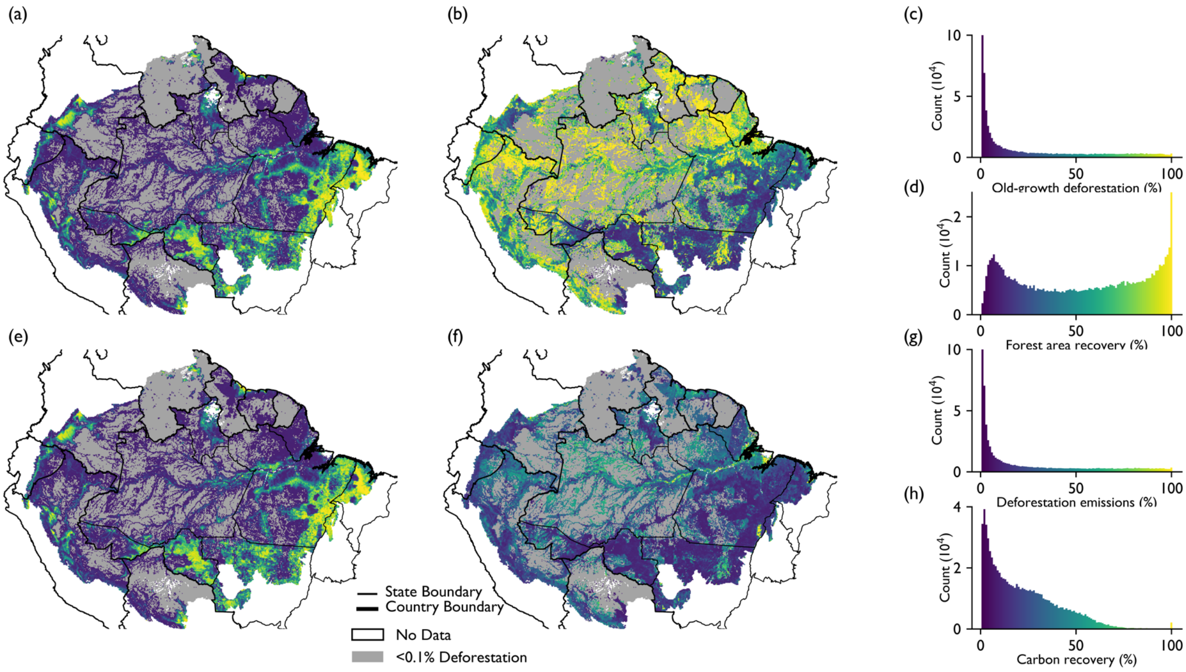

Figure 3: Old-growth deforestation, secondary forest recovery, carbon emissions and carbon accumulation in the Amazon biome in 2017.

The spatial distribution of (a) old-growth deforestation, (b) secondary forest recovery, (e) carbon emissions from old-growth deforestation and (f) carbon accumulation in secondary forest for the Amazon biome in 2017. Values were calculated over a regular grid of ~59.8 km^2 cells. Old-growth deforestation is measured as the percentage of the cell area cleared of forest. Secondary forest recovery is measured as the percentage of deforested land occupied by secondary forest. Old-growth deforestation emissions are measured as the percentage of the original old-growth above-ground carbon lost to deforestation. Carbon recovery measured as secondary forest carbon stock as a percentage of old-growth deforestation emissions. The distribution of cell values for each variable is shown in panels c, d, g, and h, respectively, which also define the colours used in panels a, b, e and f.

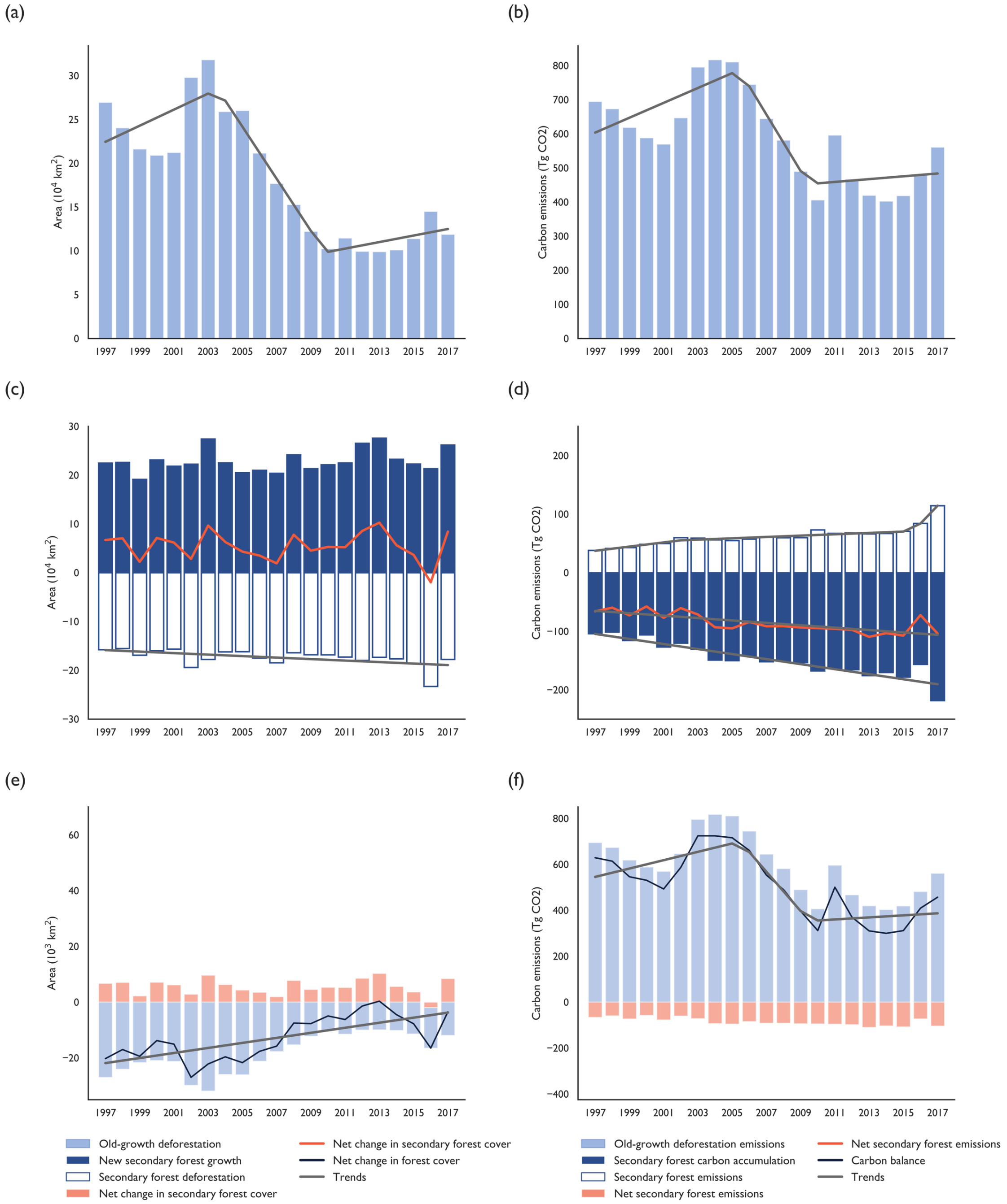

Figure 4: Annual change and temporal trends in forest cover and carbon emissions in the Amazon biome from 1997 to 2017

(a) The annual change in the extent of old-growth deforestation and (b) its associated carbon emissions. (c) The annual change in secondary forest extent comprising new secondary forest growth (dark), secondary forest clearance (white) and the net change in secondary forest extent (red line). (d) The annual carbon balance of secondary forests, comprising carbon accumulation from new and existing secondary forests (dark), carbon emissions from secondary forest clearance (white) and net change in secondary forest carbon (red). (e) The annual balance of forest extent with old growth deforestation (blue), net change in secondary forest extent (red) and the net change in total forest cover (dark blue line). (f) The annual balance in carbon emissions with old-growth deforestation emissions (blue), net change in secondary forest carbon (red) and the net carbon emissions from old-growth deforestation after offset by secondary forest carbon accumulation (dark blue line). The best-fit models (where AICc ≥ 2) for temporal trends are shown in grey: broken stick for old-growth deforestation extent and emissions, secondary forest gross carbon emissions, and net emissions from forest cover change; and generalised linear model for secondary forest clearance, carbon accumulation and net carbon emissions, and the net change in total forest cover.

Table 1 : Old-growth deforestation, secondary forest growth and their associated carbon emissions in the Amazon Biome in 2017

Region	**Percent of the Amazon Biome (%)**	**Area of old-growth deforestation (km²)**	**Old-growth forest loss (%)**	**Old-growth carbon loss (Tg C)**	**Old-growth carbon loss (%)**	**Area of secondary forest (km²)**	**Percentage of total forest area (%)**	**Forest area recovery (%)**	**Secondary forest carbon (Tg)**	**Secondary forest carbon 95% CI (Tg)**	**Carbon recovery (%)**	**Carbon recovery 95% CI (%)**
Brazil	61.9%	689,451	17.6%	5,057.7	15.8%	180,215	5.3%	24.8%	391.5	65.7	7.7%	1.3%
Amazonas	*23.6%*	*37,403*	*2.5%*	*337.1*	*1.9%*	*16,462*	*1.1%*	*44.0%*	*59.4*	*9.3*	*17.6%*	*2.7%*
Pará	*18.4%*	*262,869*	*22.7%*	*2,060.4*	*15.1%*	*58,800*	*6.2%*	*22.4%*	*165.3*	*27.3*	*8.0%*	*1.3%*
Mato Grosso	*7.3%*	*170,288*	*37.0%*	*1,175.3*	*29.3%*	*21,541*	*6.9%*	*12.6%*	*59.2*	*10.1*	*5.0%*	*0.9%*
Rondonia	*3.6%*	*92,835*	*41.4%*	*712.5*	*32.7%*	*8,909*	*6.4%*	*9.6%*	*24.3*	*4.0*	*3.4%*	*0.6%*
Roraima	*2.7%*	*12,029*	*7.0%*	*96.3*	*5.2%*	*4,588*	*2.8%*	*38.1%*	*12.1*	*2.4*	*12.5%*	*2.5%*
Acre	*2.6%*	*22,756*	*13.7%*	*207.9*	*10.7%*	*3,851*	*2.6%*	*16.9%*	*11.1*	*1.8*	*5.3%*	*0.9%*
Amapá	*1.8%*	*4,606*	*4.0%*	*44.1*	*2.2%*	*3,182*	*2.8%*	*69.1%*	*11.8*	*1.8*	*26.9%*	*4.0%*
Maranhão	*1.6%*	*66,832*	*66.7%*	*348.0*	*54.7%*	*17,280*	*34.2%*	*25.9%*	*38.4*	*7.2*	*11.1%*	*2.1%*
Tocantins	*0.4%*	*19,833*	*82.9%*	*76.0*	*80.4%*	*3,674*	*47.2%*	*18.5%*	*9.9*	*1.8*	*13.0%*	*2.4%*
Peru	11.5%	49,852	6.9%	630.7	7.3%	25,579	3.7%	51.3%	73.8	15.4	11.7%	2.4%
Colombia	7.4%	35,393	7.6%	267.5	5.3%	11,055	2.5%	31.2%	31.5	5.5	11.8%	2.1%
Venezuela	6.1%	7,996	2.1%	54.6	1.3%	3,528	0.9%	44.1%	9.3	1.9	17.0%	3.5%
Bolivia	5.2%	10,592	3.2%	93.1	2.7%	3,049	1.0%	28.8%	9.7	2.4	10.4%	2.5%
Guyana	3.0%	5,558	3.0%	57.2	1.9%	3,046	1.6%	54.8%	13.6	2.5	23.8%	4.4%
Suriname	2.1%	2,816	2.1%	27.0	1.3%	1,344	1.0%	47.7%	6.0	1.2	22.3%	4.5%
Ecuador	1.5%	12,160	12.7%	139.7	12.3%	6,922	7.7%	56.9%	16.4	3.7	11.7%	2.6%
French Guiana	1.3%	126	0.2%	1.3	0.1%	57	0.1%	45.0%	0.1	0.0	10.1%	1.5%
Amazon	100.0%	813,944	13.4%	6,328.8	8.6%	234,795	4.1%	28.8%	616.3	111.3	9.7%	1.8%

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