Article:

Wang, Y, Ziv, G orcid.org/0000-0002-6776-0763, Adami, M et al. (6 more authors) (2020) Upturn in secondary forest clearing buffers primary forest loss in the Brazilian Amazon. Nature Sustainability, 3. pp. 290-295. ISSN 2398-9629

https://doi.org/10.1038/s41893-019-0470-4

Accepted - Nature Sustainability, 2020
(https://doi.org/10.1038/s41893-019-0470-4)

Upturn in secondary forest clearing buffers primary forest loss in the Brazilian Amazon

Yunxia Wang[1*], Guy Ziv[1], Marcos Adami[2], Cláudio Aparecido de Almeida[3], João Francisco Gonçalves Antunes[4], Alexandre Camargo Coutinho[4], Júlio César Dalla Mora Esquerdo[4], Alessandra Rodrigues Gomes[2], David Galbraith[1*]

[1]School of Geography, University of Leeds, Leeds, UK.

[2]National Institute for Space Research (INPE), Amazon Regional Center, Belém, PA, Brazil.

[3]National Institute for Space Research (INPE), Image Processing Division, São José dos Campos, SP, Brazil

[4]Brazilian Agricultural Research Corporation (EMBRAPA), Agricultural Informatics, Campinas, SP, Brazil.

[*]Correspondence to: wangyx.tina@outlook.com. D.R.Galbraith@leeds.ac.uk

Abstract

Brazil contains two-thirds of remaining Amazonian rainforests and is responsible for the majority of Amazon forest loss. Primary forest loss in the Brazilian Amazon has declined considerably since 2004, but secondary forest loss has never been quantified. We use a recently-developed high-resolution land use/land cover dataset to track secondary forests in the Brazilian Amazon over 14 years, providing the first estimates of secondary forest loss for the region. We find that secondary forest loss increased by (187 ± 48) % from 2008 to 2014. Moreover, the proportion of total forest loss accounted for by secondary forests rose from (37 ± 3) % in 2000 to (72 ± 5) % in 2014. The recent acceleration in secondary forests loss occurred across the entire region and was not driven simply by increasing secondary forest area but likely a conscious preferential shift towards clearance of a little-protected forest ecosystem (i.e. secondary forests). Our results suggest that secondary forests loss have eased deforestation pressure on primary forests. However, this has been at the expense of a lost carbon sequestration opportunity of 2.59-2.66 Pg C over our study period.

Accepted - Nature Sustainability, 2020
(https://doi.org/10.1038/s41893-019-0470-4)

The Amazon rainforest provides significant ecosystem services locally, regionally and globally. The biome's forests are home to one-quarter of global biodiversity[1,2], store in excess of 100 billion tonnes of carbon in their biomass[3,4] and play a crucial role in the provision of rainfall in South America[5]. Deforestation control is essential for maintaining the functional integrity of Amazon rainforests. In the Brazilian Amazon, which accounts for over two-thirds of Amazonian forests[6], deforestation of primary forests fell by 82% from peak rates in 2004 to 2014[7]. This substantial decline reflects the efficacy of Brazil's PPCDAm Program[8] (The Action Plan for the Prevention and Control of Deforestation in the Legal Amazon), which was launched in 2004 to reduce deforestation rates and support sustainable development in Amazonia. This program resulted in the implementation of new policies, enhanced detection frameworks[9] and control measures to curtail deforestation in the Brazilian Amazon, and international mechanisms such as the soybean[10,11] and beef moratoria[12,13]. However, these mechanisms do not protect secondary forests, defined here as re-growing forests on previously deforested land.

Currently, secondary forests comprise approximately 21% of previously deforested areas in the Brazilian Amazon[14]. They can accumulate carbon very rapidly[15], thereby providing a key pathway for Brazil to reduce net carbon emissions and mitigate climate change[16]. At the same time, secondary forests are an important component of land management systems in the Brazilian Amazon, as their regrowth restores soil functioning, ensuring productivity of pastures and small-scale agriculture[17]. Despite the importance of secondary forests for conservation planning, environmental policy and land management in Amazonia, a historical lack of spatio-temporal data on secondary forest area has precluded evaluation of their large-scale dynamics. Although a recent localised study[18] for the state of Pará illustrates the dynamic nature of secondary forests, a comprehensive analysis of secondary forest loss in Amazonia does not exist.

Here we use a recently-developed 30 m land cover dataset for the Brazilian Amazon (TERRACLASS)[14,19], which provides unprecedented information on secondary forest occurrence over a 14-year period (2000-2014), to undertake the first large-scale assessment of the spatio-temporal dynamics of secondary forests in Amazonia. TERRACLASS takes the deforested areas from PRODES[7] as an input layer and classifies each deforested patch into one of twelve different land covers (Supplementary Table 1), including secondary forest. From TERRACLASS, we computed the areas of secondary and primary forest cleared annually, generated secondary forest loss by age structure and evaluated the fate (land cover type) of cleared secondary forests. To account for classification error in the TERRACLASS base map, we use a sampling-based approach combined with expert validation, following best practice in the field[20,21]. The summary forest loss estimates presented in the main text of this manuscript refer to sampling-based estimates. A comparison of sampling-based estimates and map-based calculations is provided in the supplementary information (Supplementary Table 8).

Results

Our results reveal two distinct phases of secondary forest loss in Amazonia. Between 2000-2008, we find a marked decline in secondary forest loss, mirroring the declines in primary forest loss seen over this period. During this period of declining deforestation, the pressure on both primary and secondary forests dropped markedly. However, we find that secondary forest loss between 2008-2014 increased sharply from approximately 6,040 ± 1,417 km^2 yr^{-1} to 10,757 ± 1,486 km^2 yr^{-1}, despite an apparent levelling off of primary forest loss over this period (Fig. 1). This second period, therefore, was marked by an increased pressure on forest ecosystems, which was largely absorbed by intensified secondary forest loss. These large increases in secondary forest loss translate into considerable overall increases (123 ± 21 %) in total (primary and secondary) forest loss between 2008-2010 and 2012-2014, reversing the downward trend in total forest loss up to 2008 (Fig. 1). Over our study period, the proportion of total forest loss due to secondary forest clearance increased from 37 ± 3 % in 2000-2004 to 72 ± 5 % in 2012-2014 (Fig. 1). Map-based areas of forest loss were very consistent with those derived from our sampling-based analysis and exhibited the same temporal pattern (Supplementary Figure 2).

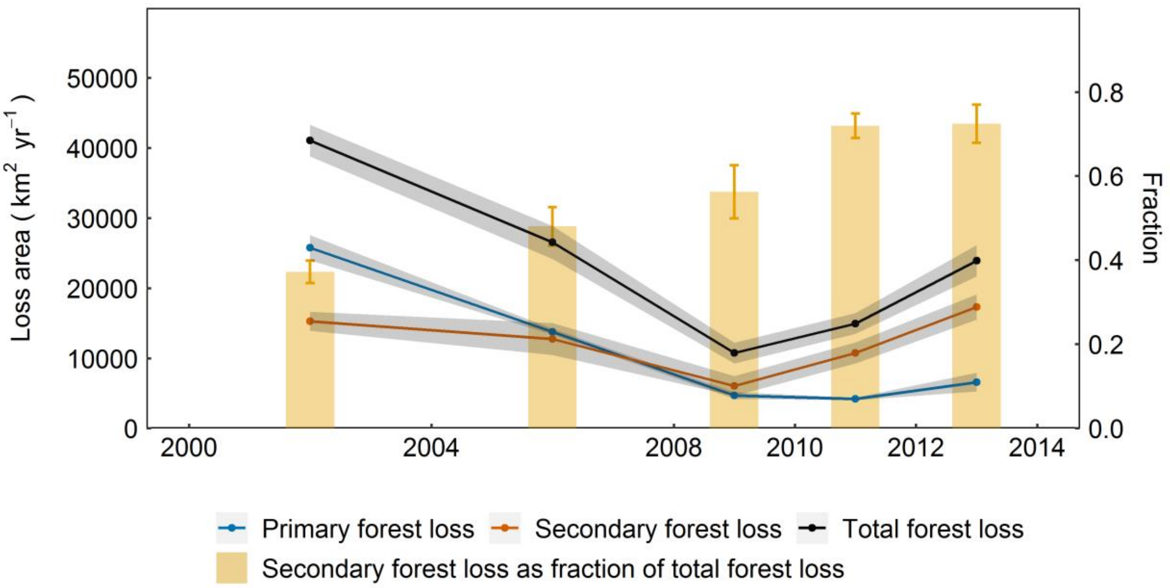

Fig. 1 | Sample-based estimates of annual primary and secondary forest loss in the Brazilian Amazon from 2000-2014. Total forest loss is the sum of primary and secondary forest loss. The uncertainties (grey shaded areas) denote Standard Errors (SE) from our sample-based validation (all intervals) as well as time-interval corrections which account for missed secondary forest loss in 4-year intervals (2000-2004 and 2004-2008 only). See Supplementary Table 8 for numerical values and comparison to map-based calculations.

The preferential cutting of secondary forests was found to be geographically widespread. In 2000-2004, secondary forest loss mainly outstripped primary forest loss in the far northeast of the Brazilian Amazon (Fig. 2) which has historically been subject to high primary forest deforestation, with little remaining primary forest (Supplementary Figure 4). By 2012-2014, however, secondary forest loss exceeded primary forest loss across almost all of the Brazilian Amazon (Fig. 2).

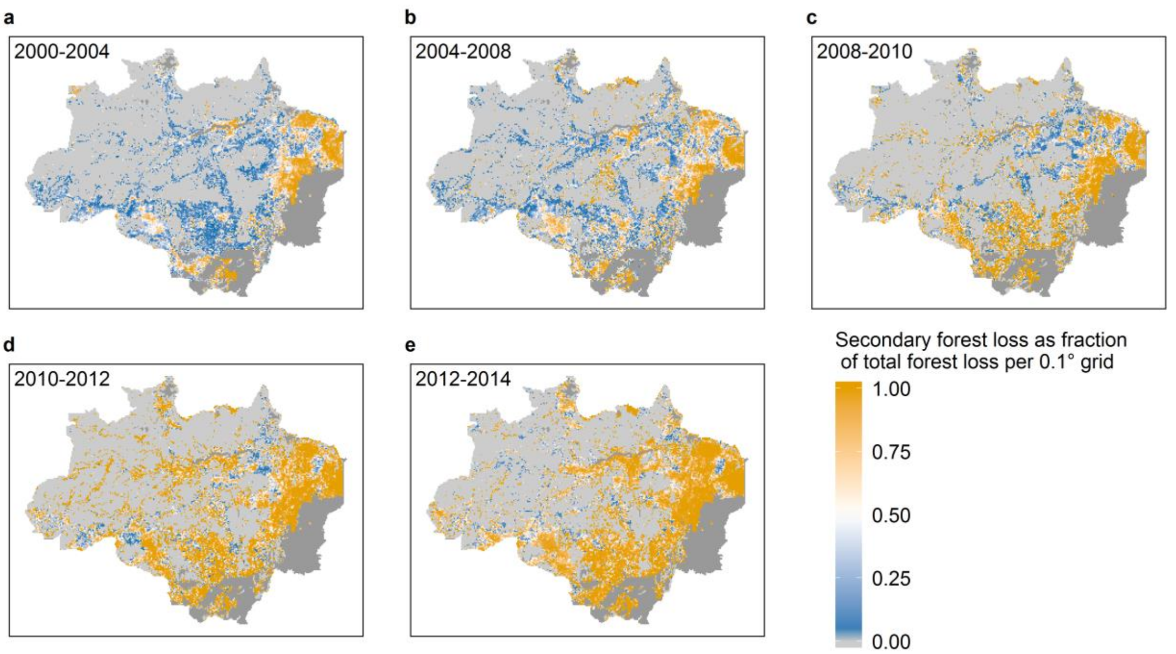

Fig. 2 | Spatio-temporal variation of secondary forest loss as fraction of total forest loss in the Brazilian Amazon. Darker blue (warmer orange) colours indicate areas where majority of forest loss occurred in primary (secondary) forests. The lighter grey colours represent areas with no recorded forest loss. Darker grey colours represent non-forest areas (e.g. savannas). Time interval corrections were applied in the first two intervals (i.e. 2000-2004, 2004-2008). See Supplementary Figure 3 for the spatial distribution of the absolute area of secondary forest loss. Analysis of spatial patterns was undertaken directly on the TERRACLASS wall-to-wall maps.

We further examined the age structure of secondary forest loss. Within any given interval, we find that the percentage loss rate of secondary forests declines progressively with increasing secondary forest age (Supplementary Table 9). In the 2012-2014 interval, for example, the percentage loss rate of the youngest secondary forest age category (0-2 years) was over five times greater than that of the oldest age category (>12 years old). Between 2008-2014, increases in secondary forest loss were observed across all age categories (Fig. 3) but were particularly marked for young (0-4 years) secondary forests (Fig. 3a). Over this time period, the annual percentage loss rates of young secondary forests increased by 250% from

6% in 2008-2010 to 21% in 2012-2014 (Fig. 3a, mean), compared to increases of 192% and 106% for intermediate (4-8 years) and old (>8 years) secondary forests respectively (Fig. 3b-c).

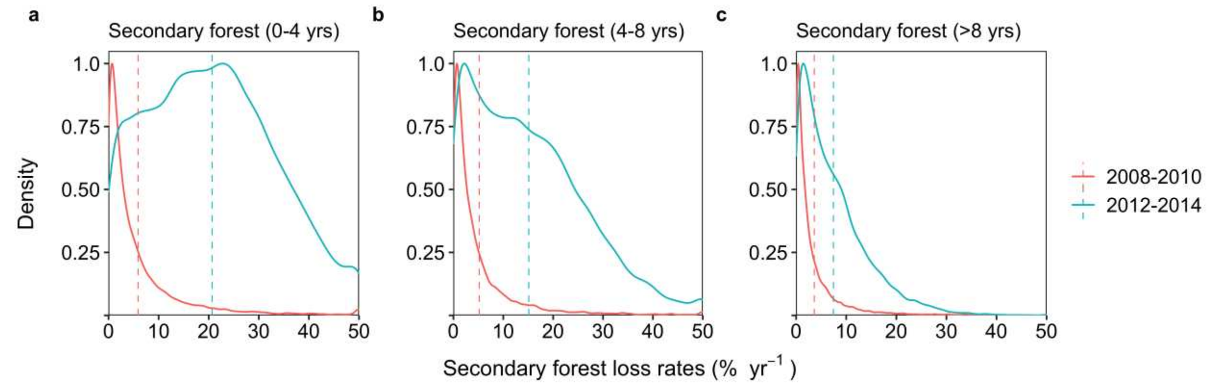

Fig. 3 | Distribution of percentage loss rate of secondary forests by age group (0-4 years, 4-8 years and over 8 years). Annual percentage loss rates of secondary forests were computed for individual 0.1° grid cells, based on TERRACLASS maps. Grid cells without secondary forest loss were excluded. Panel **a**, 10539 valid grid cells, 87% of which showed an increase in secondary forest loss rates; Panel **b**, 10915 valid grid cells, 81% of which showed an increase in secondary forest loss rates; Panel **c**, 11248 valid grid cells, 76% of which showed an increase in secondary forest loss rates. Solid lines depict density distributions of secondary forest loss rates across all valid grids. Dashed vertical lines denote mean values.

Fate of secondary forest loss

The vast majority (91%) of cleared secondary forests (almost identical for young, intermediate and old secondary forests) in the Brazilian Amazon over our study period became pastureland (Supplementary Table 10 and Table 11), mirroring the fate of deforested primary forests[21]. Pasture expansion from primary forest deforestation in Amazonia slowed considerably following the establishment of the 2008 beef moratorium[13], in which retailers pledged to stop purchasing meat produced on illegally deforested land. Since these measures were introduced, secondary forests have absorbed much more of the pasture expansion in the Brazilian Amazon, with conversion of secondary forest to pastureland increasing by 282%

Accepted - Nature Sustainability, 2020
(https://doi.org/10.1038/s41893-019-0470-4)

between 2008-2010 and 2012-2014 (Supplementary Table 10). Conversely, about 90% of new secondary forests observed in TERRACLASS between 2008 and 2014 were previously identified as pasture (Supplementary Table 10). Although conversion of secondary forest to agricultural land increased by 106% between 2008-2010 and 2012-2014, the absolute area of secondary forest converted to agricultural land in 2012-2014 was >40 times lower than that converted to pastureland and only accounted for approximately 2% of the total cleared secondary forest area (Supplementary Table 10).

Overall, our results point to an acceleration of the pasture-forest-pasture management system since the introduction of the beef moratorium. Post-deforestation landscapes in the Brazilian Amazon are highly dynamic in nature. In these landscapes, secondary forests are often cut and usually burned, as part of the pasture cycle. Their regrowth on pasturelands improves soil integrity by replenishing nutrients, enhancing organic matter storage and improving the physical structure of soils, which can become heavily degraded following sustained pasture activity[22]. Our results suggest that the permanence time of secondary forests in these cycles has decreased substantially over time, as cutting rates have accelerated greatly but with no underlying trend over time in the fate of secondary forests. Whereas only 2.86 ± 0.67 % of total secondary forest area was cut annually between 2008 and 2010, this increased to 7.43 ± 0.81 % in 2012-2014 (Supplementary Table 5 and Table 7).

Area of secondary forests

The upturn in overall forest loss, including both primary and secondary forests, since 2008 indicates an enhanced demand for new pasture and agricultural lands. This enhanced demand has increasingly been met by secondary forests, thus providing a buffer that has stalled deforestation of primary forests. Ultimately, however, the strength of this buffer depends on the area of secondary forest available. Between 2000-2010, the sampling-derived area of secondary forest increased by 34,183 ± 12,392 km^2 (an overall change of 0.87 ± 0.29% in

Accepted - Nature Sustainability, 2020
(https://doi.org/10.1038/s41893-019-0470-4)

agreement with Aguiar *et al.* (2016)[23]), but did not change significantly over the last two intervals (Supplementary Table 12). Moreover, the area of stable secondary forest (secondary forests which persisted over an entire TERRACLASS interval) increased progressively over time up to the last interval, when it declined for the first time (Supplementary Tables 3-7). Future depletions in secondary forest area would likely lead to increasing pressure on primary forests as the available pool of easily accessible secondary forests for cutting is diminished.

Discussion and Conclusion

While primary forests have benefited from strong legal protection in the Brazilian Amazon, secondary forests have little protection status in Brazilian law. This partially stems from the lack of clear definitions for secondary forests themselves - e.g. the point in the recovery process where they effectively become ‘forests’. Pará is currently the only Brazilian state to adopt an explicit definition of secondary forests, where secondary forests are defined as those that have regenerated from previously cleared land and that can no longer be considered as fallow[24]. The right to cut secondary forests in Pará is directly related to forest age, as state law[25] dictates that areas younger than five years can be cleared irrespective of their physical structure, whilst areas older than 20 years must be conserved. Clearance of forests in intermediate stages of succession (5-20 years) follows basal area thresholds which vary according to background forest cover status. While such legislation is beneficial for ensuring the recovery of older forests, it may encourage the cutting of secondary forests before they reach the age or basal area thresholds that would render their cutting illegal. In other Brazilian Amazon states, legislation governing the cutting of secondary forests has yet to be developed. This limited legal protection means that secondary forest loss is largely unregulated.

To formally test whether the increase in secondary forest loss over time can be explained purely by increasing availability of secondary forests relative to primary forests, we compared the observed secondary forest cutting to a null model which assumes a time-invariant

Accepted - Nature Sustainability, 2020
(https://doi.org/10.1038/s41893-019-0470-4)

preference for secondary forest clearance relative to primary forest clearance. We find that across the Brazilian Amazon, this null model predicted secondary forests losses well up to 2008-2010. In the last two intervals, however, the null model greatly underestimated secondary forest loss and its relative contribution to total forest loss (Fig. 4). This recent rise in secondary forest clearance may reflect a conscious behavioural shift towards preferential cutting of secondary forests over primary forests - i.e. the increase in secondary forest loss in our statistical model would only be captured if the bias for cutting secondary forest relative to primary forest was allowed to increase over time.

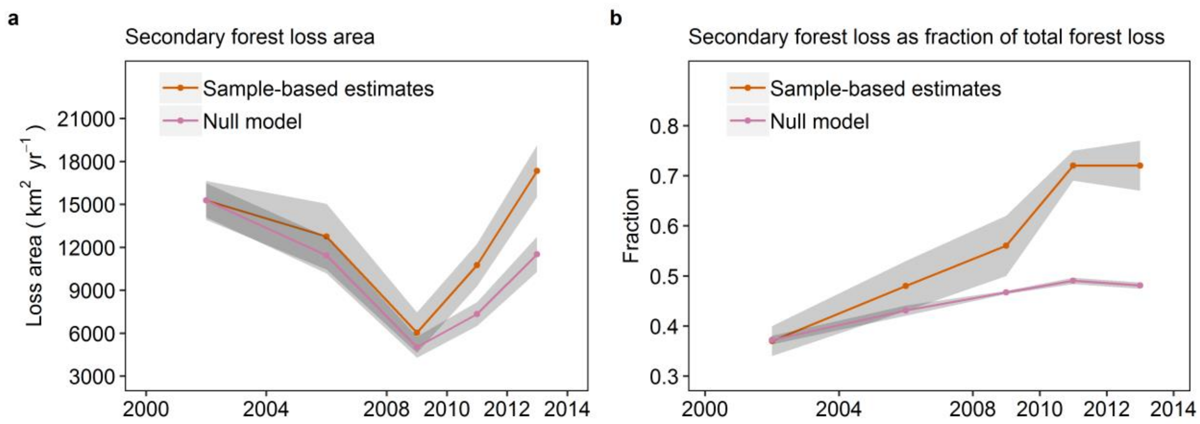

Fig. 4 | Comparison of secondary forest loss between actual estimates from TERRACLASS and null model predictions. The null model predicts secondary forest loss by sampling without replacement based on Fisher's non-central hypergeometric distribution, given known available areas of primary and secondary forests in each interval and assuming a bias (odds ratio, estimated to be 13.69) for cutting secondary forests relative to primary forest computed for the first interval (2000-2004) and subsequently maintained across all intervals. Points on the null model curves are based on mean values from Fisher's non-central hypergeometric distribution. See Supplementary Table 12 for numerical values.

The large losses of secondary forests observed in this study have significant implications. On the one hand, their accelerated cutting has been important for curbing losses of primary

Accepted - Nature Sustainability, 2020
(https://doi.org/10.1038/s41893-019-0470-4)

forests whose biodiversity value is irreplaceable[26]. The enhanced preference for cutting secondary forests instead of primary forests also reinforces the effectiveness of measures in place to inhibit primary forest loss. On the other hand, secondary forests are themselves an important biodiversity reservoir in an increasingly fragmented landscape[27,28], and if left to regrow, can act as substantial carbon sinks[29]. Brazil has committed to restore 120,000 km^2 of forest land by 2030 as part of its Nationally Determined Contribution (NDC) for the Paris Agreement[30]. A cost-effective way to do this would be to allow part of its existing Amazonian secondary forest area to recover naturally. Over the 14-year period of our study, over 180,329 ± 11,760 km^2 of secondary forests were cut, exceeding its total NDC commitment by over 60,329 ± 11,760 km^2. Applying a simple biomass accumulation model (see Methods), we estimate that this loss of secondary forests prevented the potential accumulation of 2.59-2.66 billion tonnes of carbon. This represents approximately 18 years of Brazil's fossil fuel emissions, based on 2014 emissions[31].

Despite the recent acceleration of secondary forest loss, the Brazilian Amazon still has in excess of 235,718 ± 7,773 km^2 of secondary forests. Managing this ecosystem sustainably so as to maximise the conservation value of these forests, while not intensifying pressure on primary forests, requires an integrated strategy that includes active monitoring of secondary forests in Amazonia and strengthening of their governance.

Accepted - Nature Sustainability, 2020
(https://doi.org/10.1038/s41893-019-0470-4)

Methods

We used the land use/land cover classification maps produced by the TERRACLASS Project[19] (*https://www.terraclass.gov.br*) as the basis for all the analysis of secondary forest dynamics conducted in this study.

TERRACLASS. TERRACLASS, developed by INPE (National Institute for Space Research in Brazil), maps post-deforestation land cover at 2 to 4 year intervals across the Brazilian Legal Amazon. We used all TERRACLASS maps available at the time of the study (2000, 2004, 2008, 2010, 2012 and 2014). TERRACLASS assigns areas designated as deforested by PRODES (primary forest deforestation monitoring program for the Brazilian Amazon) into one of twelve different land cover types (Supplementary Table 1). In this study, we combined shrubby pasture and herbaceous pasture categories into a single pasture category and further combined perennial agriculture, semi-perennial agriculture and temporal agriculture into a single agriculture category. For areas not observed in a specific TERRACLASS year due to persistent cloud cover, we assume the same land use categories as for the preceding TERRACLASS map. Non-forest and hydrology categories were excluded from the study. TERRACLASS 2004-2014 products inherited historical PRODES misalignment issues[32] which were subsequently corrected for TERRACLASS-2000. To ensure consistency across all TERRACLASS products, we aligned the TERRACLASS-2000 to other TERRACLASS products using an image displacement algorithm in Google Earth Engine (See supplementary Figure 1 for the example image for diaplacement correction).

Accepted - Nature Sustainability, 2020
(https://doi.org/10.1038/s41893-019-0470-4)

Estimates of forest loss. We computed forest loss estimates from TERRACLASS in two ways: 1) simple wall-to-wall calculations based directly on the TERRACLASS map, and 2) a sampling-based approach in which classification accuracy and the map areas of different land cover categories are used to construct forest loss estimates with appropriate error quantification[19,31].

We calculated annual primary and secondary forest loss as well as secondary forest gain for five individual time intervals: 2000-2004, 2004-2008, 2008-2010, 2010-2012, 2012-2014. Primary forest loss was considered as the land use change from primary forest to any non-primary forest categories (i.e. pasture, agriculture, secondary forest, urban, mining, others, and reforestation). Secondary forest loss was regarded as the land use change from secondary forest to other non-forest categories. Secondary forest was defined as being represented only by the 'secondary forest' class from TERRACLASS. No post-hoc re-classification of any other land classes (e.g. shrubby pasture) as secondary forest was applied. Thus, all estimates of secondary forest area and loss reported in this study refer specifically to the 'secondary forest' category from TERRACLASS. Total forest loss was computed as the sum of primary forest loss and secondary forest loss. Secondary forest gain was defined as the regrowth of secondary forests following abandonment from other non-forest categories. Wall-to-wall primary/secondary forest loss rates were constructed by summing the pixel areas of all pixels that were defined as primary/secondary forest at the beginning of a TERRACLASS interval but not these classes at the end of the interval.

We used the map-based calculations to evaluate spatial patterns of secondary/primary forest loss. To do this, we applied a 0.1 degree grid over the Brazilian Amazon and computed the fraction of total forest loss accounted for by secondary forests within each grid cell.

Sampling-based estimates. Our wall-to-wall calculations may be subject to biases related to TERRACLASS classification errors[14]. To account for this, we estimated forest loss by applying

Accepted - Nature Sustainability, 2020
(https://doi.org/10.1038/s41893-019-0470-4)

an unbiased estimator to a stratified sample of reference observations following best practice recommendations[20,33]. For each TERRACLASS time interval (i.e. 2000-2004, 2004-2008, 2008-2010, 2010-2012, 2012-2014), we used stratified random sampling to generate an independent set of samples, for subsequent visual assessment by three experts. Sampling was stratified according to six land cover change categories: 1) stable primary forest, 2) primary forest loss, 3) stable secondary forest, 4) secondary forest loss, 5) secondary forest gain, and 6) stable others (e.g. pasture, agriculture, mining). The stable primary forest stratum occupied >70% of the study area (Supplementary Table 1). Given the very large area of this stratum, stable forest samples interpreted as change categories in the reference classification will carry a disproportional area weight and may considerably reduce the accuracy of estimates of change categories[34]. To account for this, we introduced a buffer stratum (1 km) for stable primary forest areas surrounding areas of primary forest loss and partitioned our stable forest sample to account for stable forests inside and outside of this buffer[34]. We calculated the total sample size *n* following Olofsson et al. (2014)[20], as follows:

$$n = \left(\frac{\sum(w_i S_i)}{S(\hat{O})}\right)^2 \qquad (1)$$

where w_i is the mapped proportion of area of stratum *i*, $S(\hat{O})$ is the standard error of the estimated overall accuracy that we would like to achieve (0.015), S_i is the standard deviation of stratum *i*, $S_i = \sqrt{U_i(1-U_i)}$ where U_i is the anticipated user's accuracy of stratum *i* (0.70 for all strata in this study). This yielded a total of 933 sampled pixels for each time interval with 50-100 pixels allocated to the smaller strata and the remaining pixels proportionally allocated to other strata based on their area weights (w_i)[20,34] (Supplementary Table 1). All pixels were sampled so that they were at least 200 m away from the edge of an individual stratum to avoid potential misalignments between TERRACLASS and the reference images[32].

Accepted - Nature Sustainability, 2020
(https://doi.org/10.1038/s41893-019-0470-4)

Reference classification for each sampled pixel was conducted through Collect Earth Online[35] by three experts through visual interpretation of annual Landsat composite images acquired during 1st July – 31st August and, when available, very high resolution imagery from Digital Globe and Google Earth. Information from time-series trajectories of Landsat spectral bands (red and short-wave infrared bands) and vegetation indices (NDVI-normalized difference vegetation index, NDWI- normalized difference water index) were also utilized by the experts for the reference classification. Each sampled pixel was classified by the experts as stable forest, forest loss, forest gain or stable others, and flagged if no clear Landsat image was available. Experts did not distinguish between stable primary forest and stable secondary forest or between primary forest loss or secondary forest loss as TERRACLASS only classifies land use/cover on historically deforested areas, so that misclassifications between primary and secondary forests are not technically possible in TERRACLASS. Initially, each expert assessed each reference pixel independently. Pixels with disagreement between experts were subsequently revisited until agreement was reached. Flagged pixels (with no clear Landsat imagery between 1st July and 31st August) were re-interpreted using Landsat composite imagery for the entire year or excluded if no clear reference image was available for that year.

Area estimates of each individual reference class were based on the above reference data and sample classification protocol. Following Olofsson *et al.* (2014)[20], the estimated area of reference class *k* was computed as:

$$\hat{A}_k = A \times \hat{p}_{\cdot k} \qquad (2)$$

where *A* is the total area of the entire domain considered (3,924,375.63 km^2), and $\hat{p}_{\cdot k}$ is the proportion of area of class k as determined from the reference classification, which was computed as:

$$\hat{p}_{\cdot k} = \sum_{i=1}^{q} w_i \frac{n_{ik}}{n_i} \qquad (3)$$

Accepted - Nature Sustainability, 2020
(https://doi.org/10.1038/s41893-019-0470-4)

where q represents the number of mapped strata (i), w_i is the proportion of area of each mapped stratum i, n_{ik} is the number of samples from mapped stratum i interpreted as reference class k, and n_i is the total number of samples for mapped stratum i.

The standard error for the proportion of area of reference class k was computed as[20]:

$$S(\hat{p}_{\cdot k}) = \sqrt{\sum_i \frac{w_i \hat{p}_{ik} - \hat{p}_{ik}^2}{n_i - 1}} \qquad (4)$$

where $\hat{p}_{ik}$ is the proportion of area from mapped stratum i interpreted as reference class k, $\hat{p}_{ik} = w_i \frac{n_{ik}}{n_i}$ (refer to the above eq. (3)).

The standard error of the estimated areas was then computed as:

$$S(\hat{A}_k) = A \times S(\hat{p}_{\cdot k}) \qquad (5)$$

The summary forest loss estimates reported in the main text of this manuscript denote the sampling-based estimates $\hat{A}_k \pm S(\hat{A}_k)$.

Correcting for varying interval lengths. The time structure of TERRACLASS products (2000/2004/2008/2010/2012/2014), is such that the first two intervals used to compute forest loss span four years while the remaining intervals span two years. These differences in interval length do not affect calculation of primary forest loss but do have implications for secondary forest loss and gain due to the much more transient nature of secondary forests, which are often cleared within 2 years of regrowth. Thus, 4-year intervals can miss the clearance of secondary forests that have established and been cut again within the interval. To account for this, we derived a correction factor α, where secondary forest loss/gain estimates for 4-year intervals were rescaled as:

$$A_{corrected} = A_{uncorrected} \times \alpha \qquad (6)$$

where $A_{uncorrected}$ is the original, uncorrected loss/gain over 4-year TERRACLASS intervals (2000-2004, 2004-2008). We calculated α as follows, based on available 2-year TERRACLASS intervals (2008-2014), which we then regrouped into 4-year intervals (e.g. 2008-2012, 2010-2014):

$$\alpha = \left(B_{2yr(i)} + B_{2yr(ii)}\right)/B_{4yr} \qquad (7)$$

where B_{4yr} is the secondary forest loss/gain over the regrouped 4-year interval and $B_{2yr(i)}$ and $B_{2yr(ii)}$are secondary forest loss/gain for 1st and 2nd 2-year intervals respectively. We found that on average, 4-year intervals underestimated secondary forest loss by 16.84-26.52% and underestimated secondary forest gain by 10.31-24.61% relative to 2-year intervals.

We applied the above underestimates of secondary forest loss/gain to provide revised best estimates (based on mean underestimates) of secondary forest loss/gain for 4-year intervals and used the full range of underestimates (minimum and maximum values) to provide uncertainty bounds on our re-scaled values.

The interval length corrections were applied to both our map-based and sampling-based estimates for the 4-year intervals (i.e. 2000-2004, 2004-2008). For sample-based estimates, the total errors for the loss rates were computed by adding the sampling-derived errors in quadrature with the interval correction errors (only relevant for 4-year intervals).

Determining secondary forest loss from different forest ages. To calculate secondary forest loss for different forest age groups, we generated four age category maps for 2004, 2008, 2010 and 2012 by tracking individual secondary pixels in time back to their year of first emergence in the dataset (Supplementary Table 8). To account for the differences in forest area among different age groups, we report secondary forest losses as proportional loss rates whereby the annual secondary forest loss for individual age categories were divided by the corresponding total secondary forest area for that age category (Supplementary Table 8). The number of age categories that we considered increased over time for each map. For example, the secondary forest age map for 2004 only has two age categories (0-4, >4 years), while the secondary forest age map for 2012 contains five age categories (0-2, 2-4, 4-8, 8-12, >12 years). As it was not possible to compare the same age category across all intervals, we restricted our analysis of changes in forest loss by age category to two intervals (2008-2010 and 2012-2014) for which it was possible to compare identical age categories (0-4, 4-8, >8 years). For these two intervals, we computed the percentage of secondary forest loss annually for each age categories (i.e. 0-4, 4-8 and >8 years) within individual $0.1° \times 0.1°$ grid cells and compared the pixel-level forest loss distributions between both intervals.

Null model analysis. To test whether the accelerated loss of secondary forest was driven simply by increases in secondary forest area relative to primary forest area over time, we compared TERRACLASS secondary forest loss estimates to predictions from a statistical null model based on Fisher's non-central hypergeometric distribution, a modification of the hypergeometric distribution which allows the sampling probabilities of two binomially distributed variables to be adjusted according to an odds ratio. The odds ratio for cutting of secondary forests relative to primary forests was computed for the first TERRACLASS interval (2000-2004), based on the known total areas of both secondary and primary forest at the beginning of the interval from sample-based estimates (stable secondary forest + secondary forest loss within the interval) and the known secondary and total forest loss during the interval. For the first interval (2000-2004), this odds ratio was found to be 13.69 (i.e. secondary forests were >13 times more likely to be cut than primary forests). We applied the null model to each TERRACLASS interval, considering interval-specific total forest loss and available primary and secondary forest areas but maintaining the same odds ratio for preferential cutting of secondary forests as in the first interval. The null model analysis was conducted in R using the 'BiasedUrn' package.

Calculating carbon sequestration forgone due to the clearance of secondary forest. To estimate the lost carbon sequestration potential arising from secondary forest cutting, we applied a Michaelis-Menten model commonly used in assessments of secondary biomass recovery[15,36,37]. In this model, the amount of carbon sequestered in secondary forests at age t is given by: $C(t) = (C_{max} * t)/(\alpha_{50} + t)$, where C_{max} is average old-growth carbon storage for Amazon forests (170.60 Mg C ha^{-1})[30], α_{50} is the half-saturation content denoting the time taken to reach half of the maximum carbon sequestration (35 years)[37], and age t is the average age of secondary forest when cleared. We estimated t as the area-weighted mean age of secondary forest loss in the last time interval (Supplementary Table 9, 2012-2014 time interval), taking the midpoint of each age category to represent the actual age of the secondary forest when cut. For the oldest age category, we conducted a sensitivity analysis where the mean age varied from 12-20 years. The final value of t used in the calculation above ranged from 5.50-6.57 years, once the uncertainty associated with the midpoint of the oldest age category was accounted for. The lost carbon sequestration opportunity due to secondary forest cutting was calculated by subtracting the secondary forest carbon sequestration at average cutting age t ($C(t)$) from its potential maximum carbon sequestration (C_{max}) and scaling this by the total area of lost secondary forest over our study period (180,329 ± 11,760 km^2 from sample-based estimates).

Data availability

The data that support the findings of this study are available from the paper or from the supplementary materials. The TERRACLASS dataset used in current study is freely available from *https://www.terraclass.gov.br/* .

Code availability

The Google Earth Engine (GEE) codes analysed during current study are available in the Y.W.'s GEE repository: *https://code.earthengine.google.com/?accept_repo=users/wangyxtina/public*

References

1 Dirzo, R. & Raven, P. H. Global state of biodiversity and loss. *Annual review of Environment and Resources* **28**, 137-167 (2003).

2 Malhi, Y. *et al.* Exploring the likelihood and mechanism of a climate-change-induced dieback of the Amazon rainforest. *Proceedings of the National Academy of Sciences* **106**, 20610-20615 (2009).

3 Baccini, A. *et al.* Estimated carbon dioxide emissions from tropical deforestation improved by carbon-density maps. *Nature Climate Change* **2**, 182-185 (2012).

4 Avitabile, V. *et al.* An integrated pan-tropical biomass map using multiple reference datasets. *Global change biology* (2016).

5 Spracklen, D. V., Arnold, S. R. & Taylor, C. Observations of increased tropical rainfall preceded by air passage over forests. *Nature* **489**, 282 (2012).

6 RAISG. Amazonia under Pressure. 10 (2012).

7 PRODES, p. Projecto Prodes: Monitoramento de Floresta Amazonica Brasileira por satelite. http://www.obt.inpe.br/prodes/index.php. *Instituto Nacional de Pesquisas Espaciais* (2018).

8 Maia, H., Hargrave, J., Gómez, J. J. & Röper, M. Avaliação do Plano de Ação para Prevenção e Controle do Desmatamento na Amazônia Legal: PPCDAm: 2007-2010. (2011).

9 Assunção, J., Gandour, C. & Rocha, R. DETERring deforestation in the Brazilian Amazon: environmental monitoring and law enforcement. *Climate Policy Initiative*, 1-36 (2013).

10 Gibbs, H. K. *et al.* Brazil's soy moratorium. *Science* **347**, 377-378 (2015).

11 Rudorff, B. F. T. *et al.* The soy moratorium in the Amazon biome monitored by remote sensing images. *Remote Sens-Basel* **3**, 185-202 (2011).

12 Gibbs, H. K. *et al.* Did ranchers and slaughterhouses respond to zero-deforestation agreements in the Brazilian Amazon? *Conservation Letters* **9**, 32-42 (2016).

13 Massoca, P. E. D. S., Delaroche, M. & Lui, G. 4.6 Lessons from the soy and beef moratoria in Brazil. *Zero deforestation: A commitment to change*, 151 (2017).

14 Almeida, C. A. d. *et al.* High spatial resolution land use and land cover mapping of the Brazilian Legal Amazon in 2008 using Landsat-5/TM and MODIS data. *Acta Amazonica* **46**, 291-302 (2016).

15 Poorter, L. *et al.* Biomass resilience of Neotropical secondary forests. *Nature* **530**, 211 (2016).

16 Chazdon, R. L. *et al.* Carbon sequestration potential of second-growth forest regeneration in the Latin American tropics. *Science Advances* **2**, e1501639 (2016).

17 Kato, O., KATO, M. d. S., SÁ, T. d. A. & Figueiredo, R. Plantio direto na capoeira. *Embrapa Amazônia Oriental-Artigo em periódico indexado (ALICE)* (2004).

18 Carvalho, R., Adami, M., Amaral, S., Bezerra, F. G. & de Aguiar, A. P. D. Changes in secondary vegetation dynamics in a context of decreasing deforestation rates in Pará, Brazilian Amazon. *Appl. Geogr.* **106**, 40-49 (2019).

19 TerraClass, p. TERRACLASS: mapping land uses/land covers for all previous deforested areas in the Brazilian Amazon. https://www.terraclass.gov.br. *National Institute for Space Research (INPE) and Brazilian Agricultural Research Corporation (EMBRAPA)* (2018).

20 Olofsson, P. *et al.* Good practices for estimating area and assessing accuracy of land change. *Remote Sens Environ* **148**, 42-57 (2014).

21 Tyukavina, A. *et al.* Types and rates of forest disturbance in Brazilian Legal Amazon, 2000–2013. *Science advances* **3**, e1601047 (2017).

22 Cordeiro, I. M. C. C., Rangel-Vasconcelos, L. G. T. & Schwartz, G. O manejo da floresta secundária na Amazônia Oriental. *Embrapa Amazônia Oriental-Capítulo em livro científico (ALICE)* (2017).

23 Aguiar, A. P. D. *et al.* Land use change emission scenarios: anticipating a forest transition process in the Brazilian Amazon. *Global change biology* **22**, 1821-1840 (2016).

24 Vieira, I. C. G., Gardner, T., Ferreira, J., Lees, A. C. & Barlow, J. Challenges of governing second-growth forests: A case study from the Brazilian Amazonian State of Pará. *Forests* **5**, 1737-1752 (2014).

25 Pará State Government. INSTRUÇÃO NORMATIVA SEMA Nº 08, DE 28-10-2015. *Available at: https://sogi8.sogi.com.br/Arquivo/Modulo113.MRID109/Registro1230833/instrucao%20normativa%20no%2008.pdf*, 3-4 (2015).

26 Gibson, L. *et al.* Primary forests are irreplaceable for sustaining tropical biodiversity. *Nature* **478**, 378 (2011).

27 Brockerhoff, E. G., Jactel, H., Parrotta, J. A., Quine, C. P. & Sayer, J. Plantation forests and biodiversity: oxymoron or opportunity? *Biodiversity and Conservation* **17**, 925-951 (2008).

28 Lennox, G. D. *et al.* Second rate or a second chance? Assessing biomass and biodiversity recovery in regenerating Amazonian forests. *Global change biology* **24**, 5680-5694 (2018).

29 Martin, P. A., Newton, A. C. & Bullock, J. M. Carbon pools recover more quickly than plant biodiversity in tropical secondary forests. *Proc. R. Soc. B* **280**, 20132236 (2013).

30 UNFCCC. Nationally Determined Contributions (NDCs). (2015).

31 CO2 emissions (metric tons per capita). *World Bank* (2014).

32 PRODES. Correcting the PRODES Mask. http://www.obt.inpe.br/OBT/assuntos/programas/amazonia/prodes/pdfs/nt_deslocamentomascara.pdf. *National Institute for Space Research (INPE)* (2017).

33 Olofsson, P., Foody, G. M., Stehman, S. V. & Woodcock, C. E. Making better use of accuracy data in land change studies: Estimating accuracy and area and quantifying uncertainty using stratified estimation. *Remote Sens Environ* **129**, 122-131 (2013).

34 Arévalo, P., Olofsson, P. & Woodcock, C. E. Continuous monitoring of land change activities and post-disturbance dynamics from Landsat time series: A test methodology for REDD+ reporting. *Remote Sens Environ*, 111051 (2019).

35 Saah, D. *et al.* Collect Earth: An online tool for systematic reference data collection in land cover and use applications. *Environmental Modelling & Software* **118**, 166-171 (2019).

36 Batterman, S. A. *et al.* Key role of symbiotic dinitrogen fixation in tropical forest secondary succession. *Nature* **502**, 224 (2013).

37 Galbraith, D. *et al.* High-resolution Assessment of the Net Biomass Balance of the Brazilian Amazon: 2004-2014. *Global change biology* **In review** (2019).

Correspondence and requests for materials should be addressed to Y.W.

Acknowledgments

This work was funded by a China Scholarship Council/University of Leeds grant to Y.W. (201506300051), a Google Earth Engine Research Award to G.Z. and D.G., a NERC-funded standard grant to D.G. (TREMOR project NE/N004655/1), a Royal Society Newton Advanced Fellowship to M.A (NAF/R1/180405), and a Horizon 2020 programme grant to G.Z. (ECOPOTENTIAL project grant agreement no. 641762). We would like to thank Lucyana Santos and Tamires Lisboa for the contribution of visual interpretation of our sampling pixels. We also would like to thank the large number of dedicated staff at INPE and EMBRAPA who produce the PRODES and TERRACLASS products. These efforts are critical for understanding land use change dynamics in the Brazilian Amazon. We would also like to thank Tim Baker and Sarah Batterman for providing useful feedback on an earlier version of the manuscript.

Competing interests

The authors declare no competing interests.

Author contributions

Y.W., D.G. and G.Z. developed the concept and methodological work plan. Y.W. performed the data analysis with support from G.Z. and D.G.. M.A., C.A.A., J.F.G.A., A.C.C., J.C.D.M.E. and A.R.G. coordinated the development of the TERRACLASS products. M.A. performed visual interpretation of the sampled pixels for sample-based estimates, with other two experts (acknowledged in the acknowledgement). Y.W., D.G. and G.Z. wrote the paper with contributions from M.A.. All authors discussed results and commented on the manuscript.

Additional information

Supplementary information is available for this paper at…