Appendix S1. Supplementary information and data

1. Characteristics of the study area

Acre has a humid equatorial climate with high temperatures all year round. Palm trees are dominant in over 85% of the rainforest area, whereas bamboos are dominant in 10% of the forests, mostly concentrated in the Purus and Juruá regions (Government of Acre 2017). The state of Acre has a high total species richness for birds, mammals and amphibians relative to the rest of the Brazilian Amazon (Jenkins et al. 2015).

The state of Acre is home to over 816,000 people (Government of Acre 2017). Today, more than 73% of the population of Acre lives in urban areas and 56% of the population is situated within the municipalities of Rio Branco and Cruzeiro do Sul (Government of Acre 2017). The area of Acre is 164,124 km2, and around 46% of the area is protected (Government of Acre 2017). Indigenous areas are counted as one important conservation category and they cover 2,390,112 ha, or around 14.5% of the land. The combined population of the indigenous groups is 19,962 inhabitants, or around 2.5% of the population, and they have a total of 209 villages in Acre (Government of Acre 2017). Sustainable use conservation units cover 3,569,818 ha, or roughly 22%, and integral protection conservation units (strictly protected areas) 1,563,769 ha which equals to around 9.5% of the area of Acre.

Acre is famous for its conservation history and is no stranger to conflicting interests between those incentivized to deforest and those with interests to conserve. In 1988, the now famous rubber tapper and rainforest activist Chico Mendes was murdered in Acre by ranchers, following his efforts to curb deforestation (Climate Focus 2013), leading to a lasting social and political transformation which has favoured forest conservation and sustainable use ever since (Climate Focus 2013). The state has also sought to counteract its deforestation pressures with the world’s first jurisdictional REDD+ program, which was initiated there through state law in 2010.

Between 2000 and 2015, the amount of deforestation in Acre dropped from 547 km² to 264 km², resulting in a reduction of the annual rate from 0.33% to 0.16%. From 2010 to 2017 the amount of deforestation stayed relatively level, with some fluctuation between years, but between 2018 and 2020 deforestation in the state has increased substantially (INPE 2021). Road building and paving within the state has been projected to lead to a large increase in deforestation by 2030 and 2050 (Soares-Filho *et al*. 2006).

2. Details of the methods

We included all PAs of Acre in our study, except for one indigenous area (Kaxinawa da Colônia Vinte e Sete) that was too small to sample. No new PAs were designated in Acre during the study period (2011–2016).

2.1. Deforestation and forest cover

To obtain a deforestation dataset for the years 2011-2016, we combined the annual PRODES deforestation polygons (INPE 2017) into one layer and then rasterized that to the same resolution as the baseline forest cover dataset (~250 m).

To account for the areas that did not have forest cover in 2010, such as already deforested areas, we used the 2010 Vegetation Continuous Fields (VCF) collection (DiMiceli et al. 2011) as the baseline forest cover dataset.

To avoid assessing deforestation in non-forested areas, we defined forests as those pixels that in 2010 had VCF > 45%, i.e., a higher than 45% forest cover value. Forest edge was defined to be either road, river or a vegetated pixel with VCF ≤ 45%. The roads and rivers were gathered from OpenStreetMap (OSM) layers downloaded using the QuickOSM plugin (Trimaille 2018; version 1.4.7, we used the plugin with QGIS v2.18.15).

Our definition of forests as pixels with 45% or above forest cover in the VCF dataset, and non-forest as pixels below this threshold was arbitrary. A different threshold may yield differing results because the potential to omit forests that had experienced deforestation declines when the threshold is lowered. However, the trade-off is that simultaneously the chance of sampling non-forest areas that cannot experience deforestation grows. Using a 25% forest cover value would have resulted in much less overlap between the PRODES data and the areas classified as non-forest. Overall, there were 4.5 times as many occurrences of deforestation in areas we classified as “non-forested” with the 45% limit (389 occurrences) than would have been with a 25% limit (87 occurrences). The percentage of “non-forest” pixels with deforestation, that were excluded from sampling, were the highest for PAs 5 (2.0%), 29 (1.1%) and 14 (0.6%). PA 10 had the largest number of occurrences (169; 0.1%). The impact of these PAs may therefore have been slightly overestimated. For the non-protected area, the occurrences were 3.6 times more common in the 45% limited forest cover layer than with the 25% limit (6886 compared with 1873, out of a total of 143359 non-protected points, which equal to 4.8% and 1.3%, respectively).

2.2. Covariates

We used elevation, slope, floodable areas, and precipitation datasets as proxies for agricultural suitability of the land, and as potential deforestation drivers (Laurance et al. 2002). We controlled accessibility to forests by calculating a surface layer which had the shortest Euclidean distance to forest edge for each pixel in Acre.

To control for access to regional markets, we calculated a new travel time layer utilizing code provided by Weiss et al. (2018). Our approach differed from that of Weiss et al. (2018) in the following ways: We only used OSM road datasets; we did not take elevation differences into account (the entire study area is in the lowlands); when calculating the effect of topographical properties for travel by foot, we calculated the slope adjustment in the Tobler’s Hiking Function using a slope layer that we created in QGIS from the 90 m Shuttle Radar Topography Mission (SRTM) elevation data, using the Slope function; we used the OSM Town and City layers to identify points to which travel time was calculated; distances were calculated to the nearest town or city with more than 10,000 people (this limit excluded all smaller settlements, included in the OSM village dataset), as these might create relevant demand for the products that are connected to deforestation in Acre (cattle, agricultural products, wood, etc.). The spatial analyses were performed with QGIS (v3.2.3-Bonn) and the travel times were calculated in R (R Studio, version 1.1.453).

2.3. Matching

We used a computationally efficient matching method developed by Eklund et al. (2016) to estimate the impact of each individual PA in Acre, during a six-year period since the beginning of Acre’s REDD+ program.

First, we determined the number of forested pixels in the baseline forest cover layer for each PA and the non-protected area of Acre (Figure S1, step 1). Then, we took a random sample of points from within the forested areas of each PA (and similarly from within the non-protected area of Acre) equal to 10% of the forested pixels in each area (Figure S1, step 2). These samples were compiled into a table that contained the non-protected sample and a sample from each of the PAs and overlaps. Sampling of the PAs was repeated ten times to control for the potential effect of the random sample on our results, and to gain a measure of uncertainty. In each of the resulting ten datasets, the coordinates of the sample points were used to extract data from the same coordinates in the covariate rasters. The random sampling was performed in R, using the sp package (Pebesma & Bivand 2005).

The total sample size of each sampling effort was 273,940 points, of which 143,359 points were non-protected and 130,581 were protected. Of the protected samples, 2,592 were in the overlapping areas. Therefore, the total number of sample points over all 10 sampling efforts was 2,739,400.

In the counterfactual matching method we applied (as described in Eklund et al. 2016), Mahalanobis distances between a focal point and all other points (which could be either within or outside the PA, but not within other PAs) were calculated using their covariate values (Figure S1, step 3). Following this, the 500 most similar points were identified for each focal point and selected to form a so called “similarity set” (Eklund et al. 2016). The matching was performed 10 times in total, once for each of the datasets acquired from sampling.

Following Eklund et al. (2016), we calculated the Mahalanobis distance by scaling the covariate values of the points, applying a Mahalanobis transformation on them and calculating the Euclidean distance between all points. The Mahalanobis distance was calculated in R using the Vegan library (Oksanen et al. 2018). The Mahalanobis distance was used because it accounts for both collinearity among the covariates and differences in their variabilities. This allows giving each covariate an appropriate weight when determining which 500 points match each focal point best, i.e. are environmentally most similar to it. Only those focal point similarity sets that had at least 10% of the matched points from the non-protected area were included in the analyses following the matching process (Figure S1, step 4). In theory, the 500 most similar control points can be located anywhere in the non-protected area. This is the benefit of using the matching method we selected, because it allows us to estimate the pressure for PAs even when they are surrounded by other PAs, in part or fully. For a detailed description of the matching method, see Eklund et al. (2016).

2.4. Estimates of impact

We estimated PA impact in each of the 10 runs with a process that used all the included similarity sets of each PA to calculate the mean fraction of deforestation within PAs and the corresponding fraction for the matched controls (Figure S1, step 4). Protected and non-protected points in each similarity set were used separately to calculate the fractions, and then the mean of the resulting fractions was taken for each group, giving us the fraction of deforestation within each PA and the fraction of deforestation in the matched controls.

We have abbreviated the fraction of deforestation within each PA is here as PAm (originally called PA multidimensional by Eklund et al. 2016) and for fraction in the matched set of (environmentally most similar) non-protected control points we use BLm (orig. baseline multidimensional).

Comparing like with like, we calculated the difference between the fraction of deforestation within each PA compared to the fraction in the corresponding counterfactual control (BLm minus Pam). Thus, the resulting impact estimate gives the fraction of forested area in each PA that would have been expected to be deforested if the area was not under protection (counterfactual). Or, in the rare case that the fraction of deforestation is higher within PAs than in the comparable areas, the impact estimate will give the fraction of forested area in each PA that would not have been expected to be lost if the PA had not existed.

The BLm can be interpreted as the average expected pressure towards each area under protection, i.e. the expected fraction of deforestation, based on deforestation in comparable areas.

To estimate the influence of including the covariates in matching, we compared the fractions of deforestation in the matched similarity sets to the overall fraction of deforestation in the non-protected sample, which was calculated as the average over 100,000 random 500 point sets that were resampled from the non-protected sample data without considering covariates. This background deforestation rate measure of the non-protected areas of Acre is here referred to as BLnom (orig. baseline non-multidimensional).

The confounding effect of the covariates was calculated as BLnom minus BLm. Covariates help compare like with like, which typically creates a positive confounding effect indicating the amount by which the deforestation fraction would have been overestimated without matching. If the comparable control points experience high deforestation, the confounding effect can also be negative, causing the estimated impact to increase instead.

2.5. Aggregate impact and confidence intervals

To achieve the final impact estimates for each PA we calculated the means of PAm, BLm and BLnom of each area over the results of the ten runs (Figure S1, step 5). We calculated 95% confidence intervals using bootstrapping, where a measure of confidence is derived by resampling the data (the 10 different impact estimates of each PA) 5000 times with replacement. We determined this number of replications to be high enough to provide consistent confidence intervals when repeating the bootstrapping process. For each 5000 replications, we calculated a sample mean and used it to calculate the adjusted bootstrap percentile (BCa) interval, which is a confidence interval measure that adjusts against skewness and bias. The bootstrap confidence intervals were calculated using the boot package (v1.3-20) by Canty & Ripley (2017), which uses the functions and datasets for bootstrapping as described in Davison & Hinkley (1997).

2.6. Avoided deforestation and carbon emissions

Using the final mean-based impact estimate and the number of forested pixels in each PA, we calculated an estimate of avoided deforestation in hectares. The 95% confidence intervals of the impact estimates were used to calculate the confidence range for the hectare estimates. Following this, we calculated a mean carbon density per hectare for each PA using a biomass layer obtained from Rödig et al. (2017) with the assumption that the carbon content of the biomass is 47.1% (Thomas & Martin 2012).

Following previous studies (Houghton et al. 2000; Numata et al. 2011), we partitioned deforested biomass into four fractions: burnt (20%), slash (70%), removed for products (8%), and elemental carbon (2%). The latter two represent the fraction of CO2 that is not released into the atmosphere in the years following deforestation, assuming that all slash is converted into CO2 and that all CO2 in the biomass removed for products is permanently bound.

Based on all the above, we calculated the avoided CO2 emissions for each PA by multiplying the carbon density of each PA by the hectares of forest loss that PA had avoided, and then multiplying the result by 0.9, i.e. the fraction of biomass converted into CO2 following deforestation (Figure S1, step 5.4.). Rödig et al. (2017) also provided a layer with the coefficient of variation for the biomass estimates, and this we used together with the lower and upper 95% confidence interval values of the estimated hectares of avoided deforestation to calculate a low and high estimate for the avoided carbon emissions.

We performed the analyses using Taito supercluster which enabled parallel computation with 256 cores (computational resources available for research by CSC – IT Center for Science, Finland). The Rmpi library (Yu 2002) in R was used for parallelization in the CSC Linux environment. A flowchart visualizing the entire approach is provided below.

**1. Calculating sample sizes and preparing covariates**

Sample sizes for each PA and the non-protected area were calculated as 10% of the number of VCF pixels in each area.

**4. Calculating effectiveness measures and results from the output files**

(4.1) From each similarity set that had a minimum of 10% non-protected matches, the mean fraction of deforested points out of the protected points (**PAm**) and the mean fraction of deforested points out of the non-protected points (**BLm**) were calculated. (4.2) These were used to calculate observed deforestation and estimated pressure for each PA. (4.3) PAm was subtracted from BLm to calculate **a mean-based impact estimate** for all PAs. (4.4) A baseline deforestation estimate without covariates was calculated from simulated sets of points (**BLnom**). (4.5) BLm and BLnom were used to calculate **the confounding effect** (effect of the covariates for the estimated deforestation pressure).

**2. Creating the data with an algorithm**

Datasets were created with a loop. (2.1) In each iteration the algorithm created sample points, (2.2) intersected them with the covariate layers, (2.3) checked that no sample points existed in non-forest areas, and (2.4) saved individualized datasets for each PA.

Visual check of the sample.

**A) Sampling from the protected areas (PAs) and the non-protected area**

**C) From outputs to results for each sampling iteration**

**B) Matching**

**Legend:**

QGIS

R

CSC Taito supercluster

**5. Final steps**

(5.1) The quality of the similarity sets was assessed. (5.2) Mean impact estimates and confidence intervals were calculated for each PA from the results of the 10 sampling efforts (aggregating the estimates). (5.3) Statistical tests were performed. (5.4) The avoided deforestation and carbon emissions were calculated.

**3. Finding matches for the focal points of each PA**

Matching done separately for each of the ten sampling efforts. Parallel computation with 256 cores. Batch files ran R scripts, performing the matching analyses for each PA separately as follows:

(3.1) Covariates were scaled and used to calculate the closest 500 pixels to each sampled pixel, forming a “similarity set” for each. (3.2) The fraction of points that were both protected and deforested was calculated from the similarity sets. (3.3) Individual output files were created for each PA.

**D) Calculating aggregate results**

Flowchart S1. Flowchart of the work process, from input data to results. The programs used in each step of the work are indicated with different background shades and border lines, as shown in legend. The work was performed using QGIS and R Studio, and the actual matching part was performed with R using the CSC Taito supercluster which is available for research use by CSC – IT Center for Science, Finland.

3. Avoided carbon emissions

Impact reductions that seem small compared to other PAs can be substantial. For example, PA 24, an indigenous area of the Nukini tribe, prevented an estimated 72 ha of deforestation and an average of 8 kt of carbon emissions during the six years, equal to 1.3 kt of avoided emissions per year. The average carbon footprint of the EU and the United Kingdom is around 7.9 tonnes per capita per year (UNEP 2020), meaning that the 8 kt of carbon emissions avoided by the small indigenous area were equivalent to the total annual emissions of over 1000 Europeans. Therefore, the 1.3 kt average for each year was equivalent to the total annual emissions of around 165 Europeans. Extending this analysis, the total emissions avoided by all PAs in Acre each year (on average) were equal to the annual emissions of around 122,575 Europeans.

4. Results for actual PA types

In addition to the 28 indigenous areas (out of which 27 were included in our study), Acre has six types of protected areas: one ecological station (ESEC), two environmental protection areas (APA), two areas of relevant ecological interest (ARIE), two parks (PARNA), three national forests (FLONA), and five extractive reserves (RESEX). These are the actual protection types in use, but due to the small sample size of each type, meaningful statistical comparisons between them are not possible at the state level.

All ecological stations (ESEC), national parks (PARNA), and national forests (FLONA) had similar positive impacts during the study period, ranging from 0.3 to 0.9% avoided deforestation (average impact) (Figure S1, Table S1). All PAs in the extractive reserve (RESEX) category also had a positive impact but there was great variation within this category, from 0.2% to 1.8% average impact (Figure S1, Table S1). For the two environmental protection areas (APA), the average impact estimate was 3.6% for PA 14 while PA 29 had an average of 0.2%, although the results for PA 29 were inconclusive due to high variation between the ten sampling efforts (Figure 2, Figure S1). Similarly, for the two areas of relevant ecological interest (ARIE), the average impact of PA 31 was very positive at 2.0%, whereas the impact of PA 5 was very negative at -15.6% (Figure 2, Figure S1).

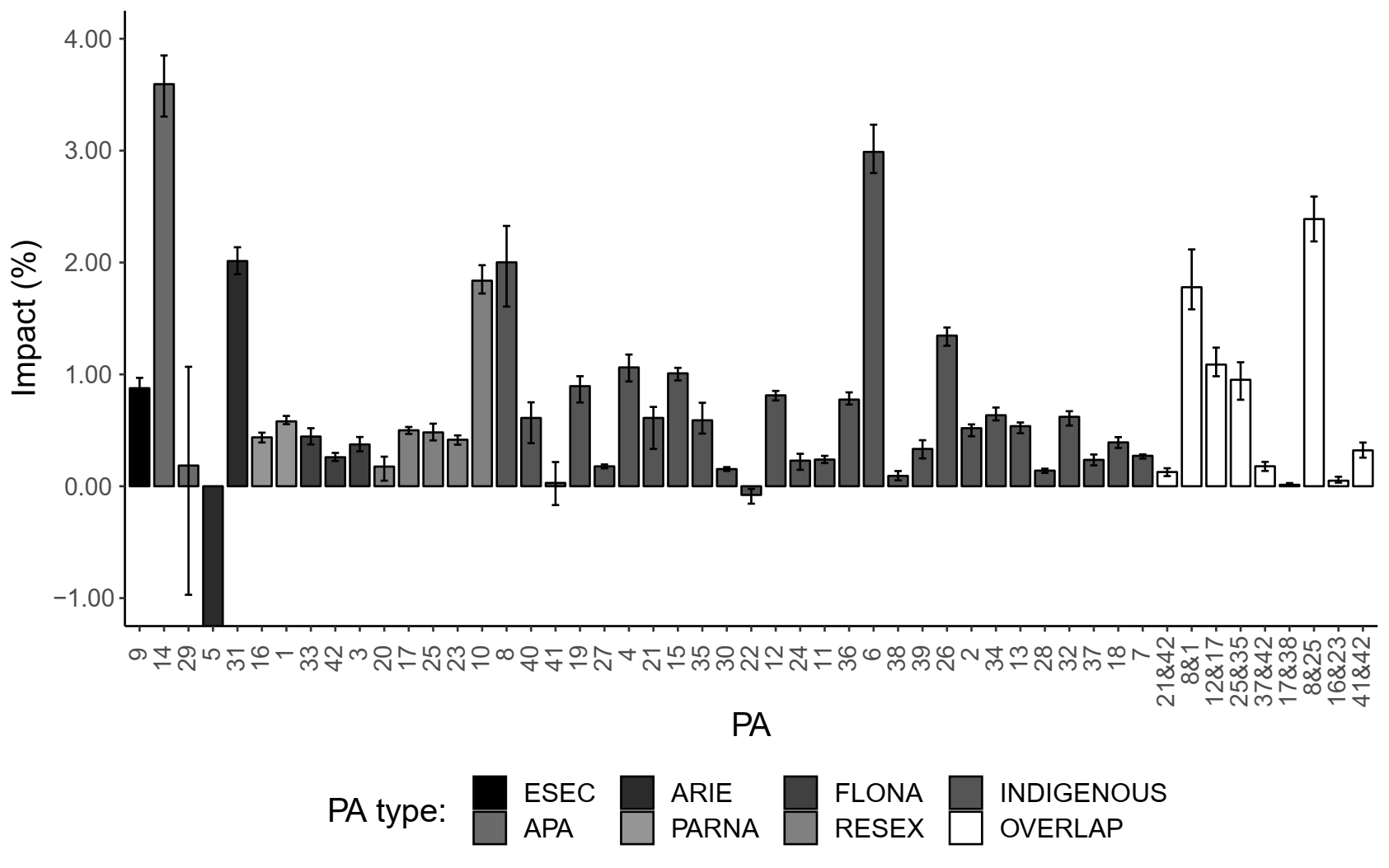


Figure S1. Estimated protected area (PA) impacts, showing the fraction of forested area in each PA that would have been expected to be deforested if the area was not under protection during the study period. Grouped by actual protection types and ordered from smallest to largest PA, within each type, by the number of forested pixels in each PA. A negative value implies that a PA has induced deforestation rather than reduced it. Y-axis is limited as PA 5 extended to -15.59 % (CI -21.82 to -12.43 %). 95% confidence intervals derived with a bootstrap method. PA type abbreviations, in the order they are represented in the figure (left to right): ESEC = Ecological Station, APA = Environmental Protection Area, ARIE = Area of relevant ecological interest, PARNA = National park, FLONA = National forest, RESEX = Extractive reserve.

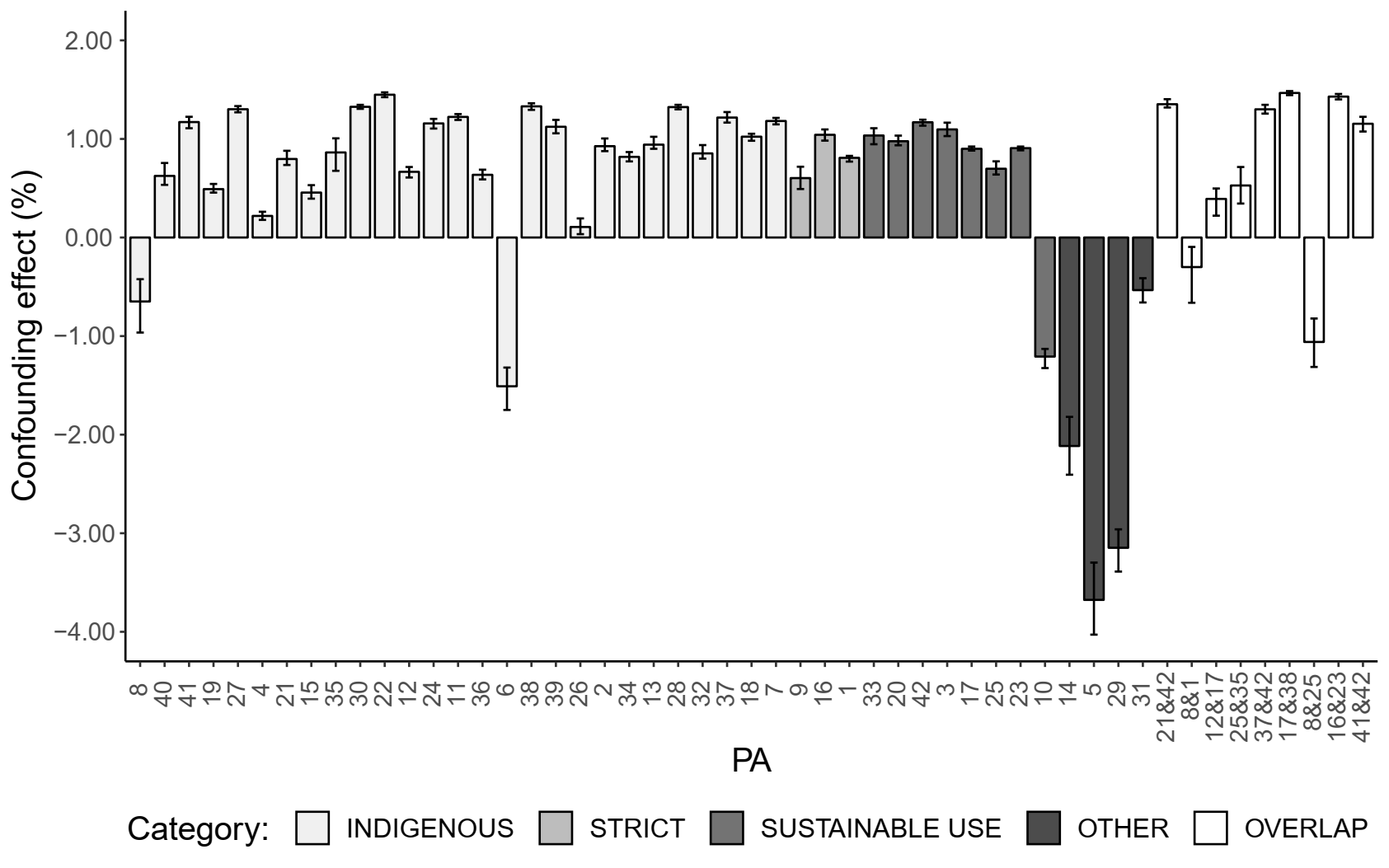


Figure S2. Aggregate confounding effect estimates. Grouped to broad PA categories and ordered from smallest to largest PA, within each category, by the number of forested pixels in each PA. 95% confidence intervals derived with a bootstrap method. Several PAs had a negative confounding effect, indicating environments that were more likely than average to experience deforestation during the study period.

Table S1. Protected area (PA) names and additional information. Year refers to the year the area was designated. Abbreviations: ESEC = Ecological Station, APA = Environmental Protection Area, ARIE = Area of relevant ecological interest, PARNA = National park, FLONA = National forest, RESEX = Extractive reserve; ICMBio = Instituto Chico Mendes de Conservação da Biodiversidade (Chico Mendes Institute for Biodiversity Conservation); FUNAI = Fundação Nacional do Índio (National Indian Foundation); SEMA = Secretaria de Estado de Meio Ambiente do Acre (Secretary of State for the Environment of Acre).

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **PA** | **PA name (in Portuguese)** | **Year** | **Type** | **Category** | **IUCN category** | **Management authority** |
| 1 | PARNA da Serra do Divisor | 1989 | Park | STRICT | II | ICMBio |
| 2 | Kaxinawá do Rio Jordão | 1996 | Indigenous Area | INDIG | - | FUNAI |
| 3 | FLONA do Macauã | 1988 | National forest | SUS. USE | VI | ICMBio |
| 4 | Katukina/Kaxinawá | 1999 | Indigenous Area | INDIG | - | FUNAI |
| 5 | ARIE Seringal Nova Esperança | 1999 | Area of Relevant Ecological Interest | OTHER | IV | ICMBio |
| 6 | Cabeceira do Rio Acre | 1999 | Indigenous Area | INDIG | - | FUNAI |
| 7 | Mamoadate | 1999 | Indigenous Area | INDIG | - | FUNAI |
| 8 | Arara do Rio Amônia | 2009 | Indigenous Area | INDIG | - | FUNAI |
| 9 | ESEC do Rio Acre | 1981 | Ecological Station | STRICT | Ia | ICMBio |
| 10 | RESEX Chico Mendes | 1990 | Extractive Reserve | SUS. USE | VI | ICMBio |
| 11 | Kulina Igarapé do Pau | 2001 | Indigenous Area | INDIG | - | FUNAI |
| 12 | Campinas/Katukina | 1999 | Indigenous Area | INDIG | - | FUNAI |
| 13 | Alto Tarauacá | 2009 | Indigenous Area | INDIG | - | FUNAI |
| 14 | APA Lago do Amapá | 2005 | Environmental Protection Area | OTHER | - | SEMA |
| 15 | Poyanawa | 2002 | Indigenous Area | INDIG | - | FUNAI |
| 16 | Parque Estadual Chandless | 2004 | Park | STRICT | II | SEMA |
| 17 | RESEX Riozinho da Liberdade | 2005 | Extractive Reserve | SUS. USE | VI | ICMBio |
| 18 | Alto Rio Purus | 2002 | Indigenous Area | INDIG | - | FUNAI |
| 19 | Igarapé do Caucho | 1998 | Indigenous Area | INDIG | - | FUNAI |
| 20 | RESEX do Alto Tarauacá | 2000 | Extractive Reserve | SUS. USE | VI | ICMBio |
| 21 | Kaxinawá Nova Olinda | 2002 | Indigenous Area | INDIG | - | FUNAI |
| 22 | Jaminawa/Arara do Rio Bagé | 1999 | Indigenous Area | INDIG | - | FUNAI |
| 23 | RESEX do Cazumbá-Iracema | 2002 | Extractive Reserve | SUS. USE | VI | ICMBio |
| 24 | Nukini | 1997 | Indigenous Area | INDIG | - | FUNAI |
| 25 | RESEX do Alto Juruá | 1990 | Extractive Reserve | SUS. USE | VI | ICMBio |
| 26 | Kampa do Rio Amonea | 1995 | Indigenous Area | INDIG | - | FUNAI |
| 27 | Kampa do Igarapé Primavera | 2002 | Indigenous Area | INDIG | - | FUNAI |
| 28 | Rio Gregório | 2007 | Indigenous Area | INDIG | - | FUNAI |
| 29 | APA Igarapé São Francisco | 2005 | Environmental Protection Area | OTHER | - | SEMA |
| 30 | Jaminawa do Igarapé Preto | 1999 | Indigenous Area | INDIG | - | FUNAI |
| 31 | ARIE Japiim-Pentecoste | 2009 | Area of Relevant Ecological Interest | OTHER | - | SEMA |
| 32 | Kampa e Isolados do Rio Envira | 1999 | Indigenous Area | INDIG | - | FUNAI |
| 33 | FLONA de São Francisco | 2001 | National forest | SUS. USE | VI | ICMBio |
| 34 | Kaxinawá do Rio Humaitá | 1996 | Indigenous Area | INDIG | - | FUNAI |
| 35 | Kaxinawa Ashaninka do Rio Breu | 2002 | Indigenous Area | INDIG | - | FUNAI |
| 36 | Kaxinawá da Praia do Carapanã | 2002 | Indigenous Area | INDIG | - | FUNAI |
| 37 | Riozinho do Alto Envira | 2007 | Indigenous Area | INDIG | - | FUNAI |
| 38 | Arara do Igarapé Humaitá | 2006 | Indigenous Area | INDIG | - | FUNAI |
| 39 | Kulina do Rio Envira | 1996 | Indigenous Area | INDIG | - | FUNAI |
| 40 | Kaxinawá do Baixo Rio Jordão | 2002 | Indigenous Area | INDIG | - | FUNAI |
| 41 | Jaminaua/Envira | 2003 | Indigenous Area | INDIG | - | FUNAI |
| 42 | FLONA de Santa Rosa do Purus | 2001 | National forest | SUS. USE | VI | ICMBio |

Table S2. Detailed matching results. Match percentage is the fraction of points included in the impact calculations (after omitting similarity sets with less than 10% non-protected matched points). PAm is the mean fraction of deforested points within the protected points of the similarity sets, whereas BLm is the fraction for the non-protected points of the similarity sets. Sample size is the mean number of included points across the ten sampling efforts, rounded to whole numbers. Mean Eff. is the mean-based impact estimate and Conf. Eff. is the mean confounding effect across the sampling efforts.

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **PA** | **Category** | **Match%** | **Match% SD** | **PAm mean (%)** | **BLm mean (%)** | **Sample size** | **Sample size SD** | **Conf. Eff. (%)** | **Mean Eff. (%)** |
| 1 | STRICT | 94.33 | 0.23 | 0.09 | 0.67 | 14582 | 36.02 | 0.81 | 0.58 |
| 2 | INDIG | 73.80 | 1.65 | 0.03 | 0.55 | 1209 | 26.98 | 0.93 | 0.52 |
| 3 | SUS | 79.90 | 1.57 | 0.01 | 0.38 | 2674 | 52.70 | 1.10 | 0.37 |
| 4 | INDIG | 100.00 | 0.00 | 0.20 | 1.26 | 426 | 0.00 | 0.22 | 1.06 |
| 5 | OTHER | 100.00 | 0.00 | 20.74 | 5.16 | 42 | 0.00 | -3.68 | -15.59 |
| 6 | INDIG | 99.04 | 0.48 | 0.00 | 2.99 | 1419 | 6.90 | -1.51 | 2.99 |
| 7 | INDIG | 63.84 | 0.96 | 0.03 | 0.30 | 3647 | 54.72 | 1.18 | 0.27 |
| 8 | INDIG | 100.00 | 0.00 | 0.13 | 2.13 | 112 | 0.00 | -0.65 | 2.00 |
| 9 | STRICT | 59.16 | 3.73 | 0.00 | 0.88 | 847 | 53.33 | 0.60 | 0.88 |
| 10 | SUS | 99.99 | 0.01 | 0.85 | 2.69 | 17058 | 1.70 | -1.21 | 1.84 |
| 11 | INDIG | 100.00 | 0.00 | 0.02 | 0.26 | 833 | 0.00 | 1.22 | 0.24 |
| 12 | INDIG | 100.00 | 0.00 | 0.00 | 0.81 | 579 | 0.00 | 0.67 | 0.81 |
| 13 | INDIG | 90.79 | 0.96 | 0.00 | 0.54 | 2378 | 25.14 | 0.94 | 0.54 |
| 14 | OTHER | 100.00 | 0.00 | 0.00 | 3.59 | 19 | 0.00 | -2.12 | 3.59 |
| 15 | INDIG | 100.00 | 0.00 | 0.01 | 1.02 | 446 | 0.00 | 0.46 | 1.01 |
| 16 | STRICT | 83.21 | 1.11 | 0.00 | 0.44 | 10235 | 136.01 | 1.04 | 0.44 |
| 17 | SUS | 100.00 | 0.00 | 0.08 | 0.58 | 5856 | 0.00 | 0.90 | 0.50 |
| 18 | INDIG | 100.00 | 0.00 | 0.06 | 0.46 | 4823 | 0.00 | 1.02 | 0.39 |
| 19 | INDIG | 100.00 | 0.00 | 0.09 | 0.99 | 223 | 0.00 | 0.49 | 0.89 |
| 20 | SUS | 100.00 | 0.00 | 0.33 | 0.50 | 2767 | 0.00 | 0.98 | 0.18 |
| 21 | INDIG | 100.00 | 0.00 | 0.07 | 0.68 | 432 | 0.00 | 0.80 | 0.61 |
| 22 | INDIG | 100.00 | 0.00 | 0.11 | 0.03 | 537 | 0.00 | 1.45 | -0.08 |
| 23 | SUS | 71.55 | 0.74 | 0.16 | 0.57 | 9796 | 101.67 | 0.91 | 0.42 |
| 24 | INDIG | 100.00 | 0.00 | 0.09 | 0.32 | 582 | 0.00 | 1.16 | 0.23 |
| 25 | SUS | 79.30 | 1.15 | 0.30 | 0.78 | 7598 | 110.03 | 0.70 | 0.48 |
| 26 | INDIG | 100.00 | 0.00 | 0.03 | 1.37 | 1579 | 0.00 | 0.11 | 1.35 |
| 27 | INDIG | 100.00 | 0.00 | 0.00 | 0.18 | 404 | 0.00 | 1.30 | 0.18 |
| 28 | INDIG | 100.00 | 0.00 | 0.02 | 0.16 | 3519 | 0.00 | 1.32 | 0.14 |
| 29 | OTHER | 100.00 | 0.00 | 4.44 | 4.63 | 182 | 0.00 | -3.15 | 0.18 |
| 30 | INDIG | 100.00 | 0.00 | 0.00 | 0.15 | 486 | 0.00 | 1.33 | 0.15 |
| 31 | OTHER | 100.00 | 0.00 | 0.00 | 2.01 | 427 | 0.00 | -0.53 | 2.01 |
| 32 | INDIG | 96.97 | 0.51 | 0.01 | 0.63 | 4118 | 21.81 | 0.85 | 0.62 |
| 33 | SUS | 100.00 | 0.00 | 0.00 | 0.44 | 400 | 0.00 | 1.03 | 0.44 |
| 34 | INDIG | 100.00 | 0.00 | 0.03 | 0.66 | 2376 | 0.00 | 0.82 | 0.63 |
| 35 | INDIG | 100.00 | 0.00 | 0.03 | 0.62 | 467 | 0.00 | 0.86 | 0.59 |
| 36 | INDIG | 100.00 | 0.00 | 0.07 | 0.84 | 1109 | 0.00 | 0.64 | 0.77 |
| 37 | INDIG | 70.62 | 1.36 | 0.03 | 0.26 | 3333 | 64.01 | 1.22 | 0.24 |
| 38 | INDIG | 100.00 | 0.00 | 0.06 | 0.15 | 1466 | 0.00 | 1.33 | 0.09 |
| 39 | INDIG | 100.00 | 0.00 | 0.02 | 0.36 | 1525 | 0.00 | 1.12 | 0.33 |
| 40 | INDIG | 100.00 | 0.00 | 0.24 | 0.85 | 156 | 0.00 | 0.63 | 0.61 |
| 41 | INDIG | 100.00 | 0.00 | 0.28 | 0.31 | 181 | 0.00 | 1.17 | 0.03 |
| 42 | SUS | 100.00 | 0.00 | 0.05 | 0.31 | 2797 | 0.00 | 1.17 | 0.26 |
| 8&1 | OVERLAP | 100.00 | 0.00 | 0.00 | 1.78 | 44 | 0.00 | -0.30 | 1.78 |
| 8&25 | OVERLAP | 100.00 | 0.00 | 0.15 | 2.54 | 211 | 0.00 | -1.06 | 2.39 |
| 12&17 | OVERLAP | 100.00 | 0.00 | 0.00 | 1.09 | 44 | 0.00 | 0.39 | 1.09 |
| 16&23 | OVERLAP | 100.00 | 0.00 | 0.00 | 0.05 | 538 | 0.00 | 1.43 | 0.05 |
| 17&38 | OVERLAP | 100.00 | 0.00 | 0.00 | 0.01 | 183 | 0.00 | 1.47 | 0.01 |
| 21&42 | OVERLAP | 100.00 | 0.00 | 0.00 | 0.13 | 38 | 0.00 | 1.35 | 0.13 |
| 25&35 | OVERLAP | 100.00 | 0.00 | 0.00 | 0.95 | 94 | 0.00 | 0.53 | 0.95 |
| 37&42 | OVERLAP | 100.00 | 0.00 | 0.00 | 0.18 | 134 | 0.00 | 1.30 | 0.18 |
| 41&42 | OVERLAP | 100.00 | 0.00 | 0.00 | 0.33 | 1306 | 0.00 | 1.15 | 0.32 |

Table S3. Estimates for the avoided deforestation and carbon emissions in protected areas (PAs) of Acre, Brazil. Forested pixels indicate the number of forested pixels within each PA. Mean carbon density is the mean amount of carbon in tonnes per hectare. Mean ha avoided is the amount of forest loss prevented by the PA according to the aggregate mean of its impact estimates, in hectares. Mean kt C avoided is the mean curbed carbon emissions in kilotonnes, based on the mean avoided deforestation in hectares and the mean carbon density of the PA.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **PA** | **Category** | **Forested pixels** | **Mean C t/ha** | **Mean ha avoided** | **Mean kt C avoided** |
| 1 | STRICT | 154577 | 146.00 | 4822.40 | 596.93 |
| 2 | INDIG | 16380 | 170.87 | 457.30 | 66.24 |
| 3 | SUS\_USE | 33473 | 149.48 | 673.13 | 85.31 |
| 4 | INDIG | 4261 | 168.66 | 243.42 | 34.81 |
| 5 | OTHER | 420 | 116.83 | -352.16 | -34.88 |
| 6 | INDIG | 14332 | 149.07 | 2303.88 | 291.16 |
| 7 | INDIG | 57129 | 149.34 | 835.74 | 105.81 |
| 8 | INDIG | 1117 | 146.89 | 120.28 | 14.98 |
| 9 | STRICT | 14308 | 154.04 | 674.54 | 88.09 |
| 10 | SUS\_USE | 170586 | 134.54 | 16860.44 | 1923.17 |
| 11 | INDIG | 8329 | 156.55 | 106.78 | 14.17 |
| 12 | INDIG | 5786 | 145.24 | 252.89 | 31.14 |
| 13 | INDIG | 26185 | 167.17 | 756.46 | 107.21 |
| 14 | OTHER | 188 | 73.50 | 36.35 | 2.26 |
| 15 | INDIG | 4462 | 125.95 | 242.21 | 25.86 |
| 16 | STRICT | 123010 | 159.74 | 2892.16 | 391.68 |
| 17 | SUS\_USE | 58556 | 157.19 | 1575.11 | 209.91 |
| 18 | INDIG | 48230 | 147.11 | 1016.84 | 126.82 |
| 19 | INDIG | 2227 | 159.22 | 107.19 | 14.47 |
| 20 | SUS\_USE | 27667 | 168.58 | 261.69 | 37.40 |
| 21 | INDIG | 4319 | 149.78 | 141.88 | 18.02 |
| 22 | INDIG | 5371 | 166.14 | -22.47 | -3.16 |
| 23 | SUS\_USE | 136922 | 148.21 | 3062.85 | 384.86 |
| 24 | INDIG | 5819 | 132.23 | 71.64 | 8.03 |
| 25 | SUS\_USE | 95822 | 162.88 | 2480.61 | 342.54 |
| 26 | INDIG | 15790 | 162.40 | 1143.80 | 157.48 |
| 27 | INDIG | 4036 | 158.49 | 38.59 | 5.19 |
| 28 | INDIG | 35187 | 163.64 | 264.53 | 36.70 |
| 29 | OTHER | 1817 | 89.58 | 18.08 | 1.37 |
| 30 | INDIG | 4859 | 140.48 | 40.09 | 4.77 |
| 31 | OTHER | 4272 | 113.13 | 462.56 | 44.37 |
| 32 | INDIG | 42460 | 164.92 | 1417.42 | 198.19 |
| 33 | SUS\_USE | 3995 | 147.30 | 95.50 | 11.93 |
| 34 | INDIG | 23759 | 158.77 | 810.96 | 109.16 |
| 35 | INDIG | 4665 | 171.16 | 147.94 | 21.47 |
| 36 | INDIG | 11088 | 160.84 | 462.04 | 63.00 |
| 37 | INDIG | 47186 | 163.39 | 598.07 | 82.85 |
| 38 | INDIG | 14657 | 148.98 | 72.93 | 9.21 |
| 39 | INDIG | 15246 | 164.81 | 273.31 | 38.19 |
| 40 | INDIG | 1556 | 155.01 | 51.10 | 6.72 |
| 41 | INDIG | 1814 | 158.93 | 2.90 | 0.39 |
| 42 | SUS\_USE | 27970 | 160.73 | 390.21 | 53.17 |
| 8&1 | OVERLAP | 440 | 156.81 | 42.11 | 5.60 |
| 8&25 | OVERLAP | 2107 | 143.22 | 270.64 | 32.86 |
| 12&17 | OVERLAP | 440 | 148.98 | 25.74 | 3.25 |
| 16&23 | OVERLAP | 5379 | 154.98 | 14.39 | 1.89 |
| 17&38 | OVERLAP | 1834 | 160.25 | 1.27 | 0.17 |
| 21&42 | OVERLAP | 378 | 156.92 | 2.58 | 0.34 |
| 25&35 | OVERLAP | 936 | 165.68 | 47.90 | 6.73 |
| 37&42 | OVERLAP | 1344 | 161.31 | 12.91 | 1.77 |
| 41&42 | OVERLAP | 13063 | 159.45 | 225.27 | 30.45 |
|  | Totals: | 1305754 | 7695.39 | 46553.99 | 5810.06 |

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