The role of protected areas in maintaining natural vegetation in Brazil

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The destruction of natural vegetation in recent decades has been concentrated in the tropics, where ecosystem processes underpin global homeostasis and harbor most of the world’s biodiversity. Protected areas (PAs) are the primary societal tool to avoid this destruction, yet their effectiveness is often questioned. Here, we quantified the impact of PAs and indigenous lands in avoiding 34 years of vegetation destruction in forested and nonforested biomes in Brazil. We showed that the odds of destruction in the PA network are four times lower than in unprotected areas, and generally, this positive effect extends to a buffer zone around PAs. Among the most effective groups of PAs are those that are older, larger, located in the Amazonian region, and indigenous lands. Despite recent setbacks for the Brazilian PA system, we highlight the benefits of PAs for biodiversity and climate if they were instead strengthened.

INTRODUCTION

Brazil figures as a key country for conservation, harboring tens of thousands of endemic species across its different biomes, and as a provider of essential ecosystem services (1), including the largest tropical forest in the world, the Amazon. Brazil has also become a global leader in conservation, playing a central role in the main global efforts for environmental conservation. In 1992, the country hosted the Earth Summit and signed the Convention on Biological Diversity (CBD), including a commitment to expand the national protected area (PA) network. This commitment was formalized more recently in 2010, with the CBD target of protecting 17% of land surfaces and 10% of the marine realm by 2020 to “improve the status of biodiversity by safeguarding ecosystems, species, and genetic diversity” (2). Although Brazil has achieved the intended PA coverage (3), changes in political leadership have undermined environmental policies (4), and the effective protection of PAs is far from guaranteed (5, 6). In a context of the definition of the policies for the next decade (7), it is necessary to evaluate the benefits obtained so far (7). Further challenges for Brazilian PAs are that they are not always well funded (8), managed, or enforced (9) and are often located in remote areas (10) where patrols and monitoring are challenging. In areas of intense conflicts over land use, it is expected that after the designation of PAs, human impacts are simply displaced to their periphery (11) or that PAs are subject to human invasions. In addition, PAs are often downsized, downgraded, or degazetted some years after their designation (5). These threats have increased with the election of an anti-environment government (12). Thus, considering this context of pressure both locally and politically on the one hand and the need for transformation to avoid the worst consequences of global changes (13) on the other hand, it is important to quantify the impacts of Brazilian PAs on conservation of natural areas.

Here, we conducted a three-step analysis to evaluate different aspects of PA performance in Brazil (n = 1082; Fig. 1A) and some of their consequences for conservation. First, we quantified the mitigation of natural vegetation conversion within the boundaries of established PAs. Then, we tested for evidence of displacement of pressure by analyzing vegetation conversion in buffers surrounding PAs. Last, we estimated the amount of natural vegetation spared from conversion and the carbon emissions avoided because of the protective effect of PAs.

For data on vegetation conversion, both inside and outside the PAs, we used an annual land-use dataset available for Brazil from 1985 to 2018 (14) and quantified the amount of intact and anthropic areas (table S1). For PA data (15, 16), we considered as PAs what Brazil’s legislation recognizes as “conservation units,” which can be broadly categorized as those with strict protection of natural resources [International Union for Conservation of Nature (IUCN) categories I to IV] and those that allow the sustainable use of natural resources (IUCN categories V and VI) (17). Despite not being recognized as a “conservation unit,” we also included indigenous lands as a category of PA in our analysis, since they have legislation that promotes conservation actions with participation of the indigenous people (18) and prohibit agricultural activities by outside groups [(19), but see (20, 21)], making these areas less prone to degradation. A proper effectiveness assessment hinges on quantifying the extent to which the presence of PAs has prevented loss of natural vegetation (22). Thus, the so-called counterfactual approach requires a comparison between PAs and unprotected areas that are similar in other relevant variables in relation to a desired conservation outcome (23). Considering the outcome as mitigation of the vegetation loss, areas should be compared on the basis of similarity in pressure for conversion. However, determining the pressure for conversion of an area is not trivial. Here, we combined theory and an observational approach using machine learning to find the main determinants of vegetation loss in Brazilian biomes. We assumed that accessibility (24), agricultural suitability (24), and the socioeconomic context (25) are the main factors that influence the pressure for conversion (table S2). On the basis of 12 covariates that represent these factors, we trained random forest models to predict the remaining vegetation in the year 2000 in each biome. Last, we used statistical matching to pair treatments (PAs and buffers) and controls (unprotected areas), on the basis of the sets of variables that had the greatest balance of explanatory power and simplicity in the models of remaining vegetation prediction. We then estimated the odds ratio of loss of
natural vegetation in PAs between the years of designation of each PA up until to 2018 and compared to unprotected areas with similar pressure for vegetation conversion. The same comparison was done between buffer areas from 0 to 20 km around PAs and unprotected areas between 2000 and 2018 to determine whether the effects of PAs were displaced to their periphery and, if so, to what extent. The odds ratio also allowed us to estimate what would be the amount of remaining vegetation in 2018 in the absence of PAs.

In addition, by using our data of vegetation loss in PAs and using a map of aboveground carbon biomass of the year 2010 (26), we estimated how much carbon emissions to the atmosphere were avoided due to the presence of PAs. We assumed that 50% of the aboveground carbon biomass is in the vegetation and 85% of the vegetation carbon is emitted when this vegetation is converted (27). Following this, we estimated the carbon biomass in vegetation of PAs for 2010 and 2018 based on the amount of vegetation. The avoided emissions were calculated as the difference between carbon emitted in the scenario of the presence of PAs and that in the scenario of the absence of PAs.

RESULTS
We found that during the period that vegetation loss was officially monitored (1985–2018), Brazil lost natural vegetation from 939,050 km² (10.9%) of its territory (fig. S1). Almost one-third of this loss (338,774 km²) occurred in the Cerrado, which is, proportionally, the most impacted biome, with a decrease of 16.6% of its vegetation. In the same period, PAs in Brazil, which cover 2.2 million km², had 37,491 km² of their natural vegetated areas converted (1.7% of total original vegetation in PAs). Inside PAs, Caatinga was the biome with the proportionally most acute loss, with 3,639 km² of its vegetation converted.
The approach of matching the protected pixels with controls improved the balance of their distribution for all covariates (figs. S2 and S3). It was not possible to find a representative number of controls (see Materials and Methods) for 42 PAs, which were discarded from the analysis. PAs have lost less natural vegetation than their matched controls (Mann-Whitney $U = 246,321, P < 0.01$; fig. S4). The median loss that occurred inside PAs from their designation up to 2018 was 0.2%, compared to 3.4% vegetation loss in the control areas. Further, we estimate that the PAs have prevented the loss of 10,489 km$^2$ [95% confidence interval (CI) = 10,456 to 10,521] of natural vegetation during the time of the study. This represents 1.1% of the total observed loss. Considering the vegetation whose loss was averted from 2010 onward, this would mean that, on average, 9.03 Tg year$^{-1}$ of carbon (CI = 3.93 to 14.17) was not emitted to the atmosphere due to the presence of PAs. For comparison, in the same period, the average emissions in Brazil due to land-use change were equivalent to 207.4 Tg year$^{-1}$ of carbon (28).

Compared with matched controls, we found that 887 PAs (85.3%) were effective in mitigating loss of natural vegetation, while 141 (13.5%) were less effective than unprotected areas, and 12 (1.1%) had no difference from controls (data file S1). The odds ratio for the overall network of PAs was 0.32, while the mean odds ratio weighted by the size of the PAs was 0.22 (SD = 0.49) when considering each PA individually. These results mean that for every square kilometer of natural vegetation lost inside a given PA, on average, 4.54 km$^2$ would be lost if the area was not protected. The most effective PA in conserving natural vegetation was “Boa Vista do Sertão do Promirim,” an indigenous territory in the Atlantic Forest, with an odds ratio of 0.0003 (95% CI = 0.00002 to 0.005). On the other hand, “Kaxinawa do Rio Jordão,” an indigenous territory in the Amazon, was the least effective, with an odds ratio of 12.7 (95% CI = 12.3 to 13.1).

Considering the biomes individually, each one of them had a median odds ratio below 1 for the PAs (Fig. 1, B and C). Despite being generally effective, the level of PA effectiveness varied between biomes (Kruskal-Wallis $\chi^2 = 169.06, df = 5, P < 0.01$; Fig. 1C). PAs in the Amazon were more effective than those in other biomes (Dunn’s test, $P < 0.05$) with a median odds ratio equal to 0.19, but the Amazon biome also presented the highest variation in effectiveness (SD = 1.15). For instance, although only 38.8% of the analyzed PAs are in the Amazon, this biome includes 60% of the 50 least effective PAs.

The effectiveness of PAs differed according to their assigned category (Kruskal-Wallis $\chi^2 = 23.19, df = 2, P < 0.01$). Indigenous lands were generally more effective, with a median odds ratio of 0.36 (SD = 1.14; Dunn’s test, $P < 0.05$; Fig. 2A), while there was no difference between strictly protected (median odds ratio = 0.63; SD = 0.44) and sustainable use (median odds ratio = 0.66; SD = 0.39) PAs (Dunn’s test, $P < 0.05$). We also found variation in effectiveness depending on the type of governance regime that the PAs are under (Kruskal-Wallis $\chi^2 = 23.77, df = 2, P < 0.01$). PAs governed by indigenous people were more effective (Dunn’s test, $P < 0.05$; Fig. 2B) (median odds ratio = 0.36; SD = 1.13), and there was no difference between those governed by municipal (median odds ratio = 0.68; SD = 0.47), state (median odds ratio = 0.65; SD = 0.39), and federal institutions (median odds ratio = 0.62; SD = 0.39; Dunn’s test, $P > 0.05$). Effective PAs also accounted for a significant part of the total area of the PA network. From the 2,228,257 km$^2$ area covered by the PAs analyzed here, 2,148,643 km$^2$ (96.4%) are from effective PAs. Larger PAs were more effective [Pearson’s $r$ between log (PA size) and odds ratio = −0.44; 95% CI = −0.49 to −0.39; fig. S5].

The effectiveness of the PA network was not constant throughout the period covered by our study (Fig. 3). As a general pattern, we found that the effectiveness of the network was lower in the early years and improved as time passed. In biomes such as Caatinga, Cerrado, Atlantic Forest, and Pantanal, a decrease in effectiveness was observed in the most recent years. The worst performance was in 1992 in the Caatinga with odds ratio = 1.12, while the best performance was in the Amazon in 2005 with odds ratio = 0.1.

We also found that the areas surrounding PAs had a lower probability of having their natural vegetation converted when compared with controls, except for the Caatinga. We identified three patterns of how the odds ratio varies with distance to PAs (Fig. 4). In the first pattern, exhibited by the Amazon, the probability of vegetation

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Fig. 2. Aspects of PA management and PA effectiveness. Comparing the odds of PAs having their natural vegetation converted (A) considering their type of use and (B) considering their governance. The dashed line indicates the threshold of effectiveness. Below the line are effective PAs and above the line are ineffective PAs. The y axis is on a logarithmic scale. Gray areas around the boxplot indicate the distribution of the odds ratio values.
loss increases with distance from the PA. In the second pattern, vegetation loss was most likely in the immediate periphery of PAs (within 5 or 10 km) and decreased slightly at greater distances; this pattern was observed in Caatinga, Cerrado, and Atlantic Forest. In the last pattern, observed in the Pampa and Pantanal biomes, the PAs’ immediate periphery is even less prone to vegetation loss than inside their boundaries, with the odds ratio decreasing up until a distance of 10 km, but increasing at greater distances.

Fig. 3. Variation in remaining natural vegetation and the effectiveness of PAs through time in Brazil (A) and the biomes (B) Amazon, (C) Caatinga, (D) Cerrado, (E) Atlantic Forest, (F) Pampa and (G) Pantanal. The blue dots and lines represent the odds ratio of vegetation loss inside the PAs of a biome compared with its unprotected areas. Values below 1 (dashed line) indicate that PAs experienced less vegetation loss than unprotected areas. Above the dashed line are ineffective PAs. To calculate a unique value of odds ratio for the PA network of a biome, we used an aggregation of the data of each PA pertaining to the biome and their controls. The green line represents the remaining natural vegetation of the biome as a whole.
effective than their unprotected counterparts, the practical size of even greater than previously thought.

roundings, as they show that positive effects of a PA usually extend time passes, with some exceptions in recent years. Our results also add pieces of evidence to the debate on how PAs impact their sur-

te gency of the PA network of Brazil to be more effective as being less prone to suffer from vegetation conversion. We also showed

addition to that, other characteristics such as size, time of designation, and type of use of PAs were correlated with their effectiveness, with older and larger PAs, and those governed by indigenous people being less prone to suffer from vegetation conversion. We also showed a general trend of the PA network of Brazil to be more effective as time passes, with some exceptions in recent years. Our results also add pieces of evidence to the debate on how PAs impact their sur-

Our results show that, despite the majority of PAs being more effective than their unprotected counterparts, the practical size of their protective effect is still minor when compared to the total extent of vegetation conversion and carbon emissions observed in Brazil. Also, it is known that PAs in Brazil tend to be located places with low intensity of land use (10), which indicates that the places where the presence of PAs would have more impact in containing vegetation conversion are less protected. Most studies on the effectiveness of PAs report a positive but weak effect of PAs (23, 29). However, here we estimate that Brazilian PAs have an average odds ratio of 1:4 of loss of natural vegetation compared to unprotected areas. We must consider what is the degree of effectiveness, associated with a given extent and location of the PA network that is sufficient to reverse the biodiversity crisis predicted for this century. Moreover, it is worth noting that stakes involved in PA designations extend beyond biodiversity and carbon, with socioeconomic repercussions that also have to be considered (30–32).

There is an ongoing debate on whether PAs with stricter restrictions on resource use have a greater impact on conservation (33–35). Originally, the conception of PAs was to guarantee the perpetuation of biodiversity based on the isolation of its external threats (36), and these threats include many human activities. More recently, PAs have taken on a broader meaning, integrating in their purposes the provision of natural resources and the guarantee of land rights and livelihoods to traditional and indigenous peoples. In some instances, the recognition of local communities as stakeholders of PAs coupled with their integration in planning and management has simultaneously improved the performance of PAs' biodiversity indicators (33, 37) as well as the quality of life of the local population (37, 38). A similar pattern was found in our study, where indigenous lands figured as the most effective category of PA, reinforcing that the human presence in the natural environment is not necessarily incompatible with the conservation of biodiversity. We also found that the difference in effectiveness between strictly protected and sustainable use PAs was indistinguishable [but see (34, 35)], which might be associated with a lack of differentiation in the management strategies applied to these two categories of PAs (9). However, it should also be considered that in Brazil, strictly protected PAs are located in areas with a higher occurrence of species, endemism, and phylogenetic diversity than other PA categories (39). Therefore, in the current scenario of the country, raising the level of effectiveness of strictly protected PAs might improve the conservation of a more representative portion of biodiversity.

Another important debate is whether the presence of a PA has a negative or positive conservation effect on its surroundings through “leakage” or “spillover” effects (40–43). The results presented here show that, for both more remote biomes, such as the Amazon and biomes with intense anthropogenic pressure, such as Cerrado and Atlantic Forest, the surroundings of PAs are still more effective than distant unprotected areas. This is consistent with other studies (42), but we still found in our results instances of PAs associated with negative effects on their surroundings. This negative effect was more apparent in the Caatinga biome and might be attributed to a pressure shift or leakage effect. The Caatinga is a populous and historically impacted biome, having already lost half of its natural vegetation and with the remnants disturbed by human activities (44). Furthermore, it is a biome with few investments in conservation, with only 4% of conservation projects between 1985 and 1996 directed to this biome (45). On the other hand, the Amazon, although considered a remote biome, was the only biome to exhibit a clear pattern of decreasing probabilities of vegetation loss the closer an area is to a PA [but see (43)].
Our analysis is not a complete assessment of PA effectiveness since we only accounted for the loss of natural vegetation that PAs have mitigated. The capacity of PAs to inhibit other threats to biodiversity, such as poaching, selective harvesting, or invasive species, must also be considered. Nevertheless, our analysis is a relevant assessment of the role of PAs in conservation because the loss of natural vegetation is the leading cause of species extinction and an essential regulator of carbon emissions, water control, and other ecosystem services. Agricultural area is expected to increase in the next decades (46), placing pressure on PAs and acting synergistically with other threats to biodiversity (47, 48).

The matching methodology used in the present study has been widely used for counterfactual assessments of PA effectiveness, but it has limitations (19). By comparing vegetation loss in protected and unprotected areas, the matching aims to reduce the bias of selected controls as to the likelihood of vegetation conversion. This, however, depends on the inclusion of the main determinants of vegetation loss, which are not always known. We believe that our empirical approach of training machine learning models to find key determinants is an improvement on existing methods. Although this approach is more robust, our models showed a non-negligible degree of error when trying to estimate the remnants of natural vegetation.

Our results indicate that PAs have played a role in mitigating habitat loss and climate change for at least 30 years and underline their potential to maintain natural vegetation into the future, especially given projections of agricultural expansion in Brazil (46). Unfortunately, this potential has been jeopardized in Brazil’s recent history, which is marked by setbacks in environmental policies and conservation (4, 12, 49). For instance, the proposed bill PL 490/2007 (21) aims to change fundamental aspects of the current indigenous lands’ legislation. One of the main proposed changes is that indigenous lands can only be recognized as such when it is possible to prove that they have been occupied by indigenous people before 1988. Also, under this new law, the expansion of already established indigenous lands would be prohibited, but activities such as mineral exploration and the construction of hydroelectric dams on these territories would be allowed. This bill can weaken the role of indigenous lands in conserving native vegetation, as demonstrated here, and it can have negative implications for the livelihoods of indigenous people. Another example is the 2019 spikes of deforestation in the Amazon, comparable to 2009 levels, which occurred after years of continual decrease in deforestation between 2004 and 2012 (50) and likely reflect a decrease in government commitment to conservation.

The expansion and strengthening of the PA network have become imperative and the CBD established as new targets for 2030 the protection of 30% of the Earth, aiming to recover species populations, prevent extinctions, and restore as well as stabilize and increase ecosystems and their services (7). Future expansion and development of the PA network in Brazil has to be well planned, enforced, and long-lasting if we expect to reach these goals.

**MATERIALS AND METHODS**

**Overview**

When resources are allocated to create PAs, there is an expectation that this effort will yield a positive impact on biodiversity conservation. That is, the desired outcome of the PA’s presence is the mitigation of loss of biodiversity in opposition to a scenario of no intervention (22). For our impact assessment, we measured as the outcome of interest the amount of vegetation spared from being converted to anthropic uses. Accordingly, we used as observation unit samples inside the PAs with a resolution of approximately 600 m × 600 m. As we also aim to assess the impact of PAs on their surroundings, we made a separate analysis, this time using samples of the buffer areas of the PAs. In both cases, we used unprotected areas with similar pressure for conversion and similar baseline of remaining vegetation as source of comparison. Therefore, in our analysis, a PA or the buffer zones were considered to have a positive impact on conservation if they have had experienced less vegetation loss across the years if compared with their controls.

**Data**

We performed the analyses using the delimitations of the six main biomes of the Brazilian territory (Amazon, Cerrado, Caatinga, Atlantic Forest, Pampa, and Pantanal) (51). To quantify the dynamics of natural vegetation, we used annual land-use data from the Project MapBiomas Collection 4.1 (14), with a resolution of 30 m × 30 m. This dataset classifies the land use into 26 categories, which we have grouped into five broader categories, to quantify the remaining natural vegetation in each pixel (table S1). These new categories are natural vegetation, nonvegetated natural area, anthropic area, water bodies, and others. For each year from 1985 to 2018, we counted the number of 30 m × 30 m pixels of natural vegetation and anthropic area within each pixel of a grid with 600 m × 600 m resolution.

We overlaid our grid with polygonal spatial data for PAs obtained through The World Database on Protected Areas (15) for April 2019 and from the Ministry of the Environment (originally abbreviated in Portuguese as MMA) (16). In this way, it was possible to determine which pixels are under formal protection and to which PA categories they belong. The Brazilian legislation regarding PAs (originally abbreviated in Portuguese as SNUC) classifies them in two broad categories: strictly protected, those for which primary purpose is to protect nature, allowing only indirect use of natural resources, and sustainable use, which aims to balance conservation with the exploitation of natural resources (17). These categories are approximately equivalent to the IUCN Protected Areas Management Categories I to IV and V and VI, respectively. In addition, indigenous lands have an essential role in conservation, despite not being regulated by SNUC and not having the main objective of protecting natural resources. Therefore, pixels covered by SNUC PAs or indigenous lands (collectively referred to as PAs hereafter) were considered protected in our analysis. In the case of overlapping PAs on the same pixel, we did the following: The pixel was deemed to be covered by the oldest PA until a new overlapping PA is established. From this year on, if SNUC PAs of the same category overlaid the pixel, the pixel was still considered as part of the oldest PA. However, if the SNUC PAs had different categories, we considered the pixel part of the stricter PA. If the pixel were overlaid by a SNUC PA and an indigenous land, we considered it part of the SNUC PAs. We excluded from the analysis marine, coastal, and sites that are not PAs according to IUCN criteria. We only quantified the effectiveness of the PAs with area >10 km² and that were designated between the years 1985 and 2017. This way, our dataset consisted of 1082 PAs (n strict protection = 219, n sustainable use = 456, and n indigenous lands = 407), which represents approximately 88% of the total terrestrial area currently covered by PAs in Brazil. PAs outside these lands in conserving native vegetation, as demonstrated here, and it can have negative implications for the livelihoods of indigenous people.
criteria and Ramsar sites were used as a mask so that their pixels could not be considered controls. To avoid interference of the zone of influence of the PAs in our analysis, we followed previous studies (35) and determined a 10-km buffer around each PA in which pixels could not be considered control for the analysis of PA effectiveness. However, we do not know in practice the real extent of the zone of influence of PAs and, therefore, we conducted a separate assessment of the impact of the PA on their surroundings. For this, we determined concentric buffer areas from the border of the PAs up to 20 km, by increments of 5 km, and compared the dynamics of the natural vegetation of these pixels to controls outside the 20-km threshold. For this analysis, we established the year 2000 as a baseline since around that period most of the current Brazilian PAs were already established (10); thus, we were able to have a larger sample size.

Once the pixels were classified as protected, controls, or buffers, we paired the protected and buffer pixels with similar control pixels. This pairing’s relevance is related to the heterogeneity of pressure for vegetation. We assumed that accessibility (24), agricultural suitability (24), and the socioeconomic (25) context are the main factors related to the likelihood that a site will undergo a loss of natural vegetation. Then, we made a preselection of 12 covariates that represent these factors: distance to roads, distance to water bodies, distance to the coast, distance to urban spots, travel time to large cities, rainfall, agricultural potential, elevation, slope, municipal human development index (MHDI), population density, and rural density (see Table S2 for detailed description and justification). All covariates were spatialized and resampled to 600 m × 600 m resolution and then overlaid on the grid.

In addition, we used a global aboveground biomass carbon map for the year 2010 (26) to estimate how much the PAs’ presence had avoided the emissions of carbon to the atmosphere due to the conservation of natural vegetation. The map we used provides an estimate in Mg of carbon biomass per hectare in a 300 m × 300 m resolution.

**Analysis**

To select a simplified set of covariates that best explain the probability of a grid cell covered by natural vegetation to undergo a loss of vegetation, we used the machine learning algorithm random forest to discard covariates with weak explanatory power or that are redundant (see the Supplementary Material). For this, we created a model for the probability of natural vegetation conversion for each biome. Each dataset consisted of unprotected pixels outside the 10-km range of the PAs designated until the year 2000. In these datasets, we included the preselected 12 covariates as predictors and, the remaining natural vegetation for the year 2000, as a response variable. To the remaining vegetation quantification, we assumed that all area that is currently anthropic was once natural vegetation. Therefore, the remaining natural vegetation was given by natural vegetation / (natural vegetation + anthropic area). Our approach to select the covariates resembles the methods used in (52). First, we trained our model using all predictors and with 70% of the samples, obtaining the rank of importance of the predictors and an out-of-bag error. We repeated the training in each iteration removing the predictor with the least importance, based on the first training, until we trained a model with only one predictor (table S3). The model chosen for each biome was that one with the least number of predictors but with the out of bag error within 1 standard error of the smallest out-of-bag error (fig. S6). We used the remaining 30% of the dataset to predict natural vegetation remnants based on the model with all predictors and the selected model (fig. S7). This way, we could compare the performance of the two models. A limitation of this approach was the use of the year 2000 as a baseline for training our models. Since variables such as MHDI or distance for roads are not constant over the period of time of the study, this may have affected the reduction of bias in the choice of controls.

On the basis of the covariates selected, we paired the protected and buffer pixels (treatments) with similar control pixels using statistical matching. This type of approach allows finding correspondent control for each treatment grid cell based on the similarity quantified according to a set of covariates. In this way, we expect to control the potential biases that different social-economic contexts and pressure for conversion could cause in our analysis of effectiveness (23, 35). For our analysis, each treatment pixel could only be paired with a control pixel within the same biome, but controls could be paired again with another treatment if this treatment belonged to another PA (tables S4 and S5). For computational processing purposes, we limited the number of treatments to 100,000 pixels for each PA and, in the case of the buffer analysis, for each biome. These treatments could be paired with controls within a pool of 500,000 control pixels. In cases of PAs and biomes with a greater number of cells, we randomly selected pixels within this limit. If a PA belonged to multiple biomes, the limits were applied for each of the biomes to which the PA belonged to. The set of covariates used for pairing depended on the biome to which the pixel belongs. We also included as a covariate the remaining natural vegetation in the year of creation of each PA or the year 2000 for buffers, to ensure that controls and treatments had a similar baseline. We used the nearest neighbor algorithm based on Mahalanobis distance to find the control and treatment pairs. The cutoff threshold of maximum differentiation between control and treatment was 0.5 SDs. We discarded from the analysis PAs with less than 50% of their treatments matched. To assess the quality of each match, we obtained the absolute mean standardized difference between controls and treatments. In cases that a regression analysis is conducted posteriorly, a threshold of 0.25 difference of means is recommended (53).

We considered the odds ratio of a given treatment pixel of natural vegetation to be converted into an anthropic area when compared to an unprotected pixel as the effectiveness metric in our analysis. To quantify the odds ratio, we annually counted the number of pixels of natural vegetation to be converted into an anthropic area when compared to an unprotected pixel as the effectiveness metric in our analysis. Thus, the odds ratio was given by

\[
\text{Odds ratio} = \frac{\left(\sum_{j=m}^{2018} A_{tj}\right) \times \left(\sum_{j=m}^{2018} N_{tj}\right)}{\left(\sum_{j=m}^{2018} A_{tj}\right) \times \left(\sum_{j=m}^{2018} N_{tj}\right)}
\]

Thus, the odds ratio was given by

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\]

\[
\text{Odds ratio} = \frac{\left(\sum_{j=m}^{2018} A_{tj}\right) \times \left(\sum_{j=m}^{2018} N_{tj}\right)}{\left(\sum_{j=m}^{2018} A_{tj}\right) \times \left(\sum_{j=m}^{2018} N_{tj}\right)}
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\text{Odds ratio} = \frac{\left(\sum_{j=m}^{2018} A_{tj}\right) \times \left(\sum_{j=m}^{2018} N_{tj}\right)}{\left(\sum_{j=m}^{2018} A_{tj}\right) \times \left(\sum_{j=m}^{2018} N_{tj}\right)}
\]

\[
\text{Odds ratio} = \frac{\left(\sum_{j=m}^{2018} A_{tj}\right) \times \left(\sum_{j=m}^{2018} N_{tj}\right)}{\left(\sum_{j=m}^{2018} A_{tj}\right) \times \left(\sum_{j=m}^{2018} N_{tj}\right)}
\]
where $A$ and $N$ are, respectively, the number of anthropic pixels and the number of pixels of natural vegetation in a given year $j$, with $j$ having an initial value $m$, which refers to the year of the designation of the PA or 2000 for buffers and the final value of 2018. Here, $t$ indicates treatment pixels and $c$ denotes the control pixels. In the case of a PA with multiple biomes, we added each biome’s contingency tables and then calculated the odds ratio. We also analyzed the all-time and yearly effectiveness of the PA network. In these cases, the odds ratio was calculated from the sum of all PAs’ contingency tables established in a given year. We applied the Haldane-Anscombe correction (54), adding 0.5 to each of the contingency tables’ cells to avoid infinitesimal results. Odds ratio values lower than 1 indicate that treatments are more effective than their controls. Values of 1 indicate that there is no difference between treatments and their controls. Values greater than 1 indicate that the controls are more effective than their treatments.

We used the Wilcoxon–Mann-Whitney test, Kruskal-Wallis test, and the post hoc Dunn’s test to compare the differences in the median of effectiveness across biomes, types of PAs, and instances of governance. We also compared the relationship between the size of the PA and its effectiveness using the Pearson correlation coefficient.

To estimate the total of natural vegetation that was spared from being converted due to the presence of PAs, we first calculated for each protected pixel the weighted mean by year of odds ratio from $t_0$ to $t_1$, in this case, from 1985 to 2018. Then, we considered that, without PAs, the total of natural vegetation ($V_{eg}$) lost ($L$) in the time period from $t_0$ to $t_1$ would be given by

$$L_{t_0\rightarrow t_1 \text{ Estimated}} = \frac{V_{eg_{t_0 \text{ Observed}} \text{ – } V_{eg_{t_1 \text{ Observed}}}}}{\text{Odds ratio}_{t_0\rightarrow t_1}}$$

When the loss estimated was larger than the amount of vegetation observed, we considered that all the vegetation was lost ($L_{t_0\rightarrow t_1 \text{ Estimated}} = V_{eg_{t_0 \text{ Observed}}}$). Conversely, when the estimated gains of vegetation surpassed the pixel’s total area, we assumed that all the pixel was composed of natural vegetation ($L_{t_0\rightarrow t_1 \text{ Estimated}} = 0.36 \text{ km}^2$).

With this, we could estimate the amount of natural vegetation in a given year $t_1$ if no PA was present

$$V_{eg_{t_1 \text{ Estimated}}} = V_{eg_{t_0 \text{ Observed}} \text{ – } L_{t_0\rightarrow t_1 \text{ Estimated}}}$$

Therefore, to estimate the amount of carbon saved to be emitted to the atmosphere due to the PAs’ presence, we first quantified the amount of natural vegetation remaining in 2018 in the absence of PAs. Since our carbon biomass dataset is from the year 2010, we estimated the natural vegetation amount but considering $t_0$ to $t_1$ if no PA was present.

To estimate the total of natural vegetation that was spared from being converted due to the presence of PAs, we first calculated for each protected pixel the weighted mean by year of odds ratio from $t_0$ to $t_1$. Then, we considered that, without PAs, the total of natural vegetation ($V_{eg}$) lost ($L$) in the time period from $t_0$ to $t_1$ would be given by

$$C_{t_0\rightarrow t_1 \text{ Spared}} = 0.85 \times (V_{eg_{t_1 \text{ Observed}}} - V_{eg_{t_1 \text{ Estimated}}})$$

Therefore, considering that 85% of the carbon contained in vegetation is released to the atmosphere when the vegetation is lost (27), we lastly estimated the total of emissions spared as

$$C_{t_0\rightarrow t_1 \text{ Spared}} = 0.85 \times (V_{eg_{t_1 \text{ Observed}}} - V_{eg_{t_1 \text{ Estimated}}})$$

**SUPPLEMENTARY MATERIALS**

Supplementary material for this article is available at https://science.org/doi/10.1126/sciadv.abh2932

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