UNIVERSIDADE FEDERAL DA BAHIA - UFBA

Programa de Pós-Graduação em Ecologia: Teoria, Aplicação e Valores

Mestrado em Ecologia: Teoria, Aplicação e Valores

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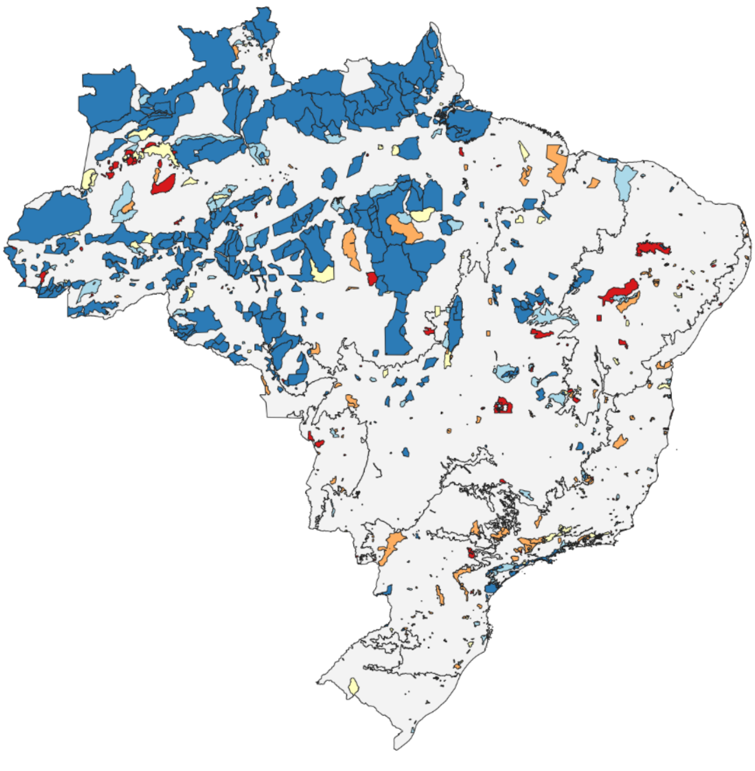
EFETIVIDADE DAS UNIDADES DE CONSERVAÇÃO E TERRAS INDÍGENAS DO BRASIL EM CONTER A PERDA DE VEGETAÇÃO NATURAL



Salvador, janeiro de 2021

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Dissertação apresentada ao Programa
de Pós-Graduação em Ecologia:
Teoria, aplicação e Valores, como parte dos
requisitos exigidos para obtenção
do título de Mestre em
Ecologia: Teoria, aplicação e Valores.

Orientador: Prof. Dr. Ricardo Dobrovolski

Salvador, janeiro de 2021

“A verdadeira viagem de descobrimento não consiste em procurar novas paisagens, mas em ter novos olhos” (Marcel Proust)

Dedico este trabalho às musas.

Sumário

Agradecimentos

À Universidade Federal da Bahia e ao Instituto de Biologia pela infraestrutura que permitiu o desenvolvimento da minha pesquisa.

À Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES) pelo apoio financeiro.

Ao meu orientador Prof. Ricardo Dobrovolski pelos quase 6 anos de mentoria, compreensão das dificuldades dos seus orientados, disponibilidade e interesse em discutir a minha pesquisa, além do incentivo à minha independência como pesquisador e apoio aos meus direcionamentos.

Aos Prof. Bruno Vilela e Prof. Ben Phalan por gentilmente aceitarem participar da banca de acompanhamento e oferecerem contribuições importantes para elaboração da dissertação e do artigo.

A Prof. Pavel Dodonov por estar sempre aberto a discutir, auxiliar e dar sugestões em nossas pesquisas.

Aos Prof. Charbel El-Hani & Prof. Pedro Rocha pelo incentivo às discussões filosóficas.

Aos meus colegas de laboratório Anderson Medina, Thaís Dória, Carol Birrer e Vitor Dantas por todos os bate-papos científicos e não-científicos.

Aos colegas de mestrado por tornar o dia-a-dia mais leve.

À Bruno Cajado pelo compartilhamento das lamentações e vitórias acadêmicas.

À minha família pelo o apoio às minhas empreitadas.

Resumo

A conservação da biodiversidade e de todos os benefícios advindos da integralidade da natureza é um valor central para as sociedades do mundo. No Brasil, considerando as Unidades de Conservação e as Terras Indígenas, mais de 2,5 milhões de km² do território são designados como áreas protegidas (APs). No entanto, estudos que avaliam a efetividade da rede de APs no Brasil em proteger a biodiversidade são limitados, a despeito da importância global do país para a conservação. No presente estudo, nós usamos uma abordagem contrafactual para testar a efetividade da rede de proteção brasileira de 1.082 APs terrestres em evitar a destruição da vegetação natural entre 1985 e 2018. Além disso, testamos o efeito das APs nas suas zonas de amortecimento. Constatamos que cerca de 85,3% das APs são mais eficazes do que as áreas não protegidas e, em média, a razão entre a quantidade de vegetação perdida nas APs, e aquela perdida em áreas não protegidas semelhantes é de 1:4. Entre os biomas, a Amazônia tem as APs mais efetivas, embora algumas das APs menos eficazes também estejam localizadas ali. As Terras Indígenas aparecem como a categoria mais eficaz de APs. Além disso, a efetividade está positivamente correlacionada com o tamanho, e APs mais antigas se mostraram mais efetivas. Também descobrimos que geralmente o efeito positivo dos APs se estende além das suas fronteiras oficiais. Como consequência da presença de APs, mais de 10.000 km² de vegetação natural foram poupados de conversão e anualmente mais de 9 Tg de carbono deixaram de ser emitidos para a atmosfera. Mostramos aqui que as APs desempenham um papel estratégico no Brasil e no mundo ao proteger efetivamente a vegetação natural e, consequentemente, a biodiversidade e os serviços ecossistêmicos, contribuindo para o bem-estar das pessoas no mundo.

Palavras-chave: Perda de habitat; Conversão de Habitat, Vegetação natural, Leakage, Spillover; Matching

Abstract

The conservation of biodiversity and all the benefits arising from nature's integrality is a central value for the world's societies. When accounting for the conservation units and indigenous lands in Brazil, more than 2.5 million km² of the territory are designated as protected areas (PAs). However, studies that assess the effectiveness of the PA network in Brazil in protecting biodiversity are limited, despite its global conservation significance. Here we used a counterfactual approach to test the effectiveness of the Brazilian terrestrial conservation network of 1,082 PAs in avoiding natural vegetation destruction since 1985. Additionally, we tested the PAs' impact on their buffer areas' vegetation. We found that about 85.3% of PAs are more effective than unprotected areas and, on average, for each km of vegetation lost in PAs, 4.54 km are lost in similar unprotected areas. Among the biomes, Amazon had the most effective PAs, although some of the least effective ones are also placed there. Indigenous lands appeared as the most effective category of PAs. Besides that, the effectiveness is positively correlated with size but negatively correlated with the year of designation. We also found that PAs' positive effect generally extended beyond their official boundaries. The consequence of PAs is more than 10,000 km² of natural vegetation spared of conversion, and annually more than 9 Tg of carbon has not been emitted to the atmosphere. We showed here that PAs play a strategic role in Brazil and the world by effectively protecting natural vegetation and, consequently, biodiversity and ecosystem services, contributing to people's wellbeing in the world.

Keywords: Habitat loss; Habitat conversion, Natural vegetation, Leakage, Spillover; Matching;

Introdução geral

A biodiversidade, para além do seu valor intrínseco, traz inúmeros benefícios diretos e indiretos para a humanidade, como a provisão de água e alimento, regulação climática, prevenção de deslizamentos de terra, recreação, entre muitos outros (Millennium Ecosystem Assessment, 2005; Diaz et al., 2015). Apesar disso, algumas das ações humanas resultam na superexploração dos recursos naturais, que por sua vez causam a perda da biodiversidade (Barnosky et al., 2011; Ceballos et al., 2017) e o esgotamento desses serviços ecossistêmicos que dela provêm (Vitousek et al., 1997). Com o reconhecimento do papel da biodiversidade no bem-estar humano e a conseguinte importância de manter a integridade da natureza, foi concebido o instrumento que é atualmente um dos pilares da conservação: as áreas protegidas (APs).

Em sentido estrito, as APs têm como objetivo fundamental garantir a perpetuação da biodiversidade a partir do isolamento entre essa e as suas ameaças externas (Margules & Pressey, 2000). Mais recentemente, as APs passaram a abranger um significado mais amplo, integrando em seus propósitos a provisão de recursos naturais e a garantia do direito à terra e a subsistência para povos tradicionais e indígenas. Em algumas instâncias, essa integração melhorou simultaneamente o desempenho dos indicadores de biodiversidade das APs (Nelson & Chomitz, 2011; Sarkar & Montoya, 2011), bem como a qualidade de vida da população local (Sarkar & Montoya, 2011; Naidoo et al., 2019; porém ver Mascia et Aa., 2010; Adams & Hutton, 2007). Exemplos positivos de desempenho como esses, estimularam globalmente a contínua designação de APs, sendo atualmente mais de 16% do território terrestre e 8% do território marinho do planeta sob proteção formal (UNEP-WCMC, 2020).

No entanto, a designação de uma AP por si só não garante que todo o seu potencial de conservação da biodiversidade será de fato atingido. Isso porque a efetividade das APs pode ser afetada por diversos fatores como por exemplo interesses socioeconômicos (Sarkar & Montoya, 2011), contexto local (Kere et al., 2017), restrições estabelecidas para o uso de recursos dentro das APs (Nelson & Chomitz, 2011), além da qualidade da gestão das APs (Coad et al., 2015). Portanto, tendo em vista a miríade de fatores que precisam ser equilibrados para assegurar a boa performance das APs, uma vez que estas são planejadas e estabelecidas, elas devem ser avaliadas regularmente para assegurar que estão de fato mitigando do impacto negativo das atividades antrópicas nos habitats e as populações de espécies que se almeja conservar (Margules & Pressey, 2000).

Uma das questões a serem consideradas na avaliação de efetividade das APs é a escolha do indicador que será usado como critério norteador de performance, mais precisamente, qual aspecto pode ser diretamente mensurado e que sinaliza que uma AP está beneficiando a biodiversidade. Dentre os indicadores de performance possíveis, tendências históricas de abundância de espécies é a abordagem mais direta para medir a efetividade de uma AP. No entanto, devido à dificuldade de obtenção de dados abrangentes e consistentes de abundância (porém ver Gray et al., 2016), a efetividade dos APs é geralmente avaliada de maneira mais indireta, seja por meio de medição da incidência de ameaças humanas (por exemplo, Nepstad et al., 2006), dados complementares de gestão (por exemplo, Geldmann et al., 2018), ou dados de mudanças no uso da terra (por exemplo, Joppa et al., 2008; Payés et al., 2013). Esse último tornou-se mais proeminente devido a grande quantidade de dados disponíveis nos últimos anos de uso da terra baseado em sensoriamento remoto.

A maioria das tentativas de se avaliar a importância de ações de conservação para a biodiversidade se baseiam em estudos de monitoramento, ou seja, estudos que avaliam como a performance de algum indicador variou ao longo tempo (Ferraro, 2009). Nesses estudos, a melhora da performance do indicador é entendida como evidência de que determinada intervenção foi benéfica. No entanto, a melhora por si só não é suficiente, uma vez que diversos fatores além da intervenção de conservação podem ser causadores da variação e, portanto, é importante o controle dessas variáveis de confusão para mensurar a contribuição de fato de determinada intervenção. A alternativa para isso são as análises de impacto, que buscam responder à pergunta "A intervenção funciona melhor do que nenhuma intervenção (ou uma intervenção alternativa proposta)?" (Ferraro, 2009).

No caso das APs, uma avaliação de impacto apropriada deve ser baseada no quanto o fato de uma AP estar presente em determinada localidade evitou que essa tivesse sua biodiversidade negativamente impactada (Pressey et al., 2015). Contudo, não é possível saber diretamente qual teria sido o rumo da biodiversidade de um local na ausência de proteção. Desta forma, a abordagem denominada contrafactual requer a comparação entre APs e áreas não protegidas (controles) que sejam o mais semelhante possível das APs. Além disso, para realisticamente estimar o impacto das APs, é preciso entender quais os mecanismos operando ali que influenciam na perda de biodiversidade para além do fator de ausência ou presença de proteção formal. A partir disso, deve-se garantir que os controles selecionados estejam expostos a pressões semelhantes por exploração dos recursos naturais (dos Santos Ribas et al., 2020) e dessa forma esses controles possam ser utilizados como linha de base confiável para a avaliação de impacto das APs. Estudos mais recentes (por exemplo, Andam et al., 2008; Soares-Filho et al., 2010) adereçaram essa questão incorporando na busca áreas controle indicadores como potencial agrícola, distância de grandes cidades, densidade populacional, entre outros.

Na literatura relacionada à efetividade das APs encontra-se diversos estudos que se utilizam de abordagens “inocentes”, ou seja, que pressupõem que a escolha de bons controles (aqueles semelhantes e independentes às APs), pode ser feita utilizando unicamente como critério a distância espacial entre as APs e seus controles para garantir a semelhança entre esses (dos Santos Ribas et al., 2020). Porém, a presença de uma AP pode afetar positivamente ou negativamente a biodiversidade no seu entorno (Pfaff & Robalino, 2012), dessa forma, utilizar áreas da periferia imediata das APs como controle causa distorção na percepção da efetividade de uma AP (Ewers & Rodrigues, 2008). A influência positiva das APs em seu entorno pode ocorrer devido a uma autocorrelação espacial do efeito protetor das APs, enquanto a influência negativa (*leakage*) pode ocorrer devido ao deslocamento das ameaças para a periferia. Portanto, a seleção de controles para a avaliação contrafactual da efetividade não deve se restringir ao entorno das APs.

A maior parte dos estudos de efetividade de APs são referentes ao Neotrópico e, de maneira geral, se restringem aos biomas florestais (dos Santos Ribas et al., 2020). No Brasil mais de 2,5 milhões de km² são oficialmente protegidos, se considerarmos apenas as Unidades de Conservação e as Terras Indígenas (UNEP-WCMC, 2020), mas ainda são necessários estudos que examinem a efetividade da rede de APs em escala nacional e com metodologia consistente. Seguindo a tendência geral, estudos anteriores que investigaram a efetividade das APs no Brasil em evitar a perda da vegetação natural se deu nos biomas florestais Amazônia e da Mata Atlântica (Soares-Filho et al., 2010, Joppa et al., 2008), com poucos em relação ao Cerrado (Carranza et al., 2014; Brum et al., 2019), e nenhum referente à Caatinga, Pampa e Pantanal, apesar da importância desses biomas para a conservação (Loyola et al., 2009; da Silva et al., 2018). O Brasil é um país importante para o monitoramento da efetividade das APs, uma vez que é um local de intensos conflitos pelo uso da terra e ao mesmo tempo abriga uma grande variedade de biomas que vão desde savanas, florestas, pântanos e campos, tem a maior biodiversidade do mundo e é país chave para a regulação do clima mundial (Bebber & Butt, 2017). Desta forma, quantificar sistematicamente a efetividade de APs no Brasil em conter a perda de vegetação natural significa entender o papel de um país protagonista da conservação em proteger parcela significativa da biodiversidade global de suas principais ameaças: a perda de habitat e mudanças climáticas.

Referências Bibliográficas

Adams, W. M., & Hutton, J. (2007). People, parks and poverty: political ecology and biodiversity conservation. *Conservation and society*, 5(2), 147-183.

Andam, K. S., Ferraro, P. J., Pfaff, A., Sanchez-Azofeifa, G. A., & Robalino, J. A. (2008). Measuring the effectiveness of protected area networks in reducing deforestation. *Proceedings of the National Academy of Sciences*, 105(42), 16089-16094.

Barnosky, A. D., Matzke, N., Tomiya, S., Wogan, G. O., Swartz, B., Quental, T. B., ... & Mersey, B. (2011). Has the Earth's sixth mass extinction already arrived? *Nature*, 471(7336), 51.

Bebber, D. P., & Butt, N. (2017). Tropical protected areas reduced deforestation carbon emissions by one third from 2000–2012. *Scientific reports*, 7(1), 1-7.

Brum, F. T., Pressey, R. L., Bini, L. M., & Loyola, R. (2019). Forecasting conservation impact to pinpoint spatial priorities in the Brazilian Cerrado. *Biological Conservation*, 240, 108283.

Carranza, T., Balmford, A., Kapos, V., & Manica, A. (2014). Protected area effectiveness in reducing conversion in a rapidly vanishing ecosystem: the Brazilian Cerrado. *Conservation Letters*, 7(3), 216-223.

Ceballos, G., Ehrlich, P. R., & Dirzo, R. (2017). Biological annihilation via the ongoing sixth mass extinction signaled by vertebrate population losses and declines. *Proceedings of the National Academy of Sciences*, 114(30), E6089-E6096.

Coad, L., Leverington, F., Knights, K., Geldmann, J., Eassom, A., Kapos, V., ... & Nolte, C. (2015). Measuring impact of protected area management interventions: current and future use of the Global Database of Protected Area Management Effectiveness. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 370(1681), 20140281.

da Silva, J. M. C., Leal, I. R., & Tabarelli, M. (Eds.). (2018). Caatinga: the largest tropical dry forest region in South America. Springer.

Díaz, S., Demissew, S., Carabias, J., Joly, C., Lonsdale, M., Ash, N., ... & Bartuska, A. (2015). The IPBES Conceptual Framework—connecting nature and people. *Current Opinion in Environmental Sustainability*, 14, 1-16.

dos Santos Ribas, L. G., Pressey, R. L., Loyola, R., & Bini, L. M. (2020). A global comparative analysis of impact evaluation methods in estimating the effectiveness of protected areas. *Biological Conservation*, 246, 108595.

Ewers, R. M., & Rodrigues, A. S. (2008). Estimates of reserve effectiveness are confounded by leakage. *Trends in ecology & evolution*, 23(3), 113-116.

Ferraro, P. J. (2009). Counterfactual thinking and impact evaluation in environmental policy. *New directions for evaluation*, 2009 (122), 75-84.

Gray, C. L., Hill, S. L., Newbold, T., Hudson, L. N., Börger, L., Contu, S., ... & Scharlemann, J. P. (2016). Local biodiversity is higher inside than outside terrestrial protected areas worldwide. *Nature Communications*, 7(1), 1-7.

Joppa, L. N., Loarie, S. R., & Pimm, S. L. (2008). On the protection of “protected areas”. *Proceedings of the National Academy of Sciences*, 105(18), 6673-6678.

Kere, E. N., Choumert, J., Motel, P. C., Combes, J. L., Santoni, O., & Schwartz, S. (2017). Addressing contextual and location biases in the assessment of protected areas effectiveness on deforestation in the Brazilian amazônia. *Ecological economics*, 136, 148-158.

Loyola, R. D., Kubota, U., da Fonseca, G. A., & Lewinsohn, T. M. (2009). Key Neotropical ecoregions for conservation of terrestrial vertebrates. *Biodiversity and Conservation*, 18(8), 2017.

Margules, C. R., & Pressey, R. L. (2000). Systematic conservation planning. *Nature*, 405(6783), 243.

Mascia, M. B., Claus, C. A., & Naidoo, R. (2010). Impacts of marine protected areas on fishing communities. *Conservation Biology*, 24(5), 1424-1429.

Millennium Ecosystem Assessment (2005). Ecosystems and Human Well-being: Synthesis. Island Press, Washington, DC.

Naidoo, R., Gerkey, D., Hole, D., Pfaff, A., Ellis, A. M., Golden, C. D., ... & Fisher, B. (2019). Evaluating the impacts of protected areas on human well-being across the developing world. *Science Advances*, 5(4), eaav3006.

Nelson, A., & Chomitz, K. M. (2011). Effectiveness of strict vs. multiple use protected areas in reducing tropical forest fires: a global analysis using matching methods. *PloS one*, 6(8), e22722.

Nepstad, D., Schwartzman, S., Bamberger, B., Santilli, M., Ray, D., Schlesinger, P., ... & Rolla, A. (2006). Inhibition of Amazon deforestation and fire by parks and indigenous lands. *Conservation biology*, 20(1), 65-73.

Payés, A. C. L. M., Pavão, T., & dos Santos, R. F. (2013). The conservation success over time: Evaluating the land use and cover change in a protected area under a long re-categorization process. *Land Use Policy*, 30(1), 177-185.

Pfaff, A., & Robalino, J. (2012). Protecting forests, biodiversity, and the climate: predicting policy impact to improve policy choice. *Oxford Review of Economic Policy*, 28(1), 164-179.

Pressey, R. L., Visconti, P., & Ferraro, P. J. (2015). Making parks make a difference: poor alignment of policy, planning and management with protected-area impact, and ways forward. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 370(1681), 20140280.

Sarkar, S., & Montoya, M. (2011). Beyond parks and reserves: The ethics and politics of conservation with a case study from Perú. *Biological Conservation*, 144(3), 979-988.

Soares-Filho, B., Moutinho, P., Nepstad, D., Anderson, A., Rodrigues, H., Garcia, R., ... & Maretti, C. (2010). Role of Brazilian Amazon protected areas in climate change mitigation. *Proceedings of the National Academy of Sciences*, 107(24), 10821-10826.

UNEP-WCMC (2020). Protected Planet Aichi Target 11 Dashboard. Available at: < https://www.protectedplanet.net/target-11-dashboard> (acessado 19 de agosto 2020).

Vitousek, P. M., Mooney, H. A., Lubchenco, J., & Melillo, J. M. (1997). Human domination of Earth's ecosystems. *Science*, 277(5325), 494-499.

O papel das áreas protegidas na manutenção da vegetação natural no Brasil

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Artigo submetido ao periódico *Science*

Title: The role of protected areas in maintaining natural vegetation in Brazil

Short title: Protected areas effectiveness in Brazil

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Abstract: The destruction of natural vegetation in recent decades has been concentrated in the tropics, where vital ecosystem services underpin global homeostasis and harbor most biodiversity. Protected areas (PAs) are the primary societal tool to avoid this destruction, yet their effectiveness is often questioned, particularly in the context of post-truth politics. We quantified the impact of PAs in avoiding 34 years of vegetation destruction in forested and non-forested biomes in Brazil. We showed that the odds of destruction in the PA network is four times lower than unprotected areas, and generally, this positive effect extends to a buffer zone around PAs. The most effective PAs included Amazonian PAs, indigenous lands, older and larger PAs. Despite recent setbacks for the Brazilian PA system, we highlight the benefits of PAs for biodiversity and climate if they were instead strengthened.

One Sentence Summary: Protected areas in Brazil are effective in reducing loss of natural vegetation, especially in Amazon and indigenous lands.

Main Text:

Brazil figures as a key country for conservation, as home to tens of thousands of endemic species across its different biomes, and as a provider of essential ecosystem services (*1*), including from 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 to plan environmental conservation. Many developments have occurred since 1992, when the country hosted the Earth Summit and signed the Convention on Biological Diversity (CBD). Among other things, the signatories of this convention pledge to expand their protected area (PA) network. In this regard, the latest CBD target aimed to protect 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*), its political instability has undermined environmental policies (*3*), and the effective protection of PAs is not guaranteed (*5*-*6*), with the recent election of an anti-environment government. Besides this, Brazilian PAs are not always well funded (*7*), managed, or enforced (*8*), and are often located in remote areas where patrols and monitoring are challenging (*9*). 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 (*10*), or PAs are subject to human invasions. In addition, PAs often downsized, downgraded, or are degazetted after some years of their designation (5). As they come under pressure both locally and politically, it is important to quantify the impacts of Brazilian PAs on conservation of natural areas.

Here we conducted a three step analyzes to evaluate the aspects of PAs' overall performance in Brazil (n = 1,082, Fig. 1A) and some of its consequences to conservation. First, we quantified how much the PAs are mitigating vegetation conversion within their established boundaries. Then, we looked for indications of displacement of pressure by repeating the analyzes of vegetation conversion mitigation to the surroundings of PAs (buffers). Finally, we estimated the amount of natural vegetation spared from conversion, and the carbon emissions avoided due to the PAs' presence.

We considered as PAs indigenous lands, and what Brazil's legislation recognizes as "conservation units" — which can be broadly categorized as those with strict protection of natural resources (IUCN categories I-IV), and those that allow the sustainable use of natural resources (IUCN categories V-VI) (*11*). A proper effectiveness assessment hinges on quantifying the extent to which PAs' presence have spared natural vegetation from being impacted (*12*). Thus, the so-called counterfactual approach requires a comparison between PAs and unprotected areas that are similar in relevant variables in relation to a desired conservation outcome (*13*). In an analysis that considers the outcome as mitigation of the vegetation loss, areas should be compared based on 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 by using machine learning to find the main determinants of vegetation loss in Brazilian biomes. We assumed that accessibility (*14*), agricultural suitability (*14*), and the social-economic (*15*) context are the main factors that influence the pressure for conversion (Table S1). Based on that, we trained random forest models to predict the remaining vegetation of unprotected areas in the year 2000 in each biome, using 12 covariates that represent these factors. Finally, we used statistical matching to pair treatments (PAs and buffers) and controls (areas not protected), based on 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 of PAs and unprotected areas between 2000 and 2018 to determine if the effects of PAs were displaced to their periphery and in which extent it occurred. The odds ratio also allowed us to estimate what the remaining of vegetation in 2018 would be in the absence of PAs. Also, by using a map of aboveground carbon biomass of the year 2010 (*16*) and calculating the difference of vegetation loss between 2010 and 2018 for scenarios of presence and absence of PAs, we were able to estimate how much carbon emissions to the atmosphere were spared due to the presence of PAs. For this, we assumed that the carbon 50% of the aboveground carbon biomass is in the vegetation and 85% of the vegetation carbon is emitted in the case of conversion (*17*). We then estimated the carbon biomass in vegetation for 2010 and 2018 based on the amount of vegetation in the scenario of presence of PAs and in the scenario of absence of PAs. The spared emissions were given by the carbon difference emitted in the scenario of presence of PAs and in the scenario of absence of PAs

We found that during the period that vegetation loss was officially monitored (1985–2018), Brazil has lost 939,050 km² (10.9%) of its natural vegetation (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 the biome's vegetation. In the same period, PAs in Brazil had 37,491 km² of their natural vegetated areas converted (1.7% of total original vegetation in PAs). Inside the PAs, Caatinga was the biome with proportionally more acute loss, with 3,639 km² (6.2 %) of its vegetation converted.

The approach of matching the protected pixels with controls improved the balance of their distribution for all covariates (Fig. S6–S7). It was not possible to find a representative number of controls for 42 PAs, which were discarded from the analysis (see supplementary material). PAs have lost less natural vegetation than their matched controls (Mann–Whitney U = 246321, $p < 0.01$; Fig. S2D; Fig. S3). The median loss that occurred from the PAs' designation to 2018 inside PAs was 0.2%, compared to 3.4% vegetation loss in the control areas. Further, we estimate that the PAs have spared 10,489 km² (95% CI = 10,456 - 10,521) of natural vegetation from being lost during the time of the study. This represents only 1.1% of the total of observed loss. Considering the spared vegetation from 2010 onwards, this would mean that on average 9.03 Tg y^{-1} of carbon (CI = 3.93 - 14.17) were 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 y^{-1} of carbon (*18*).

Compared with matched controls, we found that 887 PAs (85.3%) were effective in mitigating natural vegetation loss, while 141 (13.5 %) were less effective than unprotected areas, and 12 (1.1%) had no difference from controls. 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, 4.54 km² are lost outside the protected areas. 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 - 0.005]). On the other hand, "Kaxinawa do Rio Jordão," an indigenous territory from Amazon, was the least effective, with an odds ratio of 12.7 (95% CI = 12.3 - 13.1).

Considering the biomes individually, each one of them had a median odds ratio below 1 for the PAs (Fig. 1B-C). Despite being generally effective, the PAs' level of effectiveness varied between biomes (Kruskal-Wallis $\chi 2 = 169.06$, df = 5, $p < 0.01$; Fig. S2A). 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 Amazon, this biome includes 60% of the 50 least effective PAs.

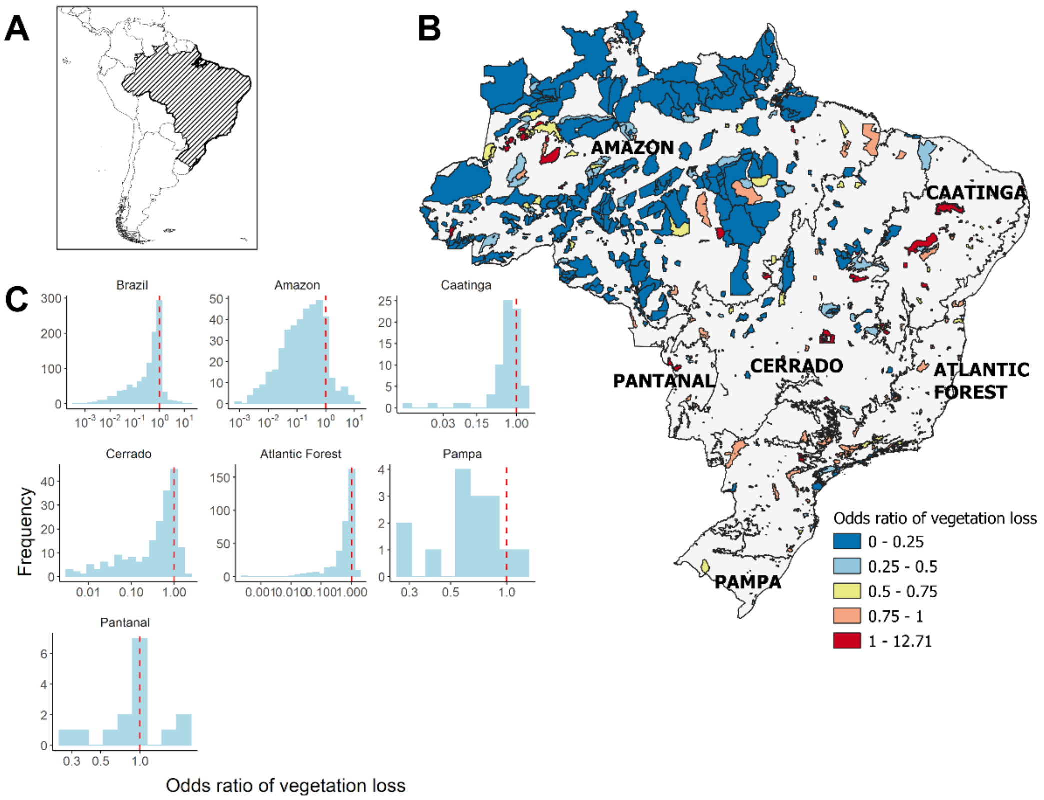

Fig. 1 – Study area (**A**) and distribution of the PAs network's effectiveness across biomes (**B** – **C**). The effectiveness is measured by the odds ratio of a given PA have their natural vegetation converted when compared with a similar unprotected area. The red dashed line in the histograms indicates the threshold of effectiveness. On the left of the line are effective PAs and on the right of the line are ineffective PAs. The x-axis is on a logarithmic scale.

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. S2B), 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, $p < 0.01$). Protected areas governed by indigenous people were more effective (Dunn's Test $p < 0.05$; Fig. S2C) (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) or 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, -0.39]; Fig. S4).

The PA network's effectiveness was not constant throughout the period covered by our study (Fig. 2). 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, and Atlantic Forest, a decrease in effectiveness is observed in the most recent years. The worst PAs network's 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.

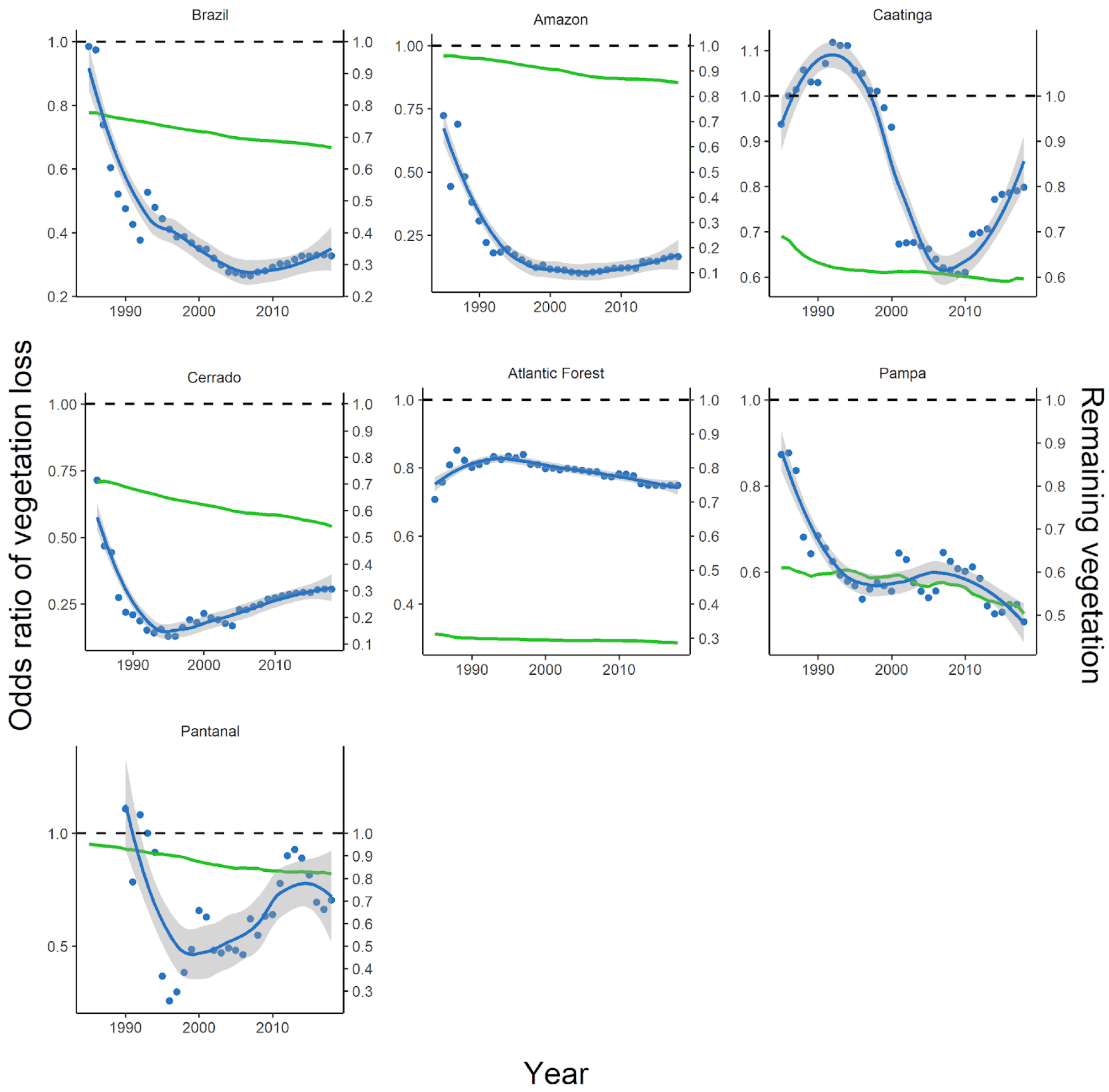

Fig. 2 – Variation of effectiveness (in blue) and remaining natural vegetation of the biomes (in green) across the time period of the study. The dashed line indicates the threshold of effectiveness. Below the line are effective PAs and above the line are ineffective PAs.

We also found that the areas surrounding PAs had less probability of having their natural vegetation converted when compared with controls, except for the Caatinga. There seemed to be three patterns of how the odds ratio varies with distance to PAs (Fig. 3). In the first pattern, exhibited only by the Amazon, the probability of an area to have its vegetation lost 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.

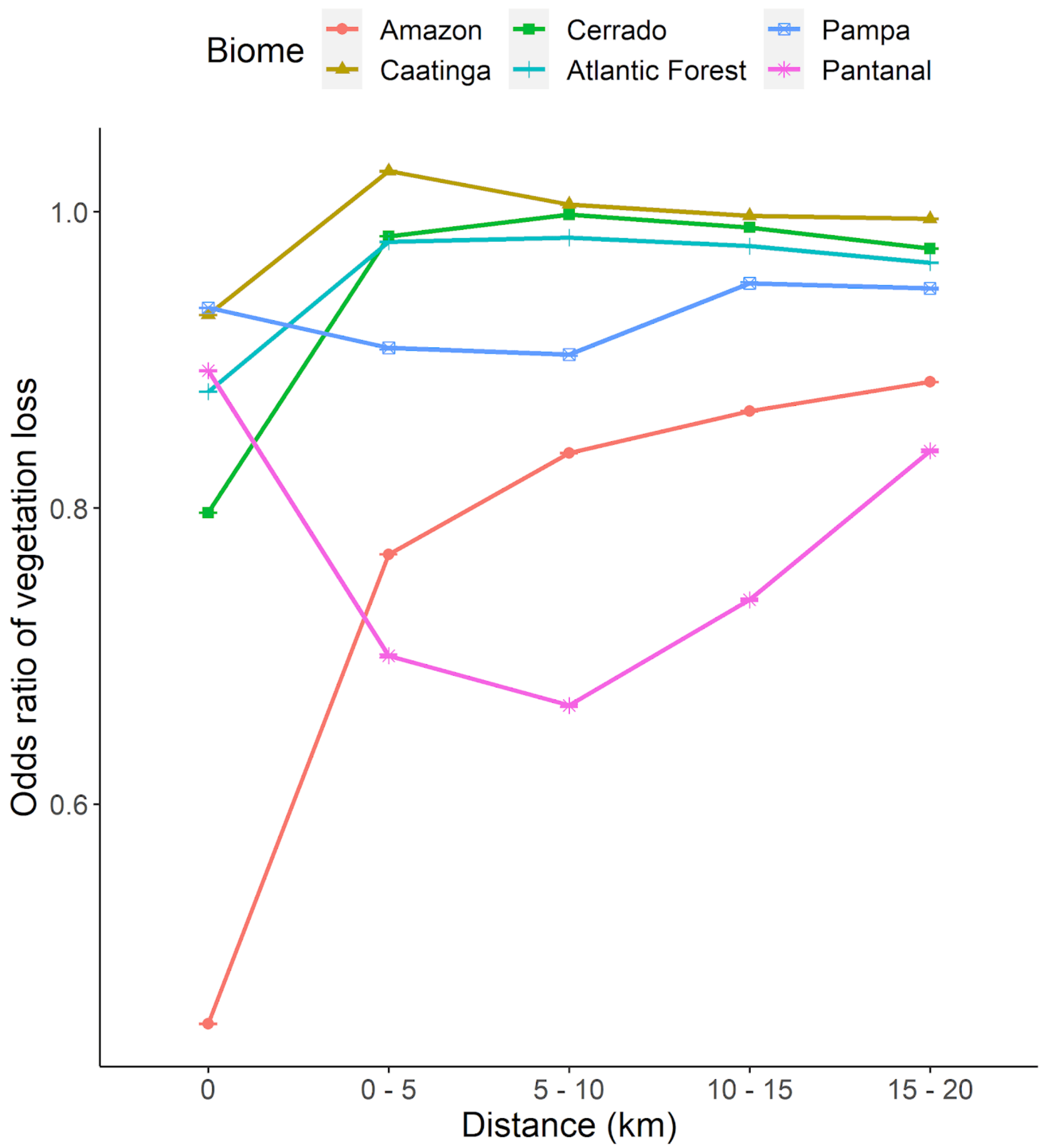

Fig. 3 – Relationship across biomes between the distance from the closest PA and the odds ratio of losing natural vegetation when compared with control areas farther than 20 km from a PA.

This study showed that most of the PAs of Brazil are contributing to mitigate the loss of natural vegetation, and some of the PAs' characteristics are correlated with their effectiveness. Older and bigger PAs that are governed by indigenous people seem less prone to suffer 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 of how PAs affect their surroundings, as it shows that positive effects of a PA usually extend beyond their official borders and the extent of this "spillover" can be even greater than previously thought.

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. Therefore, to ensure substantial conservation outcomes, it is necessary to improve not only the PAs effectiveness but their location (*9*), extent, and management as well.

Our analysis is not a complete assessment of PAs' effectiveness since we only accounted for the loss of natural vegetation that PAs have mitigated. PAs' ability 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 PAs' role in conservation because the loss of natural vegetation is the leading cause of species extinction and an essential regulator of carbon emissions. Also, natural vegetation destruction might act synergistically with other threats to biodiversity (*21-22*).

Our results indicate that PAs have played a role in mitigating habitat loss and climate change for at least 30 years, and there is still great potential to increase the benefits of these PAs in the future. Unfortunately, this potential has been jeopardized in Brazil's recent history, which has been marked by setbacks in environmental policies and conservation (*4, 23*). For instance, the proposed bill PL191/2020 establishes concessions for mineral exploration and the hydroelectric dams' construction on indigenous lands. As well as its negative implications for the livelihoods of indigenous peoples, this bill can weaken the role of indigenous lands in conserving native vegetation loss, as demonstrated here. 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 and likely reflect a decrease in government commitment to conservation (*24*). The expansion and strengthening of the PA network have become imperative, and the CBD established as one of the new targets for 2030 to protect 30% of the earth, aiming to recover species populations, prevent extinctions, and restore as well as stabilize and increase ecosystems and their services (*25*). 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.

References and Notes:

1. D. P. Bebber, N. Butt, Tropical protected areas reduced deforestation carbon emissions by one third from 2000-2012. *Sci. Rep*. **7**, 1–7 (2017).
2. Convention on Biological Diversity (CBD), Conference of the Parties Decision X/2: Strategic plan for biodiversity 2011–2020 (https://www.cbd.int/decision/cop/?id=12268, 2010).
3. Ministério do Meio Ambiente (MMA), Unidades de Conservação (http://dados.gov.br/dataset/unidadesdeconservacao, 2019).
4. R. Dobrovolski, R. Loyola, L. Rattis, S. F. Gouveia, D. Cardoso, R. Santos-Silva, D. Gonçalves-Souza, L. M. Bini, J. A. F. Diniz-Filho, Science and democracy must orientate Brazil's path to sustainability. *Perspect Ecol Conserv* **16**, 121–124 (2018).
5. E. Bernard, L. A. O. Penna, E. Araújo, Downgrading, downsizing, degazettement, and reclassification of protected areas in Brazil. *Conserv Biol* **28**, 4 (2014).
6. R. E. Golden Kroner, S. Qin, C. N. Cook, R. Krithivasan, S. M. Pack, O. D. Bonilla, K. A. Cort-Kansinally, B. Coutinho, M. Feng, M. I. M. Garcia, Y. He, C. J. Kennedy, C. Lebreton, J. C. Ledezma, T. E. Lovejoy, D. A. Luther, Y. Parmanand, C. A. Ruíz-Agudelo, E. Yerena, V. M. Zambrano, M. B. Mascia, The uncertain future of protected lands and waters. *Science* **364**, 881–886 (2019).
7. A. P. C. de Oliveira, E. Bernard, The financial needs vs. the realities of in situ conservation: an analysis of federal funding for protected areas in Brazil's Caatinga. *Biotropica* **49**, 745–752 (2017).

8. R. M. Chiaravalloti, C. Delelis, C. Tofoli, C. V. Padua, K. Torres Ribeiro, G. A. Menezes, Federal protected areas management strategies in Brazil: sustainable financing, staffing, and local development. *Perspect Ecol Conserv* **13**, 30–34 (2015).
9. R. R. S. Vieira, R. L. Pressey, R. Loyola, The residual nature of protected areas in Brazil. *Biol. Conserv.* **233**, 152–161 (2019).
10. L. N. Joppa, S. R. Loarie, S. L. Pimm, On the protection of "protected areas." *Proc. Natl. Acad. Sci. U.S.A* **105**, 6673–6678 (2008).
11. Brasil, Lei 9.985, 18 de julho de 2000: institui o Sistema Nacional de Unidades de Conservação da Natureza: 1–16. (http://www.planalto.gov.br/ccivil_03/leis/l9985.htm, 2000).
12. R. L. Pressey, P. Visconti, P. J. Ferraro, Making parks make a difference: poor alignment of policy, planning and management with protected-area impact, and ways forward. *Phil. Trans. R. Soc. B.* **370**, 20140280 (2015).
13. L. G. dos Santos Ribas, R. L. Pressey, R. Loyola, L. M. Bini, A global comparative analysis of impact evaluation methods in estimating the effectiveness of protected areas. *Biol Conserv* **246**, 108595 (2020).
14. K. Chomitz, & D.A. Gray. Roads, lands, markets, and deforestation: a spatial model of land use in Belize. The World Bank Economic Review, **10**, 487–512 (1996).
15. E. N. Kere, J. Choumert, P. C. Motel, J. L. Combes, O. Santoni, S. Schwartz.. Addressing contextual and location biases in the assessment of protected areas effectiveness on deforestation in the Brazilian Amazônia. *Ecol. Econ* , **136**, 148-158 (2017).
16. S. A. Spawn, C. C. Sullivan, T. J. Lark, H. K. Gibbs, Harmonized global maps of above and belowground biomass carbon density in the year 2010. *Sci Data*. **7**, 112 (2020).
17. B. Soares-Filho, P. Moutinho, D. Nepstad, A. Anderson, H. Rodrigues, R. Garcia, L. Dietzsch, F. Merry, M. Bowman, L. Hissa, R. Silvestrini, C. Maretti, Role of Brazilian Amazon protected areas in climate change mitigation. Proceedings of the National Academy of Sciences. 107, 10821–10826 (2010).

18. Sistema De Estimativa De Emissões De Gases De Efeito Estufa (SEEG) (http://plataforma.seeg.eco.br/, 2020).
19. M. B. Mascia, C. A. Claus, R. Naidoo, Impacts of Marine Protected Areas on Fishing Communities: MPA Social Impacts. *Conserv. Biol.* **24**, 1424–1429 (2010).
20. O. Venter, R. A. Fuller, D. B. Segan, J. Carwardine, T. Brooks, S. H. M. Butchart, M. Di Marco, T. Iwamura, L. Joseph, D. O'Grady, H. P. Possingham, C. Rondinini, R. J. Smith, M. Venter, J. E. M. Watson, Targeting Global Protected Area Expansion for Imperiled Biodiversity. *PLoS Biol* **12**, e1001891 (2014).
21. M. Tabarelli, J. M. Cardoso da Silva, C. Gascon, Forest fragmentation, synergisms and the impoverishment of neotropical forests. *Biodivers. Conserv.* **13**, 1419–1425 (2004).
22. B. Brook, N. Sodhi, C. Bradshaw, Synergies among extinction drivers under global change. *Trends Ecol. Evol.* **23**, 453–460 (2008).
23. D. Abessa, A. Famá, L. Buruaem, The systematic dismantling of Brazilian environmental laws risks losses on all fronts. *Nat Ecol Evol* **3**, 510–511 (2019).
24. Instituto Nacional de Pesquisas Espaciais (INPE), Projeto PRODES: Monitoramento da Floresta Amazônica Brasileira por Satélite (http://www.obt.inpe.br/prodes, 2020).
25. Convention on Biological Diversity (CDB), Zero draft of the post-2020 global biodiversity framework (https://www.cbd.int/doc/c/efb0/1f84/a892b98d2982a829962b6371/wg2020-02-03-en.pdf , 2020).
26. Instituto brasileiro de geografia e estatística (IBGE) (http://www.ibge.gov.br/, 2019).
27. Projeto MapBiomas, Coleção 4.1 da Série Anual de Mapas de Cobertura e Uso de Solo do Brasil (https://mapbiomas.org/download, 2020).
28. UNEP-WCMC & IUCN, Protected Planet: [The World Database on Protected Areas (WDPA)/The Global Database on Protected Areas Management Effectiveness (GD-PAME)] [On-line], [abril/2019], Cambridge, UK: UNEP-WCMC and IUCN. (www.protectedplanet.net, 2019).
29. Ministério do Meio Ambiente (MMA) (http://mapas.mma.gov.br/i3geo/datadownload.htm, 2019).

30. T. Carranza, A. Balmford, V. Kapos, A. Manica, Protected Area Effectiveness in Reducing Conversion in a Rapidly Vanishing Ecosystem: The Brazilian Cerrado: Protected area effectiveness in Cerrado. *Conserv. Lett.* **7**, 216–223 (2014).
31. R. Díaz-Uriarte, S. Alvarez de Andrés, Gene selection and classification of microarray data using random forest. *BMC Bioinformatics*. **7**, 3 (2006).
32. D. B. Rubin, Matched Sampling for Causal Effects (*Cambridge University Press*, Cambridge, 2006).
33. J. B. S. Haldane, The mean and variance of the moments of chi-squared, when used as a test of homogeneity, when expectations are small. *Biometrika*, **29**, 133-134 (1940).
34. F. J. Anscombe, On estimating binomial response relations. *Biometrika*, **43**, 461–464 (1956).

Acknowledgments: Acknowledgments follow the references and notes but are not numbered. Acknowledgments should be gathered into a paragraph after the final numbered reference. This section should start by acknowledging non-author contributions and then should provide information under the following headings: **Funding:** DGS was benefited by a master's scholarship from CAPES. RD research is supported by CNPq (grant 461665/2014-0) and FAPESB (grant JCB0051/2016); BV research is supported by CNPq (grant 436154/2018-8); **Author contributions: Daniel Gonçalves-Souza**: Conceptualization, Methodology, Data curation, Formal analysis, Validation, Writing - original draft, Writing - review & editing, Funding acquisition. **Bruno Vilela:** Conceptualization, Methodology, Writing - original draft, Writing - review. **Ben Phalan:** Conceptualization, Methodology, Writing - original draft, Writing - review. **Ricardo Dobrovolski:** Conceptualization, Formal analysis, Data curation, Funding acquisition, Methodology, Supervision, Validation, Writing - original draft, Writing - review & editing **Competing interests:** Authors declare no competing interests; **Data and materials availability:** All data is available in the main text or the supplementary materials.

Supplementary Materials:

Materials and Methods

Figures S1-S8

Tables S1-S5

References (*26*-*34*)

Supplementary Materials for

The role of protected areas in maintaining natural vegetation in Brazil

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This PDF file includes:

Materials and Methods

Supplementary Text

Figs. S1 to S8

Tables S1 to S5

Materials and Methods

Overview

When resources are allocated to a PAs' project, there is an expectation that this effort will yield in a positive impact on biodiversity. That is, the desired outcome of the PA's presence is the mitigation of loss of biodiversity in contraposition to the scenario of no intervention (*12*). For our impact assessment, we measured as the outcome of interest the amount of vegetation spared from been 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 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, Atlantic Forest, Caatinga, Cerrado, Pampa, and Pantanal) (*26*).

To quantify the dynamics of natural vegetation we used annual land use data from the Project MapBiomas Collection 4.1 (*27*), 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, in order to quantify the remaining natural vegetation in each pixel (Table S1). These new categories are: natural vegetation, non-vegetated 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 600 m × 600 m of the grid.

We overlaid our grid with PAs' polygonal spatial data obtained through The World Database on Protected Areas (*28*) for April 2019 and from the Ministry of the Environment (MMA) (*29*). 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 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 (*11*). These categories are approximately equivalent to the IUCN Protected Areas Management Categories I-IV and V-VI, respectively. Additionally, 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 establishing a new overlapping PA. From this year on, if SNUC PAs of the same category overlaid the pixel, the pixel was 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 data set consisted of 1,082 PAs (n strict protection = 219, n sustainable use = 456, n indigenous lands = 407), which represents approximately 88% of the total terrestrial area currently covered by PAs in Brazil. PAs outside these 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 (*30*) and determined a 10 km buffer around each PA in which pixels could not be considered control for the analysis of PAs 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 this period that most of the current Brazilian PAs were already established (*9*), thus, we were able to have a larger number of treatment pixels.

Once the pixels were classified as protected, buffers, or controls, 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 (*14*), agricultural suitability (*14*), and the social-economic (*15)* context are the main factors related to the likelihood that a site will undergo a loss of natural vegetation. Then we made a pre-selection 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 x 600 m resolution and then overlaid on the grid.

Additionally, we used a global aboveground biomass carbon map for the year 2010 (*16*) 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 converting a grid cell covered by natural vegetation, we used the machine learning algorithm random forest to discard covariates with weak explanatory power or that are redundant (Supplementary text). 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 pre-selected 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 reference *31*. First, we trained our model with all predictors and 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 S4). 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. S7). 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. S8). 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.

Based on 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 (*13, 30*). 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 S3-S4). 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 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. 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 cut-off threshold of maximum differentiation between control and treatment was 0.5 standard deviations. 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, the threshold is 0.25 difference of means is recommended (*32*).

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 counted annually the number of pixels of natural vegetation and anthropic area within the treatments and their corresponding controls. Then, we combined this information in 2 × 2 contingency tables to calculate the odds ratio:

	Anthropic area	Natural vegetation
Protected	$\left(\sum_{j=m}^{2018} A_{tj}\right)$	$\left(\sum_{j=m}^{2018} N_{tj}\right)$
Non protected	$\left(\sum_{j=m}^{2018} A_{cj}\right)$	$\left(\sum_{j=m}^{2018} N_{cj}\right)$

Thus, the odd's ratio was given by:

$$Odd's\ ratio = \frac{\left(\sum_{j=m}^{2018} A_{tj}\right) * \left(\sum_{j=m}^{2018} A_{cj}\right)}{\left(\sum_{j=m}^{2018} N_{tj}\right) * \left(\sum_{j=m}^{2018} N_{cj}\right)}$$

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 the control pixels. In the case of a PA with multiple biomes, we added each biome's contingency tables then calculated the odds ratio. We also analyzed the all-time and yearly effectiveness of the PA network. The odds ratio was calculated from the sum of all PAs' contingency tables established in a given year. We applied the Haldane-Anscombe correction (*33*-*34*), 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 one 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 government administration. We also compared the relationship between the size of the PA and their effectiveness using the Pearson correlation coefficient.

To estimate the total of natural vegetation that was spared being converted due to the presence of PAs, we first calculated for each protected pixel the weighted mean by year of odds ratio from t0 to t1, in this case from 1985 to 2018. Then, we considered that, without PAs, the total of natural vegetation (Veg) lost (L) in the time period from t0 to t1 would be given by:

$$L_{t0-t1\ Estimated} = \frac{Veg_{t0\ Observed} - Veg_{t1\ Observed}}{\overline{Odd's\ ratio_{t0-t1}}}$$

When the loss estimated was larger than the amount of vegetation observed we considered that all the vegetation was lost ($L_{t0-t1\ Estimated} = Veg_{t0\ Observed}$). Conversely, when the estimated gains of vegetation surpassed the pixel's total area, we assumed that all the pixel was composed of natural vegetation ($L_{t0-t1\ Estimated} = 0.36\ km^2$).

With this, we could estimate the amount of natural vegetation in a given year *t1* if no PA was present:

$$Veg_{t1\ Estimated} = Veg_{t0\ Observed} - L_{t0-t1\ Estimated}$$

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 de natural vegetation but considering *t0* = 2010 and *t1* = 2018.

We then resampled the carbon map to the 600 m × 600 m resolution and calculated the total amount of carbon in each cell. We used the standard approach of considering that 50% of the total aboveground carbon biomass is present on the vegetation. To estimate the total of carbon (*C*) observed in the vegetation in 2018, we did a cross multiplication:

$$\mathrm{C_{t1\ Observed}} = \frac{\mathrm{C_{\ t0\ Observed}} * \mathrm{Veg_{t1\ Observed}}}{\mathrm{Veg_{\ t0\ Observed}}}$$

The same was done considering the vegetation of 2018 in the absence of PAs:

$$C_{\text{t1 Estimated}} = \frac{C_{\text{t0 Observed}} * \text{Veg}_{\text{t1 Estimated}}}{\text{Veg}_{\text{t0 Observed}}}$$

Therefore, considering that 85% of the carbon contained in vegetation is released to the atmosphere when the vegetation is lost (*17*), we finally estimated the total of emissions spared as:

$$C_{t0-t1\,Spared} = 0.85 * (C_{\text{t1 Observed}} - C_{\text{t1 Estimated}})$$

Supplementary Text

Random forest and the importance of the covariates

Random forest is an ensemble method based on the agreement of multiple decision trees. Each decision tree randomly divides the dataset of each predictor variable into two sets so that similar values for the response variable remain in the same group. The random forest can be used to select the more important variables in a model. When building the decision trees, each predictor variable's contribution to estimate the response variable is quantified.

It is worth noting that the value of importance attributed to a variable is not always representative of the variable's real significance. For instance, when dealing with categorical data, the random forest is biased in favor of those with more levels. Also, the random forest tends to give less priority to redundant variables. Therefore, combining closely correlated variables in the same model, might result in the exclusion of some of them, even though both could be, in fact, important.

For our model of variables that explain natural vegetation remnants, we established the threshold of Pearson's $r \geq 0.7$ between variables to exclude them before running the model, avoiding multicollinearity. Since none of the correlations between covariates had a coefficient greater or equal to 0.7, we retained all variables *a priori*.

We made independent model selections for each of the six biomes with the following protocol. We used 70% of the datasets to train the models with all variables. The training returns the impurity of the nodes, representing the variable's importance to the variance of the response variable. We summed the values of the importance and calculated each variable's relative importance to the total sum. With this information, we could rank the most important variables. We then ran the models successively, removing the least important variable according to the rank until only one was left. To select the best models, we used the number of variables and out-of-bag error as criteria. The chosen models were those with the least number of predictors within one standard error of the smallest out-of-bag error (Table S5). The number of variables present in each biomes' selected model varied from 3–5. Coast distance and rainfall were the only variables present in the selected models of all biomes.

With the remaining 30% of the datasets, we tested the models with all variables and the selected models. From the results of these tests, we adjust linear regressions relating the observed and predicted vegetation remnants to assess the models' performance. Both models performed generally well, with R^2 varying from 0.73 to 0.82 in the complete models and 0.67 to 0.78 in the selected models (Fig. S8).

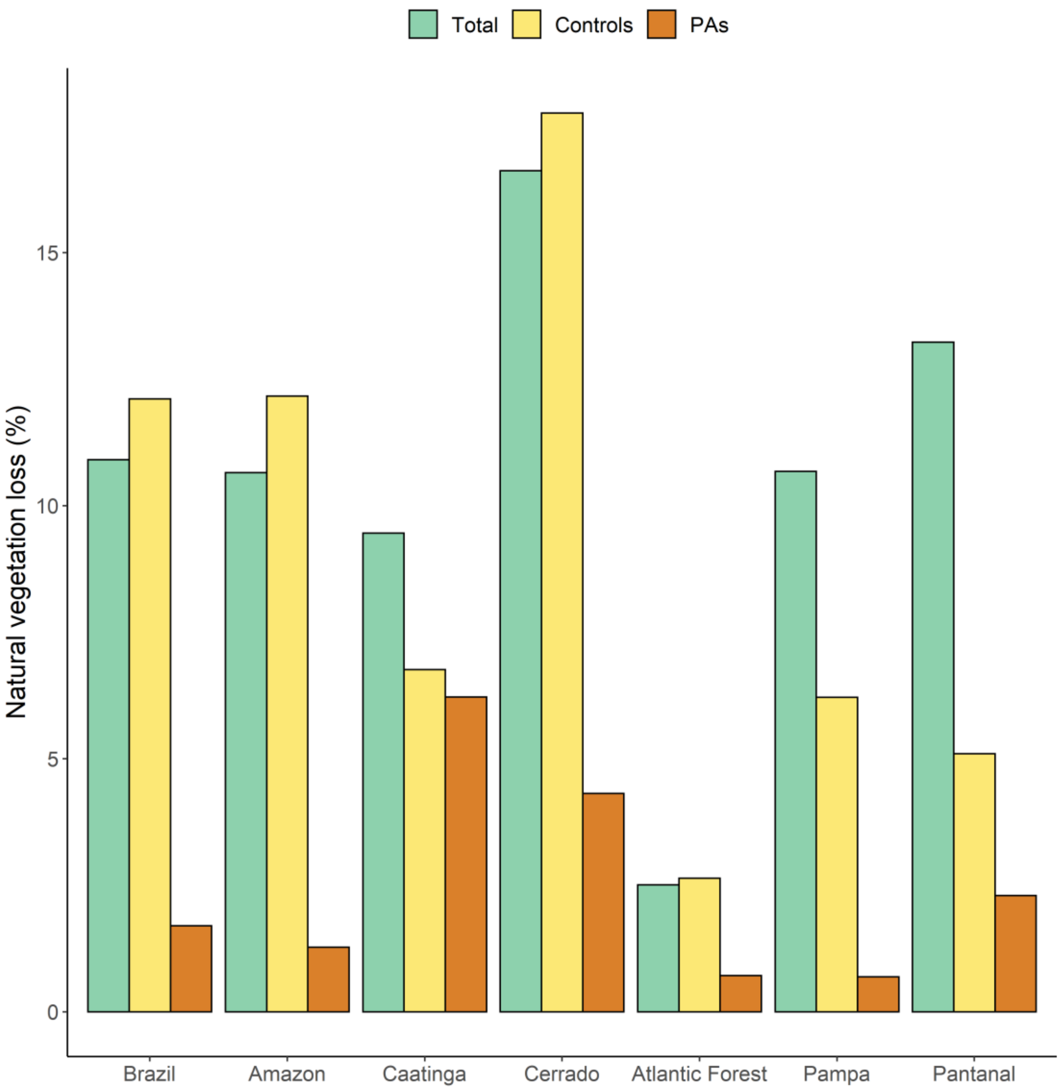

Fig. S1.

Proportional loss of natural vegetation across biomes, comparing grid cells inside the PAs and their controls. The total refers to the loss of vegetation of the biome as a whole.

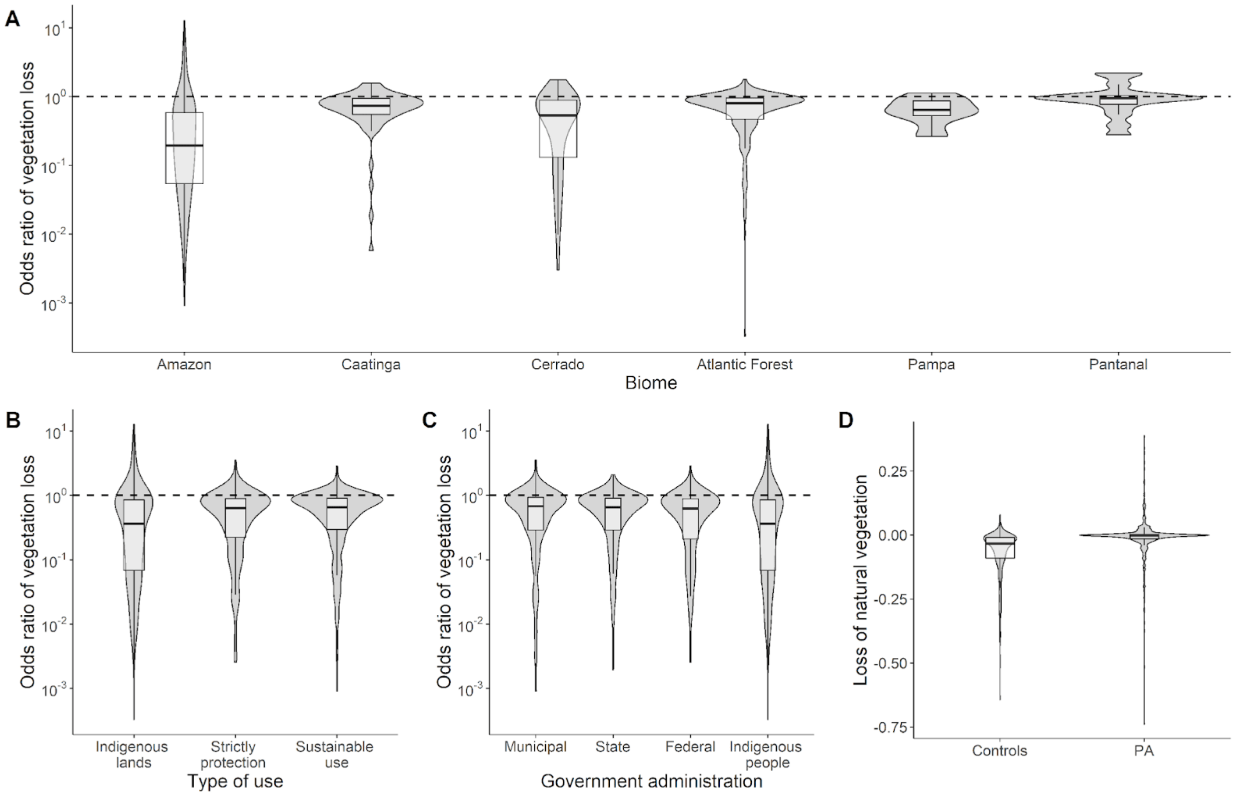

Fig. S2.

Boxplots of the comparison of the effectiveness of PAs regarding their biome (**A**), type of use (**B**), and government administration (**C**). The dashed line indicates the threshold of effectiveness. Below the line are effective PAs and above the line are ineffective PAs. (**D**) Comparison of the PAs and their controls regarding the amount of natural vegetation lost between the year of the designation of the PAs and 2018. The y-axis is in logarithmic scale in **A-C**. Gray areas around the boxplot indicates the distribution of the odds ratio values.

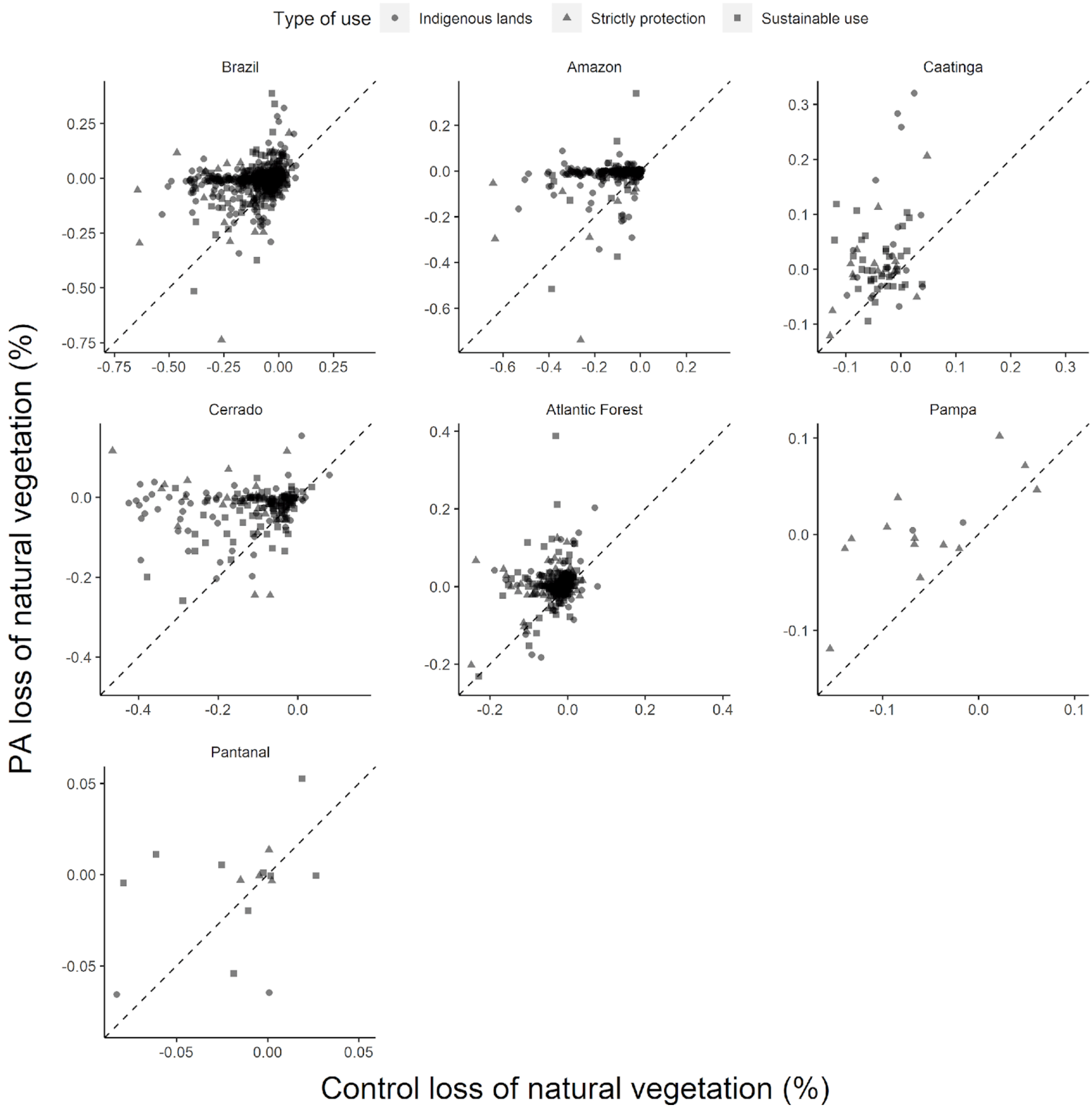

Fig. S3.

Comparison across biomes between PAs and their controls regarding the percentage of natural vegetation lost between PA's year of designation and 2018. Negative values indicate gain in vegetation. The dashed line refers to the 1:1 relationship, or no difference between PAs and controls.

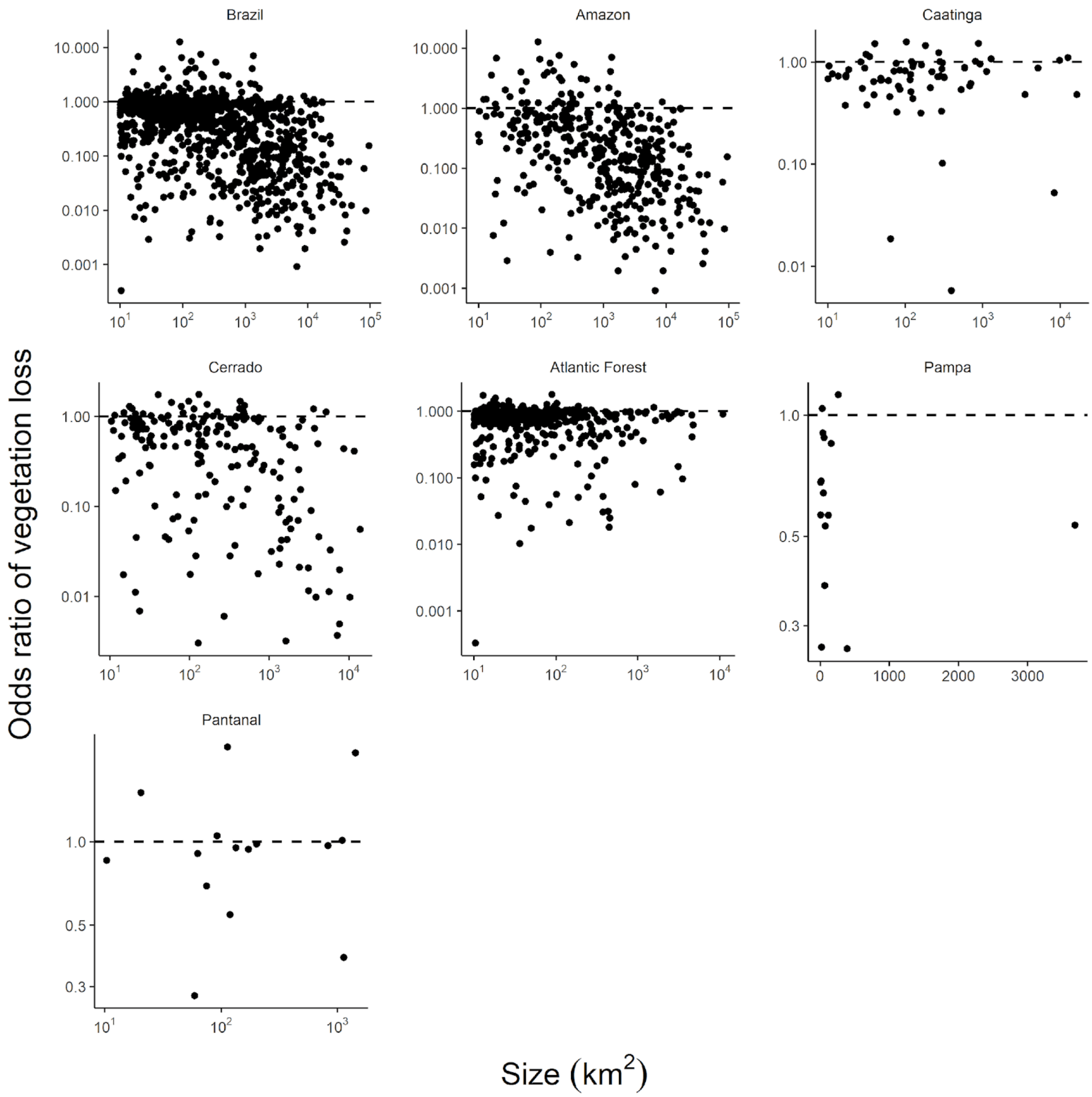

Fig. S4.

Scatterplot of the relationship between the size of the PAs and their effectiveness. The dashed line indicates the threshold of effectiveness. Below the line are effective PAs and above the line are not effective PAs. The y-axis is in logarithmic scale in all plots and the x-axis is logarithmic in all plots except Pampa.

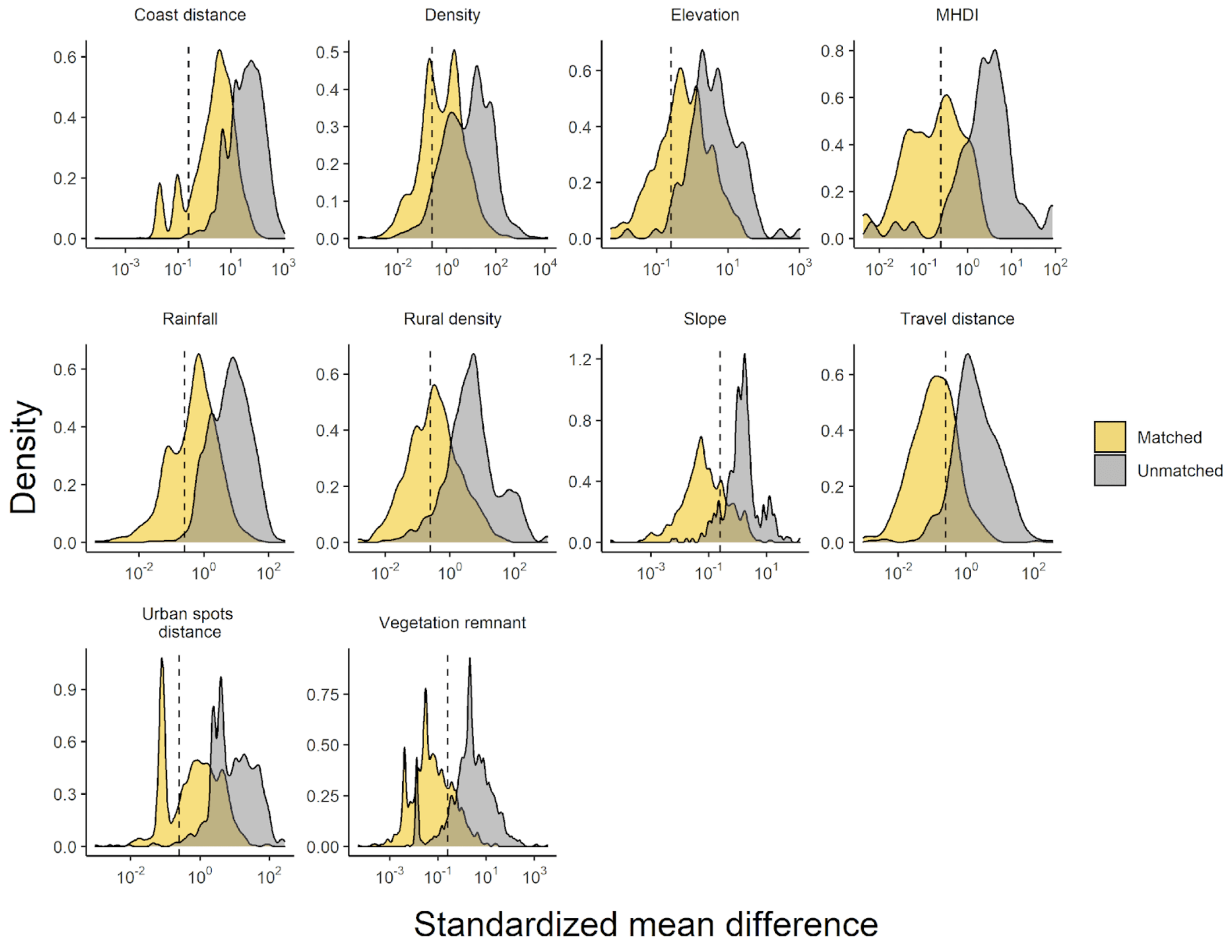

Fig. S5.

Density plots of the absolute standardized mean difference between PA's treatment and controls regarding their covariates. In each plot, the yellow curve represents the mean difference after the pairing with matching, and the gray is before the matching. The dashed line represents the recommended 0.25 threshold for the standardized mean difference. The number of samples that a PA has is equal to the number of biomes they pertain. The x-axis is on a logarithmic scale.

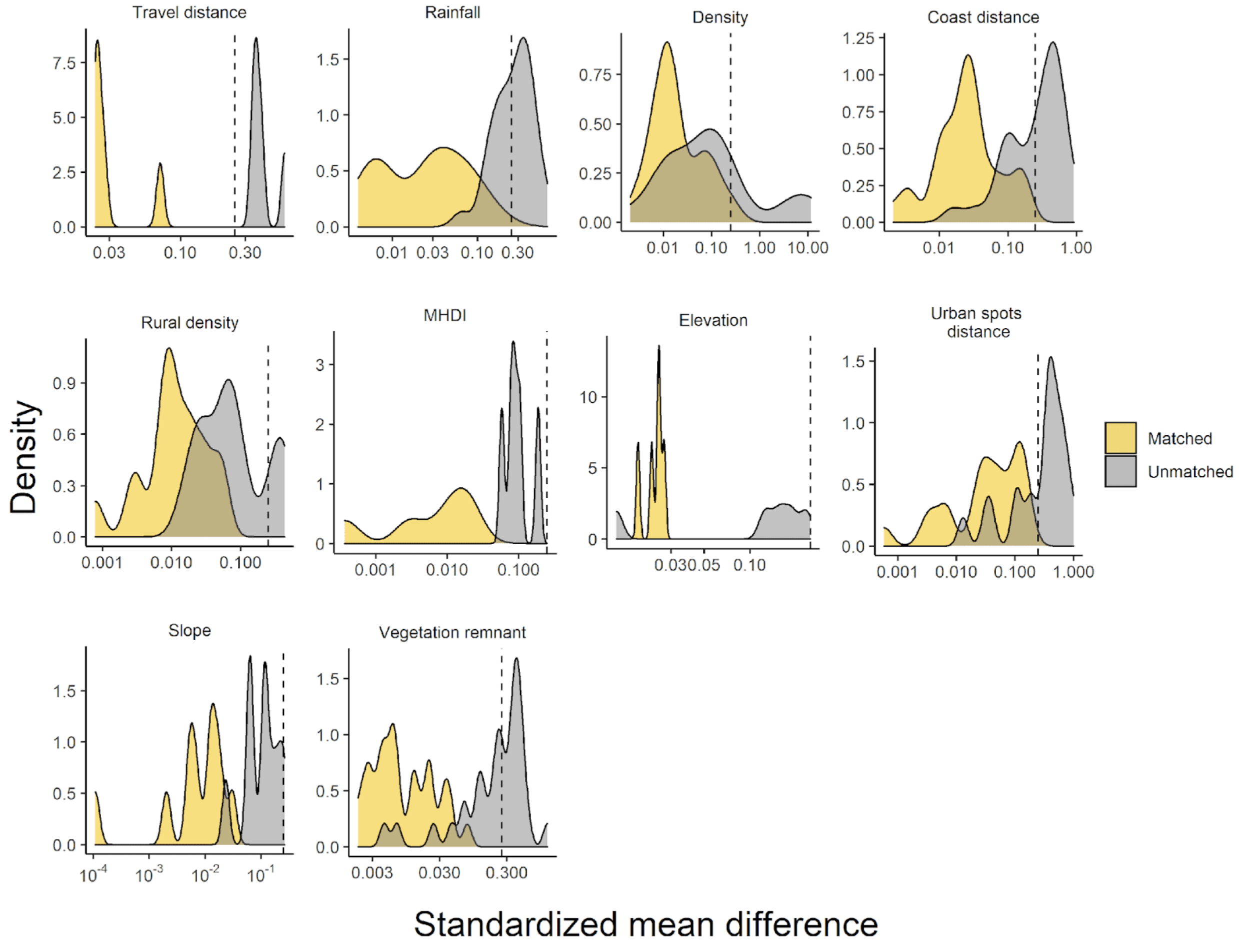

Fig. S6.

Density plots of the absolute standardized mean difference between treatment and controls of the PAs zone of influence regarding their covariates. In each plot the yellow curve represents the mean difference after matching, and the gray is before the pairing. The dashed line represents the recommended 0.25 threshold for the standardized mean difference. The x-axis is on a logarithmic scale.

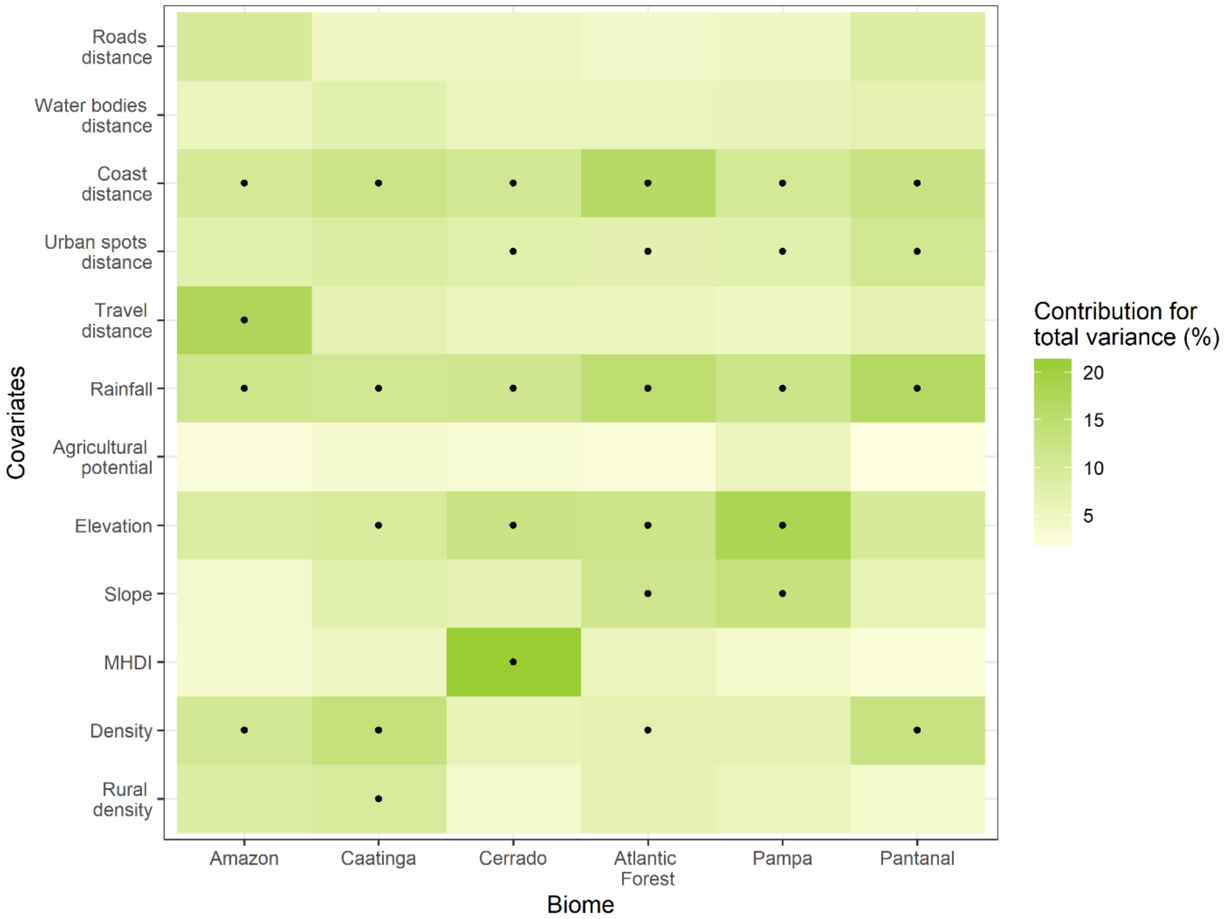

Fig. S7.

Importance of the variables in the random forest model training to explain the remnants of natural vegetation in the control pixels in 2000 in the biomes. Darker shades of green indicate more relative importance of each variable. We selected the covariates identified with the dots for the simplified model.

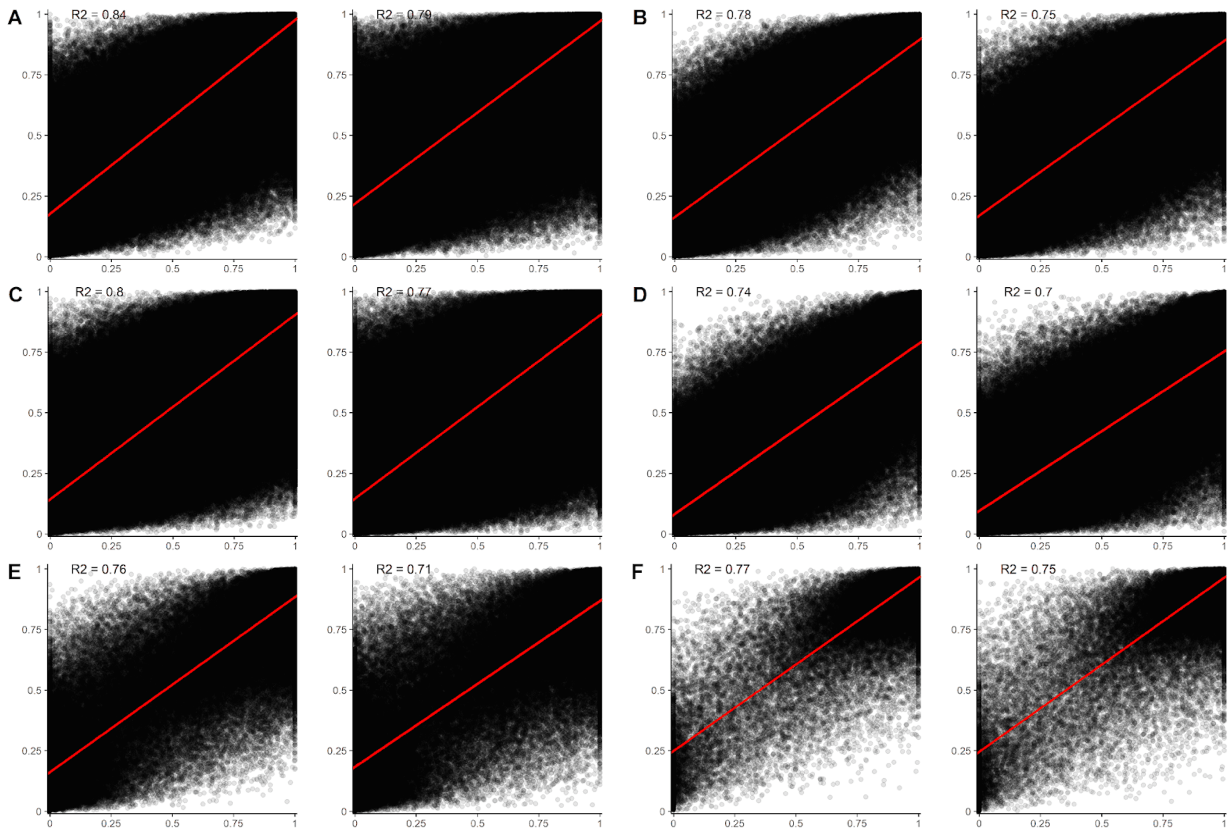

Fig. S8.

Performance analysis of the random forest models for the probability of natural vegetation conversion in the biomes: (A) Amazon, (B) Caatinga, (C) Cerrado, (D) Atlantic Forest, (E) Pampa and (F) Pantanal. Each plot is the linear regression between the observed remnants of natural vegetation in 2000 in control pixels and the predicted remnants by the random forest algorithm. The red line is the fitted line of the regression. On the left are the models' plots with the full set of covariates. On the right are the models with only the most important covariates.

Table S1.

Correspondence between our land use classification and the original MapBiomas v.4.1 categories

New categories	**Original categories**
Natural vegetation	Forest
	Natural forest
	Forest formation
	Savanna formation
	Mangrove
	Non forest natural formation
	Wetland
	Grassland
	Salt flat
	Other non-forest natural formation
Anthropic area	Forest plantation
	Farming
	Pasture
	Agriculture
	Annual and perennial crop
	Semi-perennial crop
	Mosaic of agriculture and pasture
	Urban infrastructure
	Mining
Non-vegetated natural area	Beach and dune
	Rocky outcrop
Others	Non vegetated area
	Other non-vegetated area
	Non observed
Water bodies	Water
	River, lake and Ocean
	Aquaculture

Table S2.

Variables used as indicators of accessibility, agricultural suitability, and social-economic context and used to train the model of probability of conversion of natural vegetation. All variables were spatialized to a resolution of 600 m x 600 m.

Indicator	Covariate	Justification	Description
Accessibility	Distance to roads (km)	Roads are an important way of connecting with the consumer market.	Euclidean distance from roads[1]. Planned roads were not considered. Data from the 2008 National Logistics and Transport Plan (PNLT) and vector data obtained through MMA.
	Distance to water bodies (km)	Water bodies are used for irrigation of agricultural crops and can also be used for transportation of agricultural production.	Euclidean distance from water bodies[1]. Vector data obtained through the 2017 IBGE cartographic base.
	Distance to the coast (km)	Due to the historical process of colonization, regions closer to the coast were first colonized and suffered long-term processes of loss of natural vegetation.	Euclidean distance from the Brazilian Atlantic coast[1]. Vector data obtained through the Bathymetry Project of the Geological Service of

			Brazil - CPRM in partnership with the National Petroleum Agency (ANP)
	Distance to urban centers (km)	Urban centers are consumer markets for agricultural products.	Euclidean distance from urban concentrations with a population greater than 100,000 people[1]. Vector data from the IBGE Urbanized Areas 2015 project.
	Travel time to large cities (minutes)	Complementary measure of access to consumer markets that considers the conditions of access to estimate travel time.	Data represents the estimated travel time to the nearest city of 50,000 people or more. Baseline year of 2000. Data obtained through the Global Environment Monitoring Unit with a resolution of 1 km.
Agricultural suitability	Rainfall (mm)	Regions with an adequate rainfall regime for agriculture may have a higher appeal to risk of loss of vegetation.	Raster data with an approximate resolution of 1 km obtained through World Clim 2.0. We used as a metric the average rainfall in the months of the year 2000.
	Agricultural potential (1 - 5)	Areas with greater agricultural potential are preferred for cultivation.	Measured through the 2002 Agricultural Potential Map of Brazil provided by IBGE, which classifies

			areas in Brazil according to agricultural potential on a discrete scale from 1 to 5, with the value 1 being areas with the lowest potential and 5 with the greatest potential.
	Elevation (km)	Areas with higher altitude and slope are thought as less interesting for agriculture and urbanization due to greater difficulty in access and settlement.	Altimetric data were extracted from the raster relief map provided by the Consortium for Spatial Information (CGIAR-CSI), based on NASA's Shuttle Radar Topography Mission v. 4.1 (SRTM), with 90m resolution. With this map, the slope was calculated using the GRASS 7.4 software.
	Slope (°)		
Social-economic context	Municipal Human Development Index (0 -1)	The Municipal Human Development Index (MHDI) can be an indicator of a place's dependence on agricultural products.	Municipal level index that varies between 0 and 1 and it refers to human development dimensions, such as longevity, education and income. Data obtained through the Human Development Atlas of the year 2000.

	Density (nº of people / km²)	Places with a higher concentration of people have greater pressure to use natural resources. We use data from rural density in addition to population density as we believe that in more intact regions the rural density would be a better indicator of pressure for conversion.	Data obtained through the Gridded Population of the World, Version 4 (GPWv4) with a resolution of 1 km.
	Rural density (nº of people / km²)		Rural density at the municipal level. Obtained through the demographic census of 2000 by IBGE.

[1] We calculated the Euclidean distance by converting vector data to raster and calculating the distance using the GRASS 7.4 software.

Table S3.

Summary of the sampling methodology for treatments and controls for the effectiveness analysis.

Analysis	Sampling	Treatments		Controls	
		Distance	**Number of samples**	**Distance**	**Number of samples**
PAs' effectiveness	Pixels from each PA.	0km from the PA.	Up to 100,000 pixels*.	> 10km from any PA	Same as the number of treatments selected from a pool of 500,000 pixels*.
Buffers	Buffer pixels from each biome	> 0km & ≤ 20km from any PA.	Up to 100,000 pixels per biome.	> 20km from any PA	Same as the number of treatments selected from a pool of 500,000 pixels.

* If a PA was located in more than one biome the number of samples are multiplied by number of biomes that the PA are located.

Table S4.

Summary of the output of the random forest training model for each biome. RMSE represents the root-mean-square error of the model

	Amazon		**Caatinga**		**Cerrado**		**Atlantic Forest**		**Pampa**		**Pantanal**	
Number of covariates	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	Out-of-bag error	R^2
12	0.114	0.835	0.181	0.772	0.184	0.792	0.162	0.732	0.192	0.757	0.116	0.756
11	0.113	0.836	0.182	0.771	0.184	0.792	0.162	0.733	0.193	0.755	0.116	0.759
10	0.114	0.835	0.183	0.768	0.184	0.791	0.163	0.73	0.193	0.753	0.115	0.76
9	0.111	0.842	0.184	0.765	0.186	0.787	0.164	0.724	0.196	0.745	0.115	0.76
8	0.114	0.835	0.186	0.76	0.191	0.775	0.165	0.721	0.197	0.743	0.114	0.765
7	0.117	0.825	0.189	0.752	0.193	0.771	0.169	0.71	0.2	0.736	0.114	0.765
6	0.12	0.816	0.182	0.769	0.199	0.756	0.175	0.689	0.202	0.73	0.115	0.76
5	0.124	0.804	0.191	0.746	0.194	0.768	0.181	0.667	0.209	0.71	0.118	0.751
4	0.131	0.78	0.214	0.681	0.216	0.714	0.205	0.57	0.232	0.642	0.121	0.737
3	0.196	0.511	0.27	0.496	0.252	0.61	0.214	0.532	0.282	0.473	0.136	0.667
2	0.237	0.28	0.35	0.148	0.288	0.489	0.263	0.294	0.341	0.23	0.182	0.404
1	0.269	0.077	0.404	-0.134	0.315	0.388	0.309	0.028	0.397	-0.044	0.255	-0.17

Table S5.

Table summarizing the pairing of treatments and controls. The number of treatments is the number of pixels inside the PAs that were paired. Number of duplicated treatments concerns the pixels that were overlaid by multiple PAs. Pool of controls is the number of pixels that were available for pairing with the treatments. Number of duplicated controls refers to the pixels that were matched multiple times with treatments of different PAs.

Biome	Number of treatments	Number of duplicated treatments	Ratio of duplicated treatments	Pool of controls	Number of controls	Number of duplicated controls	Ratio of duplicated controls
Amazon	4,536,818	81,106	0.018	2,915,742	4,536,818	2,375,844	0.524
Caatinga	165,004	4,166	0.025	1,559,403	165,004	12,266	0.074
Cerrado	554,367	26,240	0.047	3,590,109	554,367	66,807	0.121
Atlantic Forest	253,120	20,794	0.082	1,529,251	253,120	54,493	0.215
Pampa	12,569	158	0.0126	453,353	12,569	331	0.026
Pantanal	14,910	0	0	295,999	14,910	808	0.054

Conclusões Gerais

Este é o primeiro estudo a analisar a efetividade das APs no Brasil que abrange todos os principais biomas do país. Dessa forma, usando uma metodologia consistente, comparamos o desempenho das APs em mitigar a perda de uma ampla gama de tipos de vegetação. Encontramos que o nível de efetividade varia entre os biomas, ainda que a maioria das APs do Brasil esteja contribuindo para a mitigação da perda de vegetação natural. Além disso, encontramos que algumas das características como tamanho, tempo de criação e categoria de uso das APs parecem estar correlacionadas com a efetividade. Por fim, nossos resultados evidenciam que, de maneira geral, as APs têm um efeito protetivo também em seus entornos.

Apesar ser uma boa notícia o achado de que a rede de APs no Brasil é efetiva, é preciso considerar outros aspectos ao se avaliar a relevância das APs para a conservação e para a sociedade. Por exemplo os locais protegidos por APs tendem a ser locais com baixa intensidade de uso da terra (Vieira et al., 2019), o que indica que os locais onde a presença de APs seria de fato significativa tendem a ser menos protegidos. Além disso, as ações de conservação não se dividem apenas em eficientes e não-eficientes e, portanto, considerar o grau de efetividade é fundamental para pesar seus méritos. A maioria dos estudos sobre a efetividade das APs relata um efeito positivo, porém fraco das APs (Geldmann et al., 2013; dos Santos Ribas et al., 2020). No entanto, aqui estimamos que as APs brasileiras têm uma razão de probabilidade média de 1:4 de perda de vegetação natural em comparação com áreas desprotegidas. Devemos ponderar qual o grau de efetividade que, associado a uma dada extensão de área da rede de APs, é suficiente para reverter a crise da biodiversidade prevista para esse século.

Há um debate na literatura onde se discute se as APs com diretrizes mais rígidas de uso de seus recursos são preferíveis para a conservação. No Brasil são previstas as Unidades de Conservação mais rígidas, as de proteção integral, e as mais permissivas, as de uso sustentável (Brasil, 2000), além das Terras Indígenas. Nelson & Chomitz (2011) encontraram que unidades de uso sustentável e Terras Indígenas são mais eficazes na redução de incêndios do que as unidades de proteção integral, mas Carranza et al. (2013) e Nolte et al. (2013) observaram que as unidades de proteção integral experimentaram conversão de habitat em menor grau do que os unidades de uso sustentável ou Terras Indígenas. Em nosso estudo, as Terras Indígenas se mostraram o tipo mais eficaz de APs, o que demonstra que nem sempre a presença humana no ambiente natural é incompatível com a conservação da biodiversidade e que outros modos de organizações da sociedade são legítimos e devem ser respeitados. Por outro lado, a diferença de efetividade entre proteção integral e uso sustentável foi indistinguível, o que pode estar associado à falta de diferenciação nas estratégias de manejo desses dois tipos de APs (Chiaravalloti et al., 2015). É preciso considerar também que as APs de proteção integral têm maior ocorrência de espécies, endemismo e diversidade filogenética que as outras categorias de APs (Oliveira et al., 2017). Portanto, elevar o nível de efetividade das APs de proteção integral garantirá a proteção de uma parcela mais representativa da biodiversidade.

Outro debate importante é se a presença de uma AP tem efeitos de conservação negativos ou positivos em seu entorno. Os resultados aqui apresentados apontam que, tanto para biomas remotos, como a Amazônia, quanto biomas com intensa pressão antrópica, como Cerrado e Mata Atlântica, os arredores de APs ainda são mais eficazes do que áreas desprotegidas distantes. Isso é consistente com outros estudos (Andam et al., 2008), porém ainda encontramos em nossos resultados exemplos de APs exercendo um efeito negativo em seu entorno. Esse efeito negativo foi mais aparente na Caatinga e pode ser atribuído ao deslocamento de pressão A Caatinga é um bioma populoso e historicamente mais impactado, já tendo perdido metade de sua vegetação natural e com os remanescentes perturbados por atividades antrópicas (Antongiovanni et al., 2020). Além disso, é um bioma com poucos investimentos em conservação, sendo apenas 4% dos projetos de conservação entre 1985 e 1996 direcionados para esse bioma (Leal et al., 2005). Por outro lado, embora considerado um bioma remoto, a Amazônia foi o único bioma a exibir um padrão claro de diminuição das probabilidades de perda de vegetação quanto mais próxima uma área está de uma AP (mas ver Ford et al., 2020).

A metodologia de *matching* usada no presente estudo tem sido amplamente utilizada para avaliações contrafactuais de efetividade de APs, porém ela apresenta limitações (dos Santos Ribas et al., 2020). Ao comparar a perda de vegetação em áreas protegidas e desprotegidas, o pareamento visa reduzir o viés dos controles selecionados quanto à probabilidade de conversão da vegetação. No entanto, isso depende da inclusão dos determinantes da perda de vegetação e a maioria dos estudos se apoiam apenas em considerações teóricas para essa inclusão. Acreditamos que nossa abordagem empírica de criar modelos de *machine learning* para encontrar os principais determinantes minimiza esse problema. Ainda que essa abordagem seja mais robusta, nossos modelos apresentaram um grau de erro não desprezível ao tentar estimar os remanescentes de vegetação natural.

Esperamos que o presente estudo contribua para o corpo de conhecimento relacionado à capacidade das APs de evitar a perda de habitats tanto florestais quanto não florestais. Os resultados reforçam o efeito positivo das APs para mitigar a crise da biodiversidade, mas também mostram que existe um potencial ainda inexplorado de APs pouco efetivas. O fortalecimento da rede de APs é um passo importante na antecipação de impactos negativos na biodiversidade, mas as várias instâncias de redução e degradação de APs (Bernard et al., 2014; Kroner et al., 2019) dificultam o cumprimento das metas de conservação no país. Devemos considerar também que os resultados aqui apresentados são uma avaliação histórica da efetividade das APs e, portanto, mais estudos que incluam modelagens relacionadas à expansão agrícola e mudanças climáticas (por exemplo, Dobrovolski et al., 2011; Lemes et al., 2013; Brum et al., 2019) são necessários para nos anteciparmos aos próximos desafios.

Referências Bibliográficas

Andam, K. S., Ferraro, P. J., Pfaff, A., Sanchez-Azofeifa, G. A., & Robalino, J. A. (2008). Measuring the effectiveness of protected area networks in reducing deforestation. *Proceedings of the National Academy of Sciences*, 105(42), 16089-16094.

Antongiovanni, M., Venticinque, E. M., Matsumoto, M., & Fonseca, C. R. (2020). Chronic anthropogenic disturbance on Caatinga dry forest fragments. *Journal of Applied Ecology*, 57(10), 2064-2074

Bernard, E., Penna, L. A., & Araújo, E. (2014). Downgrading, downsizing, degazettement, and reclassification of protected areas in Brazil. *Conservation Biology*, 28(4), 939-950.

Brasil. Lei 9.985, 18 de julho de 2000: institui o Sistema Nacional de Unidades de Conservação da Natureza: 1–16, 2000. Disponível em: http://www.planalto.gov.br/ccivil_03/leis/l9985.htm. Acessado em 11 de dezembro de 2019.

Brum, F. T., Pressey, R. L., Bini, L. M., & Loyola, R. (2019). Forecasting conservation impact to pinpoint spatial priorities in the Brazilian Cerrado. *Biological Conservation*, 240, 108283.

Carranza, T., Balmford, A., Kapos, V., & Manica, A. (2014). Protected area effectiveness in reducing conversion in a rapidly vanishing ecosystem: the Brazilian Cerrado. *Conservation Letters*, 7(3), 216-223.

Chiaravalloti, R. M., Delelis, C., Tofoli, C., Padua, C. V., Ribeiro, K. T., & Menezes, G. A. (2015). Federal protected areas management strategies in Brazil: sustainable financing, staffing, and local development. *Natureza & Conservação*, 13(1), 30-34.

Dobrovolski, R., Loyola, R. D., De Marco Jr, P., & Diniz-Filho, J. A. F. (2011). Agricultural expansion can menace Brazilian protected areas during the 21st century. *Natureza & Conservação*, 9(2), 208-213.

dos Santos Ribas, L. G., Pressey, R. L., Loyola, R., & Bini, L. M. (2020). A global comparative analysis of impact evaluation methods in estimating the effectiveness of protected areas. *Biological Conservation*, 246, 108595.

Ford, S. A., Jepsen, M. R., Kingston, N., Lewis, E., Brooks, T. M., MacSharry, B., & Mertz, O. (2020). Deforestation leakage undermines conservation value of tropical and subtropical forest protected areas. *Global Ecology and Biogeography*, 29(11), 2014-2024.

Geldmann, J., Coad, L., Barnes, M. D., Craigie, I. D., Woodley, S., Balmford, A., ... & Burgess, N. D. (2018). A global analysis of management capacity and ecological outcomes in terrestrial protected areas. *Conservation Letters*, 11(3), e12434.

Kroner, R. E. G., Qin, S., Cook, C. N., Krithivasan, R., Pack, S. M., Bonilla, O. D., ... & He, Y. (2019). The uncertain future of protected lands and waters. *Science*, 364(6443), 881-886.

Leal, I. R., Da Silva, J. M. C., Tabarelli, M., & Lacher Jr, T. E. (2005). Changing the course of biodiversity conservation in the Caatinga of northeastern Brazil. *Conservation Biology*, 19(3), 701-706.

Lemes, P., Melo, A. S., & Loyola, R. D. (2014). Climate change threatens protected areas of the Atlantic Forest. *Biodiversity and Conservation*, 23(2), 357-368.

Nelson, A., & Chomitz, K. M. (2011). Effectiveness of strict vs. multiple use protected areas in reducing tropical forest fires: a global analysis using matching methods. *PloS one*, 6(8), e22722.

Nolte, C., & Agrawal, A. (2013). Linking management effectiveness indicators to observed effects of protected areas on fire occurrence in the Amazon rainforest. *Conservation Biology*, 27(1), 155-165.

Oliveira, U., Soares-Filho, B. S., Paglia, A. P., Brescovit, A. D., De Carvalho, C. J., Silva, D. P., ... & Stehmann, J. R. (2017). Biodiversity conservation gaps in the Brazilian protected areas. *Scientific reports*, 7(1), 1-9.

Vieira, R. R., Pressey, R. L., & Loyola, R. (2019). The residual nature of protected areas in Brazil. *Biological Conservation*, 233, 152-161.