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Contribution of the Amazon protected areas program to forest conservation

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ABSTRACT

Established in 2002, the Amazon Protected Areas Program (ARPA) supports 120 Conservation Units (CUs) in the Brazilian Amazon, covering 62 Mha. Here, we quantified the impact of ARPA support on reducing deforestation and CO_2 emissions between 2008 and 2020. We started by examining critical methodological choices, often brushed over in the impact evaluation studies on protected areas (PAs). We then applied a covariate balancing method to control for variation in covariates so as to compare differences in deforestation between Strictly Protected (SP) and Sustainable Use (SU) CUs with and without ARPA support as well as to assess the influence of ARPA investment mechanism on the differential reductions. Next, we estimated total reductions in deforestation and CO_2 emissions by using the *Adjusted Odds Ratio*. We found that ARPA support accounts for additional deforestation reductions of 9 % in SP CUs and 39 % in SU CUs in relation to non-supported CUs. The effects of ARPA investment mechanism were statistically significant for both categories of CUs. CUs plus Indigenous Lands (i.e., PAs) reduced by 21 % (2.0 ± 0.3 Mha) Amazon deforestation between 2008 and 2020. Of this total, ARPA CUs accounts for 264 ± 25 thousand ha, the equivalent of 104 ± 10 Mtons of CO_2 emissions. If deforestation continues unabated, PAs will become the last citadels of the Amazon. However, protecting the Amazon only with PAs does not suffice. Additional investments in a comprehensive conservation policy mix are needed along with a monitoring and evaluation strategy to provide evidence on what works for effective and socially equitable forest conservation.

1. Introduction

Brazil's past success in reducing deforestation in the Amazon hinged on PPCDAm (the Action Plan for the Prevention and Control of Deforestation in the Legal Amazon). In response to rampant deforestation rates that reached 28 thousand km^2 in 2004 (INPE, 2022), PPCDAm, in its first phase (2004–2008), focused on improving environmental law enforcement (Casa Civil, 2004) and designating large tracts of public lands as protected areas (PAs), including the creation of conservation units (CUs) and the demarcation of indigenous lands (ILs) (Soares-Filho and Rajão, 2018). In Brazil, PAs comprise two broad categories of CUs, namely strictly protected areas, which are intended to preserve biodiversity, and sustainable use reserves, which seek to balance conservation with the sustainable use of natural resources (MMA, 2022). Moreover, Indigenous Lands (ILs) and Quilombola (Maroon community) territories exist as sanctuaries for indigenous peoples and traditional populations, respectively (CBD-WGPA, 2007; Soares-Filho et al., 2010).

Commonly established in remote areas of high biodiversity (Myers et al., 2000), the creation of CUs in regions of intense land conflict to act as green barriers against deforestation, based on the fact that land designation discourages land grabbing, established a new paradigm in the history of conservation (Soares-Filho et al., 2010). In 2003, there were 79 CUs in the Amazon biome under the administration of the federal government, totaling 34.2 Mha (million hectares). By 2008, federal CUs had expanded to 58.0 Mha with the designation of more 40 units in addition to newly created 21.4 Mha of state and municipal ones (Fig. 1). Today, the network of PAs in the Amazon, including ILs and CUs under strictly protected (SP) and sustainable use (SU) categories at

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various administrative levels, encompasses 198 Mha (overlaps excluded), the equivalent of 47 % of the biome's territory or 58 % of its remaining vegetation (Fig. 2).

PAs are globally recognized as one of the most effective strategies for conserving biodiversity (Bruner, 2001; Juffe-Bignoli et al., 2014; Geldmann et al., 2019). Indeed, Amazon PAs have proven to reduce deforestation rates within their areas (Soares-Filho et al., 2010; Nolte et al., 2013; Pfaff et al., 2015; Herrera et al., 2019; Gonçalves-Souza et al., 2021), even under increasing environmental threats (Ferrante and Fearnside, 2020), constituting the centerpiece for a comprehensive conservation strategy (Soares-Filho et al., 2006; Soares-Filho et al., 2010). Therefore, the expansion and consolidation of PAs have enormous implications for the conservation of a wide range of ecosystem services that the Amazon forests provide, such as climate and water regulation, materials and food provision (Strand et al., 2018) and biodiversity (Oliveira et al., 2017). In addition, PAs are enormous reservoirs of forest carbon (Walker et al., 2020) and home to diverse traditional and indigenous peoples that make up the region's rich cultural heritage (Carvalho-Ribeiro et al., 2018).

Given their role in reducing CO_2 emissions from deforestation (Soares-Filho et al., 2010) and forest fires (Oliveira et al., 2022), the consolidation of PAs is key for Brazil to meet the goal of its Nationally Determined Contribution (NDC). Furthermore, PAs have an enormous economic importance, given that the Amazon Forest provides essential ecosystem services that sustain the productivity of Brazil's agribusiness (Leite-Filho et al., 2021). However, effectively maintaining the wide-ranging network of PAs in such a diverse regional context hinges on sufficiently large and reliable funding. To this end, Brazil established in 2002 the Amazon Protected Areas Program (ARPA) to support the consolidation of a total of 60 Mha of CUs in the Amazon, creating the world's largest initiative for conservation of tropical forests (FUNBIO, 2022).

Coordinated by the Ministry of the Environment (MMA) and managed by the Brazilian Fund for Biodiversity (FUNBIO), the ARPA Program was implemented in three distinct phases. In the first phase, 23 Mha of CUs were created between 2003 and 2009. From 2010 to 2017, the second ARPA phase supported the consolidation of 95 CUs, totaling 52.2 Mha. Since the launch of "*Arpa para Vida*" (Arpa for Life) at Rio + 20, the ARPA program is based on an approach called Project Finance for Permanence (PFP), which helps establish public policies and secure necessary funding to meet specific goals within a defined, long-term period (Cabrera et al., 2021). This approach contributes to the objective of conserving 30 % of the Planet by 2030, in view of the new post-2020 target for the biodiversity conservation agenda (IUCN, 2021). In 2014, ARPA's Transition Fund began supporting the long-term financial sustainability of its CUs through the gradual transition of funding to the Federal and State governments, including budgetary allocations and alternative funding sources. Currently, ARPA supports 120 CUs, including federal and state strictly protected and sustainable use units, totaling 62.5 Mha or the equivalent of 20 % of the remaining Amazon Forest in Brazil, hence surpassing the initial goal of the Program (Figs. 1 and 2). As such, the ARPA Program currently represents the main biodiversity conservation strategy for the Amazon Biome, as it bolsters a part of the National System of Conservation Units – SNUC (MMA, 2022), providing not only funding but also operational means for building management capacities in the supported CUs.

Although much has been said about the pivotal role of PAs in protecting biodiversity (Ribas et al., 2020), only a few studies so far have examined the effects of PA management on biological outcomes (Powlen et al., 2021). For example, Nolte and Agrawal (2012) found a weak link between PA management indicators and fire occurrence in the Amazon. Powlen et al. (2021) pointed out that Mexican PAs with higher management effectiveness had a greater effect on reducing deforestation. In turn, Oliveira et al. (2021) determined that Cerrado CUs with brigades for fire suppression reduced burned area by 12 %, on average, compared with those without brigades. CUs that also included prevention practices reduced burned areas by an additional 6 % from CUs with only fire suppression practices (Oliveira et al., 2021). And West et al. (2022) indicated that Amazon PAs with approved management plans protect forests more effectively over time.

Yet, we know little about the specific contribution of the ARPA program as the current backbone of a comprehensive strategy for conserving the world's largest tropical forest. As the program celebrates its 20th anniversary in 2022, filling this knowledge gap can contribute to enhancing future program design. This paper thus evaluates the effect of the ARPA program on reducing deforestation and associated CO_2 emissions in the Amazon between 2008 and 2020. We also provide evidence on the role of the investment mechanism through which the program supports CUs and examine some critical methodological choices of impact evaluation studies to inform our quasi-experimental design.

2. Methods

Several econometric methods exist to assess the effect of a given treatment (i.e., ARPA support) on a specific outcome (i.e., deforestation). The core evaluation challenge is to establish a counterfactual scenario that credibly reflects what would have happened in the absence of treatment. For example, if control group observations differ from treated observations in various covariates, statistical hypothesis testing

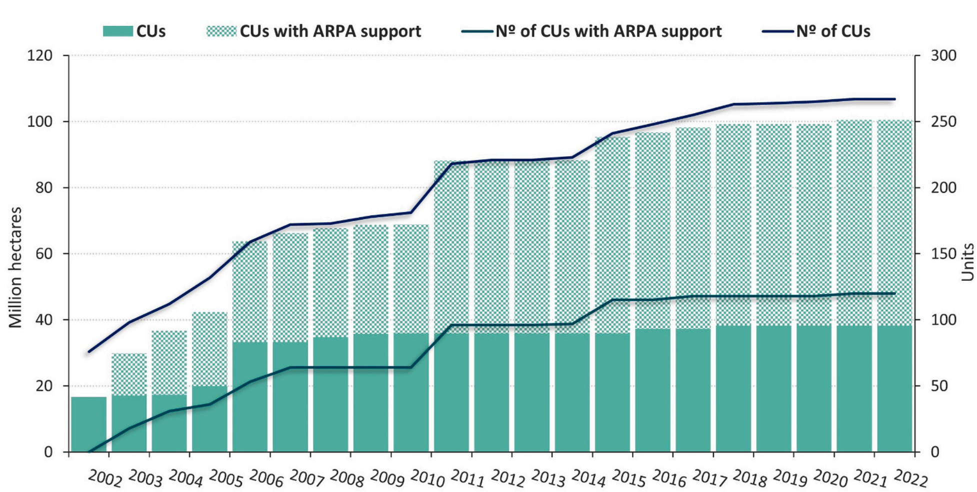

Fig. 1. Areal expansion of Conservation Units in the Amazon (columns) and number of total units and the ones supported by the ARPA Program over time (lines). Overlaps with IL not excluded.

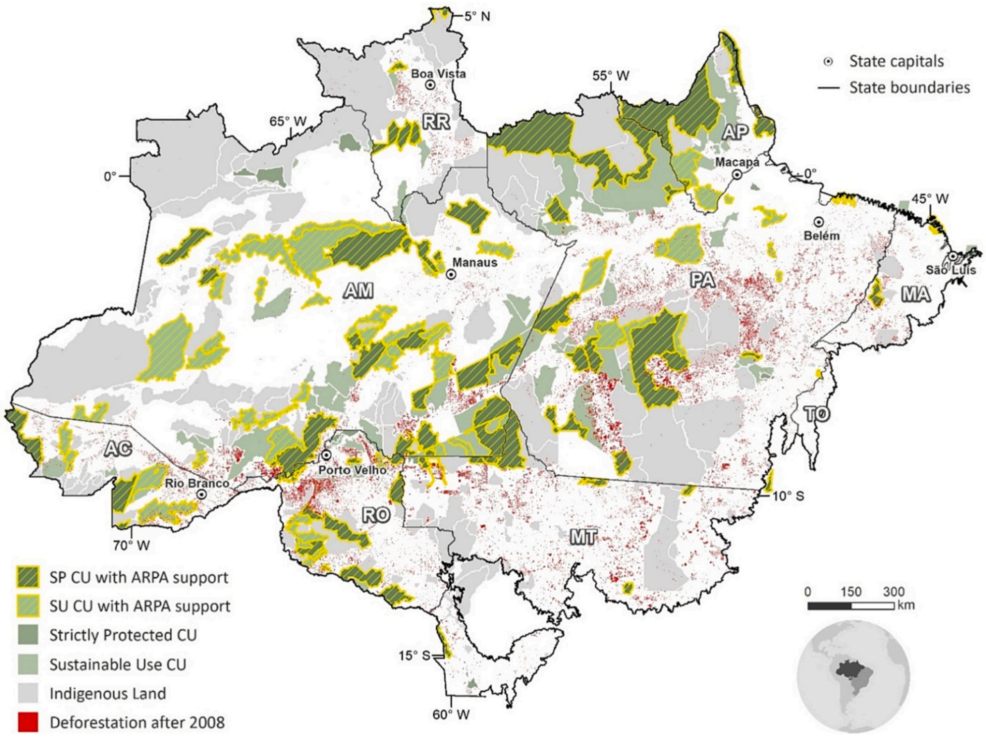

Fig. 2. Indigenous Lands and Conservation Units in the Amazon biome per category and with and without ARPA support. States: AC - Acre, AM - Amazonas, AP - Amapá, MA - Maranhão, MT - Mato Grosso, PA - Pará, RO - Rondônia, RR - Roraima, TO - Tocantins.

will be affected by selection bias (Rosenbaum, 2020). A common way to minimize selection bias in studies that cannot be conducted as controlled experiments is the application of covariate or propensity score matching (Schleicher, 2019; Börner et al., 2020). Matching involves selecting paired or "matched" samples of treated and non-treated observational units with similar observable characteristics; so as to compare "apples to apples" when subsequently applying hypothesis testing models (Pfaff et al., 2015). The use of matching is often labeled as a non-naïve approach in contrast to evaluation methods that disregard the selection process behind interventions, which in our case, may co-determine differences in deforestation inside versus outside PA boundaries (Ribas et al., 2020). However, also the results of non-naïve evaluations are sensitive to multiple methodological choices. To motivate our evaluation approach, we thus discuss alternative choices of deforestation data and covariates, methods for calculating the likelihood of deforestation, sampling strategies, and methods for hypothesis testing (see Online Supplementary Information).

2.1. The quasi-experiment

Measuring the effect of investments and actions that promote sound conservation management is not a trivial undertaking since CUs in both control and treatment groups differ greatly in terms of deforestation pressure. In addition, deforestation is not constant over time, which makes a pure before-after comparison uninformative as an evaluation approach. To test the hypothesis as to whether ARPA program had an effect on reducing deforestation, we could use matching to select a subsample of paired CUs with similar deforestation pressure, arguably the most important potential source of selection bias. However, matching tends to reduce the number of observations, which compromises the statistical power of hypothesis tests.

Instead of trying to find matched samples, an alternative consists of weighting the samples according to differences in observed confounding factors, creating, as a result, a balanced experiment for a fair comparison of treated and untreated samples (Imai et al., 2008; Andam et al., 2010; Morgan and Winship, 2014). For doing so, we applied the covariate balancing method that creates weights for the samples (CUs with and without ARPA support) using a Newton-Raphson algorithm with backtracking (Chan et al., 2016). For weighting the samples, we utilized a kernel density map (Silverman, 1986) of 2001–2002 deforestation (Fig. S5). The kernel function employed a radius of 250 km (Fig. S5). This map is thus a generalization that broadly depicts the deforestation frontiers and, as such, characterizes well the PA locations in terms of deforestation pressure. We then estimated the Average Treatment Effect on the Treated (ATT) (Holland, 1986; Johansson et al., 2016) by comparing differences in deforestation between groups of CUs with and without ARPA support. We analyzed strictly protected and sustainable use UCs separately, given that these categories differ in terms of management, with the latter allowing the sustainable use of natural resources by local or traditional peoples. To estimate the statistical significance for this test, we used the Z test (Sprinthall, 2011). For both covariate balancing and ATT tests, we employed the ATE package of the R software (Chan et al., 2016; Josey et al., 2021; Mudombi et al., 2021).

We measured historical deforestation from 2008 to 2020 within CUs using PRODES maps at 30-m spatial resolution (INPE, 2022). Since both year of designation and the beginning of ARPA support vary among units, we used the average annual deforestation calculated only for the period after CU designation and, for ARPA supported CUs, for the period after the beginning of support. Finally, because of difference in area and in the number of units between CU groups (ARPA support includes 60 SP and 60 SU CUs while the group without support contains 34 SP and 113 SU CUs), we divided the resulting deforestation annual average for a CU by its area and estimated ATT using this ratio as the dependent variable.

The effect of ARPA's investments on reducing deforestation can be better understood if the program effects are broken down into causal mechanisms. Inspired by the Mechanism Average Treatment Effect on the Treated – MATT (Ferraro and Hanauer, 2014), we developed a test that isolates the effect of financial investments on the treatment using the difference between the estimated means of two ATT tests– i.e., a conventional one that only controls for the confounding factors, and another one that also controls for the causal mechanism we want to test (Ferraro and Hanauer, 2014). To carry out this test, we accounted for the overall funding by ARPA in each supported CU in addition to budgetary costs of Amazon CUs (Silva et al., 2021). To convert the effects of the ARPA investments into percentage of reduced deforestation, we used the percentage difference between the estimated mean coefficients from the ATT tests for CUs with and without ARPA support.

2.2. Effect of PA designation and ARPA support on reducing deforestation and associated CO_2 emissions

The above tests assess the differential effect of ARPA by comparing groups of CUs with and without support. To estimate the total effect of CUs, or more broadly PA designation, on reducing deforestation, we employed the Adjusted Odds Ratio method (Soares-Filho et al., 2010). This technique is an adaptation of the Bayesian method of odds ratio to take into account the likelihood of deforestation cell-by-cell (i.e., in spatially-explicit way) so as to balance differences in the chances of deforestation across PAs boundaries. The odds ratio is defined as the probability of an event (deforestation) occurring over the probability of it not occurring. A PA is considered effective in inhibiting deforestation if its odds ratio is <1, and this effect increases in magnitude as the value approaches zero. The advantages of the method are various. First, it is applied in a continuous way (wall-to-wall), that is, considering all cells (pixels) of the map within the comparison zones. It does not depend on the autocorrelation of deforestation, and the matching is carried out also in a spatially continuous way by using the values of a deforestation probability map as the propensity score for balancing the occurrence of cells of deforestation (transition) and of forest permanence within comparison zones. Accordingly, we can also calculate counterfactual deforestation. This is derived using the odds ratios calculated for the internal and external comparison buffers for each CU, so that:

$$D_{estimated} = \frac{D_{observed} * Odd(D|Bout) / (1 + Odd(D|Bout))}{Odd(D|Bin) / (1 + Odd(D|Bin))} \quad (1)$$

where $D_{estimated}$ refers to the estimated deforestation in the case there was not CU designation, $D_{observed}$ is the historical deforestation measured within the internal buffer (Bin) and $Odd(D|Bout)$ and $Odd(D|Bin)$ are the odds ratios of deforestation (D) calculated for the PA internal (Bin) and external ($Bout$) buffers of comparison, respectively (see Eqs. (S1) to (S10) for demonstration and Fig. S12). We then subtracted from the estimated deforestation in the absence of a PA the observed one for each year between 2008 and 2020 to arrive at the amount of reduced deforestation for each category of PA.

Because most PAs were already designated before 2008 (the initial year of our time-series), they ended up influencing the spatial distribution of deforestation, even if not included as a covariate (supplementary methods). Hence for calculating the Adjusted Odds Ratios, we applied the first principal component to determine the deforestation favorability of a given location based solely on the degree of access to main roads, urban centers, navigable rivers and elevation, given that deforestation in the Amazon is mostly driven by accessibility (Soares-Filho et al., 2006) (Fig. S6). Adjacent internal and external 10, 20 and 30 km buffer zones were derived specifically for each CU and overlaid with maps of annual deforestation between 2008 and 2020 from the PRODES project (INPE, 2022). The calculation of the Adjusted Odds Ratio was only considered after the year of designation for all CUs, and specifically for the case of ARPA, after the beginning of support. Statistically non-significant odds ratio values were also discarded from the analysis. We also compared the odds ratios estimation using samples for matching, with values for adjusted and unadjusted Odds Ratio calculated using maps of 30 m and 500 m spatial resolution (Figs. S9–S11). We found that the most conservative values are from buffer zones of 10 and 20 km with deforestation calculated using the 30-m spatial resolution map, so we averaged the results from these two buffer zones derived by using the full spatial resolution of 30 m and used the differences as the uncertainty bounds.

Next, we calculated CO_2 emissions by superimposing a biomass map (MCTI, 2021) on deforestation between 2008 and 2020 that occurred within PAs. We applied an emission factor of 0.85 (Houghton et al., 2000) and calculated reduced emissions by multiplying the emissions from deforestation within PAs by a ratio between estimated reduced deforestation and observed deforestation, so that:

$$Reduced\_deforestation = Estimated\_deforestation - Observed\_deforestation \quad (2)$$

$$Reduced\ Emissions = Observed\ Emissions * Reduced\_deforestation / Observed\_deforestation \quad (3)$$

All models were run using Dinamica EGO 7* freeware (Soares-Filho et al., 2013). Probability maps were calculated using the weights of Evidence operators and the Biodinamica sub library (Oliveira et al., 2019) for the other methods. R code for ATT and MATT was embedded into EGO operators that are freely available on Dinamica EGO online store.

3. Results

The ATT test indicated that both groups of CUS (strictly protected and sustainable use) with ARPA support have lower deforestation rates ($p < 0.05$) than those of control groups (Tables S1, S2). By calculating the percentage difference between ATT estimates, we deduced that ARPA support accounts for 9 % less deforestation in strictly protected (SP) CUs and 39 % in sustainable use (SU) CUs in relation to non-supported CUs of the same categories, respectively. The effects of ARPA investment on causing lower deforestation rates in both SP and SU CUs were statistically significant ($p < 0.001$) in the MATT tests. For SP CUS, financial investments accounted for 30 % less deforestation. In turn, for SU CUs, financial investments accounted for 49 % (Table S3).

It was not possible to find statistically significant differences between the average values of Adjusted Odds Ratio calculated from 2008 to 2020 for CUs with and without ARPA support. Nonetheless, both categories of ARPA CUs showed a declining trend in the annual average values of Adjusted Odds Ratio, possibly indicating that their inhibiting effect on deforestation is increasing over time (Figs. S7, S8).

By using the difference between observed and expected deforestation from the Adjusted Odds Ratio analysis, we estimated that Amazon PAs, including ILs and CUs of all categories have reduced deforestation between 2008 and 2020 by 21 %. This overall reduction amounts to 2.0 ± 0.3 Mha and is equivalent to 622 ± 81 Mtons of CO_2 emissions. Of this total, reductions by ILs accounts for 1.34 ± 0.3 Mha and 396 ± 64 Mtons of CO_2. In turn, CUs as a whole have contributed to reducing deforestation by 623 ± 54 thousand ha, which corresponds to 226 ± 17 Mtons of CO_2 emissions. In turn, the share of reduced deforestation by CUs with ARPA support totals 264 ± 25 thousand ha (Fig. 3), the equivalent of 104 ± 10 million tons of reduced CO_2 emissions CUs that most reduced deforestation are located along the arc of deforestation, the most active deforestation frontier spanning from southeastern Acre, Rondônia, southern Amazonas state, to the center of Pará state and along the Transamazon and Cuiabá-Santarém highways. In this respect, it is worth

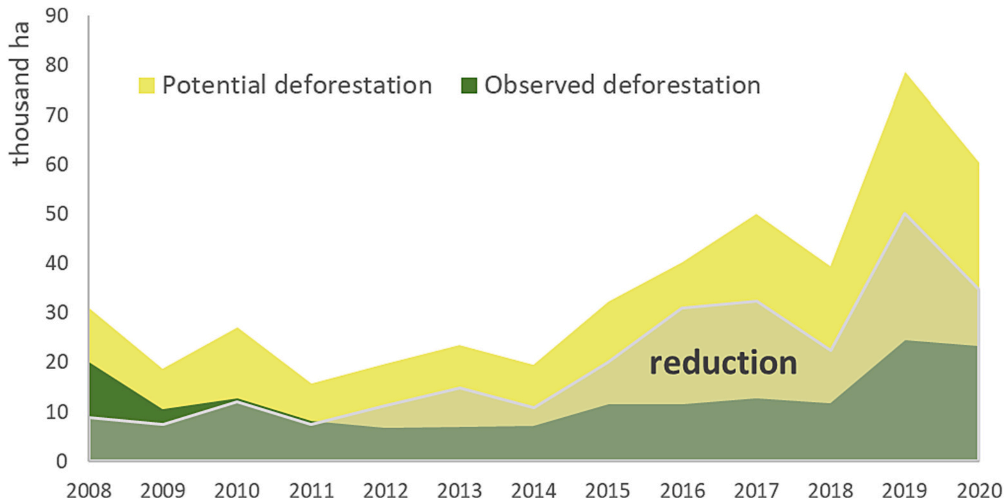

Fig. 3. Annual deforestation observed in CUs with ARPA support compared with the estimated potential one in case of non-protection together with associated reduction.

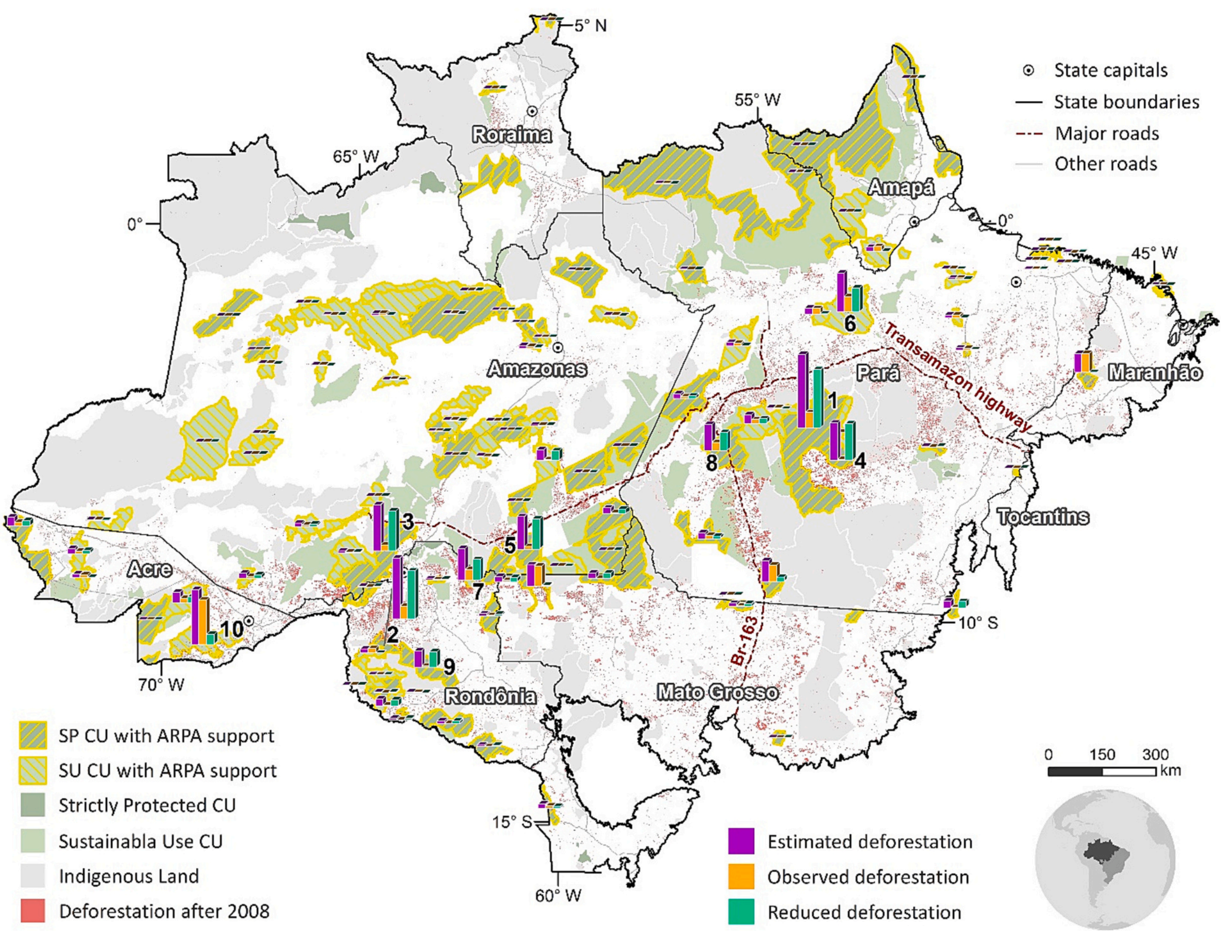

Fig. 4. Top ten ARPA CUs with largest deforestation reductions. 1 - Ecological Station of Terra do Meio (SP), 2 - State Park of Guajará-Mirim (SP), 3 - National Park of Mapinguari (SP), 4 - National Park of Serra do Pardo (SP), 5 - National Park of Campos Amazônicos (SP), 6 - Extractivist Reserve Verde Para Sempre (SU), 7 - Extractivist Reserve Rio Preto-Jacundá (SU), 8 - National Park of Jamanxim (SP), 9 - National Park of Pacaás Novos (SP), 10 - Extractivist Reserve Chico Mendes (SU).

mentioning the crucial role of the ecological station of Terra do Meio and the National Park of Serra do Pardo in blocking deforestation in a region of intense land conflict. (Fig. 4).

Despite reductions by PAs, external factors spurred deforestation after 2012 in the Amazon. Above all, from 2018 onwards, there has been an increase in deforestation even in the CUs supported by ARPA due to the dismantling of environmental law enforcement (Carvalho et al., 2019; Rajão et al., 2020; Vale et al., 2021). Yet this increase observed in ARPA's CUs represents only 39 % of what would be expected if there were no support (Fig. 3).

4. Discussion and conclusions

There is a large body of literature on the effectiveness of PAs in reducing deforestation (Ribas et al., 2020). A common concern to these studies is whether this reduction simply displaced deforestation elsewhere, what is known as leakage. Although the assessment of leakage was not part of this study, earlier work suggests that the large expansion of PAs in the Amazon during the early 2000s took place without provoking leakage (Soares-Filho et al., 2010).

Matching has become the state-of-art method for compensating for bias arising from locating PA in remote areas (Vieira et al., 2019) with relatively low deforestation pressure. However, matching studies based on samples as opposed to wall-to-wall data are vulnerable to sampling bias. Because deforestation within PAs is usually much lower than that of their outside regions (Soares-Filho et al., 2010), sampling tends to miss part of those deforestation occurrences, hence inflating the hypothesis testing in favor of PAs. Here, we showed that sampling introduces a more pronounced bias than that of comparing non-matched samples if comparison zones are constrained to the PA vicinity (Figs. S9–S11). In this respect, sampling also needs larger areas for finding matching units, thus tending to draw cells from more distant areas from the PAs in question, and hence possibly from a different context (Negret et al., 2020). Another important issue, often overlooked, refers to the robustness of the hypothesis testing, which must account for spatial autocorrelation in deforestation. Moreover, it is important to examine the method selected to integrate the influence of covariates to estimate the likelihood of deforestation, either for matching or weighting the comparison units, so as to attain a covariate balance between treated and non-treated observations (Garrido et al., 2014). In essence, the advantage of the approach applied here lies in using wall-to-wall data for ATT and MATT tests and the Adjusted Odds Ratios (Soares-Filho et al., 2010).

The ATT tests indicated that both groups of CUs (strictly protected and sustainable use) with ARPA support have lower deforestation rates than those of control groups and that ARPA investments played a role in causing this difference. Amazon PAs, including ILs and CUs of all categories, have reduced by 21 % deforestation between 2008 and 2020. This overall reduction amounts to 2.0 $\pm$ 0.3 Mha and is equivalent to 622 $\pm$ 81 Mtons of CO_2 emissions. Of this total, ILs avoided 1.34 $\pm$ 0.3 Mha and 396 $\pm$ 64 Mtons of CO_2 emissions. These results highlight the role of indigenous people as the guardians of the Amazon Forest. In turn, the share of reduced deforestation by CUs with ARPA support totals 264 $\pm$ 25 thousand ha (Fig. 3), the equivalent of 104 $\pm$ 10 Mtons of reduced CO_2 emissions. Considering the total of BRL 409 million executed by the Program until the end of 2020 (personal communication) (Fig. 5), these reductions equate to a cost of around BRL 4 per ton of CO_2 (i.e., less than U$ 1) and are equivalent to the total carbon emissions by American domestic aviation in 2020 (OECD, 2022), which responds for about 17 % of the global domestic aviation sector (Graver et al., 2019).

The demonstrated effectiveness of the ARPA program in reducing deforestation and associated CO_2 emissions can be attributed to its funding profile that focuses on structural investments, which are usually absent in public budgets (Silva et al., 2021), making ARPA support even more relevant. In such a manner, ARPA ensures continuous and long-term funding through cumulative and permanent investment. As pointed out by the MATT test, this is of particular relevance for programs that support the traditional livelihood of forest peoples living inside SU CUs, providing, as a result, alternative income from collecting non-timber forest products, such as açaí, rubber and Brazil nuts, along with recreational and community-based tourism (Carvalho-Ribeiro et al., 2018; Bachi and Carvalho-Ribeiro, 2022). Additionally, ARPA governance mechanisms and management instruments, which have been constantly developed and improved over the last two decades, have also contributed to the Program's success. For doing so, the Program developed several instruments and mechanisms for facilitating the financial management and execution of resources (MMA, 2000), so that managers can effectively plan ways to attain their short-term and long-term goals and hence perform better their actions according to the real needs and without pressure of immediacy. In this respect, the map of observed versus reduced deforestation for each CU (Fig. 4) could be a guide to prioritize investments to those CUs under more imminent threat of deforestation.

Moreover, the challenges posed by the Amazonian reality resulted in the need for constant improvement of the adopted mechanisms and the development of new approaches, making ARPA an innovative program in its operationalization (FUNBIO, 2017). Throughout its execution, ARPA promotes the implementation of various training initiatives focusing on different aspects of management, many of which are later on incorporated into institutional strategies. This resulted in a culture of planning, execution and monitoring of goals – efforts that are important for strengthening the CU management, contributing to a continuous process of improving planning and execution of ARPA resources. Finally, ARPA has a governance structure that includes donors, state and federal governments, as well as the civil society so as to minimize the impact of political-economic change. Thus, all these factors contribute to and explain the performance of the CUs supported by the program in reducing deforestation.

In short, in supporting this large network of Amazon CUs, ARPA

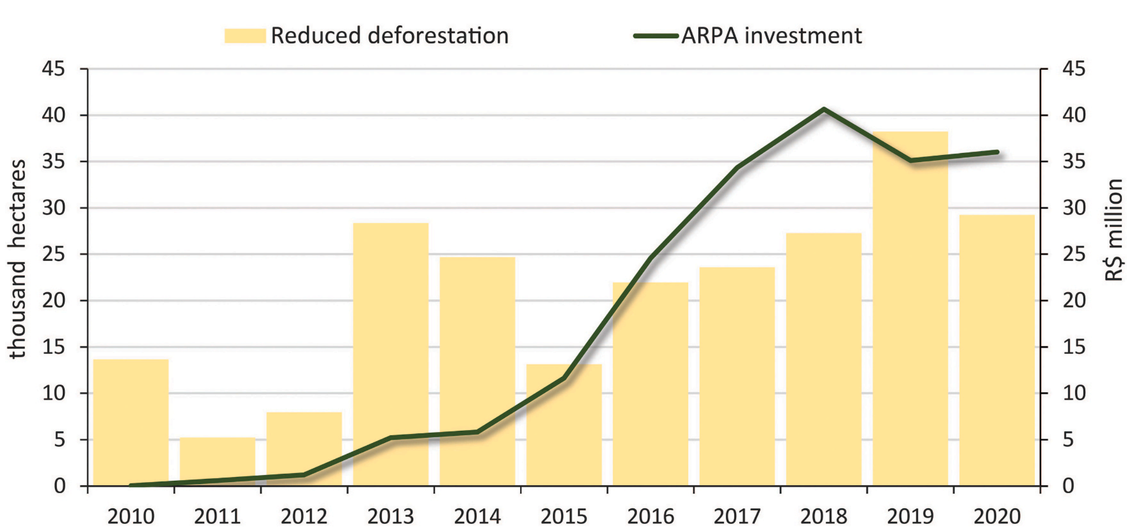

Fig. 5. Direct investment by ARPA in supported CUs compared with their annual deforestation reductions.

plays a pivotal role in conserving the Amazon forests along with their invaluable ecosystem services that have vital importance for the country and the world. For this reason, ARPA has become a milestone for area-based conservation strategies and so considered as an example and inspiration for the establishment of other PFPs, such as the Herencia Colombia, Bhutan for Life and Heritage of Peru (Cabrera et al., 2021).

Although the results of this study indicated that additional finance resources, like those provided by ARPA, are fundamental for the successful implementation of PAs, this support needs to be accompanied by effective public policies aimed at curbing illegal deforestation, of chief importance among them is the efficient environmental law enforcement including appropriate sanctions for offenders (Soares-Filho and Rajão, 2018). To this end, Brazil needs to put its successful public conservation policies from the past back on track. To do so, it is important to develop concerted actions involving all stakeholders from local practitioners to national decision-makers as well as support by the international community. Initiatives must also be built upon a sound science and policy interface (Barlow et al., 2018) so as to identify and replicate successful conservation initiatives, like the ARPA program. These actions are needed promptly to avert a tipping-point of the Amazon Forest, as the synergy between more frequent droughts and intense forest fires driven by climate change and continued deforestation is transforming the forest from a carbon sink into a net source (Gatti et al., 2021) with major implications for biodiversity, climate change and the societies that depend on it.

To revert current trends, Brazil could designate new CUs on public lands, which still total about 60 Mha (Soares-Filho and Rajão, 2018) and fend off political pressure to downsize or degazette PAs (Ferrante and Fearnside, 2020; Dutra and Fearnside, 2022). Under a scenario of weak environmental governance (Soares-Filho et al., 2006; Rochedo et al., 2018), PAs would ultimately become the last stronghold of Amazon conservation. However, protecting the Amazon only with PAs does not suffice, as today's illegally grabbed land tends to be legalized over time. As Brazil and its international partners return to investing in forest conservation, it is important to monitor and evaluate the impact of these investments. Our study thus contributes to this objective by providing evidence on what works to effectively protect forests and the livelihoods of indigenous and traditional populations that depend on it.

CRediT authorship contribution statement

Britaldo Silveira Soares Filho: Conceptualization, Methodology, Funding acquisition, Investigation, Formal analysis, Writing – review & editing. **Ubirajara Oliveira:** Methodology, Investigation, Formal analysis, Writing – review & editing. **Mariana Napolitano Ferreira:** Writing – review & editing. **Fernanda Figueiredo Constant Marques:** Writing – review & editing. **Amanda Ribeiro de Oliveira:** Formal analysis, Writing – review & editing. **Fábio Ribeiro Silva:** Writing – review & editing. **Jan Börner:** Conceptualization, Funding acquisition, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.biocon.2023.109928.

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