Collaborative management partnerships strongly decreased deforestation in the most at-risk protected areas in Africa since 2000

Sébastien Desbureaux* [1], Ibrahim Kabore[2,3], Giulia Vaglietti[4,5,3], Mujon Baghai[6], Peter Lindsey[7], Ashley Robson[8], Philippe Delacote[5,3], and Antoine Leblois[1,3]

[1]CEE-M (Univ Montpellier, CNRS, INRAE, Institut Agro), France

[2]EDEHN (Université Le Havre Normandie), France

[3]Climate Economics Chair, France

[4]Fondazione Eni Enrico Mattei, Milan, Italy

[5]BETA (Université de Lorraine, AgroParisTech, INRAE), France

[6]Independent Consultant, United States

[7]Lion Recovery Fund, Wildlife Conservation Network, Zimbabwe

[8]Institute for Communities and Wildlife in Africa, Department of Biological Science, University of Cape Town, Cape Town, South Africa

Published version: https://www.pnas.org/doi/10.1073/pnas.2411348121

*Corresponding author: sebastien.desbureaux@inrae.fr

We thank the staff from several wildlife agencies and PAs who generously provided information to construct the database and assemble the shapefiles of CMPs, including Maryn van der Laarse for Chinko, Marc Stalmans for Gorongosa and Ollier Duranton Andrianambinina for Madagascar National Parks. We thank Julia Girard and participants to the "Forest & People: from skyview to local dynamics" workshop, four reviewers and the and the Associate Editor for their useful comments and suggestions. This work was supported by the French Agence Nationale de la Recherche through the Chaire de Professeur Junior-POLCB. The BETA contributes to the Labex ARBRE ANR-11-LABX-0002-01. This research is part of the Agriculture and Forestry research program by the Climate Economics Chair. Contributions: SD,PD and AL conceptualized the study. IK, SD, MB and PL constructed the database. SD,IK and GV analysed the data. SD,IK, PD and AL wrote the manuscript. GV, MB, PL and AF provided extensive comments on the analysis and the manuscript. PD et AL are co-last authors. Standard disclaimers apply.

Abstract Collaborative Management Partnerships (CMPs) between state wildlife authorities and non-profit conservation organizations to manage protected areas (PAs) have been used increasingly across Sub-Saharan Africa since the 2000s. They aim to attract funding, build capacity, and increase the environmental effectiveness of PAs. Our study documents the rise of CMPs, examines their current extent and measures their effectiveness in protecting habitats. We combine statistical matching and Before-After-Control-Intervention regressions to quantify the impact of CMPs, using tree cover loss as a proxy. We identify 127 CMPs located in 16 countries. CMPs are more often located in remote PAs, with habitats that are least threatened by human activity. Our results indicate that, on average, each year in a CMP results in an annual decrease in tree cover loss of about 55% compared to PAs without CMPs. Where initial anthropogenic pressure was low, we measure no effect. Where it was high, we see a 66% decrease in tree cover loss. This highly heterogeneous effect illustrates the importance of moving beyond average effect size when assessing conservation interventions, as well as the need for policy makers to invest public funds to protect the areas the most at risk.

Significance Statement Protected areas (PAs) are vital for nature conservation but in Sub-Saharan Africa, they often fall short due to funding, management, and institutional challenges. Since the early 2000s, Collaborative Management Partnerships (CMPs) have emerged to tackle these issues. We provide the most complete and recent census of CMPs, document their location and provide a robust statistical analysis of their causal effect on tree cover loss over two decades. As of the end of 2023, our work identified 127 CMPs across 16 countries. However, CMPs are more often created in remote areas that faced low anthropogenic pressures initially. On average, our counterfactual analysis reveals that tree cover loss was 55% lower between 2001 and 2023 in CMP-managed PAs compared to similar PAs without CMPs. While there was no effect of CMPs in remote areas, the effect was largest in high pressure environments.

1 Introduction

Protected areas (PAs) are central policy instruments to conserve natural habitats, biodiversity and carbon sinks [1–3]. However, their effectiveness at protecting ecosystems is highly variable [4–6], and challenged by the structural lack of funding [7, 8], limited management capacities [9], weak institutions and governance [10, 11].[1] In Sub-Saharan Africa, the home of 13% of global species richness and about 20% of global forest cover, the environmental performance of PAs has been limited [18–20].

Collaborative management partnerships (CMPs) between government bodies and non-profit organizations have emerged as a solution to increase funding and management capacities of existing PAs [21–24]. Three broad categories of CMPs can be distinguished along a spectrum of increased sharing and delegation of authority from governments to non-governmental organizations (NGOs): financial-technical support, co-management, and delegated management Baghai *et al.* [25]. In financial-technical arrangements (FT), NGOs provide financial support and technical advice without having a formal long-term role in governance or management decision making. FT arrangements have predominated across Sub-Saharan Africa from the 1960s to the 2000s Struhsaker *et al.* [26] Co-management and delegated management arrangements, which started in the late 1990s, grew significantly since the mid-2000s. They include a sharing of management and, often, governance of the PA between the NGO and the Government Fitzgerald [24]. The median funding for PAs with co-management is 2.6 times higher than baseline State budgets. This number grows to 14.6 for delegated management arrangements [23]. However, though CMPs appear to have positively contributed to biodiversity conservation outcomes [27], there is a dearth of hard data to demonstrate their additionality [28–30].

Here, we provide a quantitative evaluation of whether CMPs increase the effectiveness of PAs at conserving habitats, as proxied by satellite-measured tree cover loss [31], across all of Sub-Saharan Africa between 2001 and 2023. We specifically focus on the types of arrangement that delve the furthest in terms of cooperation and delegation, and that are growing the fastest: co-management and delegated CMPs.

Building on previous efforts Baghai *et al.* [21] and Fitzgerald [24], we first map all existing CMPs across Sub-Saharan Africa. Our work notably includes Madagascar for the first time in this literature - a biodiversity hotspot that is home to 50% of the co-management and delegated

[1] Other factors influencing the effectiveness of PAs include the level of economic development in nearby villages [12], their locations [13], the type of PAs [14], spillovers [15], the occurrence of crisis such as Covid-19 [16] and the presence or lack of human settlement [17]

CMPs on the continent. Second, we use counterfactual statistical models to quantify the causal effect of establishing CMPs on the protection of natural habitats in terrestrial PAs. Because CMPs were conceived to primarily reinforce the management of existing PAs, and not to create new PAs, our empirical strategy compares the evolution of tree cover loss between PAs with and without CMPs. These PAs without CMPs, which we include in the control group, may receive some FT support from donors and NGOs. However, their management remains fully under the responsibility of Governments.

Understanding whether CMPs are effective at better protecting natural habitats - a necessary condition to halt the collapse of biodiversity [32] - is a central question to orient conservation planning in low-income countries, including across the African continent [33]. As governments, NGOs, and donors are considering renewing existing agreements and signing new ones, there is a growing necessity to understand the conservation benefits of these arrangements [27]. Beyond the nature-conservation sphere, our results contribute to understanding the effect of Public-Private Partnerships more broadly, which is especially relevant given their proliferation since the 1980s in low- and middle-income countries Fabre & Straub [34].

2 Results

2.1 Collaborative Management Partnerships across Africa

We first document the evolution of the spatial distribution of co-management and delegation agreements, from their beginning to the end of 2023 (Figure 1A).

The first co-management arrangement documented in our database, Kasanka National Park (NP) in Zambia, was established in 1990 between the Department of National Parks and Wildlife Service and a British-registered NGO, Kasanka Trust. The early 2000s saw further growth of CMPs with the establishment of agreements in Mozambique (Cabo de São Sebastião in 2000), Tanzania (Grumeti and Ikogorongo Game Reserves in 2002), Malawi (Mejete Wildlife Reserve in 2003), and the Democratic Republic of the Congo (the Garamba landscape in 2005, comprising a NP and three hunting reserves). The number of CMPs continued to increase steadily, reaching 25 PAs with CMPs in 2014.

In 2015, 64 new CMPs were established. Sixty-three of them were located in Madagascar where CMPs facilitated the establishment of new PAs. This contrasts with the rest of the continent where CMPs contributed to the reinforcement of existing PAs.

By of the end of 2023, 127 PAs located in 16 Sub-Saharan African countries were under a

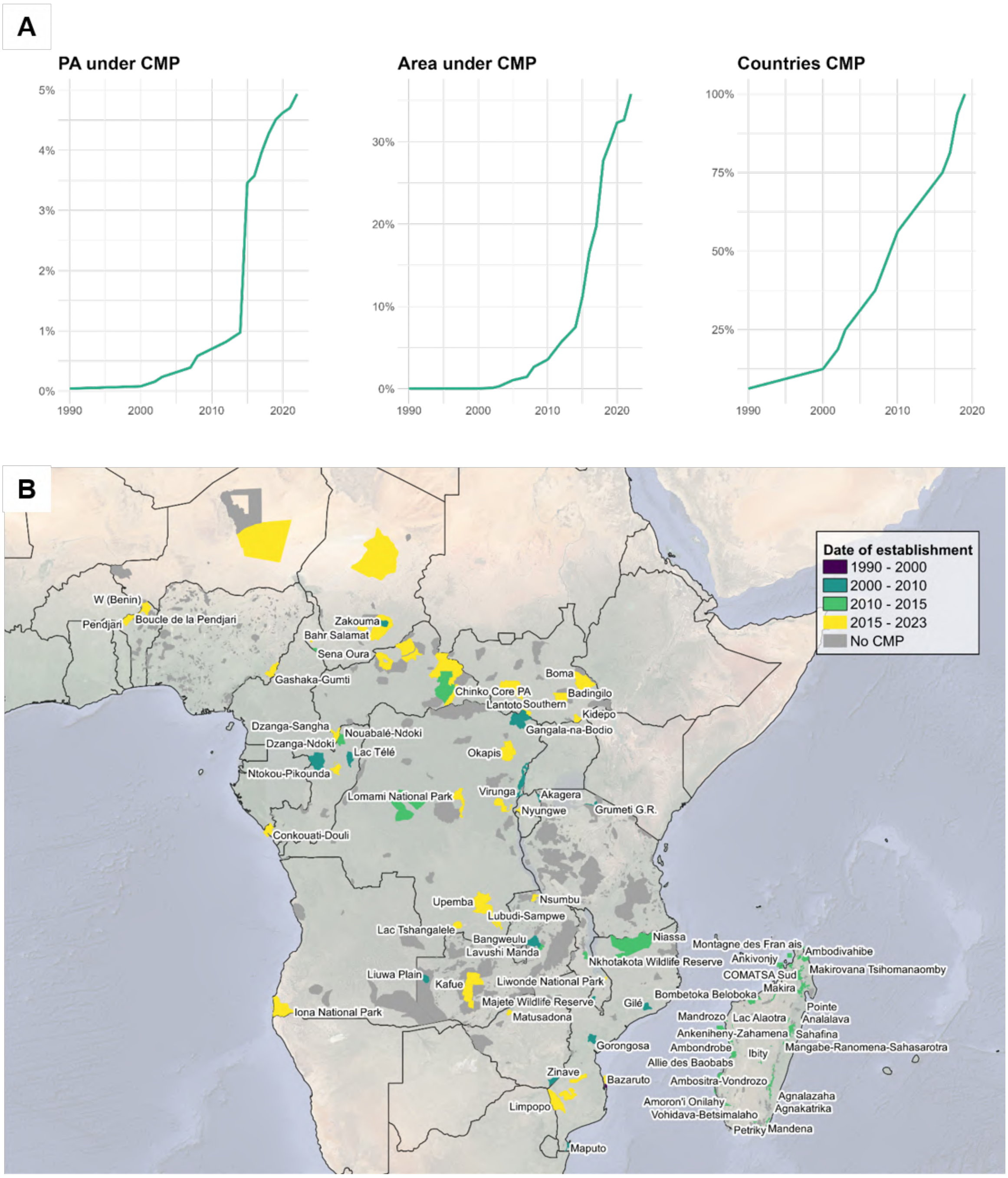

Figure 1: Collaborative Management Partnerships (CMP) for Protected Areas (PA) across time and space. (A): Temporal evolution of PAs with CMPs. Left: Share of PAs with CMP among all the PAs from the same 16 countries that have a similar designation. Center: Percentage of area of PAs with CMPs compared to the area of all PAs in the same 16 countries that have a similar designation. Right: Share of countries with PAs with CMPs among the 16 countries that have CMPs by the end of 2023. (B): Spatial distribution of current PAs with CMPs and possible control PAs. PAs with CMPs in Sub-Saharan Africa are color coded in yellow to purple based on the year of establishment of the CMPs. PAs without CMPs, that have the same designation of the ones with CMPs and located in the same 16 countries, are represented in gray.

co-management or delegated CMP model (Figure 1B and Table S1). Out of these, 5 CMPs were in Marine PAs and 122 in terrestrial PAs. The 122 terrestrial PAs with CMPs represent 5% of all similarly-designated PAs within these 16 countries and 35% of the area under protection. This surface represents 979,387 km^2.

All but one PA with a CMP were initially managed by national authorities. Most were designated as NPs of IUCN category I or II. Only one of the PAs with CMP is registered as a community reserve (Lac Télé in the Republic of Congo).

Forty-eight partner organizations participate in co- and delegated management agreements. Forty-six of them are not-for-profit organizations. Two are for-profit organizations and both operate in Madagascar.

Of the 48 partner organizations, 27 international NGOs manage 96 CMPs, and 21 national organizations manage 31 CMPs. The African Parks Network, for which CMPs are their *raison d'être*, has the largest portfolio with 26 CMPs. Other international conservation NGOs, such as the Wildlife Conservation Society (19 CMPs), not only manage PAs through CMPs in these 16 countries, but also provide FT support and manage integrated conservation and development programs in other countries. CMPs run by national organizations are mostly found in Madagascar.

2.2 Differences in location between PAs with and without Collaborative Management Agreements

First, we compare countries that have CMPs with those who do not. Co-management and delegated CMPs are found in 16 out of 48 countries in Sub-Saharan Africa: Angola (1 CMP), Benin (3), the Central African Republic (6), the Democratic Republic of Congo (11), the Republic of Congo (5), Madagascar (63), Mozambique (9), Malawi (4), Niger (1), Nigeria (1), Rwanda (2), South Sudan (5), Chad (6), Tanzania (2), Zambia (6) and Zimbabwe (2). These CMPs are predominantly located in central Africa and parts of southern and east Africa. However, few CMPs are established in West Africa and several countries that are prominent for biodiversity conservation don't have any co-management or delegated CMPs, including some where FT support has long been implemented. This applies to Cameroon, Kenya, South Africa, and to a lesser extent Tanzania and Namibia which only host three CMPs in total.

In Figure S1, we show that CMPs are located in countries with a lower GDP per capita than countries without CMPs (\$1,481 vs \$3,789, $p - value = 0.007$). Furthermore, CMPs are located in countries with a lower basic state function score (Figure S1) than countries without

CMPs - a variable that measures the ability of states to keep a monopoly on the use of force and to provide basic public services [35]. This difference is, however, not statistically significant (5.5 vs 6.25 on a 1 to 10 scale (most functioning), $p - value = 0.25$).

Second, we focus on the 16 countries that have CMPs and explore the differences between PAs with and without CMPs. Within these countries, we identify 2,572 PAs without CMPs that share a common designation status with the PAs with CMPs. PAs with CMPs are, on average, significantly larger than those without CMPs (5,539 km^2 vs 515 km^2, $p - value < 0.001$, Table S2). This difference is partly explained by the presence of some particularly big PAs among those with CMPs (e.g., Termit et Tin-Toumma in Niger and Ouadi Rimé-Ouadi Achim in Chad have an area of over 90,000 km^2 and 80,000 km^2 respectively).

Still within these 16 countries, we divide PAs into a regular grid of 0.05 x 0.05 degrees (approximately 5 x 5 km, Methods 4) and compare the ecological characteristics and the initial anthropogenic pressures between gridcells from PAs with CMPs and gridcells from PAs without CMPs (gray triangles in Figure 2 and Tables S3). Gridcells from PAs with CMPs are more likely to be tropical and subtropical moist broadleaf forests, while grasslands and savannas are underrepresented in CMPs. Regarding anthropogenic pressures, gridcells belonging to PAs with CMPs are on average significantly further away from cities and villages and have less initial population than those without CMPs. This suggests that PAs with CMPs are located in areas that face, on average, less anthropogenic pressure than other PAs. This is coherent with the fact that in 2000, gridcells from PAs with CMPs had a larger forest cover and less croplands than those without CMPs. These results suggest that the selection of CMPs is subject to location bias.

2.3 Impact of Collaborative Management Agreements on tree cover loss

Finally, we use our gridcell database to analyze whether the establishment of CMPs decreased annual tree cover loss measured through satellite images between 2001 and 2023 [31].

We proceed in two steps to quantify possibly causal impacts of CMPs. First, we correct the location bias using statistical matching. We find an appropriate match for 62% of gridcells with CMPs (Table S4). Nevertheless, no match could be found for gridcells from 15 PAs with CMPs (Figure S2). After matching, no difference in observable characteristics remains between gridcells in PAs with and without CMPs based on commonly used thresholds of similarities [36] (Figure 2, green circles and Table S4). Second, we estimate a Before-After-Control-Intervention event-study model, allowing for staggered entry in the treatment, heterogeneous treatment

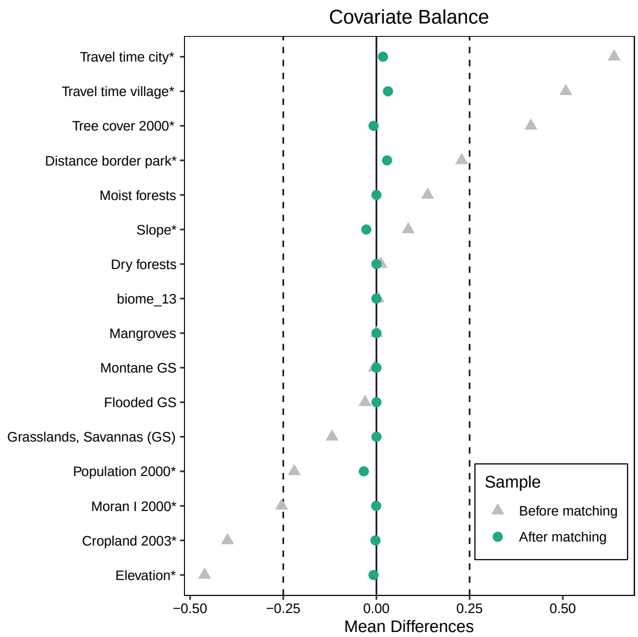

Figure 2: Differences in observable characteristics between gridcells from PAs with CMPs and gridcells from PAs without CMPs. In this figure, data comes from the final database used for the impact evaluation. Starting from the original database, we dropped cells that had no pixel of initial tree cover (using a 25% tree cover threshold), PAs with an area smaller than 25 km^2 (corresponding to the area of a gridcell in the impact evaluation), and control PAs that had a different designation status from PAs with CMPs. The final database contains 94 PAs with CMP and 991 PAs without CMPs - corresponding to 19,707 gridcells before matching. After matching, 7,224 gridcells were kept.

effects, and country and biome specific time dynamics [37]. Our main specification uses the percentage of tree cover loss as a dependent variable. We construct it by dividing, for each year t between 2001 and 2023, the number of hectares of tree cover loss during year t by the number of hectares of tree cover at the beginning of year t. Baseline results are displayed in Panel A of Figure 3, where we compare the difference in tree cover loss between treated and control gridcells, both before and after the creation of CMPs.

In the ten years before the establishment of CMPs, the difference in tree cover loss is small. However, in four of the five years before the establishment of a CMP, tree cover loss is already between 3 and 11 percentage points lower in gridcells that will become CMPs than in similar gridcells that will not become CMPs.

After the establishment of CMPs, tree cover loss in PAs with CMPs becomes lower than in matched gridcells from PAs without CMPs. The effect is gradual and increases with the number of years spent under a CMP. In the first four years of implementation, the magnitude of the difference in tree cover loss between gridcells with and without CMPs is similar to the one that existed in the last few years prior the establishment of the CMP. After five years, this difference in tree cover loss increases. Eventually, the point estimates become less accurate as sample size decreases.

The size of the impact is notable. The aggregated average treatment effect (ATE) is - 0.14 percentage points each year In comparison, the average tree cover loss of the matched control observations is -0.25 percentage points. Hence, each year spent under CMPs decreased tree cover loss by 56% (Figure 3).

2.4 Heterogeneity

We explore how the effect of CMPs varies across different contexts. The previous section highlighted the existence of a strong location bias of CMPs towards areas with an initial lower anthropogenic pressure. We construct an index of anthropogenic pressures for each gridcell using the covariates from the matching process. We then compare the effect of CMPs on tree cover loss for gridcells below and above the median value of our of anthropogenic pressure index.

Where anthropogenic pressure is low, so is tree cover loss. The average yearly tree cover loss rate in control gridcells is 0.10 percentage points in low anthropogenic pressure areas. This is over 50% lower than in all control PAs (0.25 percentage points). Consequently, the additional effect of CMPs is null (Panel B in Figure 3 and Table S6).

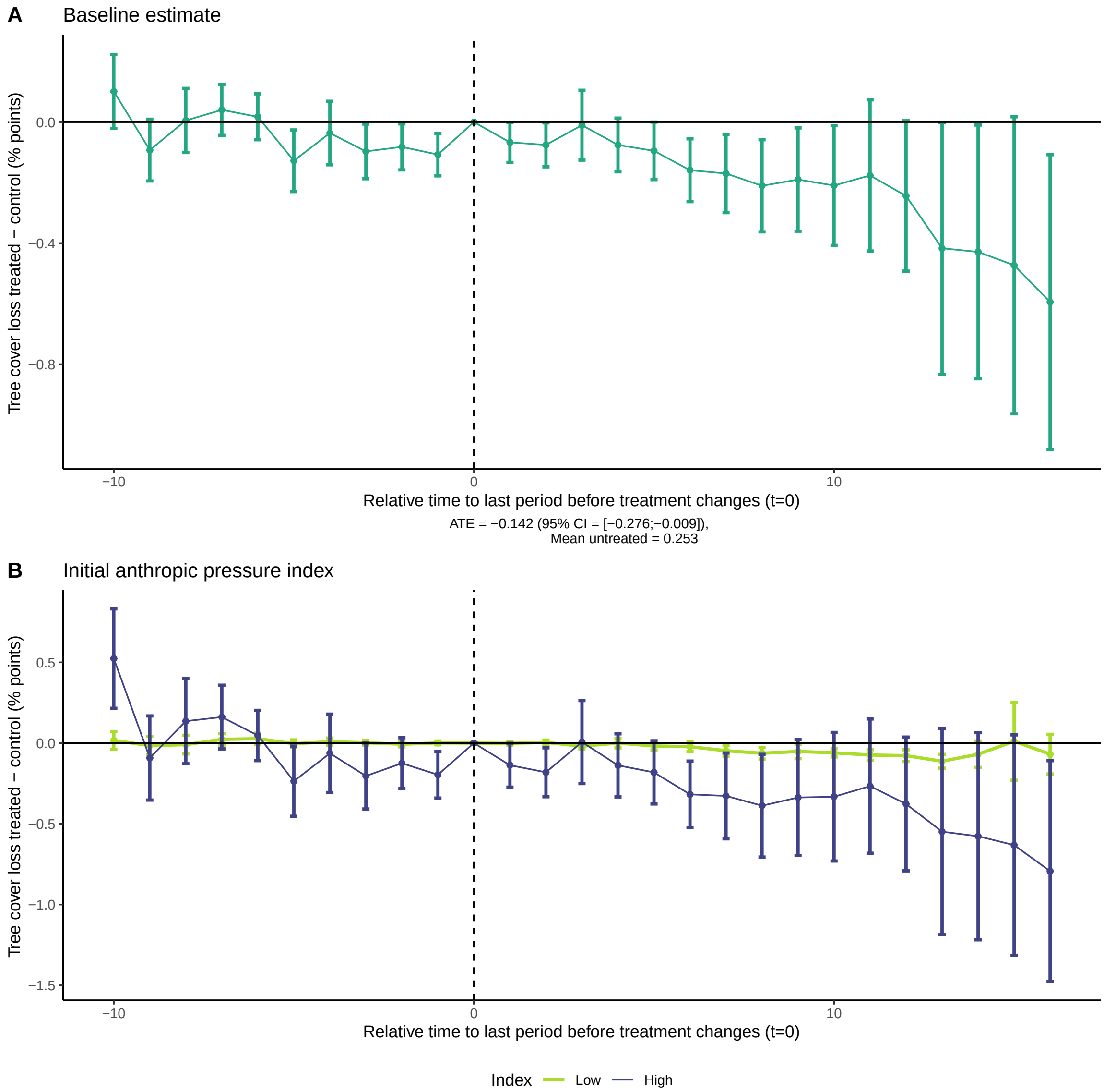

Figure 3: The formal establishment of a Collaborative Management Partnership (CMP) is followed by a decrease in deforestation compared to similar Protected Areas without CMPs, notably in cells with an high initial level of anthropogenic pressure. (A) Baseline estimate of the effect of CMP. (B) Heterogeneity of the effect between cells facing initially low anthropogenic pressures (green) and high anthropogenic pressures (purple). Dots represent the point estimate of the impact (difference in the tree cover loss between treated and control units) for each year ranging from 10 years before and after the establishment of a co-management or delegated agreement to 16 years after its establishment. Lines represent the 95% confidence interval of the estimates. The effects are detailed in Table S5 (baseline results), Table S6 (low anthropogenic pressures areas) and Table S7 (high anthropogenic pressures areas). The model is estimated using the procedure developed by de Chaisemartin and d'Haultfœuille [37].

Where anthropogenic pressure is high, so is tree cover loss. The average yearly tree cover loss rate in control gridcells is 0.39 percentage points in high anthropogenic pressure areas. This is three times higher than in low anthropogenic pressure areas, and 50% higher than in all control PAs. In these highly pressured areas, CMPs decreased annual tree cover loss by 0.26 percentage points on average (Table S7). This corresponds to a 66% decrease in annual tree cover loss.

The heterogeneity of the impact of CMPs for the individual variables that we use to construct the anthropogenic index is explored in Figures S3 to S5. The effect of CMPs is particularly strong in gridcells located at lower elevation, in those with lower tree cover in 2000, more croplands, higher population, closer to villages and cities, and in flatter areas.

2.5 Robustness

We present robustness checks for our baseline estimate. Event studies are displayed in Figures S6 to S21.

First, we show that being two times stricter (caliper = 0.25SD) or two times more permissive (caliper = 1SD) in the selection of matched controlled gridcells does not change the baseline results. When matching is stricter (Figure S6), the aggregated ATE (-0.394 ; 95% CI = [-0.803;0.016]) becomes larger relatively to the tree cover loss in controlled gridcells (0.18 percentage point). When our matching is more permissive (Figure S7), the aggregated ATE (-0.1 ; 95% CI = [-0.202;0.002]) becomes relatively smaller. We also show that results are robust when conducting matching with replacement, meaning that a same gridcell can be the control gridcell for several treated ones (Figure S8), when forcing pairs to belong to the same country (Figure S9), when dropping trends from the BACI regression (Figure S10), when calculating annual tree cover loss rate using the year 2000 as a reference instead of a rolling rate (Figure S11), and when weighting gridcells by the areas of the PAs (Figure S12). In this last case, deforestation before the establishment of CMPs is quite different in controled and future-treated observations, which complicates the causal interpretation of the results.

Madagascar CMPs in Madagascar were used to expand the network of PAs and not to strengthen existing PAs. Because of the singularity of this context, the effect of CMPs in Madagascar can differ from the rest of the continent, and taking PAs as controls might be less appropriate. We estimate our baseline model by dropping observations from Madagascar (Figure S13). The results become relatively larger (-0.146 ; 95% CI = [-0.285;-0.006], Mean untreated = 0.161).

Alternative estimator We re-estimate our baseline model using the econometric approach developed by Sun and Abraham [38] which is conceptually similar to the method of de Chaisemartin and d'Haultfœuille [37] mobilized in our paper. The results obtained with this alternative estimator are extremely close to those from our baseline estimate (ATT = -0.17 (95% CI = [-0.315;-0.024], Mean untreated = 0.253, Figure S14).

Alternative grid size In spatial analysis, the choice of the geographic unit, which is often arbitrary, can impact the results [39]. We test the robustness of our findings using a coarser spatial grid (10 km x 10 km). We are able to construct a control group that is extremely similar to treated observations (Figure S15). The effect size from the post-matching BACI regression is significant, and larger than with our main grid (-100% of tree cover loss on average). Estimates are, however, less precisely estimated (Figure S16).

In addition, we assess the robustness of the results by using a finer grid of 2.5 x 2.5 km. Here too, we are able to construct a convincing control group (Figure S17). We also find that CMPs are associated with lower tree cover loss (Figure S18). However, the pre-trends are now entirely convincing in this analysis, likely because, at this spatial scale, 40% of cells experienced no deforestation over two decades - making an Ordinary Least Square model less suitable for these data.

Spatial auto-correlation Our main estimate accounts for spatial auto-correlation by sampling 1/3 of grid cells. As a robustness test, we use all available grid cells instead of sampling them, and adjust standard errors by clustering them at different spatial resolution: a 50 x 50 km grid (Figure S19), a 100 x 100 km grid (Figure S20) and at the park level (Figure S21). A 50 x 50 km grid provides smaller standard errors than our main model, hence increasing the statistical significance of the results. A 100 x 100 km grid provides standard errors that are comparable to the ones from the main estimate, which leave the results unchanged. Finally, clustering the standard errors at the park level leads to a decrease in the precision of the standard errors during the latest years of the treatment for which we have a small number of clusters. The aggregated impact becomes significant only at a 10% level.

3 Discussion

PAs, a cornerstone instrument of conservation policies, can deliver important environmental outcomes [6, 40]. However, their ability to do so in under-resourced, highly threatened areas of Sub-Saharan Africa is often limited [16, 17]. CMPs are ambitious approaches to inverse the dynamic of habitat destruction in African PAs. Their number has been increasing rapidly and they are attracting important funding. Our results show that these CMPs have delivered a large decrease in tree cover loss (56% per year on average).

Our results show that tree cover loss starts to decrease in the four years preceding the creation of CMPs. Although the magnitude of this decrease is small, it is statistically significant. The presence of some anticipation effect is a likely interpretation of this result. Indeed, the formal establishment of a CMP is the end-result of a process that takes several years. The CMP toolkit, coordinated by the World Bank [24], presents nine detailed case studies in which the CMPs took between 1 and 4 years to be finalized. As a consequence, the decrease in tree cover loss that we observe in the years prior to the official CMP creation date could reflect that some activities already started in the PAs prior to the official establishment of the CMP.

Furthermore, the literature has for long established that PAs are often located in areas that are more remote than unprotected areas [13]. In these remote areas, pressures on habitats are generally low and the presence of PAs does not result in better protection [5]. Our results highlight that gridcells with CMPs are subject to an even stronger location bias, as CMPs tend to be primarily established among the most remote PAs. Some of the CMPs are even too remote for us to be able to pair them with similar PAs without CMPs despite considering a large pool of over 1,000 control PAs. Indeed, while the average gridcell of a control PA is located 12 hours away from the closest city of more than 500,000 inhabitants, several gridcells within Salonga, Lomami and Chinko NP (three CMPs in the D.R. Congo and the Central African Republic) are located as far as 46 hours away. Similarly, the average control gridcell is located 5 hours from the nearest village of 5,000 or more inhabitants while several parts of Lomami and Maiko NP are located over 12 hours from such a village. As a consequence, we show that the establishment of CMPs that faced below-median anthropogenic pressure but for which we were still able to find a correct match, led to a precisely estimated null effect on tree cover loss.

Not all CMPs are located in remote areas. Virunga NP in the Democratic Republic of Congo is a good illustration, as over five million people live directly around the NP. The travel time between some gridcells of Virunga NP and the city of Goma (one of the fastest growing cities on the continent with already over 1.5 million inhabitants) is 10 minutes. Likewise, some gridcells from Kahuzi-Biega NP, also in the Democratic Republic of Congo, are located 42 min away from the large city of Bukavu.

While protecting PAs that face high anthropogenic pressure is challenging, our results highlight that CMPs have a positive and large effect on habitat conservation specifically in the gridcells that faced above-median anthropogenic pressure. This suggests that the positive impact of CMPs may even become greater if NGOs are willing to take on the management of these tough contexts - and get donors to understand the higher associated risk of not succeeding. More generally, our results highlight that the average effect of conservation policies can hide large heterogeneity, making the average a poorly informative indicator for policy makers.

In addition, our results illustrate that it can take several years before conservation policies turn into large measurable effects. In our study, the effect of CMPs was limited over the first five years of their establishment. This effect slowly increased from years 6 to 10 and increased even after 10 years. This result raises two important points. First, it is key that wildlife authorities engage in long-term partnerships. Second, long-term rather than short-term evaluations are crucial to assess accurately the effect of conservation policies.

We do not mean to present CMPs as being the only policy option or as being uniformly effective. Examples of CMPs that do not appear to be delivering effective management exist [23]. These appear to be due to a combination of poorly-designed partnership agreements and lack of proficiency on the part of the NGO and wildlife authorities [25]. Thus, it is important for governments to select partners wisely and to monitor outputs such that steps can be taken in the event of non-performance. Furthermore, the importance and effectiveness of management of natural habitats by local communities and indigenous peoples is well evidenced [41]. We do not see CMPs as an alternative, but rather as a complement, to community involvement. This can take the form of community conservancies where legislation recognizes community land rights.

Our research opens lines for further work. While our paper analyzes the effect of CMPs on habitat conservation, PAs actually face a confluence of threats going beyond deforestation, such as wild meat hunting and high value poaching [42–45]. Due to the large demand for bushmeat across the continent and the high value of the commodity, it is likely that the threat from poaching is insidious and more difficult to control than that of deforestation. Thus, while well-financed and well-managed CMPs could effectively limit both deforestation and bushmeat poaching, less well-managed and financed CMPs may deliver on limiting deforestation without effectively controlling bushmeat poaching. More research into the impact of CMPs on poaching and other threats is therefore needed. It would also be important to study the effect of CMPs on species abundance and diversity [46, 47], and on the ability to safeguard critical ecosystem services.

Finally, it would be interesting to analyze whether the encouraging outcomes of CMPs in terms of habitat protection are achieved in synergy with or at the expense of local socio-economic development. Under-financed and under-staffed PAs can be either an opportunity or a burden for local communities [48]. Some community members may benefit from conducting unsustainable activities within PAs that are vital for their subsistence [49] and enforcing laws may negatively impact these households [50]. Furthermore, under-financed and under-staffed PAs are also prone to larger-scale natural resource trafficking, sometimes coordinated by armed groups [51], which has direct negative effects on local communities. Many CMPs have invested in supporting alternative livelihoods, developing social infrastructure, and promoting tourism and security, which can have important knock-on effects for local economies [23]. A critical issue is whether CMPs or state-run models generate greater resources for engaging and benefiting communities. So far, this question has mostly been explored through measuring attitudes and perceptions, with mixed results [52–54]. A recent paper provides a quantitative assessment using satellite-derived measures of poverty for the CMP of one organization, African Parks Network [30]. Further research is required to better understand the cost-benefit of CMPs on the well-being of local communities and on on macroeconomic outcomes [55].

4 Materials and methods

4.1 CMP database

We built on previous analyzes to create an updated database of PAs with CMP management Baghai *et al.* [21], Fitzgerald [24], and Brugiere [56]. We categorized PAs as falling under a 'CMP' when they are jointly managed by a State authority and a private partner, or when their management has been exclusively delegated to a private partner by legal mandate. Following Fitzgerald Fitzgerald [24], we did not consider PAs that receive only a Financial or Technical (FT) support from a private partner as a CMP. This is because FT support represents a more heterogeneous set of approaches, and it is hard to distinguish different levels of FT support between PAs. Most PAs in our database previously received FT support prior the establishment of a co-managed or delegated CMP.

We updated existing lists using expert knowledge to have an exhaustive list of CMPs as of December 2023. This update fills an important gap in terms of spatial coverage, notably for Madagascar that was absent or under-reported in previous assessments. We geo-referenced our database of CMPs using primarily the World Database of Protected Areas [57] (version: April 2024). When PAs with CMPs were missing in the WDPA or when their shapefiles were imprecise, we used shapefiles provided by local or national authorities. This was the case of Chinko in Central African Republic, Gorongosa NP in Mozambique and all PAs in Madagascar for which the precision of shapefiles in the WDPA is debated Andrianambinina *et al.* [58] and Eklund *et al.* [59]. Our final database results in 127 PAs with CMPs. For each of them, we determined the year of establishment of the first agreement. The database is available in Table S1and in an open repository in a tabular format (linked to be provided when published).

4.2 Impact evaluation

We quantified the environmental impact of CMPs by examining changes in tree cover loss over 23 years compared to a control group comprising similar PAs but without CMPs. Tree cover loss is measured annually from 2000 to 2023 using version 1.11 of the Hansen Hansen *et al.* [31] dataset. A 30m x 30m pixel is defined as 'lost' in Hansen when at least 50% of its initial tree cover is lost. Given Hansen's limitations in accurately capturing data in arid regions, we concentrated on pixels that had a minimum canopy cover of 25% in the year 2000. We tested the robustness of the estimates when using a more conservative threshold of 50% of canopy cover.

4.2.1 Inclusion criteria for CMPs in the impact evaluation Out of the 127 PAs with CMPs, we excluded from the impact evaluation (a) five PAs that are primarily classified as marine PAs in the WDPA because tree cover loss is not a relevant criteria, (b) two PAs for which a CMP was signed before or in 2000 in order to keep only PAs for which we have tree cover loss observations before and after the intervention, (c) 17 PAs that have an area below 25 km^2 (all in Madagascar, the size of our unit of observation), and (d) four PAs that had less than 1ha of forest in 2000 using the 25% threshold.

4.2.2 Selection of possible control PAs Next, we constructed a control group of PAs without CMPs. Using the WDPA and the Madagascar shapefile of PAs, we selected terrestrial PAs without CMPs that are located in the same countries as PAs with CMPs, that are larger than 25 km^2, that had more than one hectar of forest in 2000, and that have a similar designation as PAs with CMPs (eg: National Park, Game Reserve, Hunting Reserve). We obtained a total of 991 PAs that we consider as possible controls.

4.2.3 Grid PAs included in the study have heterogeneous areas (min = 26 km^2, max =45,824 km^2 sd = 6,310 km^2, Table S2.To obtain observations that are comparable, we followed the literature and subdivided PAs into a regular grid [60]. Working at the cell and not a 30 x 30m pixel helps limit non-classical measurement error which can be found in remote sensing data for deforestation Alix-García & Millimet [61].

We created a grid of approximately 25 km^2 over each PA (5 x 5 km). We clipped the grid to the PA borders and kept pixels that are inside the PA. As a consequence, grid cells that are bordering the PA delimitation can have an area smaller than 25 km². To limit disparities in terms of areas between grid cells, we combined adjacent gridcells that have an area smaller than 12.5 km^2 ; and excluded cells that have an area smaller than 12.5 km^2 and which could not be combined with another adjacent cell. Finally, we randomly sampled 1/3 of these grids to limit spatial auto-correlation Schleicher *et al.* [62]. We summarized this procedure in Figure S14. Our final database contains 17,953 cells in which we follow deforestation annually between 2001 and 2023.

4.2.4 Outcome variable and covariates We measure tree cover loss using the Global Forest Watch (GFW) data v1.10 [31]. The data are available on a yearly basis from 2001 to 2023 and are produced with a consistent methodology at a global level. We extracted tree cover loss data for each grid cell using the *gfcanalysis* package in R [63]. We calculated the rolling deforestation rate, i.e the annual share of tree cover that is lost, as our main outcome of interest. The GFW data have been shown to under-report deforestation in certain contexts [61] and to be less precise in areas with low tree cover densities [64]. It has the advantage of not being specific to certain biomes (e.g., [65]).

We constructed a set of time-invariant covariates using other spatial data. For each cell, we calculated the average elevation and slope using AWS Open Data Terrain Tiles Tiles [66] and the *elevatr* R package Hollister *et al.* [67], the dominant biome Dinerstein *et al.* [68], population in 2000 [69], travel time to the nearest village or town of 5,000 or more inhabitants and travel time to the nearest city of 500,000 or more inhabitants Nelson *et al.* [70], and the earliest estimate of the surface of croplands available for our study period, a composite image between 2000 and 2003 [71]. We also computed the Euclidean distance between the centroid of each cell and the border of the PA, and the area of each PA. We extracted precipitation data using the CHIRPS database [72] and calculated a yearly Standard Precipitation Index.

4.2.5 Statistical model In the absence of a true experimental framework, we combine pre-matching techniques to ensure comparability between treated and comparison PAs at baseline, along with panel regression analysis incorporating fixed effects. This methodology, which combines panel regression with pre-processing matching techniques, has been demonstrated to approximate a true experiment more effectively [73, 74]. It has been employed in various prior studies examining conservation policies (e.g., Neugarten *et al.* [60]).

We used statistical matching to correct for the possible difference in time-invariant observable characteristics between PAs with and without CMPs. We implemented a nearest-neighbor matching without replacement and using a mahalanobis distance in *matchit* Ho *et al.* [75]. We set a caliper of 0.5 standard deviation to keep acceptable pairs. We matched on the following variables: the initial forest cover in 2000, the Moran I statistic of forest cover in 2000, the distance between the cell and the boarder of the PA, population in 2000 in the gridcell, the distance between the gridcell and the nearest village, the distance between the gridcell and the nearest large city, the surface of croplands in the gridcell in 2000-03, the average elevation and average slope. We imposed that pairs of treated and control observations belong to the same biome[2], but not necessarily the same countries as forcing pairs to belong to the same country would decrease by two the number of observations for which we can find an appropriate match (Figure S9).

Second, we estimated the impact of CMPs on annual tree cover loss using a Difference-in-Difference (DID) model, which are also known as Before-After-Control-Intervention (BACI) [76], on the matched dataset. When more than two time periods are available, such as in our case, DID models are usually estimated using a Two-Way Fixed Effects (TWFE) model. We estimated non-normalized event study a model of the form:

$$Def_{i,t} = \alpha_i + \gamma_t + \sum_{k=-10}^{-2} \beta^k \cdot CMP_{i,t}^k + \sum_{k=0}^{16} \beta^k \cdot CMP_{i,t}^k + \sum_c \tau_1 \cdot Country_c \times Year_t + \sum_b \tau_2 \cdot Biome_b \times Year_t + \epsilon_{i,t}$$

Where $Def_{i,t}$ is the deforestation rate in gridcell i during year t, α_i is a gridcell fixed-effect, γ_t is a year fixed-effect, $CMP_{i,t}^k$ is an indicator for unit i being k periods away from initial treatment at year t. The first summation captures the effect time periods leading up to the treatment (placebo) and the second summation captures the time period following treatment (effect). We included country-year and biome-year trends to capture more finely time-varying unobserved factors.

Recent advances have demonstrated that TWFE can assign negative weights to observations when the treatment was staggered and that the treatment effect was heterogeneous

[2]Among: Tropical & Subtropical Moist Broadleaf Forests, Tropical & Subtropical Dry Broadleaf Forests, Tropical & Subtropical Grasslands, Savannas & Shrublands, Flooded Grasslands & Savannas, Montane Grasslands & Shrublands, Deserts & Xeric Shrublands, Mangroves

(e.g., varying through time, [77]). These negative weights lead to a biased estimates of the average treatment effect of an intervention. In particular, the classic TWFE approach provides contaminated estimates of time-dynamic effects De Chaisemartin & d'Haultfoeuille [37].

New methods were developed to correct negative weights and provide unbiased estimates of average treatment effects. In particular, the approach of De Chaisemartin & d'Haultfoeuille [37] consists of computing cohort-specific weights, and aggregates treated cohort × relative time to treatment dummies into an unbiased Average Treatment Effect (ATE) for each period and the entire post-treatment period. This approach relies on a weakened parallel trend assumption compared to the canonical BACI model. We rely on their procedure and package to estimate treatment effect [78]. We report non-normalized results. All coefficients are long-difference compared to the outcome from one year prior to the establishment of CMP.

4.2.6 Heterogeneity We test the heterogeneity of the effect of CMPs depending on whether the gridcell is exposed to low or high initial anthropogenic pressures. To that end, we construct an index for anthropogenic pressure that add or subtract eight standardized continuous variables:

Index = Population - travel time to the nearest city - travel time to the nearest village - initial forest cover + initial cropland cover - slope - elevation - distance to the boarder of the PA

Next, we determine if a gridcell is above the median of the index in the matched dataset (high anthropogenic pressure) or below this median (low anthropogenic pressure).

4.3 Data and codes

All analyses were conducted using R software (version 4.2.3) Data and codes are available on https://zenodo.org/records/14195855.

References

1. Brodie, J. F. *et al.* Landscape-scale benefits of protected areas for tropical biodiversity. *Nature* **620,** 807–812 (2023).
2. Justin Nowakowski, A. *et al.* Protected areas slow declines unevenly across the tetrapod tree of life. *Nature,* 1–6 (2023).
3. Duncanson, L. *et al.* The effectiveness of global protected areas for climate change mitigation. *Nature Communications* **14,** 2908 (2023).

4. Watson, J. E., Dudley, N., Segan, D. B. & Hockings, M. The performance and potential of protected areas. *Nature* **515,** 67–73 (2014).

5. Geldmann, J., Manica, A., Burgess, N. D., Coad, L. & Balmford, A. A global-level assessment of the effectiveness of protected areas at resisting anthropogenic pressures. *Proceedings of the National Academy of Sciences* **116,** 23209–23215 (2019).

6. Wauchope, H. S. *et al.* Protected areas have a mixed impact on waterbirds, but management helps. *Nature* **605,** 103–107 (2022).

7. Bruner, A. G., Gullison, R. E., Rice, R. E. & Da Fonseca, G. A. Effectiveness of parks in protecting tropical biodiversity. *Science* **291,** 125–128 (2001).

8. Lindsey, P. A. *et al.* More than $1 billion needed annually to secure Africa's protected areas with lions. *Proceedings of the National Academy of Sciences* **115,** E10788–E10796. eprint: https://www.pnas.org/doi/pdf/10.1073/pnas.1805048115. https://www.pnas.org/doi/abs/10.1073/pnas.1805048115 (2018).

9. West, T. A., Caviglia-Harris, J. L., Martins, F. S., Silva, D. E. & Börner, J. Potential conservation gains from improved protected area management in the Brazilian Amazon. *Biological Conservation* **269,** 109526. ISSN: 0006-3207. https://www.sciencedirect.com/science/article/pii/S0006320722000799 (2022).

10. Bonilla-Mejía, L. & Higuera-Mendieta, I. Protected areas under weak institutions: Evidence from Colombia. *World Development* **122,** 585–596 (2019).

11. Herrera, D., Pfaff, A. & Robalino, J. Impacts of protected areas vary with the level of government: Comparing avoided deforestation across agencies in the Brazilian Amazon. *Proceedings of the National Academy of Sciences* **116,** 14916–14925 (July 2019).

12. Pfaff, A., Robalino, J., Herrera, D. & Sandoval, C. Protected Areas' Impacts on Brazilian Amazon Deforestation: Examining Conservation - Development Interactions to Inform Planning. *PLOS ONE* **10,** 1–17 (July 2015).

13. Joppa, L. N. & Pfaff, A. High and Far: Biases in the Location of Protected Areas. *PLOS ONE* **4,** 1–6. https://doi.org/10.1371/journal.pone.0008273 (Dec. 2009).

14. Amin, A. *et al.* Neighborhood effects in the Brazilian Amazônia: Protected areas and deforestation. *Journal of Environmental Economics and Management* **93,** 272–288 (2019).

15. Robalino, J., Pfaff, A. & Villalobos, L. Heterogeneous Local Spillovers from Protected Areas in Costa Rica. *Journal of the Association of Environmental and Resource Economists* **4,** 795–820. eprint: https://doi.org/10.1086/692089. https://doi.org/10.1086/692089 (2017).

16. Lindsey, P. *et al.* Conserving Africa's wildlife and wildlands through the COVID-19 crisis and beyond. *Nature ecology & evolution* **4,** 1300–1310 (2020).

17. Lindsey, P. A. *et al.* The performance of African protected areas for lions and their prey. *Biological Conservation* **209,** 137–149 (2017).

18. Craigie, I. D. *et al.* Large mammal population declines in Africa's protected areas. *Biological conservation* **143,** 2221–2228 (2010).

19. Scholte, P. *et al.* Conservation overstretch and long-term decline of wildlife and tourism in the Central African savannas. *Conservation Biology* **36,** e13860 (2022).

20. Meng, Z. *et al.* Post-2020 biodiversity framework challenged by cropland expansion in protected areas. *Nature Sustainability,* 1–11 (2023).

21. Baghai, M. *et al.* Models for the collaborative management of Africa's protected areas. *Biological Conservation* **218,** 73–82 (2018).

22. Maxwell, S. L. *et al.* Area-based conservation in the twenty-first century. *Nature* **586,** 217–227 (2020).

23. Lindsey, P. *et al.* Attracting investment for Africa's protected areas by creating enabling environments for collaborative management partnerships. *Biological Conservation* **255,** 108979 (2021).

24. Fitzgerald, K. H. *Collaborative Management Partnerships for Protected Areas: A Resource Guide* tech. rep. (World Bank, 2021).

25. Baghai, M., Lindsey, P., Everatt, K. & Madope, A. Collaborative management models for conservation areas in Mozambique. *Regional Best Practices, Current models in Mozambique and a framework for enhancing partnerships to protect biodiversity assets and promote development. Report for USAID SPEED* (2018).

26. Struhsaker, T. T., Struhsaker, P. J. & Siex, K. S. Conserving Africa's rain forests: problems in protected areas and possible solutions. *Biological Conservation* **123,** 45–54 (2005).

27. Hatchwell, M. Public–private partnerships as a management option for protected areas. *Animal Conservation* **17,** 3–4 (2014).

28. Robson, A. *et al.* Over 80% of Africa's savannah conservation land is failing or deteriorating according to lions as an indicator species. *Conservation Letters* **15,** e12844 (2022).

29. Desbureaux, S. Subjective modeling choices and the robustness of impact evaluations in conservation science. *Conservation Biology* **35,** 1615–1626 (2021).

30. Denny, S., Englander, G. & Hunnicutt, P. Private management of African protected areas improves wildlife and tourism outcomes but with security concerns in conflict regions. *Proceedings of the National Academy of Sciences* **121,** e2401814121 (2024).

31. Hansen, M. C. *et al.* High-resolution global maps of 21st-century forest cover change. *science* **342,** 850–853 (2013).

32. Brondízio, E. S., Settele, J., Diaz, S. & Ngo, H. T. *Global assessment report on biodiversity and ecosystem services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services* tech. rep. (2019).

33. Bakarr, M. I. Reimagining protected and conserved areas in Africa: Perspectives from the first Africa Protected Areas Congress. *Conservation Letters* **16,** e12944 (2023).

34. Fabre, A. & Straub, S. The Impact of Public–Private Partnerships (PPPs) in Infrastructure, Health, and Education. *Journal of Economic Literature* **61,** 655–715 (2023).

35. Bertelsmann Transformation Index. *Basic state functions* Processed by Our World in Data (Our World in Data, 2022).

36. Imbens, G. W. & Wooldridge, J. M. Recent developments in the econometrics of program evaluation. *Journal of economic literature* **47,** 5–86 (2009).

37. De Chaisemartin, C. & d'Haultfoeuille, X. Difference-in-differences estimators of intertemporal treatment effects. *Review of Economics and Statistics,* 1–45 (2024).

38. Sun, L. & Abraham, S. Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics* **225,** 175–199 (2021).

39. Avelino, A. F. T., Baylis, K. & Honey-Rosés, J. Goldilocks and the raster grid: selecting scale when evaluating conservation programs. *PLoS One* **11,** e0167945 (2016).

40. Langhammer, P. F. *et al.* The positive impact of conservation action. *Science* **384,** 453–458 (2024).

41. Sze, J. S., Carrasco, L. R., Childs, D. & Edwards, D. P. Reduced deforestation and degradation in Indigenous Lands pan-tropically. *Nature Sustainability* **5,** 123–130 (2022).

42. Cawthorn, D.-M. & Hoffman, L. C. The bushmeat and food security nexus: A global account of the contributions, conundrums and ethical collisions. *Food Research International* **76,** 906–925 (2015).

43. Batumike, R., Imani, G., Urom, C. & Cuni-Sanchez, A. Bushmeat hunting around Lomami National Park, Democratic Republic of the Congo. *Oryx* **55,** 421–431 (2021).

44. Ondoua Ondoua, G. *et al. An assessment of poaching and wildlife trafficking in the Garamba-Bili-Chinko transboundary landscape* tech. rep. (Traffic, 2017).

45. Lindsey, P. A. *et al.* The bushmeat trade in African savannas: Impacts, drivers, and possible solutions. *Biological conservation* **160,** 80–96 (2013).

46. Burivalova, Z., Game, E. T. & Butler, R. A. The sound of a tropical forest. *Science* **363,** 28–29 (2019).

47. Zwerts, J. A. *et al.* FSC-certified forest management benefits large mammals compared to non-FSC. *Nature,* 1–6 (2024).

48. Ferraro, P. J. & Hanauer, M. M. Quantifying causal mechanisms to determine how protected areas affect poverty through changes in ecosystem services and infrastructure. *Proceedings of the national academy of sciences* **111,** 4332–4337 (2014).

49. Desbureaux, S. *et al.* The long-term impacts of Marine Protected Areas on fish catch and socioeconomic development in Tanzania. *Conservation Letters,* e13048 (2024).

50. Anaya, F. C. & Espírito-Santo, M. M. Protected areas and territorial exclusion of traditional communities. *Ecology and Society* **23** (2018).

51. On Drugs, U. N. O. *The globalization of crime: A transnational organized crime threat assessment* (United Nations Publications, 2010).

52. Yousefpour, R., Mayaux, J., Lhoest, S. & Vermeulen, C. The complexity of the conservation-development nexus in Central African national parks and the perceptions of local populations. *Journal for Nature Conservation* **66,** 126150 (2022).

53. Janssens, I. *et al.* Conservation conflict following a management shift in Pendjari National Park (Benin). *Biological Conservation* **272,** 109598 (2022).

54. Manda, L. *et al.* Co-management brings hope for effective biodiversity conservation and socio-economic development in Vwaza Marsh Wildlife Reserve in Malawi. *Frontiers in Conservation Science* **4,** 1124142 (2023).

55. Damania, R. *et al. When Good Conservation Becomes Good Economics: Kenya's Vanishing Herds* tech. rep. (2019).

56. Brugiere, D. *Public-Private Partnership for protected areas: current situation and prospects in French-speaking Africa* tech. rep. (Papaco, 2020).

57. IUCN and UNEP-WCMC. *The World Database on Protected Areas (WDPA)* Version February 2023 (Cambridge, UK: UNEP-WCMC, 2020). www.protectedplanet.net.

58. Andrianambinina, F. O. D., Waeber, P. O., Schuurman, D., Lowry, P. P. & Wilmé, L. Clarification on protected area management efforts in Madagascar during periods of heightened uncertainty and instability. *Madagascar Conservation & Development* **17,** 25–28 (2022).

59. Eklund, J. *et al.* Elevated fires during COVID-19 lockdown and the vulnerability of protected areas. *Nature Sustainability* **5,** 603–609 (2022).

60. Neugarten, R. A., Rasolofoson, R. A., Barrett, C. B., Vieilledent, G. & Rodewald, A. D. The effect of a political crisis on performance of community forests and protected areas in Madagascar. *Nature Communications* **15,** 2963 (2024).

61. Alix-García, J. & Millimet, D. L. Remotely incorrect? Accounting for nonclassical measurement error in satellite data on deforestation. *Journal of the Association of Environmental and Resource Economists* **10,** 1335–1367 (2023).

62. Schleicher, J. *et al.* Statistical matching for conservation science. *Conservation Biology* **34,** 538–549 (2020).

63. Zvoleff, A. *gfcanalysis: Tools for Working with Hansen et al. Global Forest Change Dataset* R package version 1.6.0 (2020). https://CRAN.R-project.org/package=gfcanalysis.

64. Achard, F. *et al.* Determination of tropical deforestation rates and related carbon losses from 1990 to 2010. *Global change biology* **20,** 2540–2554 (2014).

65. Vancutsem, C. *et al.* Long-term (1990–2019) monitoring of forest cover changes in the humid tropics. *Science Advances* **7,** eabe1603 (2021).

66. Tiles, A. 4. O. D. T. accessed February 2023 (). https://registry.opendata.aws/terrain-tiles.

67. Hollister, J. *et al. elevatr: Access Elevation Data from Various APIs* R package version 0.99.0 (2023). https://github.com/jhollist/elevatr/.

68. Dinerstein, E. *et al.* An ecoregion-based approach to protecting half the terrestrial realm. *BioScience* **67,** 534–545 (2017).

69. IUCN and UNEP-WCMC. *Population of the World, Version 4 (GPWv4): Administrative Unit Center Points with Population Estimates* Version February 2023 (Center for International Earth Science Information Network - CIESIN - Columbia University, Palisades, NY: NASA Socioeconomic Data and Applications Center (SEDAC), 2016). http://dx.doi.org/10.7927/H4F47M2C.

70. Nelson, A. *et al.* A suite of global accessibility indicators. *Scientific data* **6,** 266 (2019).

71. Potapov, P. *et al.* Global maps of cropland extent and change show accelerated cropland expansion in the twenty-first century. *Nature Food* **3,** 19–28 (2022).

72. Funk, C. *et al.* The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. *Scientific data* **2,** 1–21 (2015).

73. Ho, D. E., Imai, K., King, G. & Stuart, E. A. Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference. *Political analysis* **15,** 199–236 (2007).

74. Ferraro, P. J. & Miranda, J. J. Panel data designs and estimators as substitutes for randomized controlled trials in the evaluation of public programs. *Journal of the Association of Environmental and Resource Economists* **4,** 281–317 (2017).

75. Ho, D. E., Imai, K., King, G. & Stuart, E. A. MatchIt: Nonparametric Preprocessing for Parametric Causal Inference. *Journal of Statistical Software* **42,** 1–28 (2011).

76. Wauchope, H. S. *et al.* Evaluating impact using time-series data. *Trends in Ecology & Evolution* **36,** 196–205 (2021).

77. De Chaisemartin, C. & d'Haultfoeuille, X. Fuzzy differences-in-differences. *The Review of Economic Studies* **85,** 999–1028 (2018).

78. Ciccia, D., Knau, F., Malezieux, M., Sow, D. & de Chaisemartin, C. *DIDmultiplegtDYN: Estimation in Difference-in-Difference Designs with Multiple Groups and Periods* R package version 1.0.5 (2024). https://CRAN.R-project.org/package=DIDmultiplegtDYN.

Supplementary Information

A Supplementary Figures

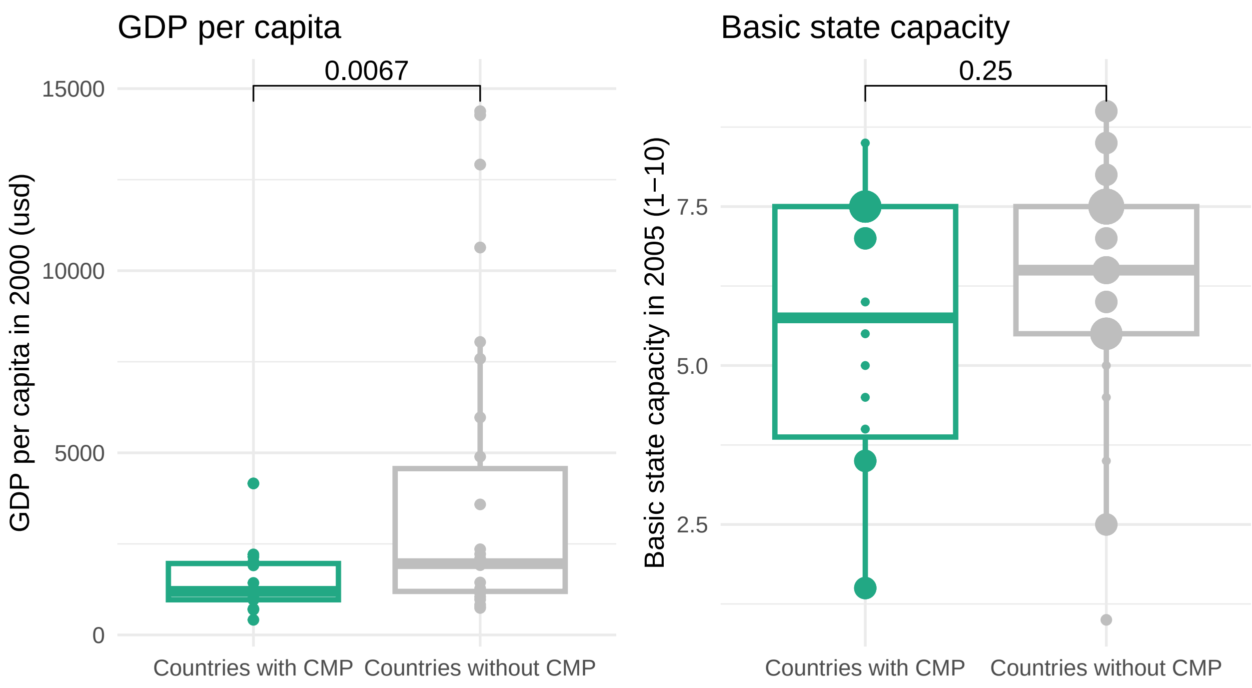

Figure S1: Boxplots of GDP per capita in 2000 (left) and basic state capacity score in 2005 (right) for all Sub-Saharan Countries, depending on whether they had CMP during the study period or not. For each sub-figure, we present the p-value of a t-test of equal mean. GDP per capita data come from the Maddison Project Database. We took the GDP per capita for the year 2000, prior to the creation of all but one CMP (Kasanka NP in 1990). Basic state function score data come from the Bertelsmann Transformation Index project. It "indicates the extent to which the state has the monopoly on the use of force and provides basic public services across the country. It ranges from 1 to 10 (most functioning)" and starts in 2005. As a consequence, we took the value of the score in 2005. The size of each points is proportional to the number of countries having a given score (among countries with and countries without CMP). Both datasets were downloaded from Our-WorldinData.

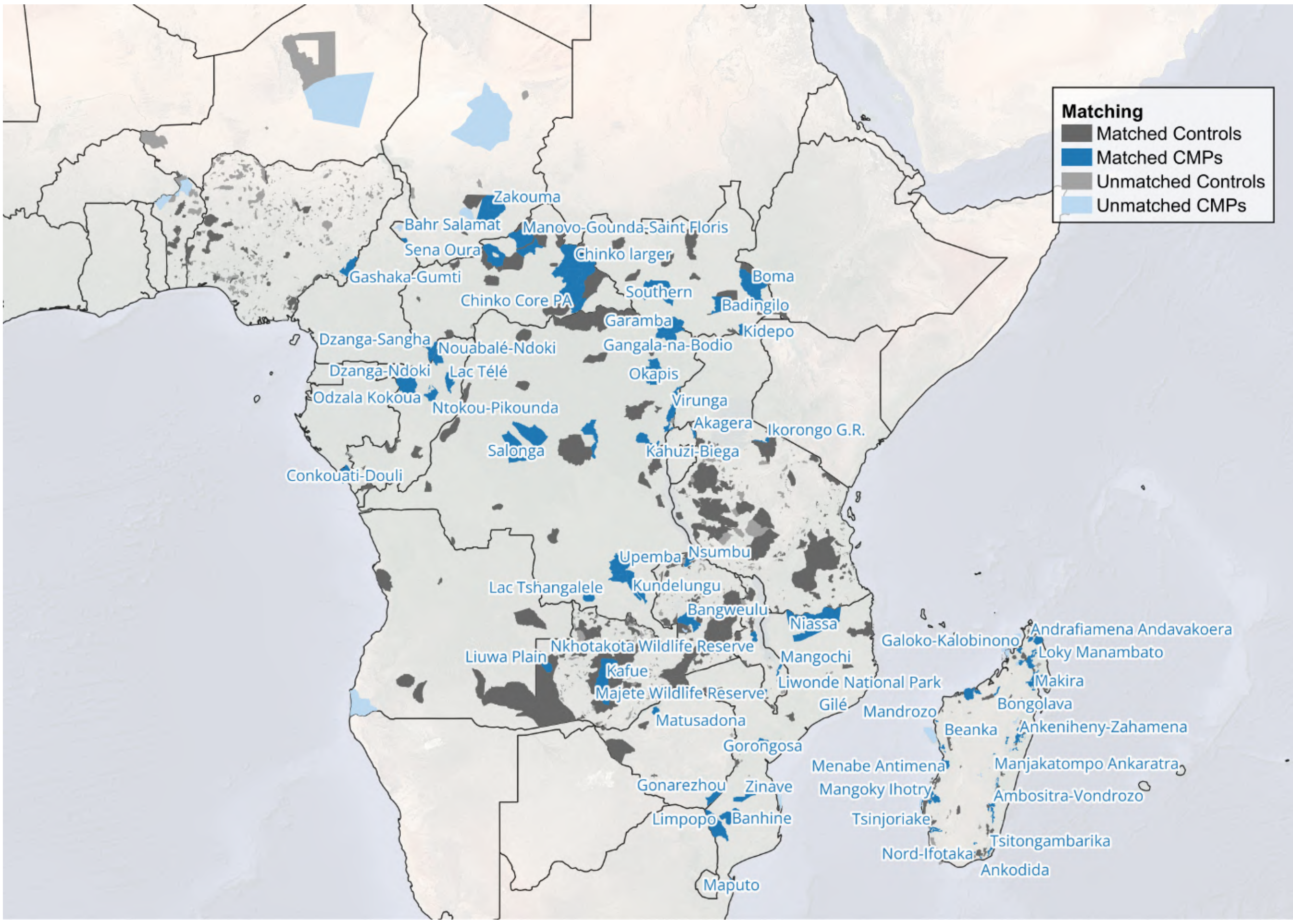

Figure S2: Parks kept (dark color) and parks dropped (light color) during the matching procedure. The matching was conducted at the grid level (5km x 5 km). The map was done with parks instead of gridcells for visibility. A park was considered as kept for this figure if at least one of its gridcell was matched.

1.A. Heterogeneity of the impact of CMPs

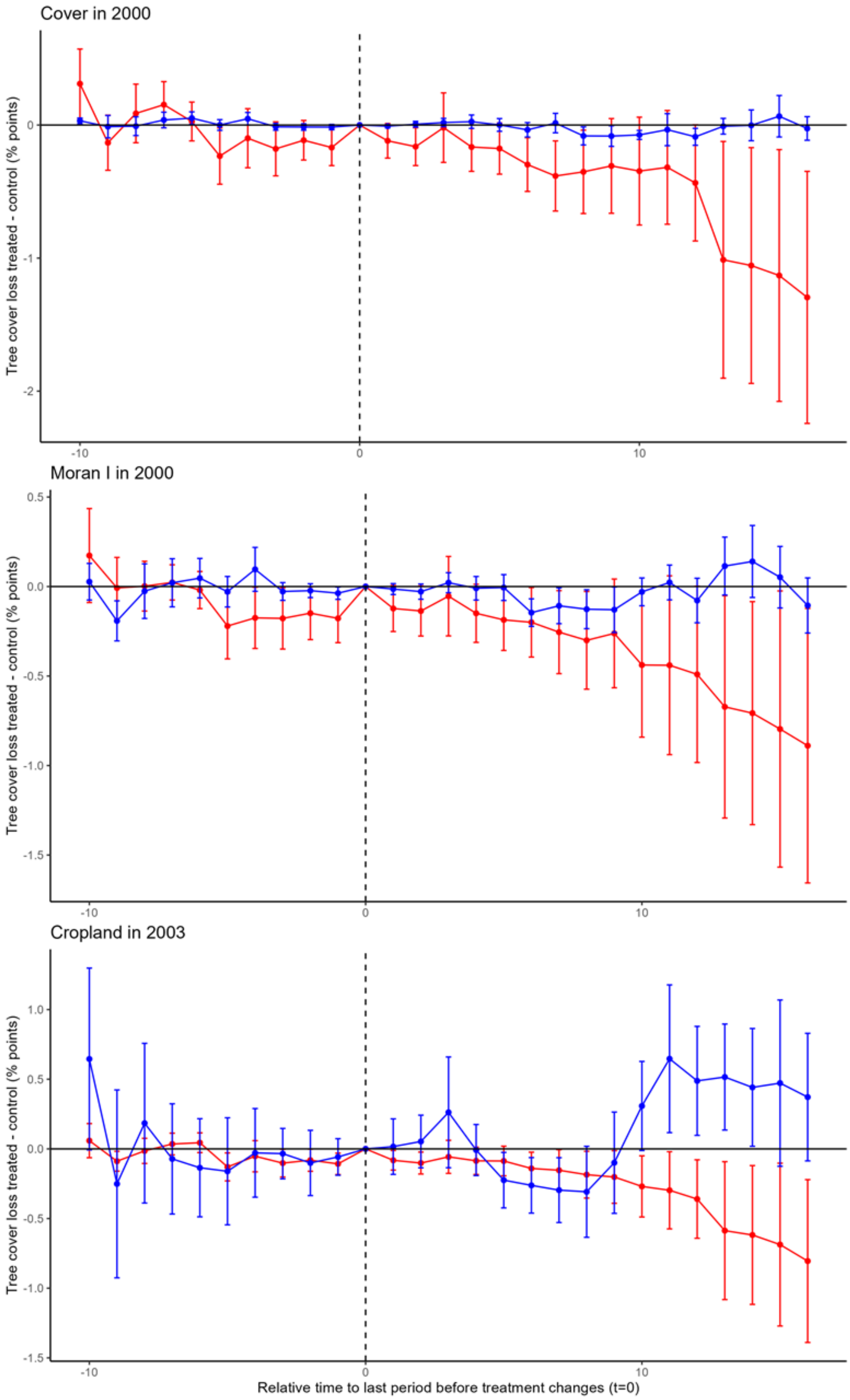

Figure S3: Heterogeneity of the effect of CMPs based on baseline characteristics: tree cover, Moran I and Cropland (composite image between 2000 and 2003). For each dimension of heterogeneity, we estimated the models on the sub-samples of observations that are below the median of the characteristic (red), and above the median (blue). The impact of CMP on tree cover loss was stronger in gridcells that initially had a lower forest cover and a lower Moran I (meaning, a higher variability in the spatial composition of forest in 2000). Likewise, the effect of CMP was larger in gridcells with a lower percentage of croplands in 2003.

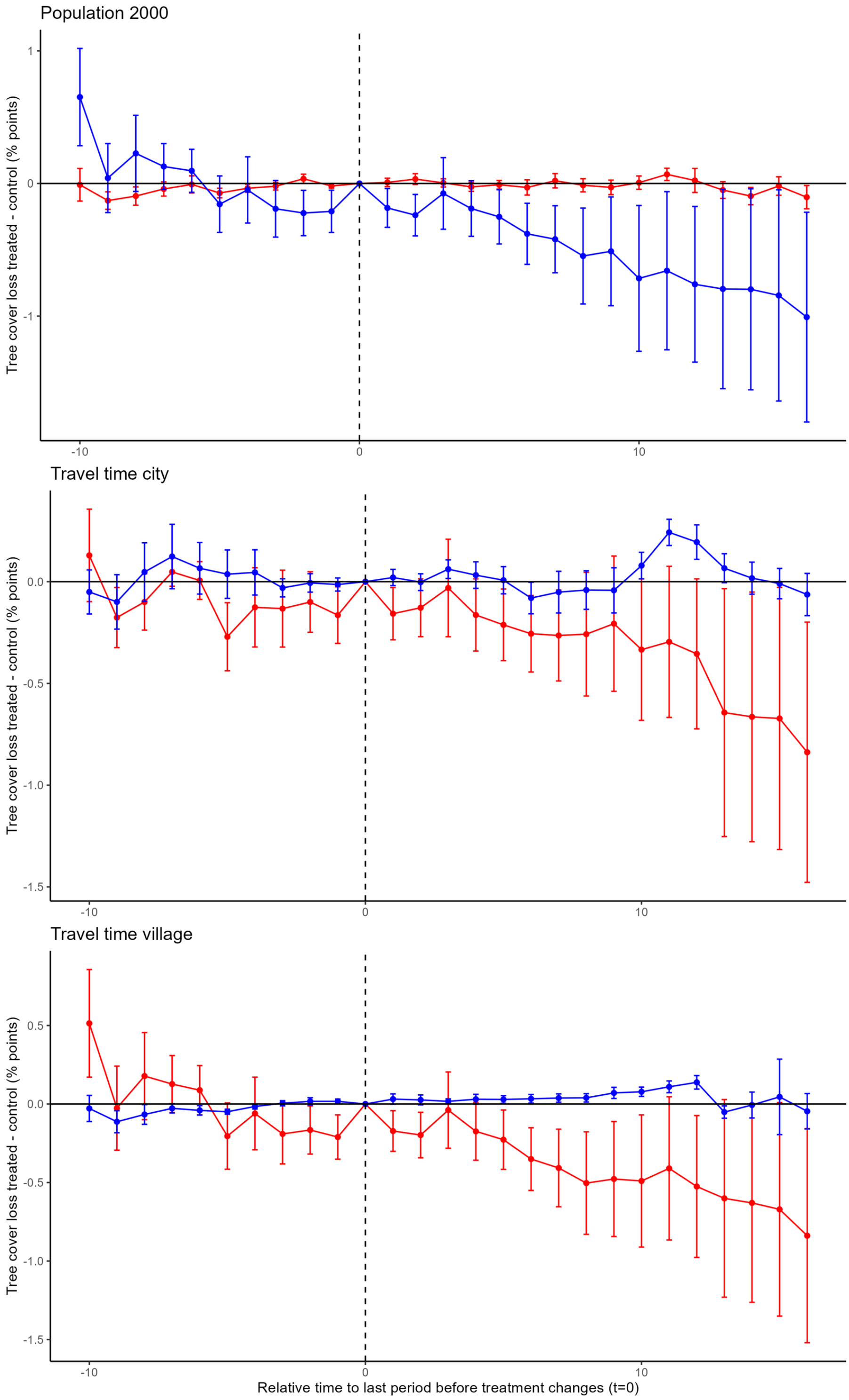

Figure S4: Heterogeneity of the effect of CMPs based on baseline characteristics: population, travel time to the nearest city and travel time to the nearest village. For each dimension of heterogeneity, we estimated the models on the sub-samples of observations that are below the median of the characteristic (red), and above the median (blue). The impact of CMP on tree cover loss was stronger in gridcells that initially had a higher population and that are closer from cities and villages.

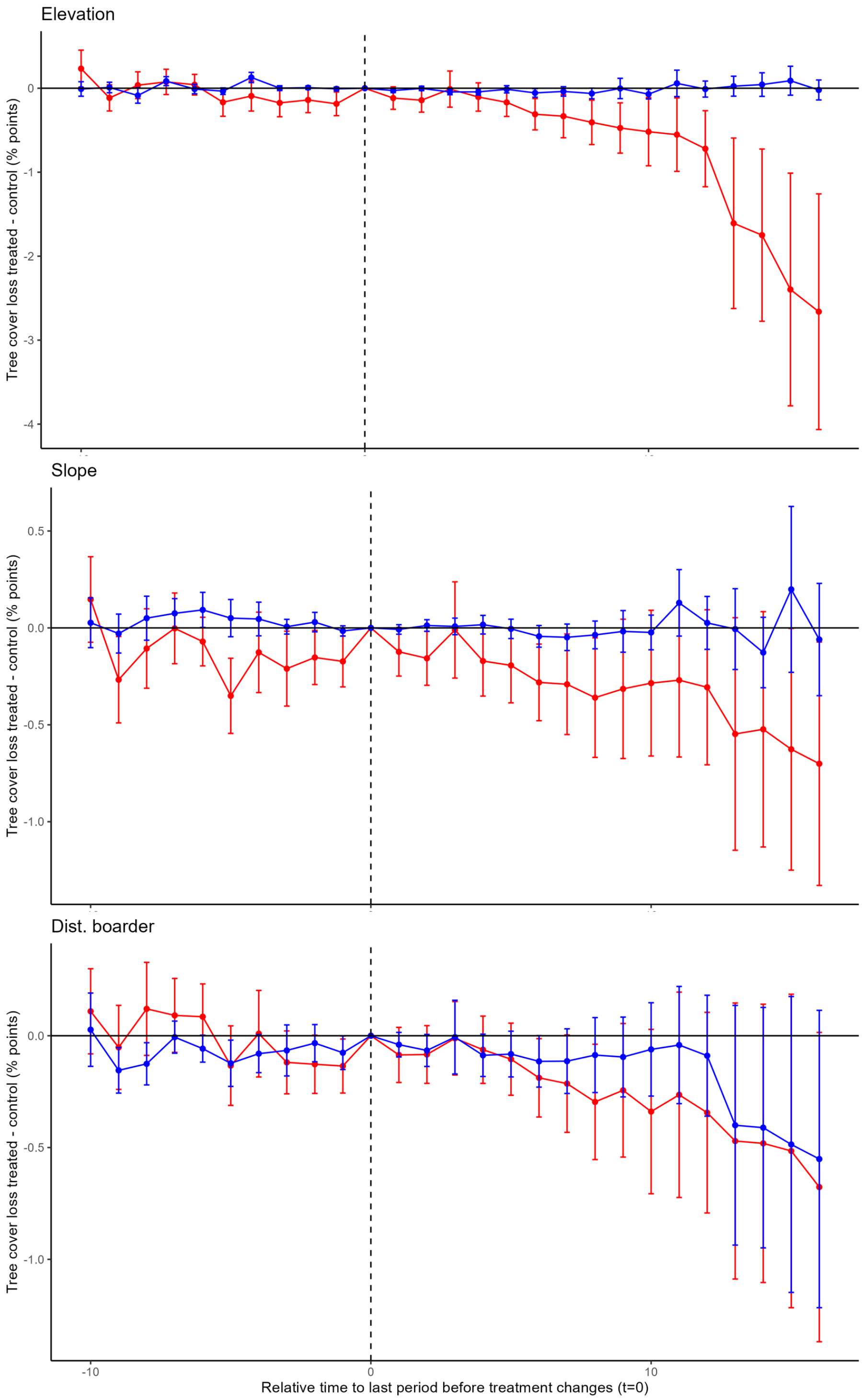

Figure S5: Heterogeneity of the effect of CMPs based on baseline characteristics: average elevation, average slope and distance between a gridcell and the boarder of the PA. For each dimension of heterogeneity, we estimated the models on the sub-samples of observations that are below the median of the characteristic (red), and above the median (blue). The impact of CMP on tree cover loss was stronger in gridcells located at lower elevation and that are flat. The dynamic of deforestation in gridcells close and far from the boarder of the park looks comparable.

1.B. Robustness of the impact of CMPs

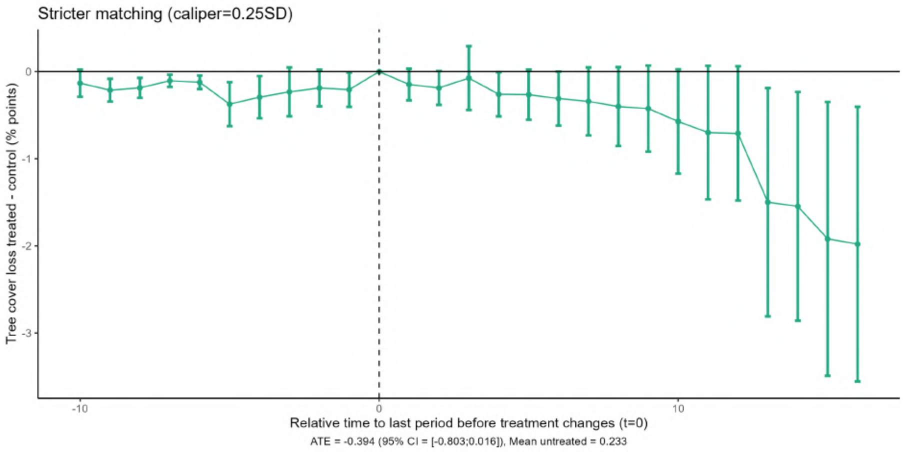

Figure S6: Robustness of the results when implementing a stricter matching than in the baseline specification (caliper of 0.25SD instead of 0.5SD)

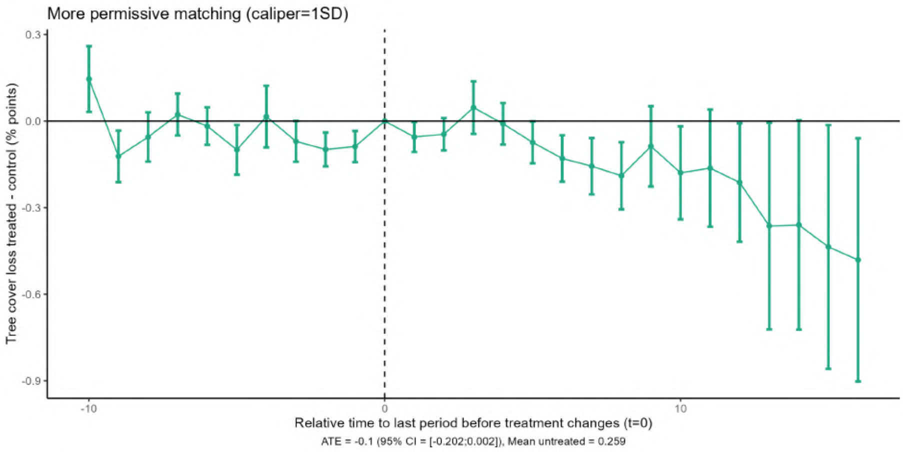

Figure S7: Robustness of the results when implementing a more permissive matching than in the baseline specification (caliper of 1SD instead of 0.5SD)

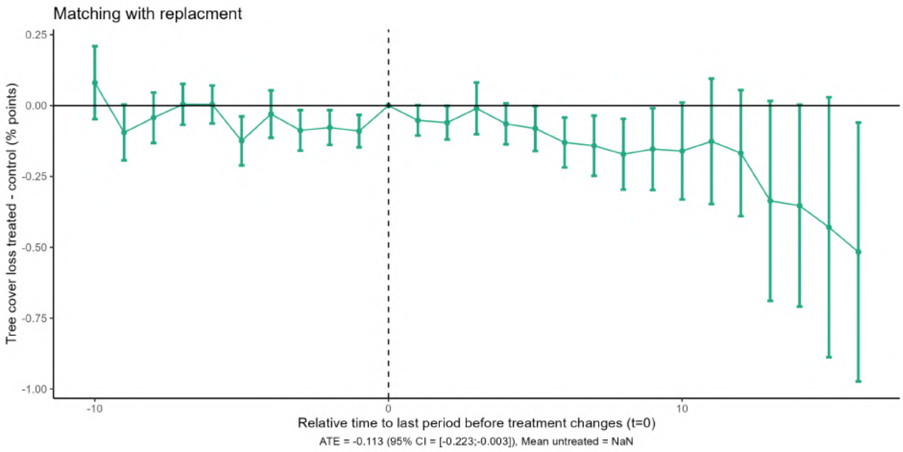

Figure S8: Robustness of the results when implementing matching with replacement. This allows a control observation to be selected as the "paired" control for several treated grid cells.

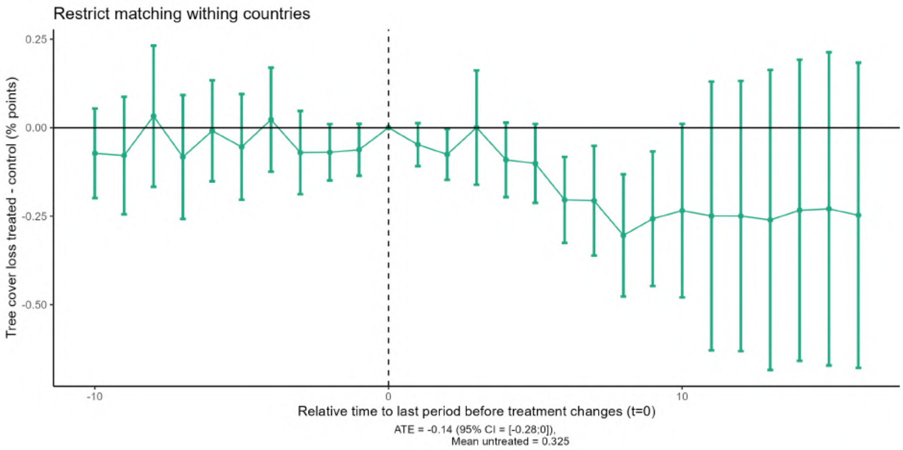

Figure S9: Robustness of the results when forcing pairs to belong to the same country in the matching procedure. When doing that, the matching procedures only finds valid pairs for 33% of the treated observations. This number was of 62% in the main estimate. We notably lose 25 treated PAs out of 94 if we were to force the pairs to belong to the same country. As a consequence, the spatial representativeness of this robustness result is more limited. Overall, the dynamic of the effect is pretty to the main specification. However, estimates are less precise because of the fewer number of observations - particularly when looking at long term impacts for which we have a small number of PAs when forcing matches to belong to the same country.

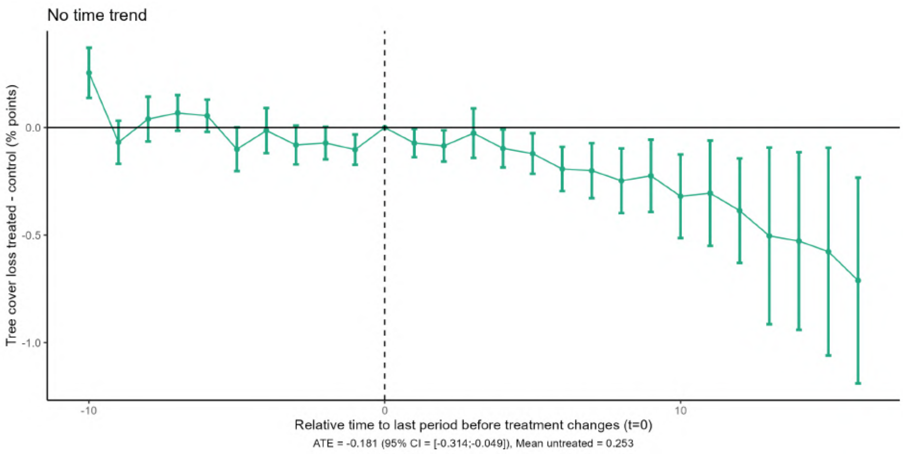

Figure S10: Robustness of the results when estimating the staggered DID model without biome- and country-year trends.

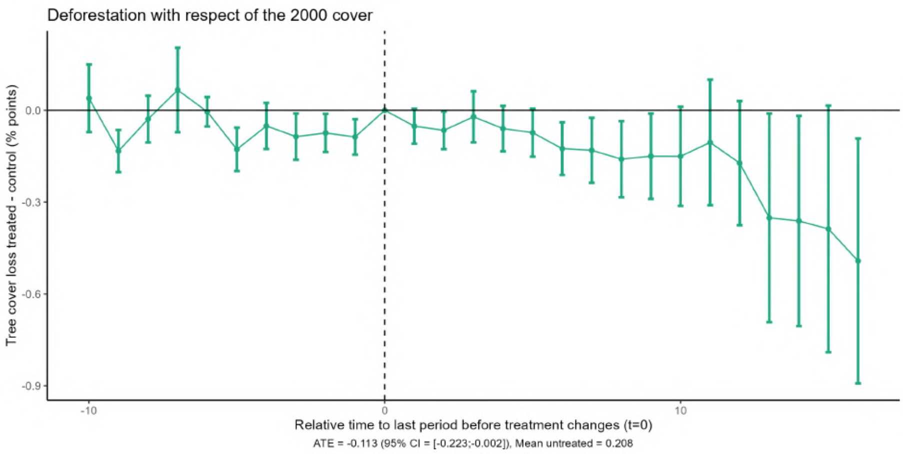

Figure S11: Robustness of the results when using deforestation rate with respect to the year 2000 as an outcome variable (instead of calculating a rolling deforestation rate with respect of the tree cover at the start of each year.

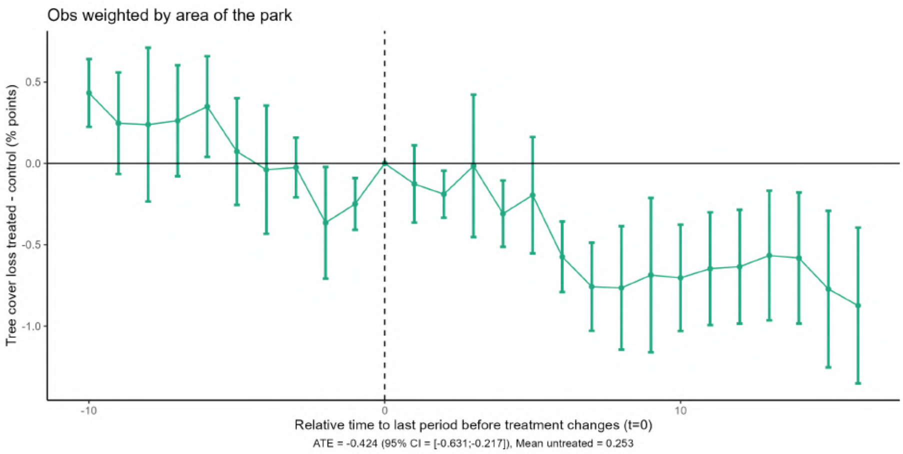

Figure S12: Robustness of the results when weighting each gridcell by the inverse of the area of its park. This gives each park (and not each gridcell) the same weight in the estimation of the effect.

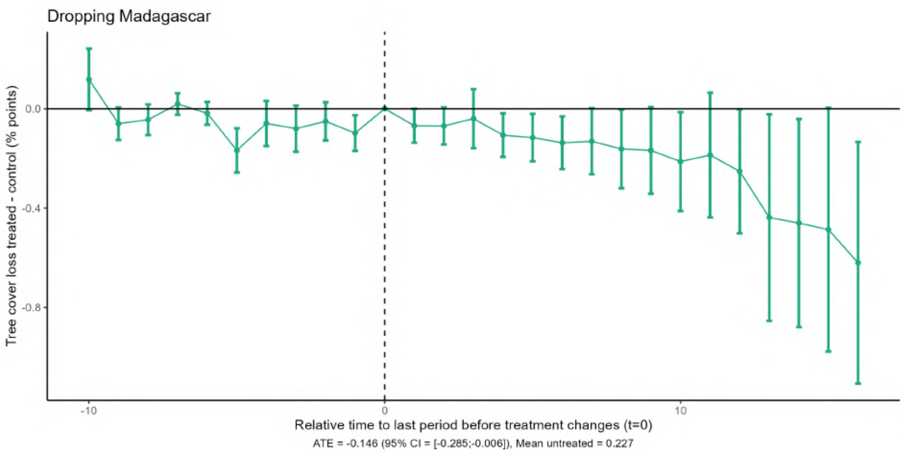

Figure S13: Robustness of the results when dropping observations from Madagascar.

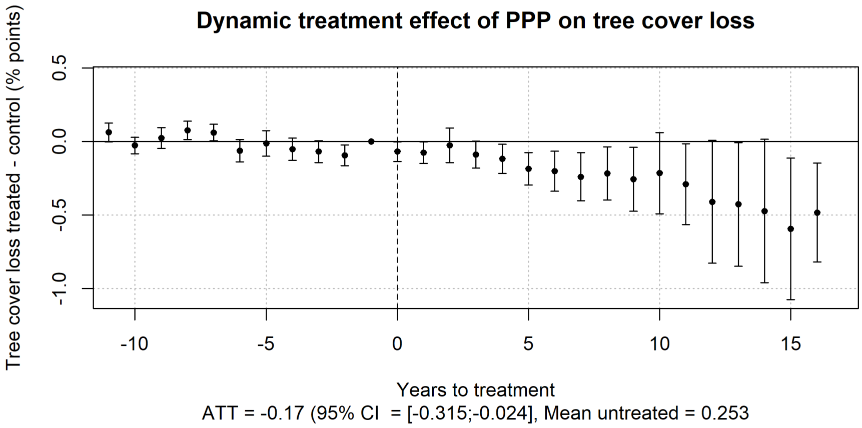

Figure S14: Robustness of the results when estimating the model with an alternative estimator and packaged developed by Sun and Abraham (2021) instead of De Chaisemartin et al. (2024).

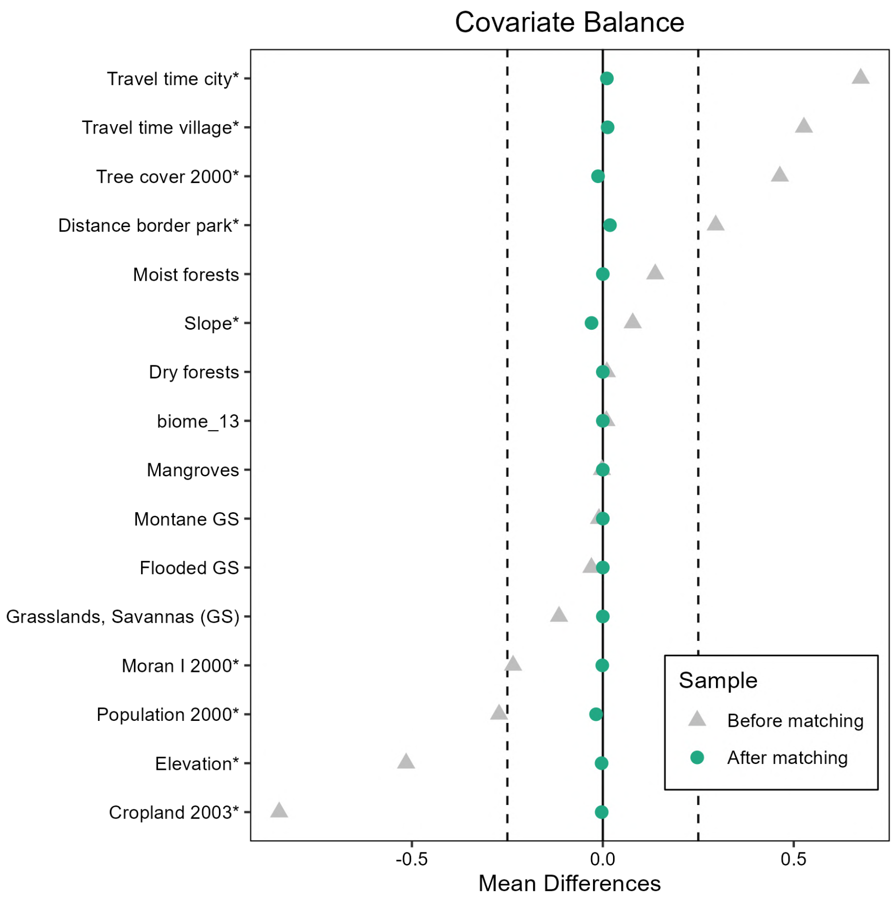

Figure S15: Robustness of the results: covariate balance when using a 10 x 10 km grid. An appropriate match was found for 834 out of 1586 treated cells (53% vs 62% in the main model with a 5 x 5 km grid).

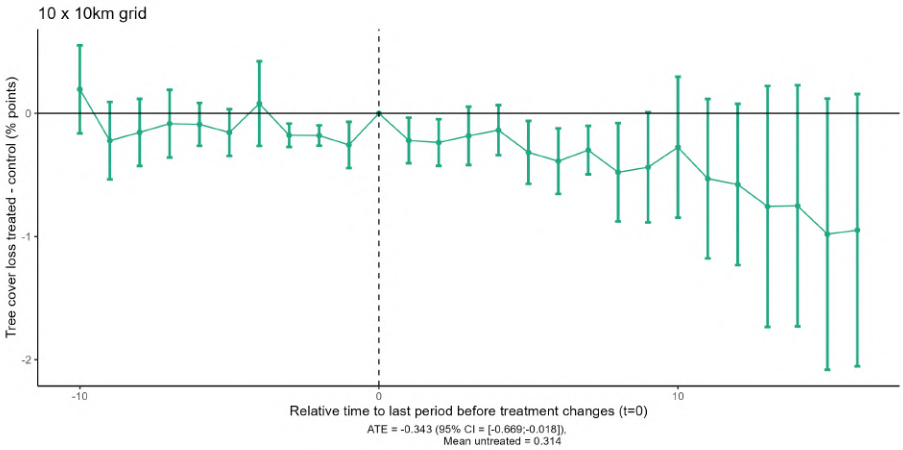

Figure S16: Robustness of the results when estimating the model on a 10 x 10 km grid.

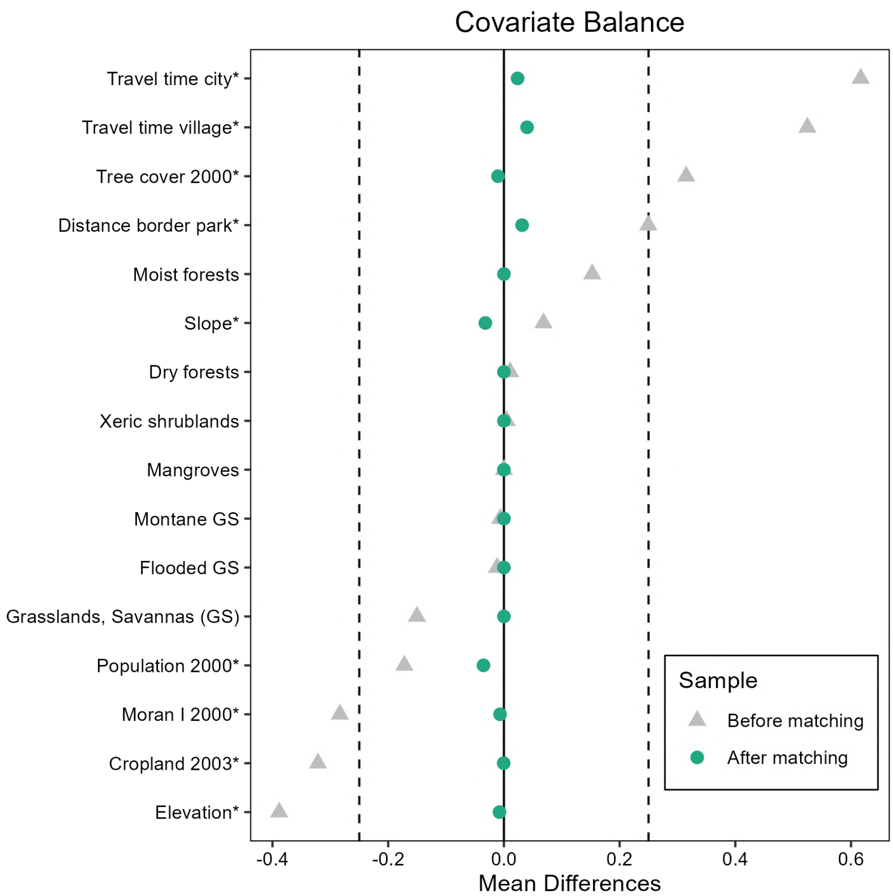

Figure S17: Robustness of the results: covariate balance when using a 2.5 x 2.5 km grid. An appropriate match was found for 14105 out of 20852 treated cells (67% vs 62% in the main model with a 5 x 5 km grid).

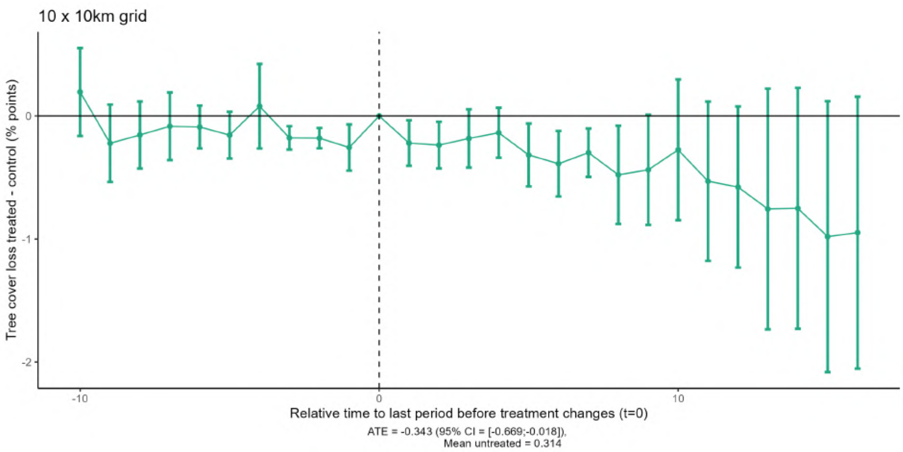

Figure S18: Robustness of the results when estimating the model on a 2.5 x 2.5 km grid.

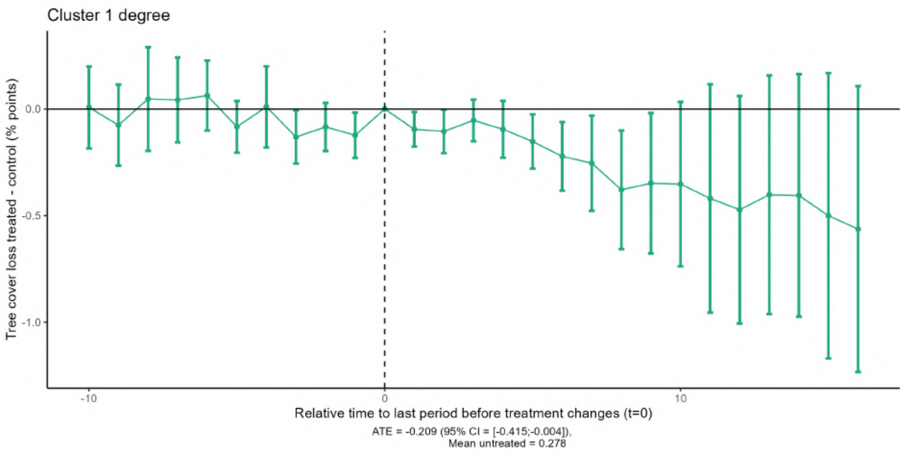

Figure S19: Robustness of the results when clustering standard errors at a 1 degree grid. In this sample, we did not sampled 1/3 grids but included them all.

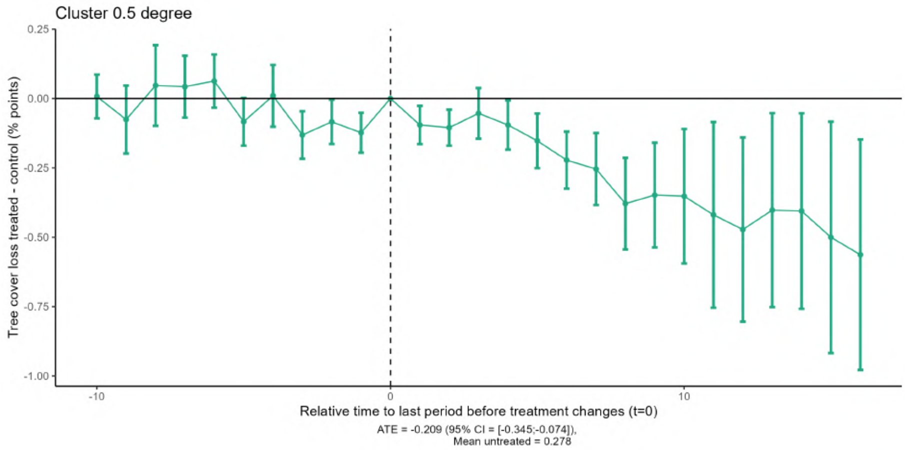

Figure S20: Robustness of the results when clustering standard errors at a 0.5 degree grid. In this sample, we did not sampled 1/3 grids but included them all.

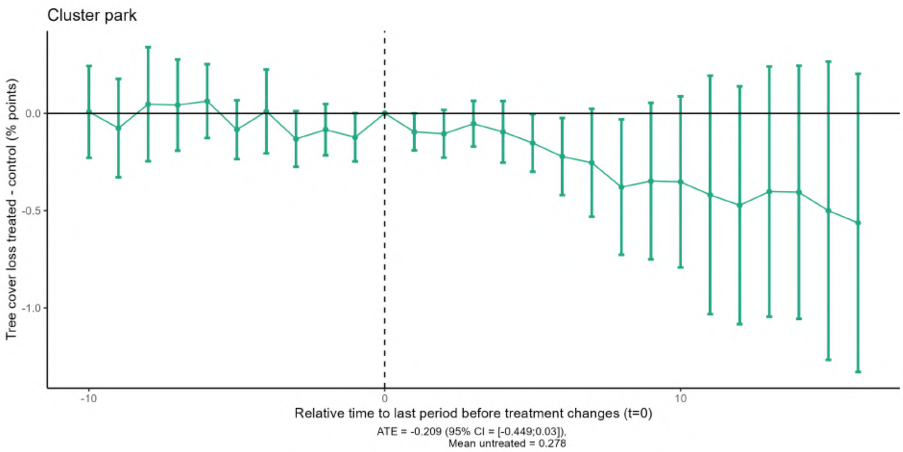

Figure S21: Robustness of the results when clustering standard errors at the park level. In this sample, we did not sampled 1/3 grids but included them all.

1.C. Illustration of the steps to construct our main units of observation (gridcells)

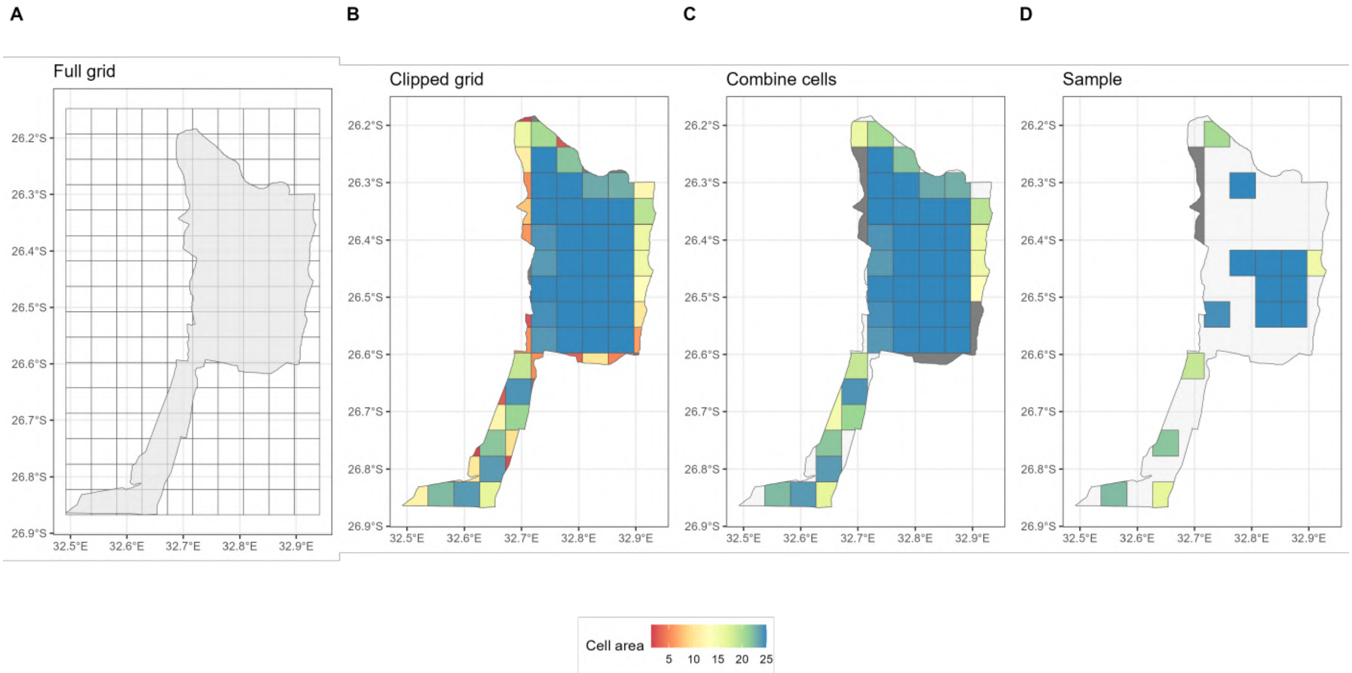

Figure S22: Illustraion of the four steps to create a grid for each park. A: we divide the PA into a regular grid. B: We clip the grid to the contour of the PA and calculate the area of each cell. C: Adjacent small cells are combined together to keep cells of comparable area. D: We sample 1/3 of the cells.

B Supplementary Tables

Table S1: List of co-managed and delegated Collaborative Management Partnerships

Country	PA	Year CMP	Partner
AGO	Iona National Park	2019	African Parks Network (APN)
BEN	Boucle de la Pendjari	2017	African Parks Network (APN)
BEN	Pendjari	2017	African Parks Network (APN)
BEN	W (Benin)	2020	African Parks Network (APN)
CAF	Chinko Core PA	2014	African Parks Network (APN)
CAF	Bamingui-Bangoran	2018	Wildlife Conservation Society (WCS)
CAF	Manovo-Gounda-Saint Floris	2018	Wildlife Conservation Society (WCS)
CAF	Dzanga-Ndoki	2019	World Wide Fund for Nature (WWF)
CAF	Dzanga-Sangha	2019	World Wide Fund for Nature (WWF)
CAF	Chinko larger	2020	African Parks Network (APN)
COD	Garamba	2005	African Parks Network (APN)
COD	Gangala-na-Bodio	2005	African Parks Network (APN)
COD	Virunga	2008	Virunga Foundation (VF)
COD	Salonga	2015	World Wide Fund for Nature (WWF)
COD	Upemba	2017	Forgotten Parks Foundation (FPF)
COD	Kundelungu	2017	Forgotten Parks Foundation (FPF)
COD	Lubudi-Sampwe	2017	Forgotten Parks Foundation (FPF)
COD	Lac Tshangalele	2017	Forgotten Parks Foundation (FPF)
COD	Okapis	2019	Wildlife Conservation Society (WCS)
COD	Lomami National Park	2019	Frankfurt Zoological Society (FZS)
COD	Kahuzi-Biega	2022	Wildlife Conservation Society (WCS)
COG	Lac Télé	2008	Wildlife Conservation Society (WCS)
COG	Odzala Kokoua	2010	African Parks Network (APN)
COG	Nouabalé-Ndoki	2014	Wildlife Conservation Society (WCS)
COG	Ntokou-Pikounda	2018	World Wildlife Fund
COG	Conkouati-Douli	2021	Noe
MDG	Makira	2012	Wildlife Conservation Society
MDG	Iles Barren	2014	ONG Blue Ventures
MDG	Bongolava	2015	Fikambananana Bongolava Maintso
MDG	Mahavavy Kinkony	2015	Asity Madagascar
MDG	Mangoky Ihotry	2015	Asity Madagascar
MDG	Tsitongambarika	2015	Asity Madagascar
MDG	Torotorofotsy	2015	Asity Madagascar
MDG	Beanka	2015	Biodiversity Conservation Madagascar
MDG	Sahafina	2015	Biodiversity Conservation Madagascar
MDG	Velondriake	2015	Association Velondriake, ONG Blue Ventures
MDG	Ambodivahibe	2015	Conservation International
MDG	Ankeniheny-Zahamena	2015	Conservation International
MDG	Ambositra-Vondrozo	2015	Conservation International
MDG	Bombetoka Beloboka	2015	Development and Environmental Law Center
MDG	Ambondrobe	2015	Durrell Wildlife Conservation Trust
MDG	Lac Alaotra	2015	Durrell Wildlife Conservation Trust

MDG	RiviAre Nosivolo	2015	Durrell Wildlife Conservation Trust
MDG	Allie des Baobabs	2015	Association Fanamby
MDG	Andrafiamena Andavakoera	2015	Association Fanamby
MDG	Anjozorobe-Angavo	2015	Association Fanamby
MDG	Loky Manambato	2015	Association Fanamby
MDG	Menabe Antimena	2015	Association Fanamby
MDG	Maromizaha	2015	Groupe d'Etude et de Recherche sur les Primates de Madagascar (GERP)
MDG	Tsinjoriake	2015	Association TAMIA
MDG	Nosy Antsoha	2015	Lemuria Land
MDG	Ampanangandehibe-Behasina	2015	Madagasikara Voakajy
MDG	Analabe Betanatanana	2015	Madagasikara Voakajy
MDG	Mahialambo	2015	Madagasikara Voakajy
MDG	Mangabe-Ranomena-Sahasarotra	2015	Madagasikara Voakajy
MDG	Agnakatrika	2015	Missouri Botanical Garden
MDG	Agnalazaha	2015	Missouri Botanical Garden
MDG	Ampasindava	2015	Missouri Botanical Garden
MDG	Analalava	2015	Madagasikara Voakajy
MDG	Ankarabolava	2015	Missouri Botanical Garden
MDG	Alandraza Analavelo	2015	Missouri Botanical Garden
MDG	Galoko-Kalobinono	2015	Missouri Botanical Garden
MDG	Makirovana Tsihomanaomby	2015	Missouri Botanical Garden
MDG	Ibity	2015	Missouri Botanical Garden
MDG	Oronjia	2015	Missouri Botanical Garden
MDG	Pointe	2015	Missouri Botanical Garden
MDG	Vohidava-Betsimalaho	2015	Missouri Botanical Garden
MDG	Antrema	2015	Museum National d'Histoire Naturelle
MDG	Ambatoatsinanana	2015	QIT Madagascar Minerals - Rio Tinto
MDG	Petriky	2015	QIT Madagascar Minerals - Rio Tinto
MDG	Mandena	2015	QIT Madagascar Minerals - Rio Tinto
MDG	Itremo	2015	Royal Botanical Gardens, Kew
MDG	Montagne des Fran ais	2015	SAGE
MDG	Tsimembo Manambolomaty	2015	The Peregrine Fund
MDG	Mandrozo	2015	The Peregrine Fund
MDG	Bemanevika	2015	The Peregrine Fund
MDG	Mahimborondro	2015	The Peregrine Fund
MDG	Manjakatompo Ankaratra	2015	Vondrona Ivon'ny Fampandrosoana
MDG	Ankarea	2015	Wildlife Conservation Society
MDG	Ankivonjy	2015	Wildlife Conservation Society
MDG	Soariake	2015	Wildlife Conservation Society
MDG	Amoron'i Onilahy	2015	World Wide Fund for Nature
MDG	Ankodida	2015	World Wide Fund for Nature
MDG	COMATSA Nord	2015	World Wide Fund for Nature
MDG	COMATSA Sud	2015	World Wide Fund for Nature
MDG	Nord-Ifotaka	2015	World Wide Fund for Nature
MDG	Ambatofotsy	2015	Madagasikara Voakajy
MDG	Ampotaka-Ankorabe	2015	Madagasikara Voakajy
MDG	Analalava	2015	Madagasikara Voakajy
MOZ	Cabo de São Sebastião	2000	Santuario Bravio de Vilanculos (SBV)
MOZ	Gilé	2007	IGF Foundation
MOZ	Maputo	2008	Peace Parks Foundation (PPF)
MOZ	Gorongosa	2008	Carr Foundation

MOZ	Niassa	2012	Wildlife Conservation Society (WCS)
MOZ	Zinave	2016	Peace Parks Foundation (PPF)
MOZ	Bazaruto	2017	African Parks Network (APN)
MOZ	Banhine	2018	Peace Parks Foundation (PPF)
MOZ	Limpopo	2018	Peace Parks Foundation (PPF)
MWI	Majete Wildlife Reserve	2003	African Parks Network (APN)
MWI	Liwonde National Park	2015	African Parks Network (APN)
MWI	Nkhotakota Wildlife Reserve	2015	African Parks Network (APN)
MWI	Mangochi	2018	African Parks Network (APN)
NER	Termit et Tin-Toumma	2018	Noe
NGA	Gashaka-Gumti	2018	Africa Nature Investors
RWA	Akagera	2010	African Parks Network (APN)
RWA	Nyungwe	2020	African Parks Network (APN)
SSD	Southern	2016	Fauna and Flora International (FFI)
SSD	Kidepo	2022	Enjojo Foundation
SSD	Boma	2022	African Parks Network (APN)
SSD	Badingilo	2022	African Parks Network (APN)
SSD	Lantoto	2022	Enjojo Foundation
TCD	Zakouma	2010	African Parks Network (APN)
TCD	Sena Oura	2012	Wildlife Conservation Society (WCS)
TCD	Ouadi Rimé-Ouadi Achim	2016	Sahara Conservation Fund (SCF)
TCD	Bahr Salamat	2017	African Parks Network (APN)
TCD	Siniaka-Minia	2017	African Parks Network (APN)
TCD	Binder-Léré	2021	Noe
TZA	Grumeti G.R.	2002	Grumeti Fund
TZA	Ikorongo G.R.	2002	Grumeti Fund
ZMB	Kasanka	1990	Kasanka Trust
ZMB	Liuwa Plain	2003	African Parks Network (APN)
ZMB	Bangweulu	2008	African Parks Network (APN)
ZMB	Lavushi Manda	2014	Kasanka Trust
ZMB	Nsumbu	2017	Frankfurt Zoological Society (FZS)
ZMB	Kafue	2022	African Parks Network (APN)
ZWE	Gonarezhou	2007	Frankfurt Zoological Society (FZS)
ZWE	Matusadona	2019	African Parks Network (APN)

Table S2: Comparison of PAs with and Without CMPs

(area in km^2, distribution of designation, IUCN categories and type of ecosystems)

Table S2: List of CMPs

		Without CMP		With CMP			
		Mean	Std. Dev.	Mean	Std. Dev.	Diff. in Means	Std. Error
Area in km^2		515.5	2665.4	5539.5	13031.7	5023.9***	1157.6
		N	Pct.	N	Pct.		
Designation	Classified Forest	30	1.2	1	0.8		
	Community Reserve	2	0.1	1	0.8		
	Faunal Reserve	10	0.4	4	3.1		
	Forest Reserve	2126	87.0	1	0.8		
	Game Management Area	35	1.4	1	0.8		
	Game Reserve	53	2.2	3	2.4		
	Hunting Area	13	0.5	2	1.6		
	Hunting Zone	2	0.1	1	0.8		
	Monument	0	0.0	2	1.6		
	National Park	111	4.5	42	33.1		
	Nature Reserve	13	0.5	2	1.6		
	Paysage Harmonieux	2	0.1	39	30.7		
	Protected Area	8	0.3	3	2.4		
	Reserve	23	0.9	18	14.2		
	Sanctuary	10	0.4	1	0.8		
	Special Reserve	0	0.0	3	2.4		
	Wildlife Reserve	7	0.3	3	2.4		
IUCN	I	2	0.1	0	0.0		
	Ib	7	0.3	0	0.0		
	II	93	3.8	40	31.5		
	III	3	0.1	2	1.6		
	IV	121	4.9	11	8.7		
	Not Reported	2146	87.8	9	7.1		
	V	4	0.2	39	30.7		
	VI	69	2.8	25	19.7		
	NA	0	0.0	1	0.8		
Terrestrial / Marine	Marine	15	0.6	5	3.9		
or Partial	Partial	118	4.8	11	8.7		
	Terrestrial	2312	94.6	111	87.4		

Table S3: Comparison of gridcells from PAs with and Without CMPs before matching

(biophysical and socio-economic characteristics)

Table S3: Comparison of treated and control gridcells before matching

		Without CMP		With CMP			
		Mean	Std. Dev.	Mean	Std. Dev.	Diff. in Means	Std. Error
Initial forest cover (2000)		1278.1	936.4	1646.4	888.5	368.3***	14.1
Moran I forest (2000)		0.5	0.2	0.5	0.3	-0.1***	0.0
Population cell (2000)		21.2	271.1	10.2	49.9	-11.0***	2.4
Travel time to nearest village (in min)		298.5	284.9	542.9	480.9	244.4***	6.7
Travel time to nearest city (in min)		720.2	476.6	1157.2	685.3	436.9***	9.8
Initial cropland (2003)		0.3	1.3	0.1	0.5	-0.2***	0.0
Average elevation (in m)		818.1	432.2	643.4	378.9	-174.6***	6.2
Average slope (in deg)		0.1	0.1	0.1	0.1	0.0***	0.0
		N	Pct.	N	Pct.		
Biome	Moist forest	2198	15.8	1723	29.6		
	Dry forest	199	1.4	154	2.6		
	Grassland, Savanna (GS)	10443	75.2	3689	63.3		
	Flooded GS	765	5.5	143	2.5		
	Montane GS	88	0.6	7	0.1		
	Desert and xeric shrubland	133	1.0	80	1.4		
	Mangrove	56	0.4	29	0.5		

Table S4: Comparison of gridcells from PAs with and Without CMPs after matching

(biophysical and socio-economic characteristics)

		Without CMP		With CMP			
		Mean	Std. Dev.	Mean	Std. Dev.	Diff. in Means	Std. Error
Initial forest cover (2000)		1518.8	908.9	1512.0	914.8	-6.8	21.5
Moran I forest (2000)		0.5	0.3	0.5	0.3	0.0	0.0
Population cell (2000)		8.4	19.2	6.8	20.1	-1.7***	0.5
Travel time to nearest village (in min)		385.9	331.4	400.8	339.4	14.9+	7.9
Travel time to nearest city (in min		932.9	549.7	944.9	543.8	12.1	12.9
Initial cropland (2003)		0.0	0.2	0.0	0.2	0.0	0.0
Average elevation (in m)		645.0	333.9	642.0	341.5	-3.0	7.9
Average slope (in deg)		0.1	0.0	0.1	0.0	0.0+	0.0
		N	Pct.	N	Pct.		
Biome	Moist forest	668	18.5	668	18.5		
	Dry forest	39	1.1	39	1.1		
	Grassland, Savanna (GS)	2727	75.5	2727	75.5		
	Flooded GS	125	3.5	125	3.5		
	Montane GS	0	0.0	0	0.0		
	Desert and xeric shrubland	51	1.4	51	1.4		
	Mangrove	2	0.1	2	0.1		

Table S4: Comparison of treated and control gridcells after matching

Table S5: Baseline results

Period	Estimate	SE	LB.CI	UB.CI	N	Switchers
Placebo 10	0.10	0.06	-0.02	0.22	8398.00	685.00
Placebo 9	-0.09	0.05	-0.19	0.01	12403.00	1042.00
Placebo 8	0.01	0.05	-0.10	0.11	22116.00	1245.00
Placebo 7	0.04	0.04	-0.04	0.12	27112.00	1581.00
Placebo 6	0.02	0.04	-0.06	0.09	39101.00	2335.00
Placebo 5	-0.13	0.05	-0.23	-0.03	51278.00	2589.00
Placebo 4	-0.04	0.05	-0.14	0.07	57491.00	2873.00
Placebo 3	-0.10	0.05	-0.19	-0.01	70539.00	3076.00
Placebo 2	-0.08	0.04	-0.16	-0.01	77445.00	3565.00
Placebo 1	-0.11	0.04	-0.18	-0.04	87219.00	3600.00
Effect 1	-0.07	0.03	-0.13	0.00	94443.00	3611.00
Effect 2	-0.08	0.04	-0.15	0.00	91845.00	3611.00
Effect 3	-0.01	0.06	-0.13	0.11	84773.00	3122.00
Effect 4	-0.08	0.05	-0.16	0.01	78431.00	3085.00
Effect 5	-0.10	0.05	-0.19	0.00	72150.00	2801.00
Effect 6	-0.16	0.05	-0.26	-0.06	65829.00	2614.00
Effect 7	-0.17	0.07	-0.30	-0.04	59777.00	2097.00
Effect 8	-0.21	0.08	-0.36	-0.06	53655.00	1761.00
Effect 9	-0.19	0.09	-0.36	-0.02	48074.00	1642.00
Effect 10	-0.21	0.10	-0.41	-0.01	42742.00	1285.00
Effect 11	-0.18	0.13	-0.43	0.07	36462.00	1044.00
Effect 12	-0.24	0.13	-0.49	0.00	35362.00	1044.00
Effect 13	-0.42	0.21	-0.83	0.00	29412.00	600.00
Effect 14	-0.43	0.21	-0.85	-0.01	28099.00	600.00
Effect 15	-0.47	0.25	-0.96	0.02	23236.00	516.00
Effect 16	-0.59	0.25	-1.08	-0.11	21610.00	516.00
Av tot eff	-0.14	0.07	-0.28	-0.01	158087.00	29949.00

Table S5: Point estimate, standard errors, confidence intervals (LB.CI and UP.CI) and number of switchers (N) for our baseline regression. The effect was estimated using the R package DIDmultiplegtDYN [78]. Each line corresponds to a specific year before treatment (Placebo) and after treatment (Effect). The last line report the estimated average total effect.

Table S6: Effect of CMP in low pressure PAs

Placebo_1	0.00	0.01	-0.01	0.01	36394.00	1844.00
Placebo_2	-0.01	0.01	-0.02	0.01	35199.00	1844.00
Placebo_3	0.00	0.01	-0.01	0.02	31840.00	1726.00
Placebo_4	0.01	0.01	-0.01	0.03	25304.00	1643.00
Placebo_5	0.00	0.01	-0.03	0.02	22020.00	1381.00
Placebo_6	0.03	0.02	-0.01	0.06	19184.00	1236.00
Placebo_7	0.02	0.02	-0.01	0.06	13255.00	940.00
Placebo_8	-0.01	0.03	-0.07	0.05	10893.00	782.00
Placebo_9	-0.02	0.03	-0.07	0.04	6104.00	667.00
Placebo_10	0.02	0.03	-0.04	0.07	4096.00	442.00
Effect_1	0.00	0.01	-0.01	0.01	36394.00	1844.00
Effect_2	0.00	0.01	-0.01	0.02	35199.00	1844.00
Effect_3	-0.02	0.01	-0.04	0.00	31840.00	1726.00
Effect_4	0.00	0.02	-0.03	0.03	28838.00	1711.00
Effect_5	-0.02	0.01	-0.04	0.01	25554.00	1449.00
Effect_6	-0.02	0.02	-0.05	0.01	22657.00	1304.00
Effect_7	-0.05	0.02	-0.08	-0.01	19769.00	1086.00
Effect_8	-0.06	0.02	-0.10	-0.03	16975.00	928.00
Effect_9	-0.05	0.02	-0.10	-0.01	14501.00	874.00
Effect_10	-0.06	0.01	-0.09	-0.03	11955.00	649.00
Effect_11	-0.07	0.02	-0.11	-0.04	9129.00	414.00
Effect_12	-0.08	0.02	-0.11	-0.04	8915.00	414.00
Effect_13	-0.11	0.02	-0.16	-0.07	6402.00	207.00
Effect_14	-0.07	0.04	-0.15	0.01	6169.00	207.00
Effect_15	0.01	0.12	-0.23	0.25	4077.00	146.00
Effect_16	-0.07	0.06	-0.19	0.05	3815.00	146.00
Av_tot_eff	-0.03	0.01	-0.05	-0.01	68424.00	14949.00
Mean Def Control	0.104					

Table S6: Point estimate, standard errors, confidence intervals (LB.CI and UP.CI) and number of switchers (N) for the effect of CMP in areas that faced low anthropogenic pressures initially. The effect was estimated using the R package DIDmultiplegtDYN [78]. Each line corresponds to a specific year before treatment (Placebo) and after treatment (Effect). The last line report the estimated average total effect.

Table S6: Effect of CMP in high pressure PAs

Placebo_1	-0.20	0.07	-0.34	-0.05	43669.00	1756.00
Placebo_2	-0.12	0.08	-0.28	0.03	38780.00	1721.00
Placebo_3	-0.20	0.10	-0.41	0.00	35233.00	1350.00
Placebo_4	-0.06	0.12	-0.31	0.18	28782.00	1230.00
Placebo_5	-0.24	0.11	-0.45	-0.02	25853.00	1208.00
Placebo_6	0.05	0.08	-0.11	0.20	19917.00	1099.00
Placebo_7	0.16	0.10	-0.04	0.36	13857.00	641.00
Placebo_8	0.14	0.13	-0.13	0.40	11223.00	463.00
Placebo_9	-0.09	0.13	-0.35	0.17	6299.00	375.00
Placebo_10	0.52	0.16	0.22	0.83	4302.00	243.00
Effect_1	-0.14	0.07	-0.27	0.00	47281.00	1767.00
Effect_2	-0.18	0.08	-0.33	-0.03	45956.00	1767.00
Effect_3	0.01	0.13	-0.25	0.26	42311.00	1396.00
Effect_4	-0.14	0.10	-0.33	0.06	39100.00	1374.00
Effect_5	-0.18	0.10	-0.38	0.01	36103.00	1352.00
Effect_6	-0.32	0.11	-0.52	-0.11	32964.00	1310.00
Effect_7	-0.33	0.14	-0.59	-0.06	29878.00	1011.00
Effect_8	-0.39	0.16	-0.71	-0.07	26846.00	833.00
Effect_9	-0.34	0.18	-0.70	0.02	24025.00	768.00
Effect_10	-0.33	0.20	-0.73	0.07	21500.00	636.00
Effect_11	-0.27	0.21	-0.68	0.15	18411.00	630.00
Effect_12	-0.38	0.21	-0.79	0.04	17978.00	630.00
Effect_13	-0.55	0.33	-1.19	0.09	15146.00	393.00
Effect_14	-0.58	0.33	-1.22	0.06	14607.00	393.00
Effect_15	-0.63	0.35	-1.31	0.05	12063.00	370.00
Effect_16	-0.79	0.35	-1.48	-0.11	11193.00	370.00
Av_tot_eff	-0.26	0.14	-0.53	0.01	78827.00	15000.00
Mean Def Control	0.397					

Table S7: Point estimate, standard errors, confidence intervals (LB.CI and UP.CI) and number of switchers (N) for the effect of CMP in areas that faced high anthropogenic pressures initially. The effect was estimated using the R package DIDmultiplegtDYN [78]. Each line corresponds to a specific year before treatment (Placebo) and after treatment (Effect). The last line report the estimated average total effect.