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Effectiveness of Protected Areas in the Pan-Tropics and International Aid for Conservation

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Abstract: Evaluation of the effectiveness of protected areas is critical for forest conservation policies and priorities. We used 30 m resolution forest cover change data from 1990 to 2010 for ~4000 protected areas to evaluate their effectiveness. Our results show that protected areas in the tropics avoided 83,500 ± 21,200 km^2 of deforestation during the 2000s. Brazil's protected areas have the largest amount of avoided deforestation at 50,000 km^2. We also show the amount of international aid received by tropical countries compared to the effectiveness of protected areas. Thirty-four tropical countries received USD 42 billion during the 1990s and USD 62 billion during the 2000s in international aid for biodiversity conservation. The effectiveness of international aid was highest in Latin America, with 4.3 m^2/USD, led by Brazil, while tropical Asian countries showed the lowest average effect of international aid, reaching only 0.17 m^2/USD.

Keywords: protected area; tropical deforestation; international aid; conservation; remote sensing

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1. Introduction

In 2010, the Convention on Biological Diversity (CBD) adopted a revised strategic plan for biodiversity for 2011–2020, including the Aichi Biodiversity Targets. One of the targets is to reduce the rate of loss of all natural habitats, including forests, by 2020 [1]. However, recent studies [2,3] have shown acceleration and high sustained rates of tropical deforestation since 2000. To meet the proposed goals of conservation plans, such as the Aichi Biodiversity Targets, evaluating the effectiveness of previous and current efforts to reduce tropical deforestation is essential. Within this context, assessing the effectiveness of protected areas (PAs) throughout the tropics is relevant, especially given that PAs are central to climate and biodiversity policies [4–6]. Previous efforts have been made to evaluate the effectiveness of PAs over various spatial and temporal scales [4,5,7–9]. Some studies have been conducted to evaluate the cost-effectiveness of these PAs [10,11]; these have explored the links between the value of PAs and surrounding socioeconomic drivers of tropical deforestation [12]. Others have examined the management effectiveness of PAs for limited times and spatial scales to create a framework and guidelines for the management of protected areas [13,14].

Satellite-based remotely sensed data have been used to evaluate the effectiveness of PAs in reducing deforestation because of their spatio-temporal consistency and their ability to complement ground-based observations, including filling data gaps and solving compatibility issues [4,15,16]. However, in selected locations, spatially explicit information on pan-tropical forest cover change at Landsat resolutions was not previously available beyond satellite analysis [4,17]. The lack of comprehensive long-term spatial data has precluded pan-tropical scale analysis on the effectiveness of PAs in terms of their regulating socioeconomic factors. Long-term, large-area forest cover change at 30 m resolution has recently been made available [18–20]. Based on this information, this study aims to (1) estimate avoided deforestation by PAs in each tropical country during the 2000s, and (2) compare the avoided deforestation against international aid for biodiversity conservation received by each tropical country.

2. Experimental Section

2.1. Study Area

The study covered thirty-four countries spanning the humid tropics (Figure 1), each of which was comprised of at least 50% forest biomes. Overall, forest areas in these countries comprise over 80% of forest area in the tropics and dominate the forest area of the humid tropics [2,3].

Figure 1. 34 Tropical countries and protected areas analyzed in this study.

2.2. Forest Change Data

Landsat-based forest cover change data between 1990, 2000, and 2010 [3,18,19] were used to derive net forest cover change in 34 tropical countries that comprise over 80% of forest area in the tropics [3] and dominate the forest area of the humid tropics (Figure 1). These data were derived from 5444 surface reflectance images collected for 1990, 2000, and 2010 epochs from the Global Land Survey (GLS) collection of Landsat images [21–24], supplemented by many additional images [21]. Forest cover was defined as parcels > 1 ha in area and comprising pixels with >30% tree cover [25–27]. We also combined the International Geosphere–Biosphere Programme's (IGBP) classes of forest (>60% tree cover) and woody savannas (>30% tree cover) for our definition.

We extracted the forest cover change maps for each of the 3888 designated PAs and their surrounding areas in 34 tropical countries [28] from the Landsat-based forest cover change data. We used global forest cover and change data developed by Kim et al. [3,18,19,29]. Kim et al. used the Global Land Survey collection [23] of Landsat data and decision tree-based methods to map the extent of forests in 1990, 2000, and 2010. The original GLS data were augmented with additional images to improve radiometric calibration, reduce cloud cover, and maximize spectral discrimination of forests [30]. Each image of this augmented GLS data set was atmospherically corrected to estimate surface reflectance using the LEDAPS (Landsat Ecosystem Disturbance Adaptive Processing System) [24]. Validation of the forest cover and change maps was performed globally and by eco-regions using high-resolution satellite imagery-based validation samples. The accuracy of the forest map for 1990 was 93% in relation to the reference forest cover map, and it was 84% for the forest cover change map between 1990 and 2000.

We analyzed all designated PAs in the selected tropical countries instead of using any sampling, and we did so to take full advantage of the spatially explicit, fine resolution data. Despite their conceptual importance, the effects of protected areas downgrading, downsizing, and degazetting (PADDD) [31,32] were not considered in this study, since there were only a small number of relevant PADDDs identified from the available PADDD data [33]. We derived the annual gross forest loss, gross forest gain, and net forest change rates within each PA and its surrounding area from the forest change maps. We then calculated the forest loss rate by dividing the area of forest loss by area of forest within PAs or surrounding areas. Each GLS epoch spans a range of years focused on the nominal year [23], so the forest/nonforest layer for each year was accompanied by the year of image acquisition to estimate changes over time as rates.

2.3. International Aid Data for Biodiversity Conservation

Global aid data for the period 1990–2010 were obtained from the AidData Version 3 database [34]. The database contains records of development projects from more than 90 bilateral and multilateral donors and constitutes a detailed source of project-level information on international aid [34]. We used the nominal value of currency (in USD) to account for changes in currency value over time. The project data extracted from AidData include data from all the sectors [35]. We excluded the sectors less relevant for biodiversity and natural resource management, such as reproductive health care and secondary education. Averages for the 1990s and the 2000s were calculated from each data set and the differences are used as independent variables for regression analysis.

2.4. Estimation of Avoided Deforestation by PAs

Measuring the amount of avoided deforestation by PAs is complex because it cannot be measured directly [7]. Broadly, two different approaches have been in use to estimate avoided deforestation. The first set of approaches compares differences in forest change rate between inside and outside PAs [4,5,15]. However, approaches these have been criticized for their inability to account for the spillover effect from PAs to the adjacent areas outside of Pas, as well as for selection bias due to un-randomized selection of PAs and inherently different deforestation probability between the inside and outside of PAs [36]. Second, there are statistical matching approaches that can be used to match the difference in deforestation probability between samples inside and outside PAs [7,37]. The statistical matching of samples is robust but challenging to implement due to high computational costs and difficulties in finding statistically significant matches, especially when a PA network covers large continuous tracts of land [11]. Moreover, some important factors, such as policies (e.g., concession) which contribute to deforestation probability, can be overlooked in this approach. To avoid selection bias and computational difficulties associated with previously mentioned methods, we used the Difference-In-Differences (DID) estimator to measure avoided deforestation in the 2000s compared to the 1990s for PAs in each tropical country [38,39] (Figure 2).

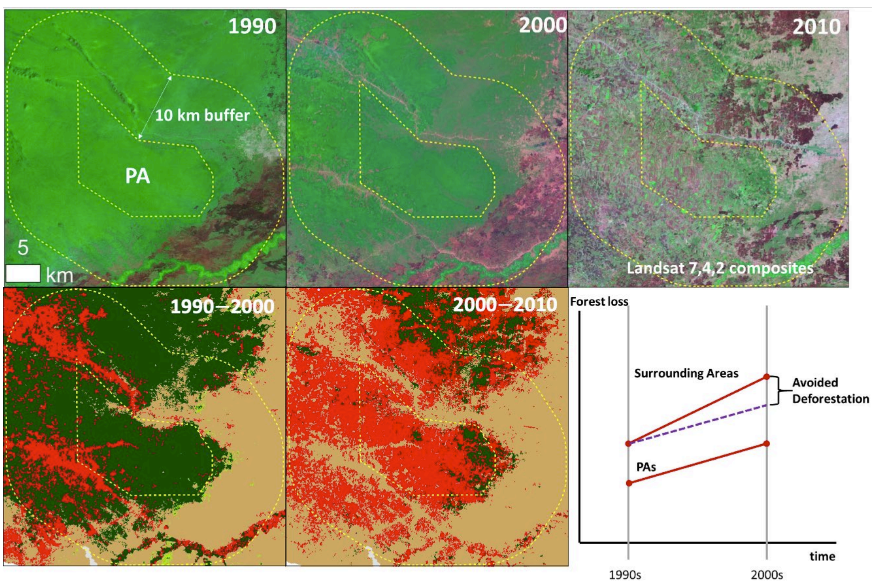

Figure 2. Avoided deforestation estimates for a designated protected area in Cambodia: top images show forest change over time in the Roniem Daun Sam wildlife sanctuary, which was designated in 1993. The bottom figures show forest cover change maps between periods and an illustration of the DID method. Avoided deforestation (DID) is estimated by calculating differences between difference in forest loss rate in the PAs before and after designation and the difference in forest loss rate in the surrounding areas over time.

This method has a relatively strong inferential ability as it eliminates selection biases by attempting to mimic an experimental research design using observational data [38,40]. The impact of a treatment on outcome Yi, which is the annual forest change rate in this study, was modeled by the following equation:

$$Yi = \alpha + \beta Ti + \gamma ti + \delta(Ti \cdot ti) + \varepsilon i \quad (1)$$

where T is the treatment status; t is the time period before and after the treatment; the coefficients given by the Greek letters α, β, γ, δ are all unknown parameters; and ε_i is a random, unobserved "error" term. In the DID estimator, the effect of treatment (avoided deforestation), δ, is defined as the difference in average outcome in the treatment group T before and after treatment minus the difference in average outcome in the control group C before and after treatment, and it is expressed as:

$$\delta = \overline{Y}_1^T - \overline{Y}_0^T - (\overline{Y}_1^C - \overline{Y}_0^C) \quad (2)$$

where the treatment group is PAs and the control group is the surrounding areas before and after the year 2000 (Figure 2). We applied this method to (a) the 3888 PAs and surrounding areas designated before 2010 to determine the accumulated effect during the 2000s, and (b) to the subset of 1253 PAs established between 2000–2010 to estimate the effect of newly established PAs.

2.5. Estimation of Spillover Effect

The spillover effect refers to the displacement of forest loss from one place to a neighboring area due to the establishment of a PA. If PAs displaced deforestation to their immediate surroundings through the spillover effect, deforestation rate increases within those areas would be higher than in other regions with similar characteristics (e.g., accessibility) [16,41]. Based on these assumptions, we measured the potential spillover or leakage effect by comparing forest loss between the 1990s and the 2000s, and avoided deforestation estimates using surrounding areas at different buffer distances (500 m, 1 km, 5 km, 10 km, 15 km, 20 km, and 25 km).

2.6. Statistical Analysis

To ensure the robustness of the DID method, we tested (1) ordinary least squares (OLS) regression analysis between treatment, time period, and estimated avoided deforestation, as expressed in Equation (1); and (2) a paired t-test between the difference in forest loss rates in PAs and the difference in forest loss rates in the surrounding areas to determine the significance of the effect of PAs before and after 2000. Effects of PAs are graphically presented with changes in frequency distributions.

3. Results and Discussion

3.1. Avoided Deforestation by Protected Areas

Our results demonstrate an overall 83,500 ± 21,200 km^2 of avoided deforestation by the PAs during the 2000s throughout the tropics, which equals 3.5% of all forest area within PAs in the study area (Figure 1, Table A1). Figure 3 shows avoided deforestation by each country along with international aid received by them.

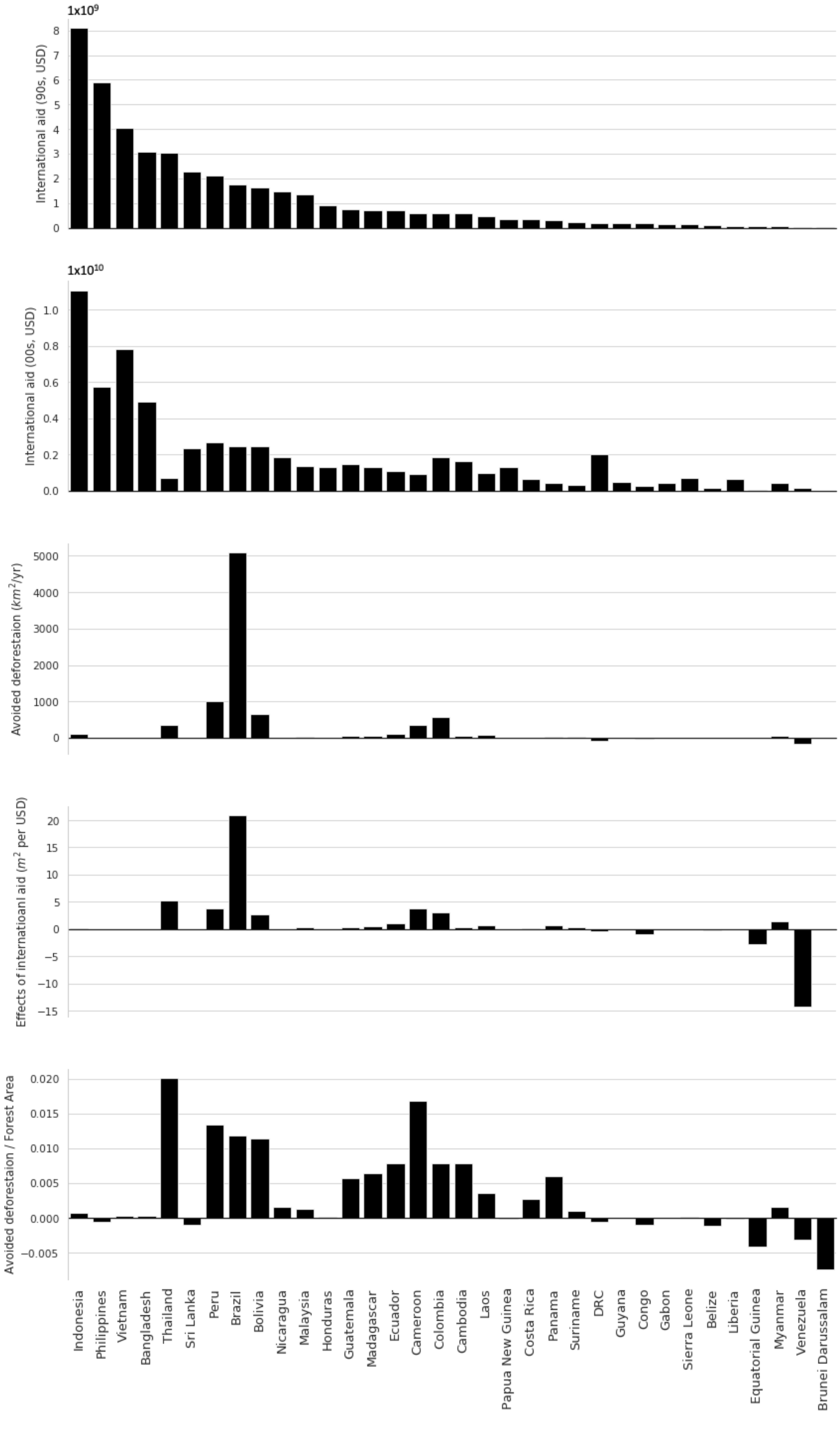

Figure 3. The amount of international funds committed to each tropical country in the 1990s and the 2000s; the amount of funds are converted to a nominal value of USD; avoided deforestation by each country; effects of international aid (amount of international aid per unit of avoided deforestation) for 34 tropical countries; and avoided deforestation divided by the entire forest area of each country.

Latin America showed the largest estimates of avoided deforestation during the 2000s (73,900 km^2). In Latin America, Brazil showed the largest avoided deforestation (50,870 km^2), followed by Peru (9970 km^2) and Bolivia (6611 km^2) for the same time-period. Venezuela was found to have the largest negative effect (-1622 km^2) among Latin American countries. The negative effect means forest loss rates within PAs exceeded the forest loss rates in surrounding areas. Relatively high rates of avoided deforestation from PAs in Brazil emphasize Brazil's important role in tropical forest conservation. Positive avoided deforestation effects of PAs in Brazil were also reported by previous studies [11,12]. Tropical Asia showed the second largest estimates of avoided deforestation of 6744 km^2, with the largest amount in Thailand, followed by Indonesia. Tropical Africa has the lowest estimates, except Cameroon, which showed the largest estimate of 3411 km^2. In terms of the percentage of avoided deforestation against the entire forest area in PAs, Africa showed the lowest estimates of 1.8%, while Latin America and Asia showed similar estimates of 3.8%. The comparison between estimates for the entire set of PAs and the PAs established after 2000 showed that PAs established post-2000 had a higher rate of avoided deforestation at 0.5% annually compared to 0.4% for the entire set of PAs. The area of avoided deforestation in PAs established during the 2000s was about 60% of estimated avoided deforestation in all PAs in the study area. In comparison, the area of avoided deforestation in PAs established during the 1990s was about 27%. Prior to 1990, estimated avoided deforestation was about 13% in all PAs in the study area.

On average, PAs in the tropics established after 2000 showed a greater avoided deforestation than PAs established before 2000. Nevertheless, old established PAs were still effective, although not as effective as recently established ones [39]. Estimates of avoided deforestation based on the median value of forest loss exhibited similar results. Changes in mean and median forest loss within PAs and the surrounding areas before and after 2000 demonstrate the positive effects of PAs on reducing deforestation (Table 1).

Table 1. Estimates of avoided deforestation by all PAs (established prior to 2010) by year of establishment to show the difference in effectiveness. Newer PAs established during the 2000s show more effectiveness compared to PAs established prior to 2000, as well as all PAs. Numbers in parenthesis represent estimates using median forest loss rate.

	Avoided Deforestation		**Mean Forest Loss Rate within Protected Areas**		**Mean Forest Loss Rate within Buffer Zones**	
Year of establishment	(%)	(km^2)	Before 2000	After 2000	Before 2000	After 2000
Prior to 2010	3.46 (4.1)	83,500	0.59 (0.09)	1.65 (0.17)	0.91 (0.46)	2.32 (0.94)
1990–2000	3.42 (4.6)	22,800	0.5 (0.01)	1.66 (0.02)	0.86 (0.46)	2.32 (1)
2000–2010	4.47 (5)	47,650	0.5 (0.02)	1.52 (0.04)	0.897 (0.35)	2.37 (0.87)

The lower deforestation rates in recent PAs and the higher rates in the recent surrounding areas after 2000 show that the greater avoided deforestation of recent PAs is not because of their remoteness (Table 1). Congo, Belize, the Philippines, and Sri Lanka showed positive avoided deforestation from PAs established since 2000, while estimates including all PAs established before 2000 showed negative effects in these countries, suggesting the old established PAs in those countries are experiencing higher rates of deforestation. The following analysis supports our estimates of avoided deforestation. First, the ordinary least squares (OLS) regression analysis of the PA effect evaluation model (Equation (1)) shows a strong association ($p < 0.001$) between forest loss rate change and protected area designation (Table A2). Second, a paired t-test between the forest loss rate changes in PAs and the surrounding areas confirms the hypothesis that the two groups show a significant difference before and after the designation of PAs ($t = 6.6$). Third, Figure 4 suggests that, at t1 (pre-2000), the forest loss rate was high inside PA areas and, at t2 (post-2000), the loss was lower, confirming the positive effects of PAs in reducing deforestation in the tropics.

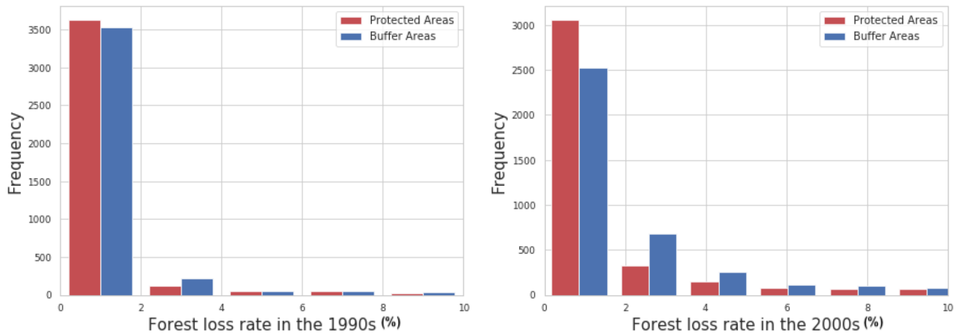

Figure 4. Frequency distribution of the difference in forest loss rates between the interior of protected areas and the surrounding 10 km buffers in the 1990s (**left**) and the 2000s (**right**).

Finally, our results show that PAs in Brazil established since 2000 avoided deforestation of 2794 km^2 annually, which is corroborated by an annual 2500 km^2 of avoided deforestation between 2004 and 2006 reported by Soares-Filho et al. [11]. Figure 5 shows the mean forest loss rates of surrounding areas with various distances from 500 m to 25 km from PAs in the 1990s (a) and in the 2000s (b).

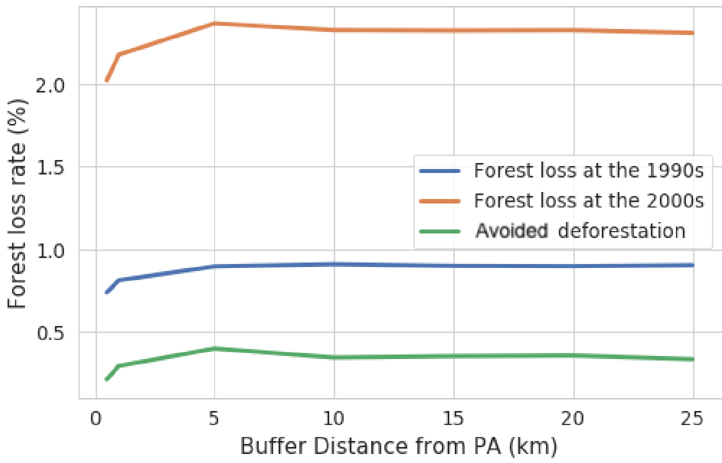

Figure 5. Mean forest loss rate in surrounding areas at various buffer distances in the 1990s and in the 2000s.

Figure 5 demonstrates that the increase in forest loss between two decades was the largest within a 10 km distance. This suggests that the spill-over effects were largest in the areas immediately adjacent to PAs, and the areas further than 10 km from PAs had marginal spill-over effects. Spill-over effect refers to the displacement of forest loss from PAs to surrounding areas due to the establishment of PAs. Relatively lower forest loss rates within surrounding areas with less than a 10 km buffer distance are because of a given PA's relative inaccessibility, isolation [4], or even better protection due to buffer zone conservation initiatives [42]. We used estimates of avoided deforestation with a 10 km buffer distance for the regression analysis, where spill-over effects start to be marginal.

3.2. International Aid for Conservation

Thirty-four tropical countries received total international aid for biodiversity conservation of USD 42 billion during the 1990s and USD 62 billion during the 2000s, with a net increase of 46% (USD 20 billion) between the two periods (Figure 3). Among continents, tropical Asian countries were the largest recipients, receiving 62% of all funds during the 2000s, followed by Latin American countries (28%). Among the countries, Indonesia received the largest amount of aid—18% of all funds received by 34 tropical countries—followed by Vietnam (1%) and the Philippines (9%) for the same period [43].

To compare the avoided deforestation against international aid for biodiversity conservation received by each tropical country, we determined the relative contribution of the international aid—"effectiveness of international aid"—by dividing the estimated avoided deforestation area with the amount of international aid for biodiversity conservation received by each country. The rationale for this assumption is that (1) the primary goal of international aid for biodiversity conservation is to enhance biodiversity conservation, regardless of the political and economic circumstances, and (2) conservation of biodiversity in the tropics has a negative association with tropical deforestation [6,34,44]. However, did not analyze causal relationships between avoided deforestation and the amount of international aid received.

The effectiveness of international aid was highest in Latin America, with 4.3 m^2/USD, led by Brazil, while tropical Asian countries showed the lowest average effect of international aid, reaching only 0.17 m^2/USD. Among the countries examined, Brazil showed the absolute highest cost-effect of 21 m^2/USD. The blue line in Figure 1 indicates that only 9 out of 34 countries were found to have higher effects of international aid than the average. Country-based estimates of avoided deforestation by PAs and effects of international aid showed a varied pattern throughout the tropics. Notably, the two largest sources of tropical deforestation during the 2000s, Brazil (2.2 Mha·yr $^{-1}$) and Indonesia (0.8 Mha·yr $^{-1}$), showed a sharp contrast [3]. Brazil showed higher estimates of avoided deforestation compared to Indonesia by a factor of 50, although Indonesia has received about 500% more international aid (USD 11 billion) compared to Brazil (USD 2.4 billion), resulting in lower estimates of the effects of international aid (0.5 m^2/USD) compared to Brazil (22 m^2/USD) by a factor of 44.

Our approach using a DID estimator with fine resolution and spatially explicit forest change data offered an alternative way to handle commonly criticized selection bias and spillover problems [7,36]. Despite the methodological advances made in this study, it has some limitations. First, our forest cover change estimates do not distinguish between primary and managed forests, leaving a potential for confusion between loss of natural forest and managed harvest. Second, the coarse spatial scale of socioeconomic data limited the regression analysis to the country scale, which prevented the regression analysis between individual PAs and their geophysical factors. Third, Brazil's success in reducing deforestation is an exceptional case made possible under a special political landscape [12,45], which is difficult to generalize to other tropical countries. Finally, for the estimates of the effect of international aid on avoided deforestation by PAs, we only considered the contribution of international monetary aid, while the amount of international aid may not be the only factor determining a given PA's effectiveness. Other domestic sources of funds (e.g., Amazon Region Protected Areas Program of Brazil) and different aspects of conservation (e.g., biodiversity) or political environment, which vary by country and over time, were not accounted for in this study. Additionally, the processes of international aid delivery were not considered in this study. For example, Norwegian funds are committed to Indonesia under the condition that they meet specific conservation goals. Further analysis is needed to estimate the effect of differences in the distribution of funds.

4. Conclusions

Our results showed an overall positive effect of pan-tropical PAs on reducing deforestation during the 2000s. The overall positive effect of PAs in reducing deforestation throughout the tropics corroborates with the findings of previous studies [7,37,39,46,47]. However, unlike many previous studies, our results provide a consistent, long-term estimate throughout the pan-tropics. The estimated avoided deforestation and effects of international aid by countries pinpoint where conservation activity and resources distribution are effectively practiced. These findings underscore the challenges that policy instruments face, and also provide a launchpad for alternative strategies for future conservation policies and initiatives. However, the study does not link its findings to political–economic contexts. Not covering these aspects remains a limitation of this study. Nevertheless, with a robust empirical approach and future data availability on socioeconomic drivers, the protection of critical ecosystem services in a coupled human–natural system can be better understood.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Summary of the avoided deforestation estimates by countries and continents. Acceleration of deforestation is indicated by percent increase in net deforestation rate from the 1990s to the 2000s (3). Avoided deforestation is presented in percent of conserved forest relative to remaining forest in PAs and total area of conserved forest. All estimates are on an annual basis. Negative effect means forest loss rates within PAs exceeded the forest loss rates in surrounding areas.

Country	Acceleration of Deforestation (%)	Avoided Deforestation (%)	Avoided Deforestation (km^2)	Area of PAs (km^2)	Forest Area in PAs (%)	No. of PAs
Cameroon	20.6	1.39	341.1	46,414	53	35
Congo	0.0	−0.23	−24.2	22,624	46	13
Democratic Republic Congo	31.2	−0.09	−77.4	219,677	41	31
Equatorial Guinea	−2.0	−0.32	−10.7	3602	93	6
Gabon	−11.5	0.01	1.5	16,677	97	8
Liberia	−8.2	−0.17	−1.5	1687	53	2
Madagascar	15.6	0.69	57.5	15,322	55	42
Sierra Leone	8.9	0.03	0.3	2955	38	31
Africa Total	6.8	0.18	286.5	328,957	47	168
Bangladesh	16.3	0.17	0.5	490	56	19
Brunei Darussalam	0.0	−0.90	−3.8	448	94	18
Cambodia	27.8	0.49	61.7	24,779	51	24
Indonesia	2.9	0.22	100.8	95,981	49	152
Laos	5.1	0.49	67.6	17,095	80	12
Malaysia	2.5	0.21	38.4	19,330	96	122
Myanmar	11.5	0.88	64.5	15,201	48	29
Papua New Guinea	1.1	−0.19	−5.1	3849	69	27
Philippines	12.0	−0.05	−9.0	26,890	64	165
Sri Lanka	19.5	−0.05	−3.0	11,860	46	210
Thailand	15.9	0.76	357.1	61,541	76	117
Vietnam	18.5	0.06	4.7	18,295	43	65
Asia Total	11.1	0.38	674.4	295,758	61	960

Table A1. *Cont.*

Country	Acceleration of Deforestation (%)	Avoided Deforestation (%)	Avoided Deforestation (km^2)	Area of PAs (km^2)	Forest Area in PAs (%)	No. of PAs
Belize	−1.1	−0.06	−2.2	4353	86	63
Bolivia	5.6	0.92	661.1	98,585	73	42
Brazil	3.3	0.34	5087.0	1,852,181	82	1321
Colombia	18.0	0.89	582.9	169,960	38	593
Costa Rica	12.0	0.23	10.8	5424	86	79
Ecuador	2.2	0.76	119.8	22,467	70	20
Guatemala	2.6	0.27	42.7	18,053	86	225
Guyana	−6.2	0.01	0.6	10,426	41	3
Honduras	8.3	0.02	1.6	11,733	56	62
Nicaragua	26.5	0.68	9.4	4597	30	61
Panama	18.8	0.76	27.3	4610	78	13
Peru	4.5	0.51	997.0	308,599	64	185
Suriname	4.4	0.05	14.2	29,041	99	7
Venezuela	26.7	−0.39	−162.2	80,919	51	85
Latin America Total	9.0	0.38	7389.8	2,620,949	75	2759
Grand Total	6.2	0.35	8350.6	3,245,663	71	3887

Appendix B

Table A2. Statistics of Difference-in-Differences analysis to calculate avoided deforestation by country and individuals. PA.

By country				
Independent variables	**Estimate**	**Std. Error**	**t Value**	**Pr (>|t|)**
(Intercept)	−0.39885	0.06	−6.020	1.62×10^{-8} ***
Period	−0.39489	0.09370	−4.215	4.61×10^{-5} ***
Treatment	0.23511	0.09370	2.50	0.0133 *
Treatment·Period	0.2719	0.13250	2.052	0.0421 *
* $p < 0.01$, *** $p < 0.0001$, independent variables are log transformed				
Residual standard error: 0.3863 on 132 degrees of freedom, Multiple R-squared: 0.2781, Adjusted R-squared: 0.2617 F-statistic: 16.95 on 3 and 132 DF, p-value: 2.257×10^{-9}				
By individual PA				
Independent variables	**Estimate**	**Std. Error**	**t Value**	**Pr (>|t|)**
(Intercept)	−0.9100	0.04603	−19.772	$<2 \times 10^{-16}$ ***
Period	−1.41258	0.04603	−21.702	$<2 \times 10^{-16}$ ***
Treatment	0.32492	0.06509	4.992	6.06×10^{-7} ***
Treatment·Period	0.34607	0.09205	3.759	0.000171 ***
*** $p < 0.0001$, independent variables are log transformed				
Residual standard error: 2.659 on 13,348 degrees of freedom, Multiple R-squared: 0.0603, Adjusted R-squared: 0.06009 F-statistic: 285.5 on 3 and 13348 DF, p-value: $< 2.2 \times 10^{-16}$				

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