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Abstract

An increasingly popular way to protect the integrity of forests is to establish protected areas such as national parks. Measuring their effect on deforestation has turned out to be methodological challenging. Recent studies on the effectiveness of protected areas (PAs) have been based on a comparison of deforestation rates of areas inside and outside of PAs using satellite data. Such approaches are, however, in danger to yield biased estimates because of spatial spill-over and because areas outside and inside might differ in many characteristics, which in turn influence also deforestation. In order to get unbiased estimates of the effect of protection we applied a propensity score matching (PSM) approach.

Taking the case of the Lore-Lindu National Park, a biodiversity hotspot on the island of Sulawesi, Indonesia, we find spill-over effects and systematic differences between the areas inside and outside of the park, which justify the use of PSM. The results after matching suggest that the establishment of the park reduced deforestation by 9.4 and 9.2 percentage points, depending on the set of covariates used. This effect is even greater than the unmatched difference in deforestation rates for regions inside and outside the park and we can conclude that the LLNP seems to actively protect against deforestation. Moreover, the results after matching are pretty robust to changes in the control area used and hence they are less affected by spatial spill-over effects. Overall, PSM seems to provide a suitable methodology to address the bias in the analysis of the effectiveness of PAs. The results of the analysis are discussed from a methodological point of view and they are used to draw policy conclusions with respect to biodiversity conservation.

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1. Introduction

Deforestation in the tropics has large scale consequences for carbon sequestration, biodiversity conservation, and ecosystem services. One way to protect the integrity of forests is to establish protected areas (PAs) such as national parks. The area under such conservation regimes increased more than tenfold over the past 4 decades with 18.8 million square km currently under protection (Chape et al. 2003). Bruner et al. (2001) assessed the effectiveness of parks in protecting tropical biodiversity and found that parks have been surprisingly effective. Their findings are, however, solely based on expert knowledge. They distributed a questionnaire to park managers, researchers, and the staff of governmental and non-governmental organisations and asked them to assess the condition within the park compared to the surroundings. While such a study design is able to gather information from many parks throughout the tropics, the quality of the gathered information has been questioned (for example regarding the incentive for park managers to overestimate effectiveness [Stern 2001 et al.]). To better quantify the effectiveness of national parks recent studies have been increasingly based on a comparison of deforestation rates of areas inside and outside of PAs using satellite data (Oliveira et al. 2007, Liu et al. 2001, Curran et al. 2004, Southworth et al. 2006, Sánchchez-Azofeifa et al. 2003). Such an approach, however, is in danger to yield biased estimates because areas outside and inside differ in many characteristics, which in turn influence also deforestation (Joppa et al. 2008). Let's consider for example a PA, which is on higher elevation than the surrounding non-protected area. Further assume that forest is mainly cleared for agricultural crops, which can only be grown up to a certain elevation. Then, it is likely that deforestation decreases at higher elevations even in the absence of the park. By just comparing deforestation rates this effect is wrongly attributed to the park and, hence, the effect of the park is overestimated. Joppa et al. (2008) call this effect 'de facto' protection. The simple comparison of deforestation rates of areas inside and outside of PAs also leads to biased estimates of the effect, when the establishment of the PA displaces deforestation to neighbouring unprotected areas (Oliveira et al., 2007). This process is called 'spatial spill-over' or 'neighbourhood leakage' (Andam et al. 2008, Oliveira et al. 2007, Gaveau et al. 2009).

A methodology, which is potentially able to yield unbiased estimates of the effect, is propensity score matching (PSM). The aim of matching is to find treatment and control units that have similar characteristics. In our case this means, that we match a pixel inside the park with pixels outside the park having the same characteristics. As many characteristics differ between the national park and its surroundings, direct matching is not possible. Instead, matching is done according to the estimated propensity score (Shadish et al. 2002). PSM has been widely applied in the evaluation of labour market programmes (see for example Heckman et al. 1999), but has gained little attention in the assessment of the effectiveness of national parks. Exceptions are studies by Andam et al. (2008) and Gaveau et al. (2009), which have used PSM to evaluate the effectiveness of PAs in Costa Rica and Sumatra, respectively. Both studies found that PSM is a suitable methodology to reduce the bias in the evaluation of PAs.

This study applies PSM to analyse the effectiveness of the Lore Lindu National Park (LLNP), Indonesia, in reducing deforestation. Specifically, it addresses the following research questions: (1) What is the estimated effectiveness of the LLNP using PSM compared to conventional approaches? (2) How do the results change when we choose a different comparison group, i.e. the area outside the national park?

The LLNP has been established in 1983 and stretches across an area of 2,290 km2. It covers both lowland and montane forests with an altitude range of 200 – 2,610 m (Shohibudin 2008). The park hosts some of the world's most unique plant and animal species. It is home to important populations of endemic bird species, like the Maleo-bird, and mammals like the Dian's tarsier, the Anoa or the Babirussa (Waltert et al., 2003).

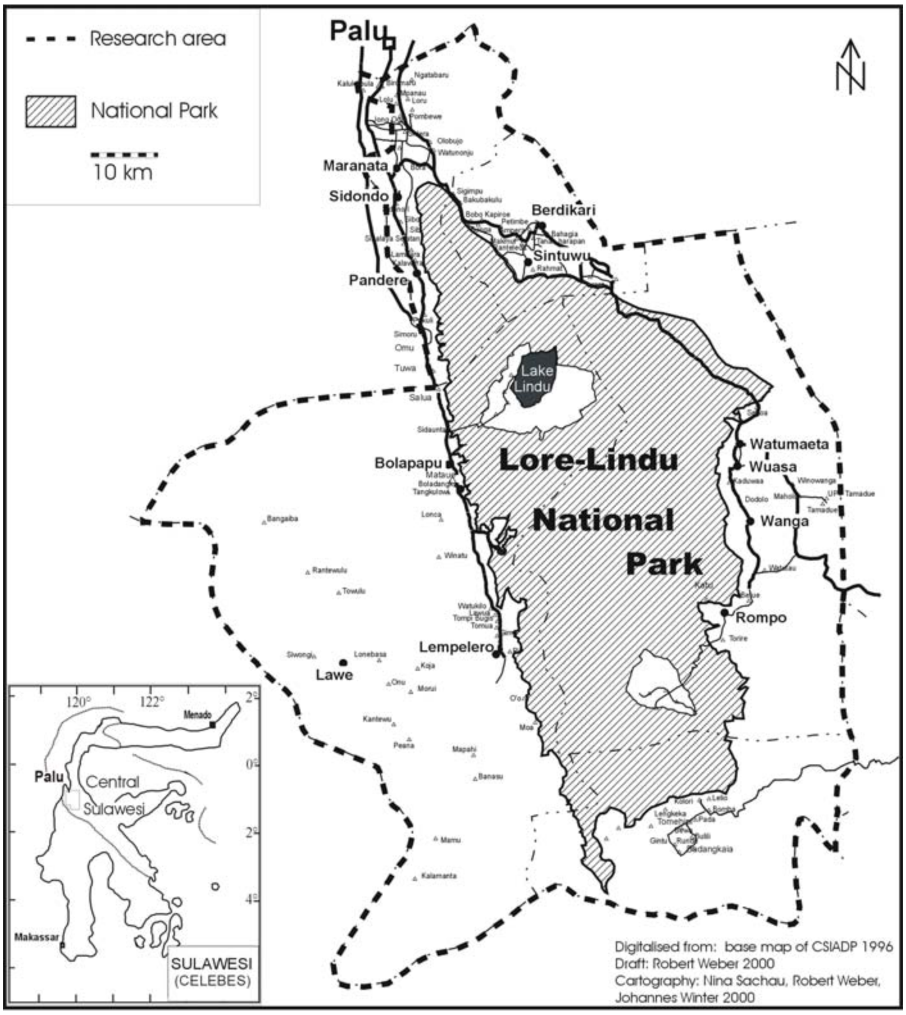
The paper is organized as follows. The next section describes how the data from different sources is matched. The following two sections describe the evaluation framework and the matching approach. Section 5 focuses on the results, while section 6 concludes.

2. Research area and data

The research area of this study comprises of the area of the Lore Lindu National Park and the area of the surrounding sub-districts (*kecamatan*), which are Sigi-Birumaru, Palolo, Lore Utara, Lore Selatan, and Kulawi (Figure 1). The area outside the national park serves as control units in the matching procedure (see section 3).

For the analysis we combined data from various sources. We use land use data derived from satellite images from 1983 and 2001 and various other geo-referenced data on elevation, slope, roads, and administrative boundaries (see Erasmi and Priess 2007 for details). This data was matched in a GIS and aggregated in a 100 x 100 meter grid. This data was exported as ascii-files and read into Stata, a statistical software package, which is used for further analysis. All geo-referenced data is available for the entire research area with a total number of forest pixels in 1983 of 632,404.

Figure 1: The research area



Due to the availability of village boundaries it is possible to match this data with information from a socio-economic village survey conducted in 2001 and with secondary data. The survey is part of an international and interdisciplinary research program known as “Stability of Rain Forest Margins” (STORMA) which studies the determinants of biodiversity and land use in this region. For the survey 80 of the 119 villages in the region were selected using a stratified random sampling method (Zeller et al. 2002). Interviews were held with groups of 4-6 people consisting of the village leader and other persons who had good knowledge about the surveyed village. Among others the survey included recall questions on important determinants of deforestation, like the access to agricultural technologies (Maertens et al. 2006). Retrospective information on population size was taken from administrative records available in each village, which is very reliable and not based on possibly biased recall information.

Thus, we have information on major drivers of deforestation in 1983, the time when the park has been just established, and in 2001. As described later, particularly the information from before the establishment of the park is important to get unbiased estimates of the effectiveness of the park. After matching the data sets, however, the number of forest pixels in 1980 decreased from 632,404 to 396,679, because we have had information from 80 villages only.

3. The evaluation framework and matching

The aim of the study is to evaluate, whether the establishment of the LLNP (the so-called treatment) has a causal impact on deforestation (the outcome) at pixel i beyond any other influencing factors. Formally, we want to estimate

(1) $\Delta_i = Y_i^1 - Y_i^0$

where Y_i^1 denotes the outcome in the case that the pixel i is part of the park and Y_i^0 if it is not part of the park. In the literature on treatment effects Y_i^0 is called the counterfactual outcome. As pixel i can be either treated or not, Y_i^0 cannot be observed and it is not possible to estimate the impact at pixel level (Wooldridge 2002; Caliendo and Hujer 2005; Lee 2005).

Giving up on observing both Y_i^1 and Y_i^0, the most common approach is to analyse the mean outcomes of pixels inside ($E(Y^1)$) and outside ($E(Y^0)$) of the park (Caliendo and Hujer 2005). The parameter of interest in our case is the so called average treatment effect on the treated (ATT), which is given by

(2) $E(\Delta_i \mid D = 1) = E(Y^1 \mid D = 1) - E(Y^0 \mid D = 1)$.

We are still not able to observe $E(Y^0 \mid D = 1)$, but we can estimate ATT by comparing the mean outcomes between pixels in the park and pixels outside the park. This requires that there is overlap between the two groups and that $E(Y^0 | D = 1) = E(Y^0 | D = 0)$. The latter condition means, that pixel inside and outside of the park have the same outcome in the absence of the park. This assumption is likely to hold only in randomised experiments (Shadish et al. 2002). In non-experimental studies further assumptions have to be introduced so that equation (2) can be solved. One possible strategy is to assume, that potential outcomes are independent of treatment assignment given a set of observable covariates X, which are not affected by treatment. This so called conditional independence assumption (CIA) means in our case that all variables which influence park establishment and deforestation are observed (known) by the researcher (Caliendo and Hujer 2005). This is a strong assumption, but, because of the rich data set at hand, we are confident that it holds true in our case. Additionally, we tested the sensitivity of our estimated ATT to violations of the CIA (see next section). A second requirement for using matching is that treatment and control group overlap. This assumption prevents perfect predictability of D given X (Heckman et al. 1999). Hence, it ensures in our case that pixels with the same X values have a positive probability of being both in and outside the park (Heckman et al. 1999). Thus in our analysis we performed matching only over the area of common support (see next section).

Conditioning on many observable covariates is limited, because of the high number of possible matches. To deal with this dimensionality problem, Rosenbaum and Rubin (1983) suggest to use the propensity score, which in our case here is the probability for a pixel to be located in the national park given its observed covariates X. They show that if potential outcomes are independent of treatment conditional on covariates X, they are also independent of treatment conditional on the propensity score.

4. Implementation of propensity score matching

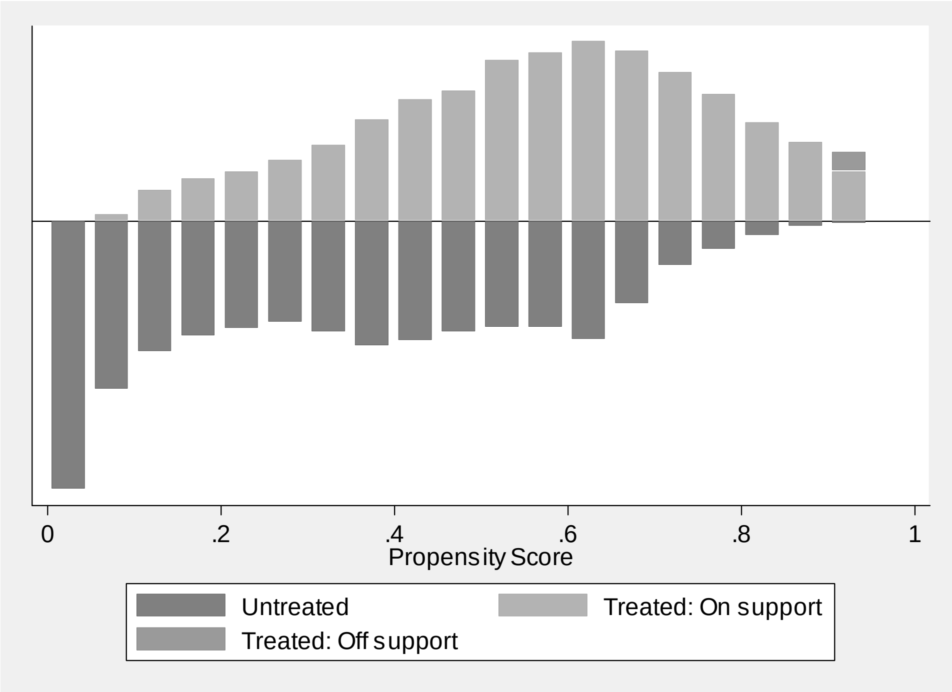
The aim of matching is to find treatment and control units that have similar characteristics. In our case, we match a pixel inside the park with pixels outside the park having the same characteristics. Ideally, the only difference between matched pixels should be their location in and outside the park. The implementation of PSM involves the following steps: (1) selection of the variables to estimate the propensity score; (2) estimation of the propensity score (3) choice of the matching algorithm (4) assessment of overlap and common support (5) evaluation of the matching quality and calculation of the effect and (6) sensitivity analysis (Caliendo and Kopeinig 2008).

We start the implementation of PSM by reviewing the literature on determinants of deforestation. Maertens (2003) and Steffan-Dewenter (2007) use a spatially explicit econometric model to identify the causes of deforestation for exactly the same area. Based on their results we identify a set of variables which significantly influence deforestation. This set includes geophysical variables (elevation, slope, aspect), distance variables (distance to roads, to the next non-forest pixel, and to district centres), and socio-economic variables (population density, availability of agricultural technologies). The matching strategy further requires that only variables that are different between park and non-park areas and that simultaneously influence deforestation should be included. Moreover, only variables that are unaffected by the protection status should be added. To ensure this, we only use variables, which are fixed over time or which have been measured before the establishment of the park. Besides these theoretical considerations, the selection is further guided by statistical significance of the covariates included in the logit model, which is used to estimate the propensity score in the second step (Heckman et al. 1997). To reduce the bias caused by spatial autocorrelation in the econometric estimation we draw a regularly spatial sample with a lag of four pixels in X and Y direction. This leads to a reduction in the number of pixels from 396,679 to 24,757. We then begin with estimating a logit model including only variables which are statistically significant and which increase the share of correctly predicted observations. This leads to a parsimonious model with the variables 'distance to roads' and 'distance to nearest non-forest pixel'. We then iteratively add variables to the model. A variable is kept if it is statistically significant at the 5% level. Additionally to the two above mentioned variables the following ones are included in the full model: slope, availability of technical irrigation in 1980, distance to district centres, population density in 1980, and the availability of hand tractors in 1980. In the following we report the results of both the parsimonious and the full model, because of the importance of the CIA. The results, however, do not differ much and illustrate the robustness of the estimated propensity score.

As a second step a logit model with the protection status as the dependent variable is used to estimate the propensity score. As a matching algorithm we have chosen nearest neighbour matching. As a fourth step we assess the common support because matching requires an overlap of the estimated propensity score between treatment and control group. Figure 2 shows the propensity score histogram by treatment status. It illustrates that there is a sufficient overlap between treatment and control group (i.e. e. untreated). Just for propensity scores, which are close to zero, it is not possible to match a pixel from the treatment group with a pixel from the control group. Thus, we drop all treatment observations whose propensity score is higher than the maximum propensity of the control group. Out of 10,859 pixels in the treatment group 441 are off support and the number of pixels used for the calculation of the effect decreased to 24,306. In the full model we have had to discard 869 pixels due to lacking overlap leading to a sample size of 23,861 observations. As the share of pixel, which are off-support, is pretty low, we conclude, that this assumption does not influence our results.

After matching it is crucial to evaluate the quality of the matches before the effect is calculated. We followed an approach proposed by Rosenbaum and Rubin (1985) and assessed the standardised bias, which is for every variable the difference of sample means in the treated and matched control group as a percentage of the square root of the average of sample variances in both groups. As a threshold the difference in characteristics between pixels in and outside the park should be below 10%, which holds true for both of our models (see section 5).

Figure 2: Propensity score histogram by treatment status for the parsimonious model



Source: Own data.

The last step in implementing PSM is to assess the selectivity of the estimated effect with respect to the common support problem and to unobserved covariates (Caliendo and Kopeinig 2008). As we have excluded only a small fraction of treatment observations due to lacking overlap, it is very unlikely that this exclusion has an effect on our results.

Another source of bias might be introduced in the analysis by unobservable covariates. We assessed this problem by applying the Stata ado (Stata ado files are programs that add new commands to Stata) mhbounds (Becker and Caliendo 2007), which uses the bounding approach proposed by Rosenbaum (2002). It reveals how strongly an unmeasured variable must influence the selection process in order to undermine the implications of the matching analysis. All the analysis has been performed in Stata using the ados psmatch2, pstest, and psgraph (Leuven and Sianesi 2003).

5. Results

5.1 Deforestation patterns and land characteristics

In the research area the forest area decreased from 6,324 km2 to 6,093 km2 between 1983 and 2001 (Table 1), which is exclusively driven by the expansion of agricultural area. In the late 1990s this process has accelerated due to the cocoa boom. Since 1980 the cocoa acreage has increased from almost zero hectares to almost 19,000 ha in 2000 (Maertens 2006). The change in forest cover translates into a deforestation rate of 8.5% and an annual rate of deforestation of 0.21% per year. There are, however, strong differences between the area inside and outside the park. The deforestation rate outside the LLNP is 10.8%, while it is just 4.0% inside the LLNP (Table 1).

Table 1: Losses in forest cover and deforestation rates between 1983 and 2001

	Total area	Inside LLNP	Outside LLNP
Forest cover in 1983 (km^2)	6,324	2,167	4,157
Forest cover in 2001 (km^2)	5,787	2,079	3,707
Deforestation (km^2)	537	87	450
Deforestation rate (%)	8.5	4.0	10.8
Annual deforestation rate (% per year)	0.5	0.2	0.6

Source: Own calculation

If pixels inside and outside the park would have the same outcome in absence of the establishment of the park, the impact can be simply calculated as the difference in deforestation rates, which is 6.8 percentage points. That means that the establishment of the park reduced deforestation rates by 6.8 percentage points between 1983 and 2001. This measure of impact is unbiased only if there are no differences between forest areas within and outside the park. However, there are significant differences between forest areas within and outside the park that are also likely to influence deforestation (Table 2). For example, forests inside the park are on average at higher elevation levels, have lower slopes, and are closer to district centres and roads. The distance to the next non-forest pixel is higher compared to forest areas outside the national park indicating less fragmentation inside the LLNP. Due to these significant differences the simple comparison of deforestation rates of areas inside and outside of the LLNP leads to biased results of the effect and we apply PSM to get unbiased estimates of the effect of the national park.

Table 2: Characteristics of the area inside and outside of the LLNP in 1983

Mean	Total area	Inside LLNP	Outside LLNP
Elevation (m)***	1,293	1,312	1,279
Slope (degree)***	15.6	15.5	15.7
Aspect***	182.7	186.7	179.5
Distance to village centre (m)***	7,026	6,803	7,203
Distance to roads accessible by car in 1983 (m)***	11,117	7,837	13,708
Distance to the next non-forest pixel in 1983 (m)***	1,263	1,551	1,035
Population density in 1983 (population/ha)***	0.21	0.24	0.18
Availability of hand-tractor in 1983 (1=yes)***	0.06	0.07	0.05
Availability of technical irrigation in 1983 (1=yes)***	0.01	0.02	0.01

Source: Own calculation

***: t-test significant at 1% level

N=396,679

5.2 Matching Results

Based on the selection criteria described before we used a parsimonious and a full model to estimate the propensity score. The matching approach leads to a strong reduction in the differences between pixels inside and outside the LLNP in case of the full model (Table 3) as well the parsimonious model (Table 4). Particularly in case of the two variables with the strongest disparity between park and non-park areas, distance to roads and distance to the next non-forest pixel, we were able to reduce the difference considerably. Matching for example reduced the mean distance to roads accessible by car from 13,731m in the unmatched sample to 7,557m in the matched sample. This is equivalent to an improvement in the standardised bias from -90.0% to 4.3%. Moreover, the standardised bias for all variables is below the threshold of 10% implying less biased estimates of the effectiveness of the park.

Table 3: Covariate characteristics before and after matching (full model)

Mean	Inside LLNP	Outside LLNP	Standardised bias (%)
Full model			
Distance to roads accessible by car in 1983 (m)			
Unmatched	7,841	13,731	-90.0
Matched	7,868	7,610	3.9
Distance to the next non-forest pixel in 1983 (m)			
Unmatched	1,551	1,037	46.9
Matched	1,323	1,285	3.4
Slope (degree)***			
Unmatched	15.6	15.8	-2.7
Matched	15.5	15.0	5.1
Availability of technical irrigation in 1983			
Unmatched	0.02	0.01	15.4
Matched	0.02	0.03	-5.1
Distance to village centre (m)***			
Unmatched	6,802	7,213	-9.7
Matched	6,624	6,333	6.9
Population density in 1983 (population/ha)***			
Unmatched	0.11	0.14	-13.4
Matched	0.11	0.12	-2.0
Availability of hand-tractor in 1983 (1=yes)***			
Unmatched	0.07	0.05	8.2
Matched	0.08	0.09	-3.9

Source: Own calculation

N=24521

Table 4: Covariate characteristics before and after matching (parsimonious model)

Mean	Inside LLNP	Outside LLNP	Standardised bias (%)
Parsimonious model			
Distance to roads accessible by car (m)			
Unmatched	7,841	13,731	-90.0
Matched	7,842	7,557	4.3
Distance to the next non-forest pixel (m)			
Unmatched	1,550	1,037	46.9
Matched	1,411	1,345	5.9

Source: Own calculation

N=24757

After evaluating the quality of the matches we calculated the effect of the national park, which is shown in Table 5. The results suggest the unbiased effect of the national park to be 9.4 and 9.2 percentage points, respectively. The first result means, that the establishment of the park reduced deforestation by 9.4 percentage points. This effect is 1.6 percentage points bigger than the unmatched difference in deforestation rates for regions inside and outside the park. The LLNP thus seems to actively protect against deforestation.

Table 5: Deforestation rates (%) before and after matching

	Inside LLNP	Outside LLNP	Effect
Unmatched	3.3	11.1	7.8
Unmatched (controls restricted to 10 km)	3.3	16.7	13.4
Matched (parsimonious model)	3.3	12.8	9.4
Matched (full model)	3.5	12.3	8.8

Source: Own calculation

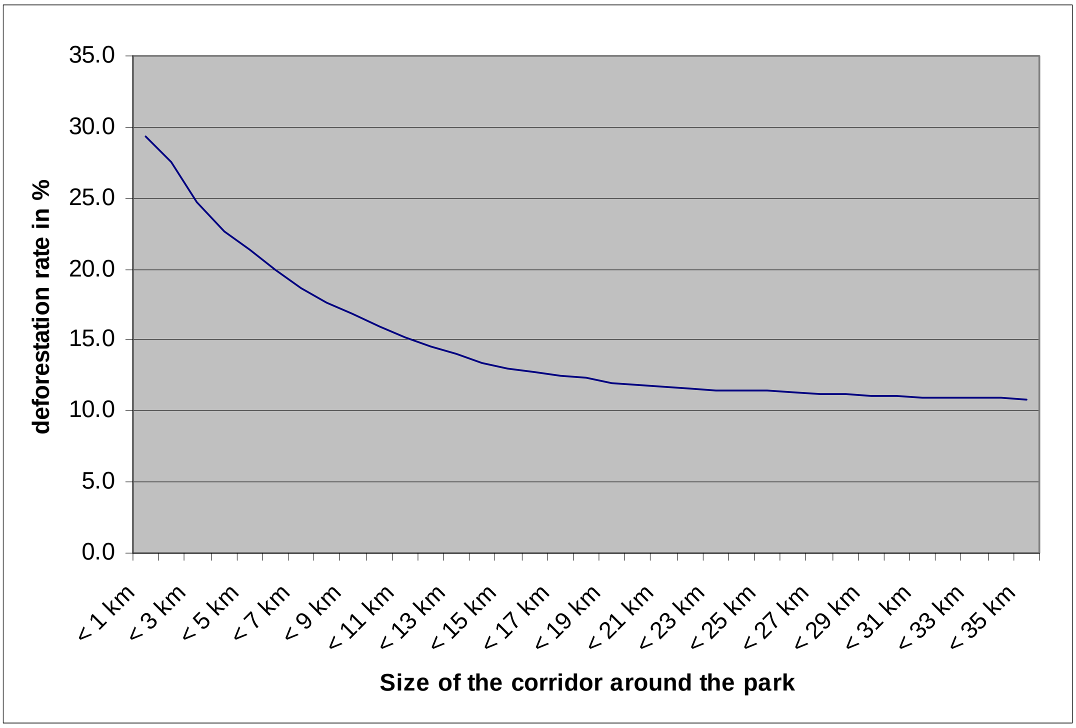
N=24521

Another approach often used in the conventional literature is to restrict the controls to a corridor of 10 km around the PA, because it can be expected that controls closer to the park are more identical with pixels inside the park than controls further away from the park. Using restricted controls the effect of the park increases to 13.4 percentage points, which is greater than the unmatched and the matched effect of the LLNP. However, when restricting the controls to 10 km there is the danger of taking into account spatial spillovers, which will be investigated in more detail in the next section.

5.3 Spatial spill-over and matching

The analysis in the previous section has shown that deforestation rates are particularly high in the 10 km zone around the national park. These high deforestation rates might not be connected to the LLNP, but they could also be a cause of the establishment of the national park. Farmers, who would have cleared land for agricultural production inside the park, are now forced to use forest areas outside the PA. In this section we will describe this effect and show how PSM deals with the issue.

Figure 3: Deforestation rates in corridors of increasing distance from the park border



Source: Own calculation

We first calculate the deforestation rates for different distances from the border of the park beginning with a corridor of 1 km (Figure 3). We increase the corridor in steps of 1 km until we include all forest pixels outside the park. The results show that deforestation is highest just outside the park with a rate of 29.4%. The deforestation rate then decreases to 11.7% when taking a corridor of 21km. When we further increase the corridor deforestation rates decrease only slightly. This pattern of deforestation around the LLNP reveals the weakness of simply comparing deforestation rates of areas inside and outside of PAs. Depending on the chosen control area, deforestation rates change and hence also the estimated effect of the LLNP.

The establishment of the LLNP had consequences for many farmers in the research area, because the traditional land reserve of many villages is located at least partly inside the national park (Burkard 2002). After the park was set up, the villagers first used the forest land outside the park. They only have turned inside the park since forest land outside the park, which is suitable for agricultural production, got more and more scarce. This village effect can also be observed if we compare the controls from villages bordering the park with villages not bordering the park (Table 6). In villages bordering the park the deforestation rate outside the park is 16.0%, while it is just 8.1% in villages without a border with the national park.

Table 6: Deforestation rates (%) before matching using restricted controls

	Inside LLNP	Outside LLNP	Effect
Unmatched	3.3	11.2	7.8
Unmatched (controls restricted to villages bordering the park)	3.3	16.0	12.7
Unmatched (controls restricted to villages not bordering the park)	3.3	8.1	4.8

Source: Own calculation

How is PSM dealing with this issue? To answer this question we used the same approach as above but with restricted controls (Table 7). For the parsimonious model the estimated effect after matching is 8.3 percentage points in case of controls restricted to villages bordering the park and 9.4 percentage points if the controls are restricted to villages not bordering the park. If we compare this to the unmatched results the results after matching are much less sensitive to changes in the control group. The same holds true for the full model, which includes a larger set of covariates.

Table 7: Deforestation rates (%) after matching using restricted controls

	Inside LLNP	Outside LLNP	Effect
Matched (parsimonious model)	3.4	12.9	9.4
Matched (parsimonious model, controls restricted to villages bordering the park)	3.6	11.9	8.3
Matched (parsimonious model, controls restricted to villages not bordering the park)	3.4	12.8	9.4
Matched (full model)	3.5	12.3	8.8
Matched (full model, controls restricted to villages bordering the park)	3.5	12.0	8.5
Matched (full model, controls restricted to villages not bordering the park)	3.7	13.9	10.2

Source: Own calculation

5.4 Sensitivity analysis

When applying PSM an important assumption is selection on observables. There exists no formal statistical test for the violation of this assumption. It is, however, possible to investigate how strongly an unmeasured variable must influence the selection process in order to undermine the implications of the matching analysis. We applied the Stata ado mhbounds (Becker and Caliendo 2007), which uses the bounding approach proposed by Rosenbaum (2002). In our analysis we find a negative effect of the establishment of the LLNP on deforestation and therefore we are only interested in the test-statistic for the lower bound assuming that we have underestimated the effect. That means, if due to unobserved factors pixels in the park have always a lower deforestation rate even in the absence of treatment, the lower bound Q- will become insignificant for a certain value of Γ.

Table 7 contains the test results for the parsimonious and for the full model. Starting from $\Gamma=1$, which indicates an absence of unobserved factors, we slightly increased the value of Γ in steps of 0.25. The increase in Γ simulates an increasing influence of unmeasured variables. In case of the full model, the lower bound Q- gets significant at $\Gamma=3.25$. This means, that the results of the model are insensitive to a bias that would more than triple the odds, which is a rather unlikely situation. In case of the parsimonious model, Q- gets significant at even greater values of Γ. These results indicate, that both models are pretty unaffected by unobserved factors.

Table 8: Mantel-Haenszel bounds

	Parsimonious model		Full model	
Γ	Q-	p-	Q-	p-
1.00	22.1274	0.000	19.7015	0.000
1.25	18.2982	0.000	16.0431	0.000
1.50	15.3103	0.000	13.1779	0.000
1.75	12.8653	0.000	10.8258	0.000
2.00	10.7974	0.000	8.8305	0.000
2.25	9.0053	0.000	7.0969	0.000
2.50	7.4234	0.000	5.5630	0.000
2.75	6.0065	0.000	4.1860	0.000
3.00	4.7225	0.000	2.9356	0.002
3.25	3.5477	0.000	1.7894	0.037
3.50	2.4641	0.007	0.7302	0.233
3.75	1.4577	0.072	0.1849	0.427
4.00	0.5176	0.302	1.1064	0.134

Γ: odds of differential assignment due to unobserved factors

Q-: Mantel-Haenszel statistic

p- : significance level

We further analysed whether the results change considerably when using a different spatial sample or applying a calliper to improve the matching quality. We introduced calliper of the size of 0.01, 0.001, and 0.0001, as well as regular spatial samples of every 8th, 12th, and 16th pixel, respectively. Due to brevity we do not report the results here, but they are available on request from the authors. None of these changes in the model specification, however, changed the qualitative conclusions about the effectiveness of the LLNP.

6. Discussion and conclusions

This study has contributed to the measurement of the effectiveness of PAs by comparing the estimated effectiveness of the LLNP using PSM to the results of conventional approaches, which are based on a simple comparison of deforestation rates of areas inside and outside of PAs (Oliveira et al. 2007, Liu et al. 2001, Curran et al. 2004, Southworth et al. 2006, Sánch-chez-Azofeifa et al. 2003). Such conventional approaches, however, are in danger to yield biased estimates because of spatial spill-over (Gaveau et al. 2009) and because areas outside and inside might differ in many characteristics, which in turn influence also deforestation (Andam et al. 2009, Joppa et al. 2008). Our study has shown that both concerns are valid in case of the LLNP. Firstly, there exist systematic differences between areas inside and outside of the LLNP and, secondly, there also exist spatial spill-over effects. Deforestation rates are highest adjacent to the park border. They then decrease with increasing distance from the border before they stabilise at distances greater than 21km. Depending on the chosen control area the effectiveness changes when the analysis is based on simply comparing deforestation rates of areas inside and outside of the LLNP. In general, our results strongly suggest, that the above described conventional approach is hardly a suitable methodology to assess the effectiveness of PAs. The study also illustrates that the estimation of the effectiveness of PAs can be improved by controlling for systematic differences between areas inside and outside of parks. It shows that PSM is able to reduce the bias that arises from such systematic differences, which in turn influence deforestation. This result confirms similar findings of studies by Andam et al. (2008) for Costa Rica and by Gaveau et al. (2009) for Sumatra, which both applied PSM to measure the effectiveness of PAs. Moreover, the results after matching are much less sensitive to changes in the control area. Compared to the results of conventional approaches, which are very affected by the chosen control group, the results after using PSM are pretty stable. The choice of the control group seems to be less relevant when applying PSM as long as there is sufficient common support.

When using PSM researchers have to make many decisions concerning its implementation, which might influence the results. Thus the sensitivity of the estimated effect needs to be carefully assessed. Our results, where we assessed different sets of covariates, changes in the calliper and in the spatial sampling, show, however, that these decisions have little influence on the estimated effect and that they do not influence the qualitative conclusions. Andam et al. (2008) and Gaveau et al. (2009) draw similar conclusions indicating the stability of the results obtained from using PSM.

Our matched results suggest that the effect of the LLNP is 9.4 and 9.2 percentage points, depending on the set of covariates used. This effect is even greater than the unmatched difference in deforestation rates for regions inside and outside the park and we can conclude that the LLNP seems to actively protect against deforestation. Nevertheless, caution is required if this result is used as an argument for the establishment of additional PAs. Firstly, there is further research needed why the LLNP was successful in reducing deforestation. Is the success more related to the monitoring activities of the park rangers or to the insecure property rights inside the park, which are particularly important for cocoa farmers? To learn from the experiences of the management of the LLNP requires the identification of the site-specific success factors. Secondly, the major aim of conservation policies is to secure the long term viability of forests, which is often essential for biodiversity conservation. Even when the park was successful in reducing deforestation between 1983 and 2001 we still found deforestation inside the national park. This implies that additional efforts have to be made in the future to protect the integrity of the park in the long-run. One possibility is the establishment of so-called Community Conservation Agreements (Meinzen-Dick 2001). They have already been set up formally in a few villages bordering the LLNP, but their implementation is still challenging (Birner and Mappatoba 2002). Another way to reduce deforestation within the park boundaries, which is popular among conservationists (see for example Fischer 2008), is to improve law enforcement, which basically means to prevent people from entering the park. While it is a costly effort given the size of the border of the LLNP, it is the local population who has to give up economic opportunities and hence would bear additional opportunity costs. Moreover, there is the danger of increased spill-over as agricultural activities are still the major source of income of the growing population (Schwarze and Zeller 2005). Instead of clearing land inside the LLNP people would gradually move to areas outside the park.

This spill-over effect, which we have already observed between 1983 and 2001, lead to a strong reduction in forest cover in areas close to the park boundary. This reduction has negative consequences for biodiversity conservation outside the park. But also inside the park biodiversity conservation is threatened because of an increased isolation of the LLNP. This trend can be observed in many PAs throughout the tropics and calls for an integration of park management within the land use dynamics of the surrounding landscape (DeFries et al. 2005).

From this discussion we can conclude that restricting activities in the LLNP will not be successful in preserving forests and biodiversity if the prevailing economic development strategy, which is based on the expansion of cacao acreage, continues. Instead, there is the need for improving productivity on the already existing plots so that the people do not need to go into the LLNP to clear land for the cultivation of crops.

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