Clear, but don’t invest: protected areas discourage some land uses more than others

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Abstract

Illegal land-use change inside protected areas (PAs) in the global south is common. Yet little is known about whether PAs disproportionately discourage conversion of forests to capital-intensive land uses (CILUs) like coffee and oil palm—an important consideration because CILUs likely have outsized adverse ecological and political-economic effects. We use remotely sensed fine-scale data on tree cover loss and land use along with quasi-experimental statistical methods that control for confounding factors to identify the effect of PAs on CILUs in Honduras, where rates of deforestation both inside and outside PAs are among the highest in the world. We find that PAs do have disproportionate effects on the conversion of forestland to CILUs: on average, they reduce by more than two-thirds the probability that forestland will be converted to a CILU versus traditional agriculture or pasture. Land characteristics moderate this effect. Social media abstract. Protected areas disproportionately discourage conversion of forests to capital-intensive land uses.

1. Introduction

Protected areas (PAs) remain the cornerstone of global efforts to stem tropical deforestation. Unfortunately, however, shortages of funding and institutional support, among other factors, curb their efficacy (Bruner \textit{et al} 2004, Naughton-Treves \textit{et al} 2005, Blackman \textit{et al} 2015). Remote sensing data have revealed that illegal forest loss and degradation inside PAs are common throughout the global south (Joppa and Pfaff 2010, Nelson and Chomitz 2011). For example, Leisher \textit{et al} (2013) found that 45% of the PAs in 19 Latin American countries experienced forest and land degradation between 2004 and 2009 and that this degradation affected more than 1 million hectares.

Less well understood is whether PAs’ efficacy varies across cleared land uses—that is, whether PAs do a better job of discouraging some cleared land uses versus others. Research on agricultural investment in developing countries suggests they should. This research demonstrates that tenure insecurity tends to dampen agricultural investment (Yiriyibin and Bouayad Agha 2018, Robinson \textit{et al} 2014, Deininger and Jin 2006, Goldstein and Udry 2008, Abdulai \textit{et al} 2011). Even when only minimally funded or managed, PAs create tenure insecurity for those who contravene land-use change restrictions, notably the risk that investments on cleared land will be appropriated by state authorities. Hence, one would expect PAs to disproportionately discourage conversion to capital-intensive land uses (CILUs), such as coffee, oil palm, and irrigated or otherwise ‘technified’ agriculture.

That PAs do a better job of discouraging conversion to CILUs than conversion to traditional agriculture and pasture seems a logical proposition. Yet, as discussed in the supplementary information (SI) Evidence Base section (available online at stacks.iop.org/ ERL/14/104002/mmedia), to our knowledge, compelling evidence supporting it is virtually nonexistent.

What type of evidence would be compelling? Not simply demonstrating that the rates of conversion to CILUs inside PAs are lower than outside. The reason is that PAs tend to be sited in sparsely populated, inaccessible areas—characteristics that discourage clearing of any type (Joppa and Pfaff 2009) and very likely discourage clearing for CILUs in particular, since these
land uses generally require market access to be profitable. Hence, credibly demonstrating that PAs differentially discourage conversion to CILUs requires controlling for the preexisting characteristics of land where PAs are sited. Failure to do so risks conflating effects on CILUs of these confounding factors with the effects of PAs themselves.

From a policy perspective, it matters whether PAs have differential effects on conversion to CILUs, for several related reasons. First, the political and economic costs of restoring forest on cleared lands inside PAs depend on the type of cleared land use. In fact, recent research suggests conversion of land inside a PA to commercial uses sometimes threatens the PAs’ existence following such conversion, or in anticipation of it, PAs are sometimes downgraded, downsized, or degazetted (Mascia and Pailler 2010, Tesfaw et al. 2018, Kroner et al. 2019, Naughton-Treves and Holland 2019). So, understanding PAs’ effects on CILUs could help policymakers promote forest restoration inside PAs and, more broadly, PAs’ institutional viability. Second, different cleared land uses have different ecological effects. For example, CILUs like coffee and oil palm typically entail significant use of agrochemicals (Rice 1999, Comte et al. 2012). So, understanding how PAs affect different land uses can help us assess PAs’ ecological effects. Third, different cleared land uses likely have different socioeconomic implications. For example, one would not expect households in the lowest socioeconomic strata to be associated with CILUs. Hence, shedding light on PAs’ effects on CILUs can help policymakers better assess PAs’ influence on livelihoods. And finally, knowing how PAs affect different types of land-use change can help stakeholders design policies to strengthen the efficacy of PAs in stemming such change. So, for example, if PAs stem CILUs but not traditional agriculture, then policymakers can target expansion of traditional agriculture.

Here we use fine-scale, remotely sensed data on forest loss and land use along with quasi-experimental statistical methods that control for confounding factors to identify the 2010–2012 effect of PAs on CILUs in Honduras, a country where rates of deforestation both inside and outside PAs are among the highest in the world (see SI background). We essentially compare land uses on recently cleared plots inside PAs with land uses on observationally similar recently cleared plots outside.

As described in detail in the Methods section and SI Data section, our analysis involves five steps. First, we use two fine-scale data sets derived from satellite images—one that maps forest loss between 2010 and 2012 and a second that maps land use in 2013—to identify 88,278,430 × 30 m pixels in Honduras that were forested in 2000, cleared sometime between 2010 and 2012, and then converted to a ‘cleared’ land use by 2013. For each pixel, we observe one of five cleared land uses: technified agriculture, coffee, oil palm, urban, and pasture or crops (figure 1; table 1). Given the criteria used to classify these five land uses, the first four are CILUs and the last is not (Duarte et al. 2014). Second, we use a variety of spatial data sets to discern the preexisting geophysical and socioeconomic characteristics of these 882,784 pixels, all of which likely affect the probability of conversion to a CILU. These include whether the pixel was inside a PA, average annual temperature and precipitation, travel time to the nearest large city, altitude, directional orientation, slope, the opportunity cost of retaining forest cover, percentage tree cover and biomass density prior to clearing, and recent changes in population density. Third, for this sample of 882,784 recently cleared pixels, we use propensity score matching to create a matched regression sample (n = 408,290) consisting only of pixels inside PAs and pixels outside that are similar in terms of the characteristics listed above. Fourth, we use this matched sample together with probit and
multinomial logit regression models to identify the effect of PAs on the probability that a plot of forest is converted to a CILU (technified agriculture, coffee, oil palm, urban) versus a non-CILU (pasture, crops). We combine nonparametric matching with standard regression because doing so generates treatment effect estimates that are more robust to misspecification and omitted variables bias than regression alone (Ho et al. 2007, Imbens and Wooldridge 2009, Ferraro and Miranda 2017). Finally, we use probit regression models to determine whether preexisting land characteristics and PA characteristics moderate these effects. The Methods section provides a conceptual framework for our econometric analysis. The intuition is straightforward: a land manager’s choice to convert a forested plot to a CILU versus pasture or crops, and her choice among CILUs, is dictated by the relative returns to these cleared land uses, which in turn depend on whether the plot is inside a PA and on its preexisting geophysical and socioeconomic characteristics (average annual precipitation, travel time to nearest city, etc).

As discussed in SI Evidence Base, our paper makes three contributions. As noted above, to our knowledge, it is the first to use quasi-experimental methods to focus directly on identifying the effect of PAs on different types of land-use change. In this respect, it responds to recent calls to extend in new directions the quasi-experimental literature evaluating the effects of conservation investments (Miteva et al. 2012, Börner et al. 2016). Second, it is the first to demonstrate that even after controlling for confounding factors, PAs do a better job of discouraging CILUs than other cleared land uses. And finally, it adds to the literature evaluating land-use and land-cover change in Honduras.

2. Results

As detailed in the Methods section and SI Data, we use a matched regression sample together with two types of regression models to identify the effect of PAs on land use. We use a probit model to explain the probability that a cleared pixel is converted to any of the four CILUs we consider—technified agriculture, coffee, oil palm, and urban—and we use a multinomial logit model to identify the effect of PAs on the probabilities that a cleared pixel is converted to each of these four CILUs. The latter model addresses the question of whether PAs have differential effects on specific CILUs. We begin with a brief discussion of propensity score matching, which is used to generate our regression sample, and then proceed to the probit and multinomial logit regression results.

2.1. Propensity score matching

We fit a probit model (equation (1)) used to generate propensity scores, which in turn are used to match recently cleared pixels inside PAs with observationally similar, recently cleared pixels outside (table S1). All but one of the covariates are statistically significant at the 1% level. The results indicate that compared with recently cleared pixels outside PAs, those inside tend to be cooler, wetter, farther from large cities, at lower elevation, and not north facing, and they tend to provide lower economic returns after being cleared, to be more densely forested at baseline, to have higher rates of population growth, to store more carbon, and to have been cleared in 2010 and 2011 (versus 2012). These results underscore the importance of controlling for preexisting pixel characteristics and echo findings from other quasi-experimental analyses of PA effects (Joppa and Pfaff 2009, 2010, Blackman et al. 2015).

2.2. Probit regressions

Results from our probit regression (equation (5)) indicate that even after controlling for preexisting pixel characteristics, location inside PAs is negatively correlated with conversion to CILUs (figure 2; table S2). Our treatment variable, protected area (see SI Data), is negative and statistically significant at the 1%
level in models using both the unmatched and the matched samples. The marginal effect of protected area for the matched sample indicates that location inside a protected area reduces the probability that a pixel will be converted to a CILU by 1.5 percentage points. Expressed as a percentage change relative to the counterfactual rate of conversion to a CILU (the average predicted probability of conversion when protected area = 0, which is close to the mean rate of conversion for the regression sample; see tables S2 and S7), this amounts to a 68% reduction in the probability of conversion. Marginal effects for the unmatched sample generate a similar qualitative result. In this case, location inside a protected area reduces the probability that a pixel will be converted to a CILU by 4.9 percentage points. Expressed as a percentage change relative to the counterfactual conversion rate, this amounts to a 76% reduction in the probability of conversion.

2.3. Multinomial logit regressions

Our multinomial regression results indicate how location inside a PA affects the probability of conversion to each of our four CILUs—technified agriculture, coffee, oil palm, and urban—as opposed to traditional agriculture or pasture. In the matched sample, RRRs indicate that for a pixel located in a PA, the relative risk of conversion to technified agriculture decreases by...
(1−0.15 =) 84%, that for conversion to coffee decreases by 79%, and that for conversion to urban decreases by 89%. Although these results might seem to suggest that protected areas have a weaker effect on oil palm than on the other three CILUs, that interpretation is not supported because the regression coefficient for palm oil is not statistically significant. Although the other three coefficients are statistically significant, differences among them are not.

2.4. Moderating effects

As noted above, we use a probit model with interaction terms to determine whether PA characteristics and land characteristics moderate the effect of PAs on the probability of conversion to CILUs. We examine two PA characteristic variables: a binary dummy variable indicating that the PA is mixed use versus strictly protected and a binary dummy variable identifying PAs established before 1987. In addition, we examine all 10 land characteristic variables included in our probit regression (table S5).

We find that PA characteristics do not moderate the effect of PAs on land use: interaction terms for mixed-use and pre-1987 PAs are not statistically significant (table S5). However, we find that land characteristics moderate the effect of PAs on the probability of conversion to CILUs, albeit only in some geophysical environments. None of the coefficients for the 10 land characteristic interaction terms are statistically significant when evaluated at means of these covariates. However, for the continuous covariates (nine of 10 total), marginal effects evaluated over the entire distribution for each covariate paint a more complex picture: most covariates have statistically significant effects over at least part of their distributions. Figure 4 indicates that the effect of PAs on the probability of conversion to a CILU is stronger in areas that have moderate rainfall, are closer to cities, lower in elevation, more steeply sloped, generate lower returns from conversion, have relatively dense tree cover at baseline, support more above-ground biomass, and have moderate population densities.

3. Discussion

We use fine-scale satellite data on forest loss and land use along with quasi-experimental statistical methods
(postmatching regression) to analyze the effect of PAs on CILUs relative to traditional agriculture and pasture. We find that the observable characteristics of land inside PAs are significantly different from those of land outside, and as a result, identifying the effect of PAs on CILUs requires controlling for land characteristics. Having done that, we find that PAs disproportionately discourage CILUs relative to other land uses: on average, they reduce by more than two-thirds the probability that land inside a PA will be converted to a CILU. In addition, we find that several land characteristics moderate this effect. For example, we find that PAs are more effective in discouraging CILUs in areas that are closer to cities, are lower in elevation, are more steeply sloped, generate lower returns from conversion, have relatively dense tree cover at baseline, support more above-ground biomass, and have moderate population densities.

Rigorously identifying the causal mechanisms that drive our finding that PAs disproportionately discourage conversion to CILUs is beyond the scope of this analysis and represents a fruitful area for future research. However, structured interviews with four Honduran national and regional PA managers conducted in summer 2019 provide some hints. Three of the interviewees reported that they are particularly concerned about conversion of forest inside PAs to CILUs. Two explained that in their regions, conversion of forests to coffee is a leading cause of forest loss inside PAs, an especially worrisome phenomenon because that crop is water intensive. Another interviewee said that the main concern in his region is conversion of PA forests to urban land uses, which tend to trigger additional land-use changes. All four interviewees agreed that PAs tend to disproportionately discourage conversion to CILUs. They collectively described three types of agents that discourage such conversion: regulators who enforce land-use restrictions inside PAs, including by confiscating land and assets; communities in and around PAs, whose help regulators enlist in monitoring and enforcing land-use change restrictions; and environmental nongovernmental and intergovernmental organizations like Fuerza de Tarea, a multistakeholder initiative that focuses on environmental crimes, and the Roundtable on Sustainable Palm Oil, an international organization that restricts the ability of producers operating inside PAs to sell in international markets. According to interviewees, all three sources of pressure heighten the risks land managers face when they convert PA forestland to CILUs.

As discussed in the Methods and SI Data sections, our study has limitations related to both our data and our methods. Our forest loss data (Hansen et al 2013) could pick up conversion of agroforests to cleared land uses as well as conversion of natural forests. We have attempted to mitigate that problem by restricting our sample to pixels with more than 50% tree cover at baseline. In addition, our empirical strategy does not explicitly control for unobserved factors that might confound our attempts to identify the effect of PAs on conversion to CILUs. In principle, unobserved political and economic factors correlated with both our treatment, PAs, and our outcome, CILU conversion, could partly explain the negative correlation between PAs and CILU conversion. For example, it could be that policymakers tend to site PAs in areas with weak governance and that weak governance discourages CILUs. We have tried to address this issue by relying on postmatching regression, which typically reduces the influence of unobserved confounders (Ho et al 2007, Stuart 2010). Notwithstanding these limitations, we believe our analysis makes a significant contribution: to our knowledge, it is the first quasi-experimental study to directly focus on the effect of PAs on CILUs, and we hope it lays the foundation for future research.

What are the policy implications of our findings? Simple descriptive statistics make clear that the main driver of forest cover change in Honduran PAs is non-technified agriculture and pasture: they account for 94% of the clearing inside PAs between 2010 and 2012 (table 1). However, the 6% of clearing for CILUs like coffee and oil palm may have outsized effects on outcomes that are important from a policy perspective. For example, it may be that the political costs of restoring PA forests are substantially higher when agents have made significant capital investments on cleared forestland. It may also be that CILUs inside PAs create a perception that legal restrictions on land-use change are not going to be enforced, spurring a downward spiral of forest clearing. And, as recent research suggests, they may ultimately increase the chances that the PAs in which they are located will be downgraded, downsized, or degazetted (Mascia and Pailler 2010, Tesfaw et al 2018, Kroner et al 2019, Naughton-Treves and Holland 2019). Given such potential deleterious effects, our findings that PAs—even those in Honduras with inadequate funding and management—significantly reduce the probability of conversion to CILUs is welcome news.

Our analysis of moderating effects provides some hints about how to strengthen PA effectiveness in deterring CILU conversion. If deterring conversion of PAs forests to CILUs is a concern, policymakers need to pay particular attention to geographies where PAs are least effective at doing so: those that are farther from cities, at higher elevation, and flatter, and that have relatively sparse baseline tree cover.

Finally, our study suggests several fruitful areas for future research. Similar analyses in other countries would help determine whether and how our results generalize across geographies. Research on our hypotheses about the link between CILUs, forest restoration, and PA sustainability would help shed light on the relevance of this line of research for policy. And additional land manager-level primary research could help identify the causal mechanisms that explain our results.
4. Methods

As discussed above, to identify the effect of PAs on the probability that recently cleared pixels are converted to a CILU, we need to control for their preexisting characteristics. To that end, we combine nonparametric matching with standard regression, an approach that, as noted above, typically generates treatment effects estimates that are more robust to misspecification and omitted variables bias than regression alone (Ho et al, 2007, Imbens and Wooldridge 2009, Ferrarini and Miranda 2017).

4.1. Propensity score matching

To match pixels outside PAs to those inside, we first use a probit model to estimate a propensity score for each pixel—the probability that the pixel was treated (inside a PA). Propensity scores can be interpreted as weighted indices of the observable pixel characteristics that explain treatment (Rosenbaum and Rubin 1983). The probit model is specified as

\[ \Pr(T_i = 1|X_i) = F(X'_i \psi), \]

where \( i \) indexes pixels, \( T \) is a binary dummy variable indicating whether a pixel is inside a PA, \( X \) is a vector of covariates that affect whether a pixel is protected, \( F \) is the standard normal cumulative distribution function, and \( \psi \) is a vector of regression coefficients. Having estimated a propensity score for each pixel in our sample, we create a control group of pixels outside PAs by matching pixels outside to those inside on the basis of propensity scores. We use nearest-neighbor 1-to-1 matching with replacement and enforce a common support (Cochrane and Rubin 1973). All unmatched control pixels are dropped from our regression sample.

4.2. Postmatching regression

We use a simple latent variable framework to motivate our probit and multinomial logit postmatching regression models (Wooldridge 2002). This approach is well known, so we present only a brief sketch here. As noted above, the intuition is straightforward: land managers’ choice to convert a forested plot to a CILU versus pasture or crops, and their choice among CILUs, is dictated by the relative returns to these cleared land uses, which in turn depend on whether the plot is inside a PA and on its preexisting geophysical and socioeconomic characteristics.

We assume that the maximum return from converting a cleared pixel to any given land use is a linear additive function of preexisting pixel characteristics, including whether the pixel is located inside a PA. That is

\[ R_{ij} = \alpha_j T_i + X'_i \gamma_j + \omega_{ij}, \]

where \( R_{ij} \) is the maximum return from converting a cleared pixel \( i \) to any given land use \( j \), \( X \) is a vector of preexisting pixel characteristics that affect the return to that land use, \( \alpha \) is a regression coefficient, \( \gamma \) is a vector of such coefficients, and \( \omega \) is an error term. The probability that a land manager chooses to convert any given cleared pixel to a specific land use is the probability that the maximum return to that land use is higher than the maximum return to any other land uses. That is

\[ P_{ij} = \Pr(R_{ij} - R_{ik} \geq 0) \text{ for } j \neq k, j = (1, 2 \ldots n), \]

where \( P_{ij} \) is the probability of converting pixel \( i \) to land use \( j \), \( n \) is the number of land uses, \( R_{ij} \) is the maximum return to land use \( j \), and \( R_{ik} \) is the maximum return to an alternative land use.

4.2.1. Probit

If we aggregate CILUs into one category and alternative land uses into a second category, then equation (3) becomes

\[ \Pr(T_{ic} = 1|X_{ic}) = F(X'_{ic} \psi), \]

where \( c \) indexes the CILUs and \( a \) indexes alternative land uses. Substituting equation (2) into (4) and combining terms, we have

\[ P_{ic} = \beta T_{ic} + X'_{ic} \theta + \epsilon, \]

where \( \beta \) is a regression coefficient, \( \theta \) is a vector of such coefficients, and \( \epsilon \) is an error term. If we assume the error terms are independent and normally distributed, we can use maximum likelihood to estimate equation (5) as a probit. The marginal effect of \( T_i \) can be interpreted as an average treatment effect on the treated (ATT); it measures the effect of location inside a PA on the probability that a cleared pixel is converted to any of the four CILUs we consider. We cluster standard errors at the level of second-level administrative units (municipios, \( n = 298 \)) to help control for spatial correlation of errors.

4.2.2. Multinomial logit

If we do not aggregate land uses into two categories, and if we substitute equation (2) into (3) and assume that error terms are independent and have a Weibull distribution, we have a multinomial logit model:

\[ P_{ij} = \exp(\beta_j T_i + X'_i \theta_j) / \sum_j \exp(\beta_j T_i + X'_i \theta_j) \]

\[ j = (1, 2 \ldots n). \]

Here, too, the marginal effects of \( T_i \) can be interpreted as ATTs: they measure the effect of location inside a PA on the probability that a cleared pixel is converted to a particular land use. Again, we cluster standard errors at the level of second-level administrative units to help control for spatial correlation of errors.

4.3. Moderating effects

In addition to estimating ATTs, we also investigate whether (i) preexisting land characteristics and (ii) preexisting PA characteristics moderate these effects. To determine whether preexisting land characteristics moderate the effects of PAs on land-use
change, we use our matched sample to estimate a set of 10 probit models, each of which includes an interaction between our treatment dummy variable and one of 10 land characteristic variables. That is, we estimate

\[ P(Y=1|x) = \beta_0 + \beta_1 x_1 + \ldots + \beta_{10} x_{10} + \eta_1 l_1 + \ldots + \eta_{10} l_{10}, \]

where \( z \) is an index of the land characteristics, \( L \) is the land characteristic variable itself, and \( \eta \) is a regression coefficient. We report estimated coefficients of the land characteristic variables and, again, cluster standard errors at the level of second-level administrative units.

We test for moderating effects of two PA characteristics: PA type as defined by IUCN category and PA vintage. To test the effect of PA type, we use our matched sample to estimate a probit model that includes an interaction between our treatment dummy variable and a dummy variable that indicates whether the PA is mixed use (IUCN categories V and VI) or strictly protected (categories I–IV). To test the effect of PA vintage, we use our matched sample to estimate a second probit model that includes an interaction between our treatment dummy variable and a dummy variable that indicates whether the PA was established before 1987 or in 1987 or after. The specification of both models is similar to equation (7). We report estimated coefficients and cluster standard errors at the level of second-level administrative units.

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Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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