Protected Areas' Impacts Upon Land Cover Within Mexico:
the need to add politics and dynamics to static land-use economics

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Abstract

Incentives for REDD − i.e., reductions in emissions from deforestation and degradation − motivate application of static economic modeling of land use to assess heterogeneity over space in the business-as-usual baselines for land use required for forest policy evaluations. That some forested locations face higher threats is now recognized as an important factor in the evaluation and targeting of policy. Given this point − now often included in impact evaluation via matching − further theory is required to explain variations in policy impact. We show this need by analyzing impacts of Mexican protected areas (PAs) on land cover. Applying static land-use economics improves the baselines for our impact estimation and we find, on average, a 2.5% lower rate of 2000-05 natural land cover loss within the PAs. Stricter PAs appear closer to cities and have greater impact (4.4%) than less strict (2.3%), yet static baselines do not explain why. Nor do they explain why impact gradients by type differ across countries, or why PA spillovers vary across states − as we show for Mexico. We suggest an initial political economy model of impacts by type of PA and also provide examples of the economic and political dynamics required to understand PAs' spillovers.

Keywords

Mexico, tropical forest, biodiversity, deforestation, conservation, protected areas, siting, selection bias, impact evaluation, matching

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1. Introduction

National and international effort to reduce forest loss has had some impact, in recent decades, but has not substantially slowed tropical forest losses. Such losses now account for perhaps one sixth of anthropogenic greenhouse-gas emissions. Adding climate change to existing forest concerns, such as habitat, underscores a need to learn what influences deforestation in order to take action. For instance, in the UN Framework Convention on Climate Change (UNFCCC), international stakeholders are assessing how to generate incentives for reducing forest-based emissions. On parallel tracks, the U.S. Congress and bodies in other countries − including some with significant tropical forest areas − have developed legislative proposals for emissions-reduction policies. Climate-related incentives for forest conservation could provide new influences upon the various programs and policies that affect deforestation. New programs will, most likely, be performance-based, i.e., emphasize monitoring, reporting and verification of outcomes. Such emphases, along with financial incentives, could increase policy impacts on deforestation rates (Pfaff *et al*. 2013a).

While without question conditions change over time, many determinants of land use seem robust. Thus, understanding past policy impacts on land cover should help to design better future policy. It is crucial for countries interested in financing or purchasing emission reductions, and countries interested in hosting these activities, to know what has and has not worked in reducing forest loss and, further, to understand why. Here, following recent work that has provided improved impact evaluations for conservation policies like protected areas (PAs; review in Joppa and Pfaff 2010a), we estimate a number of types of impacts of PAs upon recent land-cover change within Mexico. For 2000-2005 land cover, we estimate the average impact of PAs then, to stimulate discussion of how one might predict such results, we also then demonstrate: differences in estimated impact between more and less strict types of PAs; and variation, by state, in PAs' land-cover spillovers.

First, though, we present models of PA impact. We start with a classic model of land use, taking PA location and enforcement as given. To spur more work next we suggest the nature of a model of political economy that predicts impact across PA types due to varied location and enforcement. The first model motivates our application of matching to improve estimated land-cover impacts and we find that PAs in Mexico did lower land-cover change during this time period − albeit less than would be estimated if ignoring differences across the landscape in baseline rates of clearing. Specifically, we find that on average the PAs across Mexico reduced land-cover change by 2.5%.

The second model suggests that, depending on the political economic context − which influences not only the siting of protection but also its enforcement − either more or less strict protection can have greater impacts on land-cover change. For this time period for Mexico, it is stricter PAs that block more land-cover change versus baseline (4.4%) relative to less strict protection (2.3%). That might seem intuitive, as enforcement might be expected to be tougher for stricter protection. However, we show this result is influenced also by relative locations that may be counterintuitive, and differ from results for other nations, yet may be explained by shifts in relevant local politics.

Finally, as another empirical spur to the consideration of further theories within policy evaluation, we present estimates of spatial spillovers from PAs to the land-cover change in nearby locations. For Mexico on average and for some states, if anything PAs seem to lower nearby clearing a bit. Yet for other states, the total impact of a PA seems to be lowered by increases in nearby clearing ("leakage"). We note that while a static land-use idea is helpful in predicting where leakage goes, the consideration of where spillovers overall are positive or negative involves further dynamics.

The paper proceeds as follows. Section 2 provides background for Mexico and prior literature evaluating PA impacts. Section 3 presents the models noted above, plus examples for spillovers. Section 4 then describes our data and methods, Section 5 gives results, and Section 6 concludes.

2. Background & Literature

2.1 Forests in Mexico

Mexican forests cover 67 million hectares, about one third of the country (198 million hectares). Forestry, along with agriculture and fishing, accounted for 5.4% of the country's GDP in 2006 (Johnson et al., 2010) and Mexico may suffer disproportionate impacts from climate change (i.e., droughts, sea-level rise and increased severity of tropical storms). The agriculture and forestry sector in Mexico is one of the major sectors where GHGs can be reduced. It generated about 135 $MtCO_2e$ in 2002, which accounted for 21% of Mexico's total emissions (Johnson et al., 2010), and two thirds were from the forest subsector (Johnson et al., 2010). The proximate causes of deforestation and degradation in Mexico are conversion to grassland, slash-and-burn agriculture, illegal logging and natural occurrences like fire. The underlying forces appear to include a lack of investment in the forestry sector, low income from forest activities, agricultural and livestock activities in forest areas, uncertainty related to use rights, and poverty and lack of opportunities for forest owners (The REDD Desk, 2011). These drivers are complex and vary between regions.

Hence, the forestry subsector can be key in both reducing deforestation and capturing carbon. There is also widespread acknowledgement of the unquantified benefits that these interventions and programs perhaps could have in terms of improved ecosystem services, the preservation of ecosystems, income generation and employment, among others co-benefits (Johnson et al., 2010). Interventions in forestry, with 'REDD' (reduced emissions from deforestation and degradation) as a motivation for some such as reforestation and commercial plantations, account for 85% of the government's proposed mitigation in the agriculture and forestry sector (Johnson et al., 2010). Successful interventions would depend, however, on institutional changes in forest management, better public financing mechanisms and sustainable-forest-product markets (Johnson et al., 2010).

REDD appears to have some support in Mexico, which is moving towards a broader ('REDD+') portfolio of activities for implementation until 2020, following a stakeholder process. This must consider issues such as the emergence of a large illegal timber market, a lack of financial and human resources, limited operational capabilities, permitting cycles and (drug-related) insecurity. Within this strategy, Mexico is emphasizing the development of a national, multi-functional and multi-scale monitoring, reporting and verification (MRV) mechanism that would be based upon remote sensing as well as ground-based forest inventory methodologies (The REDD Desk, 2011). It would be expected to include early detection systems for changes in land cover and land use (The Forest Carbon Partnership, 2012). Such a mechanism for national MRV could provide the relevant authorities with a more precise measure of land cover/land use change that could solve some of the issues with detecting small-scale changes unobservable through satellite imagery.

2.2 Evaluation of PA Impacts

Joppa and Pfaff (2010a) review literature on protected areas' impacts, as do Naughton-Treves 2005, Nagendra 2008, and Campbell et al. 2008. Joppa and Pfaff emphasize the hurdles for solid empirical inference concerning protected areas' impacts on forest given new documentation that, at least on average globally (Joppa and Pfaff 2009), the distribution of protection across nations' landscape is not random but, instead, rather significantly biased in deforestation-relevant ways.

Protected areas' impacts have been evaluated through various methods. Some really just observe, e.g., that Costa Rican PAs are fully forested (Sanchez-Azofeifa, 1999) or see Fuller et al. (2004) view that PAs in Kalimantan are unfeasible in light deforestation they endured during 1996-2002. Such implicit analyses lack comparisons with counterfactuals for the protected parcels, i.e., some view of what would have happened had they not been protected. As it is impossible to observe such counterfactuals, one must infers them from other sites and several options have been tried.

One might compare PAs with all unprotected lands, as do Gaveau et al. (2007), Messina et al. (2006) for Ecuador's Amazon, Sanchez-Azofeifa et al. (1999) for Sarapiqui region in Costa Rica and DeFries et al. (2005) for the globe. However, protected areas could have lower deforestation because they are protected or, instead, because the lands on which they were located are different.

One might compare with the areas around PAs, presuming that similarity follows from proximity, as do Bruner et al. (2001) across 22 tropical countries using survey data, Liu et al. (2001), Viña et al. (2007) revisiting Wolong from where Liu et al. (2001), Sanchez-Azofeifa et al. (1999) around 132 PAs in Costa Rica, Sader et al. (2001) for a northern Guatemalan Maya Biosphere reserve, Kinnaird et al. (2003) for Bukit Barisan Selatan National Park on the Indonesian island of Sumatra (also analyzed by Gaveau et al., 2007), Fuller et al. (2004), Curran et al. (2004) for Kalimantan (Indonesian Borneo). This type of analysis can be very insightful but without some land characteristics to compare explicitly, it is hard to know whether proximity means similarity.

Matching methods (such as we use) have been applied to Costa Rica − a leading country for PAs. For 1960-1997, for over 150 PAs, Andam et al. (2008) match on a variety of land characteristics. This greatly increased the similarity of the controls used for evaluation to the protected points. Andam et al. (2008) conclude that about 11% of the protected area would have been deforested without protection. For the same data, comparing to all unprotected pixels estimates that 44% of protected area would have been deforested, while comparing to a buffer estimates a 38% impact. This suggests the importance of measuring characteristics. Joppa and Pfaff (2010b) demonstrate that the resulting correction to estimated PA impacts is empirically important around the globe. Using less precise data as well as fewer control factors, as dictated by constraints on global data, they also find average impact estimates using 'matched' comparisons are far lower (under half) than from the approaches typical in prior literature. That is the initial basis for the analyses here.

Yet policy guidance may require more than an average. If some PAs have greater impacts, then future policy could target their circumstances. Pfaff, Robalino et al. (2009) revisit Costa Rican protected areas using matching. For 1986-97 deforestation, again matching greatly lowers impact estimates but the key point is predictable variations across the landscape in terms of PA impacts. For protected areas within 85 km of the capital, San Jose, impact was 3% avoided deforestation. Areas further away had ~1% impact. For the PAs within 6 km of a national road, they find that the impact was ~5% of forest saved, yet impact was nonexistent for foress that was further away. Slope, an extremely important agricultural factor in Costa Rica, was critical for impacts of PAs. PAs on low slopes (flat land) blocked 14% deforestation but protection placed on steeper lands had close to zero forest impact. Joppa and Pfaff (2010b) also find such predictable variation in their global study of PA impact. Such results can help to guide and improve conservation policy.

The Brazilian Amazon has much more forest and is a more active frontier. Yet such insight from Costa Rica and elsewhere appears relevant. Pfaff and Robalino (2012) generate similar results in terms of not only correcting average impact estimates but also impact variation in the landscape. Key variations include both market distances, as for Costa Rica, and the types of protected areas (Delgado *et al.* 2008 provide a focused case study on type, complemented by Pfaff *et al.* 2013b).

Finally, Blackman et al. (2014) is analogous to our study (noting other approaches in Mas 2005, Durán-Medina et al. 2005, Figueroa and Sánchez-Cordero 2008) but is for an earlier time period in Mexico for which it is widely asserted that PAs were severely under-resourced or 'paper parks'. As discussed further in the following section, such a lack of capacity should affect PA locations. Naturally, it should also affect average performance and indeed Blackman et al. (2014) finds that on average natural protected areas did not statistically significantly reduce the deforestation rates within their borders. A reputed shift over time, in political will to enforce, motivates our analyses.

3. Modeling PA Impact

3.1 PA Impact by Location (static land-use economics)

Private land-use decision making often implies varied deforestation pressure across a landscape. From von Thunen (1826) to the 'monocentric model' of urban land use, many landscape analysts assert that clearing pressure falls as we move outward along a road leading from a market center (in Figure 1, a city where the '0' axis hits the left axis). Transport costs imply that, all else equal, moving to the right profits fall from agricultural production whose output is to be sold in the city. If all land is originally forested and only transport matters, then forests stand farther from market (in Figure 1, forests remain to the right of where the 'Expected Profits' line crosses the '0'axis).

Of course, factors other than transport also affect relative profits from agriculture versus forests: e.g., high slopes near markets may stay forested; and good soils far from market may be cleared. From an analyst's point of view, some of these factors are observed, while others are unobserved as there are limits on all datasets. The empirical analyses we review do include observed factors. However, Figure 1 does not explicitly depict them, focusing on representing unobserved factors in the form of a distribution, or varying density, of land-parcel profits around the expectation line.

Conservation policies intend to keep existing forests standing, though that requires enforcement. Further, even if a PA remains fully forested, depending upon location that may not imply impact. The impact of even such perfect protection equals the baseline deforestation rate that is avoided; thus, if private land use also would have featured standing forest, the policy did not have impact. More generally, a conservation policy's impact equals the private or 'baseline' deforestation rate that would have arisen without the policy minus the deforestation rate observed with the policy. Within Figure 1, if transport cost is a significant factor in the private ('baseline') rate of clearing, then even a fully forested conservation area far to the right may not have much impact on forest.

3.2 PA Impact by Type (adding political economy)

If policy's forest impacts vary by location due to private deforestation pressure − as in Figure 1 − then the distribution of conservation's locations across the landscape determines average impact. Further, the political economy of conservation policies must involve their development tradeoffs, e.g., what somebody loses from a PA, and that tends to push conservation towards low pressure: land where agricultural profits would be high is expensive to buy for conservation; and when public lands are allocated − without a price − lobbying against PAs may rise with the profit level.

Formally, if simply, the implicit theory of PA location above is that for a PA to be established its costs − including local profits in Figure 1, which would be foregone − must be below its benefits (which can vary with who decides, as World Bank 2013 demonstrates for the Brazilian Amazon). For a fixed benefit, this predicts that PAs avoid pressure. Joppa and Pfaff 2009, e.g., confirm that.

Extending this to predict varied impact by PA type requires elements of types' decisions to differ. Political incentives certainly differ by country and across time periods within any given country. They may differ by PA type. For instance, the tradeoffs in creating a 'strict' PA likely differ from those for 'loose' PAs that feature profits and local livelihoods and, perhaps, less anti-PA lobbying. Thus, different PA types may end up with different locations; in particular, if the differences in PA regulations are enforced, we may expect to see strict PAs even further to the right in Figure 1. That certainly can be the case − as seen in Nelson and Chomitz 2011 as well as Pfaff et al. 2013b.

That said, optimal PA-location decisions are interdependent with optimal enforcement decisions. For instance, with no enforcement there is no reason for systematic variation in location by type: if locals believe PAs are 'paper parks' (see 2.2 for Mexico), they do not have any reason to lobby. Further, like profit, potential for state enforcement may fall with isolation (see, e.g., Albers 2010). Thus, pressure-enforcement interactions could produce varied patterns of PA impacts over space.

3.3 PA Spillovers (adding dynamics)

Conservation policies net impacts involve more than impact within the boundary of that policy. Once a PA's location and enforcement are established, relevant private and public actors respond. Such dynamics can affect forest and socioeconomic outcomes in areas proximate to the new PA. For instance, labor and capital may be drawn to tourism-based opportunities created by the PA. Alternatively, people may migrate and state investments may shift away from promising areas if the creation of the PA signals that federal government, e.g., will no longer invest in development.

In general, private and public actors are likely to respond to all other private and public actions. For example, migration and private investment and private lobbying for more public assistance could lead to new roads and health clinics following growth in tourism generated by the new PA. Private actors then may respond to the new roads and to additional public development policies. Such path-dependent spatial dynamics affect long-run impacts of conservation and development. Relevant for our empirics, such 2^{nd}-order or ‘spillover’ effects can differ greatly across locations. For instance, the level of tourism that is generated by a conservation policy varies significantly. Also, spatially-path-dependent development dynamics concern developing frontiers and thus are most likely to be relevant within areas characterized by low past private deforestation pressure.

Within a limited empirical record on PAs' deforestation spillovers, there is evidence of variation. For Costa Rica, Robalino et al. (2014) go beyond the average spillover tests in Andam et al. 2008 − that find no average spillovers − by looking for spillovers where land-use economics predicts. Away from the PAs' entrances, 'leakage' (deforestation spillover from a PA) is found near roads, while near the entrances it appears that tourism neutralizes such effects. In contrast, Pfaff et al. 2014 examine PAs in the Brazilian Amazon frontier − very different economic dynamics − and find 'blockage' or lower deforestation near PAs, consistent with migration or infrastructure shifts.

4. Data & Matching Methods

4.1 Land Cover Data

This Mexico data is part of a global data set with land cover for 2000 (Bartholome and Belward, 2005) and land cover for 2005 (ESA). Though the datasets were not constructed for comparison, there is also 2000-2005 'land-cover change' data. I will analyze this dataset and the 2005 as well.

The land cover for 2000, GLC2000, has 23 classifications of land cover. For comparisons, this was reclassified to two categories, 'natural' and 'human modified' (modified by anthropogenic land use), with the latter including categories 16 (cultivated and managed areas), 17 (mosaic of cropland with tree cover or other natural vegetation), 18 (mosaics of cropland, with shrubs or grass cover), 19 (bare areas), and finally also 22 (artificial surfaces and associated areas). The same process was carried out for the land-cover dataset for 2005, i.e., the GLOBCOVER300 data. Again the multiple categories in the data have been categorized into "natural" and "modified", with the latter including categories 11 (irrigated croplands), 14 (rain fed croplands), 20 (mosaic cropland (50-70%)), 30 (mosaic cropland (20-50%) and finally also 190 (urban areas >50%).

The change between these two datasets − which we have labeled the 'vegchange' variable − was calculated after the transformations described above. In other words, through the transformations, these land-cover data in principle track change from a 'natural' to a 'human modified' landscape. Since we want to consider the recent changes that could be affected by the presence of protection, even though they are net changes (as the land-cover changes can go in both directions, i.e., from 'natural' to 'human modified' and vice versa − which could be quite important for whether it is a good indicator for species habitat), this is the dependent variable on which we focus. It could be sufficient to assess whether the large-scale patterns within the snapshots (recalling that we will also analyze the spatial patterns in the 2005 land cover) remain within the estimate of changes.

4.2 Land Characteristics Data

Table 1 provides descriptive statistics for land characteristics in our analysis. Elevation (m) is from the Shuttle Radar Topography Mission (USGS 2006), with slope in degrees from horizontal. The roads and urban areas used to compute distances (km) are from VMAP0 Roads of the World (NIMA 2000) and the Global Rural Urban Extent data (UNEP 2006). While not the best quality, these VMAP0 data are the only ones that are freely accessible to define the global road network.

PAs (protected areas) are from World Database on Protected Areas (WCMC 2007). In these data, Categories I-II allow less human intervention, while Categories III-VI tend to be less protected, allowing for multiple uses. If an overlap occurs between categories, a pixel is categorized in the stricter category. We create three dummy variables: 'protected' for any protection (regardless of IUCN category); 'loose' for IUCN categories III-VI; and 'strict' if the IUCN category is I or II.[1]

World Wildlife Fund classified ecoregions (Olson 2001). Unclassified ecoregions were dropped (n=1,747). We create dummy variables for the two ecoregions with the highest frequency. The dummy variable 'pineoakdum' (10.7% of total) takes on a value of '1' if the ecoregion is Sierra Madre Occidental Pine Oak Forest, '0' otherwise. The dummy variable 'chidesertdum' (15.6% of total) equals '1' if the ecoregion is Chihuahuan desert, '0' otherwise. Agricultural suitability is from the International Institute for Applied Systems Analysis' Global Agro-Ecological Zones data (Fischer *et al.* 2002). It uses climate, soil type, land cover, and slope to assign a value to each grid cell, from 0 (no constraints) to 9 (severe constraints). We created two dummy variables from this: 'low' for more agricultural constraints, i.e., agricultural suitability 8 or higher; and 'high' for situations with fewer agricultural constraints, i.e., agricultural suitability 5 or lower. The fire variable as a continuous metric simply captures the number of fires from 2001 to 2006.

[1] This was based on Joppa & Pfaff (2010b) and Nelson & Chomitz (2011) with a robustness check using groups I-IV and V-VI. Additionally, since we are explaining 2000-2005 land-cover change, we analyze the impacts only of PAs established by 2000.

The ‘firedum’ dummy created from it takes a value of ‘1’ if that pixel experienced any fires ($\geq$1). Finally, the distance-to-edge variable measures the distance to the edge of a protected area (km) from the pixel in question − noting that a negative value indicates the observation is inside a PA.

These variables are not expected to fully explain land-cover change or the location of protection. Nevertheless, all are proven to influence profit from agricultural production, as relevant for PAs, i.e., are statistically significant predictors of deforestation (Joppa and Pfaff 2010b). Moreover, as resistance to protection may rise with profitability, it is not surprising that these factors correlate with a location being protected (less likely if they indicate more profit; Joppa and Pfaff 2010b). It is the combination of relevance to protection and forests that makes them useful for this effort.

The data contain approximately 1,935,301 observations (1-km^2 pixels of land) and 13 variables. As noted, Table 1 presents summary statistics for the aforementioned variables. For our results, we explore their impacts on land-cover change as well as their significance for locations of PAs.

4.3 Matching Methods

If protection were implemented randomly, its deforestation impact would be easy to estimate, as we would only need to look at the difference between deforestation inside and outside of the PAs. Deforestation outside would be an unbiased estimate of what would have been the deforestation inside the PA boundaries had there been no protection, since all other factors would cancel out. However neither PAs in general, nor any PA type, seems to be distributed as if at random and in general that non-randomness often appears to be along dimensions that can affect deforestation. To remove the influences of these differences to isolate PA impact, we use ‘matching’ methods. The principle is to find improved control groups by ‘matching’ each protected point to the most similar unprotected point(s), for ‘apples-to-apples’ comparisons. Thus, PAs are compared not to all unprotected land but only to the most similar land. We apply propensity-score matching here.

In propensity-score matching, ‘similarity’ is based on the probability of a pixel being protected. Thus, protected pixels are compared to pixels not in PAs with similar enough site characteristics to yield a similar probability of protection. Probabilities are generated by a probit model that uses factors in protection and deforestation to explain where protection occurred (see Rosenbaum and Rubin 1983). More weight is given to the variables that are important determinants of protection.

However, selecting the most similar points does not guarantee that the controls are in fact similar. Thus, we also must check, explicitly, whether the selected unprotected points are, in fact, similar. We examine balance, i.e., whether the average values for key factors are distinguishable between matched unprotected and PA observations. It should not be. Assuming differences to begin with, we would expect at least a significant reduction in differences between groups from matching.

Given good balancing in covariate averages, matched unprotected deforestation is an estimate of the counterfactual deforestation rate that would have occured within a PA without the protection. PA impact is then simply that counterfactual minus the observed deforestation (given protection). However, still there will be differences between these groups, in terms of characteristics relevant for deforestation. Thus, our preferred matching estimates involve first matching then regressions, which we refer to as ‘bias adjustment’ since this addresses remaining characteristics differences.

The use of regression immediately raises standard questions about issues with regression errors. If the unobservables or unincluded factors are correlated with treatment, i.e., where the PAs are, that could bias impact estimates. Matching can control only for the included observable factors. For instance, we do not know anything about the populations in the PA versus unprotected sites. We suspect that the factors we do observe, however, such as road and city distances, correlate with unobservables. Thus given our observables, we are not sure of the sign of residual biases. As a robustness check, we compute Rosenbaum bounds to estimate how sensitive are our results.

5. Results

5.1 <u>Descriptive Statistics</u>

Table 1 provides means for our outcomes and drivers, including the protection treatments, i.e., not only protection in general but also stricter and less strict (or 'loose') protection. To start, note that 79% of protection is of the looser sort, with an average IUCN category of 6, while the 21% of PA observations in stricter PAs have an average IUCN category of 1.3. The types are distinct.

In terms of drivers of deforestation other than PAs, Table 1 leads with a very important factor that also is the factor that differs most in these data not only between PAs and unprotected points but also between the two types of PAs. That is urban distance, critical for effective market access. Protected points are on the order of three times as far unprotected, while less strict protection is on the order of twice as far as strict protection. That difference is central to our impacts by types. Further, relative locations differ from what is found in the Brazilian Amazon (Pfaff et al. 2013b) and globally − as demonstrated within Nelson and Chomitz 2011 concerning PA impacts on fire.

Relative locations of PAs versus unprotected points, though, do fit our initial political economy model in which for a given societal benefit we expect high opportunity costs of PAs in profitable locations to drive PAs to relatively unprofitable sites. Table 1 shows this not only for the urban distance but also, to a lesser extent, road distance and the fractions of high and low quality soils. Without considering such differences in location, the last row of Table 1 provides an estimate of PAs' average impact in that a 2.9% loss of natural land cover in PAs is lower than the 9.2% loss for unprotected observations. Further, Table 1 suggests that there was actually some enforcement difference across stricter and less strict PAs. The land-cover loss of 2.2% is lower for strict PAs, despite the fact that the only major difference in characteristics is that strict are *closer* to market. Naturally, though, any such estimates require revisiting with controls for all land characteristics.

5.2 Drivers of Protection

While Table 1 already suggests what sorts of locations are more likely to be protected, Table 2 revisits that question using multi-variate regression to control for each factor in assessing others. As in Table 1, we start with a highlighted characteristic, urban distance. PA observations clearly are further from urban areas than are unprotected points. Further, as expected from Table 1, the coefficient on urban distance for less strict PAs is larger than for strict, i.e., less strict are farther (although we note that the smaller differences in road distance support that less strict are closer[2]). The other findings in Table 2, e.g., for agricultural suitability, also reflect Table 1's differences.

5.3 Drivers of Land-Cover Change

Before estimating PA impacts on land cover with controls for the effects of other determinants, we would like to have an empirically informed sense of what the loss of natural land cover in Mexico in this time period. To do this, we examine rates of loss within just unprotected locations. Table 3 presents OLS regressions of both land-cover loss and 2005 land cover on characteristics. (note that we would expect the coefficients in the two colums to have exactly the opposite signs).

Table 3 also leads with urban distance and, as expected, it appears to have a significant effect on profitability of clearing land cover − lowering it − as greater distance lowers loss of land cover. Also as expected, road distance matters even controlling for urban distance as transport is critical. Higher elevation and slope also discourage whatever land uses involve the loss of natural cover, again as expected. Further, also expected, better conditions for agriculture increase loss of cover. Noting that over a quarter of the observations are in these regions, without specific interpretation we note that Sierra Madre pine oak forest and Chihahuan desert are significant control variables.

[2] In principle, PAs could be near ejidos in rural areas where there is nonetheless some level of road access to support commerce. In Mexico, 53% of land and 70% of land with forest cover is owned by *ejidos*, which are mostly rural, indigenous communities. Mexico's 1992 Agrarian Law, Article 1 gave these communities legal status and land ownership. They are eligible to participate in conservation programs, such as Mexico's Payment for Ecosystem Services Program (The REDD Desk, 2012).

5.4 Matching on Drivers of Land-Cover Change

Before presenting any impacts results making use of controls, we discuss our efforts in matching. Given the significant differences seen in Table 1 in terms of urban distance, Table 4 presents our matching balance starting with that key factor. For each treatment, i.e., all PA points or instead the subsets of more and less strict protection, Table 4 shows that large reductions in differences between unprotected controls and the PA observations were brought about through the matching. As the other differences noted in Table 1 were for road distance and high agricultural suitability, we note that Table 4 shows similarly large reductions in pre-match difference through the match (the percent reductions are a bit smaller but the initial differences for these factors were smaller). That is also the case for the significant sized and significantly important controls for ecoregions.[3]

5.5 Average PA Impacts

For loss of natural land cover and the 2005 amount of land cover, Table 5 presents PAs' impacts. The table's first column presents average impact, i.e., the treatment here is any kind of protection. This discussion focuses on the loss of natural land cover as impacts on 2005 cover are analogous.

Table 5's first row shows means differences, analogous to the impact estimate implied by Table 1 (a little different because as seen in Table 3's first column, this outcome has fewer observations). Its second row introduces controls for the effects of other determinants of natural land-cover loss using regression analysis with all bservations. This cuts the estimate impact by more than half, just as found in Andam et al. 2008 for Costa Rica, World Bank 2013 for the Brazilian Amazon, and globally, at least on average, as found in analyses of 141 countries in Joppa and Pfaff 2010b. The matching estimate in Table 5's third row then confirms robustness − per use of observables − as a 2.5% loss reduction, found using just matched observations, is very similar to the prior result.

[3] We also conducted analyses using calipers of 0.01 and 0.001. Results are not included, as this did not improve on our matching.

5.6 Impacts by PA Type

Table 5's second and third column separate the protection treatment into more and less strict PAs. Note that the simple differences in means in the top row, where the loss rate within each PA type is compared to the loss rate within all unprotected observations, illuminate enforcement choices. Despite that fact that less strict PAs are further from cities, which should lower clearing pressure, clearly more loss of natural land cover is occurring in those PAs as this simple impact estimate is lower for the less strict PAs (5.5%) than for the stricter PAs (6.4%). Enforcement is occurring and, in particular, enforcement choices differ by PA type, in that clearing differs within PA types.

The differences between Table 5's first row and its second and third rows, which employ controls, illuminate location choices. The more biased are locations towards low pressure, as we predicted when enforcement is expected to occur (which per Blackman et al. 2014 was not always so here), the greater a reduction in estimated PA impact we should see when controlling for characteristics. Both the more strict and the less strict PA impact estimates fall, consistent with the first column. However, if anything the less strict falls by more, consistent with greater urban distance (and this pattern of slightly larger corrections based on characteristics is supported by the 2005 land cover). Putting the enforcement and location choices together, the more strict PAs have greater impacts. That could be explained by an increase in enforcement after locations during 'the paper park era'.

5.7 PA Spillovers By State

Finally, simply as part of our appeal for greater focus on the dynamics of conservation impacts, we have also estimated 10km spillovers from PAs by state. Mexico on average, and some states, appear to feature small clearing reductions nearby. However, other states have sizeable "leakage" or increases in clearing nearby (especially nearer to roads, consistent with Robalino et al. 2014). As for examples above, to predict these it is clear we need more understanding of local dynamics.

6. Conclusion

With two motivations, we estimated a suite of impacts of PAs on land-cover changes in Mexico. One motivation was to study a period after a 'paper park era', by which politics may have shifted. Another was to demonstrate the need for more politics and dynamics to understand PAs' impacts.

PAs did reduce the loss of natural land cover within their boundaries during the 2000-05 period, though by under half of what one estimates without controls based on static land-use economics. Further, a combination of location and enforcement choices yielded different impacts by PA type, with more strict PAs yielding greater loss reductions within their boundaries than less strict PAs. We conveyed that one must add political economy to have any prediction for such key decisions − sketching a simple model consistent with average impacts here and impacts by type elsewhere. However, impacts by PA type here appear to reflect change over time in politics of conservation, since PA locations chosen earlier seem to reflect PAs' types less than enforcement choice later on.

Finally, we also estimated the PAs' spillover effects to the changes in natural land cover nearby. By way of emphasizing the importance of the particular local economic and political dynamics, we estimated spillovers not only for Mexico on average but also for states with high PA density. Even the sign of the spillovers, i.e., whether the nearby land-cover change was higher or lower, varied across the states. Just as that is the case in a limited empirical literature for varied settings, this is perfectly consistent with the existence of different land-use dynamics within the country.

Various extensions could improve and build upon these analyses. To start, the data for land cover are not ideal and perhaps Mexico's development of a new MRV mechanism could offer options. Additionally, to further inform forward-looking policy choices more recent data could be used. Finally, clearly more intense study of different dynamics across space, e.g., states within Mexico, could further contribute to understanding of the conditions that drive the impacts of protection.

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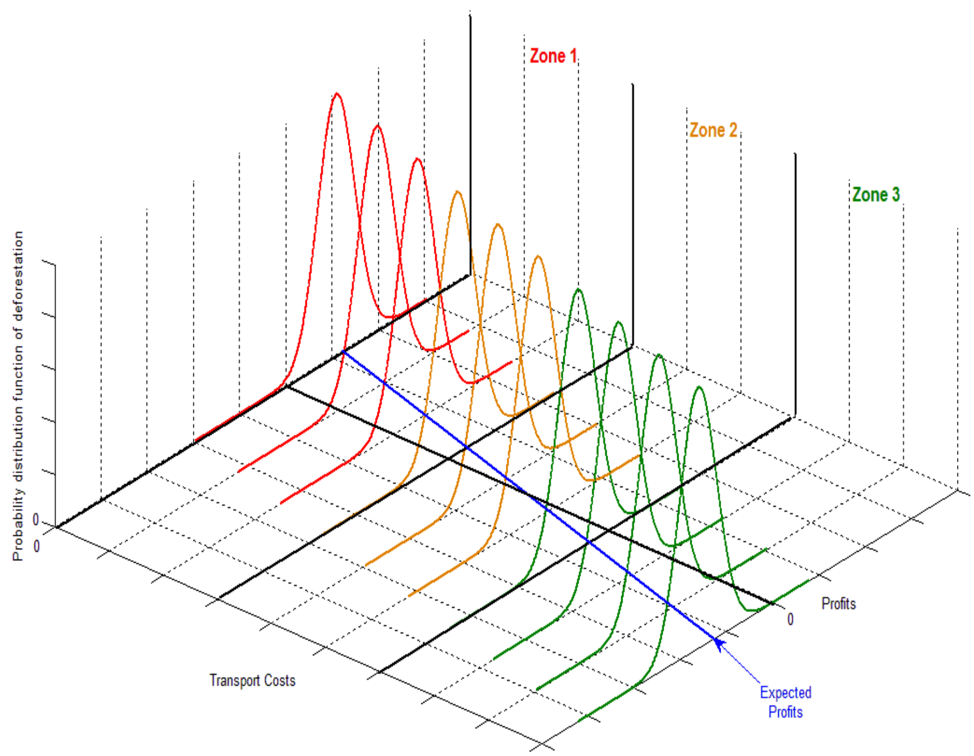
Figure 1



Zone 1
Zone 2
Zone 3
Probability distribution function of deforestation
0
0
Transport Costs
Profits
0
Expected Profits

Table 1

Land Characteristics and Land Cover (including PA Type)

	Unprotected	Protected	Protected -- Strict Subset	Protected -- Loose Subset
Protected -- Loose (1/0)	0	0.79	0	1
Protected -- Strict (1/0)	0	0.21	1	0
IUCN Category (1-6)	0	5.0	1.3	6.0
Distance Outside PA Edge (km)	55.8	-14.0	-10.5	-15.0
Urban Distance (km)	35.6	95.7	58.4	105.3
Road Distance (km)	8.5	12.6	14.3	12.2
Elevation (m)	1081	622	885	554
Slope (degrees)	2.813	2.852	3.424	2.703
Agricultural Suitability (0-9)	6.171	6.811	6.566	6.875
[derived] Low Agric. Suitability (1/0)	0.386	0.56	0.38	0.60
[derived] High Agric. Suitability (1/0)	0.372	0.21	0.22	0.21
Fires (# in 2000-06)	0.005	0.003	0.004	0.003
[derived] Fire Dummy (1/0)	0.005	0.003	0.004	0.003
Pine Oak Forest Dummy (1/0)	0.115	0.003	0.005	0.003
Chihuahua Desert Dummy (1/0)	0.163	0.064	0.012	0.078
GLC 2000 Natural Land Cover (1/0)	0.840	0.920	0.912	0.921
Globcover 2005 Natural Land Cover (1/0)	0.862	0.957	0.970	0.954
2000-2005 Loss of Natural Cover (1/0)	0.092	0.029	0.022	0.031
# observations	*1,801,935*	*121,847*	*25,096*	*96,751*

Table 2

Drivers of Protection

(including by type)

	Protected	Protected -- Strict Subset	Protected -- Loose Subset
Urban Distance	0.00220*** (0.000)	0.00034*** (0.000)	0.00216*** (0.000)
Road Distance	0.00005* (0.000)	0.00046*** (0.000)	-0.00047*** (0.000)
Elevation	-0.00001*** (0.000)	0.00001*** (0.000)	-0.00002*** (0.000)
Slope	0.00127*** (0.000)	0.00102*** (0.000)	-0.00007 (0.000)
High Agricultural Suitability	-0.02164*** (0.000)	-0.00502*** (0.000)	-0.01767*** (0.000)
Pine Oak Forest	-0.04907*** (0.000)	-0.02307*** (0.000)	-0.02963*** (0.000)
Chihuahuan Desert	-0.02783*** (0.000)	-0.01306*** (0.000)	-0.01930*** (0.000)
constant	-0.00005 (0.000)	-0.00889*** (0.000)	0.00306*** (0.000)
# obs	1,923,782	1,827,031	1,898,686
R^2	0.235	0.045	0.251
Adjusted R^2	0.235	0.045	0.251

Robust standard errors in parentheses

**** p<0.001, ** p<0.01, * p<0.05*

Table 3

Drivers of Natural Land Cover – Explaining Both Loss & Final Amount

(Outside PAs)

	***Natural Land Cover* Loss 2000 - 2005**	***Natural Land Cover* Amount 2005**
Urban Distance	-0.00074*** (0.000)	0.00075*** (0.000)
Road Distance	-0.00094*** (0.000)	0.00137*** (0.000)
Elevation	-0.00006*** (0.000)	0.00008*** (0.000)
Slope	-0.00617*** (0.000)	0.00729*** (0.000)
High Agricultural Suitability	0.01095*** (0.001)	-0.01562*** (0.001)
Pine Oak Forest	0.06677*** (0.001)	-0.08450*** (0.001)
Chihuahuan Desert	-0.05856*** (0.001)	0.05519*** (0.001)
constant	0.22752*** (0.001)	0.72280*** (0.001)
# obs	1,514,249	1,801,935
R^2	0.06	0.10
Adjusted R^2	0.06	0.10

Robust standard errors in parentheses.

**** p<0.001, ** p<0.01, * p<0.05*

Table 4

Matching Balance

Propensity Score Matching	**Protected**	**Protected -- Strict Subset**	**Protected -- Loose Subset**
Urban Distance			
Pre-match difference	58.930***	18.199***	67.409***
Post-match difference	-7.655*	-0.689	-1.909***
% reduction	87.0%	96.2%	97.2%
Road Distance			
Pre-match difference	3.428***	5.409***	2.810***
Post-match difference	1.547*	-2.298***	0.394**
% reduction	54.9%	74.6%	86.0%
Elevation			
Pre-match difference	-541.608***	-294.187***	-587.132***
Post-match difference	-54.947	33.526***	-8.670
% reduction	89.9%	88.6%	98.5%
Slope			
Pre-match difference	.048***	0.554***	-0.082***
Post-match difference	-0.420*	-0.052	0.108**
% reduction	-†	90.6%	-†
High Agric. Suitability			
Pre-match difference	-0.130***	-0.094***	-0.136***
Post-match difference	-0.035	0.010*	0.0160***
% reduction	73.1%	89.4%	88.2%
Pine Oak Forest			
Pre-match difference	-0.133***	-0.123***	-0.131***
Post-match difference	-0.005	-0.005***	-0.004***
% reduction	96.2%	95.9%	96.9%
Chihuahuan Desert			
Pre-match difference	-0.147***	-0.192***	-0.130***
Post-match difference	-0.015	-0.009***	-0.006*
% reduction	89.8%	95.3%	95.4%

Means differences, scale & sign.

† increased small difference

**** p<0.001, ** p<0.01, *p<0.05*

Table 5

PA Impact Estimates

(within boundary)

	Protected	Protected -- Strict Subset	Protected -- Loose Subset
2000-2005 Natural Land Cover Loss			
Pre-match difference in means	-5.9 % ***	-6.4 % ***	-5.5%***
Pre-match regression (all the data)	-2.6 % ***	-4.1 % ***	-1.8 % ***
Post-match regression (most similar)	-2.5 % ***	-4.4 % ***	-2.3 % ***
2005 Natural Land Cover			
Pre-match difference in means	9.1 % ***	10.0 % ***	8.5 % ***
Pre-match regression (all the data)	3.5 % ***	5.2 % ***	2.5 % ***
Post-match regression (most similar)	3.4 % ***	6.0 % ***	3.3 % ***

**** p<0.001, ** p<0.01, * p<0.05*