PROTECTED AREA IMPACTS ON LAND COVER IN MEXICO

by

Francisco J. Santiago-Ávila

Dr. Alexander Pfaff, Adviser

Apr 2013

Masters project submitted in partial fulfillment of the

requirements for the Master of Public Policy degree in

the Sanford School of Public Policy of

Duke University

2013

Abstract

Although national and international efforts to mitigate deforestation during the last few decades have had some limited impact, they have failed to substantially slow the loss of tropical forests. This MP applies an approach for providing more evidence on what has worked or not worked in terms of conservation policies intended to reduce tropical natural land cover. Specifically, the work and approaches used in my analysis should help to illuminate the tradeoffs currently facing Mexico, a country which is seriously considering pursuing REDD policies, but also knows it would not be without economic costs. My main objective is to answer the question: "have conservation parks affected change in land cover in Mexico?" while a related objective is to assess if some types of parks have had reliably more impact. Due to the nonrandom establishment of protected areas (PAs), I employ a matching approach (propensity score) in order to construct a plausible counterfactual by controlling explicitly for land characteristics that proved to be significant drivers of both land cover change and protection status. My results indicate not only that my approach improved impact estimates, but also, in particular, that PAs lower land cover change pressure by 3.1%, and that strict protection seems to avoid more land cover change (5.3%) than loose (multi-use) protection (2.7%). While these results are suggestive, I would recommend also trying to get better and more data to test their robustness.

Objective

The main objective is to answer the question: *have conservation parks affected change in land cover in Mexico?*

A related objective is to also answer: *have some types of parks had reliably more impact on land cover?* The IUCN classifies parks, including from those completely restricted to outside intervention and land use to those allowing certain forest uses and practices (including restricted deforestation) for the local communities (which could also be allowed to live inside parks). It is essential to learn if a certain type of conservation park has reliable more impact on land cover than another in order to inform authorities considering such park types and the tradeoffs involved with each.

Introduction

Although national and international efforts to mitigate deforestation during the last few decades have had some limited impact, they have failed to substantially slow the loss of tropical forests (see Kaimowitz and Angelsen, 1998). Tropical deforestation now accounts for around 17% of anthropogenic greenhouse gas (GHG) emissions (Pfaff et al, 2009). A renewed concern about climate change, added to the recognition that programs for reducing emissions from deforestation and degradation (REDD) can have a larger influence in climate change mitigation, underscores the need to learn from previous factors influencing rates of deforestation.

Within the UN Framework Convention on Climate Change (UNFCCC), international stakeholders are assessing how to generate incentives for REDD and other forest-centered carbon mitigation activities in post-2012 efforts. On a parallel track, for instance, the U.S. Congress as well as others are developing legislative proposals for GHG emissions reduction policy.

Thus, given the current efforts to incentivize REDD, in principle, environmental policies that target reduced deforestation could mobilize new and sustained funding for forest conservation within developing countries (Pfaff et al, 2009). Such climate-related incentives for forest conservation could give U.S. policymakers and the international community as a whole new avenues from which to influence the various programs and policies that affect deforestation. These new programs will most likely be performance-based, emphasizing the monitoring, reporting, and verification of all outcomes. This emphasis, together with financial incentives, could increase these policies' impacts on deforestation rates (Pfaff et al, 2009).

Lessons from past policies concerning deforestation should aid in designing better policies that are effective, efficient, and equitable (Pfaff et al, 2009). It is crucial for the countries interested in financing or purchasing emission reductions as well as the countries interested in hosting these activities to know and understand what has and hasn't worked in reducing forest loss and degradation, and why. Knowing this, new investments and policies then can choose to replicate and improve what has actually worked, reducing policy failures.

This MP applies an approach for providing more evidence on what has worked or not worked in terms of conservation policies intended to reduce tropical deforestation. Given some recent work providing improved evaluations of conservation's forest impact (Joppa & Pfaff, 2010a/b), alongside the need to address the specifics of each country if trying to be policy relevant, my work here should help to illuminate the tradeoffs currently facing Mexico, a country which is seriously considering pursuing REDD policies but also knows they would not be without economic costs.

In this MP, I will provide some basic facts about Mexico, the state of its forests and the importance of tackling deforestation in this country. I will then proceed to provide a brief overview of the current state of the literature on protected areas' impacts on deforestation, as well as the literature on the 'matching' processes used to provide improved impact estimates. Next, I will describe the data and matching methods I will use for our analyses. I will then present my analysis and conclude by presenting and discussing my findings.

My results indicate that PAs lower land cover change pressure, but by far less than estimated by methods simpler than mine. Through matching on land characteristics, I obtained an estimate of 3.1% reduced land cover change from PAs. Strict protection also seems to avoid more land cover change (5.3%) than loose protection (2.7%). Through my analysis, I confirmed that land characteristics have a significant impact on land cover change as well as protection decisions. The Rosenbaum bounds test suggests that my results are sensitive to the presence of unobserved variables. However, my analysis, the first in assessing PA impacts in Mexico, contributes to the literature of these policies and what to take into account when designing them. Better data could provide for a more comprehensive analysis.

Mexico

Forests in Mexico cover 67 million hectares, approximately 34% 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).

Mexico has strong incentives to become a leader in an international climate agreement due to the likeliness of suffering disproportionate impacts from climate change (i.e. droughts, sea level rise and increased severity of tropical storms, among others). The agriculture and forestry sector in Mexico is one of the major sectors where GHGs can be reduced. This sector generated approximately 135 $MtCO_2e$ in 2002, accounting for 21% of Mexico's total emissions (Johnson et al., 2010). Two thirds of these were generated by the forest subsector (Johnson et al., 2010). The main, proximate, causes of deforestation and degradation in Mexico are: forest land converted to grassland, slash-and-burn agriculture, illegal logging and natural occurrences. The underlying forces for these causes appear to be: forest area use limitations, lack of investment in the forestry sector, low income derived from forest activities, agriculture/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 various unquantified benefits that these interventions and programs could have in terms of improved ecosystem services, preservation of ecosystems, income generation and employment, among others (Johnson et al., 2010).

Interventions in forestry, REDD among them (i.e.: reforestation, commercial plantations, etc.) account for 85% of the government's proposed mitigation in the agriculture and forestry sector (Johnson et al., 2010). Successful expansion of forestry sector interventions depends on institutional changes in forest management, improved public financing mechanisms and the development of a market for sustainable forest products (Johnson et al., 2010).

REDD is progressing nicely in Mexico, which is moving towards redesigning it to include REDD+ activities and is planned for implementation between 2012 and 2020. (The REDD Desk, 2011). The National REDD+ strategy (ENAREDD+) is soon to be released following a stakeholder process at the end of 2012. This strategy will tackle issues such as the emergence of a large illegal timber market, lack of financial and human resources, limited operational capabilities, long permitting cycles and (drug-related) insecurity.

In this strategy, Mexico is emphasizing the development of a national, multi-functional and multi-scale monitoring, reporting and verification (MRV) mechanism based on remote sensing and ground-based forest inventory methodologies (The REDD Desk, 2011). It is expected to include early detection systems for land cover/land use change (The Forest Carbon Partnership, 2012). This National MRV mechanism could provide 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, thus allowing for better analysis of which policies are more effective for reducing deforestation.

Literature Review

Joppa and Pfaff (2010a) review literature on protected areas' impacts (see also reviews by Naughton-Treves, 2005, Nagendra, 2008, and Campbell et al., 2008). They emphasize the hurdles for solid inference about protection's impacts on forest given new documentation that, globally (Joppa and Pfaff 2009), the distribution of protection across countries' landscape is not random but rather it is significantly biased in deforestation-relevant ways.

Protected areas' impacts have been evaluated, but through various methods. Some evaluations do not really compare anything but only observe; for example, statements that Costa Rican protection succeeded since areas are fully forested (Sanchez-Azofeifa, 1999) or Fuller et al.'s (2004) suggestion that protected areas in Kalimantan are unfeasible given the considerable deforestation they endured from 1996 to 2002. These sorts of "conclusions" lack a comparison of what happened inside a protected area with its counterfactual (what would have happened had it been left unprotected). Since it is impossible to observe this counterfactual, one infers it using other sites. Several options for doing so have been tried.

Some evaluations compare outcomes within protected-area boundaries to outcomes in all unprotected areas. Gaveau et al. (2007) discusses deforestation rates for all unprotected areas from 1972 to 2002, comparing a ~2.9% rate of clearing per year with lower rates of deforestation inside the protected areas. This could lead to the conclusion that protection lowered deforestation. Along these lines are Messina et al. (2006) on the Ecuadorian Amazon, Sanchez-Azofeifa et al. (1999) about the Sarapiqui region of Costa Rica, and DeFries et al. (2005) for the globe. However, protected areas could be more efficient in forests because they are protected or, instead, because the lands they are located on differ considerably.

Many past evaluations compare protection's outcomes to those in buffer zones surrounding protection, presuming their similarity (in essence, proximity is a land characteristic). While criticized later (Vanclay 2001), Bruner et al. (2001) examined deforestation in and around 93 protected areas across 22 tropical countries using survey data. Liu et al. (2001) found deforestation was equal to or higher inside the reserve than in a 3km buffer zone. In 2007, Viña et al. (2007) revisited the Wolong analysis, updating from 1997, when Liu et al. (2001) left off, to 2001 and finding across the entire study period (1965 to 2001) that rates of habitat loss were on average ~17% lower inside the protected area than in the buffer zone. Sanchez-Azofeifa et al. (1999) analyzed deforestation rates from 1960 to 1997 in and around 132 protected areas using 0.5, 1.0, and 10.0km buffer zones. Sader et al. (2001) examines the northern Guatemalan Maya Biosphere reserve, comparing it with a the buffer zone surrounding it. Kinnaird et al. (2003) examined deforestation rates around Bukit Barisan Selatan National Park on the Indonesian island of Sumatra (also analyzed by Gaveau et al., 2007). From 1985 to 1999, forest cover declined to 52% (from 80%) inside the park, and to 1.6% (from 15%) in a 10km buffer. In the same area as Fuller et al. (2004), Curran et al. (2004) illustrated that the Kalimantan, Indonesian Borneo's protected forests declined by 56% from 1985 to 2001. Curran also provided a detailed case study of the Gunung Palung National Park using a 10km buffer zone. The buffer was being cleared while the reserve maintained its forest cover, up until most of the buffer zone had become deforested. This type of analysis could also prove to be useful, but it is hard to know whether proximity means similarity without some land characteristic to compare.

Matching Using Land Characteristics

The method suggested for application here has been demonstrated for a leading country in protection, Costa Rica. For 1960-1997, Andam et al. (2008) used matching for more than 150 protected areas, controlling for a variety of land characteristics, such as: land productivity and distances from forest edge, roads, and cities. Matching (i.e., going from all unprotected points to just the matched [most similar] unprotected points) greatly increased each covariate's similarity in the groups used for the comparisons that provide the impact estimates. 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 land characteristics plus controlling explicitly for them. Joppa and Pfaff (2010b) demonstrate that this correction is important around the globe. Using less precise data and fewer control factors, as dictated by the constraints upon global data, they find (as do Andam et al., 2008) that average impact estimates using such 'matched' comparisons are far lower (under half) than the estimates from approaches typical in the literature. That approach is the initial basis for this analysis.

Yet guiding policy may require more than an average impact. If policy has more impact in some circumstances, this means that future policies can target those circumstances. Pfaff, Robalino et al. (2009) revisit Costa Rican protected areas using matching for 1986-97. Estimates are on average less than a third of other methods'; however, the focus is on impacts' *variations*. For areas within 85 km of the capital of San Jose, impact was 3% avoided deforestation, while those further away had an impact of ~1%. For parks within 6 km of a national road, they find that the impact was 5% o the forest saved, but the impact was nonexistent for forests that were further away. Slope, an important agricultural factor in Costa Rica, was critical for impact. Parks on lower slopes (flatter land) blocked 14% deforestation but the protection placed on steeper lands had close to no impact. Observations such as this one could help guide and improve policies.

Yet the application of these kinds of lessons will not have its greatest focus in Costa Rica going forward into the future. The Brazilian Amazon, for example, is a much larger forest area and is also a more active deforestation frontier. Evaluations supporting planning in the Amazon are critical.

Pfaff Robalino et al. (forthcoming) apply the approach taken in Pfaff, Robalino et al. (2009) to the Brazilian Amazon. Delgado et al. (2008) provide an application to a very well known case in Acre. This specific case also happens to demonstrate that using 'matching' comparisons can be supportive of estimated impacts when parks are in areas under relatively high threat of clearing. For this case, the Chico Mendes extractive reserve has had non-trivial deforestation over time. While the extractive designation suggests that some productive land use is expected, some might conclude that the reserve has not avoided deforestation or has not avoided as much as it should have. Yet the area is close to the Inter Oceanic Highway, much more so than the average for all of Acre. Comparing forest outcomes for Mendes to other places under similarly high pressure (including sites similarly near to the highway) shows that Mendes has avoided significant deforestation.

Available Data

Land Cover

For my analysis, I used a Mexico data set, based on a global data set, with land cover for 2000 (Bartholome and Belward, 2005), land cover for 2005 (ESA). Despite these 2000 and 2005 datasets not being constructed for comparison, there is also 2000-2005 'land-cover change' data. I will analyze this dataset using Stata (11.2).

The land cover for 2000, GLC2000, has 23 classifications of land cover. In order to be comparable, the variable was reclassified into two categories: 'natural' and 'human modified' (natural environment modified by anthropogenic land use), with the latter including category 16 (cultivated and managed areas), category 17 (mosaic of cropland with tree cover or other natural vegetation), category 18 (mosaics of cropland, with shrubs or grass cover), category 19 (bare areas), and category 22 (artificial surfaces and associated areas).

The same process was carried out for the land cover for 2005, the GLOBCOVER300 data. Its legend was meant to be comparable to that of GLC2000, and again the data have been categorized into "natural" and "modified", with the latter including category 11 (irrigated croplands), category 14 (rain fed croplands), category 20 (mosaic cropland (50-70%)), category 30 (mosaic cropland (20-50%), and category 190 (urban areas >50%).

Change between the two datasets, captured through the 'vegchange' variable, was calculated after the transformation described above. In other words, through this transformation, these land cover variables track the change from a 'natural' to a 'human modified' landscape, and thus also provide me with vegetation change from 2000 to 2005. This variable tracks land cover changes both ways ('natural' to 'human modified' and viceversa). As a result, this is a noisy estimate of actual land-cover change. For instance, I have concerns regarding change in land cover relevant for ecosystem services, including carbon and species habitat. However, it could prove fruitful to assess if the large-scale patterns within the snapshots remain within the change estimate.

Land Characteristics

Table 1 provides some preliminary descriptive statistics for the land characteristics I will be including in our analysis. Elevation (in meters) comes from the Shuttle Radar Topography Mission [USGS], with slope calculated in degrees from horizontal. The roads and urban areas used to compute distances (in kilometers) are from VMAP0 Roads of the World [NIMA, 2005] and the Global Rural Urban Extent data [UPEP]. Although not the best quality data, VMAP0 data is the only one that is freely accessible to define the global road network.

The World Wildlife Fund classified the ecoregions [Olson, 2001]. Unclassified ecoregions were dropped from the analysis (n=1,747). After taking a look at the values, I decided to generate two dummy variables taking into account the two ecoregions with 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 was retrieved from the International Institute for Applied Systems Analysis' Global Agro-Ecological Zones data [Fisher]. The data uses climate, soil type, land cover, and slope of terrain to measure agricultural suitability, ranking each grid cell from 0 (no constraints) to 9 (severe constraints). It is unlikely that these variables changed after protected-area creation. For my analysis, I divided the 'agricultural suitability' variable into two dummies: 'lowagsuitability' indicates more agricultural constraints, taking a value of '1' if the agricultural suitability variable is 8 or higher; 'highagsuitability' indicates less agricultural constraints, taking a value of '1' if the agricultural suitability is 5 or less ('0' otherwise). Considering that high agricultural suitability will have a higher impact on land cover change and, thus, the treatment (being in a protected area), I decided to only include 'highagsuitability' in the matching analysis.

PAs (protected areas) were taken from the World Database on Protected Areas [WCMC]. Countries protecting more than 100km^2 of IUCN Category I-VI were included. Noting that categories I-VI are in descending order of protection, Categories I-II tend to allow less human intervention, while Categories III-VI tend to be less protected, allowing for multiple uses. In each instance, it was determined that the most protected IUCN category determines the category in the dataset. Therefore, if an overlap occurred between categories I and II, e.g., I classified that pixel as category I. For the analysis, I constructed three dummy variables with these categories: the 'protected' dummy takes a value of '1' if the area is protected (regardless of IUCN category), '0' if it's unprotected; 'loose' takes a value of '1' if the IUCN category is III-VI (less protected), '0' otherwise; and 'strict' takes a value of '1' if the IUCN category is I or II, '0' otherwise.[1]

The fire variable simply captures the number of fires from 2001 to 2006. The 'firedum' dummy takes a value of '1' if that pixel experienced any fires ($\geq$1). Distance to edge measures the distance to the edge of the protected area (in kilometers). A negative value indicates the observation is inside a PA.

The variables available are not expected to fully explain either land cover change pressure or the location of protection (i.e.: cost and benefits of biodiversity could also play a role). Nevertheless, all these variables have proven to influence profit from agricultural production, which makes them statistically significant predictors of deforestation rates (Joppa & Pfaff, 2010b). Moreover, as resistance to protection designations may rise with land profitability, it is not surprising that these factors often correlate with being within a protected area (less likely if they indicate more profit) (Joppa and Pfaff, 2010b). A combination of relevance to protection and forests makes them useful for this analysis.

The dataset contains approximately 1,935,301 observations (1 km^2 pixels of land) and 13 variables. Table 1 contains some summary statistics for the aforementioned variables, by PA status. In my analysis and results, I explored the impacts of these variables on land cover change as well as their significance in allocating a PA status.

[1] The IUCN category split was based primarily on methods found in Joppa & Pfaff (2010b), Nelson & Chomitz (2011) and Pfaff et al (2013). As a robustness check, I also ran the analysis splitting the IUCN categories I-IV and V-VI. Results were insignificant to my analysis, as there were only 169 observations in category III and none in category IV.

In general, roughly 8% of total observations fall inside PAs. According to the land cover change variable (‘vegchange’), 2.8% of PAs switched from a ‘natural’ to a ‘human modified’ landscape.

Matching Analysis

If protected areas were randomly distributed across the landscape within Mexico, then simply comparing protected lands with unprotected ones could reveal causal impacts estimates of the treatment (protection), since randomness of assignment would ensure similarity within the key land characteristics. Randomness would make sure that these areas are representative of their regions’ landscape (Joppa & Pfaff, 2010a). Yet in reality this is not the case, and protection has often been located on lands unsuitable for other profitable uses (e.g.: steep slopes, poor soil, far from markets, among others).

One way to address differences between protected and unprotected lands’ characteristics is a “matching” approach. Matching is a policy evaluation design that can help to mitigate the influence of the non-random application of a “treatment” (in this case, being in a protected area). For each protected observation included in this type of policy evaluation, matching picks the most similar unprotected points in order to provide better comparisons. The main objective is that the use of land characteristics to do the matching can improve the similarity between treatment groups (protected and unprotected).

One might compare two different estimates of protected-area impact. Without matching, one might subtract the percent clearing in the protected sample from that in the sample of unprotected points. Matching allows us to subtract percent clearing in the protected group from that within the unprotected group but now using a subset of unprotected sites most similar to the protected ones. According to Joppa and Pfaff (2010b), the idea is that matching improves estimates of the treatment’s (protection) impact.

Based on the literature, I matched the sites on all variables considered to affect land productivity and, thus, land cover change and probability of being protected (i.e.: agricultural suitability, slope, distance to roads, etc.). For the matching approach, I implemented propensity score matching.

‘Similarity’ in propensity score matching is measured by the probability of a pixel being protected. Hence, I compared protected pixels with unprotected that have similar probabilities of being protected, taking into account their land characteristics. I generated these probabilities through a probit model that controls for factors that would affect land cover change and protection (i.e. land characteristics) (Rosenbaum and Rubin, 1983), giving more weight to variables that are important in determining protection.

After the matching process, I employed a postmatching regression, in order to adjust for any remaining imbalances on covariates between protected and unprotected points and compare the results with those from the matching process. I also checked the similarity of matches through a ‘balance’ exam in which I examined if the average values of the covariates were different between groups, and how much the matching improved the matches. I applied Rosenbaum bounds to check the robustness of my estimates against hidden bias from unobservables.

Results

Since my analysis focused on the effect of PAs on land cover change for the period 2000-2005, I dropped from the analysis all PAs established after 2000. I want to analyze change in order to best assign impacts to the PAs created before the period with change (pre-2000). PAs established after 2000 received the treatment (protection) after the initial measurement of land cover, preventing me from estimating any land cover change that could have occurred after the initial measurement of land cover, but before implementation of treatment. I also restricted my analysis of the 'vegchange' variable to pixels that were 'natural' in 2000 ('glc'=1). By doing this, I focused the analysis on tracking land cover change from 'natural' to 'human modified'.

However, as I previously stated, our 'vegchange' variable provides me with a noisy, weaker interpretation of land cover change than I would want. Because of this, I included estimates for our 2005 land cover variable ('globcover') as an analogous cross-section, in order to cover the greatest period of time. Through use of 'globcover' I will analyze the same endpoint as our 'vegchange' variable, but leaving open the baseline, providing me with another robustness check for my impact estimates.

Drivers of Land Cover Change

Before estimating any changes on land cover, I wanted to know what drives land cover change. To do this, I regressed my two land cover variables on the land characteristics for the unprotected points. Table 2 shows the results for my OLS regressions of land cover on land characteristics.[2]

The effect of each land characteristics on both land cover variables was significant, and the direction of their impact coincides with my expectations. My results suggest that land characteristics have a significant impact on land cover change. Higher elevation and slope, and longer distance to urban areas and roads have a positive effect on 'natural' land cover, with slope having the highest positive impact. Distance to urban areas seems to contribute more to keeping 'natural' land cover than distance to roads. Meanwhile, having a high agricultural suitability has a negative effect on 'natural' land cover, and a higher impact than any of my other land characteristics, with the exception of the pixel being located in a pine oak forest.

The ecoregion dummies I included seem to have the opposite effect. Being in the Sierra Madre Occidental Pine Oak Forest has a negative impact on 'natural' land cover (and a higher impact overall than any other land characteristic), and the Chihuahuan Desert

[2] Due to the construction of the land cover variables (described above), I should expect the coefficients from the land characteristics to present opposite signs for each land cover variable.

dummy has a positive effect. This was also expected, as pine oak forests allow for a lot more alternative land uses (including deforestation) than desert land.

All land characteristics included in my regressions proved to be significant drivers of land cover and land cover change (all p-values < 0.001). This suggests that I take all of them into account when estimating land cover change, as well as in our matching approach.

Drivers of Protection

I proceed to assess if and which land characteristics impact protection decisions. If allocation of protection is non-random, I would expect protection to be influenced by land characteristics that also affect land profitability and land cover.

Comparing the means of the different groups (Table 1) provides an idea of what influences protection decisions. My 'vegchange' variable indicates that there is more land cover change in unprotected pixels, followed by multiple use PAs, while strict PAs appear to be subject to less land cover change. This mean comparison of the land cover change variable provides me with a first, naïve PA impact, since I am only looking at the difference by PA status without controlling for any land characteristics that could affect both land cover and protection decisions.

The means of my land characteristics also suggest that these influence protection decisions. Unprotected points seem to be in higher elevation areas than PAs, and strict PAs seem to be located in much higher elevation than multiple use PAs. The slope also seems to be higher for 'strict' points.

PAs also seem to be farther away from urban areas. The means for distance to urban areas also suggests that multiple use (loosely protected) PAs are located farther away from urban areas than strict PAs. However, multiple use PAs seem to be located closer to roads. These two variables also point out that unprotected points are closer to both urban areas and roads. The means for the agricultural suitability variable seem to indicate that PAs might be located in lands that are less suitable for agriculture.

The differences in means in land cover and land characteristics by PA status suggest the need to control further in estimating if land characteristics are drivers of different types of protection. In order to correct for these differences and formalize if there truly are differences in location of PAs, I conduct an OLS regression of the PA status variables on land characteristics. Table 3 shows results for the three OLS regressions.

My OLS results provide evidence suggesting that all the land characteristics included are significant drivers of protection decisions (all p-values < 0.001). Elevation seems to have a small negative effect on being in a PA. However, it still has a significant, although minuscule, positive effect on designation of a strict PA. Slope seems to have a positive effect on PA designation, and a higher impact for strict PA designation (as compared to loose).

PAs also seem to be located significantly farther away from urban areas and roads than unprotected points. Also, multiple use PAs seem to be located farther away from urban areas than strict ones. However, as seen in the mean comparison table (T1), while strict PAs seem to be located farther from roads, loose PAs seem to be located significantly closer to roads than unprotected points. This is a very interesting finding. A possible explanation for multiple use parks being located closer to roads, but farther from urban areas could be that these parks are located in or near *ejidos* in rural areas, but near access roads to allow for the extraction of certain forest resources and products.[3]

As expected, the high agricultural suitability coefficients suggest a negative impact of being agriculturally suitable on PA status. This impact more than doubles for strict parks when compared to multiple use parks. Both ecoregion dummies indicate these have a negative effect on park establishment, with the Chihuahuan Desert variable having a higher impact for all parks.

In this analysis, I should underscore that it is possible that my OLS regressions might be correcting for everything I need to assess PA type and location, but this also may not be the case. Nevertheless, the significant impact of land characteristics in determining both land cover and PA status suggests that I should address these differences in my matching approach to better provide for comparisons in estimating the impact of protection on land cover change.

Avoided Land Cover Change Estimates

Before the matching analysis, I estimated land cover change estimates through an OLS regression for both land cover variables. I regressed the outcome(s) on protection status and land characteristics. I also ran separate regressions for the PA types (strict/loose). These regressions provide the average treatment effect of the PA variables on the outcome variables, controlling for land characteristics. Table 4 illustrates the results of the regressions.

My results reaffirm that all protection types and land characteristics are significant determinants of land cover in 2005 and land cover change. Estimates of avoided land cover and land cover change due to protection are similar for both outcomes. The 'protected' coefficient tells me that being inside a PA results in an avoided land cover change of 3.8% (4% for land cover in 2005) compared to unprotected points. As for 'strict' PAs, the results are consistent with intuition that this PA status would help in avoiding more land cover change. 'Strict' PAs avoided a land cover change of 5.6% of their natural area (6.7% for land cover in 2005) when compared to unprotected points. Meanwhile, multiple use ('loose') PAs estimates of avoided land cover change are lower, approximately 2.9% of their natural area.

[3] In Mexico, 53% of land and 70% of its 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 ownership of the land. Ejidos are eligible for participation in several environmental conservation programs, such as Mexico's Payment for Ecosystem Services Program and designation of PAs inside their lands (The REDD Desk, 2012).

My OLS analysis is still making use of all observations for the impact estimates, without controlling explicitly for differences in protected and unprotected land characteristics. It is accurate that this regression analysis might be able to control for all observable sources of bias. However, my matching analysis provides me with a cleaner way to control for differences without having to make considerable parametric assumptions (Andam et al, 2008). Moreover, the differences between the points might be too much of a burden for an OLS regression.

Table 5 presents a balance table for the land characteristics used in my matching analysis, for the three treatment groups. I use a one-to-one match (n=1), given the high number of observations.

My matched set shows improved balance between treatment groups. Although there are still some significant differences between protected and unprotected points, matching reduced the difference between treatment groups by a significant amount (the lowest reduction in differences from matching was 63%: slope in loose PAs). I confirmed the results in my balance table by repeating the process with two 10% samples (with replacement). Results for these tests were similar to those in Table 5. The improved balance between treatment groups also provides me with a cleaner estimate of the difference in land cover between treatment groups, shown in Table 6.[4]

The post-matching estimated differences in land cover decreased significantly for the matched groups while still remaining significantly different, suggesting that PA status significantly impacts land cover change. Post-match differences were reduced by more than two-thirds (69.4%, loose protection) at the most, and close to half at the least (43.9%, strict protection). PAs seem to avoid only 2.6% land cover change (compared to 6.4%); strict protection seems to avoid 3.7% change (instead of 6.6%); and loose protection estimates drop to 1.9% avoided land cover change (down from 6.2%). The reduced differences in land cover change estimates provide more evidence indicating that matching on land characteristics considered to affect land cover change improves estimates of the treatment's (protection) impact. They also coincide with the literature, suggesting that impact estimates using matching are far lower than those taken from other, more typical approaches (Joppa & Pfaff, 2010b).

As I previously stated, post-matching regressions will help adjust for any remaining imbalances on covariates between our matched groups, and provide me with a cleaner estimate of PA impacts on land cover change. Table 7 presents my post-matching OLS regressions.

With the exception of elevation for strict and loose protection PAs, all other land characteristics are still significant (all p-values < 0.05), and the signs on the coefficients are still intuitive. Table 8 compares the impact estimates for all my previous approaches, including my post-matching OLS regressions.

[4] I also conducted the analysis using calipers of 0.01 and 0.001. Results are not included, as the matches did not seem to improve with either caliper. The final, post-matching OLS regression impact estimates (with calipers) changed slightly with the 0.001 caliper, but only on an order of 0.001 (0.1%). The similarity of estimates suggests that the matches without calipers were just as good.

The first three columns of Table 8 present the land cover change impact estimates for the three PA groups. The first row includes my first, naïve (pre-matching) average estimate of PA impacts, while the third row presents our post-matching average impact estimates (both calculated via difference in means). As I stated previously, matching considerably reduces the average impact estimates. The same could be said about our pre and post-matching regressions. Our post-matching OLS regressions provide lower impact estimates than the pre-matching model, but not by much. Impact estimates for all PAs drop from 3.8% avoided land cover change to 3.1%. Strict and loose protection estimates drop even less (from 5.6% to 5.3% for strict and from 2.9% to 2.7% for loose).

Robustness checks and sensitivity analyses

Non-random application of treatment implies that the estimators are non-experimental. Due to their non-experimental nature, my estimators could contain bias if either land cover change or protection is determined by variables not taken into account in my analysis (as I have stated is probably the case). I use Rosenbaum bounds to measure how strong the effect of unobservable covariates (unmeasured variables) has to be to affect selection into treatment in order to undermine my results (Ferraro et al, 2007). I chose this test because it is free of parametric assumptions and because it is relatively easy to interpret how unobservables would affect the results.

In this test, matched plots may differ in their odds of being protected by a factor of Γ ("gamma"). The higher the values are significantly different from zero, the stronger the relationship between PA status and land cover change. This mean that there is a smaller chance of the avoided land cover change estimated being an artifact of matching treated pixels with untreated ones that are (unobservably) more likely to be deforested (Andam et al, 2008). In general, results are considered highly sensitive to hidden bias if $\Gamma = 1$ or only slightly larger. Results are considered robust if my conclusions change only for values of $\Gamma > 1$ (the literature does not indicate threshold values to assert robustness). Table 9 presents my results for our Rosenbaum bounds tests for the estimates of each PA status.

My robustness analysis suggests that the estimators for both 'protected' and 'loose protection' are considerably sensitive to presence of hidden bias. If an unobserved variable caused the odds ratio of protection to differ between (loosely) protected and unprotected plots by a factor of (1.7) 1.9, my estimates for these treatments would not be significantly different from zero. My strict protection coefficient, however, remains robust even in the presence of moderate bias (2.4). Overall, my robustness test suggests that my results are sensitive to the presence of unobserved covariates not included in my analysis, which is something I expected given the data and variable limitations.

Discussion and Conclusions

My main results suggest that PAs lower land cover change pressure from 'natural' to 'human modified'. In addition (and consistent with the literature), matching considerably reduces the average impact of PAs by close to half, compared to unmatched, difference in means approaches. The final, post-matching estimates suggest that PAs reduce land cover change by 3.1%, when using matching based on land characteristics. Strict protection seems to avoid more land cover change (5.3%) than loose (2.7%).

Land characteristics have a significant impact on land cover change, as well as protection decisions. This proves to be extremely relevant for designing REDD policies. Policy-makers should take into account land characteristics when assessing how much land cover change will be blocked by protection (and protection type). According to my analysis, high threat areas are, on average, closer to urban areas, with low slope and high agricultural suitability. However, establishing PAs in areas with these land characteristics, while more effective, could be more costly, since there would be bigger tradeoffs with other alternative land uses, such as agricultural profitability.

My analysis suffered from several limitations. As I previously stated, my land cover datasets (2000 and 2005) are not intended for comparison. For both variables, land cover measures were reclassified in order to be comparable. Since the land cover change variable was created through the subtraction of these land cover variables, it provides only a shaky estimate of land cover change. This analysis could also be improved with more recent data, or data for a longer time period. Mexico's development of a new MRV mechanism combining remote sensing with on-the-ground efforts could help to improve measurements of land cover and detection of clearing, since there might also be unobserved, small-scale clearing not captured in my data.

Moreover, my variables are not expected to completely explain either land cover change pressure or location of protection. In fact, the Rosenbaum bounds test indicates that my results are sensitive to hidden bias from unobserved covariates. Other environmental as well as socio-economic variables (i.e.: biodiversity, endangered species, income, population density) also play a role in land use and protection decisions. Including these in subsequent analyses can only improve PA estimates.

Several extensions could also be added to my analysis. A possible extension should include assessing spillover impacts from PAs to nearby, unprotected lands. Measurement of spatial spillovers from PAs remains a crucial issue for correctly assessing the full impact of PAs, especially for policies such as REDD and payment for ecosystem services programs, where spillovers could reduce their efficiency.

Seeing as my analysis suggests that location is relevant for land cover change estimates, including state variable dummies could help to improve my land cover change impact estimates. The use of state dummies could help control for unobservables that affect land cover change and protection in those states. Combined with better data and more covariates, inclusion of state variables could also provide us with a bigger, more complete picture of impact variations by state. Since policies should aim to take into account context and impact variations, this could prove to be crucial for state policies aimed at reducing land cover change through the designation of PAs.

Tables

T1. Group mean comparison of Land Cover and Land Characteristics, by PA Status

Variables	Unprotected	Protected	Strict Protection	Loose Protection
loose (protected) (0-1)	0	0.203	1	0
strict (protected) (0-1)	0	0.797	0	1
elevation (m)	1078	600	863	533
slope (degrees from horizontal)	2.806	2.826	3.409	2.678
urbandistance (km)	35.6	96.7	61.1	105.7
roaddistance (km)	8.5	13.5	16.6	12.7
agriculturalsuitability (0-9)	6.162	6.706	6.453	6.770
lowagsuitability (0-1)	0.385	0.553	0.377	0.598
highagsuitability (0-1)	0.373	0.219	0.238	0.215
fire (# of fires, 2000-06)	0.005	0.003	0.004	0.003
firedum (0-1)	0.005	0.003	0.004	0.003
pineoakdum (Sierra Madre Occidental Pine Oak Forest, 0-1)	0.114	0.003	0.004	0.003
chidesertdum (Chihuahuan Desert, 0-1)	0.163	0.061	0.011	0.074
iucncategory (1-6)	0	5.043	1.301	5.995
distancetoedge (km)	55.7	-13.8	-10.6	-14.7
glc (0-1)	0.841	0.923	0.914	0.925
globcover (0-1)	0.863	0.958	0.969	0.956
vegchange (0-1)	0.092	0.028	0.023	0.029
Observations	1,807,949	127,352	25,819	101,533

T2. Drivers of Land Cover and Land Cover Change
Unprotected Observations

Variables	*Land Cover change '00-'05*	*Natural Land Cover '05*
Elevation (m)	-0.00004***	0.00006***
	(0.000)	(0.000)
Slope (Degrees from horizontal)	-0.00436***	0.00562***
	(0.000)	(0.000)
Distance to urban areas (km)	-0.00099***	0.00135***
	(0.000)	(0.000)
Distance to roads (km)	-0.00075***	0.00066***
	(0.000)	(0.000)
High Agricultural Suitability (0-1)	0.03853***	-0.06239***
	(0.001)	(0.001)
Sierra Madre Occidental Pine Oak Forest (0-1)	0.06394***	-0.06881***
	(0.001)	(0.001)
Chihuahuan Desert Dummy (0-1)	-0.02110***	0.02024***
	(0.001)	(0.001)
Constant	0.19595***	0.75506***
	(0.001)	(0.001)
Observations	1,520,131	1,807,949
R-squared	0.034	0.058
Adj. R-squared	0.034	0.057

Standard errors in parentheses

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

T3. Drivers of protection, by PA Status

Variables	*protected*	*strict protection*	*loose protection*
Elevation (m)	-0.00001***	0.00000***	-0.00002***
	(0.000)	(0.000)	(0.000)
Slope (Degrees from horizontal)	0.00111***	0.00041***	0.00032***
	(0.000)	(0.000)	(0.000)
Distance to urban areas (km)	0.00255***	0.00033***	0.00251***
	(0.000)	(0.000)	(0.000)
Distance to roads (km)	0.00040***	0.00083***	-0.00019***
	(0.000)	(0.000)	(0.000)
High Agricultural Suitability (0-1)	-0.01412***	-0.01011***	-0.00477***
	(0.000)	(0.000)	(0.000)
Sierra Madre Occidental Pine Oak Forest (0-1)	-0.10704***	-0.03239***	-0.08445***
	(0.001)	(0.000)	(0.001)
Chihuahuan Desert Dummy (0-1)	-0.10753***	-0.03391***	-0.08649***
	(0.000)	(0.000)	(0.000)
Constant	0.00539***	0.00449***	-0.00377***
	(0.000)	(0.000)	(0.000)
Observations	1,935,301	1,833,768	1,909,482
R-squared	0.189	0.025	0.202
Adj. R-squared	0.189	0.025	0.202

Standard errors in parentheses

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

T4. Estimated difference in Land Cover and avoided Land Cover change as a proportion of natural area
OLS regression on PA status and land characteristics

Variables	*Land Cover change '00-'05*			*Natural Land Cover '05*		
protected	-0.03754***	-	-	0.04045***	-	-
	(0.001)	-	-	(0.001)	-	-
strict protection	-	-0.05612***	-	-	0.06676***	-
	-	(0.002)	-	-	(0.002)	-
loose protection	-	-	-0.02891***	-	-	0.02900***
	-	-	(0.001)	-	-	(0.001)
Elevation (m)	-0.00004***	-0.00004***	-0.00004***	0.00006***	0.00006***	0.00006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Slope (Degrees from horizontal)	-0.00410***	-0.00436***	-0.00411***	0.00527***	0.00559***	0.00532***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Distance to urban areas (km)	-0.00079***	-0.00096***	-0.00082***	0.00108***	0.00130***	0.00113***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Distance to roads (km)	-0.00068***	-0.00054***	-0.00086***	0.00073***	0.00049***	0.00088***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
High Agricultural Suitability (0-1)	0.03898***	0.03820***	0.03917***	-0.06296***	-0.06206***	-0.06311***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Sierra Madre Occidental Pine Oak Forest (0-1)	0.05641***	0.06045***	0.05935***	-0.05986***	-0.06488***	-0.06325***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Chihuahuan Desert Dummy (0-1)	-0.02659***	-0.02350***	-0.02481***	0.02746***	0.02300***	0.02541***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.18541***	0.19206***	0.18892***	0.76625***	0.75919***	0.76246***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	1,637,632	1,543,734	1,614,029	1,935,301	1,833,768	1,909,482
R-squared	0.035	0.034	0.035	0.059	0.057	0.059
Adj. R-squared	0.035	0.034	0.035	0.059	0.057	0.059

Standard errors in parentheses
**** p<0.001, ** p<0.01, * p<0.05*

T5. Balance Tables for Matching Covariates
Propensity Score matching

	protected	*strict protection*	*loose protection*
Elevation (m)			
Pre-match difference	-477.705***	-186.271***	-541.423***
Post-match difference	-112.712***	25.027**	-59.179***
% reduction in difference from Matching	76.4%	86.7%	89.1%
Slope (Degrees from horizontal)			
Pre-match difference	0.020*	0.610***	-0.137***
Post-match difference	-0.622***	-0.107*	0.011
% reduction in difference from Matching	-3010.0%	82.5%	92.0%
Distance to urban areas (km)			
Pre-match difference	61.033***	21.787***	69.706***
Post-match difference	-2.378	0.025	-2.675***
% reduction in difference from Matching	96.1%	99.9%	96.2%
Distance to roads (km)			
Pre-match difference	4.965***	7.808***	4.073***
Post-match difference	-0.489	1.980***	1.509***
% reduction in difference from Matching	90.2%	74.6%	63.0%
High Agricultural Suitability (0-1)			
Pre-match difference	-0.153***	-0.127***	-0.156***
Post-match difference	-0.050***	0.015***	-0.005
% reduction in difference from Matching	67.3%	88.2%	96.8%
Sierra Madre Occidental Pine Oak Forest (0-1)			
Pre-match difference	-0.111***	-0.104***	-0.110***
Post-match difference	-0.007	-0.002*	-0.005***
% reduction in difference from Matching	93.7%	98.1%	95.5%
Chihuahuan Desert Dummy (0-1)			
Pre-match difference	-0.102***	-0.147***	-0.087***
Post-match difference	-0.022*	-0.000	-0.017***
% reduction in difference from Matching	78.4%	100.0%	80.5%

Note: Differences in means, showing scale and sign.
**** p<0.001, ** p<0.01, * p<0.05*

T6. Estimated difference in Land Cover as a proportion of natural area
Propensity Score matching

	protected	*strict protection*	*loose protection*
Natural Land Cover 2005 (0-1)			
Pre-match difference	0.096***	0.101***	0.092***
Post-match difference	0.033***	0.057***	0.023***
% reduction in difference from Matching	65.6%	43.6%	75.0%
Land Cover Change 2000-2005 (0-1)			
Pre-match difference	-0.064***	-0.066***	-0.062***
Post-match difference	-0.026**	-0.037***	-0.019***
% reduction in difference from Matching	59.4%	43.9%	69.4%

Note: Differences in means, showing scale and sign.
**** p<0.001, ** p<0.01, * p<0.05*

T7. Estimated difference in Land Cover and avoided Land Cover change as a proportion of natural area
Post-matching OLS regressions on PA status and land characteristics

Variables	*Land Cover change '00-'05*			*Natural Land Cover '05*		
protected	-0.03104***	-	-	0.03512***	-	-
	(0.001)	-	-	(0.002)	-	-
strict protection	-	-0.05251***	-	-	0.06458***	-
	-	(0.002)	-	-	(0.003)	-
loose protection	-	-	-0.02732***	-	-	0.02936***
	-	-	(0.001)	-	-	(0.001)
Elevation (m)	-0.00000***	-0.00000	-0.00000	0.00002***	0.00001***	0.00002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Slope (Degrees from horizontal)	-0.00120***	-0.00139***	-0.00118***	0.00118***	0.00197***	0.00100***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Distance to urban areas (km)	-0.00040***	-0.00025***	-0.00038***	0.00053***	0.00037***	0.00053***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Distance to roads (km)	0.00013*	0.00037***	-0.00017***	-0.00000	-0.00044***	0.00037***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
High Agricultural Suitability (0-1)	0.03278***	0.01230***	0.04502***	-0.05089***	-0.02962***	-0.06296***
	(0.003)	(0.003)	(0.002)	(0.004)	(0.003)	(0.002)
Sierra Madre Occidental Pine Oak Forest (0-1)	0.04854***	0.05963**	0.02607**	-0.04199***	-0.05069*	-0.02442*
	(0.008)	(0.021)	(0.010)	(0.008)	(0.021)	(0.010)
Chihuahuan Desert Dummy (0-1)	-0.02824***	-0.02044**	-0.02919***	0.02863***	0.02548***	0.02654***
	(0.002)	(0.007)	(0.002)	(0.002)	(0.007)	(0.002)
Constant	0.10114***	0.09170***	0.10093***	0.86816***	0.88184***	0.86452***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
Observations	188,567	39,514	149,691	208,709	44,559	164,547
R-squared	0.034	0.022	0.037	0.050	0.033	0.056
Adj. R-squared	0.034	0.022	0.037	0.050	0.033	0.056

Standard errors in parentheses
**** p<0.001, ** p<0.01, * p<0.05*

T8. Estimated PA impact on Land Cover and avoided Land Cover change as a proportion of natural area, by PA Status Comparison of Approaches

Approaches	*Land Cover change '00-'05*			*Natural Land Cover '05*		
	protected	*strict protection*	*loose protection*	*protected*	*strict protection*	*loose protection*
Pre-match difference	-0.064***	-0.066***	-0.062***	0.096***	0.101***	0.092***
Pre-matching OLS Regression	**-0.03754*** **	**-0.05612*** **	**-0.02891*** **	**0.04045*** **	**0.06676*** **	**0.02900*** **
Post-match difference	-0.026**	-0.037***	-0.019***	0.033***	0.057***	0.023***
Post-matching OLS Regression	**-0.03104*** **	**-0.05251*** **	**-0.02732*** **	**0.03512*** **	**0.06458*** **	**0.02936*** **

T9. Sensitivity Test for unobservable bias*
Land Cover Change, '00' - 05

Γ	Critical P-values for treatment effects		
	protected	*strict protection*	*loose protection*
1.0	< 0.001	< 0.001	< 0.001
1.1	< 0.001	< 0.001	< 0.001
1.2	< 0.001	< 0.001	< 0.001
1.3	< 0.001	< 0.001	< 0.001
1.4	< 0.001	< 0.001	< 0.001
1.5	< 0.001	< 0.001	< 0.001
1.6	< 0.001	< 0.001	0.0033
1.7	< 0.001	< 0.001	0.0763
1.8	0.0056	< 0.001	
1.9	0.4492	< 0.001	
2.0		< 0.001	
2.1		< 0.001	
2.2		< 0.001	
2.3		0.0006	
2.4		0.0083	
2.5		0.0583	

**Null of no effect.*

Literature Citations

Andam, K. et al. (2008) "Measuring the effectiveness of protected area networks in reducing deforestation". *Proc. Natl. Acad. Sci. USA* **105**: 16089-16094.

Bartholome, E., & Belward, A. (2005) GLC2000: a new approach to global land cover mapping from Earth observation data. *Int. J. Remote Sens.* **26**(9):1959-1977.

Bruner, A. et al. (2001) "Effectiveness of parks in protecting tropical biodiversity". Science 291: 125–128.

Campbell, A., S. Clark, L. Coad, L. Miles, K. Bolt & D. Roe. (2008) Protecting the future: carbon, forests, protected areas and local livelihoods. *Biodiversity*. 9: 117-122.

Curran, L. et al. (2004) "Lowland forest loss in protected areas of Indonesian Borneo". Science 303: 1000–1003.

European Space Agency (ESA) and ESA GlobeCover Project lead by MEDIAS-France. Ionia GlobCover. Available from http://ionia1.esrin.esa.int/news/_faq.asp?id=35 (accessed 2009).

Ferraro, P., McIntosh, C. & Ospina, M. (2007). "The effectiveness of the US Endangered Species Act: An econometric analysis using matching methods." Journal of environmental Economics and Management 54: 245-261.

Fischer G, van Velthuizen H, Nachtergaele F, Medow S. (2002) Global Agro-Ecological Zones (Global-AEZ)[CD-ROM and web site http://www. fao. org/ag/AGL/agll/gaez/index. htm], Food and Agricultural Organization. International Institute for Applied Systems Analysis (FAO/IIASA). Available from http://www. iiasa. ac. at/Research/LUC/GAEZ/index. htm.

The Forest Carbon Partnership. (2012). "REDD Readiness Progress Fact Sheet. Country: Mexico, June 2012" Retrieved February 3, 2012 from http://www.forestcarbonpartnership.org/sites/forestcarbonpartnership.org/files/Documents/PDF/June2012/Mexico%20FCPF%20REDD%20Readiness%20Progress%20Sheet_June%2013%202012.pdf

Fuller, D., T. Jessup & A. Salim. (2004). "Loss of forest cover in Kalimantan, Indonesia, since the 1997–1998 El Nino". Conserv. Biol. 18: 249–254.

Gaveau, D.L.A., H. Wandono & F. Setiabudi. (2007) "Three decades of deforestation in southwest Sumatra: have protected areas halted forest loss and logging, and promoted re-growth?" Biol. Conserv. 134: 495–504.

Johnson, T., Alatorre, C., Romo, Z., Feng, L. (2010) "Low-Carbon Development for Mexico". The World Bank.

Joppa, L. and A. Pfaff (2009). "High & Far: biases in the location of protected areas". PLoS ONE 4(12): e8273. doi:10.1371/journal.pone.0008273

Joppa, L. and A. Pfaff (2010a). "Re-assessing the forest impacts of protection: the challenge of non-random protection & a corrective method". Annals of the New York Academy of Sciences 1185:135–149.

Joppa, L. and A. Pfaff (2010b). "Global Park Impacts: how could protected areas avoid more deforestation?" Proceedings of the Royal Society B.

Kaimowitz, D. & A. Angelsen. (1998) "Economic Models of Tropical Deforestation: A Review". Center for International Forestry Research. Jakarta.

Kinnaird, M.F. et al. (2003) "Deforestation trends in a tropical landscape and implications for endangered large mammals". Conserv. Biol. 17: 245–257.

Liu, J.G. et al. (2001) "Ecological degradation in protected areas: the case of Wolong Nature Reserve for giant pandas". Science 292: 98–101.

Messina, J.P. et al. (2006) "Land tenure and deforestation patterns in the Ecuadorian Amazon: conflicts in land conservation in frontier settings". Appl. Geogr. 26: 113–128

Nagendra, H. (2008) "Do Parks Work? Impact of Protected Areas on Land Cover Clearing". Ambio 37: 330-337.

National Imagery and Mapping Agency (NIMA). (2000) Vector Map Level.

Naughton-Treves, L., M. B. Holland & K. Brandon. (2005) "The role of protected areas in conserving biodiversity and sustaining local livelihoods". Annual Review of Environment and Resources 30: 219-252.

Nelson, A. & Chomitz, K. (2011). "Efectiveness of Strict vs. Multiple Use Protected Areas in Reducing Tropical forest Fires: A Global Analysis Using Matching Methods." PLoS ONE 6(8): 322722. doi:10.1371/journal.pone.0022722

Olson D, et al. (2001) "Terrestrial ecoregions of the world: a new map of life on earth". *BioScience*. 51(11):933-938.

Pfaff, A. et al. (2009) "Policy Impacts on Deforestation. Lessons from Past Experiences to Inform New Initiatives." Nicholas Institute for Environmental Policy Solutions.

Pfaff, A. et al. (2013) "The Governance, Locations and Forest Impacts of Protected Areas: governance's development tradeoffs affect siting, outweighing its direct effect". Accepted at World Development.

Pfaff, A., J. Robalino & L.D. Herrera. (forthcoming) "REDDer (=Better?) Protection: where are PA impacts highest?" Mimeo, Duke University.

Pfaff, A., J. Robalino & G.A. Sanchez-Azofeifa. (2009) "Payments for Environmental Services: Empirical Analysis for Costa Rica". Terry Sanford Institute for Public Policy Working Paper.

The REDD Desk. (2011). "REDD in Mexico." Retrieved February 3, 2013 from www.theredddesk.org/countries/mexico/readiness_overview

Rosenbaum, P. R., & Rubin, D. B. (1983). "The central role of the propensity score in observational studies for causal effects." *Biometrika, 70*(1), 41-55. doi: 10.1093/biomet/70.1.41.

Sader, S. et al. (2001) "Forest change monitoring of a remote biosphere reserve". Int. J. Remote Sensing 22: 1937– 1950.

Sanchez-Azofeifa, G.A. et al. (1999) "Protected areas and conservation of biodiversity in the tropics". Conserv. Biol. 13: 407–411.

United States Geological Survey (USGS). (2006) Shuttle Radar Topography Mission, 30 Arc Second scene SRTM_GTOPO_u30, Mosaic. (Global Land Cover Facility, College Park, Maryland). Available from http://www2.jpl.nasa.gov/srtm/ (accessed 2008).

United Nations Environment Program – Center for International Earth Science Information Network (UNEP-CIESEN). (2006) Global Rural-Urban Mapping Project (GRUMP), Alpha Version: Urban Extent. (Socioeconomic Data and Applications Center). Available from http://sedac.ciesin.columbia.edu/gpw/ancillaryfigures.jsp.

United Nations Environment Program – World Conservation Monitoring Center (UNEP-WCMC). World Database on Protected Areas (WDPA). (2007) World Conservation Union (IUCN) and UNEP-World Conservation Monitoring Center Cambridge, UK. Available from (http://www.wdpa.org/).

Vanclay, J.X. (2001) "The effectiveness of parks". Science 293: U1–U2.

Viña, A. et al. (2007) "Temporal changes in Giant Panda habitat connectivity across boundaries of Wolong Nature Reserve, China". Ecol. Appl. 17: 1019–1030.