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Mexico Deforestation Vulnerability Analysis and Capacity Building. Final Project Report

Environmental Defense Fund (Consortium Lead), Conservation International, and Center for Global Development

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1. Executive Summary

In 2010, Mexico ranked 8th among countries with the largest area of primary forest (FAO 2010). Mexico's forests, covering about a third of the nation, provide a number of services including carbon sinks, high levels of endemism and species richness, and subsistence resources for local population. These services are being eroded as Mexico continues to experience forest cover loss. Mexico has lost about half its forest area since 1950. From 2005-2010, the country maintained an average deforestation rate of 0.24% according to FAO, reducing its capacity for carbon sequestration and increasing land conversion related emissions. Land use, land-use change and forestry was recently estimated to emit about 10% of Mexico's total GHG emissions.

The Mexico-REDD Alliance (MREDD) is supporting Mexico's efforts to reduce its emissions from deforestation and forest degradation and to enhance forest carbon stocks are currently supported by. The program has identified Early Action Areas (Áreas de Acción Temprana or AATR), or high risk – high reward areas located in Mexican states that are recognized as having high biodiversity, cultural diversity as well as high rates of deforestation. Research related to forest cover loss in Mexico has so far focused on drivers of deforestation, including the impact of land ownership types unique to the country (community forestry, protected areas, and private lands). Missing from the sizeable literature are two topics of particular importance for the identification of vulnerable regions and the design of conservation strategies under MREDD: the first is an analysis of drivers of deforestation that is specific to the AATRs. The second is an analysis of the effect of geographic characteristics or policy measures that is disaggregated by land ownership type.

To help address these gaps, we conduct a series of analyses that combine both national and local scale modeling to aid the MREDD Alliance partners in assessing the vulnerability of Mexico's forests to deforestation. These analyses focus on the vulnerability of forested lands within Mexico's AATRs, accounting for Mexico's unique forest management dynamics through disaggregating the results by land ownership types. These analyses are ultimately meant to inform national and subnational policy, paving the way for incentive based programs, and ultimately reduced deforestation vulnerability in Mexico. Our methodology includes three different and complementary approaches: (i) reviewing the existing literature, (ii) a national econometric analysis and associated scenario simulation modeling, and (iii) local-level spatial spatial modeling for each AATR. Key findings from each of these three parts of the report are summarized below.

1.1. Key Findings

Literature Review of Drivers of Deforestation in Mexico.

- While deforestation has decreased over the past decades, forest loss continues at about 0.24% per year, accoriding to UN-FAO, generating about 6% of the country's total greenhouse gas emissions in 2010. Deforestation is mostly occurring in the more densely forested areas of south-eastern Mexic and largely attributed in the literature to crop and cattle development.

- Land tenure (community land management, including *ejidos*), rural agricultural support, and payments for ecosystems services are major focuses of the literature. Conclusions on the role of the major land tenure type in Mexico, community land management, are mixed. Studies are also in disagreement on the role of such rural agricultural support programs as PROCAMPO.
- Most studies agree that payments for ecosystems services decrease deforestation risk, with some caveats related to regional differences and starting deforestation risk.
- These relationships were mirrored in the meta-analysis: regression results were mixed for *ejidos* and rural income support, while results for PES tended to be associated with decreased deforestation. Furthermore, results from the meta-analysis revealed other variables with consistent relationships to deforestation in Mexico. The variables most associated with reduced deforestation in Mexico were associated with protection measures (as proxied by protected areas and PES), reduced accessibility (elevation), reduced resource competition (property size) and community forestry.
- The variables most associated with increased deforestation were related to areas where economic returns to agriculture are higher (proximity to agriculture and agriculture returns), biophysical conditions for conversion are favorable (soil suitability), and competition for resources are high (population).
- Most of these relationships were robust when results were disaggregated to the Yucatán Peninsula. Notably however, at the national level, poverty appears to be linked to increases in deforestation, while in the Yucatán Peninsula poverty is associated with decreased deforestation. Conversely, indigenous population is associated with decreased deforestation.

National Analysis of Deforestation in Mexico.

- The national analysis reveals that a critical driver of deforestation has been the anticipated economic returns from land conversion, specifically from agriculture as proxied by crop production in our study. Key factors modulating deforestation vulnerability include land ownership type and initial forest area within a grid cell.
- We estimate the responsiveness of gross deforestation to changes in net economic incentives for land conversion. A 1% decrease in potential agricultural returns over 2000-2012 would have decreased cumulative gross deforestation nationally over this period by an estimated 0.24%. Conversely, a 1% increase would have boosted gross deforestation by an estimated 0.26%. Similarly, a 10% decrease in potential agricultural returns over 2000-2012 would have decreased cumulative gross deforestation nationally over this period by an estimated 2%. Conversely, a 10% increase would have raised gross deforestation by an estimated 3.3%.
- A preliminary examination suggests that decreasing potential crop returns (or increasing benefits to low emissions activities that avoid deforestation) by the amount of PROCAMPO subsidies on *ejidos* and agrarian community lands would have decreased deforestation by about 5% over 2000-2012.

- Based on the economic profitability of agriculture and starting forest cover in 2012, the model predicts an overall 27% "business-as-usual" increase in annual deforestation in Mexico over the next ten years, relative to 2000-2012.
- On the one hand, there is relatively high sensitivity to agricultural returns and high estimated future vulnerability to deforestation among forest remants in areas with relatively sparser forest cover, including in the Northwest and Bajio and Northeast regions. *Comunidades* and protected areas were the land types projected to have the biggest proportional increase in forest losses over the next 10 years and are also estimated to have the greatest percent declines in response to a potential carbon incentive.
- The most sensitive areas, however, are not that important in absolute terms. The greatest amount of deforestation is projected to occur in the South and Yucatan Peninsula region, as well as within *ejidos* and private land types. These areas, particularly the Yucatan Peninsula, hold the lion's share of estimated potential for reducing deforestation and emissions.
- The seven AATRs are not all concentrated in the areas with the highest projected future deforestation, and some of sites are located in areas with low historical rates of forest loss, compared to the national average. Nevertheless, overall as a group, AATRs and their surrounding regions have higher projected deforestation increases than other forested areas nationally, as well as regionally, as well as the majority of the potential to cost-effectively avoid deforestation.
- We use our statistical parameters to estimate national and regional carbon emissions cost curves, based on a hypothetical carbon incentive focusing only on above-ground forest carbon. We find that there is rising potential nationally to reduce emissions at costs ranging from \$5 to \$100/ton CO_2, at which point about 90% of the emissions are avoided. About half of the estimated reductions available at prices of \$10/ton CO_2 or below and more than two thirds of the estimated reductions available at prices of \$20/ton CO_2 or below. The national and regional cost curves are rising at an increasing rate, indicating that it costs more and more to avoid deforestation on lands with greater agricultural potentials.

Local Modeling of Deforestation in Mexico.

- Judging from the projected deforestation scenarios, the greatest benefits from implementing REDD+ or another incentive based conservation activity would be felt in AATR sites that are primarily unfragmented forest, meaning that they still contain large areas of undisturbed core forest, and are experiencing frontier expansion, usually stemming from population centers or access points. Sites such as Sierra PUCC Chene and Oaxaca Istmo display these characteristics as compared to sites like Oaxaca Mixteca or Sierra Raramuri which are highly fragmented and experience lower rates of deforestation.
- Variables related with accessibility and markets were most influential in the less fragmented reference regions, while variables related to biophysical suitability were most influential in the fragmented sites. The variable, distance to megacites, was important in

the two regions that contained them (Sierra Rararmuri near Culiacun and Cutzemala Valle Bravo near Toluca).

- There may be multiple patterns of forest change present in the reference regions; loss of primary forest, loss of secondary forest, fallow rotations and agro-forestry. Models could be strengthened by addressing these separately or focusing on a particular pattern.
- The interpretation of the local models should include both the soft and hard predictions under the various scenarios as well as the general pattern of the soft transition surface.
- Future work could include a more thorough examination of the effects of land-use practices within *comunidades* and *ejidos*, as these designations had some influence over the models, however the results were mixed.

2. Introduction

2.1. Global Greenhouse Gases and Mexico's Forests

Greenhouse gas emissions from agriculture, forestry and other land-use activities account for an estimated 24% of global emissions, second only to emissions produced by fossil fuel combustion (IPCC 5th Assessment Report, 2014). In 1990, official estimates are that deforestation, forest degradation, and other land-use changes in Mexico produced over 100 $MtCO_2e$ of emissions per year, accounting for 18.2% of national emissions. More recently in 2010, forests and land-use changes produced close to 47 $MtCO_2e$ or about 6.3% of total emissions (SEMARNAT/INECC, 2012). Mexico is currently undertaking efforts to reduce its emissions from deforestation and forest degradation and to increase sequestration by enhancing forest carbon stocks (REDD+), supported by the Mexico-REDD (MREDD) Alliance program.[1] Crucial to the success of anti-deforestation policies is an understanding of how spatial variation in geographic characteristics, land ownership, economic profitability, and policy measures affect Mexico's vulnerability to forest cover loss. It is also important to understand how potential changes in these factors over time might affect deforestation in the future.

Mexico has lost roughly half its forest area since 1950. From 2005 to 2010, the country lost 155,000 hectares of forest cover, an average deforestation rate of 0.24% (FAO, 2010). Forest conservation in Mexico provides biodiversity co-benefits beyond climate, as the country boasts both high levels of endemism and species richness (Barsimantov & Kendall, 2012). While deforestation rates have decreased and reforestation efforts are evident (FAO, 2010), widespread deforestation continues to threaten communities and ecosystems that depend on forests. There is a need to better understand deforestation in Mexico to identify vulnerabilities and inform policies that aim to reduce forest loss.

2.2. Report Outline

Missing from the sizeable literature on land-use change in Mexico are two topics of particular importance for the identification of vulnerable regions and the design of and low-emissions development strategies under MREDD: the first is an analysis of drivers of deforestation that is specific to the REDD+ early action areas (AATRs) under the MREDD program.[2] The second is an analysis of the effect of geographic characteristics or policy measures that is disaggregated by land ownership type (e.g. *ejido*, protected area, private lands).

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[1] The Allianza MREDD+ is a partnership of The Nature Conservancy, Rainforest Alliance, the Woods Hole Research Center, Mexico's government, and civil society to help lay the basis for efforts to reduce emissions from deforestation, forest degradation, and other forestry activities (i.e. REDD+). (see: www.alianza-mredd.org)

[2] Áreas de Acción Temprana (AATR) are REDD+ Early Action areas located in Mexican states with high biodiversity, cultural diversity and high rates of deforestation, but also great REDD+ potential. Lessons learned in these subnational target areas could help scale up best practices.

To address these gaps, we conduct a series of analyses that combine both national and local-scale modeling to support the MREDD Alliance partners in assessing the vulnerability of forested lands to deforestation in Mexico, focusing on the vulnerability of forested lands within Mexico's AATRs, with the results disaggregated by land ownership types. The goal is to inform national and subnational policy, paving the way for incentive based programs, and ultimately reduced deforestation vulnerability in Mexico. Our analysis only considered forest losses, rather than gains, due to data limitations. While increasing forest gains could be an important piece of REDD+ programs, a focus on avoiding deforestation should capture the largest near-term opportunities for reducing net emissions from forests.

This project generated several analytic results as well as data products, including:

- A vulnerability dataset: a spatially explicit raster dataset in which each cell has a value indicating the relative risk of future deforestation, both at the national and regional scale.
- A future deforestation projection: a spatial dataset projecting locations of future deforestation as a function of the vulnerability dataset and predicted rates of future deforestation.
- A database of all variables in the modeling analyses.
- A database of econometric studies of the drivers of deforestation in Mexico (and other countries.

This report describes our vulnerability analysis and key findings, along with the methods used to generate the "soft" and "hard" deforestation projections--the vulnerability map and deforestation projections, respectively. Our methodology includes three different and complementary approaches: (i) reviewing the existing literature, (ii) conducting a national econometric analysis and building an associated policy simulation model, and (iii) conducting local-level spatial analyses. The flow diagram in Figure 2.2.1 illustrates the role of the different project components and associated inputs and outputs.

We present and discuss the main results from each of these three underlying analyses. The modeling included testing the predictive power of a series of individual "driver" datasets, which may or may not actually cause deforestation, but are potentially correlated with it. We discuss the relative predictive power of the different driver datasets, with special focus on their correlation with the spatial distribution of historic and projected deforestation with each of the seven identified AATRs. We also seek to understand how deforestation might change causally in the future with changes in the economic incentives governing forest cover loss.

The first approach is a literature review and meta-analysis of existing studies of deforestation and land-use change in Mexico and elsewhere globally to identify trends, contradictions, and to provide context on land-use decision-making in Mexico, as well as in other countries (Ferretti-Gallon & Busch, 2014). This review uncovers gaps in the literature, informs the selection of driver variables for the national and local modeling described below, and provides context for evaluating the modeling results.

The second approach models the impact of different drivers of land-use change at the national scale, to complement and provide inputs to the local analyses conducted using the IDRISI-Selva Land Change Modeler (LCM). The national analysis for Mexico adapts the approach of the Open Source Impacts of REDD+ Incentives (OSIRIS) model, which was developed for analyzing the impact of alternative REDD+ policies in Bolivia, Madagascar, Peru and Indonesia (Busch, et al., 2012).[3] Our national analysis for Mexico focuses on identifying the impact of one variable that is arguably of causal importance for deforestation: the net economic returns per hectare from converting land from forest to non-forest land uses. Using this larger geographic scale is especially important to capture broader variation in economic variables in order to explicitly measure the role of changing economic returns from competing land uses. In particular, we model deforestation in relation to variation in estimated gross agricultural revenues and proxies for fixed and variable costs using observable site characteristics. The estimated responsiveness to the economic profitability of agricultural land use provides the basis for simulating deforestation under alternative scenarios with different economic incentives for forest protection, including the effect of potential REDD+ policies.

The national simulation yields an estimated deforestation vulnerability map at the national scale at a 900m resolution. We use the national econometric model to conduct a series of simulations that yield regional predictions of deforestation under a business-as-usual (BAU) reference scenario as well as a set of hypothetical policy cases. These regional predictions provide an input to the local scale analyses to make predictions on future dynamics of forest cover at seven AATRs.

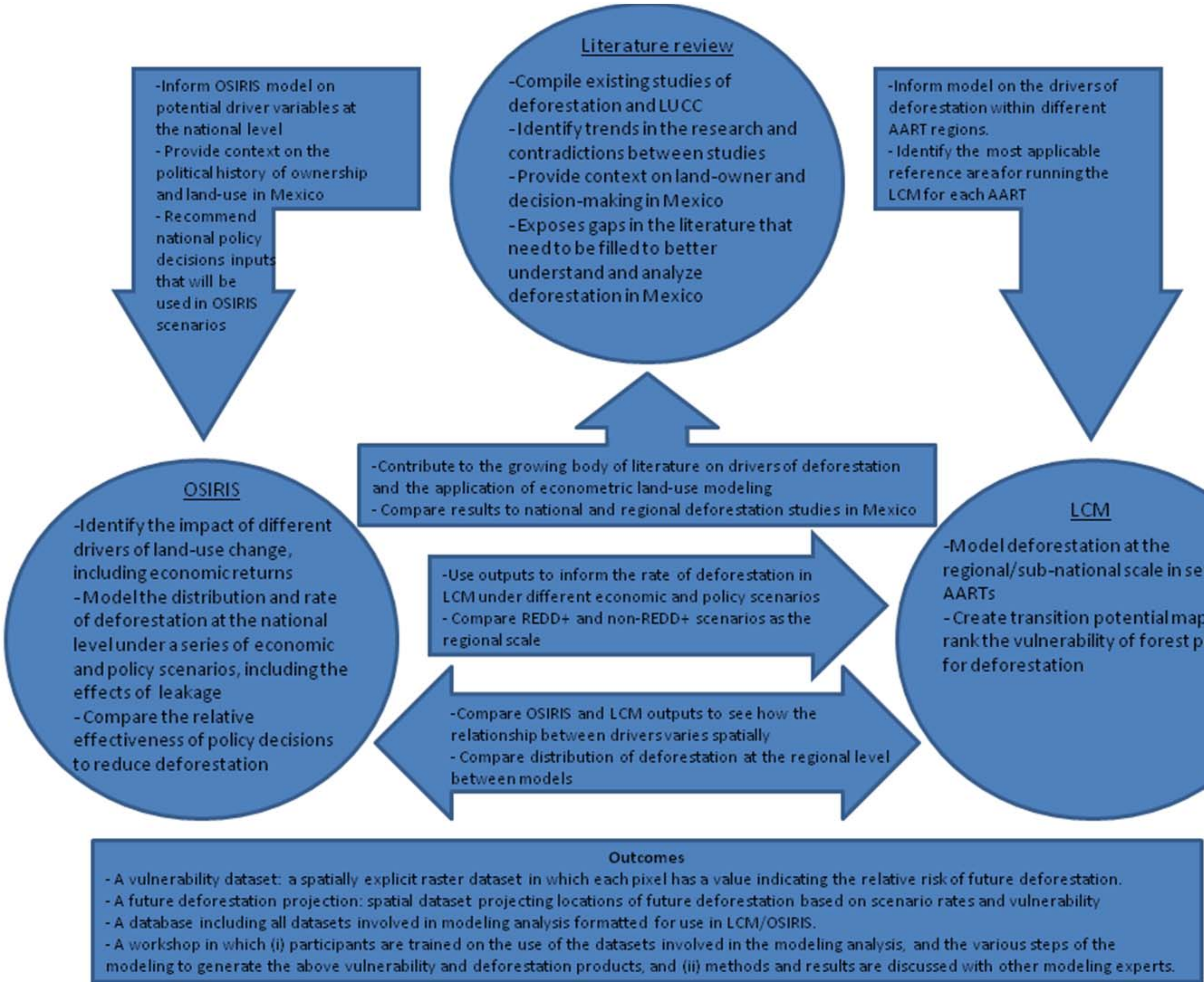
The third approach uses LCM in order to draw on its predictive spatial modeling capacity to more finely disaggregate the regional results across the landscape in the local study areas. For each of the seven AATRs, the LCM models examine the relationship between potential driver variables and observed patterns of deforestation. These models generate a “soft” vulnerability map as well as a “hard” prediction of deforestation under a series of historical and alternative scenarios, informed by the more aggregate predictions of the national level model.

The empirical analyses in this study use a new global dataset from the University of Maryland, based on Landsat satellite information, just released in January of this year (Hansen, et al., 2013). To our knowledge, this study is the first econometric study to exploit the rich spatial detail and multiple time periods from these new data. As such, results from our analysis and approach for Mexico could provide insights for analyzing deforestation in other countries and regions as well.

[3] The Open Source Impacts of REDD+ Incentives (OSIRIS) model is a suite of free, transparent, open-source, spreadsheet-based decision support tools. OSIRIS goes beyond predictions of the spatial distribution and rate of future deforestation to estimate and map the climate, forest and revenue benefits of alternative policy decisions for REDD+. See: http://sp10.conservation.org/osiris/Pages/overview.aspx

This report is divided into 6 sections. Section 3 describes the literature review of drivers of deforestation in Mexico. Section 4 discusses the national-scale econometric analysis. Section5 presents the local modeling for the AATRs. Section 6 concludes.

Figure 2.2.1. Project Flowchart


Literature review
-Compile existing studies of deforestation and LUCC
-Identify trends in the research and contradictions between studies
-Provide context on land-owner and decision-making in Mexico
-Exposes gaps in the literature that need to be filled to better understand and analyze deforestation in Mexico
-Inform OSIRIS model on potential driver variables at the national level
- Provide context on the political history of ownership and land-use in Mexico
- Recommend national policy decisions inputs that will be used in OSIRIS scenarios
-Inform model on the drivers of deforestation within different AART regions.
- Identify the most applicable reference area for running the LCM for each AART
-Contribute to the growing body of literature on drivers of deforestation and the application of econometric land-use modeling
- Compare results to national and regional deforestation studies in Mexico
OSIRIS
-Identify the impact of different drivers of land-use change, including economic returns
-Model the distribution and rate of deforestation at the national level under a series of economic and policy scenarios, including the effects of leakage
-Compare the relative effectiveness of policy decisions to reduce deforestation
-Use outputs to inform the rate of deforestation in LCM under different economic and policy scenarios
- Compare REDD+ and non-REDD+ scenarios as the regional scale
-Compare OSIRIS and LCM outputs to see how the relationship between drivers varies spatially
- Compare distribution of deforestation at the regional level between models
LCM
-Model deforestation at the regional/sub-national scale in seven AARTs
-Create transition potential maps to rank the vulnerability of forest pixels for deforestation
Outcomes
- A vulnerability dataset: a spatially explicit raster dataset in which each pixel has a value indicating the relative risk of future deforestation.
- A future deforestation projection: spatial dataset projecting locations of future deforestation based on scenario rates and vulnerability
- A database including all datasets involved in modeling analysis formatted for use in LCM/OSIRIS.
- A workshop in which (i) participants are trained on the use of the datasets involved in the modeling analysis, and the various steps of the modeling to generate the above vulnerability and deforestation products, and (ii) methods and results are discussed with other modeling experts.

3. Literature Review of Drivers of Deforestation in Mexico

3.1. Introduction

We compiled a database of econometric studies of deforestation, including 117 studies globally, of which 23 studies focus on Mexico. Appendix Table A-1 provides an annotated bibliography of the Mexico studies. From our analysis, driver variables associated with lower rates of deforestation in Mexico included protected areas, community forestry, and payments for ecosystems services. Driver variables associated with higher rates of deforestation in Mexico include agricultural activity, population, soil suitability and proximity to urban area. These associations between different "drivers" and deforestation do not necessarily indicate causal relationships. Causal studies of protected areas in Mexico have found these territories to be linked with decreased deforestation. Causal studies of *ejidos* have not been performed, suggesting the need for further study.

3.2. Overview of deforestation

3.2.1. Deforestation in Mexico

All known categories of Mexican forest cover (tropical dry, tropical wet, and montane forests) have been subject to deforestation (Vaca, et al., 2012). Deforestation is occurring mostly in Southern Mexico, with the highest rates occurring in the states of Campeche and Quintana Roo. While recent studies observe a pattern of net deforestation in Mexico (Vaca, et al., 2012), recently the nation's total annual deforestation has decreased. Between 1990 and 2000, Mexico lost 354,000 ha/year; from 2000 to 2005, the area deforested annually had decreased to 235,000; and, from 2005-2010, Mexico's forest loss further declined to 155,000 ha per year (FAO, 2010).

Reforestation has occurred in some regions of Mexico (about 178,000 ha/year from 1990-2010) (FAO, 2010). This trend has been attributed to planted forests with production as their primary function (FAO, 2010). Reforestation through tree plantations is a result of increased demand for oil palm, eucalyptus, and citrus products. Regeneration of forest cover is also seen as a result of passive transition, where farmers abandon land and migrate to areas with better paid farm jobs. It can also be a result of active transition, in which the growing scarcity of forest products encourage governments and land owners to plant trees, i.e. sustainable community forest management (Vaca, et al., 2012). There is little evidence of natural forest regeneration.

Although the deforestation rate in Mexico has declined, widespread forest cover loss persists. Most deforestation processes are attributed to agriculture (mainly coffee, maize, beans, and sugar cane) and cattle development. Other historic drivers of deforestation have included human settlement, monoculture forestry (in Southern Mexico) and natural phenomena (e.g., hurricanes and fires in the Yucatán) (Vaca, et al., 2012). Population growth, poverty, and physiogeographic variables are claimed to be significant drivers of forest loss in Mexico (Barsimantov & Kendall, 2012). However, literature on the subject renders conflicting conclusions on the effects on deforestation of other driver variables, including land ownership, subsidy programs, road density and per capita income (Barsimantov & Kendall, 2012).

3.2.2. Deforestation in the Yucatán

In Mexico, most of the Gulf Coast lowlands have already been deforested, and significant land clearance occurred in the interior Lacandon forests of Chiapas (Turner II, et al., 2001). The forests of southern Campeche and Quintana Roo have been considered the last frontier in the "west to east movement of tropical lowland development" in Mexico (Turner II, et al., 2001). The Southern Yucatán has been identified as a deforestation hot spot (Rueda, 2010). It is considered to be one of the world's important forested regions, characterized by the Calakmul Bisophere Reserve and the Mesoamerican Biological Corridor (Busch & Geoghegan, 2010). It is therefore crucial to understand drivers of land-use and land-cover change in the region.

3.3. Overview of land tenure, rural agricultural support, and payments for ecosystems services in Mexico

3.3.1. Land Tenure

Mexico has a long history of policy reforms focused on property rights and the role of land tenure on land cover change (Bonilla-Moheno, et al., 2013). There are three types of land management in Mexico: Private, public (protected areas, public enterprises, etc.), and communal (*comunidades agrarias* and *ejidos*).

3.3.1.1. Private lands

As of 2011, private lands that are owned and/or managed by companies, sharecroppers, and landless rural population represent 37% of the Mexican agrarian landscape. These private lands, however, only encompass 26% of the country's forests (Corbera, et al., 2010).

3.3.1.2. Public Lands

Public lands, in turn, belong to federal or regional public agencies, as well as to public enterprises. These lands represent just over 8% of the agrarian landscape and cover only 4% of forested areas, primarily including protected areas and bodies of water (Corbera, et al., 2010).

3.3.1.3. Communal Lands

Lands under common management is the most common type of management, representing 52% of the Mexican agrarian landscape and 70% of the forests (Corbera, et al., 2010). There are two main types of tenure arrangements: *comunidades agrarias* (agrarian communities) and *ejidos*. *Comunidades agrarias* refer to repatriated indigenous lands and *ejidos* are lands granted by the postrevolution government (Barsimantov & Kendall, 2012). Both are communally owned lands. *Nucleos Agrarios* is a general term for *ejidos* and *comunidades agrarias* in Mexico. Carrillo and Mota-Villanueva (2006) explain that this generalization is based on shared characteristics like legal status and land ownership given by Presidential Act or by the High Agrarian Court of Justice.

A. History of Communal Lands

A.a *Comunidades agrarias*

The Spanish Crown granted these land rights to groups considered original settlers. The communities that developed, therefore, consist of people who have historically inhabited a region and share language, traditions and governing institutions. Land holder types in this form of management consist of agrarian communities and individual rights holders (*comuneros*). Forest regulation is governed by a communal assembly made up of all *comuneros* (some of whom may be women). A council of authorities is renewed periodically, normally every three years (Corbera, 2010).

A.b *Ejidos*

Ejidos, on the other hand, are a more specific form of land management than *comunidades agrarias*. They were established when a group of families claims rights over a territory, and the parcel of land granted to these groups remains under communal ownership. Any rental or land sales are prohibited. Land can only be given by one *ejido* landholder (*ejidatario*) to a single descendant. Forest and land for pasture (for fuelwood collection, timber harvesting and grazing) are usually managed in common. Forest for timber harvesting, in particular, is organized through community members and groups, or through external concessions. *Ejido* timber concessions are organized through extraction quotas and corresponding benefits are defined and distributed through the *ejido* assembly and/or the council of authorities.

Both *comunidades agrarias* and *ejidos* have members (*avecindados*) who have been given a parcel to farm and another to live on, but who do not have rights to benefits from the forest. It is estimated that there are over 30,000 agrarian communities and *ejidos* in the country, occupying over 50% of the total national territory (PROCEDE, 2010). Community land management in Mexico is often claimed to have positive environmental and socioeconomic outcomes (Barsimantov & Kendall, 2012).

B. History of communal land management

Mexico's current system of land management developed from post-revolution government land management reform. After the Mexican Revolution in the 1910s, Article 27 of the 1917 Constitution declared that all lands and waters originally belonged to the nation and that the nation would grant private property rights under certain conditions (Camara de Diputados, 2008). Article 27 limited the size of private properties, parceled large private landholdings and, most importantly, granted rights to rural communities and groups of families to own land to meet their basic needs or to restore customary rights held before the 1800s (Corbera, et al., 2010). The share of communal land increased up until the early 1980s. In the early 1990s, Article 27 was reformed, legalizing the formation of joint ventures between communal landholders and private capital. This allowed community land management members and *ejido* members to become private owners, and to rent and sell land to third parties. Forests, however, could not be subdivided and sold, excluding them from privatization (Corbera, et al., 2010).

C. Impact of community forestry on deforestation

A majority of published academic studies have concluded that community forestry does not influence deforestation. For instance, Perez-Verdin concluded that deforestation is driven by resource-specific characteristics, such as location and soil productivity, and not by *ejidos*' attributes (Perez-Verdin, et al., 2009). However, a 2012 study reviewed evidence related to community forest management and forest cover, finding that common property and community forestry are significantly related to reduced rates of deforestation and increased rates of forest recovery of coniferous forests in Mexico (Barsimantov & Kendall, 2012). Their results suggest that common property can lead to greater forest conservation when there is an economically valuable asset to protect (coniferous forests) and when there are management plans in place to formalize the extraction process and revenue distribution. Another study confirmed that community land management practices have resulted in the maintenance of forested landscape in some areas of Mexico (Bray, et al., 2004). But other studies concluded that community management has mixed, if not a negative effect on forest cover (Vance & Iovanna, 2006) (Alix-Garcia, 2007). A study in 2010 demonstrated that the characteristics of the *ejido*, rather than the presence or absence an *ejidal* system, determine the impact on deforestation: population density, agricultural production and intensification within *ejidos* affected deforestation rates (Rueda, 2010). Vance and Geoghegan (2002) observed increasing deforestation as *ejido* demographics change, with age and population density being significantly positively related to deforestation. Geoghegan et al. (2004) supports this conclusion and further posited that deforestation primarily follows agricultural expansion by the *ejido* sector, the predominate form of land tenure in the southern Yucatán.

3.3.2. Rural Agricultural Support

The role of government agricultural subsidies on deforestation in Mexico is mixed. In 1999, a study was done contrasting the effects which the Banco de Desarrollo Rural or Rural Development Bank (BANRURAL) credit and technical assistance have on deforestation. It was initially thought that this type of aid would increase agricultural intensification, thereby relieving pressure on nearby forests for future conversion. The study revealed that "government subsidized credit failed to spur a process of agricultural intensification that could have substituted for cutting down forests" (Deininger & Minten, 1999). The same authors produced another study a few years later that determined that BANRURAL is, in fact, associated with significantly higher levels of deforestation, and that these credit subsidies "seem to have encouraged the cutting down of forests" (Deininger & Minten, 2002).

A second study that same year confirmed that another rural subsidy program, Programa de Apoyos Directos al Campo or Famers Direct Support Program (PROCAMPO), is also associated with higher levels of deforestation (Vance & Geoghegan, 2002). PROCAMPO is a Mexican rural support program created to alleviate the financial impact of the NAFTA on agricultural workers in 1994 (Klepeis & Vance, 2003). The program was also implemented with the intention of decreasing environmental degradation through the promotion of more efficient land use, using funds to intensify production and decrease pressure on remaining forests (Klepeis & Vance, 2003). The resulting increase in deforestation puts the program at odds with its intent. Vance and Geoghegan (2002) suggest poor integration of landowners into markets that would otherwise encourage land-intensive chemical inputs as a reason for increased agricultural expansion and, consequently, decreased forest cover. The same study also suggests that the specific terms of the program, which stipulate the area and location supported by PROCAMPO be maintained under continuous production, discourages a forest/fallow agricultural method that maintains the fertility of soils used. Later studies of PROCAMPO reported mixed results (Geoghegan, et al., 2004) or insignificant relationships (Chowdhury, 2006). Alternatively, another study found that each hectare registered in PROCAMPO actually decreased the hazard of deforestation by 2.21% (Vance & Iovanna, 2006).

A third credit program that may affect deforestation is the Programa Nacional de Solidaridad or Mexico's National Solidarity Program (PRONASOL). The most recent study on PRONASOL and forest cover change determined that the program's subsidies in northern municipalities are causing a considerable increase in forest loss, while subsidies in the south and east are not (Jaimes, 2010). The effect of Mexico's rural agricultural support programs on deforestation requires further study of the types of rural agricultural subsidies and where and to what extent they are related to deforestation.

3.3.3. Payments for Ecosystems Services

Mexico has already designed and implemented a payments for ecosystems services (PES) program, a payments for hydrological services program (PSAH), which is designed to incentivize the increased production of hydrological services through forest conservation (Alix-Garcia, et al., 2012). Through PSAH, the Mexican federal government pays participating forest owners for the benefits of watershed protection and aquifer recharge in areas where commercial forestry is not currently competitive (Munoz-Pina, 2008). Most studies have found that this application of PES in Mexico reduces deforestation to some extent. A number of studies on protected forests reveal that a combination of legal forest protection and financial incentives has helped reduce deforestation in Mexico (Honey-Roses, et al., 2011). In 2011, a study found that a combination of legal protection and PES has helped protect forest habitat for the monarch butterfly in Mexico. The study estimated that without the joint conservation initiative, losses of forest would have been 3% and 11% higher in areas with just a logging ban or with dense canopy, respectively (Honey-Roses, et al., 2011). In 2012, in another study analyzing PSAH, results suggested PES in Mexico reduced deforestation that would have occurred under BAU scenarios, but result results were uneven. It was further revealed that the program seemed to be more effective in generating avoided deforestation where poverty is lower and in the southern and north-eastern states of Mexico (Alix-Garcia, et al., 2012). A 2008 study revealed that while PSAH is associated with reduced deforestation, the program's payments have been in areas with low deforestation risk, suggesting that the selection criteria be modified to better target higher risk areas (Munoz-Pina, 2008). There is room for further study on socio-economics of the area under PSAH as well as other potential PES program designs.

3.4.Database regression results

3.4.1. A Meta-analysis of Drivers of Deforestation in Mexico: Methods

Recent technological and methodological advancements have encouraged the proliferation of econometric studies of deforestation grounded in remotely sensed evidence of forest cover loss. We have compiled a comprehensive database of 117 econometric studies of deforestation, including 23 studies in Mexico, published between 1996 and 2014. To be included in the database, studies had to meet five criteria: (1) the dependent variable must measure forest cover or forest cover change; (2) the dependent variable must be remotely sensed; (3) the dependent variable must have resulted, in part, from anthropogenic causes; (4) the article must include a table of multivariate regression outputs; and, (5) the article must have been published in a peer-reviewed journal. The database is meant to be a single source for all econometric studies of deforestation, allowing easy access and analysis of deforestation. This database was created to provide an overview of current scientific understanding of forest cover loss, to improve policy implementation aimed at deforestation mitigation, and to identify gaps in scientific evidence requiring further research.

From the individual studies we categorized driver variables (n=1159) into "meta-variables" such as elevation, proximity to road, or agricultural activity, of which 33 were included in the studies of deforestation in Mexico (Table 3.4.1). A single meta-variable is the sum of all regression results from indicators measuring the same phenomenon. For instance, the meta-variable Elevation is comprised of variables labelled "Elevation," "Mean Elevation," "Altitude" etc. While Table 3.4.1 presents a comprehensive list of driver variables collected in the database from studies in Mexico, some variables have yet to be analyzed due to the complexity of interpreting the variable (e.g. Soil Type).

For each meta-variable, within each study, we summed the number of regression outputs or matching outputs that found the association between that meta-variable and deforestation to be negative and significant, not significant, or positive and significant. These results were then organized into a database upon which we based our analysis. We termed the meta-variable to be consistently associated with lower (or higher) deforestation if the ratio of positive and significant outputs to negative and significant outputs was statistically significantly less than (or greater than) 1:1 in a two-tailed t-test at the 95% confidence level. We termed the meta-variable to be not consistently associated with lower or higher deforestation if the ratio of positive and significant outputs to negative and significant outputs was not statistically significantly distinguishable from 1:1.

Table 3.4.1 Drivers of deforestation in Mexico, by driver category

Biophysical	Built Infrastructure	Agriculture, Pasture, and Working Forests	Demographics, Poverty, and Income	Land Management
Elevation (n=15) Slope (n=16) Wetness (n=8) Forest Area (n=3) Soil Suitability (n=6) Proximity to Clearing (n=9) Proximity to Water (n=3)	Proximity to Road (n=13) Proximity to Urban Area (n=12)	Agricultural Activity (n=9) Proximity to Agriculture (n=8) Agricultural Prices (n=4) Economic Activity (n=2) Livestock Activity (n=2) Timber Activity (n=1) Timber Price (n=1) Use of Fuelwood (n=1)	Population (n=10) Poverty (n=14) Education (n=8) Indigenous Population (n=8) Age (n=1) Presence of Females: (n=1) Property Size (n=7) Rural Income Support (n=8) Off-Farm Employment (n=3)	Tenure Security (n=6) Protected Areas (n=6) Plot Size (n=4) Land Use (n=4) Logging Activities (n=3) PES (n=2) Community Forestry/Ejidos (n=15)

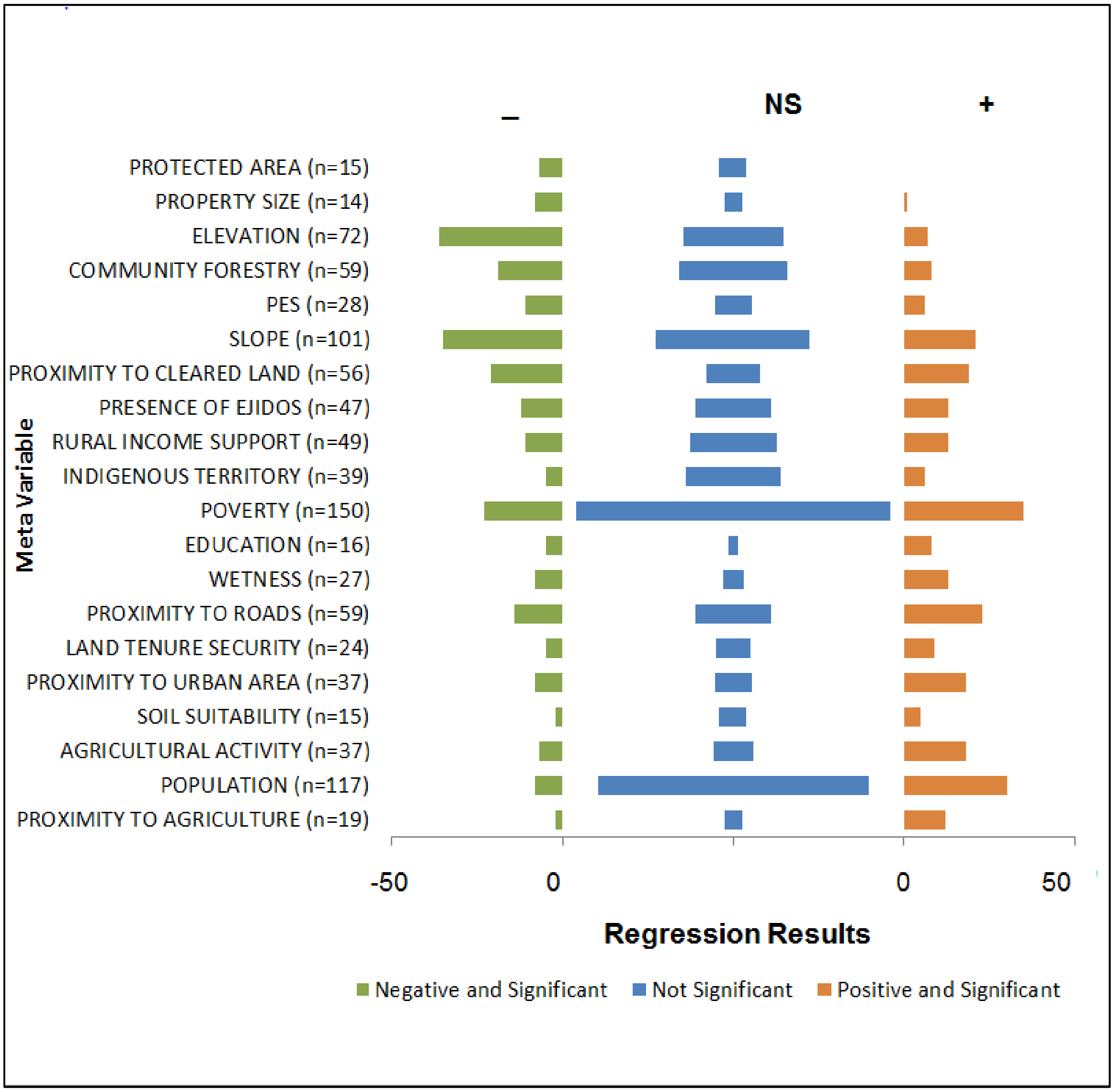
Note: "n " indicates the number of studies that have analyzed the meta-variable in relation to deforestation in Mexico, out of a total 23 studies. We categorized every regression result reported in the included studies into one of three categories. Regression results showing a negative and significant relationship between a driver variable and deforestation were coded as "-"; regression results showing a positive and significant relationship between a driver variable and deforestation were coded as "+"; regression results showing no significant relationship between a driver variable and deforestation were coded as "n.s."

3.4.2. Results for Mexico and SE sub-regions

The results for how each meta-variable is associated with deforestation across statistical studies of deforestation, are shown in Figures 3.4.1 and 3.4.2 at the end of this section and Figure A-1 in the Appendix. Figure 3.4.1 presents the database results for all studies focused on Mexico. In Mexico, variables most associated with decreases in deforestation, include protected area, property size, elevation, community forestry, and payments for ecosystems services (PES). There are some predictable results: that protected areas and PES are associated with decreased deforestation is not surprising. Forests in areas of higher elevation may well be more remote and have more limited access. That increased property size is associated with lower deforestation could reflect that bigger properties imply fewer land users, and consequently reduced competition for forest resources.

Variables associated with increased deforestation include proximity to agriculture, population, agricultural activity and soil suitability. Again, these relationships are probably not surprising: deforestation in Mexico occurs where economic returns to agriculture are higher (as proxied by proximity to cleared land and agricultural activity) and where biophysical conditions are favourable (as indicated by soil suitability). Population is also generally associated with increased deforestation, as it suggests increased competition for forest resources.

Figure 3.4.1 Drivers of Deforestation in Mexico: Results of Meta-Analysis



Note: This graph presents regression results from studies on deforestation in Mexico. Results are ordered by ratio of negative to positive association with deforestation.

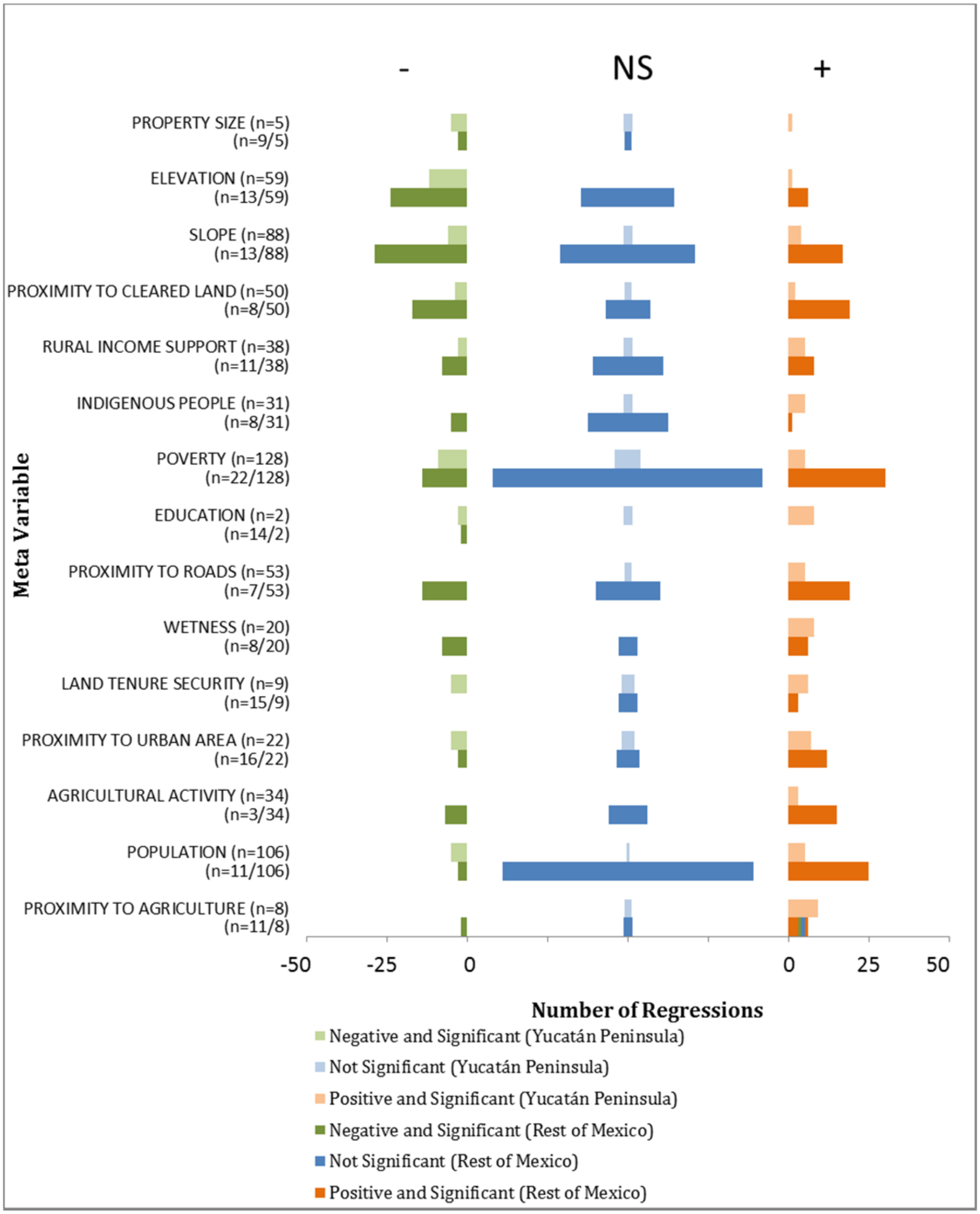
Most variables that are not consistently significant are perhaps also not surprising. As expected, results for rural income support are mixed. Surprisingly, however, community forestry is more consistently associated with less deforestation, whereas the effect of *ejidos* on deforestation is mixed. We separated variables referring specifically to *ejidos* and those referring to the broader term of community forestry. This discrepancy suggests more study is needed of the differences between various community land tenures in Mexico and their respective relationships with deforestation rates. Also surprising, variables indicating indigenous territory are not significantly related to deforestation, either positive or negative, in Mexico. In our global study we found indigenous land tenure is commonly associated with decreased deforestation (Ferretti-Gallon & Busch, 2014).

Figure A-1 in the Appendix compares results on the relationships between the variables and deforestation at the global level and in Mexico. Due to space limitations, the figure only includes the 15 top variables that have been most included in regression analyses at the Mexico level. Still, the figure suggests that variables affecting deforestation are generally the same in Mexico as at the global level. Protected area extent and elevation are both associated with decreased rates of deforestation and are robust at both levels of study. On the other hand, globally, communal forest management is associated with increased deforestation, while at the Mexico level, the community forestry (including both *ejidos* and other variables related to communal land ownership) is associated with lower deforestation. Similarly, rural income support is associated with increases in deforestation at the global level, but the results are more mixed at the Mexico level. Finally, at the global level, poverty is associated with lower deforestation, while in Mexico increased poverty appears to be associated with higher deforestation.

Figure 3.4.2 compares results disaggregated from the Mexico level to the Yucatán Peninsula (including the Yucatán, Quintana Roo, and Campeche, but excluding Tabasco). Due to space limitations, the graph again only includes the 15 top variables that have been most regressed at the Yucatán level. Variables associated with less deforestation (property size and elevation) and variables associated with more deforestation (population, proximity to agriculture and population) are robust at this level of disaggregation. Notably, poverty again has an inconsistent association with deforestation. At the national level, poverty appears linked to increases in deforestation, while in the Yucatán Peninsula poverty is associated with decreased deforestation. A similar inconsistency is noted with indigenous populations. While at the national level Indigenous territory is associated with decreased deforestation, the same variable is associated with increased deforestation at the Yucatan Peninsula level. These inconsistencies perhaps support the widely held view that Mexico's landscape and the related drivers of deforestation vary greatly by region.

It is important to emphasize the distinction between correlation, or association, and causation. To provide one well-known example, rates of deforestation might be lower within protected areas because protected areas are preventing deforestation from occurring (causality). This relationship might also be because areas that have low rates of deforestation for other reasons such as geographic remoteness have greater intact biodiversity, which led to protected areas being designated in those locations (an example of reverse causality). Disentangling these effects requires specialized techniques such as matching methods, which have been performed in Mexico for protected areas and payments for ecosystem services (Honey-Roses 2011), but not yet for *ejidos*, suggesting an avenue for further analysis.

Figure 3.4.2. Drivers of Deforestation in the Yucatán Peninsula as Compared to the Rest of Mexico: Results of Meta-Analysis



Note: This graph displays regression results from studies focused on the Yucatán Peninsula (including Campeche, Quintana Roo and Yucatán) as compared to results from the studies focused on the rest of Mexico. For each meta-variable, two sets of results are reported: the first set represents results for the Yucatán Peninsula in lighter colors, while the second set represents results for Mexico in darker colors. Results per meta-variable are ordered by ratio of average negative to average positive association with deforestation.

4. Analysis of deforestation at national level / OSIRIS

4.1. Introduction

We conducted an econometric analysis of deforestation in Mexico at the national scale in order to calibrate a simulation model to explore the impact of alternative economic and policy scenarios. In particular, we analyzed detailed spatially-explicit data on annual forest cover losses across all of Mexico over 2000-2012. Our econometric analysis is based on the idea that landowners[4] will choose, from a set of potential land uses, the option that brings the highest expected discounted returns The goal is to explicitly capture the influence of the economic net benefits from converting land from forest to non-forest uses for the purposes of calibrating a policy-simulation model that can, for example, analyze the impact of different REDD+ policy structures, or other potential payments for ecosystem services.

The national model serves to 1) measure the impact of different historical drivers of land-use change 2) generate a spatial distribution of probability of future deforestation under alternative policy and market scenarios, 3) help to identify cost-effective mitigation opportunities and estimate the opportunity costs of abating carbon emissions from deforestation, and 4) provide a basis for examining policy design elements so as to create economic incentives for the implementation of REDD+ in Mexico. In particular, results from an econometric analysis serve to calibrate the simulation and estimation on the distribution and total rate of deforestation across Mexico under a set of economic and policy scenarios that alter the economic calculus for land conversion, looking retrospectively over 2000-12 as well as out into the future over the next 10 years. The national model predicts site-level deforestation based on fitted values from the econometric model, estimated using observed deforestation. In particular, we model deforestation in relation to variation in estimated gross agricultural revenues and proxies for fixed and variable costs using observable site characteristics. The results from the simulation provide regional deforestation rates as an input to the LCM modeling of the seven AATRs.

4.2. Empirical Model

4.2.1. Econometric Specification

Several challenges arise in developing an empirically tractable specification to identify the role of economic returns in driving deforestation in Mexico. Our econometric approach focuses on addressing two main sets of issues. The first set of issues relates to the structure of our dependent variable, which is an aggregation of the native data at the 30m cell resolution. The aggregation introduces the challenge of modeling a range of potential changes in forest area within a larger grid cell, where the potential magnitude of changes is

[4] In Mexico, approximately 70% of forestland has a communal form of ownership (Corbera, et al., 2010). Therefore, for our analysis both private individuals and communities are the relevant land owners or managers.

linked to the amount of forest area within each grid. The second set of issues relates to the fact that we only have imperfect observations of economic returns for our units of observation, as mentioned above. A full discussion of our national model, econometric approach, data, and estimation results are provided in Appendix I.

4.2.1.1. Relationship of deforestation to available forest area within a 900m grid cell

Our underlying data source for deforestation, our dependent variable interest, provides binary information on the presence or non-presence of forests at the 30m cell level for each year between 2000 and 2012, providing a total of 11 observed annual changes (Hansen, et al., 2013). While we conduct the local scale analyses at this most detailed level of resolution, an analysis at this level of detail is not computationally tractable for all of Mexico as this would involve over 1 billion points per year or almost 13 billion data points across all 11 observed yearly change periods. To make the national analysis computationally feasible, we aggregate our 30m x 30m cells into larger 900m x 900m cells, each of which contain 900 potentially forested smaller cells at the 30m resolution. This procedure reduces the size of the dataset to about 1.39 million observations annually, after eliminating any 900m grid cells not containing any of the smaller 30m forested cells in the year 2000.[5] At this scale, our preferred specification still took about 24 hours to run on our most powerful computer with 24 GB of RAM.

Our constructed dependent variable is thus the annual change in forest cover from 2000 through 2012 on each 900m cell containing forests, spanning all the continental land area of Mexico (i.e., islands were excluded). Our units of analysis thus measure 900m x 900m or 810,000 m^2 (equivalent to 81 ha or 0.81 km^2). We restrict attention to 900m cells that contain at least one forested 30m cell. The change within each of these units is measured in terms of the number of constituent 30m cells that are forested at the start of the year but then change from forest to non-forest cover over the year. While we assign the same explanatory variables to all the smaller 30m cells within each of our 900m units, we thus model changes in 30m cell increments. These changes might represent decisions by one or more landowners within each 900m cell. We do not have comparable annual data for possible forest gains on these cells, so only consider forest losses in our model.[6] Thus, if a 900m cell loses all of its forest cover in a particular year, that cell does not enter into our econometric analysis in any subsequent years.

[5] Given available data, we only examine losses of forest cover in areas that were forested in 2000. Thus our deforestation analysis cannot consider deforestation on areas that were not forested in 2000 but could have subsequently gained and lost forest between 2000 and 2012. This is appropriate given our focus on the REDD+ policy and the greater carbon and biodiversity values associated with more mature forests, rather than recently regenerating forests.

[6] While (Hansen, et al., 2013) do provide data on cumulative forest gains from 2000 to 2012, an analysis of these data would have required a separate analysis and was beyond the scope of the current study.

The structure of our dependent variable raises several issues. The first issue is that our data has a “count” structure, as forest area and changes in area are measured in discrete units, ranging from 0 up to 900, the maximum number of 30m cells within a larger 900m grid cell. Given this count structure, our econometric estimation method is a Poisson quasi-maximum likelihood estimator (QMLE) which is consistent with estimating a count variable generated by independent, binary decisions at the 30m cell resolution (Wooldridge, 2002). For robustness, we also conduct the analysis using a negative binomial model, which modifies the Poisson regression model with a multiplicative random effect to represent unobserved heterogeneity. This is a way to address potential “over-dispersion,” which is a common situation in analyses of count data, where the observed variance of the dependent variable exceeds the variance of the theoretical model, indicating the model is not a good representation of the underlying phenomenon

There is another important issue to consider when estimating the magnitude of changes in forest area within a relatively small fixed geographic boundary: the amount of deforestation over a given period is closely linked to the amount of forest available to be deforested within each cell at the beginning of the period. One issue is that there is a simple physical constraint. The amount of forest that can be lost in any given year is limited by the availability of forest within the grid cell. Given our dataset without forest gains, more forest cannot be lost over a year than exists at the start of the year. Rather, when deforestation progresses over time, the available forest declines and, in some cases, is completely exhausted within a 900m grid cell.

Although the starting forest cover sets a physical limit on the potential deforestation within each 900m cell, there are also economic factors at work. The difficulty of accessing and deforesting a 30m forest cell is likely to be greater the farther away that cell is from non-forest areas, including previously forested land that has already been cleared, given greater costs in terms of travel time and effort to transport people and machinery through forests as compared to more open areas. As a result, as a cell is progressively deforested, more and more of the cell’s forested areas become accessible and easier (lower cost) to cut down. Thus, generally speaking, the costs of converting a hectare of forest within a 900m cell are likely to be inversely related to the total amount of forest area in the cell. This ignores, for the time being, the disposition of the surrounding cells as well as differences in the spatial configuration of the forest area at the 30m resolution within the 900m cell.

Another economic consideration is the fact that forest loss within a 900m grid cell is not likely to be distributed in a completely random manner. People should have an incentive to preferentially deforest those areas yielding a higher net return, either because of higher net revenues or because of lower costs of conversion. Thus, one would expect people to tend to first cut those areas that are most easily accessible or best suited for agriculture. As a result, the fact that while a certain share of the forest has been cleared, another share (one minus the deforested share) still remains in forest cover may convey certain information about the relative profitability of converting those remaining forests. For example, if five percent of the original forest extent (e.g. 45 out of 900 possible 30m cells) remains standing, while the other ninety-five percent has been cut down, this may indicate that the last five percent is relatively difficult or otherwise unprofitable to convert. This may also provide some information regarding the likely degradation and potential timber value of the remaining forest cover.

We take these dynamics into account in our model by directly controlling for the starting forest area in each 900m grid cell. In particular, we stratify the sample into 20 starting forest area categories, with the bins chosen to contain roughly similar numbers of 900m grid cells (given that these observations are our unit of analysis). This includes a bin for cells with 100% forest cover (the maximum 900 count of forested 30m cells). We then include dummy variables for each of these starting forest area categories as well as additional multiplicative terms that capture the interactions between this initial set of dummy variable and each of our key explanatory variables in the regression. This allows us to estimate how each of these different variables affect the likelihood and scale of deforestation within a grid cell, depending on the starting area of the forest. In this way, we can capture both the physical constraints imposed by the different available quantities of forest as well as the different economic dynamics of forest clearing at different stages of deforestation within a 900m cell.

Until now, the discussion has focused on how deforestation within a 900m cell depends on the extent of forest clearance within the grid cell itself. The surrounding area outside the cell should matter both in terms of making the cell more or less accessible and thus increasing or decreasing the costs of conversion, as discussed earlier. We control for the surrounding landscape by calculating a measure of the average distance of a grid cell to all of the non-forest 30m cells in the surrounding area, within a 2.5km radius. We use a "kernel density" to interpolate the influence of the non-forest area over space, assuming decreasing "gravity" of these areas as distance increases, up to the chosen 2.5km radius, at which point the influence of non-forest area is considered zero.

4.2.1.2. Observed and unobserved components of net returns from land conversion

The principal challenge in developing a model for empirical estimation is that we only have partial information on the potential net returns that landowners could obtain from the most profitable non-forest land use. We proxy for some differences in the costs of conversion and heterogeneous quality of agricultural land within a grid cell by accounting for the starting forest area on its own as well as in interaction with our key explanatory variables. Our main explanatory variable of interest is an estimate of the potential economic returns per hectare from crop production, which we consider as a proxy for the potential returns from converting land. We do not have data on the costs of producing crops in terms of labor, fertilizer, chemicals, and any other inputs nor do we have data on the costs of transporting any products to the market. We also do not have data on the (one-time) costs of conversion (as well as any potential one-time benefits of conversion such sales of timber). Both fixed and variable costs as well as revenues will determine the economic rationale for converting forests.

To account for these different costs, our approach is to introduce additional control variables at the level of the 900m cell that we expect will be correlated with production and conversion costs. All time-varying explanatory variables are lagged one year so as not to be contemporaneous with the dependent variable. The starting forest area categories, described above, provide one proxy for potential conversion costs as well as potential differences in agricultural returns with in the grid cell. As with the starting forest categories, each of the other control variables in our model is included independently and in interaction with our measure of potential revenues for each grid cell. When these variables are included independently, the estimated parameters on these additional variables will adjust the intercept in the model, capturing potential one-time conversion or other fixed costs (or benefits). When the variables are included in interactions with the agricultural revenues, the estimated econometric parameters will scale the response to the estimated economic returns based on the proxies for additional cost factors.

Our principal variables are listed in Table 4.2.1. While these variables help to adjust the fixed costs and to scale the effects of the agricultural returns, there may still be significant unobserved factors affecting economic profitability of land conversion. As a result, given the specific interest of the MREDD program in the Yucatán and Southern regions, we also introduced regional dummy variables, singly and multiplicatively (i.e. in interaction) with agricultural returns, to account for other factors, such as government policies, that may affect agricultural profitability at the broad regional level.

Table 4.2.1. Principal explanatory variables used in national regressions (900m cell)

Variable	Units	Variation over Space	Variation over Time
Potential Crop Revenue	MXN$/ha	Yes	Yes
Starting forest area category	0/1	Yes	Yes
Non-forest influence	km^2	Yes	Yes
Urban influence	km^2	Yes	No
Protected area extent	m^2	Yes	Yes
Ejido area extent	m^2	Yes	No
Comunidades area extent	m^2	Yes	No
Slope	%	Yes	No
Spatial trend surface	Lat/long	Yes	No

We compiled detailed information on PROCAMPO payments. However, we did not directly include PROCAMPO payments in our econometric model because receipt of payments from PROCAMPO (and other government programs) is not random. These payments are a fixed amount per hectare based on the size of farms, and payments are concentrated in *ejidos* and agrarian community areas. As a result, the constant terms in our model and the variable on *ejidos* and agrarian community lands within a grid cells may already capture the role of the government payments. Including these explicitly is likely to capture characteristics of the landowners (notably farm size) rather than the impact of the payments themselves. Econometrically identifying the role of PROCAMPO and other government payments would require a distinct empirical strategy, exploiting changes in the program criteria, and was beyond the scope of this study. Nevertheless, we are able to simulate the potential role of eliminating agricultural subsidies from PROCAMPO, building on the idea that the role of these programs is already captured in our estimated parameters.

4.3. Historical Simulations

4.3.1. Simulation Scenario

We use our estimated model parameters to conduct a series of simulations to explore alternative scenarios, looking back retrospectively over the 2000-2012 period. In the next Section 4.4, we consider forward looking scenarios over 2014-2024. We begin with analyses that are within the sample period to be as consistent as possible with the data used to estimate the model. The goal of these scenarios is to understand the relative effect of different variables, as well as to explore some alternative policy scenarios. We then conduct a forward-looking simulation to predict deforestation in the future in the next section (Section 3.6). We conduct six simulations over our historical period of analysis, as summarized in table 4.3.1. below.

Table 4.3.1. Simulation scenarios over historical period in data set, 2000-2012

Scenario name	Description
1) Factual simulation	All variables held at historical levels from 2000 to 2012.
2) 99% Potential Agricultural Returns on Forest Lands	Potential agricultural revenues from converting forest lands reduced by 1% relative to historical levels in all years.
3) 101% Potential Agricultural Returns on Forest Lands	Potential agricultural revenues from converting forest lands increased by 1% relative to historical levels in all years.
4) 90% Potential Agricultural Returns on Forest Lands	Potnatial agricultural revenues from converting forest lands reduced by 10% relative to historical levels in all years.
5) 110% Potential Agricultural Returns on Forest Lands	Potential agricultural revenues from converting forest lands increased by 10% relative to historical levels in all years.
6) No PROCAMPO payments on forested lands in *ejidos* or agrarian communities.	Potential agricultural returns from converting forest lands within agrarian community and *ejidos* reduced by value of PROCAMPO payments per program hectare in municipality

* The simulations regarding changes to agricultural returns are aimed at revealing the estimated sensitivity of deforestation to changes in the net benefits from converting forests to agricultural uses.

First, we establish a baseline for comparing our simulation results by conducting a "factual" simulation using the actual historical values of all the variables used in the estimation. The next four simulations examine the impact of our primary variable of interest, the estimated agricultural returns. This variable is our best guess of the potential net benefits of converting forest lands to a non-forest use. The estimated sensitivity to this variable will be used in our modeling to examine the possible impacts of alternative policies that could change the net benefits from converting forested land. Such changes in the net benefits could come through changes in the profitability of the non-forest use (e.g. because of changes in government agricultural subsidies on converted forest lands), or through changes in the relative value of maintaining land in forest cover (e.g. because of different otential incentives for forest protection).

Scenarios 2 and 3 explore the sensitivity of deforestation to our potential agricultural returns variable by, respectively, decreasing and increasing estimated potential agricultural returns by 1% relative to their factual values. This provides an estimated elasticity for changes in deforestation with respect to changing economic incentives, as captured by our model. These simulations are generally more indicative of the model findings for smaller changes in the variables that are within the range of the data used in the analysis. Nevertheless, in order to see how these results might scale with larger changes in returns, scenarios 3 and 4 repeat the exercise with a somewhat larger change in returns, decreasing and increasing estimated agricultural returns by 10% relative to their factual values.

The fourth scenario uses the estimated parameters on agricultural returns to simulate changes in the economic incentives for converting lands. Scenario 4 is a preliminary exploration of the potential influence historical impacts of the PROCAMPO agricultural support program under the assumptions that farmers weighing the potential benefits of converting land to cropland respond to expected PROCAMPO payments from the government in the same way as they respond to expected crop revenues received from the market. In reality, farmers may respond to these potential income streams in different potential ways given different perceptions over their relative uncertainty and future evolution, for example. Nevertheless, we maintain this assumption as a first approximation. While we did not explicitly include PROCAMPO payments in the model, the estimated parameters implicitly reflect the effects of these payments. Thus, reducing potential agricultural returns by the amount of these payments will reflect the effect of reducing the expected benefits from crop production, taking into account all of the policies in place from 2000-2012.

A question is by what amount to reduce potential agricultural returns given that not all cropland areas were eligible to receive PROCAMPO payments. Approximately 80% of currently planted acres over both growing seasons received PROCAMPO support last year. Between 2000 and 2012, these payments went largely to lands in *ejido* or agrarian community designations. From our analysis of the PROCAMPO data from 1999 to 2011, about 85% of lands receiving payments nationally were clearly identified as being within *ejidos* or agrarian communities , while about 8% were clearly identifiable as privately owned. The relevant issue, however, is not what share of current cropland is eligible for PROCAMPO payments but what share of forest areas that might be converted to crops was eligible to receive payments in the past and would be eligible to receive payments in the future. The share of lands eligible for payments could be significantly higher in forested areas if potential farm sizes are smaller than in other areas, which might especially be case on *ejdo* or agrarian community lands. Given lack of additional information, as a preliminary exploration, our scenario 4 assumes that PROCAMPO payments *only* went to lands in *ejidos* and agrarian communities, and that *all* new cropland acres in these designations were entitled to full level of payments. In particular, we reduce the potential agricultural return on *ejido* and agrarian community lands by the average PROCAMPO payment received on the PROCAMPO program hectares in the municipality in the prior year.[7] While it is not the case that no forested lands outside *ejidos* and *comunidades* would have been eligible to receive payments, it is also likely not the case that all lands within these lands types would have received payments. We simulate a scenario where no lands outside of *ejidos* and *comunidades* received payments in order to be conservative in not overstating the impacts of the program.

Removing the full amount of PROCAMPO payments per hectare represents about a 35% reduction in the estimated potential agricultural revenues on forested lands over the historical period for the median grid cell in the *ejidos* and agrarian communities. This scenario will likely underestimate the effect of PROCAMPO outside of communal land areas, as we are assuming zero effect at first approximation, but will likely somewhat overestimate the program's effects within the communal areas by assuming all new croplands in those designations are eligible to receive PROCAMPO program payments, despite the limits on payments according to the size of fields.

These simulations explore the effects of changing just one variable in the model, holding all others constant. In reality, all other variables would not have been constant, most specifically the starting forest area. For example, if deforestation in 2000 is lower (higher) due to lower (higher) agricultural returns, then starting forest area would have been higher (lower) in the subsequent year. We do not take this into account in our historical simulations since the goal is just to examine the sensitivity to the one variable. Nevertheless, for the purposes of the future predictions, described in the next section, we update the starting forest area in each year to reflect the deforestation in the previous year.

4.3.2. Simulation Results

4.3.2.1. Changes in Agricultural Returns

Results from the simulation at the national level are summarized in Table 4.3.2 below. We present results from our preferred model (the "negative binomial"), but include results from our alternative model (the "poisson" without fixed effects) in the Appendix.[8]

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[7] When a 900m cell was only partially in communal land ownership, we estimated a weighted average of the PROCAMPO payment assuming the *ejido* and agrarian community portions were eligible for the full payment, while the remainder was not.

[8] For the purposes of evaluating changes in response to particular variables, we prefer the negative binomial specification as Pearson test indicates the data are not a good fit to the poisson model, even though the latter has a better fit to the historical data. We report results with both models for comparison. We only report results for the poisson model without fixed effects as we are unable to conduct simulations with the "fixed effects" model given that we were only able to estimate "conditional" fixed effects model, which does not actually estimate the fixed effects for each of the 900m cells. Estimates of these effects are necessary to make absolute predictions of the dependent

Our alternative model (the "poisson" model without fixed effects) replicates the observed quantity of deforestation precisely at the national as well as regional levels. Our preferred model has a somewhat less precise fit, overestimating national deforestation over the 2000-2012 period by about 120 thousand hectares or 6.8%, with a predicted total forest loss of 1.88 million hectares versus an observed loss of 1.76 million.[9] Although this model provides a somewhat less precise fit to the data in absolute terms, we focus on results from this model as it is our preferred specification for estimating relative changes in forest loss in response to changes in particular variables.

Table 4.3.2. National Simulation Results

	Total forest loss, 2000-12 (Ha)	Difference from factual simulation (Ha)	Difference from factual simulation (%)
Observed (within sample)*	1,762,854	-120,624	-6.4%
1) Factual simulation	1,883,478	0	0.0%
2) 99% agricultural returns	1,878,961	-4,517	-0.24%
3) 101% agricultural returns	1,888,360	4,882	0.26%
4) 90% agricultural returns	1,845,771	-37,707	-2.0%
5) 110% agricultural returns	1,946,100	62,623	3.3%
6) No PROCAMPO payments	1,789,400	94,078	-5.0%

* This "observed" forest loss figure represents the observed deforestation for 900m cells within the sample used for our estimation. Actual deforestation was 1,997,765 ha or 13% higher, as we could not use all the observations due to missing data for some of the variables. Note: 2000-12 forest loss is through the end of 2011 but does not include deforestation occurring in 2012. Results in this table are from the preferred "negative binomial" model. For comparison, we report results from the alternative "poisson" model (without fixed effects) in Appendix Table A-10.

At the regional level, the preferred model captures the general distribution of forest loss, by region, as well as areas within and outside the AATR reference regions. A comparison of the observed versus modeled forest loss (the "factual simulation") for different regions and land types is shown in tables 4.4.1 and 4.4.2. The model varies in its precision by region, underestimating deforestation by almost 10% in the Yucatán Peninsula (region 6), by about 4% in the South and West (regions 5 and 3), by 7-8% in the Northwest

variable. Estimating actual fixed effects proved computationally impossible even with district-level fixed effects.

[9] For the purposes of comparing to the estimates from our models, the "observed" forest loss figure represents the observed deforestation for 900m cells within the sample used for our estimation. Actual deforestation was 1,997,765 ha or 13% higher, as we could not use all the observations due to missing data for some of the variables.

(region 1) and Bajio and Northeast (region 2), and by just 1% in the Center and East (region 4). Such variations are not surprising given that we are predicting regional and sub-regional forest losses based on an empirical estimation of deforestation responses across the whole country, with only a few region-specific dummies to capture region-specific particularities.

The results examining the sensitivity of deforestation to the potential net benefits from converting forests to cropland use confirm that greater expected potential agricultural returns were associated with increases in annual deforestation, as expected by theory. The simulations based on our preferred model indicate that a 1% decrease in potential agricultural returns over 2000-2012 would have decreased cumulative deforestation nationally over this period by 0.24%. Conversely, a 1% increase would have boosted deforestation by 0.26%. The simulations from the alternative model suggest a very similar deforestation response, with deforestation decreasing 0.26% for a 1% fall in agricultural returns, and increasing 0.27% for a 1% increase in returns (see Appendix table A-10). Results for the 10% changes in returns are roughly proportional, but show a more asymmetric response, with forest losses decreasing 2.0% for at 10% decrease in agricultural returns and increasing by 3.3% for a 10% increase.

Our final simulation suggests that decreasing crop returns by the amount of PROCAMPO subsidies on *ejidos* and agrarian community lands would have decreased deforestation by about 5%. Given that this represents around a 35% decrease in returns, this is a bit less than proportional to our finding that a 10% decrease would have reduced deforestation by about 2%. Most of the estimated reductions from eliminating the PROCAMPO payments on communal land categories occur in the Yucatán Peninsula and South regions. About 46% of the reductions occur in the Yucatán Peninsula and about 25% in the South.

The finding that deforestation increases more than it decreases for an equivalent percent increase and decrease in agricultural returns, respectively, is perhaps surprising if one imagines that progressively more and more marginal agricultural land is entering production, making it more and more difficult for land to come in. In part, this result reflects the fact that our econometric models are non-linear count data models, where the coefficients are contributions to a rate such that they do not have a simple linear interpretation in terms of absolute impacts.

The sensitivity to marginal changes in agricultural returns varies by region, as shown in Table 4.3.3. The most sensitive regions are the Northwest and Bajio and Northeast, with the least sensitive regions being the Center and East and the Yucatan Peninsula. While the former regions are estimated to respond about 0.5-0.6% and 0.8-1.0%, respectively, for every 1% change in agricultural returns, the latter region is only estimated to respond about 0.08%. In part this reflects the nature of our simulations, which considered percentage rather than absolute changes. As a result, areas with larger absolute levels of returns, experience larger changes in absolute returns, for the same percentage change. The larger response in regions 1 and 2 reflects the fact that these regions have higher potential agricultural returns and thus larger absolute increases and decreases in deforestation under these scenarios (which simulated percentage, rather than absolute changes) and, consequently, have more non-linear changes in the deforestation rate for a given percentage increase in net returns.

These regional results should not be taken too literally given that the model is most appropriate to reflect national-average responses. However, the model is also picking up some differences in the responsiveness to deforestation associated with forest categories. The larger percent response for an increase in returns in regions 1 and 2 also reflects the fact that regions contain more small areas of forest. Breaking out the simulation results by starting forest category within each region indicates that the responsiveness to 1% changes in agricultural returns generally increases as forest cover declines. This might indicate lower access costs to these grid cells, making them more sensitive to changes in gross revenues. However, in some regions, notably the South, West, and Yucatan Peninsula, there is a U-shape pattern, with the greatest sensitivity occurring at both the highest and lowest forest categories.

Table 4.3.3. Regional Simulation Results for Sensitivity to Agricultural Returns

Region	Factual simulation (scenario 1)	99% agricultural returns (scenario 2)		101% agricultural returns (scenario 3)	
	Total forest loss, 2000-12 (Ha)	Total forest loss, 2000-12 (Ha)	Difference from factual simulation (%)	Total forest loss, 2000-12 (Ha)	Difference from factual simulation (%)
Total Country	1,883,478	1,878,961	-0.24%	1,888,360	0.26%
Northwest (Region 1)	68,975	68,629	-0.50%	69,382	0.59%
Bajio & Northeast (Region 2)	179,624	178,142	-0.83%	181,373	0.97%
West (Region 3)	57,165	56,916	-0.44%	57,419	0.44%
Center and East (Region 4)	247,089	246,899	-0.08%	247,303	0.09%
South (Region 5)	456,810	455,280	-0.33%	458,346	0.34%
Yucatan Peninsula (Region 6)	873,816	873,096	-0.08%	874,538	0.08%

Note: Results in this table are from the preferred "negative binomial" model. 2000-12 forest loss is through the end of 2011 but does not include deforestation occurring in 2012.

These results suggest that relatively smaller patches of forests could contribute disproportionately to marginal changes in incentives, given that they already account for a disproportionate share of deforestation relative to the forest area (see national modeling appendix for more discussion of this issue). At the same time, relatively more intact forests in some regions appear to be at a potential economic tipping point for deforestation, where changes in net returns will cause them to begin a deforestation process, producing a jump in annual deforestation, and perhaps even more cumulative deforestation over the longer term.

As noted above, our simulations considered variations in one variable, holding all else constant, including the starting forest area. To fully capture the effects on the dynamics of deforestation, we would also want to simulate the repercussions of deforestation in one year on forest cover and its effect on deforestation in the subsequent years. We begin to explore these issues in the next section where we consider a forward-looking simulation based on an increase in agricultural returns as well as potential carbon payments for avoided deforestation.

4.4. Future projections

We conduct a future-oriented simulation under a "business as usual" scenario as well as a series of policy cases where we introduce a hypothetical comprehensive incentive to maintain forest carbon. As discussed further below, a variety of policy approaches could be used to capture potential financial flows for REDD+ and implement low-emissions practices in Mexico. Our projections serve to quantify and map the potential reductions available for future REDD+ policy in Mexico, rather than to model a particular REDD+ implementation strategy in particular. These simulations also provide an input for local modeling future deforestation at the level of each of the seven AATRs, as discussed in Section 4.

The future simulations account for the repercussions of deforestation from one year to the next by modeling deforestation at each 900m cell and accounting for its effect on starting forest cover area and category at the start of the subsequent year. While our alternative ("poisson" model) could provide better predictions, we focus on our main model (the "negative bionomial") which should be more appropriate for examining the relative changes between the BAU and policy cases. We present results from the alternative model in the Appendix for comparison purposes.

For the business-as-usual (BAU) scenario, we start with observed forest cover in 2012 (the last year of our data from the University of Maryland) and then model its evolution for each 900m cell at an annual time step through 2024. We also start with agricultural returns as of 2012 and hold these constant for the scenario. This involves almost a tripling of mean and median agricultural returns relative compared to the 2000-2012 period, though this varies over space. Combining the data over all the years and 900m cells, the average potential returns rise from 4,003 to 15,464 MXN$/ha while median returns rise from 2,470 to 9,346 MXN$/ha. The increase in median (and usually average returns) is larger in the Northwest, Bajio and Northeast, and West regions, relative to in the Center and East, South and Yucatan Peninsula.

Due to missing data on some of the variables, our estimation and historical scenarios were based on a sub-sample of the data that capture 87% of the historical deforestation over 2000-2012. Nevertheless, there is fewer missing data in the later years of the database. The sample used for our future predictions captured 98% of the observed deforestation in 2011. Given that our data is thus close to complete, we did not make any additional adjustments to the future forest loss projections for this missing information.

For the policy scenarios, we conduct a series of simulations where we introduce a comprehensive carbon incentive per ton of CO_2, starting at USD$5 and rising progressively to $100(assuming an exchange rate of MXN$13/USD). Specifically, we consider "prices" of $5, $10, $20, $30, $50, $60, $70, $80, and $100 per ton of CO_2, so as to trace out a "marginal cost" curve based on estimated emissions reductions from avoided deforestation at different price points.

We simulate an economically ideal or most comprehensive incentive which can, in theory, be viewed as one where all landowners either receive a subsidy for land preservation or pay a tax for land conversion for instantaneously releasing the carbon content of all above-ground live biomass. More practically, one can think of this as a policy that reduces the "business-as-usual" agricultural benefits (e.g. by reducing government subsidies) and translating them into economic benefits for low-emissions practices that avoid deforestation. This is implemented in our simulations by reducing the agricultural returns by the amount of the foregone carbon revenue if forests were to be deforested. We do not model any potential shifts or "leakage" of deforestation in response to possible induced changes in agricultural returns or other effects. We base our analysis on the above-ground carbon density data from WHRC/MREDD (Cartus, et al., 2014). For simplicity, this initial analysis did not consider below-ground or soil carbon losses.

While this analysis considers a notional carbon incentive that can be translated into a particular "price" and thought about as a tax or subsidy for each landowner or other land user, as already note, the results do not presuppose a particular REDD+ policy based on direct payments to landowners, such as a traditional payments for environmental services (PES) program. Rather, our analysis serves to identify the cost-effective potential emissions reductions, and their spatial distribution, given the "price" in terms of foregone agricultural revenues on the lands not being deforested. This analysis serves to quantify and spatially identify the most cost-effective reductions that could be potentially targeted under a variety of potential policy interventions and approaches for promoting low-emissions rural development and reduced deforestation emissions in Mexico. Moreover, while agricultural production might be foregone on the particular lands not being deforested, agriculture could be intensified and expanded on non-forest lands under a low-emissions agricultural development strategy. This means that agricultural production could be maintained or increased overall at the same time that expansion of agriculture into forest areas is decreased.

4.4.1.1."Business-as-usual" projection

Table 4.4.1 shows our "business as usual" projections for 2014-2024 relative to the observed and modeled deforestation in annualized terms during the historical period (2000-2012). Results are presented nationally as well as by AATR reference regions and different land ownership categories. Based on the economic profitability of agriculture and starting forest cover in 2012, the model predicts an overall 27% increase in annual deforestation in Mexico over the next ten years, relative to the recent past. Estimated changes reported are relative to the modeled deforestation (the "factual simulation") for 2000-2012. Most of this increase is due to a significant increase in deforestation in the South and Yucatan Peninsula regions, which assumes an even greater share of national deforestation, as some other regions (West and Center/East regions) experience a decrease in annual deforestation. The higher agricultural profits in 2012 relative to the historical period accounts for the overall increase in deforestation nationwide and in the more forested areas.

Despite the significant increase in the average and median agricultural returns compared to the historical period, the overall increase in deforestation is smaller than suggested by our simulations of smaller marginal changes in agricultural returns in section 2. This is likely due to the fact that we are comparing results across a whole historical period with a wide range in returns, including returns similar to our projected ones at the end of the period. We are also now accounting for the declining forest areas within each grid cell, which further reduces potential deforestation. The projected decrease in some regions relative to the historical period is likely due to smaller remaining areas of forest in 2012 relative to the historical period.

As noted before, our models are intended for national analysis but generally capture regional distributions. Map 4.4.1 shows the spatial distribution of projected aggregate forest loss under the business-as-usual scenario for the next 10 years (2014 until the start of 2024). The map shows that the greatest amount of deforestation is projected to occur in the South and Yucatan Peninsula regions. Table 4.4.2 shows how these regions are not only projected to contribute the most deforestation in absolute terms, but are also projected to experience the greatest percentage increases in deforestation, with projected deforestation rising by 72% in the South and by 26% in the Yucatan Peninsula. In contrast, deforestation increases by 17% in the Northwest, 3% in the Bajio and Northeast and percent decreases in the West and Center/East regions. Our alternative model (the "poisson") also predicts an increase in national deforestation of 27%, with the greatest proportional increases occurring in the South and Yucatan Peninsula (Appendix table A-11). The breakdown across regions is a bit different in absolute terms, but the qualitative results are still generally the same. This alternative model, which may be more precise for predictive purposes, shows relatively smaller increases in the South and Yucatan (41 and 48%, respectively) and larger increases (smaller decreases) in the rest of the country.

The relatively greater projected increases in deforestation in the South and Yucatan compared to the rest of the country contrast with the historical simulation results in Table 4.3.3 for marginal changes in returns of plus or minus 1%. While other regions appear more sensitive to small changes in returns, the greater cumulative deforestation in the South and Yucatan in the future projections may be due in part by the much larger changes in returns being considered in the business-as-usual projection, which elicits a larger response from all forest areas. The other part of the story is that we are now accounting for how forest areas evolve over time. Thus, areas with small initial forest cover might respond with a large proportional changes in deforestation in the short run but then have little forest cover remaining to continue having forest losses.

Table 4.4.1. Comparison of historical change and future predictions, 2014-2024, by AATR reference regions and land ownership category

Region/Land Category	Observed forest loss (in sample), 2000-12 (Ha/yr)*	Modeled forest loss (factual simulation), 2000-12 (Ha/yr)	Business-as-usual (BAU) forest loss, 2014-24 (Ha/yr)	Change in annual forest loss, projected BAU vs. modeled 2000-12 (Ha/yr)	% change in annual forest loss, projected BAU vs. modeled 2000-12 (%)
Total Country	160,259	171,225	217,963	46,738	27%
Non-AATR	110,299	113,679	131,434	17,755	16%
AATR regions	49,960	57,546	86,528	28,982	50%
Mixteca	1,298	1,902	3,180	1,278	67%
Sierra Norte	1,827	1,055	1,920	865	82%
Sierra Pucc	35,471	41,078	57,863	16,785	41%
Chiapas	4,546	7,165	12,847	5,682	79%
Raramuri	1,725	2,107	2,556	449	21%
Valle de Bravo	481	498	417	-81	-16%
Itsmo	4,613	3,739	7,745	4,006	107%
Comunidades	10,531	10,288	21,255	10,967	107%
Ejidos	89,613	92,800	113,070	20,269	22%
Protected areas	4,778	6,529	11,542	5,013	77%
Other lands	55,337	61,608	72,096	10,488	17%

* This "observed" forest loss figure represents the observed deforestation for 900m cells within the sample used for our estimation. Actual national deforestation was 1,997,765 ha or 13% higher than the in-sample amount as all observations could not be used due to missing data on some variables. Note: The AATR regions in this table are the AATR "reference regions" used in the local modeling discussed in section 4. The reference regions include the AATR site plus a 50km buffer. Results in this table are from the preferred "negative binomial" model. For comparison, we report results from the alternative "poisson" model in Appendix Table A-11. Protected areas are the federally protected areas considered in this analysis. 2000-12 forest loss is through the end of 2011 but does not include deforestation occurring in 2012. Similarly, 2014-24 forest loss is through the end of 2023 but does not include deforestation occurring in 2024.

Table 4.4.2.Comparison of historical change and future predictions, 2014-2024, by national regions and AATR Reference Regions

Region/Land Category	Observed forest loss (in sample), 2000-12 (Ha/yr)*	Modeled forest loss (factual simulation), 2000-12 (Ha/yr)	Business-as-usual (BAU) forest loss, 2014-24 (Ha/yr)	Change in annual forest loss, projected BAU vs. modeled 2000-12 (Ha/yr)	% change in annual forest loss, projected BAU vs. modeled 2000-12 (%)
Northwest (Region 1)					
Total	5,751	6,270	7,187	917	15%
Non-AATR	4,025	4,163	4,632	469	11%
AATR regions	1,725	2,107	2,556	449	21%
Bajio & Northeast (Region 2)					
Total	15,125	16,329	18,154	1,825	11%
Non-AATR	15,120	16,320	18,151	1,831	11%
AATR regions	4	10	3	-7	-70%
West (Region 3)					
Total	4,969	5,197	5,267	70	1%
Non-AATR	4,630	4,973	5,048	75	2%
AATR regions	339	224	219	-5	-2%
Center and East (Region 4)					
Total	22,777	22,463	15,833	-6,630	-30%
Non-AATR	21,684	21,176	14,799	-6,377	-30%
AATR regions	1,093	1,286	1,034	-252	-20%
South (Region 5)					
Total	39,863	41,528	71,262	29,734	72%
Non-AATR	28,535	28,688	46,408	17,720	62%
AATR regions	11,328	12,840	24,854	12,014	94%
Yucatan Peninsula (Region 6)					
Total	71,776	79,438	100,260	20,822	26%
Non-AATR	36,304	38,359	42,397	4,038	11%
AATR regions	35,472	41,078	57,863	16,785	41%

* This "observed" forest loss figure represents the observed deforestation for 900m cells within the sample used for our estimation. Actual national deforestation was 1,997,765 ha or 13% higher than the in-sample amount as all observations could not be used due to missing data on some variables. Note: The AATR regions in this table are the AATR "reference regions" used in the local modeling discussed in section 4. The reference regions include the AATR site plus a 50km buffer. Results in this table are from the preferred "negative binomial" model. For comparison, we report results from the alternative "poisson" model in Appendix Table A-12. 2000-12 forest loss is through the end of

2011 but does not include deforestation occurring in 2012. Similarly, 2014-24 forest loss is through the end of 2023 but does not include deforestation occurring in 2024.

The model predicts that most new deforestation in absolute terms, as well as most absolute increases in deforestation, will occur on *ejido* lands (Table 4.4.2). In percentage terms, however, forest losses within *ejidos* are projected to increase by 22% or less than the national average. In contrast, agrarian communities (*comunidades*) are projected to experience the largest increase, followed by deforestation within protected areas, with projected increases of 107% and 77%, respectively. Our alternative model projects similar qualitative patterns, though the relative differences among land types are smaller.

Map 4.4.1 indicates that the AATRs are not all located in the areas with the highest projected future deforestation. Nevertheless, as shown in Table 4.4.1, overall the AATR reference regions have higher projected deforestation increases than other forested areas (50% versus 16% for the lands outside these reference areas). The AATR reference regions discussed here are those used in the local modeling (section 4), and include the specific REDD+ early action area sites, as well as a surrounding 50km buffer. Given the national scale of the modeling, results are more appropriate at larger scales of analysis, dictating our focus on larger versus smaller areas surrounding the AATRs.

Looking specifically at the AATR reference regions, the model predicts the greatest increase in the Itsmo and Sierra Norte region and the smallest increases in the Raramuri and Valle de Bravo regions, with the latter region actually experiencing a decline in deforestation. The alternative model generates similar qualitative results, though it predicts a smaller relative increase in deforestation in the Chiapas AATR reference region (26% versus 79% increase in our preferred model).

The AATR reference regions not only have higher projected deforestation versus other lands on aggregate nationally, but they also generally have higher projected deforestation relative to other lands within each region. The comparison of AATR vs. non-AATR lands within each region is shown in table 4.4.2. The AATR reference regions generally have higher projected increases in deforestation (or smaller projected decreases in the case of the Center and East), relative to other forested lands in the same region. The exceptions are the Bajio and Northeast (Region 2) and West (Region 3), but these results are not indicative given that these regions contained trivial amounts of lands within any of the AATRs reference areas. Our alternative model generates similar findings (Table A-12).

4.4.1.2. Carbon Incentive Projections

As an example of our carbon incentive results, we present results for a hypothetical carbon incentive of USD \$10/t CO2 in table 4.4.3. This carbon incnetive translates into a median (average) subsidy/tax of about 4700 (5200) MXN\$/ha, compared to median (average) agricultural returns of about 9,300 (15,400) MXN\$/ha. This represents a median reduction in agricultural returns of 25%, with more than a 100% reduction on average. Under this simulated carbon incentive of \$10/tC, deforestation falls nationally by an estimated 35%. Map 4.4.2 shows the spatial distribution in the reduction in forest loss under the $10 carbon incentive (relative to the BAU case shown in map 4.4.1) while map 4.4.3 shows the remaining deforestation. The results for the alternative model and at the level of each AATR reference region are shown in the Appendix in maps A-15 to A-24.

In general, the regions projected to have the greatest increases in deforestation over the next decade are also estimated to be the most responsive to reducing deforestation under a carbon incentive. Overall, AATR reference regions are estimated to reduce deforestation by 41% compared to a reduction of 32% for non-AATR lands. The analysis suggests significant reductions in the specific AATRs, ranging from 35% in Raramuri to 58% in Sierra Norte. All of the AATR demonstrate greater potential reductions than the non-AATR regions of the country. However, the greatest potential reductions occur in the Yucatán Peninsula and South as seen in map 4.4.2. Similarly, most of the remaining deforestation is distributed in these regions (map 4.4.3).

Comunidades and protected areas were the land types projected to have the biggest proportional increase in forest losses over the next 10 years and are also estimated to have the greatest percent declines in response to a carbon incentive. In absolute terms, however, the greatest total estimated reductions occur on *ejidos*, as well as private and other land types apart from *comunidades* or national protected areas.

In addition to considering changes in forest area as a result of a carbon price, we also consider changes in carbon dioxide emissions from losses in above-ground biomass. Map 4.4.4 shows the spatial distribution of reduced emissions from above-ground forest biomass, associated with the reduced forest loss scenario at a $10 price shown in map 4.4.2. Estimated emissions reductions for the $10 carbon incentive are also combined with those from the other carbon incentive simulations and are used to construct cost curves shown in Figures 4.4.1 and 4.4.2. These figures show the estimated above-ground forest carbon emissions avoided annually under each of our carbon incentive scenarios, relative to the business-as-usual projection over the 10 years starting in 2014.

Under the business-as-usual scenario, represented by a carbon incentive of zero, average annual CO_2 emissions from deforestation are approximately 17 million tons of CO2 at the national level. Despite reflecting increases in future deforestation, these are about 37% of the 45.3 $MtCO_2$ for 2010 reported for land-use change emissions in the fifth national communications to the United Nations Framework Convention on Climate Change (SEMARNAT/INECC, 2012) . There are several possible explanations. Our estimates are based on new sources of information on both forest loss, as well as on above-ground forest carbon densities. Also, the numbers in the national communications include conversion of grasslands (*pastizales*), which were not considered in our analysis. Furthermore, our analysis only considered emissions from above-ground forest carbon stocks, without considering potential losses of below-ground forest carbon or soil carbon. Estimates of above and below-ground forest carbon stocks in Mexico from FAO (2005) and Ruesch and Gibbs (2008) are approximately 95 and 113 tons of C per hectare. In contrast, the mean and median forest hectare in 2012 had an estimated 23.6 and 21.8 tons of C/ha, respectively, according to the estimates used in our study (Cartus, et al., 2014). The carbon densities for the deforested hectares in our projections from 2014-2024 were a bit lower, with a mean of

21.7 and median of 19.8 tC/ha. A detailed comparison of these numbers was beyond the scope of our analysis.

Focusing only on the above-ground carbon, we find that there is rising potential nationally to reduce emissions at carbon incentives ranging from $5 to $100, at which point about 90% of the emissions are avoided. Close to half of the estimated reductions available at prices of $10/ton or below and more than two thirds of the estimated reductions available at prices of $20/ton or below. The national and regional cost curves are rising at an increasing rate, indicating that it costs more and more to avoid deforestation on lands with greater agricultural potentials.

While there are potential reductions available from all regions at prices up to $20-$30, the bulk of estimated reductions is from the South and Yucatan Peninsula, which account for about 35% and 60% of the total potential up to $100. Reductions from the other regions collectively rise steeply and are exhausted at prices of $20 and $30, at which point the cost curves turn vertical, with about 1 million tons of emissions avoided in total. This reflects the higher agricultural returns in these regions as well as smaller total amount of forest losses and carbon emissions that can be avoided. In contrast, the cost curves for the South and Yucatan Peninsula do not begin to turn upwards sharply until about $50. At prices of $5, the South and Yucatan Peninsula account for 43% and 50% of the cost-effective potential, respectively. The cost of reductions in the South rises somewhat faster than in the Yucatan Peninsula, with the South representing a smaller share of the cost-effective potential at progressively higher prices (e.g. 37% versus 56% for the Yucatan at a price of $50).

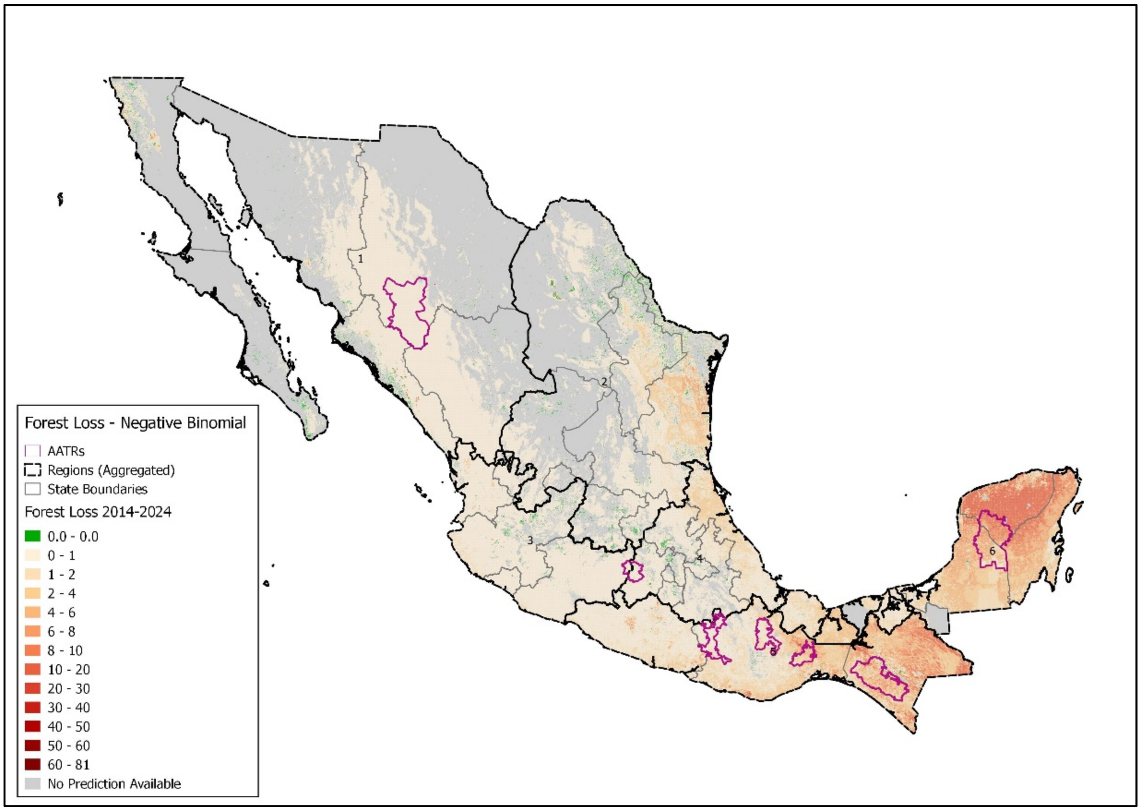
Figure 4.4.2 breaks out the cost curves according to lands within and outside of the AATR reference regions. These show that the broad AATR regions on aggregate contain more than half of the cost-effective potential reductions in emissions at each price point, with about 55% of the total modeled potential for all of Mexico. As already noted, our exercise did not presuppose the implementation of an actual carbon price or payment system. Rather, we consider a hypothetical carbon incentive so as to estimate the most cost-effective reductions potential available for a given reduction in foregone agricultural revenues on the particular lands not being deforested (though of course agricultural production might still increase on other lands). These cost-effective reductions could be achieved in practice through a variety of policy approaches. Also, while our analysis considered an idealized policy case, which is indicative of the potential for REDD+ policies, additional analysis would be needed to consider impacts on deforestation, including possible "leakage," as well as other economic implications under more realistic and likely less comprehensive policy approaches.

Table 4.4.3. Future Predictions, 2014-2024, Business-as-Usual and $10/ton CO2 Policy Case, for AATR and non-AATR regions

Region/Land category	Business-as-usual (BAU) forest loss, 2014-24 (Ha/yr)	Forest loss, 2014-24 with $10/tCO_2$ (Ha/yr)	Change in annual forest loss, $10/tCO_2$ vs. BAU (Ha/yr)	% change in annual forest loss, $10/tCO_2$ vs. BAU (%)
Total Country	217,963	141,106	-76,856	-35%
Non-AATR	131,434	89,727	-41,707	-32%
AATR regions	86,528	51,379	-35,149	-41%
Mixteca	3,180	1,466	-1,714	-54%
Sierra Norte	1,920	802	-1,118	-58%
Sierra Pucc	57,863	37,082	-20,781	-36%
Chiapas	12,847	6,324	-6,523	-51%
Raramuri	2,556	1,668	-887	-35%
Valle de Bravo	417	242	-175	-42%
Itsmo	7,745	3,795	-3,950	-51%
Comunidades	21,255	9,837	-11,418	-54%
Ejidos	113,070	77,174	-35,895	-32%
Protected areas	11,542	5,804	-5,738	-50%
Other lands	72,096	48,290	-23,805	-33%

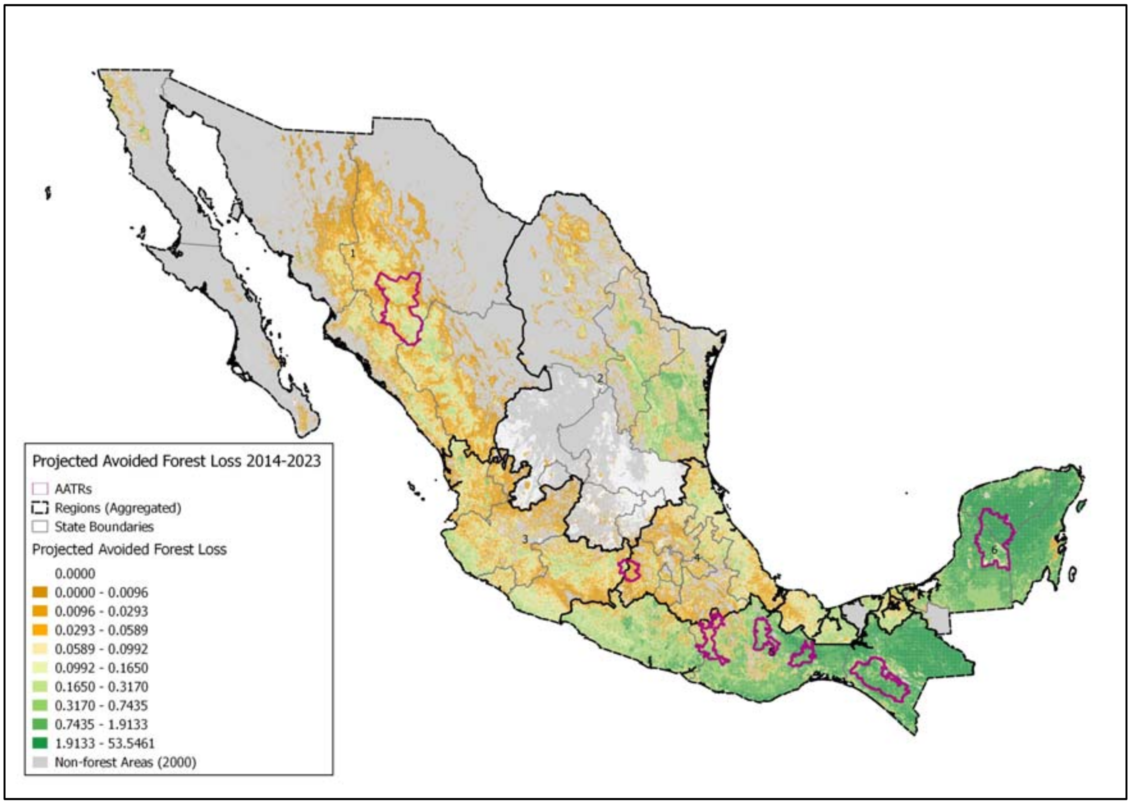
Note: The AATR regions in this table are the AATR "reference regions" used in the local modeling discussed in section 4. The reference regions include the AATR site plus a 50km buffer. Results in this table are from the preferred "negative binomial" model. For comparison, we report results from the alternative "poisson" model in Appendix Table A-13. Protected areas are the federally protected areas considered in this analysis. 2014-24 forest loss is through the end of 2023 but does not include deforestation occurring in 2024.

Map 4.4.1. Projected "Business as Usual" (BAU) Forest Loss 2014-2024



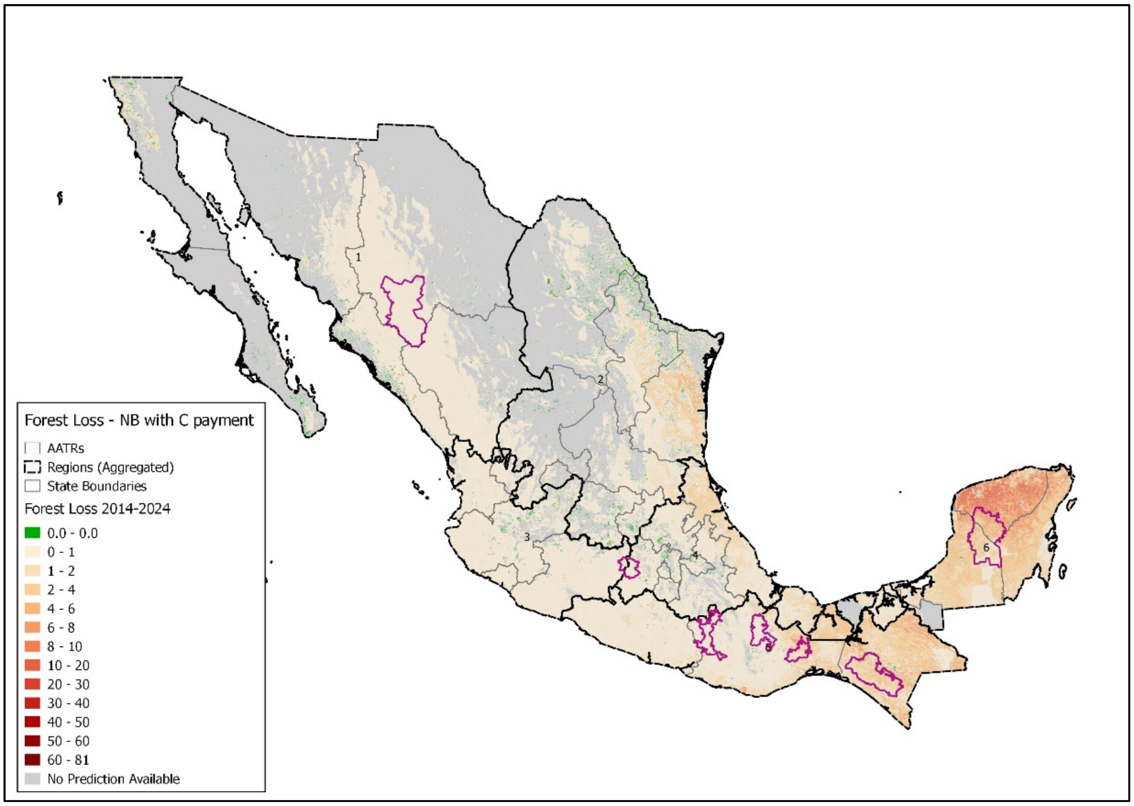
Note: This map shows projected deforestation at the 900m (81ha) resolution over 10 years starting in 2014, based on information on forest cover in 2012, estimated model parameters from 2000-12, and holding constant agricultural profits at 2012 levels. Projections are from the preferred "negative binomial" model. For comparison, we report results from the alternative "poisson" model in Appendix Map A-11. Green areas indicate no loss of forest cover. Progressively redder areas indicate greater amounts of forest loss. Grey areas are those without any forest cover in 2012 and hence no projected forest loss. 2014-24 forest loss is through the end of 2023 but does not include deforestation occurring in 2024.

Map 4.4.2. Projected Avoided Forest Loss 2014-2024, with $10/ton CO2 incentive



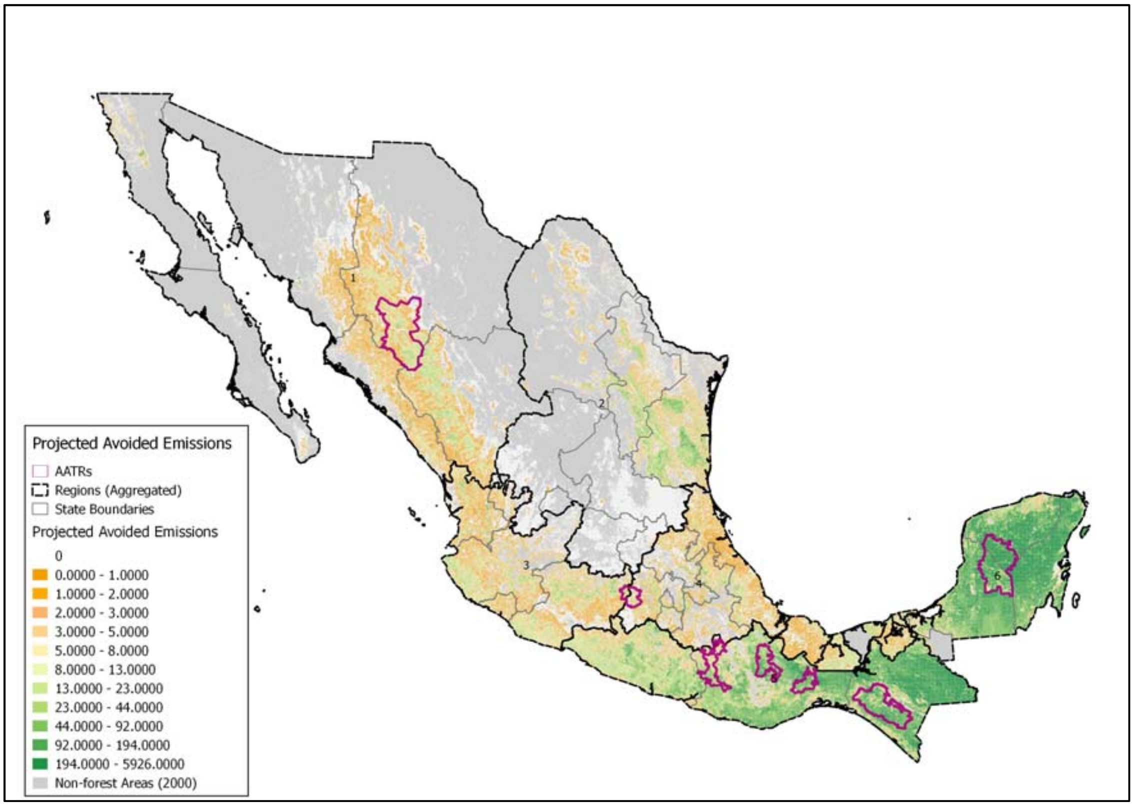
Note: This map shows projected reductions in deforestation at the 900m (81ha) resolution over 10 years starting in 2014, based on introducing an economically ideal comprehensive carbon price of $10t/CO2 on forest carbon losses. Reductions are relative to the "business-as-usual" (BAU) scenario in Map 4.4.1. This analysis does not consider potential price adjustments or other possible sources of induced shifts in deforestation and emissions (i.e. "leakage"). Projections are from the preferred "negative binomial" model. For comparison, we report results from the alternative "poisson" model in Appendix Map A-12. White color areas indicate no reduction in forest loss as a result of the carbon price. Light to dark yellow, followed by light to dark green, areas indicate progressively greater amounts of avoided deforestation under the carbon price relative to the BAU case. Grey areas are those without any forest cover in 2012 and hence no projected reduction in forest loss. 2014-24 forest loss is through the end of 2023 but does not include deforestation occurring in 2024.

Map 4.4.3. Projected Remaining Forest Loss with $10/ton CO2 incentive, 2014-2024



Note: This map shows the projected forest loss at the 900m (81ha) resolution over 10 years starting in 2014 that is estimated to remain after the introduction of the $10t/CO2 on forest carbon losses (i.e. this map shows the remaining forest loss starting from the forest loss in map 4.4.1 and subtracting out the avoided forest loss in map 34.4.2). Projections are from the preferred "negative binomial" model. For comparison, we report results from the alternative "poisson" model in Appendix Table A-13. Green areas indicate no loss of forest cover. Progressively redder areasindicate greater amounts of forest loss. Grey areas are those without any forest cover in 2012 and hence no projected forest loss. 2014-24 forest loss is through the end of 2023 but does not include deforestation occurring in 2024.

Map 4.4.4. Projected Avoided Emissions 2014-2024, with $10/ton CO2 incentive



Note: This map shows projected reductions in above-ground carbon losses at the 900m (81ha) resolution over 10 years starting in 2014, based on introducing an economically ideal comprehensive carbon price of $10t/CO2 on forest carbon losses. Reductions are relative to the forest losses in the "business-as-usual" (BAU) scenario in Map 4.4.1. This analysis does not consider potential price adjustments or other possible sources of induced shifts in deforestation and emissions (i.e. "leakage"). Projections are from the preferred "negative binomial" model. For comparison, we report results from the alternative "poisson" model in Appendix Map A-14. White color areas indicate no reduction in forest losses and associated carbon emissions as a result of the carbon price. Light to dark yellow, followed by light to dark green, areas indicate progressively greater amounts of avoided deforestation and associated emissions under the carbon price relative to the BAU case. Grey areas are those without any forest cover in 2012 and hence no projected reduction in forest losses and associated emissions. 2014-24 forest loss is through the end of 2023 but does not include deforestation occurring in 2024.

Figure 4.4.1. Estimated cost curves for CO2 emissions reductions from above-ground forest carbon losses in Mexico, by region

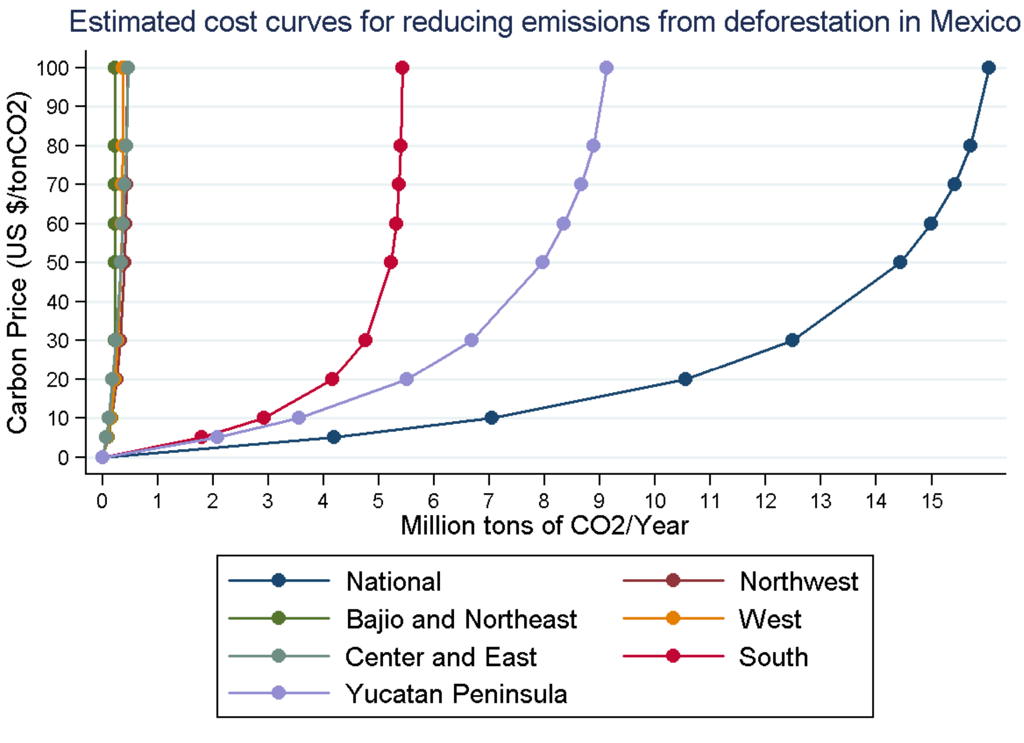
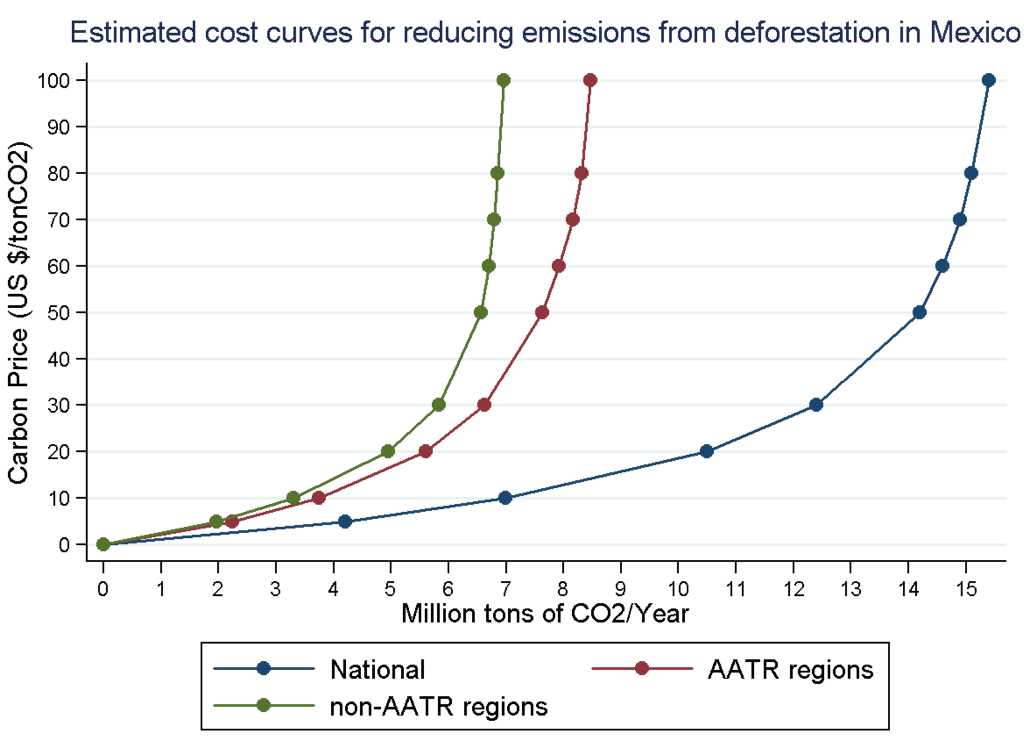


Figure 4.4.2. Estimated cost curves for reducing emissions from above-ground forest carbon losses in Mexico, by AATR and non-AATR regions.



5. Local Modeling of Deforestation

5.1. Introduction

5.1.1. Overall approach

The national-level modeling captures drivers and possible deforestation outcomes at one scale that is only arguably very relevant to the local scale. One could also claim that dynamics at the local scale have a local character, and that a model of these local dynamics should be independent of relationships derived from distant lands. Thus, we add a component to this study that models deforestation based solely on local data. We do this for the seven focus areas selected by TNC. Also, while both the national- and local-level analyses are based on spatial modeling, the national-level one is via modeling economic incentives that vary with spatial patterns of opportunity cost. At the local level, opportunity cost is less variable and information is scarcer. For these reasons, we take a different approach to spatial modeling in the local case studies.

The overall approach we take is to follow the fundamental steps found in the most-widely used methodologies for estimating reference emissions levels (RELs) for REDD+ initiatives approved by the Voluntary Carbon Standards group (VCS). However it is important to note that this was not a reference level setting exercise. We do not conduct the method to the level of detail that would be expected for a VCS Project Description (PD) document, since that would require local field data on biomass and local improvement of GIS data used in models. Nonetheless we follow the overall logic of the VCS methodologies and their fundamental steps in spatial modeling.

5.1.2. Definition of extents

First, some spatial extents are defined. This includes the site itself, which in each of the seven cases is an existing protected area (PA). Each PA is one of Mexico's REDD+ early action sites (Áreas de Áccion Temprana REDD+; AATR). We used the official PA boundary files provided to us by TNC. Second is the definition of a reference area for modeling land use inside and around each site.

Each reference area was defined by first creating a 50 km buffer around the AATR site. This buffer was combined with municipality boundaries, and the entire extent of any municipality that intersected the buffer was included in the reference region.

5.2. Data and Methods

5.2.1. Deforestation data

Within each site's reference area, we obtained data on forest cover and deforestation from 2000 to 2012. We used the same data that were used for the national-level analyses from the latest University of Maryland (UMD) assessment. Correspondingly, these data are based on the analysis of Landsat images and have a spatial resolution of 30m. However, we did not conduct any spatial degradation (coarsening of spatial resolution), as was done for the national-level analyses, since each reference is not prohibitively large to conduct analyses at full resolution.

The UMD source data can be seen as composed of two parts. First is a map of tree-cover percent for each 30m cell in year 2000. Tree cover is not the same as forest cover. One can assume that tree cover as presented in this product is related to crown cover as estimated in the field and used in national definitions. However, the two concepts are not the exact same, and such an assumption can lead to problems. For both the national and local-level modeling we used this assumption for simplicity.

The national definition of forest has, as criteria, a minimum crown-cover of 25 percent. We applied this value as a threshold to the percent tree-cover map from UMD to create a map of forest in 2000. This leads to a generous estimate of the distribution of forest in the modeling areas. We believe that most secondary forest fallows and shrub fallows associated with rotational agriculture or recently-abandoned farm land is included in the estimation of forest extent in 2000. The mapped and modeled patterns of forest cover and deforestation likely include sites with significant tree cover and areas of clearance of tree cover that are not mature forest or the clearance of "mature" forest. We believe that plantations and selectively-logged forest are also included in the forest class. Thus this definition should be kept in mind when interpreting results of this study.

The second part of the UMD data focuses on estimates of the locations of loss of tree cover for each year from 2001 to 2012. We believe that these should be robust data, since the temporal-spectral signal of such clearing events is strong, and the methods of UMD maximize the potential for their detection by mining the entire Landsat archive over the study period and employ an effective decision-tree statistical approach. Thus, we expect that the majority of deforestation is captured, as well as much of the other forms of clearance of tree cover, because of the generous definition of forest extent in 2000, as noted above.

In contrast to the national analysis that considered forest losses on an annual basis, for the local analyses, the annual loss data were grouped to create maps of forest loss over two time periods: 2000 to 2006 and 2007 to 2012. We then combined the maps of loss for these two periods with that of derived forest extent in 2000 to create a three-date product. In an effort to limit the effect of small-scale changes in tree cover that might not truly represent forest losses, we filtered the output to minimize very small artifacts and to set a minimum patch size for both the baseline forest distribution and patterns of loss. First, a three-by-three cell majority filter was applied to the merged product. Second, we filtered the output using a one-hectare sieve. This eliminates any patch of forest or forest loss that is smaller than one hectare and replaces the cells with the dominant class bordering the eliminated patch of cells. [10]

[10] We believed this filtering was prudent in the local analyses, but not necessary in the national analysis, as the latter controlled for starting forest area in the econometric procedure. In addition, the much larger amount of data used for the national study reduces the potential influence of spurious forest loss observations.

5.2.2. Other data

We obtained a suite of data from TNC and partners to explore the spatial relationships between possible "drivers" and deforestation. The data are more accurately described as geographical parameters rather than drivers. These parameters are indicative of where the drivers occur and are most likely to be linked to deforestation patterns. For example, roads themselves are not drivers, but their distribution indicates where people have easier access to forests and can rapidly move to their homes or markets. Thus, roads are a geographical parameter that allows us to understand where the interactions among people, forests and markets occur, and they thus typically are valuable in predicting where deforestation will most likely occur. However, the term "driver" is commonly used in such modeling contexts to refer to data on such geographical parameters, and we will do so here for simplicity.

The spatial data on drivers we obtained are of three data types. First type is raster data on continuous variables, such as distance to roads and elevation. The second type is polygon data that were used as class variables. These include soil type, community, etc. The third type is a dataset created specifically for this modeling exercise. To represent how "marginal" a community is, i.e. how isolated and lacking in resources and/or subsidies, we assigned a three-class variable based on a "marginalization" index to a map of locations of community centers. We then created a map of distance to each class of community.

All of these data were rasterized and created or resampled to match the 30m cell array of the deforestation map. The full list of potential driver data to use in the local models is reported in Table 5.2.1.

Table 5.2.1. Driver independent variables used for spatial models at the local level.

Variable label	Variable name	Data source	Notes
Var 1	var_dist_hi_marginalized_villages	Conabio	The marginalization index is a summary for differentiating census towns in the country, according to the global impact of deficiencies that affect the population as a result of lack of access to education, residence in inadequate housing and lack of assets.
Var 2	var_dist_low_margin_villages	Conabio	
Var 3	var_dist_medium_margin_villages	Conabio	
Var 4	var_dist_primary_road	Conabio	
Var 5	var_dist_railroad	Conabio	
Var 6	var_dist_rivers	Conabio	
Var 7	var_dist_secondary_road	Conabio	
Var 8	var_dist_small_medium_cities	Conabio	Regionally important urban centers, including state capitals
Var 9	var_dist_trail	Conabio	
Var 10	var_elev_30_30m	INEGI	Original resolution of 60 meters
Var 11	var_slope_30m	INEGI	Derived from the digital elevation model (DEM)
Var 12	var_pop_dens	Global Rural Urban Mapping Project (GRUMP)	This variable was not inlcuded in the Sierra Ramaruri model
Var 13	var_protected_areas_dummy	Conabio	Presence or absence of Federal protected areas
Var 14	var_dist_non_forest_2006	UMD/Hansen data	Derived from the input LC maps
Var 15	var_dist_megacities	Conabio	This variable was not included in models for AATRs without a megacity (population GT 75,000) within the reference region

5.2.3.Spatial modeling

We used the IDRISI Land Change Modeler tool (LCM) for all spatial modeling at the local level. This is developed by Clark Labs and one of the stronger modeling tools available for land-use modeling. Documentation on the tool and terms used in this description can be found at: http://www.clarklabs.org/products/Land-Change-Modeling-IDRISI.cfm.

The yearly deforestation data from 2001 to 2012 were grouped into three dates and two time periods: 2001-2005-2012. The first time period is used to calibrate each local model. The calibrated model is then used to predict deforestation over the following time period. Since data on actual observations of deforestation for the latter period exist, a validation of the model is possible by comparing the modeled to actual patterns of deforestation.

For class variables, we created “evidence likelihood” maps for input into models. These assign the proportional importance of a particular polygon to the study area’s overall deforestation rate. This is then used as a potential weighting factor in the modeling algorithm.

The LCM tool and methods approved by the VCS compare the spatial patterns of driver variables with those of historical deforestation. Statistical relationships are then used to produce estimates of the “potential” for deforestation in each model cell. These values of potential could be re-scaled to be values of likelihood, where their sum equals a defined total rate for the modeled period. If this is done, then the output would be similar to the national model in that cells are assigned a continuous value. The likelihood values, ranging from zero to one, could be used as if they were estimates of the proportion of the cell that is deforested. This could be called a “continuous” approach.

Another approach is to assign complete deforestation to the cells with the highest values of potential, which could be called a “discrete” approach. This produces a map where cells are either deforested or not. This assumes that deforestation entirely occurs in the sites of greatest potential or risk. While this could be argued a realistic approach, there are problems with its assumptions, i.e. that there is no finer scale variation in risk due to unobservable real-world factors. Thus, high risk sites are fully deforested and zero deforestation happens in all places other than the strictly most threatened sites. Regardless, the methods approved by VCS all require this discrete approach, and this is the approach that we applied in the local models. We do, however, maintain the continuous data on deforestation potential, and further study could explore the differences between the results of the two approaches.

The approach of this tool, and of most others used in such applications, is to calibrate with a subset of the data, whether selecting a particular time period or spatial subset, then to run the model and validate it with a later time period or separate spatial subset. We used one time period in order to allow the option of validation over the second time period. Different algorithms for modeling the relationships between drivers and deforestation exist. We selected the Multi-Layered Perceptron (MLP) algorithm within

IDRISI's LCM because of its efficiency and relatively strong performance compared to other algorithms, such as multiple regression, etc. (Eastman, 2005). The MLP is a form of a neural network that can take continuous and class variables as inputs and is not dependent on assumptions of normal data distributions.

We ran multiple models for each study area to get a general sense of performance and impacts of different type of data on drivers. We tried excluding different individual drivers or sets of drivers. Among the seven sites, we found that the data in the form of polygons almost always led to results with conspicuous artifacts. These were both in the form of sharp changes in the values of potential along boundaries of polygons. Also, subtle differences among polygons had exaggerated impacts on the resulting discrete maps of predicted deforestation. I n general, we found that the model, especially the discrete predictions of locations of deforestation, were highly sensitive to the class variables. Because of this, our final models excluded all polygon-type class variables other than protected areas. The latter was kept since this data layer yielded realistic impacts on outputs, considering the trends in deforestation rates in protected versus non-protected land evidenced by the historical deforestation maps. As a result, the most important socio-economic parameter used as an input to the final models is the distance to communities stratified by level of marginalization.

With the selection of final models, we have outputs of estimates of the potential for deforestation. To create maps of discrete locations of predicted deforestation, we required a source for the total rate of each reference area. We used the rates derived from the national models within each reference area. The rate for the reference region is then applied to the value of potential generated by the LCM model, assigning deforestation to the highest potential cells until the total change area obtained from the national model is reached. We did this for three different scenarios: the alternative (Poisson) regression model of the "business-as-usual" or non-REDD+ scenario (Alternative BAU), the rate from the preferred (negative-binomial) model of the non-REDD+ scenario (Preferred BAU), and the rate from the preferred model of the REDD+ scenario (Preferred BAU). Models were run to simulate deforestation from 2012 through 2022 and outputs were tabulated for each site and each reference area.

5.3. Results

5.3.1. Deforestation since 2000

Deforestation, as defined by a 25% threshold applied to the UMD forest cover in 2000 and yearly tree cover loss since then, has been significant in most sites, especially the Yucatán site. Forest cover in 2000 and aggregated deforestation from 2000 to 2012 are reported in Table 4.2. Annualized rates are highly variable among sites. Two sites, Comunidades Forestales de Oaxaca Mixteca and Sierra Raramuri, have rates near zero. Two other sites, Comunidades Forestales de Oaxaca Istmo and Sierra Pucc los Chenes have relatively high rates that in areas approach 0.5 percent per year. In most cases *ejidos* had higher deforestation rates than the rest of the local reference area, however in Sierra

Rairumi protected areas category had the highest rate, and in sierra Pucc los Chenes the AATR had the highest rate.

Patterns of historical deforestation are shown in Maps A-25 through A-31 in the Appendix. In all the figures, forest cover is defined by a 25% threshold applied to the Hansen, et al. (2014) data, and deforestation is a sum of all loss data within that defined forest area.

Table 5.3.1. Summary of forest cover in 2000 and deforestation from 2000 to 2012 among AATRs.

	Total land area (ha)	Forest area, 2000 (ha)	Forested fraction (2000)	Forest area, 2012 (ha)	Defor 00-12 (ha/yr)	Defor 00-12 (%/yr)
Comunidades Forestales de Oaxaca Istmo						
AATR site	265,382	213,844	0.81	206,217	636	0.30%
Land-use: Ejidos	784,033	383,469	0.49	362,324	1,762	0.46%
Land-use: Comunidades	1,755,724	1,334,791	0.76	1,308,087	2,225	0.17%
Land-use: Protected Areas (federal)	na	na	na	na	na	na
Comunidades_ Forestales de Oaxaca Mixteca						
AATR site	471,624	203,659	0.43	203,555	9	0.00%
Land-use: Ejidos	1,090,966	418,825	0.38	415,866	247	0.06%
Land-use: Comunidades	2,696,932	1,148,990	0.43	1,145,713	273	0.02%
Land-use: Protected Areas (federal)	435,452	67,044	0.15	67,021	2	0.00%
Comunidades Forestales de Oaxaca Sierra Norte						
AATR site	417,588	386,522	0.93	383,997	210	0.05%
Land-use: Ejidos	903,043	402,775	0.45	389,478	1,108	0.28%
Land-use: Comunidades	1,932,267	1,253,583	0.65	1,237,395	1,349	0.11%
Land-use: Protected Areas (federal)	187,212	55,597	0.30	55,456	12	0.02%
Cuencas Interiores de la Sierra de Chiapas						
Reference region	4,897,982	3,014,625	0.62	2,966,421	4,017	0.13%
AATR site	1,058,629	611,574	0.58	606,088	457	0.07%
Land-use: Ejidos	1,975,301	1,174,757	0.59	1,157,540	1,435	0.12%
Land-use: Comunidades	775,639	637,955	0.82	630,996	580	0.09%
Land-use: Protected Areas (federal)	639,767	526,698	0.82	523,044	304	0.06%
Cutzamala Valle de Bravo						
Reference region	3,008,360	1,011,168	0.34	1,007,582	299	0.03%
AATR site	263,333	117,204	0.45	116,480	60	0.05%
Land-use: Ejidos	1,219,455	320,089	0.26	319,202	74	0.02%
Land-use: Comunidades	229,479	111,390	0.49	110,940	38	0.03%
Land-use: Protected Areas (federal)	273,411	151,909	0.56	150,921	82	0.05%

Sierra Pucc Los Chenes						
AATR site	1,535	1,429	0.93	1,332	8	0.57%
Land-use: Ejidos	7,109	6,480	0.91	6,091	32	0.50%
Land-use: Comunidades	1	1	0.59	1	0	0.55%
Land-use: Protected Areas (federal)	1,608	1,252	0.78	1,241	1	0.08%
Sierra Raramuri						
AATR site	1,883,875	984,941	0.52	984,242	58	0.01%
Land-use: Ejidos	5,933,054	2,783,030	0.47	2,776,926	509	0.02%
Land-use: Comunidades	1,560,860	871,818	0.56	870,021	150	0.02%
Land-use: Protected Areas (federal)	70,206	47,239	0.67	46,935	25	0.05%

Note: Forest cover is defined by a 25% threshold applied to the Hansen, et al (2014) data, and deforestation is a sum of all loss data within that defined forest area. Note that deforestation values differ from those in the global analysis since the historical-deforestation maps were filtered for the local analysis. The filtering removed any patches of forest, non-forest or deforestation for a given time period smaller than one hectare.

5.3.2.Modeled deforestation beyond 2012

We ran multiple models with different combinations of driver variables. Among these, the generally consistent result was that the best performing models were the ones using all 15 input variables. Also, we found that the inclusion of distance to a non-forested edge did not improve models. This parameter tended to lead to an over-fitting of deforestation along existing edges, and exclusion of this parameter did not result in un-realistically remote deforestation in the model outputs.

Thus, our final models all were based on the MLP models using all inputs except distance to a non-forested edge. Finally, MLP randomly selects “seed cells” to begin model calibration, and model outputs may vary modestly in a random manner depending on the selection of these seeds. Thus, we report two model iterations for each final model. We applied the sensitivity analysis included in IDRISI’s MLP tool to estimate the relative importance of different input variables. Importance values are reported in Table 5.3.2.

Input variables most important to the model varied among the study areas. Distance to mega-cities was highly important for the study areas where they occurred, Cutzamala Valle de Bravo and Sierra Raramuri. For regions that are exemplary of frontier areas, accessibility, i.e. distance to roads, trails and rivers, was most important. For regions that are exemplary of heavily-fragmented forest, biophysical variables, e.g. slope, were most important. There was overall no consistent trend on the importance of the variable distance to highly-marginalized villages. In some areas sites near highly-marginalized villages had higher deforestation rates while in other areas the trend was reversed. In all but one study area, including distance to non-forest land increased model skill. Only Cutzamala Valle de Bravo, which is highly fragmented forest, didn’t have this effect.

Table 5.3.2. Relative importance of the different driver variables for models run in each of the local study areas. See Table 5.3.1 for the list of variables.

Region	Model Run	var1 Dist. hi marginalized villages	var2 Dist. low margin. villages	var3 Dist. medium margin. villages	var4 Dist primary road	var5 Dist. railroad	var6 Dist. rivers	var7 Dist. Secondary road	var8 Dist. small/ medium cities	var9 Dist. trail	var10 Elev 30 30m	var11 Slope 30m	var12 Pop density	var13 Protected areas dummy	var14 Dist nonforest: 2006	var15 Dist Megacities	Skill
Comunidades Forestales de Oaxaca (Istmo)	MLP run 1	12	8	5	10	1	13	2	3	9	4	7	11	n/a	6	n/a	**0.4935**
	MLP run 2	11	7	13	4	3	8	6	1	9	12	5	10	n/a	2	n/a	**0.5348**
	MLP run w/o dist. to non-forest	8	10	5	9	2	11	3	1	6	4	7	12	n/a	n/a	n/a	**0.4931**
Comunidades Forestales de Oaxaca (Mixteca)	MLP run 1	11	4	13	8	5	14	7	3	2	1	12	10	12	9	n/a	**0.7419**
	MLP run 2	13	4	10	11	5	9	7	2	3	1	14	12	14	8	n/a	**0.7405**
	MLP run without distance to non-forest	11	4	12	8	6	7	13	2	3	1	10	9	10	n/a	n/a	**0.6802**
Comunidades Forestales de Oaxaca (Sierra Norte)	MLP run 1	14	6	7	2	5	13	11	5	10	1	3	8	12	4	n/a	**0.5593**
	MLP run 2	14	5	13	2	5	12	8	6	10	4	3	7	9	1	n/a	**0.5958**
	MLP run w/o dist. to non-forest	13	5	4	3	6	7	11	8	12	1	2	10	9	n/a	n/a	**0.5351**
Cuencas Interiores de la Sierra de Chiapas	MLP run 1	13	5	9	6	3	10	12	4	11	2	1	13	7	8	n/a	**0.4124**
	MLP run 2	11	14	7	10	6	13	8	4	12	2	1	9	3	5	n/a	**0.4504**
	MLP run w/o dist. to non-forest	12	4	8	5	3	13	10	6	9	2	1	11	7	n/a	n/a	**0.4006**
Cutzamala Valle de Bravo	MLP run 1	8	6	10	9	12	7	3	4	15	2	13	14	5	11	1	**0.6282**
	MLP run 2	6	5	15	10	13	8	3	4	14	2	11	12	9	7	1	**0.677**
	MLP run w/o dist. to non-forest	9	7	11	6	10	8	2	5	13	4	12	14	3	n/a	1	**0.71**

Sierra Pucc Los Chenes	MLP run 1	9	11	10	4	2	12	8	3	7	14	6	5		13	1	n/a	**0.5661**
	MLP run 2	9	2	14	3	11	4	5	5	10	12	7	6		13	1	n/a	**0.5715**
	MLP run w/o dist. to non-forest	6	2	1	8	5	3	13	7	9	4	12	11		10	n/a	n/a	**0.3906**
Sierra Raramuri	MLP run 1	13	12	5	14	6	8	7	2	9	1	4	n/a		11	10	3	**0.6178**
	MLP run 2	14	12	5	13	9	8	11	2	7	1	4	n/a		10	6	3	**0.6115**
	MLP run w/o dist. to non-forest	11	10	6	7	8	9	5	3	12	1	4	n/a		13	n/a	2	**0.6224**

Note: Low numerical values indicate higher importance levels, i.e. these are rank scores. The most important three variables for each model are highlighted in yellow.

5.4. Predicting deforestation in the future:

The patterns of potential for deforestation varied among the sites, although are understandable given the differing importance of driver variables in the different study areas. It is thus useful to refer to Table 5.3.2 when interpreting the patterns of potential. Maps of potential deforestation or “soft” deforestation transition potential are shown in the maps in figures 5.4.1b-5.4.7b below. One also sees that there is more information in these maps than the hard classifications shown above each map (5.4.1a-5.4.7a), and one can interpret the patterns of relative potential beyond considering only the sites of strictly greatest potential, as is the case in the hard classifications presented later in this section.

The hard classification of future deforestation for each AATR was based on the transition potential surfaces created combined with the total rates for each reference region according the the different scenarios of the national models. These hard deforestation predictions are shown in maps in 5.4.1a-5.4.7a. The transition potential chosen for the final prediction were based on the models with the highest skill measure (shown in table 5.3.2). The rates of transition that were applied to the transition potential surfaces are shown below in Table 5.4.1, as well as the total amount of deforestation predicted for each reference region and AATR site. The quantity of deforestation predicted within each reference regions was based on the input rates shown below, and the allocation of the deforestation was determined by selecting the forest cells with the highest values in the transition potential surfaces created in LCM. This method for deforestation allocation has the advantage of being able to create thematic land-cover maps at the native resolution of the input dataset, however it also assumes that deforesting agent know which pixels are optimal for deforestation and therefore only the most highly vulnerable pixels will be transitioned.

Rates for transition were derived from both the observed historical rate in the LCM model and the modeled national rates from the national model. The transitions shown represent the total transitions from 2012 to 2022, and in the case of the national models, we present results for both a business as usual scenario (BAU) and REDD+ scenario assuming a $10/tC price. The historical rate from derived from 2000-2012 is also show and projected linearly to 2022, however, one should note that the historical rate cannot be directly compared with the modeled rates from the national model due in part to the filtering process that was used on the forest cover and deforestation data from Hansen et al. 2013. Therefore the historical rate is consistently lower than the BAU scenarios. The historical rates also do not take into account larger national trend which would have an effect on both the modeled rates and the future rates (see table 4.4.1). Therefore the historical rates are provided as context on how much deforestation might be predicted without the use of an external model, using the most simplistic approach. A more useful comparison for understanding the effect of national policy on the local models is the difference between the preferred (Negative Binomial) BAU scenario and the preferred (Negative Binomial) REDD scenario. Comparing the two negative binomial scenarios shows that at the reference region scale there were decreases between 23 – 58%, which is consistent with the national level predictions shown in Table 4.4.3.

At the AATR site scale the range is much more variation in the amount of deforestation predicted between 2012 and 2022. In the case of two AATR sites, Oaxaca Mixteca and Sierra Raramuri, there was no deforestation predicted within the site, regardless of the scenario. The reason that this was the case is due to the method which was used to assign change. As described above, because only the highest ranked pixels are transitioned and these sites have very low deforestation rates (ranging from 0.23% – 2.12% over the 10 year period). Similarly, the extremely high reduction in deforestation in the Oaxaca Sierra Norte AATR site can also be attributed to the method of allocation. In the case of these three AATR sites, REDD+ initiatives would have a minimal effect because the baseline rates under all scenarios are very low. The remaining four AATR sites observed a reduction in deforestation ranging from 20% - 67%, and in most cases these reductions were similar to those experience within the reference regions.

The hard classifications of predicted deforestation indicate different conclusions among the different study areas (Table 5.4.1). For example, for three study areas, Mixteca, Chiapas and Raramuri, both BAU models predicted rates of deforestation of over twice the historical rates. The remaining sites had predicted rates of within 50 percent of the historical rates. In almost all cases, modeled future rates for the BAU scenarios were greater than historical rates. Most of the predicted rates for the study areas were similar for both BAU models, although Chiapas and Valle Bravo models did produce quite different total rates.

One result common to all study areas was that the REDD scenario yielded lower rates than both BAU scenarios. This difference was up to two-fold for four of the seven areas. Valle Bravo had the smallest difference, and actually had a rate for the Poisson BAU scenario slightly lower than the REDD scenario. Likewise, in most cases the rates within the AATR sites were lower in the REDD scenario than in either BAU scenario. In Chiapas the REDD-scenario rate was close to the Poisson BAU rate and in Valle Bravo the REDD rate was slightly higher than the Poisson BAU rate. However, it is safest to compare the REDD scenario, based on the negative-binary model, with the similarly-modeled BAU scenario. For these, all REDD scenarios' rates were lower than those of the BAU scenarios, the percent reductions reported in the last column in Table 5.4.1. This is excluding the two cases with near-zero rates in any scenario within the AATR site, Mixteca and Raramuri.

Figures 5.4.1a-5.4.7.a show the patterns of deforestation from the hard classifications of the predictions. In these figures, red areas are places where the BAU model predicts deforestation while the REDD model does not; blue areas are where both models predict deforestation.

Two sites had close to zero historical deforestation and no deforestation in modeled scenarios, Mixteca and Raramuri. Oaxaca Sierra Norte and Sierra Chiapas do have deforestation that enters the AATR sites in both scenarios modeled, however the pattern is very disperse. At the scale of presentation in this report, these relatively small patches of deforestation do not appear. However, exploration of the full-resolution digital raster files of the model outputs will show deforestation inside these sites, especially in the lower valleys. The pattern of modeled deforestation in Cutzmala Valle Bravo is rather unique. All of the deforestation in the site is concentrated in one large patch. This pattern is suspicious, and of all the spatial models in this study, this one appears the most suspect and worthy of re-assessment.

The models for both the BAU and REDD scenarios for Oaxaca Istmo and Pucc predict relatively high rates of deforestation inside the AATR sites. In Oaxaca Istmo, this is almost entirely in the north-east of the site, from where the roads provide accessibility and the elevation nois favourable. In Pucc the predicted deforestation in both scenarios is greatest among all AATR sites. Predicted deforestation is also very well distributed thoughout the site. These sites stand out among the group both in terms of BAU deforestation and the potential for reductions in deforestation under REDD.

Table 5.4.1. Predicted deforestation from 2012-2022

	Deforestation per scenario 2012-2022				Decrease in deforestation between BAU and REDD (%)
	Historical Rate*	Alternative (BAU) 12-24	Preferred (BAU) 12-24	Preferred (REDD) 12-24	
AATR_RT 1 - Mixteca					
Reference region	0.36%	2.10%	2.12%	0.98%	
Gross Deforestation per RR, 2012-2022 (ha)	6,672	38,779	39,138	18,132	54%
Gross Deforestation in the site, 2012-2022 (ha)	-	-	-	-	0%
AATR_RT 2 - Sierra Norte					
Reference region	1.83%	1.94%	1.72%	0.72%	
Gross Deforestation per RR, 2012-2022 (ha)	42,428	44,938	39,787	16,699	58%
Gross Deforestation in the site, 2012-2022 (ha)	226	269	180	3	98%
AATR_RT 3 - Sierra Pucc					
Reference region	5.78%	8.50%	7.63%	5.01%	
Gross Deforestation per RR, 2012-2022 (ha)	448,446	659,371	591,949	388,716	34%
Gross Deforestation in the site, 2012-2022 (ha)	101,249	140,439	128,215	89,539	30%
AATR_RT 4 - Chiapas					
Reference region	1.60%	4.40%	7.83%	3.90%	
Gross Deforestation per RR, 2012-2022 (ha)	47,433	130,466	232,207	115,629	50%
Gross Deforestation in the site, 2012-2022 (ha)	5,101	22,180	43,245	19,139	56%
AATR_RT 5 - Raramuri					
Reference region	0.23%	0.58%	0.57%	0.38%	
Gross Deforestation per RR, 2012-2022 (ha)	996	2,510	2,493	1,628	35%
Gross Deforestation in the site, 2012-2022 (ha)	-	-	-	-	0%
AATR_RT 6 - Valle de Bravo					
Reference region	0.35%	0.39%	0.52%	0.40%	
Gross Deforestation per RR, 2012-2022 (ha)	3,573	3,963	5,219	4,032	23%
Gross Deforestation in the site, 2012-2022 (ha)	2,223	2,441	3,087	2,481	20%
AATR_RT 7 - Itsmo					
Reference region	3.13%	4.57%	4.19%	2.10%	
Gross Deforestation per RR, 2012-2022 (ha)	73,122	106,819	97,975	49,128	50%
Gross Deforestation in the site, 2012-2022 (ha)	3,779	6,429	5,729	1,912	67%

Note: All rates are gross over the 10 year period, percent where indicated otherwise hectares. Alternative (BAU) is the rate of deforestation from the alternative (negative binomial) regression model of the "business-as-usual" or non-REDD+ scenario; Preferred (BAU) is the rate from the preferred (negative binomial) model of the non-REDD+ scenario; Preferred (REDD) is the rate from the preferred model of the REDD+ scenario. Note that historical deforestation values differ from those in the global analysis since the historical-deforestation maps were filtered for the local analysis. The filtering removed any patches of forest, non-forest or deforestation for a given time period smaller than one hectare.

Figure 5.4.1a. "Hard" prediction of deforestation, 2012-2022, Oaxaca Istmo. AATR site highlighted in yellow thatching. The red areas indicate the predicted deforestation that would occur in a business-as-usual scenario, while the blue area is the deforestation that would occur with a $10/tCO$_2$ carbon incentive. Areas that are blue are deforested under both scenarios. Yellow areas are non-forest and black areas fall outside the boundary of the reference region.

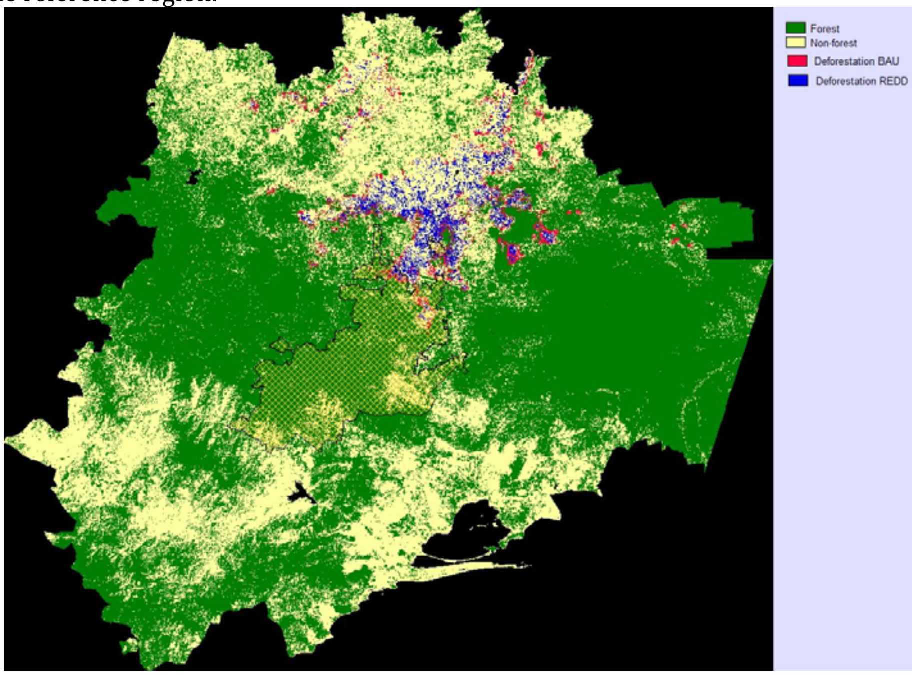


Figure 5.4.2b. "Soft" transition potential surface, Oaxaca Istmo AATR site and reference region. Areas in blue represent lower transition potential, or areas less likely to transition, and areas in red indicate high transition potential, or areas more likely to transition. Black areas are non-forest or fall outside the boundary of the reference region.

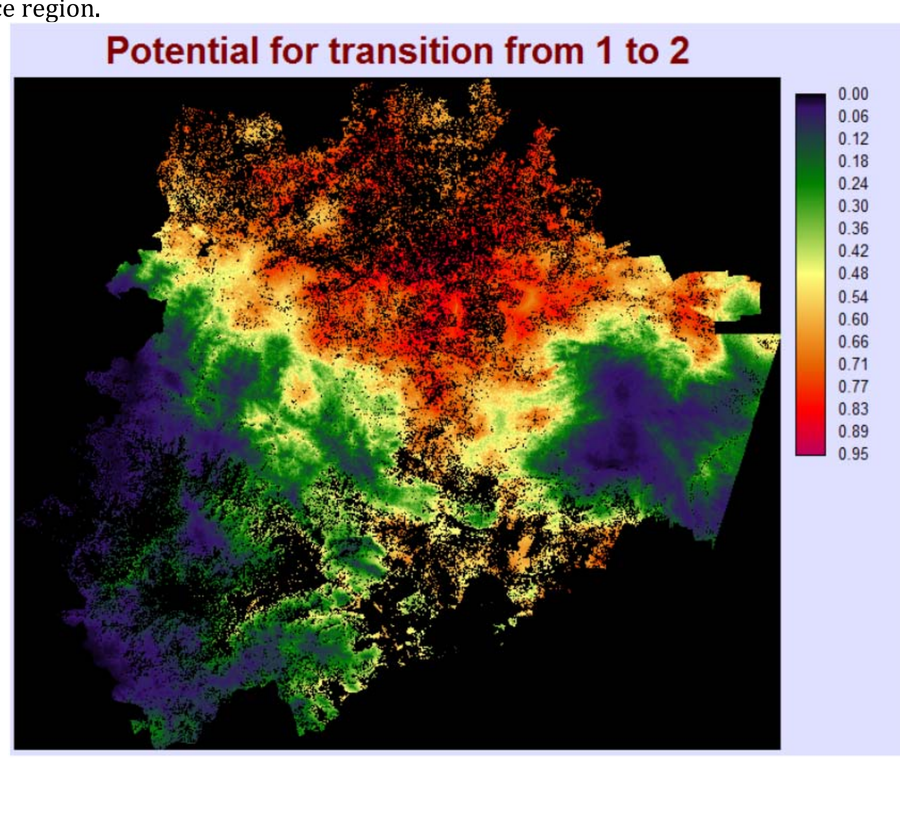


Figure 5.4.3a. "Hard" prediction of deforestation, 2012-2022, Oaxaca Mixteca. AATR site highlighted in yellow thatching. The red areas indicate the predicted deforestation that would occur in a business-as-usual scenario, while the blue area is the deforestation that would occur with a $10/tCO$_2$ carbon incentive. Areas that are blue are deforested under both scenarios. Yellow areas are non-forest and black areas fall outside the boundary of the reference region.

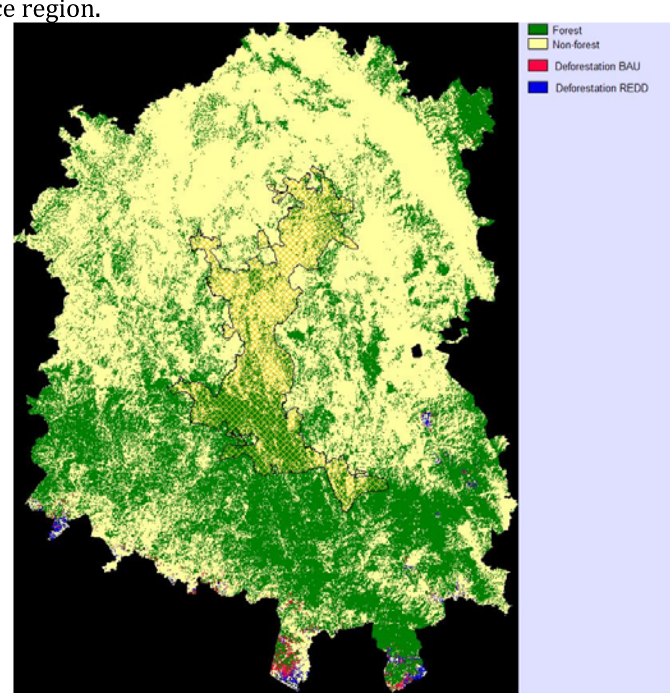


Figure 5.4.2b. "Soft" transition potential surface, Oaxaca Mixteca AATR site and reference region. Areas in blue represent lower transition potential, or areas less likely to transition, and areas in red indicate high transition potential, or areas more likely to transition. Black areas are non-forest or fall outside the boundary of the reference region.

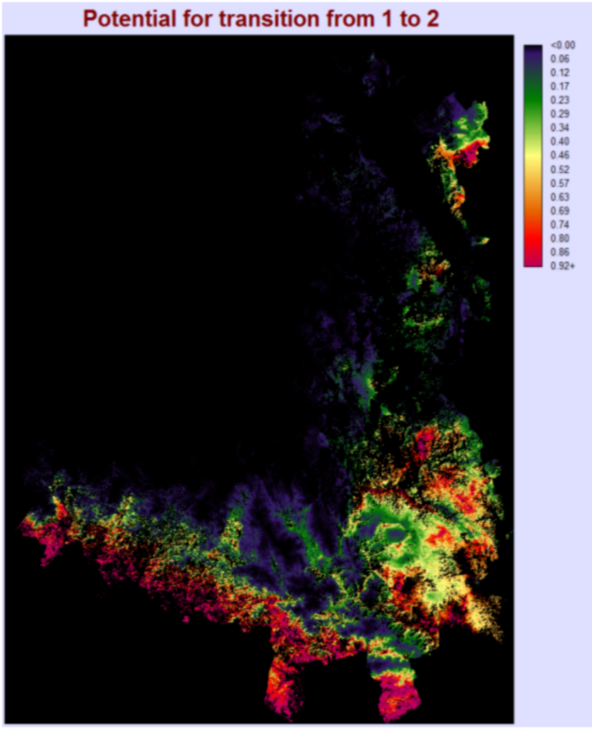


Figure 5.4.4a. "Hard" prediction of deforestation, 2012-2022, Oaxaca Sierra Norte. AATR site highlighted in yellow thatching. The red areas indicate the predicted deforestation that would occur in a business-as-usual scenario, while the blue area is the deforestation that would occur with a $10/t$CO_2$ carbon incentive. Areas that are blue are deforested under both scenarios. Yellow areas are non-forest and black areas fall outside the boundary of the reference region.

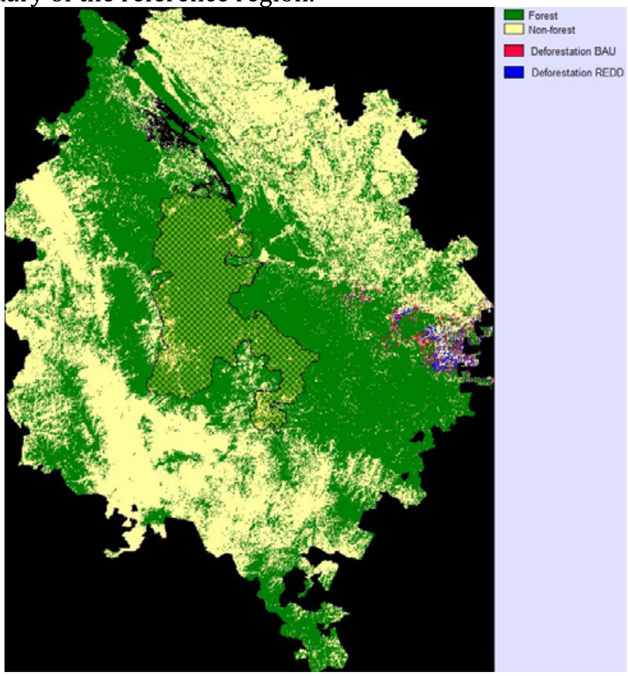


Figure 5.4.3b. "Soft" transition potential surface, Oaxaca Sierra Norte AATR site and reference region. Areas in blue represent lower transition potential, or areas less likely to transition, and areas in red indicate high transition potential, or areas more likely to transition. Black areas are non-forest or fall outside the boundary of the reference region.

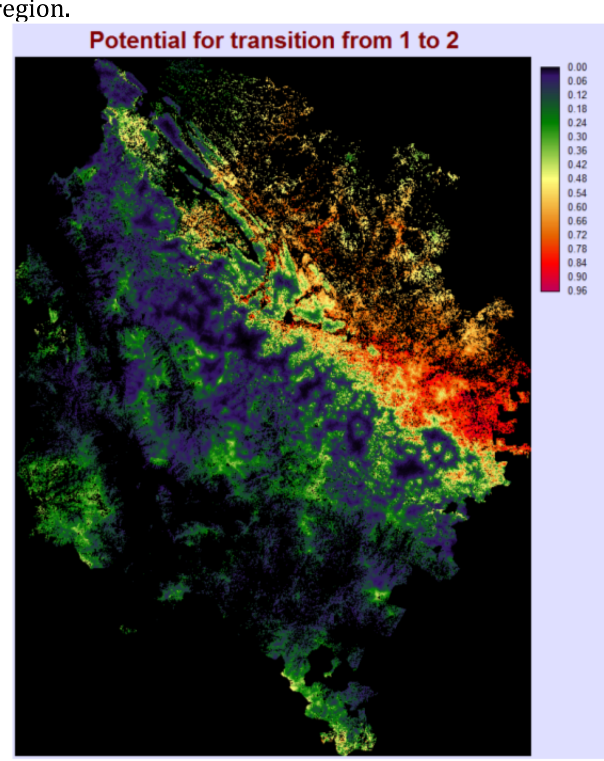


Figure 5.4.5a. "Hard" prediction of deforestation, 2012-2022, Sierra Chiapas. AATR site highlighted in yellow thatching. The red areas indicate the predicted deforestation that would occur in a business-as-usual scenario, while the blue area is the deforestation that would occur with a $10/tCO_2$ carbon incentive. Areas that are blue are deforested under both scenarios. Yellow areas are non-forest and black areas fall outside the boundary of the reference region.

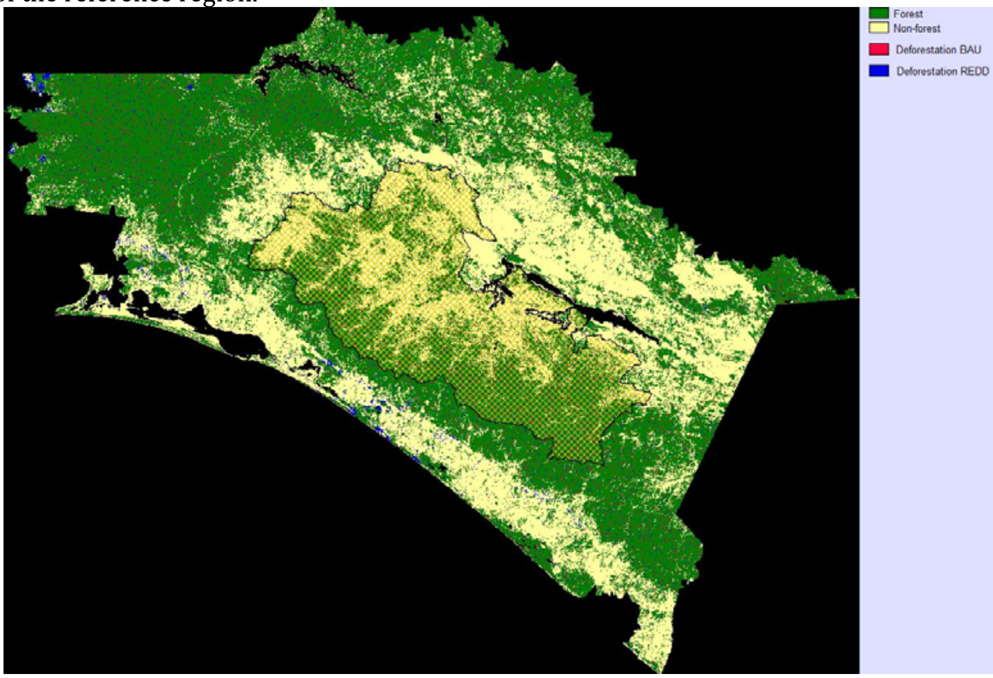


Figure 5.4.4b. "Soft" transition potential surface, Sierra Chiapas site and reference region. Areas in blue represent lower transition potential, or areas less likely to transition, and areas in red indicate high transition potential, or areas more likely to transition. Black areas are non-forest or fall outside the boundary of the reference region.

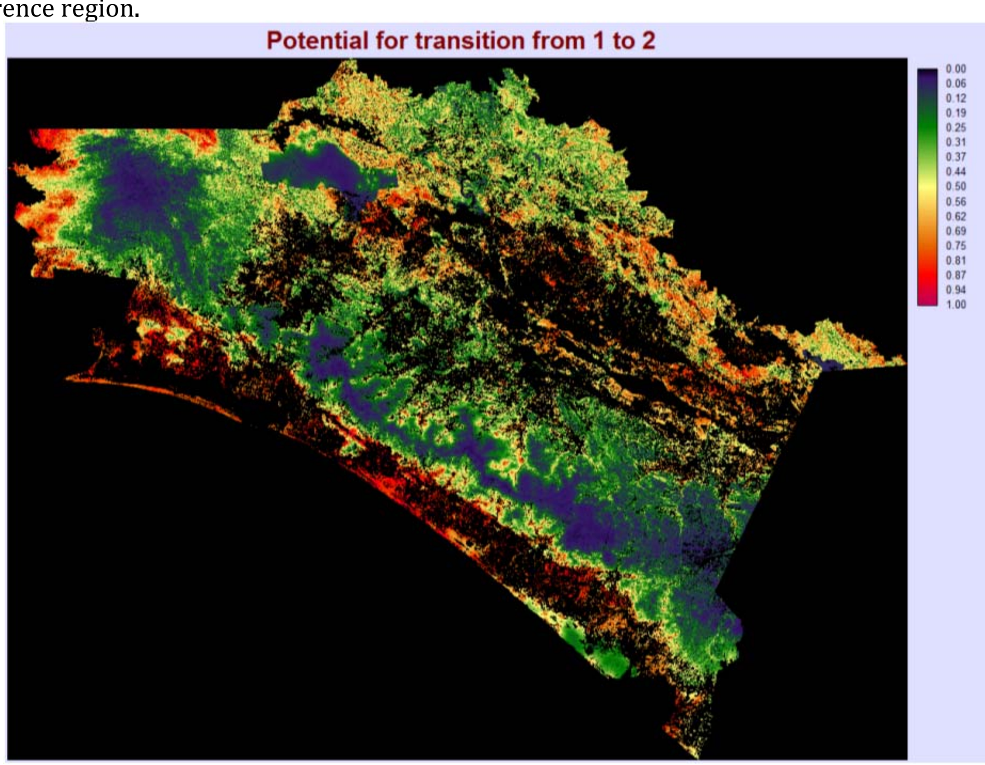


Figure 5.4.6a."Hard" prediction of deforestation, 2012-2022, Cutzmala Valle Bravo. AATR site highlighted in yellow thatching. The red areas indicate the predicted deforestation that would occur in a business-as-usual scenario, while the blue area is the deforestation that would occur with a \$10/tCO_2 carbon incentive. Areas that are blue are deforested under both scenarios. Yellow areas are non-forest and black areas fall outside the boundary of the reference region.

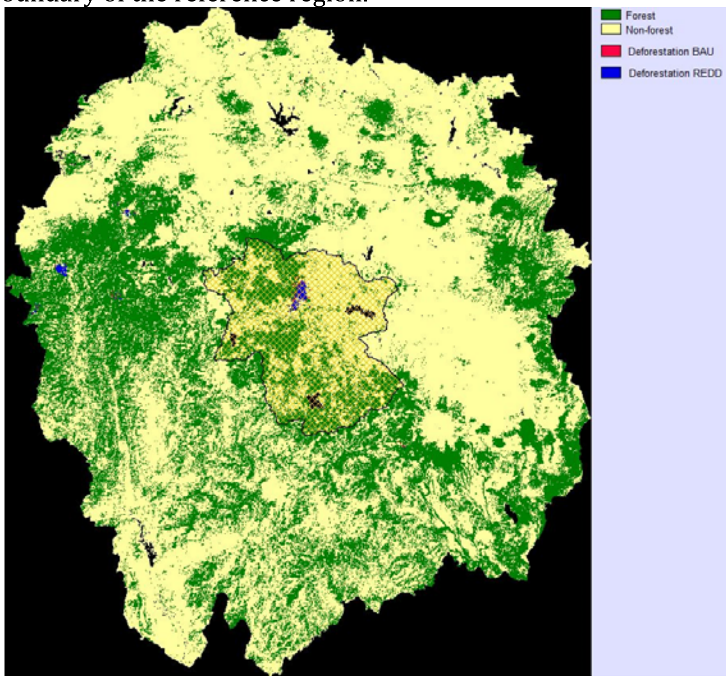


Figure 5.4.5b. "Soft" transition potential surface, Cutzmala Valle Bravo AATR site and reference region. Areas in blue represent lower transition potential, or areas less likely to transition, and areas in red indicate high transition potential, or areas more likely to transition. Black areas are non-forest or fall outside the boundary of the reference region.

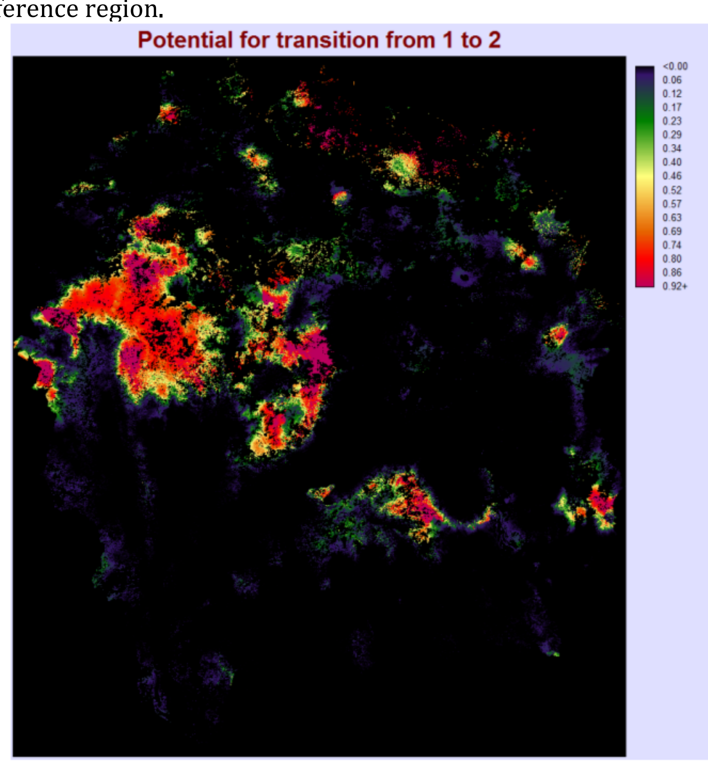


Figure 5.4.7a. "Hard" prediction of deforestation, 2012-2022, Sierra PUCC. AATR highlight in yellow thatching. The red areas indicate the predicted deforestation that would occur in a business-as-usual scenario, while the blue area is the deforestation that would occur with a \$10/tCO_2 carbon incentive. Areas that are blue are deforested under both scenarios. Yellow areas are non-forest and black areas fall outside the boundary of the reference region.

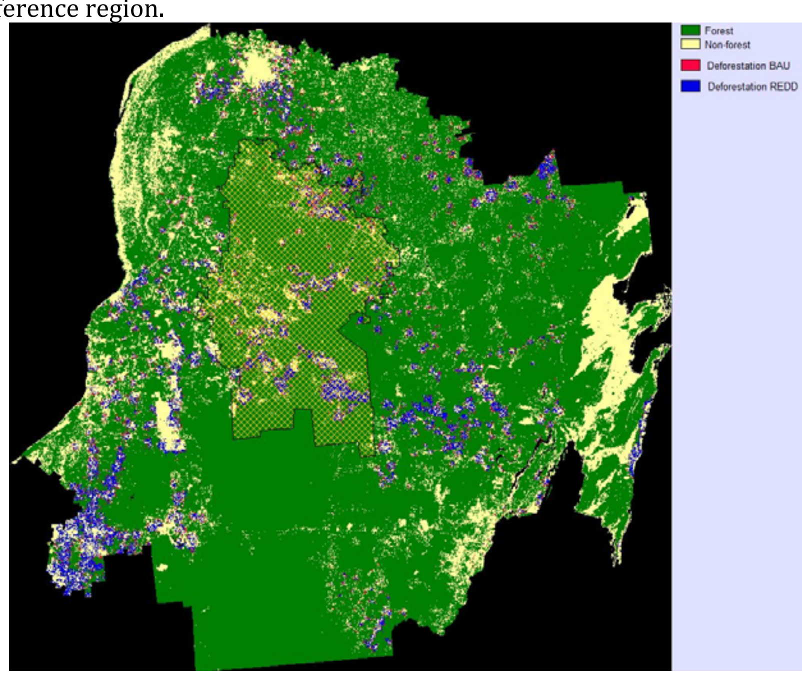


Figure 5.4.6b. "Soft" transition potential surface, Sierra PUCC site and reference region. Areas in blue represent lower transition potential, or areas less likely to transition, and areas in red indicate high transition potential, or areas more likely to transition. Black areas are non-forest or fall outside the boundary of the reference region.

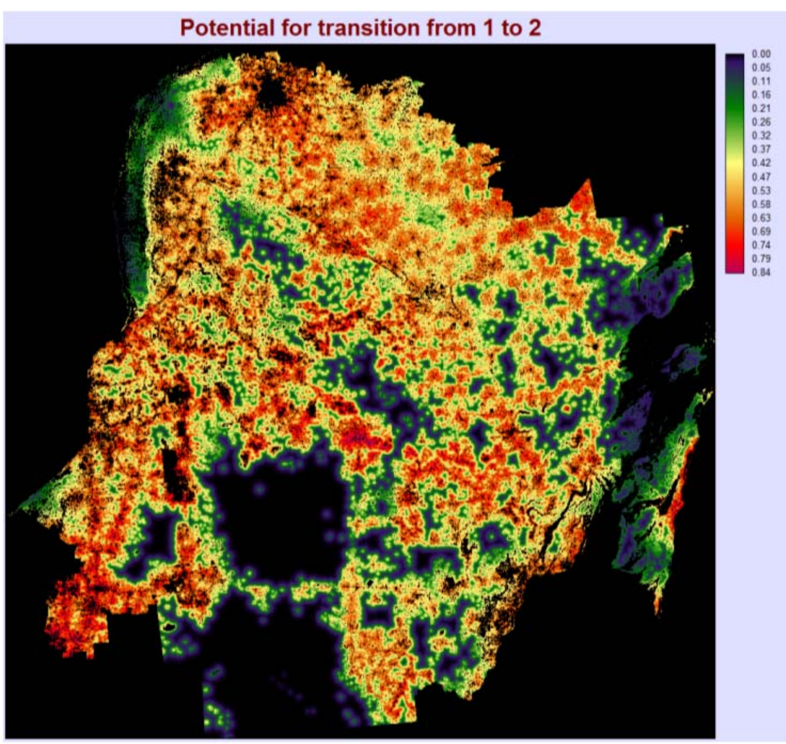


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Figure 5.4.8a. "Hard" prediction of deforestation, 2012-2022, Sierra Raramuri. AATR site highlight in yellow thatch. The red areas indicate the predicted deforestation that would occur in a business-as-usual scenario, while the blue area is the deforestation that would occur with a \$10/tCO_2 carbon incentive. Areas that are blue are deforested under both scenarios. Yellow areas are non-forest and black areas fall outside the boundary of the reference region.

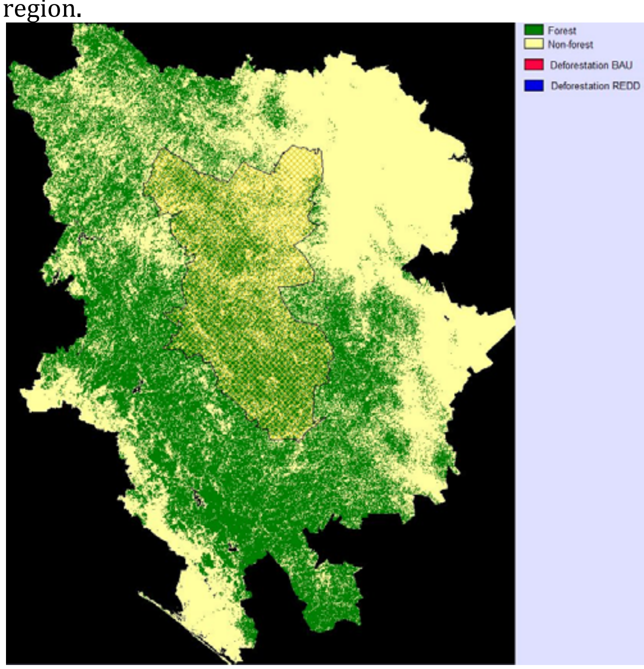
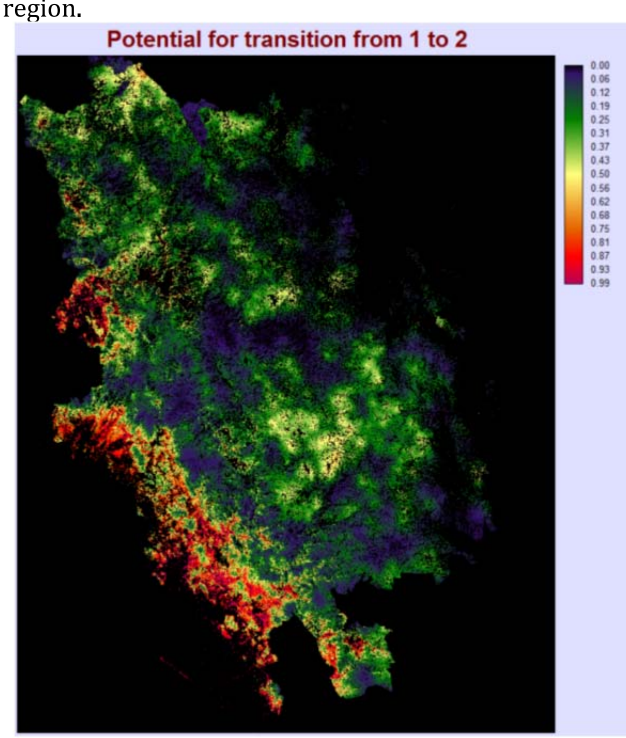


Figure 5.4.7b. "Soft" transition potential surface, Sierra Raramuri. AATR site and reference region. Areas in blue represent lower transition potential, or areas less likely to transition, and areas in red indicate high transition potential, or areas more likely to transition. Black areas are non-forest or fall outside the boundary of the reference region.



5.5. Conclusions

Among the local regions studied, deforestation is of greatest concern in Sierra Pucc Los Chenes, then followed by Oaxaca Istmo, Oaxaca Sierra Norte and Sierra Chiapas. The remaining regions had very low annual deforestation rates during 2000 through 2012. Sierra Pucc Los Chenes is of further note because within this region the percent deforestation rate was greatest inside the AATRs.

In the regions with relatively high deforestation rates, deforestation was not as locally concentrated as is often found in other areas. The deforestation patterns in Oaxaca Istmo, Oaxaca Sierra Norte and Sierra Chiapas were mostly in a sub-region, although quite spread throughout the sub-region as opposed to very concentrated around towns and major roads. In Sierra Pucc Los Chenes, deforestation was spread over most of the study region.

Land-use designations such as e*jidos* and *comunidades* were not included in the final models. However when tested they did have a large impact on the transition potential surfaces. The effects of individual e*jidos* and *comunidades* varied a lot both between sites and within sites. In some cases e*jidos* would reduce the likelihood of deforestation and in other cases they would greatly increase the likelihood. This is an indication that individual land-use and economic decisions at the e*jido* or *comunidades* level may have a strong influence on patterns of deforestation. However, further research would be required to fully explore these relationships and perhaps group e*jido* or *comunidades* based on their land-use practices.

These patterns of historical deforestation point MREDD Alliance partners to areas where further exploration may be warranted. First, we re-note that the definition of forest and the manner in which the forest 2000 benchmark was defined is significant. Much of the deforestation we see may actually be the re-clearance of fallows and / or plantations, rather than clearing of mature forest. How much deforestation in these areas is actually that of mature forest could be assessed several ways. First, one could conduct a visual qualitative assessment. This could be by superimposing the deforestation sites over the reflectance mosaic for 2000 from UMD. This could be done online via the UMD-Google site, or locally if files are downloaded.

Second, a map of a best estimate of the distribution of mature forest in 2000 could be combined with the deforestation data in a GIS. This could be one of several a national vegetation map, although that map itself should be assessed visually with the Landsat mosaic, since many national forest cover maps also have most fallows combined into the forest class. For the Chiapas and Yucutan sites, as well as another other sites of interest within the five southern states of Mexico, the Conservation International (CI) deforestation map could be used. This map reports deforestation for three dates, including 2000 (Vaca et al. 2005). The 2000 forest cover estimate could be used as an example benchmark map for thus evaluation, and CI and partners attempted to minimize any inclusion of fallows or plantations in its mature forest class.

Even though our forest definition and benchmark map include secondary forests and plantations, the patterns of tree-cover loss among these cover types plus forest are revealing. The findings may be interpreted as revealing both mature forest clearance and a form of agricultural intensification, via fallow clearing, that is often associated with the same land-use pressures that are linked to mature forest clearing.

On the models, one should interpret both the map of deforestation potential and the hard classification of predicted deforestation. The former can be seen as a distribution of the relative potential for deforestation, not too dissimilar to the continuous deforestation likelihood maps output from the national analysis. The latter is strictly the cells of greatest potential that add up to the area of deforestation predicted for the study region by the national model.

Our recommendation is to follow up this analysis with a second pass that attempts to stratify historical deforestation into that of mature forest versus other cover types. If done, the spatial models could be re-run efficiently, especially since the modeling datasets are organized and ready for additional iterations. If done, one could consider characterizing deforestation for specific land uses, however information on those would be derived from remote sensing products, rather they would need to be based on expert opinion and ancillary data.

Finally, municipal level variables, such as agricultural yield and evidence likelihood were not included in the LCM model because they had an overly powerful effect on the models. These were the polygon-level variables that we note were excluded because of extreme model sensitivity in the methods section. Essentially, all of the predicted deforestation would locate into a single municipality. However, there may be real and strong effects of municipal-level deforestation at the sub-national level in Mexico. Further exploration into other ways to incorporate this information into the models is warranted.

For either these models or later iterations of models, there are several options for validation of them. One could calibrate each model with the deforestation patterns only through 2005 or 2010, for example, and predict deforestation through 2012. The resulting distribution of deforestation would then be compared to observed deforestation in the UMD product. This is the most common approach to validation recommended in VCS-approved methods.

There are other aspects of the VCS-approved methods that we find problematic and recommend considering altering. First, the several VCS methods recommend using statistic that is calculated at the cell level is fine if the goal of a model is to predict deforestation at that level. However, that is usually not the goal. For example, if one cell is predicted as deforestation, and the actual deforestation map does not show change in that exact cell but does show change in a neighbouring cell, then the statistic would imply that the model has zero accuracy. This is why a "successful" model according to this statistic is one that has an accuracy of five percent or more. While of academic interest to model developers interested in performance at the cell level, it is difficult to accept this as logical for REDD+ projects or most regional-level applications.

For this study, and for all REDD+ projects, the question of interest is whether models predict accurately deforestation for certain management or study units, such as proposed REDD+ sites, leakage zones, political districts, etc. These units are represented by polygons, and thus the comparison should be made at the polygon level or at a scale similar to the polygons of interest. Once this is understood, there are several statistics that could be used to validation models at the polygon level.

Second, VCS-approved methods require producing the hard classification of predicted deforestation. This forces all deforestation into strictly the cells of highest potential. While interesting, this is unrealistic and a form of over-fitting. The best evidence of the lack of realism of this approach is that the historical data themselves indicate that much deforestation occurs in sites that are of moderate deforestation. The national model does not suffer from this problem since it reports a continuous estimate of sub-pixel deforestation or deforestation likelihood. The same could be done with the local models that we have run by skipping the step of producing the hard classification of predicted deforestation. Instead, one can take the map of deforestation potential and rescale the values such that they add up to the defined regional rate predicted by the national model. This essentially produces a continuous sub-cell deforestation output. These can then be summed for any set of polygons and compared to the polygon-level rates derived from observed deforestation in order to validate models.

6. Conclusion

6.1. Summary of report findings and directions for future research

We conducted a series of analyses that combine both national and local scale modeling to aid the MREDD Alliance partners in assessing the vulnerability of Mexico's forests to deforestation. These analyses focus on the vulnerability of forested lands within Mexico's AATRs, accounting for Mexico's unique forest management dynamics through disaggregating the results by land ownership types. These analyses are ultimately meant to inform national and subnational policy, paving the way for incentive based programs, and ultimately reduced deforestation vulnerability in Mexico. Our methodology includes three different and complementary approaches: (i) reviewing the existing literature, (ii) a national econometric analysis and associated scenario simulation modeling, adapting the approach of the Open Source Impacts of REDD+ Incentives (OSIRIS) model and (iii) local-level spatial spatial modeling for each AATR, conducted using the IDRISI-Selva Land Change Modeler (LCM). Key findings from each of these three parts of the report are summarized below, along with some discussion of next steps for future research.

6.1.1. Literature review and meta-analysis

The literature review yielded insights based on an overview of deforestation as well as a meta-analysis on statistical studies of drivers of deforestation. The overview suggests that, while deforestation rates in Mexico have decreased, the trend persists, leading to more biodiversity loss, increased greenhouse gas emissions, and reduced subsistence opportunities for local populations. Land tenure (community land management, including *ejidos*), rural agricultural support, and payments for ecosystems services are major focuses of the literature. Conclusions on the role of the major land tenure type in Mexico, community land management, are mixed. Studies are also in disagreement on the role of such rural agricultural support programs as PROCAMPO. However most studies agree that payments for ecosystems services decrease deforestation risk, with some caveats related to regional differences and starting deforestation risk. These relationships were mirrored in the meta-analysis: regression results were mixed for *ejidos* and rural income support, while results for PES tended to be associated with decreased deforestation. Furthermore, results from the meta-analysis revealed other variables with consistent relationships to deforestation in Mexico. The variables most associated with reduced deforestation in Mexico were associated with protection measures (as proxied by protected areas and PES), reduced accessibility (elevation), reduced resource competition (property size) and community forestry. The variables most associated with increased deforestation were associated with areas where economic returns to agriculture are higher (proximity to agriculture and agriculture returns), biophysical conditions for conversion are favorable (soil suitability), and competition for resources are high (population). Most of these relationships were robust when results were disaggregated to the Yucatan Peninsula. Notably however, at the national level, poverty appears to be linked to increases in deforestation, while in the Yucatán Peninsula poverty is associated with decreased deforestation. Conversely, indigenous population is associated with decreased deforestation at the national level, but is associated with higher deforestation in the Yucatán Peninsula.

These discrepancies support the widely held view that Mexico's landscape and the related drivers of deforestation vary greatly by region. The inconsistencies also suggest further study of the dynamics and impact of certain variables on deforestation, including community forestry, land tenure type, indigenous populations, rural agricultural support, PES, and poverty. The negative relationship between community forestry and deforestation isn't intuitive; it invites further research into the sustainability and biodiversity retention of planted forests and their impact on primary adjacent forests over time. The mixed relationships of variables associated with community land management invite a deeper understanding of the qualitative differences between such land tenure types as *communidades* and *ejidos* at household and community levels, and how these differences impact local tree cover. The apparent regional discrepancy of indigenous populations' influence on tree cover at the national level and in the Yucatan Peninsula suggests a similar qualitative investigation. The caveats to PES highlighted by the literature and the mixed meta-analysis results for rural support programs highlight the need to understand the relationship between income and deforestation, prompting research into the advantages of tying support for rural incomes to the maintenance of forest resources in higher risk areas. The regional differences of the impact of poverty on deforestation suggest that perhaps deforestation cannot be directly attributed to poverty, highlighting the need to understand this dynamic within concurrent geographical or temporal trends simultaneously affecting deforestation.

6.1.2. National modeling

We statistically analyzed detailed spatially-explicit data on annual forest cover losses across all of Mexico over 2000-2012 in relation to variation in estimated gross agricultural revenues and proxies for fixed and variable costs using observable site characteristics. The goal was to capture the influence of the economic net benefits from converting land from forest to non-forest uses for the purposes of calibrating a policy-simulation model that can, for example, analyze the impact of different policy structures to create incentives for low-emissions practices for reducing deforestation.

We aggregate data from (Hansen, et al., 2013) to the 900m resolution and model deforestation in relation to variation in estimated gross agricultural revenues and proxies for fixed and variable costs using observable site characteristics. We quantify the effects of agricultural revenue on deforestation in Mexico based on historical data, and then simulate deforestation for alternative agricultural revenue scenarios for our study period (2001-2011). We further project future deforestation (2014-2023) under a business-as-usual scenario, based on 2012 conditions, and alternative carbon incentives for practices to reduce deforestation. The results from the simulation provide regional deforestation rates as an input to the LCM modeling of the seven AATRs.

The ultimate goal of this analysis is to help inform cost-effective policy approaches to reduce deforestation. To help achieve this goal, there are several future extensions of this research, including further model validation and exploring the implications of additional variables. The current analysis focused on the role of economic returns to crop production. Additional analyses would be needed to identify the specific role of different land ownership categories, such as different types of *ejidos* and other communal lands, as well as to explicitly identify the role of PROCAMPO, as well as other agricultural and forestry development programs, along with the role of existing conservation incentives. With additional potential data, we also might be able to consider changes between forests and other land-uses beyond crop production. In terms of the carbon emissions reductions cost estimates, a priority is to extend the analysis to include below-ground carbon stocks, as well as further compare our estimates with other data sources. While this analysis considered only forest losses, an important extension would be to conduct an analysis of the data from UMD and other data sources on forest gains. This would provide a more complete picture of the forest and carbon dynamics in Mexico.

Also, with additional computational power, we could improve the spatial resolution and further refine the econometric estimation to further model the spatio-temporal processes driving deforestation. We could explicitly estimate and conduct simulations using a full fixed-effects model, as well as alternative spatial panel data models, which help control for unobserved variations that only exist between neighboring regions (or spatial autocorrelation), using spatial weighting matrix. These variations may not be controlled for with a non-spatial panel data model. Another extension would be to explicitly consider the dynamic decision-process based on survival modeling approaches. In addition, we can improve how we conduct simulations, updating the spatial pattern of the surrounding landscape at each time step.

In addition to possible extensions for the underlying analysis, a main priority for future research is to use the econometric estimation to calibrate a version of the Open Source Impacts of REDD+ Incentives (OSIRIS) model to analyze alternative REDD+ and agricultural policy scenarios in Mexico. This will require linking the econometric model to a general equilibrium model to account for possible price feedbacks, which could produce deforestation shifts or "leakage." This will also entail building an open-source interface that can make the model user-friendly and more broadly usable. These steps will enable more realistic examination of alternative policy designs for creating economic incentives for promoting low-emissions agricultural development and reducing deforestation in Mexico.

6.1.3.Local Modeling

The results of the deforestation prediction maps provides interesting useful information on areas most vulnerable to transition and the inclusion of the national model for determining the rate of transitions which account for national level policy decisions. The combination of the LCM and national model provides a significant improvement to using either model in isolation. One weakness of using the LCM in isolation is that the rate of deforestation is either solely based on the historical rates or based on subjective analyst opinion. Including deforestation rates derived from the national model provides a quantitative rational for picking a particular rate based on national and regional policy decisions. While using national model in isolation does not have the fine spatial resolution that would be necessary for local and site level analysis.

The combination of the two modeling approaches could be further strengthened by applying the same filtering and pre-processing methods. This was not done in this study as the two models were developed in parallel using the information most applicable for each individual approach. The cohesion of the models could also be improved by creating transition potentials at the reference region level and applying the rates from the national model at the AART scale, which could help to mitigate the uneven allocation of deforestation, which lead to no predicted deforestation within 2 of the AATR sites.

A final consideration for strengthening the allocation of deforestation would be to use a continuous or non-discrete allocation of deforestation. Meaning that the deforestation would be allocated at a sub-pixel level, in which all pixels available for transition would be assigned a small amount of deforestation based on the relative value of that pixel. The disadvantage to this method is that map of predicted deforestation would not be as easily visualized. However the area estimates within AATRs or other land-use categories would be more likely to represent reality. This method requires further research, but provides an alternative to mitigating the uneven allocation of deforestation, especially in sites with low transition rates.

We stress that these model outputs cannot be used for reference emissions levels for projects. The discussion section indicates several of the issues that arise from using the sources of data and methods that we have used, and suggests some possible follow-up analyses that could be done as next steps to further explore the relative threats of deforestation among these sites. However, the model results provided here do strongly indicate several findings. First, some sites have very little historical deforestation and threat over the coming decade. Second, there is a consistent trend for reductions in deforestation rates among all sites if REDD were implemented at a $10 carbon price and with the other assumptions of the national OSIRIS REDD model. Third, the study indicates which sites likely have the highest maximum potential for emissions reductions. In terms of REDD potential, these two sites have the greatest if only considering the maximum emissions reductions obtainable, as both would have high reference emissions levels. For Oaxaca, an advantage may be that the work to reduce emissions can be conducted in a fairly small area and focussed on few communities or *ejidos*. In Sierra Pucc – Los Chenes, while the maximum reduction possible is greater, a REDD project would need to work over most of the site, which may prove much more costly and riskier.

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