Modeling the Opportunity Costs of Reducing Legal Deforestation and the Implications for Forest Policy in Mato Grosso, Brazil

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ABSTRACT: In recent decades, global society has paid growing attention to tropical deforestation as it contributes significantly to global warming. One promising way of addressing the issue is to create economic incentives to protect forests. In this study, we estimate the opportunity costs of reducing legal deforestation in Mato Grosso of Brazil, based on an econometric model using fine resolution spatial data and administrative data on properties registered in the rural land registry. We find that, inside the properties that have rights to legally clear forest area, most projected demand for deforestation will fit within the legal limitations, making it essential to establish additional positive economic incentives for forest protection. Also in these properties, for the period of 2014-2030, total incentives of about US$ 279 million could reduce 77% of projected legal deforestation, from 278,257 ha to 64,287 ha. Certain incentives could come from the properties with forest restoration requirements under Brazil's forest code, since we found that our modeled incentives can only cover about 7% of the forest restoration requirement in those properties through passive land abandonment. As a result, active reforestation or purchasing the Environmental Reserve Quota from properties with legal deforestation allowance may become attractive alternatives.

Key words: Tropical deforestation, Forest policy, Opportunity cost, Brazil

1. Introduction

Tropical deforestation contributes about 15% of annual global carbon emissions. Since Brazil has a third of the world's rainforests, it plays a pivotal role in the global effort of reducing deforestation. In general, agriculture is a major cause of deforestation. For example, rapid expansion of cattle pasture is the biggest driver of deforestation in Brazil, and beef demand is expected to rise due to inexorable growth in food demand, bringing bigger threats to forest in the future.

In recent decades, global society has paid growing attention to tropical deforestation. Article 5 of the Paris Agreement under the UN Framework Convention on Climate Change affirms the critical role of reducing tropical deforestation and forest degradation in climate mitigation. Domestically, in 1965, Brazil established the Forest Code (FC) which requires landowners to maintain certain portion of their property as forest, also called "Legal Reserve" (LR). In the revised FC approved in 2012, properties that had reduced their LR below the required levels before July 2008 are allowed to come into compliance either by restoring their forests to cover their LR deficit or by compensating for their deficit by purchasing Environmental Reserve Quotas (*cotas de reserve ambiental*; CRA) from properties with an LR surplus. The Brazilian federal and state governments are currently considering regulations for implementing the CRA market, which could potentially compensate for more than half of the LR debt (Soares-Filho et al. 2013), while creating incentives for reducing legal deforestation in properties with LR surplus. Significant policy design challenges include monitoring and enforcement as well as ensuring that properties selling CRAs are under threat of deforestation so as to ensure a net reduction in legal deforestation (May et al. 2015).

This study uses an econometric approach to estimate the incentives needed to achieve Mato Grosso's targets for reducing deforestation, focusing on the deforestation that is legally allowed by the FC and which thus cannot be reduced through law enforcement alone. Mato Grosso is the largest agricultural state in the Brazilian Amazon and accounted for about a third of deforestation in Amazon during the period of 1988-2014. In the last decade, the Brazilian Amazon has been able to reduce its deforestation by about 70% (Nepstad et al. 2014). During the period of 2006-2010, deforestation in Mato Grosso "decreased to 30% of its historical average (1996-2005)" (Macedo et al. 2011). However, it is important to maintain this trend. In Paris, the state of Mato Grosso announced its intention to develop its agricultural economy while ensuring no further loss of native forests through a strategy based on three pillars (Produce, Conserve and Include). This study contributes to the literature in conducting an economic analysis based on the empirical estimation of historical data, better capturing the spatial heterogeneity of opportunity costs and deforestation, and, potentially, modeling of necessary incentives to reduce legal deforestation. Stickler et al. (2013) estimated the economics costs of compliance with the FC for both opportunity costs of protecting forests and restoring forest cover in Mato Grosso. Our econometric approach extends parts of their study in several ways by using unique fine scale spatial data from remote sensing, combined with administrative information on land use at the property level. To the best of our knowledge, this is the first econometric study to exploit this level of spatial and temporal richness for deforestation determinants for this region.

2. Methodology

2.1. Empirical model

We use a “revealed preference” approach to estimate the opportunity cost of reducing deforestation from agricultural land use. The “revealed preference” approach examines historical evidence on actual land-use decisions to study how landowners have responded in reality to variations in the net economic benefits of converting land from forests to non-forest uses (e.g., Lubowski, Plantinga, and Stavins, 2006; Busch et al. 2012). In particular, we estimate an econometric model to obtain the historical relation between deforestation and the estimated net returns from using the land for agriculture, specified as follows:

$$\begin{aligned} Def_{it} &= \beta_0 + \beta_1 PRICE_{it} + \beta_2 TYPE_i + \beta_3 DIST_{it} + \beta_4 FCAT_{it} \\ &+ \delta_1 PRICE_{it} * FCAT_i + \delta_2 PRICE_{it} * TYPE_i + \delta_2 PRICE_{it} * DIST_{it} + \delta_3 FCAT_{it} * TYPE_i + \delta_4 FCAT_{it} * DIST_{it} \\ &+ \delta_5 PRICE_{it} * FCAT_i * TYPE_i + \delta_6 PRICE_{it} * FCAT_i * DIST_i + \phi year_t + \varepsilon_{ijt} \qquad (1) \end{aligned}$$

where Def_{it} is the number of one hectare (100×100 meter) pixels deforested annually between 2003 and 2013 within an aggregated 900×900 meter (0.81 km^2) grid cell in the state of Mato Grosso. $PRICE_{it}$ is our principle independent variable, representing the spatially-interpolated estimate of the potential agricultural land price for grid-cell *i* at year *t*. Land price is used in our study to approximate the potential economic return with agricultural activities, which are believed to be the major causes of deforestation.[1] Using the share of pasture and crop land area, we generate the area-weighted prices from both pasture and crop price for any specific locations in our study area.

[1] Net returns can be approximated by land rent. We use the land price in both econometric model and simulation part, but we use land rent when presenting the results. Land price should capture the capitalized value of the expected future stream of profits from use of that asset. Using a discount rate of 10%, land price is converted to an estimated land rent by dividing ten (Rajão, R. and Soares-Filho, B., 2015).

The net returns to agricultural activities are affected by other spatial factors, such as the legal designation of the land (conservation land, protected land, indigenous land and rural settlements) where different regulations affect the chance of deforestation, and slope, proximity to roads, railroad, cities, main rivers, starting amount of forests within a grid cell, and the distance from forest to the nearest nonforest area which capture the actual costs of deforesting the land as well as the price of agricultural outputs and inputs (e.g., distance from cities as a proxy for transportation costs, distance from non-forest areas as a proxy for land conversion costs, etc.).[2] We include these spatial factors that help capture finer scale variation in the net returns to agriculture not captured by our aggregate measure of the land price (principle independent variable). In the above model, $TYPE_i$ represents several variables for different land types, such as conservation land, protected land, indigenous land, rural settlements. $DIST_{it}$ represents the distance of a specific site to the nearest town, river, road, railroad. The "forest category" $FCAT_{it}$ is the starting amount of forests within a grid cell in the beginning of the year. We include this term as a proxy for conversion costs given that as more areas are cleared within a grid cell, the remaining areas become exposed and potentially less costly to deforest (Lubowski et al. 2014). These control variables, as shown in equation (1), are also included in two-way interaction terms with land price and forest category, and three-way interaction terms with land price and forest category, so as to better capture the response of deforestation to spatially-explicit differences in the net returns to agricultural land use. We also include a year trend to capture global deforestation changes in Mato Grosso over time. $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \delta_1, \delta_2, \delta_3, \delta_4, \delta_5, \delta_6$ and ϕ are parameters to be estimated. ε_{ijt} denotes the error term.

[2] Due to the limitation of the pages, please see Lubowski et al. (2014) for full explanation of the logic of using these variables.

For our dependent variable, the maximum number of 100×100 pixels in 900×900 meter grid cell is 81. Thus, our dependent variable is bounded by zero and 81, and we can divide our dependent variable by 81 to convert it to a fraction bounded by 0 and 1 for model estimation. Given the fact that our dependent variable is a fraction of a grid cell, we estimate a fractional logit model for this bounded dependent variable.[3] We use the spatial resolution of 900×900 meter, thus we have more than one million grid cells for the whole state of Mato Grosso. Since we have 11 years of data, we have in total about 13 million observations in our econometric model. Due to the size of our data, we use the cluster computing platform from Amazon Web Services to handle the computational demand.

As the CRA demand could help provide incentives to reduce legal deforestation, we study the opportunity costs of abandoning land and enabling the natural regeneration of trees to gain insights into the potential size of the deficit that might need compensation. In particular, we regress the historical forest gains on land prices with similar model specification and the same set of independent variables given that the net returns to agriculture should also determine the profitability of converting land from agriculture to forests. The logic is that landowners will be more likely to abandon agricultural land and allow it to revert to forest cover when agricultural returns are lower. However, it should be noted that, this is not a representation of all potential reforestation but just that from natural regeneration (we have spatially removed plantations from the forest gain data).[4] As compared to the annual data of deforestation, the data on reforestation is the 12-year aggregated reforestation for the period of 2001-2012.

[3] The maximum number of 100×100 pixels in 900×900 meter grid cell is 81. Thus we divide our dependent variable by 81 to convert it to a fraction bounded by 0 and 1 for model estimation. We convert the unit back to hectare for simulation.

[4] Although plantations could also be eligible to comply with the FC by mixing with at least 50% native species, we do not consider this case here as we cannot distinguish this type of plantation in the historical data.

2.2. *Simulation of the opportunity cost of reducing legal deforestation*

Based on the estimated fractional logit model, we project deforestation with and without hypothetical conservation incentives through the year 2030 for the properties with the LR surplus where deforestation is legally permitted. We choose to simulate deforestation through the year 2030 since that is the time frame of Mato Grosso's Produce Conserve Include strategy. Since the last year of our historical data is the year 2013, our simulation is actually for the period of 2014-2030. We assume that all variables stay constant at the 2013 level in the future for our no incentive case, while we keep updating the forest category as the forest cover changes year by year. We develop an econometrically-calibrated and spatially-explicit map with the estimated opportunity costs of conserving forests given this future deforestation pressure. This is done by estimating the minimum incentive that achieves the deforestation reduction threshold. In particular, we subtract certain value from original land price to represent a reduction in the net benefit of converting forest to agriculture, and then we predict the relevant deforestation. Then we developed and used a LR map, which shows the boundaries of each property with surplus or deficit of LR according to the FC requirement, to overlay with our simulated deforestation and opportunity cost map. With alternative hypothetical conservation incentives, we are also able to estimate the aggregated marginal cost curve and the estimated total payment to reduce deforestation to certain level across all of the properties with the LR surplus.

To help explore the potential of creating incentives to reduce legal deforestation from the properties with the LR deficit, we conduct similar simulations for properties with deficit to study scenarios of reforestation through natural regeneration on abandoned agricultural land under alternative incentives to establish forests. Different from the properties with surplus, for which we model hypothetical incentives to conserve forest, here we simulate the situation that the landowners receives an incentive to convert to forestry, either through a subsidy for forestry or a fee for remaining in agriculture (with the CRA market, purchasing CRA is a way of complying with the Forest Code without having to restore forests which would entail an added cost to remaining in agriculture).[5] When this incentive per ha increases, the landowner will tend to abandon more agricultural activities which may allow natural regeneration. Based on the estimated regression model of reforestation, we project relevant future reforestation with hypothetical incentive levels. Finally, we estimate the total opportunity cost to increase reforestation to a certain level.

3. Data

Deforestation data for the period of 2003-2013 are from PRODES (Project for monitoring deforestation in the Amazon), which has the 100×100 meter resolution and annual data for the Amazon area for both forest cover and deforestation. Cerrado native vegetation data is from Terra Class Cerrado 2013 with the same 100×100 meter resolution. Forest gain data are from Hansen et al. (2013), which are total cumulative forest gains during the period of 2000-2012. Its original resolution is 30×30 meter. For both deforestation and reforestation data, we aggregate them to a resolution of 900×900 meter to lower the computational demand which gives us about 13 million of observations for model estimation.

Informa Economics FNP (Land market analysis, 2003-2013) provided the land price data, which are based on the result of surveys and market monitoring. In this data, the state of Mato Grosso has been divided into 11 regions. Inside each region, the price data is available for

[5] Although we view that the landowner receives incentives for keeping forest in the LR surplus properties and pays fines for keeping agricultural activities in the LR deficit properties, they all reflect the increasing of the opportunity cost of agricultural activities. Therefore, in the simulations for both cases, we subtract a certain value from our estimated agricultural land price.

different types of land, such as pasture, crop, and forest. For each land type price in a specific region, the relevant two or three municipalities are specified. We used the data for the period of 2002-2012. Instead of using pasture or crop price alone, we choose to use the combination of these two prices weighted by the share of their areas in each municipality[6]. In order to estimate the potential land price in areas currently in forest cover, this combined price which reflects areas currently in agriculture is further scaled to introduce spatial-explicit variations from potential yield data, obtained from the FAO Global Agro-Ecological Zones (GAEZ) Data Portal version 3.0 (http://gaez.fao.org/, accessed in May, 2016).[7]

The property map that we use is a composition of Rural-Environmental Registry data (CAR, in Portuguese), Certified Private Properties data from the National Land Institute (INCRA, in Portuguese), geo-referenced land-boundaries from Terra Legal Program for land-tenure clarification, indigenous lands data from National Indigenous Foundation (FUNAI, in Portuguese), Conservation Units data from Ministry of Environment (MMA, in Portuguese) and rural settlements data from INCRA. Surplus and deficit are calculated from PRODES data (Project for monitoring deforestation in the Amazon), Terra Class data (land-use change and cover) both from the National Spatial Research Institute (INPE) for the forest area. For non-forest native vegetation area, data are from Mato Grosso State Secretary of Environment (SEMA-MT) and Terra Class Cerrado (INPE). With deforestation dynamics from 1992 to 2015 (non-forest areas) and from 1988 to 2015 (forest areas) and data of remaining vegetation we can estimate compliance with the FC at the property level.

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[6] The crop distribution data is from Gibbs et al. (2015), and the pasture distribution data is from http://maps.lapig.iesa.ufg.br/.

[7] For each municipality, the ratio of potential yields from nonforest and forest areas is used to calibrated the average land price for nonforest areas and extend this to forest area. By doing this, we introduce spatial-explicit variations from potential yield data to the original land price. In particular, agro-climatically attainable yield at year 2000 from GAEZ is used for the following major crops: Banana, cassava, cocoa, coffee, coffee, corn, cotton, rice, sorghum, soybean, sugarcane, sunflower, sweet potato, and tomato.

The spatial files of conservation land are from Brazilian Ministry of Environment (MMA, in Portuguese), indigenous land are from FUNAI, rural settlements are from INCRA, slope, roads, railroad, cities, and main rivers are provided by the Brazilian Institute of Geography and Statistics (IBGE, in Portuguese).

4. Results

4.1. Model Validation

Our empirical estimation is based on fractional logit regression as our deforestation data can be expressed as a fraction of grid-cell with fixed area. An alternative empirical strategy is using negative binomial regression which captures the count data feature of our data – the number of 100×100 meter pixels in a 900×900 meter grid cell. We compared the out of sample prediction performance of these two methods using leave-one-out cross-validation. In particular, we set one year out of the 11-year data as the testing dataset, while the remaining ten-year as the training dataset. We fit the regression models only with the training dataset, and then compare the predicted and the observed deforestation for the testing dataset to calculate the Root Mean Squared Error (RMSE). We repeat the process for 11 times, so that each year take turns to be the testing dataset, and then compared the overall RMSE. In general, we find that the fractional logit model outperforms the negative binomial model in terms of RMSE based on leave-one-out cross-validation method. Therefore, we choose to use the fractional logit model here. In Table 1, we compare the RMSE of two models by the same testing dataset year by year, and observe that the RMSE for the fractional logit model is larger than that of the negative binomial model for 10 out of 11 years. We also calculate the Mean Percentage Error (MPE). It shows that the average is about 3.5% for both models which indicates good out-of-sample projections from our model.

4.2. Regression

We include two-way and three-way interaction terms between land price and several spatial variables in the model, which help explore the spatially-explicit relation between deforestation and agricultural land price. Meanwhile, instead of reporting the estimated coefficients, we investigate the global relation between deforestation and land price with percentage change of independent variable.[8] In particular, we reduce the land price value by 10%, and find that overall deforestation is predicted to be reduced by about 5.2%, while the elasticities do vary largely across different land characteristics which are estimated by interaction terms (see Figure 1). In the regression with reforestation, decreasing land price by 10% will increase reforestation by about 7.5%. These also show that our regression model estimation has the expected sign for the relation between deforestation/reforestation and agricultural return.

4.3. Simulation

Next, to simulate the overall deforestation/reforestation changes in the counterfactual cases where opportunity costs of agricultural activities are higher with conservation incentives, we subtract the value of the hypothetical incentive from the baseline land price.

Figure 1 (A) shows a map with spatially-explicit estimates of minimum incentives to reduce deforestation by 50%. It shows that required incentives are in general lower in the Amazon region in the northwest part of Mato Grosso, while in many regions in the southeast part of the state, it is harder to reduce deforestation by 50%. In Figure 1 (B), we further show a similar map to reduce deforestation by 90%. As expected, it generally requires higher incentives to achieve more reductions.

[8] The full regression results are available from the authors upon request.

In Figure 2, we find that the costs of reducing deforestation increases nonlinearly (at an increasing rate) as more and more incentives are needed to encourage greater forest conservation. By looking at the Amazon and Cerrado biomes separately, we find the nonlinear increasing trend in both biomes, and there are more deforestation saved in Amazon than in Cerrado for all levels of incentives. As shown in Table 2 column 1 where both illegal and legal deforested are counted (on the properties with an LR surplus), by providing up to R$ 900/ha of (US$ 405/ha)[9] conservation incentive, we can reduce about 78% of projected deforestation, from 291,528 ha to 65,000 ha for the properties with surplus during the period of 2014-2030. The total payment for these 17 years is about US$ 279.5 million if we can target incentives to each landowner over both space and time, and assume that there will be the same payment for the following years after the initial year with deforestation threat. The net present value of the total payment over 17 years with a discount factor of 10% is about US$ 108.8 million. Alternatively, if targeting is not feasible and all the landowners receive the same payment, the total payment will be about US$ 847.8 million for the period of 2014-2030, with net present value of US$ 327.1 million.

Assuming strong government enforcement, a rational landowner in a property with the LR surplus will have reduced incentives to start illegal deforestation until the entire LR surplus has been depleted. Thus in the simulation, any properties with more projected deforestation than the LR surplus indicate the existence of the illegal deforestation. The second column of Table 2 shows the case which allows legal deforestation only. With up to R$ 900/ha of conservation incentive, there is an estimated reduction of 77% of projected legal deforestation, from 278,257 ha to 64,287 ha for the period of 2014-2030. The total payment for these 17 years is about US$ 279 million if we can target incentives to each landowner over both space and time, and

[9] The exchange rate 2.22 between Brazilian R$ and US$ are the 11 year average for the period of 2003-2013. Land price was used in the analysis, and we use land rent when reporting the results.

assume that there will be the same payment for the following years after the initial year with deforestation threat. The net present value of the total payment over 17 years with a discount factor of 10% is about US$ 108.7 million. Alternatively, assuming no ability to target, if all the landowners receive the same payment, the total payment will be about US$ 847 million for the period of 2014-2030, with net present value of US$ 327 million.

Overall, we observe that most of projected deforestation in a property with the LR surplus will be able to fit into the legal deforestation quota, which means it is important to create incentives to help reduce the legal deforestation. One way to do this would be to allow selling CRA to a property that needs it. Thus next, we investigate the potential for CRA demand, which helps explore the potential of a CRA market in terms of creating incentives to help reduce legal deforestation.

In Figure 3, we can see that reforestation costs increase with an increasing rate when the forest conservation incentives become higher for the landowners to maintain agricultural activities. By looking at the Amazon and Cerrado biomes separately, we also find that the nonlinear increasing trend happens in both biomes, and there are more reforestations in Amazon than in Cerrado for all levels of incentives. Our simulation for reforestation is tested with up to R$900 of agricultural cost, given a concern of the extreme out-of-sample projection by changing the independent variable too much. As compared to the incentives for deforestation which was able to reduce deforestation by 78%, the reforestation inside the properties with deficit will increase from 288,393 ha to 654,760 ha for the period of 2014-2030. The total payment is about US$ 1,196.5 million if we can target on each landowner specifically. If we pay all the landowners the same, the total payment will be about US$ 1,732.3 million for the period of 2014-2030. If we do not count any reforestation exceed LR requirement, the numbers are slightly smaller as shown in in Table 2 column 4. We also include the results that do not count any natural regeneration exceed the LR requirement, and the relevant NPV value. We do not observe much natural regeneration higher than the LR requirement. Overall, with up to R$ 900/ha of conservation incentives, the simulated passive abandonment is only about 7% of overall deficit area, indicating large potential for CRA demand from the remaining deficit properties.[10] This could help create incentives to reduce legal deforestation.

Using the year 2009 as the sample date, Stickler et al. (2013) has reported that the costs to protect the forest lands that can be legally cleared in Mato Grosso is US$ 151 million while the costs for restoration are from US$ 950 million to 1,083 million for alternative scenarios under Forest Code 2012. In the year 2030, the last year of our simulation, which has the most area of forest under threat – about 10% of the total surplus area, we estimate a need to pay about US$ 32 million to $100 million to reduce deforestation by 78% (lower and upper bound depend on how well we can target the payment on each landowner). The costs for restoration from natural regeneration on 7% of the deficit are from US$ 123 million to $179 million. It should be noted that these two studies have difference scope. For example, we do not assume that all lands subject to legal deforestation will be deforested, but rather estimate the threat of deforestation for the period of 2014-2030. Also, the property map that we use does not cover all the properties in Mato Grosso. For the restoration part, we only report the costs to restore part of the deficit.

As reported in Table 2, in properties with surplus, the projected illegal deforestation is very small as compared to the overall deforestation for the period of 2014-2030. That means it is essential to create positive incentives to help reduce legal deforestation, as law enforcement alone will not reduce the deforestation that can occur legally. Since most projected deforestation

[10] We do not yet model the costs of active reforestation, which could potentially lower CRA demand, and may even create CRA supply from a property with the LR deficit.

can happen legally in the property with LR surplus, other mechanisms to protect forests that can be legally deforested, such as CRA and payments for reducing carbon emissions from deforestation (i.e. REDD+), are necessary to address most of the deforestation issue. We find that there may be potentially strong CRA demand from a property with deficit, as passive abandonment only covers a small portion of deficit area, and thus a CRA market could help reduce legal deforestation.

6. Conclusions

In this study, we estimate the spatially-explicit cost of reducing legal deforestation in Mato Grosso, and explore one possible source that could provide such incentives. Using a fractional logit regression model, we estimate the historical relation between deforestation/reforestation and the agricultural land price based on the data for the period of 2003-2013. As expected, deforestation (reforestation) is positively (negatively) associated with the agricultural land price. Then with the estimated historical relation, we use hypothetical conservation incentives to project the future deforestation/reforestation and its relevant costs.

With the forest conservation incentives up to R$ 900/ha (US$ 405/ha) and NPV of US$ 108.8 million for the period of 2014-2030, there is an estimated reduction of about 77% of legal deforestation. Illegal deforestation is not a major concern for the properties with a surplus. On the other hand, only 7% of the LR deficit will be abandoned to allow natural regeneration with up to R$900/ha. Therefore, it is important to implement the CRA trading system or to implement other measures to create positive economic incentives to reduce legal deforestation. Both the data and a model properly selected and specified provides a foundation for the next level of this research – an in-depth analysis of CRA market should be explored for its economic and environmental consequences.

Table 1. Compare the Root Mean Square Error and Mean Percentage Error between Negative Binomial and Fractional Logit.

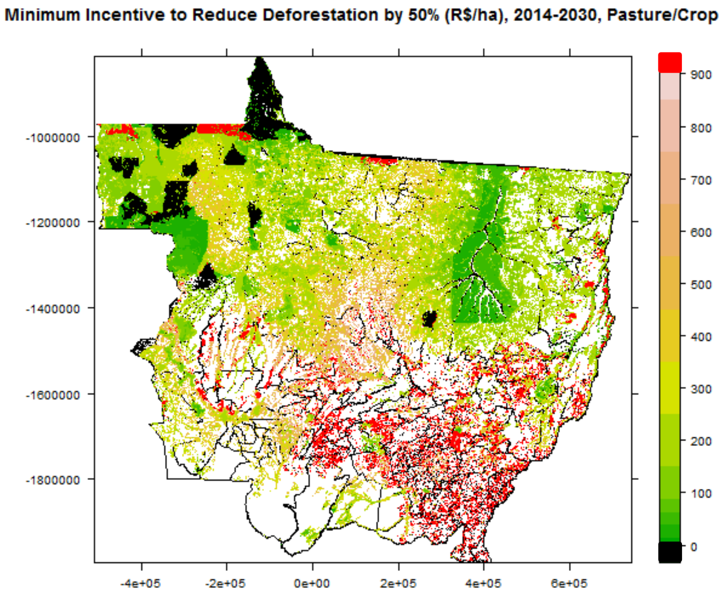
Year	Fractional Logit	Negative Binomial	Fractional Logit	Negative Binomial
	Root Mean Square Error		Mean Percentage Error	
2003	8.504	8.684	7.33%	7.71%
2004	8.608	9.029	8.88%	9.23%
2005	7.082	14.107	5.85%	6.04%
2006	4.070	4.145	3.01%	3.02%
2007	3.776	3.811	2.87%	2.83%
2008	4.087	4.106	3.45%	3.39%
2009	2.373	2.394	1.42%	1.39%
2010	1.961	1.974	1.13%	1.10%
2011	2.938	2.933	2.13%	2.10%
2012	2.406	2.416	1.30%	1.28%
2013	2.722	12.786	1.83%	1.81%
Average	4.412	6.035	3.56%	3.63%

Table 2. Deforestation and reforestation under alternative forest conservation incentives, and the total payment for the period of 2014-2030.

Modeled Forest Conservation Incentives (R$/Ha)	(1) *Deforestation on properties with LR surplus* (Ha)	(2) *Legal Deforestation* (Ha)	(3) *Reforestation on properties with LR deficit* (Ha)	(4) *Reforestation (capped at amount of LR deficit on each property)* (Ha)
0	291,528	278,257	288,393	286,465
100	204,699	198,644	302,902	293,958
200	153,751	150,717	312,802	303,694
300	120,906	119,120	330,179	320,699
400	99,180	98,037	356,030	346,130
500	84,486	83,668	391,355	380,831
600	74,833	74,188	437,205	425,381
700	68,878	68,303	495,268	481,321
800	65,814	65,219	567,069	549,470
900	65,000	64,287	654,760	630,655
Total Payment during 2014-2030 with incentives up to R$900/Ha (US$)				
Lower bound payment(Total)	279,507,641	279,318,721	1,196,512,070	1,191,492,694
Lower bound payment(NPV)	108,819,083	108,746,851	485,162,316	483,048,000
Lower bound payment(Total)	847,814,693	846,572,154	1,732,269,986	1,723,875,410
Lower bound payment(NPV)	327,094,269	326,622,153	700,077,843	483,048,000

Note: Compared to deforestation in column (1), legal deforestation in column (2) excludes any illegal deforestation that exceeds the LR surplus. Compared to Reforestation in column (3), reforestation for LR only in column (4) excludes any reforestation that exceeds the LR deficit. Lower bound payment is targeting landowners differently based on local opportunity cost, while upper bound payment assumes we pay all the landowners the same amount (R$900). Net present values are based on a discount rate of 10% for 17 years (2014-2030).

(A)



(B)

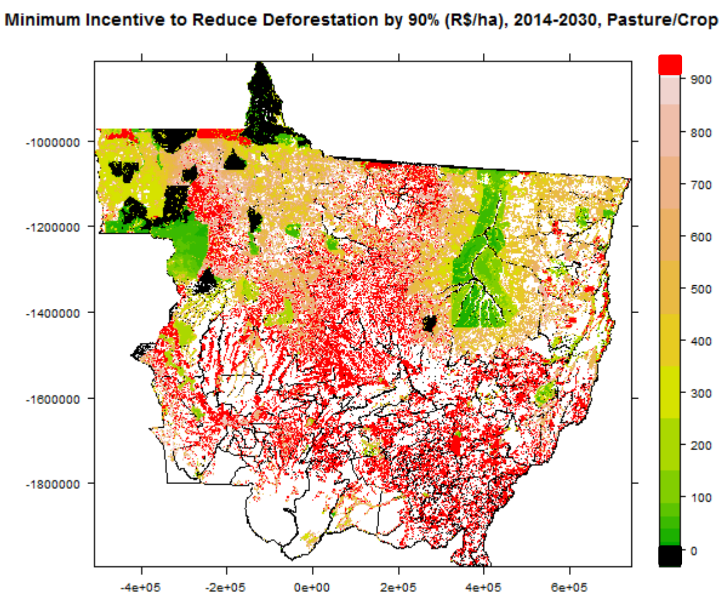


Figure 1. Minimum incentives per hectare to reduce deforestation for the period of 2014-2030. (A) by 50%. (B) by 90%. Red area represents the region that could not be reduced to the threshold (by 50% or by 90%) with incentives up to R$900/ha, while black color represents the region that has less than 0.1 hectare of projected deforestation for each 900x900 grid cell for the period of 2014-2030.

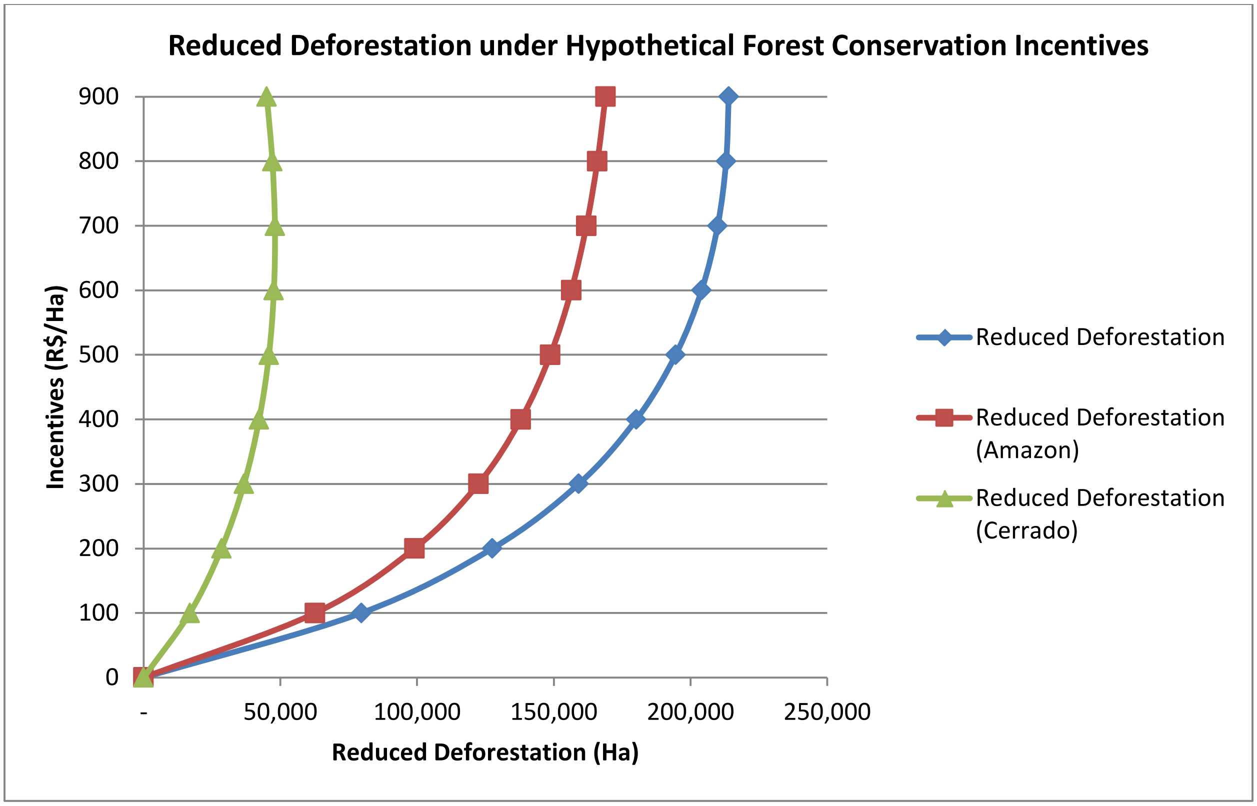


Figure 2. Reduced deforestation with forest conservation incentives for properties with LR surplus.

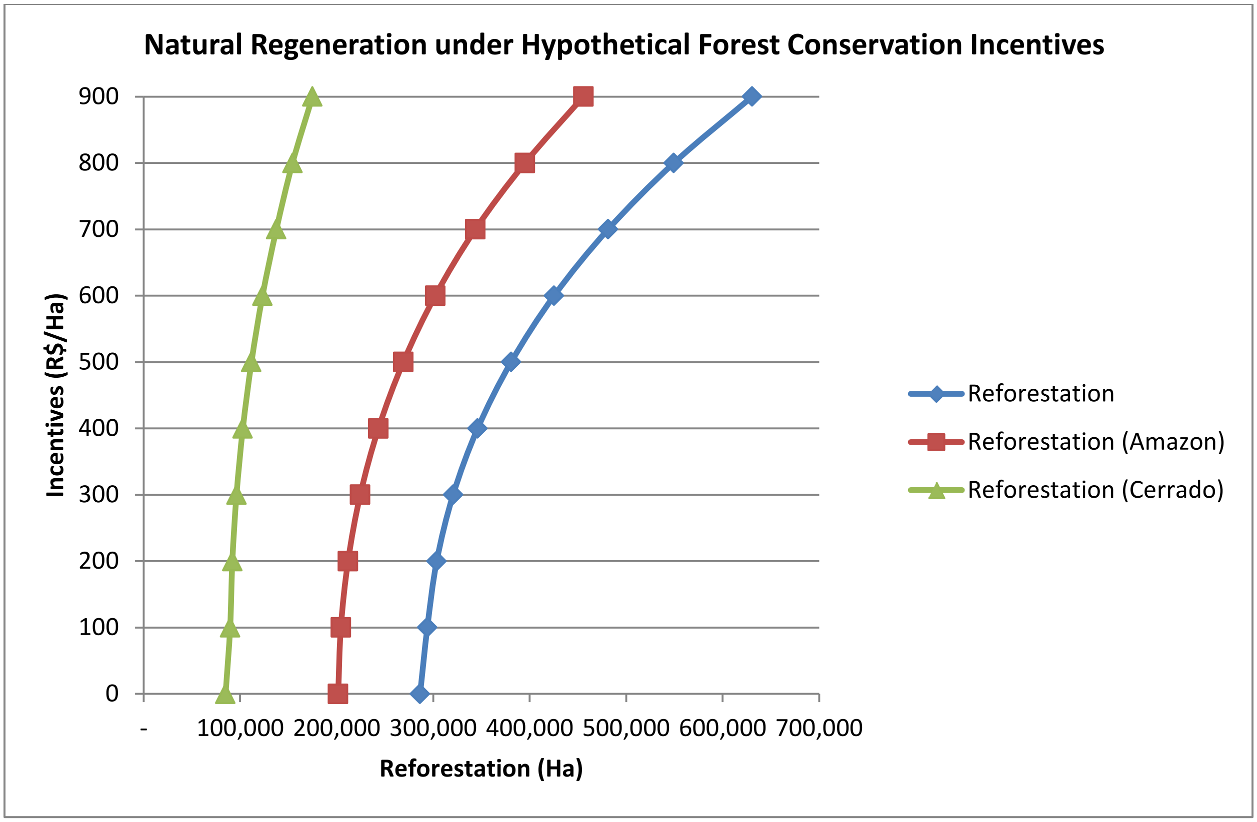


Figure 3. Natural regeneration with forest conservation incentives for properties with LR deficit.

References:

Busch, J., Lubowski, R.N., Godoy, F., Steininger, M., Yusuf, A.A., Austin, K., Hewson, J., Juhn, D., Farid, M. and Boltz, F., 2012. Structuring economic incentives to reduce emissions from deforestation within Indonesia.Proceedings of the National Academy of Sciences, 109(4), pp.1062-1067.

Gibbs, H.K., Rausch, L., Munger, J., Schelly, I., Morton, D.C., Noojipady, P., Soares-Filho, B., Barreto, P., Micol, L. and Walker, N.F., 2015. Brazil's soy moratorium. Science, 347(6220), pp.377-378.Lubowski, R.N., Plantinga, A.J. and Stavins, R.N., 2006. Land-use change and carbon sinks: econometric estimation of the carbon sequestration supply function. Journal of Environmental Economics and Management, 51(2), pp.135-152.

Hansen, M. C., P. V. Potapov, R. Moore, M. Hancher, S. A. Turubanova, A. Tyukavina, D. Thau, S. V. Stehman, S. J. Goetz, T. R. Loveland, A. Kommareddy, A. Egorov, L. Chini, C. O. Justice, and J. R. G. Townshend. 2013. "High-Resolution Global Maps of 21st-Century Forest Cover Change." Science 342 (15 November): 850–53. Data available on-line from:http://earthenginepartners.appspot.com/science-2013-global-forest. Accessed through Global Forest Watch on [January 2016]. www.globalforestwatch.org

Informa Economics FNP. 2003-2013. Land Market Analysis Bimester report.

Lubowski, R., M. Wright, K. Ferretti-Gallon, A. J.Miranda, M. Steininger, J. Busch. 2014. *Mexico Deforestation Vulnerability Analysis.* M-REDD+ Alliance. Merida, Mexico.

Macedo, M.N., DeFries, R.S., Morton, D.C., Stickler, C.M., Galford, G.L. and Shimabukuro, Y.E., 2012. Decoupling of deforestation and soy production in the southern Amazon during the late 2000s. Proceedings of the National Academy of Sciences, 109(4), pp.1341-1346.

May, P. H., P. Bernasconi, S. Wunder, and R. Lubowski. 2015. Environmental reserve quotas in Brazil's new forest legislation. An *ex ante* appraisal. Occasional Paper 131. Bogor, Indonesia: CIFOR.

Micol, L., R. Abad, and P. Bernasconi. 2013.Potencial de aplicacao da Cota de Reserva Ambiental em Mato Grosso. Instituto Centrode Vida–ICV: Cuiaba.

Nepstad, D., McGrath, D., Stickler, C., Alencar, A., Azevedo, A., Swette, B., Bezerra, T., DiGiano, M., Shimada, J., da Motta, R.S. and Armijo, E., 2014. Slowing Amazon deforestation through public policy and interventions in beef and soy supply chains. *Science*, *344*(6188), pp.1118-1123.

Rajão, R.; Soares-Filho, B. 2015. Cotas de reserva ambiental (CRA): viabilidade econômica e potencial do mercado no Brasil. 1. ed. Belo Horizonte: IGC/UFMG.

Soares-Filho, B., R. Rajão, M. Macedo, A. Carneiro, W. Costa, M. Coe, H. Rodrigues, and A. Alencar. 2014. Cracking Brazil's Forest Code. *Science*, 344, 363–364.

Stickler C.M., D.C. Nepstad, A.A. Azevedo, D.G. McGrath DG. 2013. Defending Public Interests in Private Lands: Compliance, Costs and Potential Environmental Consequences of the Brazilian Forest Code in Mato Grosso. *Phil Trans R Soc B* 368: 20120160.