Linking Remote Sensing and Economics:
Evaluating the Effectiveness of Protected Areas in Reducing Tropical Deforestation

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Introduction

Deforestation accounts for 12-20% of global carbon dioxide emissions to the atmosphere – the second largest source after fossil-fuel combustion [1]. In current climate change discussions, efforts that aim to reduce emissions from deforestation and forest degradation and enhance forest carbon stocks (REDD+) are being considered as a cost-effective strategy for mitigating global greenhouse gas emissions [2-3]. In the past decade, billions of dollars in international funds for REDD+ have spurred governments in tropical regions to establish vast networks of Protected Areas (PAs), which currently cover 54% of forested areas in the Brazilian Amazon [4]. However, the *PA effect* – the causal link between PA designation and avoided deforestation – is widely debated. The controversy surrounding the PA effect stems from the non-random placement of PAs which tend to be established on marginal lands with pre-existing low pressure for deforestation, thus biasing comparisons between PAs and unprotected areas [5-6].

The key question is: how much deforestation would have occurred without protection? Overcoming the inherent complexity of this question requires reliable data on deforestation coupled with experimental techniques that can test for counterfactuals. Due to the lack of consistent time-series data on deforestation, existing literature has been limited to cross-sectional econometric methods, such as matching techniques, which cannot adequately separate the PA effect from other confounding biophysical and socio-economic characteristics that affect deforestation over time [6-7]. In this project we will advance the current understanding of the PA effect by developing an integrated framework: (i) creating spatially explicit time-series deforestation data from remote sensing that fit econometric analysis, and subsequently (ii) applying innovative quasi-experimental matching methods on the data.

To date, we have completed satellite classifications of annual deforestation over our study area. In this paper, we summarize our deforestation data and describe the quasi-experimental model we will use to identify the PA effect.

Annual Deforestation Data

To create our novel deforestation time series, we developed a new method to track the spatially and temporally continuous changes in tree cover using the Moderation Resolution Imaging Spetroradiometer Vegetation Continuous Fields (MODIS VCF) products [9]. Compared with the traditional bi-temporal, categorical change detection, tracking continuous changes in time series tree cover has the potential to reconstruct the complete trajectory of forest dynamics such as deforestation, forest degradation, afforestation as well as reforestation. The method consists of two major steps: (i) identifying most likely change pixels using a probability-based outlier detection technique and (ii) characterizing the specific change trajectories for the detected change pixels using a least-square curve-fitting algorithm. The output of this method is a deforestation map at a spatial resolution of 250-m and at an annual time step from 2000 to 2010.

Our study area is the humid tropics biome in South America, where more than 40% of the world's deforestation emissions are located [8]. We tested our method in a large area (roughly 1.3 million km^2) corresponding to the spatial extent of the MODIS tile h12v10 across country borders of Brazil, Columbia and Paraguay in South America (Fig. 1). The northern portion of the test area is the southeastern edge of the Brazilian Amazon, a place that has been a deforestation hotspot in the past several decades. The existing large intact rainforests are protected in indigenous reserves. Our results show that this deforestation hotspot stayed active from 2000 and 2010 with a peak in year 2003 and 2004 but the rate declined shapely after year 2005 (Fig 2). In contrast, relatively less deforestation was revealed in Bolivia before year 2005, but substantial, clustered, large patches of forest clearings occurred after 2005, particularly after 2008. We have visually examined the results carefully. We also quantitatively compared our map with existing coarse-resolution deforestation maps [10], as well as high-resolution Landsat-based forest loss dataset. Both comparisons confirmed that our method accurately captured deforestation in this complex landscape. Furthermore, our classifications identify *timing* – or the year deforestation occurred – adding a new dimension to deforestation mapping that has previously only focused on identifying *location* of deforestation during a five or ten year time frame.

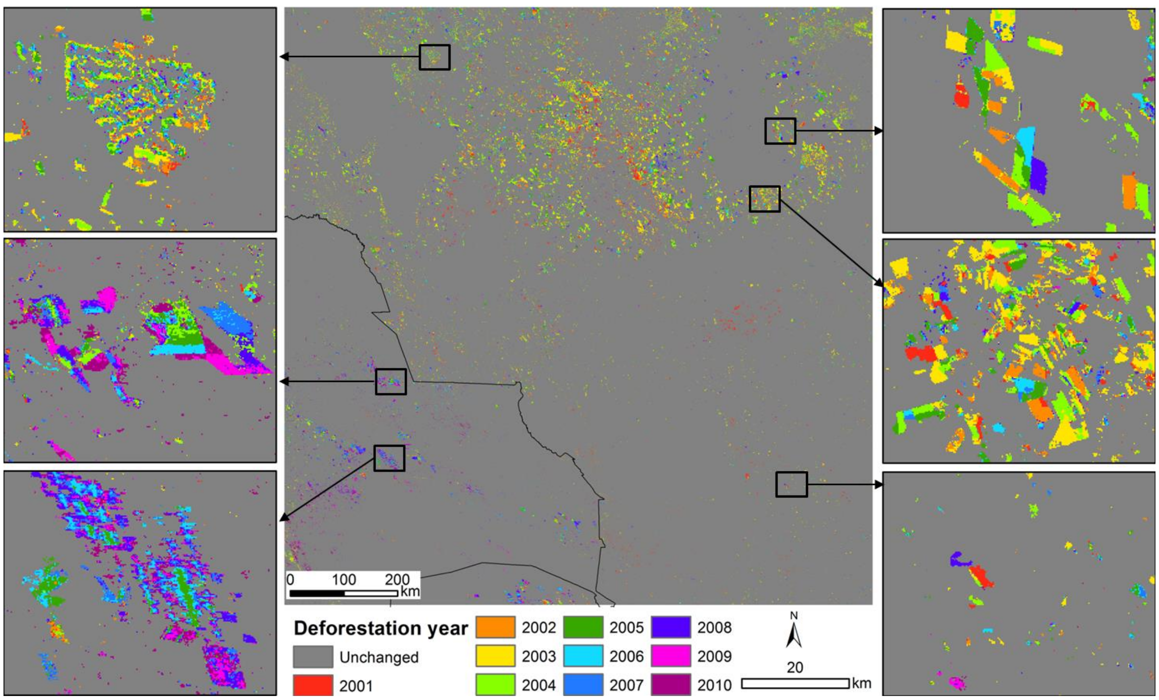

Fig. 1 Year of deforestation per 250-m MODIS pixel. The area covers roughly 1.3 million km^2. Black lines show country borders between Brazil, Bolivia and Paraguay.

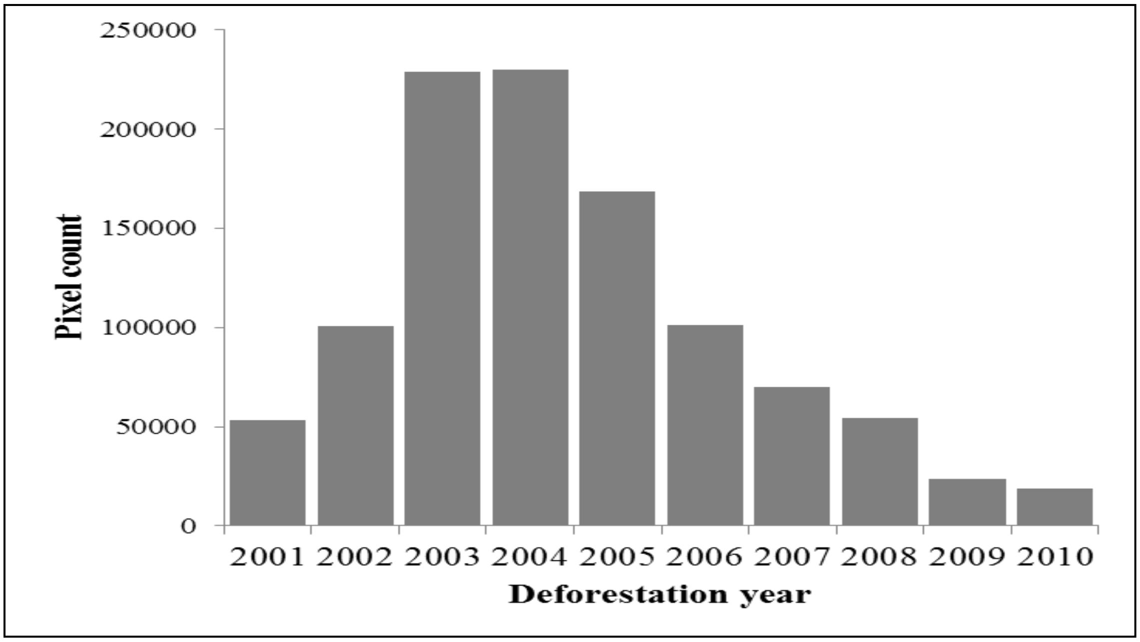

Fig. 2. Statistics of annual deforestation from 2000 to 2010 in the test area

Additional Datasets

To create variables for our quasi-experimental model, we combine information on annual deforestation with information on the location and timing of PA designations based on the World Database on Protected Areas [11]. For each 25km^2-year spatial-temporal unit of observation, we will calculate the deforestation rate as well as the PA status. Our study area includes 916 PAs established between 2001 and 2009, covering a total area of 1,297,972 km^2.

Our matching algorithms will incorporate spatial datasets relevant to deforestation, such as; the terrestrial ecoregion map, the digital elevation model (DEM) data, climate data (e.g. temperature and rainfall), major road map, human population map. Slope will be computed based on DEM, and buffer zones will be calculated based on the transportation and urban map in a Geographic Information System (GIS). These various attributes will be integrated to stratify the test area into a number of homogenous regions, which is the basic input map for matching analysis. The homogenous region map, the WDPA map as well as the deforestation map will then be overlaid in a GIS to separates pixels into treatment group (i.e. within PA) and control group (i.e. outside PA).

Furthermore, we are will apply annual socio-economic data in matching algorithms to control for potential drivers of deforestation. Specifically, we are integrating three time-series datasets across 5,500 Brazilian municipalities, including; (i) annual municipal government expenditure and revenue from 2002-2009 reported in the Finanças do Brasil (FINBRA), (ii) annual municipal GDP disaggregated by sector from 2001-2009 reported by the Instituto de Pesquisa Econômica

Aplicada (IPEA), (iii) Brazilian decadal census population and employment data produced by the *Instituto Brasileiro de Geografia e Estatística* (IBGE).

Empirical Model

For a given location, our model assumes changes in deforestation over time are affected both by changes in PA status and by other broad time-trend effects, such as agricultural commodity prices and regional economic cycles. The objective of our quasi-experimental design is to use treatment and control groups to separate the PA effect from other broad time-trend effects. Treatment locations refer to land areas that are initially unprotected in 2000 but become PAs in the years between 2001 and 2009, while control locations remain unprotected until 2010. The treatment group allows us to identify the change in deforestation rates before and after a PA designation, while the control group permits us to identify broad deforestation trends to construct a counterfactual baseline in the absence of a PA designation. The PA effect is therefore isolated by comparing changes in deforestation rates between the treatment group (PA effect + baseline) and the control group (baseline). We will employ matching methods to ensure the treatment and control groups are similar across several important biophysical and socio-economic characteristics, including initial rate of deforestation, geographic region, elevation, slope, distance to roads, and distance to cities, etc. [6].

In the simple case of a single type of PA designation our quasi-experiment would entail estimating the following two-way fixed effects model:

$$Y_{\{it\}} = \theta_{\{i\}} + \varphi\tau_{\{t\}} + \gamma\, D_{\{it\}} + \varepsilon_{\{it\}}$$

where $Y_{\{it\}}$ is the deforestation rate at location *i* in year *t*; $\theta_{\{i\}}$ are location-specific indicator variables; $\tau_{\{t\}}$ are year-specific indicator variables capturing broad trends that affect deforestation over time; and $D_{\{it\}}$ is an indicator variable equal to 1 for years after a treatment location is protected, and equal to 0 for years a location remains unprotected; ε_{it} is an error term that represents unmeasured factors. The coefficient γ isolates the *PA effect* (treatment effect); while coefficient φ separates baseline trends. More complex versions of this model will identify the relative effectiveness of different types of PAs. Although we currently do not have results to report in this abstract, we expect to complete integrating these datasets by February, at which time we will be able to begin estimation of our model.

Conclusion

Our paper will represent the first integrated framework linking annual satellite-based deforestation data with quasi-experimental methods to measure the effectiveness of PAs in reducing tropical deforestation. This project will make significant contributions to existing literature by (i) estimating annual deforestation with multi-temporal multi-resolution satellite data represents the latest progress in land use and land cover change research; (ii) applying quasi-experimental methods advances the empirical literature of PA effect to the frontier of economics. Our study is expected to generate significant policy implications for REDD+, an area of research currently of interest to the international community.

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