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Gabriela Demarchi[*] Julie Subervie[†] Thibault Catry[‡]
Isabelle Tritsch[§]

Abstract

The perpetuity and improvement of REDD+ projects for curbing deforestation require rigorous impact evaluations of the effectiveness of existing on-the-ground interventions. Today, a number of global and regional remote sensing (RS) products are publicly available for detecting changes in forest cover worldwide. In this study, we assess the suitability of using these readily available products to evaluate the impact of REDD+ local projects targeting smallholders (owning plots of less than 100 ha) in the Brazilian Amazon. Firstly, we reconstruct forest loss for the period between 2008 and 2017 of 17,066 farms located in the Transamazonian region, using data derived from two land-cover change datasets: Global Forest Change (GFC) and Amazon Deforestation Monitoring Project (PRODES). Secondly, we evaluate the consistency between the two sources of data. Lastly, we estimate the long-term impact of a REDD+ project using both RS products. Results suggest that the deforestation estimates from the two data-sets are statistically different and that GFC detects systematically higher rates of deforestation than PRODES. However, we estimate that an average of about 2 ha of forest were saved on each participating farm during the first years of the program regardless the source of data. These results suggest that these products may not be suitable for accurately monitoring and measuring deforestation at the farm-level, but they can be a useful source of data on impact assessment of forest conservation projects.

Keywords: REDD+, remote sensing products, impact evaluation, deforestation, Brazilian Amazon.

[*]CEE-M. Univ. Montpellier, CNRS, INRAE, SupAgro, Montpellier, France
[†]CEE-M. Univ. Montpellier, CNRS, INRAE, SupAgro, Montpellier, France
[‡]UMR 228 Espace-Dev, IRD, Montpellier, France.
[§]UMR 228 Espace-Dev, IRD, Montpellier, France.

1 Introduction

More than 9,700 square kilometers of the Brazilian Amazon were cleared between 2018 and 2019, representing an increase of 30% in the annual deforestation rate and the highest rate since 2008 (INPE, 2019a). Forest cover change is a leading cause of Brazil's greenhouse gas emissions and as a result, there has been a proliferation of sub-national initiatives to Reduce Emissions from Deforestation and forest Degradation (REDD+) in the Brazilian Amazon for some years (Sills et al., 2014). Brazil currently hosts about 50 REDD+ projects targeting small farmers and financed by REDD+ funds or carbon markets (Simonet et al., 2015). The perpetuity and improvement of REDD+ projects require rigorous impact evaluations of the effectiveness of existing on-the-ground interventions. Yet, robust evidence about their effectiveness remains scarce (Jayachandran et al., 2017; Mohebalian and Aguilar, 2018; Simonet et al., 2018; Roopsind, Sohngen, and Brandt, 2019). One of the reasons for this lack of evidence is related to the high cost to access the data needed for impact analysis (Blackman, 2013).

Over the past 20 years, however, remotely-sensed data for detecting changes in land cover worldwide has evolved dramatically, which offered new opportunities for the evaluation of forest conservation programs. In particular, a number of derived and modelled remote sensing (RS) products that extract information from raw Earth observation (EO) data became publicly available (Kugler et al., 2019). Though these RS products represent a great opportunity to measure changes in forest cover at a large scale, the suitability of these readily available products to perform impact evaluation of sub-national REDD+ initiatives has rarely been questioned so far (Bos et al., 2019).

For the present study, we focus on two well-known datasets: the Global Forest Change (GFC) dataset provided by the University of Maryland and the PRODES dataset provided by the National Institute for Space Research (INPE) of Brazil. GFC provides free of charge global historical record of annual tree-cover loss and has already been used to assess the effectiveness of forest conservation policies in Ecuador (Jones and Lewis, 2015; Jones et al., 2017) and French Guyana (Roopsind, Sohngen, and Brandt, 2019). In the Brazilian context, the most often used deforestation dataset has been PRODES, an accessible and transparent RS product, provided free of charge as well. In particular, it has been employed to study the effectiveness of protected areas in the Amazon (Nolte et al., 2013; Herrera, Pfaff, and Robalino, 2019).

In this study, we assessed the applicability of these RS products to evaluate the impact of REDD+ local projects targeting smallholders in the Amazon. To do so, we concentrated on a Brazilian REDD+ flagship project for curbing deforestation: Sustainable Settlements in the Amazon (Portuguese acronym PAS - Projeto Assentamentos Sustentaveis na Amazonia). We focused on a local REDD+ program implemented in a country characterized by the highest annual loss of forest in the world. This represents an unique contribution to the literature given that previous forest conservation programs targeting individual farmers rigorously evaluated to date have been implemented in areas characterized by lower deforestation rates (Pattanayak, Wunder, and Ferraro, 2010; Jayachandran et al., 2017). To the best of our knowledge, despite the abundance of REDD+ initiatives in Brazil, there are no studies drawing inferences about the causal effects of such projects, combining ready-to-use RS products and property-level data. Our study aims at filling this gap. Furthermore, this is the first study assessing the effectiveness of a Brazilian REDD+ local project using two different sources of remotely-sensed deforestation data to cross validate impact assessment results.

The paper is structured as follows: Section 2 briefly describes PRODES and GFC and the methodology used to reconstruct forest loss on individual plots. Section 3 compares the forest loss estimates from both products. Section 5 uses the forest loss estimates for evaluating the impact of the REDD+ program. Section 6 discusses implications of our findings and section 7 concludes.

2 Materials

The Amazon Deforestation Monitoring Project (PRODES)

It was created in 1988 by the Brazilian National Institute for Space Research (INPE), with the main objective to quantify and geolocalize clear-cuts on primary forests in the Brazilian Legal Amazon[1] and help the Brazilian government to make informed decisions and establish environmental and development public policies for the region[2] (Câmara, Valeriano, and Soares, 2006). Annual rates are estimated from the deforestation increments identified in Landsat images[3]. PRODES uses the seasonal year, starting on August 1st, to calculate annual deforestation, so images are selected as near to this date as possible. Next, the images are masked to exclude non-forest, previous deforestation, and water using the previous year's analysis. Finally, the identification of deforestation is done by photo-interpretation, where analysts delineate deforested polygons in the intact forest of the previous year - the patterns of clear cutting are based on three main observable elements present in the images: tone, texture and context (see INPE (2019b) for a detailed description of PRODES' methodology).

Like any RS product, PRODES has some technical limitations because its methodology can only detect contiguous areas of cleared forest that are greater than 6.25 hectares, therefore, smaller deforestation patches are not recorded in the dataset unless accumulated over several years. Also, deforestation estimates only consider primary forests and do not account for secondary or regenerating forests, and, since it relies on optical imagery, constant cloud coverage prevents Landsat sensors from capturing land cover imagery.

[1]The Brazilian Legal Amazon occupies an area that corresponds to 59% of the Brazilian territory.

[2]PRODES' data are employed in: (1) certification of agribusiness supply chains such as the Soy Moratorium; (2) national inventory reports on GHG Emissions; and (3) monetary donations from the Amazon Fund uses PRODES's data as a reference for deforestation activity in the Legal Amazon.

[3]PRODES uses mainly Landsat series images, but when there's too much cloud coverage, analysts employ SENTINEL-2 and CBERS-4 images.

The Global Forest Change dataset (GFC)

The most known global deforestation dataset currently available is the University of Maryland's Global Forest Change dataset (GFC) - also popularly called Hansen data. This dataset has the objective to produce annual globally consistent characterizations of tree cover loss (Hansen et al., 2013). GFC maps tree cover in 2000 and annual forest loss starting in 2001 at a spatial resolution of 30 meters. Cloud-free observations from Landsat images were analyzed to determine per-pixel tree cover using a supervised machine learning algorithm. For this dataset tree-cover is defined as all vegetation taller than 5 meters in height across a range of canopy densities (from 0% to 100%) for an area of approximately 0.1 hectare (Landsat pixel). Therefore, this layer can represent primary and secondary natural forests as well as tree plantations. Also, these data require users to choose a percentage threshold value to determine whether a pixel is considered forest or not. Forest loss is defined as the complete removal of tree cover canopy at the Landsat pixel scale (see Hansen et al. (2013) for complete methodological explanation).

While GFC is a major progress in the understanding and quantification of global forest change research and conservation planning there exist limits of this dataset such as (1) tree cover loss can be the result of human activities (e. g., plantation harvesting, selective logging and clear-cut) as well as natural causes (such as disease, storm and fire damage), and (2) plantations such as, cocoa, palm oil or eucalypt are included as forests (Tropek et al., 2014), though they are not considered forest according to the Brazilian Forest Code.

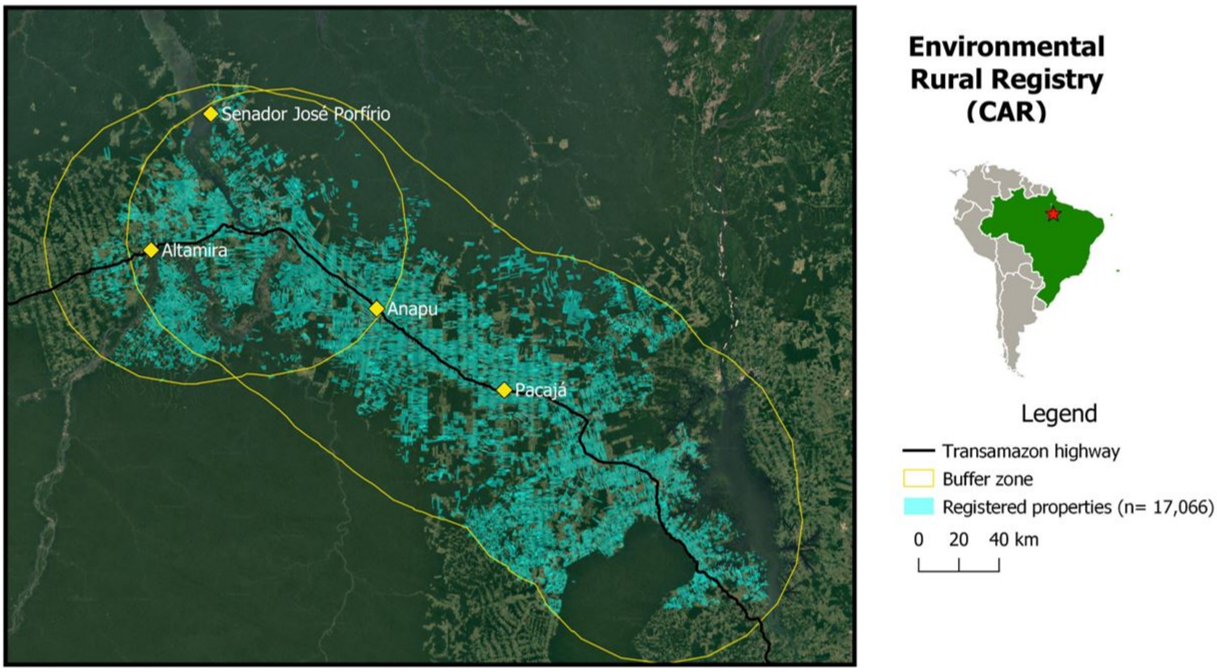
Reconstructing forest loss on individual plots

We had property boundaries from the Environmental Rural Registry (CAR in the original Portuguese acronym)[4] of 17,066 titled households in our study area (Figure 1). We delimited a 70-kilometer buffer around the Transamazonian highway for the municipalities of Altamira, Senador Jose Porfirio, Anapu and Pacaja and defined surface thresholds (minimum 15 hectares, maximum 500 hectares) in order to delimit the rural properties that would be included in our initial sample. Georeferenced data on deforestation and registered private rural properties were overlapped to enable identification of patches cleared inside properties boundaries. We used information from both RS products to determine the location of forest clearings at an annual basis. All geographical datasets were re-projected to a common spatial reference (SIRGAS 2000/UTM 22S). Our sample covers the 2008-2017 period. Since we did not have information about changes in properties' borders during our sample period, we assumed that they were constant throughout this period. For this study we used a thresh-

[4]CAR is the mandatory and self-declaratory registry for all Brazilian rural properties. To obtain CAR, landholders must document georeferenced property's boundaries, as well as within-property areas of native vegetation. CAR has a public consultation module where data from properties, detaining either temporary or permanent registrations, are available for download in vector format at http://www.car.gov.br/publico/municipios/downloads.

old of 75% of vegetation cover for GFC tree cover layer as a definition of the forest - average threshold used in studies in Amazonian context (Baker and Spracklen, 2019; Gasparini et al., 2019).

Figure 1: Study zone



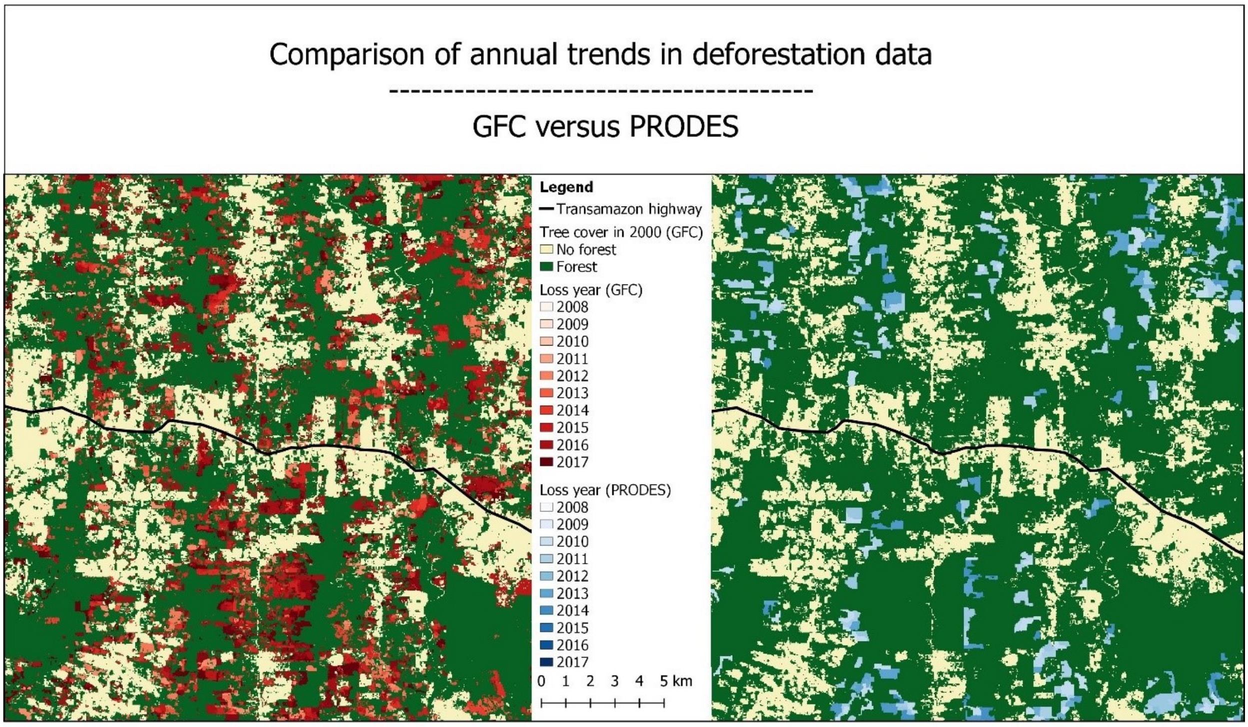
3 Comparing estimates from both RS products

The purposes and methodologies of the two datasets are quite diverging (Table 1). Firstly, GFC includes forest changes in every type of vegetation greater than 5 m in height while PRODES only focuses on primary forest loss. Secondly, GFC is a global dataset while PRODES only focuses on the Brazilian Amazon. Finally, PRODES's methodology is based on contextual classification (i. e., image segmentation and analyst interpretation) and GFC's methodology is grounded on pixel-based classifications (i. e., automated decision tree). There is therefore no reason a priori for the information relating to the loss of forest provided by the two products to coincide. Figure 2 shows in particular that PRODES' deforestation patches are less numerous but have larger dimensions than the cover loss patches of GFC dataset.

Table 1: Comparison between GFC and PRODES

	PRODES	GFC
Data source	Mainly Landsat	Landsat
Resolution	30 meters	30 meters
Minimum patch size	6.25 hectares	0.09 hectares
Coverage	Brazilian Amazon	Global
Tree cover definition	Primary forest	Vegetation taller than 5 meters
Method	Image segmentation and analyst interpretation	Automated decision tree
Observation Period	August 1 to July 31	January 1 to December 31

Figure 2: Differences on deforestation estimates (GFC vs PRODES)



Notes: As we can perceive visually, PRODES' deforestation patches are less numerous but have larger dimensions than the cover loss patches of GFC dataset.

As a first step, we compared forest cover loss from the GFC project with the deforestation extent from PRODES. A paired t-test of annual differences in deforestation revealed significant difference between the PRODES and GFC data for the years 2008 to 2017, the only exception is the year of 2015 with a p-value of 0.13 (Table 2). Furthermore, GFC detects systematically higher rates of deforestation than PRODES (except for 2010 and 2011).

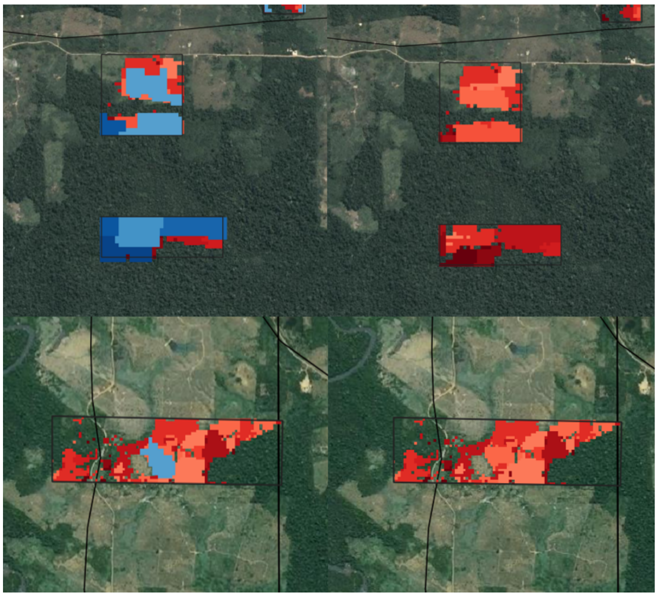
Table 2: Paired t-tests on the equality of means

Year	GFC	Std. Dev.	PRODES	Std. Dev.	ND	t	p-value
2008	3.274078	7.521317	1.989618	6.766448	0.1269598	23.07817	0
2009	2.353563	5.686867	1.01914	4.492102	0.1841338	28.21271	0
2010	1.44978	3.998299	1.982991	5.932794	0.0745298	-12.23826	0
2011	1.44215	3.650426	2.865757	7.073812	0.1788412	-26.67174	0
2012	2.42337	5.588083	0.4633146	2.226049	0.3258534	45.86309	0
2013	1.868192	4.368165	0.5360647	2.68009	0.2599366	42.63004	0
2014	3.101257	7.098502	0.7804115	3.730648	0.2894136	49.73624	0
2015	1.630968	5.765415	1.567375	5.688725	0.0078515	1.495065	0.1349
2016	2.942305	6.948409	1.293967	5.522716	0.1857104	39.61843	0
2017	4.017132	7.549779	1.306353	5.136666	0.2968598	57.61774	0

Note: When p-value is lower than 0.05, one can reject the null of equality and conclude that the two series differ.

Also, several spatial differences emerged when comparing the GFC and PRODES data (Figure 3). To highlight these differences, we aggregated deforestation pixels for the 2008-2017 period from PRODES and GFC data into binary raster layers.

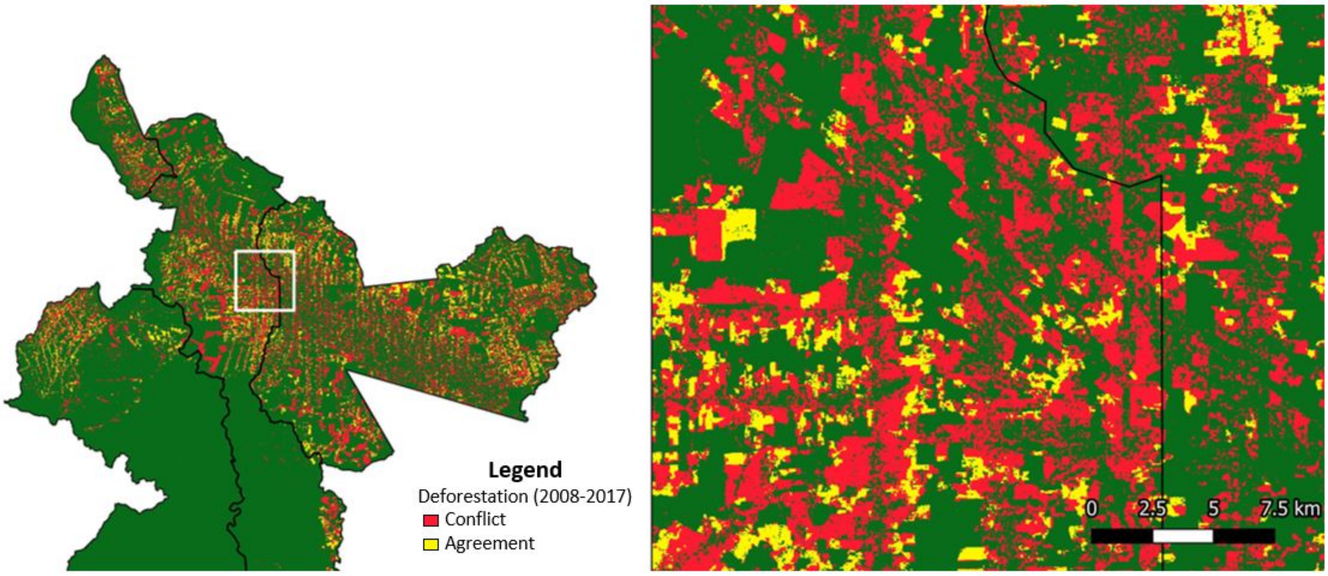
Figure 3: Disagreement between datasets



Notes: Differences between the GFC (red shades) and PRODES (blue shades). Background: Google Satellite

To measure the spatial consistency between the two RS products, we overlapped both layers and performed validation samples of the areas of agreement and conflict between the two input map products (Figure 4). Using the *r.report* function in QGis to obtain zonal statistics, we've found that datasets have a 39% agreement at the municipality scale, a 36% agreement at the settlement scale and a 27% agreement at PAS plot's scale.

Figure 4: Measuring the consistency between GFC and PRODES



Notes: Overlapped layers presenting the spatial distribution of agreement and conflict between GFC and PRODES for the 2008-2017 period.

Despite the low spatial agreement between the two products, we still need to investigate if they are useful or not to carry out impact assessments of REDD + programs in the Amazon region. For this purpose, we will focus on the PAS program.

4 Evaluating REDD+ using both RS products

The PAS project

The PAS project is a sub-national REDD+ project implemented by the Amazon Environmental Research Institute (IPAM), a Brazilian non-governmental organization involved in the design and implementation of REDD+ programs in Brazil (Cromberg et al., 2014). PAS started in 2012 and was financed by the Amazon Fund[5] until 2017. The program has offered a mix of interventions to reduce deforestation rates, including conditional PES, administrative support for registration under the CAR and assisting the adoption of sustainable livelihoods systems to 350 smallholders that live in land reform settlements located in the municipalities of Anapu, Pacaja, and Senador Jose Porfirio (Simonet et al., 2018). These three municipalities, located close to the Transamazon highway, still figure in the raking of the 10 critical municipalities for their deforestation rates until today[6].

[5]The Amazon Fund is a REDD+ instrument designed to raise donations for non-reimbursable investments in efforts to curb deforestation as well as to promote sustainable use of resources in the Brazilian Amazon.

[6]The first settlers arrived in the area during the Plan for National Integration (PIN) for the colonization of the Brazilian Amazon. At that time, poverty in north-eastern Brazil was the immediate issue, especially following an extreme drought of 1970 (Fearnside, 1984). The transfer of poor north-easterners to colonization areas along the Transamazon highway was raised as the solution by the Brazilian Government at that time. Encouraging

The value accessed by the 350 households in the PES scheme was of 150 Brazilian reais (BRL) per month (about 40 USD) from January 2014 and February 2017 (Pinto de Paulo Pedro, 2016). The payments offered to project participants were conditional on forest conservation and agricultural transition toward a fire-free production system [7]. The payments were made every 3 months, according to the compliance to the established guidelines. The monitoring of the compliance was made annually by IPAM, based on analysis of PRODES data for the forest cover and on the performance of productive activities certified by the project technical assistance team (Pinto de Paulo Pedro, 2016).

The map with the localization of the farm-holds enrolled in PAS program is publicly available at IPAM's website. Therefore, we used this available data to geolocalize 348 plots that received payments conditional on forest conservation.

Empirical Strategy

In this section we describe our empirical approach and its key assumptions. We intend to measure the impact of PAS program on forest conservation among enrolled farm-holds. To do so, we need to estimate the difference between the deforestation extent observed on participating farms and the deforestation extent that would have been observed in those farms if they weren't enrolled in PAS program. In other words, we focus on estimation of the average treatment effect on the treated (ATT).

Estimating treatment effects with observational data brings the problematic of selection bias, because the treated and untreated units might be different for reasons other than the treatment. This bias occurs because some of the factors that influence the selection of participants also determine the outcomes of interest. Observations of pre-treatment outcomes might help to correct for selection bias because they contain information on these confounding factors. Thus, matching on deforestation previous to the intervention accounts for unobserved factors that influence the outcome and whose effect vary over time (Abadie, Diamond, and Hainmueller, 2010).

Besides matching on pre-treatment outcomes, we've chosen a set of covariates that are likely to drive both the participation in the PAS project as well as decisions regarding deforestation. It is important to choose observable factors that are not affected by the project (Imbens, 2004), which is why we used pre-treatment values.

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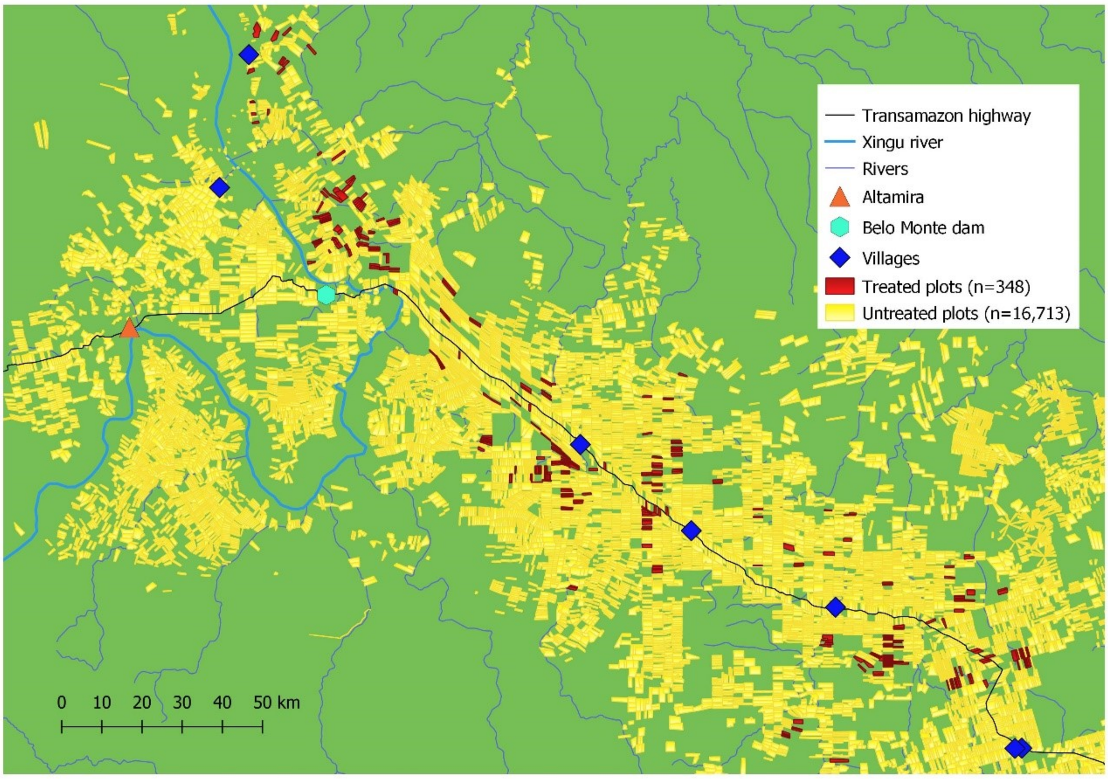
quick installation of settlers and the construction of the Transamazonian highway has intensified deforestation in the area without achieving many of its development goals. Colonizers were explicitly encouraged by the government to deforest at least 50% of their plots to pledge ownership (Souza, 2006). The livelihoods of small landowners in this area still depend on slash-and-burn agriculture and extensive cattle ranching, which are the two primary drivers of deforestation in the Brazilian Amazon (Smith et al., 1996; Soares-Filho et al., 2006).

[7] Thirty percent of the payment was conditional on conserving forest on at least 50% of the farm, another thirty percent of the payment was conditional on the maintenance of 15-meter-wide forest riparian zones and the remaining 40% of the payment relied on the adoption of fire-free practices. A minimum of 30% of forest cover was required to be eligible for payments, but only participants with at least 50% of forest cover received the full payments (see Simonet et al. (2018) for a detailed description of PAS program).

Figure 5: Indicators of accessibility



Notes: The vector layers containing the rivers, roads and villages are publicly available at the Brazilian Institute of Geography and Statistics (IBGE) website (ftp://geoftp.ibge.gov.br/). Belo Monte dam was localized through photo-interpretation.

Given that deforestation patterns are influenced by the initial forest cover and that farms with larger area of forests are more likely to participate to PAS project, we believe that we should achieve balance on the baseline forest cover. Also, we want to control for farm size, which captures characteristics of the landowner that influence deforestation decisions. Similarly, we selected covariates that are indicators of accessibility (Figure 5), such as: (1) the distance from the the main road (Transamazon highway); (2) the distance from the main navigable river (Xingu river); (3) the distance from the nearest river (secondary source of accessibility for small boats); (4) distance from the main market (Altamira city); (5) the distance from the nearest small village (local market); and (6) distance from Belo Monte dam (a hydroelectric dam complex currently under construction that may represent a source of off farm jobs for the settlers living nearby).

Table 3: Summary statistics for participants and non-participants

	Non-participants (n=16,713)				Participants (n=348)			
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Plot area (ha)	98.06	78.26	15.07	504.82	88.89	55.16	19.52	468.03
Distance from nearest river	4221.16	3648.85	0	24075.7	4437.79	4021.51	0	16651.49
Distance from nearest village	27333.67	15673.9	0	76053.16	20531.42	11313.85	239.66	50061.87
Distance from Altamira	162655.5	90276.62	0	347171.8	127081.4	59869.71	42484.13	233754.9
Distance from Belo Monte dam	136500.4	79964.72	1154.4	313873.6	91124.94	59513.2	8596.69	196173.7
Distance from Transamazon highway	23844.39	19062.79	0	69916.3	11796.57	10591.58	0	59827.86
Distance from Xingu river	108760.4	79826.77	0	284713.2	69856.78	55470.93	0	172423.5
Forest cover 2000 (GFC)	95.13	80.3	0.18	591.57	91.01	57.05	23.04	503.55
GFC 2008	3.3	7.57	0	187.83	2.13	4.55	0	32.85
GFC 2009	2.35	5.7	0	165.06	2.75	4.83	0	35.46
GFC 2010	1.46	4.02	0	84.78	0.94	2.62	0	21.78
GFC 2011	1.45	3.67	0	110.34	0.86	2.17	0	16.47
GFC 2012	2.44	5.62	0	130.77	1.78	3.59	0	24.66
GFC 2013	1.88	4.4	0	88.11	1.24	2.23	0	12.87
GFC 2014	3.1	7.12	0	232.02	3.33	6.19	0	68.04
GFC 2015	1.64	5.81	0	228.51	1.34	2.84	0	21.96
GFC 2016	2.93	6.95	0	321.03	3.67	6.89	0	63.27
GFC 2017	4.01	7.58	0	209.88	4.21	5.75	0	35.37
PRODES 2008	2.01	6.81	0	205.38	1.24	3.83	0	30.87
PRODES 2009	1.03	4.53	0	211.95	0.38	1.99	0	20.07
PRODES 2010	2	5.97	0	155.7	1.23	3.77	0	31.14
PRODES 2011	2.87	7.11	0	131.58	2.89	5.31	0	38.25
PRODES 2012	0.47	2.24	0	55.17	0.2	1.21	0	12.24
PRODES 2013	0.55	2.71	0	145.26	0.03	0.35	0	5.67
PRODES 2014	0.79	3.76	0	131.13	0.17	1.24	0	16.2
PRODES 2015	1.57	5.72	0	171.72	1.41	4.06	0	33.3
PRODES 2016	1.29	5.54	0	308.25	1.3	4.38	0	40.05
PRODES 2017	1.31	5.16	0	150.3	1.25	3.73	0	23.94

We performed an estimation for ATT using the *teffects nnmatch* program (StataCorp, 2015). This program estimates the average treatment effect on dependent variable by comparing outcomes between treated and control observations, using the nearest-neighbor matching (NNM) approach across a group of covariates. The program pairs observations to the closest matches in the opposite group to provide an estimate of the counterfactual treatment outcome.

Since we had property boundaries from the farm-holds in our study area, our unit of analysis is the household decision-making unit. Here we consider that each farm-hold, i, has two potential outcomes y^1 and y^0, where y^1 is the area deforested in 2013, 2014, 2015, 2016 and 2017 for a plot enrolled in PAS program and y^0 the deforested area at the same years for a plot not enrolled in the program. D is a dummy for the participation in the PAS program ($D = 1$ if farm-hold i was enrolled in the program and $D = 0$ if farm-hold i was not enrolled). We don't see $y^0|D = 1$, so we apply matching to estimate the ATT:

$$ATT = E(y^1 - y^0|D = 1) = E(y^1|D = 1) - E(y^0|D = 1)$$

An additional assumption for the validity of the matching approach is that the treatment received by one farmer must not affect the outcome of another farmer. This assumption is referred to as the stable unit treatment value assumption (SUTVA). To deal with this assumption in our analysis, we excluded the plots that were less than 5 km distant from a treated plot. After excluding the plots that were closer than 5 km from a treated plot we ended up with 12,581 observations. We believe that SUTVA is not likely to be threatened because the transportation infrastructure in the region is very limited. Furthermore, given the small area under PAS contracts relative to the study area, we are less concerned about general equilibrium spillover effects across farms in the region.

Results of the Impact Evaluation

We first apply the NNM estimator to our data to estimate the average effect of the PAS project on the deforestation rate of participant using the comparison group to estimate the counterfactual level of deforestation (Table 4).

Table 4: Impact on participants

Estimator		Coef.		Std. Err.	z	P>|z|	[95% Conf. Interval]	
NNM	GFC 2013	-0.657	**	0.295	-2.23	0.026	-1.236	-0.078
	GFC 2014	-0.735	*	0.384	-1.91	0.056	-1.488	0.019
	GFC 2015	-0.59	**	0.29	-2.04	0.042	-1.158	-0.022
	GFC 2016	0.479		0.437	1.09	0.274	-0.378	1.335
	GFC 2017	-0.172		0.434	-0.4	0.692	-1.023	0.678
(2 neighbors)	PRODES 2013	-0.693	***	0.182	-3.81	0	-1.05	-0.337
	PRODES 2014	-0.62	***	0.199	-3.12	0.002	-1.009	-0.231
	PRODES 2015	-0.652	*	0.36	-1.81	0.07	-1.358	0.053
	PRODES 2016	0.622	**	0.255	2.44	0.015	0.122	1.123
	PRODES 2017	0.196		0.263	0.74	0.457	-0.32	0.711

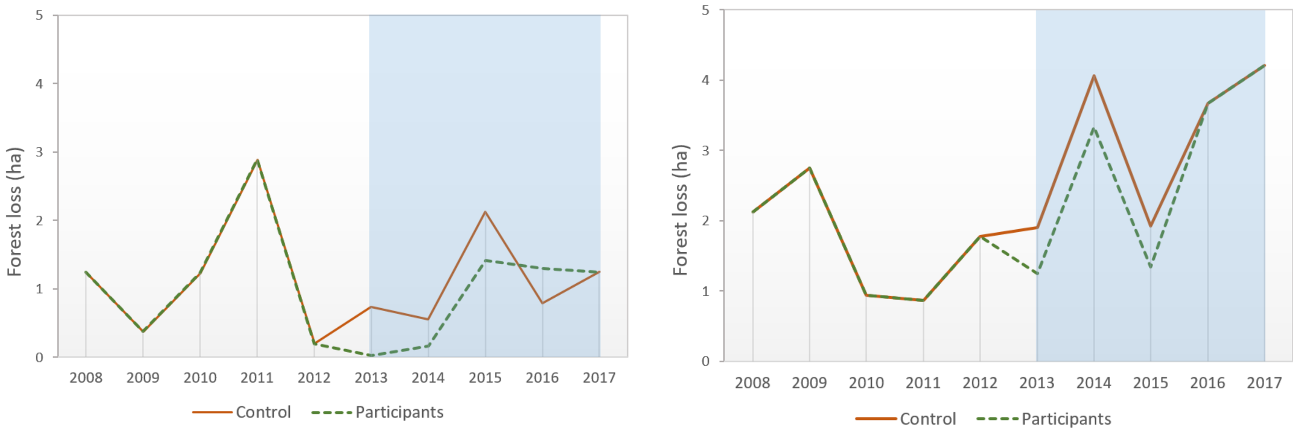
Note: ***, **, and * denote rejection of the null hypothesis of no impact at the 1%, 5% and 10% level.

For the estimations, we obtain a significant negative point estimate for the years 2013 (ATT equals -0.66 ha), 2014 (ATT equals -0.73 ha) and 2015 (ATT equals -0.59 ha) using GFC data, suggesting that the PAS prevented 1.98 ha of forest from being cleared on each participating farm (n = 348) during the first 3 years of the program. Similarly, we find a significant negative point estimate for the years 2013 (ATT equals -0.69 ha), 2014 (ATT equals -0.62 ha) and 2015 (ATT equals -0.65 ha) using PRODES data, implying that the program prevented 1.96 ha of forest from being cleared during these years on each enrolled plot. Also, we failed to detect a significant impact of the program for the year 2016 (p-value equals 0.274) using GFC data and we obtain a significant positive point estimate for the year 2016 (ATT equals

0.62 ha) using PRODES data, suggesting that PAS program increased deforestation in that year.

The results for the NNM are shown graphically on Figure 6. We observe that forest loss continues to rise in both participant and control groups after 2012. However, we see a clear break in the deforestation trend among participants for 2013, 2014 and 2015. This break can be attributed to PAS program.

Figure 6: PAS impact on participants



(a) PRODES

(b) GFC

Notes: Observed trends in tree cover loss (in hectares) for PAS participants (green dotted line) and control group (orange line). NNM results (2 neighbors) using both RS products. The PAS program was implemented from 2013 and 2017 (grey shaded rectangle)

After 2015, the estimates from the two RS products diverge. According to PRODES estimates, the deforestation rate among participants surpasses the rate from the matched group in 2016 and reaches the trend of the comparison group in 2017. According to GFC estimates, the deforestation rate among participants reaches the trend of the comparison group in 2016.

Balancing test

The goal of matching is to make the covariate distributions of participants and non-participants similar. After we compare the extent of balancing between the participant and comparison groups before and after the matching procedure. We calculate the normalized difference between these two groups for the pre-treatment covariates. The normalized difference is the most commonly accepted diagnostic used to assess covariate balance (Rosenbaum and Rubin 1985).

Table 5: Balancing test

	Means		Variances		Standardized differences		Variance ratio	
Covariates	Control	Treated	Control	Treated	Raw	Matched	Raw	Matched
Plot area (ha)	96.37	88.89	6350.9	3042.42	-0.11	0.04	0.48	1.09
Distance from nearest river	4208.36	4437.79	1.23E+07	1.62E+07	0.06	0.04	1.31	1.26
Distance from nearest village	29496.36	20531.42	2.65E+08	1.28E+08	-0.64	0.02	0.48	0.83
Distance from Altamira	171651.3	127081.4	9.52E+09	3.58E+09	-0.55	0.02	0.38	0.89
Distance from Belo Monte dam	148787.9	91124.94	6.93E+09	3.54E+09	-0.8	-0.04	0.51	1.04
Distance from Transamazon highway	27729.06	11796.57	3.80E+08	1.12E+08	-1.02	-0.11	0.3	1.21
Distance from Xingu river	119414.3	69856.78	7.12E+09	3.08E+09	-0.69	-0.02	0.43	1
Forest cover in 2000 (GFC)	92.7	91.01	6628.29	3254.36	-0.02	0.05	0.49	1.05
GFC 2008	3.26	2.13	58.49	20.72	-0.18	0.04	0.35	1.15
GFC 2009	1.89	2.75	24.54	23.29	0.18	0.06	0.95	1.06
GFC 2010	1.54	0.94	16.62	6.87	-0.17	0.07	0.41	1.04
GFC 2011	1.54	0.86	14.19	4.7	-0.22	0.06	0.33	1.2
GFC 2012	2.39	1.78	32.33	12.88	-0.13	0.09	0.4	1.13
PRODES 2008	2.02	1.24	47.98	14.69	-0.14	0.1	0.31	1.33
PRODES 2009	1.18	0.38	23.26	3.94	-0.22	0.05	0.17	1.31
PRODES 2010	1.94	1.23	33.67	14.21	-0.14	0.04	0.42	1.17
PRODES 2011	2.62	2.89	46.5	28.21	0.04	0.14	0.61	1.19
PRODES 2012	0.56	0.2	6.09	1.47	-0.19	0.03	0.24	1.33

The normalized difference is considered negligible when it is below of 0.25 standard deviations (Imbens and Wooldridge 2009). Column 6 of Table 5 shows that, before matching, the participant group (column 3) differs significantly from the comparison group (column 2) in terms of distance from nearest village, distance from Altamira, distance from Belo Monte dam, distance from Transamazon highway and distance from Xingu river Column 7 of Table 5 reports the normalized mean differences between participants and the constructed matched group. All normalized differences are below 0.25 standard deviations, which indicates that the matching procedure was successful in constructing a valid control group.

5 Discussion

RS products

Our results show that the deforestation estimates from the two datasets are statistically different, with GFC detecting systematically higher rates of deforestation than PRODES. In addition, we found that deforestation patches from both RS products have a very small spatial agreement at the individual farm-level (for example, we found only 27% of agreement for the 348 farms under program). We find that the divergence between the two products can be partially explained by the fact that small deforestation is not incorporated within PRODES estimates (deforestation activities are only reported if they accumulate beyond the 6.25-hectare threshold). Also, some of the cover loss reported in GFC dataset may be due to forest degradation (e. g. such as forest fires and selective logging). Because of the methodological differences between PRODES and GFC, forest degradation will not appear in PRODES estimates, but may possibly inflate GFC's deforestation estimates. Therefore, interpretation of small-scale deforestation must be done with caution. Incontestably, any deforestation RS product contains classification errors and deforestation area estimates from these products diverge from reality. We recommend taking this into account when evaluating the effectiveness of local REDD+ using these products.

PAS impact

We assessed the impact of PAS project over 2013-2017, comparing the 348 beneficiaries of the program to the rest of the sample. We used matching on pre-treatment outcomes (2008-2012) to adjust for self-selection of farmers into the program. Despite the inconsistency between both datasets, we estimated that an average of about 2 ha of forest were saved during the early years of PAS project (2013-2015) on each participating farm, regardless the source of RS data. Nonetheless, results from the regional-scale product (PRODES) are more precise, with smaller p-values and narrower confidence intervals associated to the estimates. Even though the size of the estimated effect is small, it is similar to impacts found on other PES-based forest conservation programs (Robalino and Pfaff, 2013; Alix-Garcia, Shapiro, and Sims, 2012).

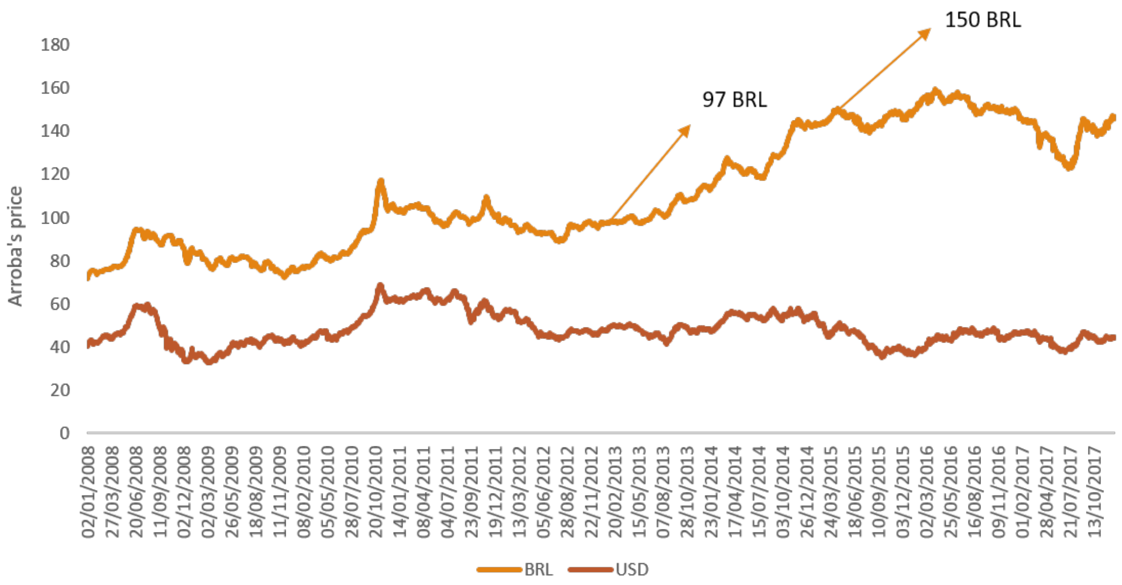
Also, we failed to detect a positive impact of the program during the last year (2016-2017), suggesting that PAS effects were primarily realized in its first years. Similarly, Giudice et al. (2019) and Fiorini et al. (2020) found that Peru's Natural Forest Conservation Program and Water and Forest Producers Program succeeded in increasing forest cover only in the program's first years.

Our estimates using PRODES data moreover suggest that participants increased deforestation over 2016-2017, because of the program. Evidence thus suggests that the PAS project may have failed on prompting a transition to more sustainable agricultural practices on the following years, as the additionality of the PES vanished even before the end of the program.

It is plausible that the cost of preserving the first hectares is smaller than the cost of preserving additional hectares (i. e., there is an increasing marginal cost for conservation). Since the price is fixed at the beginning of the program and there is no progression or adjustment in the contracts, the payments might not cover the opportunity costs of the farmers on the subsequent years.

Furthermore, the inflexibility of the contract might have prevented the landowners to adjust their conservation decision to unexpected shocks. As we can see in Figure 7, the price of cattle sharply increased from 97 BRL (January 2013) per arroba to 144 BRL (January 2015). We did not have data of interruptions of the PES contracts, however, one may think that this hasty increase in prices may have triggered a crowding out of PAS' participating farm holds from the PES scheme.

Figure 7: Evolution of cattle price in Brazil



Source: Centro de Estudos Avancados em Economia Aplicada (CEPEA)

6 Conclusion

These findings suggest that GFC and PRODES may not be suitable for accurately monitoring, reporting and verifying (MRV) annual deforestation at the farm-level. Thus, PES-based REDD+ projects should not rely on these products to verify individual-level compliance.

However, despite the inaccuracy of forest cover loss estimates at the individual plot-level, such RS products represent a valuable source of data to evaluate forest conservation projects. Since the noise in the data is randomly distributed among plots, impact evaluation techniques can be used to provide robust estimates of the average treatment effect of the program. Moreover, we recommend REDD+ project evaluators to cross-validate results using multiple datasets and to prioritize the use of locally designed RS products when available.

Also, our findings suggests that the PAS project have failed on inducing more sustainable agricultural practices on the following years, as the additionality disappeared even before the end of the program. If these findings are externally valid, and can be generalized to other similar programs, they would have significant implications for the status of PES-based REDD+ projects in the Brazilian Amazon. Suggesting that project sponsors need to emphasize permanence objectives in REDD+ contracts, in particular to safeguard against economic shocks such as the rise in agricultural commodity prices which lead to deforestation.

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