Using publicly available remote sensing products to evaluate REDD + projects in Brazil

Gabriela Demarchi, Julie Subervie, Thibault Catry, Isabelle Tritsch

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Abstract

Ensuring the perpetuity and improvement of REDD+ initiatives requires rigorous impact evaluation of their effectiveness in curbing deforestation. Today, a number of global and regional remote sensing (RS) products that detect changes in forest cover are publicly available. In this study, we assess the suitability of using these datasets to evaluate the impact of local REDD+ projects targeting smallholders in the Brazilian Amazon. Firstly, we reconstruct the forest loss of 21,492 farms located in the Transamazonian region for the period 2008 to 2018, using data from two RS products: Global Forest Change (GFC) and the Amazon Deforestation Monitoring Project (PRODES). Secondly, we evaluate the consistency between these two data sources and find that the deforestation estimates at the farm level vary considerably between datasets. Despite this difference, using microeconometric techniques that use pre-treatment outcomes to construct counter-factual patterns of REDD+ program participants, we estimate that about two hectares, or about four percent of the forest area, were saved on average on each of the 350 participating farms during the first years of the program, regardless of the data-source used. Moreover, we find that deforestation decreased on plots surrounding participating farms during the very first years of the program, suggesting that the program may have had a positive effect on neighboring farms as well. Finally, we show that participants returned to their business-as-usual pattern of clearing one to three hectares per year at the end of the program. The environmental gain generated by the program, however, was not offset by any catch-up behavior, as the two hectares saved on each farm before 2017 were not cleared in 2018. By calculating the monetary gain of the delayed carbon dioxide emissions, we find that the program's benefits were ultimately greater than its costs.

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[†]CEE-M, Univ. Montpellier, CNRS, INRAE, Institut Agro, Montpellier, France

[‡]Center for International Forestry Research (CIFOR)

[§]Address correspondence to G. Demarchi, email: gabriela.demarchidias@inrae.fr

[¶]ESPACE-DEV, Univ Montpellier, IRD, Univ Antilles, Univ Guyane, Univ Réunion, Montpellier, France

[‖]CIRAD, UPR Forêts et Sociétés, Univ Montpellier, Montpellier 34398, France

1 Introduction

Forest cover change is a leading cause of Brazil's greenhouse gas emissions (INPE, 2019). Although the annual deforestation rate in Brazil fell by 70 percent between 2005 and 2013 (Nepstad et al., 2014), more than 9,700 square kilometers of the Brazilian Amazon were cleared between 2018 and 2019, representing an increase of 30 percent in the annual deforestation rate and the highest deforestation rate since 2008 (INPE, 2019). The reasons for this recent development have been widely documented in the literature (Harding et al., 2021; Moffette et al., 2021; Mullan et al., 2021; dos Reis et al., 2021; Pailler, 2018; BenYishay et al., 2017; Bowman, 2016; de Sá et al., 2013). As a result, there has been a proliferation of sub-national initiatives financed by the REDD+ (Reducing Emissions from Deforestation and Forest Degradation) mechanism in the Brazilian Amazon in recent years (Sills et al., 2014). Brazil currently hosts about 50 REDD+ projects targeting smallholder farmers and financed by REDD+ funds or carbon markets (Simonet et al., 2015). The perpetuity and improvement of REDD+ projects require rigorous impact evaluation (Ollivier, 2012). Yet robust evidence on their effectiveness in reducing deforestation remains scarce (Jayachandran et al., 2017; Simonet et al., 2018b; Roopsind et al., 2019). One of the reasons for this lack of evidence is the high cost of collecting the survey data needed for impact analysis (Ferraro et al., 2012; Blackman, 2013; Pagiola et al., 2016).

Over the past 20 years, however, remotely sensed data for detecting changes in land cover worldwide has evolved dramatically, which offers 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 data have become publicly available (Kugler et al., 2019). Though these RS products present a great opportunity to measure large scale changes in forest cover, the suitability of these readily available datasets to perform proper impact evaluations of sub-national REDD+ initiatives has rarely been questioned (Bos et al., 2019; Neeff et al., 2020; Correa et al., 2020).

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 Brazil's National Institute for Space Research (INPE). GFC provides free of charge global historical records 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 et al., 2019). In the Brazilian context, however, the most often used deforestation dataset is PRODES, an accessible and transparent RS product, also free of charge. PRODES has been used to assess the impact of several forest conservation policies, including the effectiveness of protected areas (Nolte et al., 2013; Herrera et al., 2019), supply chain policies (Villoria et al., 2022), and command-and-control initiatives (Assunção et al., 2015; Assunção and Rocha, 2019).

In this study, we assess the applicability of these two RS datasets to evaluate, not the impact of protected areas, but that of REDD+ local projects targeting smallholders in the Brazilian Amazon. To do so, we concentrate on Brazil's REDD+ flagship project for curbing deforestation, the Sustainable Settlements in the Amazon (SSA) program, which offered technical assistance and payments for environmental services (PES) to 350 households for maintaining forest cover on at least half of their land between 2012 and 2016 (see Section 3 for program details). Forest conservation PES schemes are contracts between a landowner and the conservation buyer (typically the government or an NGO) through which the landowner receives a payment conditional to conserving the forest located on his land (Wunder et al., 2005; Engel et al., 2008).

This project was previously evaluated using survey data collected at the early stages of the program (Simonet et al., 2018b; Carrilho et al., 2022). Simonet et al. (2018b) found that in 2014 an average of 4 hectares of forest were saved on each participating farm and that this conservation came at the expense of pastures rather than croplands, which amounts to about a 50 percent decrease in the deforestation rate. Carrilho et al. (2022) extended the analysis by supplementing the panel survey data by an additional year and showed that forest loss had rebounded in 2019. A potentially important caveat in these studies, however, is that the extent to which participants might have under-declared their actual deforestation (compared to non-participants) is unknown. Unlike survey data, RS data are not susceptible to such a problem. RS data also have at least three additional advantages over survey data. First, using RS data generally makes it possible to run an analysis from larger samples than those available from surveys, thus affording increased statistical power at a much lower access cost. In the case of the SSA project, this means that we can estimate the forest loss on the individual plots of the entire population of participants rather than on only a sample of them. Second, using RS data allows us to estimate with more precision what the forest loss on these farms would have been in the absence of any program (the so-called counterfactual situation). Indeed, to make valid inferences about participants, there must be a sufficient number of non-participants with a high potential of being selected as counterfactuals. Using RS data allows access to a larger pool of candidates for the selection procedure, which increases the probability of finding good matches, that is, non-participants who will be paired with participants to estimate the impact of the program by comparing the two groups. This is referred to as the common support assumption. Those non-participants who display a pattern identical to that of the participants during the period preceding the program typically have a high potential of being selected as counterfactuals in the matching procedure. The larger the pool of non-participants, the more likely that the common support hypothesis will hold (Hill and Su, 2013). Third, the use of RS data allows us to study the effects of the program several years after its end. It is very expensive to repeatedly collect information in the field over a long period and the analysis based on survey data generally does not provide evidence of the permanence of the effects of conservation programs. In contrast, RS data make it possible to study the long-term effects of conservation programs, from the early stages of implementation to the most recent time period, by highlighting any effects of attenuation, rebounds, or compensation that may arise after the program ends.

To date, a number of forest conservation and reforestation programs have been evaluated applying microeconometric methods to RS data (see (Pattanayak et al., 2010; Samii et al., 2014; Alix-Garcia and Wolff, 2014; Börner et al., 2017) for reviews of this literature). Most studies have been conducted in Costa Rica (Sanchez-Azofeifa et al., 2007; Arriagada et al., 2012; Garbach et al., 2012; Robalino and Pfaff, 2013) and Mexico (Honey-Rosés et al., 2011; Scullion et al., 2011; Alix-Garcia et al., 2012; Sims et al., 2014; Alix-Garcia et al., 2015; Costedoat et al., 2015; Sims and Alix-Garcia, 2017). These programs typically offer participants conditional payments to reduce deforestation on their farmland. Overall, the results of these studies suggest that the impact of the programs on the average annual forest cover varies substantially across regions (Simonet et al., 2018a). Recent REDD+ impact evaluations include a study in Uganda, using remote-sensed data developed from QuickBird satellite images (Jayachandran et al., 2017), in Ecuador, using remote-sensed data developed from Landsat TM images (Mohebalian and Aguilar, 2018), in Guyana, using the GFC dataset (Roopsind et al., 2019), and in Brazil, using MapBiomas dataset (West et al., 2020). Overall, the results of these studies suggest that the impact of REDD+ programs on forest loss may be significant. Indeed, Jayachandran et al. (2017) find that tree cover in Uganda declined in the treatment villages by 4.2 percent during the two-year period under study, compared to 9.1 percent in the control villages, thus indicating a 54 percent decrease in deforestation rates. Likewise, Roopsind et al. (2019) estimate that the annual tree cover loss was 0.056 percent in Guyana compared to 0.087 percent in the counterfactual estimate, thus indicating a 36 percent decrease in annual deforestation rates as a result of the program.

Our study adds to the existing literature by providing new evidence on the effectiveness of REDD+ programs, focusing on a region characterized by the highest annual loss of forest in the world, while previous studies have focused on areas where deforestation may appear less pressing (Cisneros et al., 2022) or have evaluated REDD+ initiatives at the project level (West et al., 2020; Guizar-Coutiño et al., 2022). Two recent studies have assessed the effectiveness of REDD+ projects in the Brazilian Amazon using RS data, but their conclusions diverge. West et al. (2020) assessed the additionality of twelve REDD+ projects using PRODES data. They used rural properties recorded in the Brazilian cadastral database to construct project polygons as the unit of analysis and found mixed results on the additionality of REDD+ projects in the Brazilian Amazon. More recently, Guizar-Coutiño et al. (2022) assessed the additionality of twelve REDD+ sites in Brazil using the Tropical Moist Forests database derived from Landsat imagery. They used pixels as the unit of analysis and found that most Brazilian REDD+ projects had a small but positive impact on deforestation. We contribute to this burgeoning literature on the effectiveness of REDD+ in Brazil, by evaluating one emblematic REDD+ program at the farm level, combining ready-to-use RS products and property-level data. In particular, we provide evidence on three environmental performance indicators: the additionality of the program, i.e. the number of additional hectares of forest recorded on the participating farms compared to the counterfactual situation (the absence of REDD+ program); the permanence of the program, i.e. the number of years during which additionality is observed; and the spillovers, i.e. additionality on non-participating farms. We moreover use these additionality estimates to calculate the cost-benefit ratio under various social cost of carbon scenarios. Finally, this is the first study that assesses the effectiveness of a Brazilian local REDD+ project conservation program using two different sources of remotely-sensed deforestation data to cross-validate impact assessment results.

2 Remote-Sensing products used

The Amazon Deforestation Monitoring Project (PRODES)

PRODES was created in 1988 by Brazil's National Institute for Space Research (INPE), with the main objective to quantify and geolocalize deforestation in the Brazilian Legal Amazon and help the Brazilian government to make informed decisions and establish environmental and development public policies for the region (Câmara et al., 2006). Annual rates are estimated from the deforestation increments identified in Landsat images. 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 rely on three main observable elements present in the images: tone, texture, and context (see (INPE, 2019) for a more detailed description of PRODES methodology).

Like any RS product, PRODES has some technical limitations. Firstly, deforestation estimates only consider primary forests and do not account for secondary or regenerating forests. Secondly, since PRODES relies on optical imagery, constant cloud coverage prevents Landsat sensors from capturing land cover imagery. Lastly, although PRODES, that uses 30m resolution Landsat data, has the potential to map deforestation events at a scale inferior to one hectare, a threshold of 6.25 ha in deforestation patches detection is used in order to maintain consistency with long-term data. This criteria results in less error, but also limits the detection of smaller patches (Kalamandeen et al., 2018; Maurano et al., 2019)

The Global Forest Change dataset (GFC)

The most well-known global deforestation dataset currently available is the University of Maryland's Global Forest Change dataset (GFC). This dataset's objective is to produce annual globally consistent characterizations of tree cover loss (Hansen et al., 2013). GFC maps annual forest loss beginning in 2001. The maps produced by the GFC initiative are also based on Landsat satellite images, but the classification process is 100% automated. The classification process of cloud-free

Landsat image mosaics is carried out using decision tree algorithms. As the classification is carried out pixel by pixel, the minimum area mapped by this product is 900 square meters (30 x 30 meters).

For this dataset, tree-cover is defined as all vegetation taller than 5 meters across a range of canopy densities (from 0 percent to 100 percent) for an area of approximately 0.1 hectares (equivalent to a Landsat pixel) in the year 2000 (baseline year). Therefore, this layer can represent primary and secondary natural forests (existing prior to 2000) as well as tree plantations. In addition, this dataset requires 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 a complete methodological explanation).

While GFC represents major progress in the understanding and quantification of global forest change research and conservation planning, the dataset does have some limits. First, tree cover loss can be the result of human activities (e. g., plantation harvesting, selective logging, and clear-cut) as well as natural causes (e.g., disease, storm, and fire damage). Second, plantations, such as cocoa, palm oil, and eucalyptus, are included as forests (Tropek et al., 2014), although the Brazilian Forest Code does not classify them as such.

3 Description of the REDD+ Case Study

The SSA project is a sub-national REDD+ initiative implemented by the Amazon Environmental Research Institute (IPAM in the Portuguese acronym), a Brazilian non-governmental organization involved in the design and implementation of several forest conservation programs in Brazil (Cromberg et al., 2014). The SSA project started in 2012 and was financed by the Amazon Fund until 2017. 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. The program has offered a mix of interventions to reduce deforestation rates to smallholders living in settlements located in the Transamazon highway (SI Appendix, Figure S1). According to IPAM, about 2700 families have benefited from the program through a series of interventions such as: i) Awareness-raising meetings on environmental legislation and tenure regularization that were held between 2013 and 2017, benefiting an unknown number of participants, since those were open to the local community; ii) Administrative support for registration under the Environmental Rural Registry (or CAR in the original Portuguese acronym) to 1300 smallholders between 2012 and 2014; iii) Development of low deforestation activities (e.g., intensive cattle ranching, agroforestry and horticulture) benefiting 650 families between 2014 to 2017; and iv) PES scheme to 350 smallholders. The components of the program are described in more detail in Simonet et al. (2018b) and Carrilho et al. (2022).

Our analysis focuses on the 350 farm-holders that benefited from all the above-mentioned components. The map with the localization of the farm-holds enrolled in SSA program is publicly available at IPAM's website (http://www.pas-simpas.org.br/). Therefore, we used this available data to geolocalize the plots that belonged to the families who received payments conditional on forest conservation. These families had participated in a previous PES federal program (Proambiente) from 2003 and 2006 (Simonet et al., 2018b). The small landowners live in land reform settlements located in the state of Pará, in the municipalities of Anapu, Pacajá, and Senador José Porfírio. These three municipalities, located close to the Transamazon highway, figure in the ranking of the 10 ten critical municipalities for their deforestation rates. The livelihoods of small landowners in this area 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).

The value accessed by the 350 households in the PES scheme was 1680 Brazilian reais (BRL) per year (about 626 USD using the average conversion rate of Brazilian Real to American dollars in 2014) from January 2014 to 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. Thirty percent of the payment was conditional on conserving forest on at least 50 percent 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 percent of the payment relied on the adoption of fire-free practices. A minimum of 30 percent of forest cover was required to be eligible for payments, but only participants with at least 50 percent of forest cover received the full payments (see Simonet et al. (2018b) for a detailed description of the SSA program). The payments were made every three months, according to the compliance to the established guidelines. The monitoring of the compliance was made annually by IPAM, based on remote-sensing data and field visits (Pinto de Paulo Pedro, 2016).

As Simonet et al. (2018b) remind us, there are a variety of reasons why voluntary programs like the SSA project may not be effective in curbing deforestation. Firstly, farmers who face the lowest costs for decreasing deforestation are the most likely to enter such projects, which increases the probability of paying some farmers for doing nothing differently from what they would have done in the absence of any payment. Secondly, the impact of the project, if there is any, may be offset by negative spillovers. The empirical literature demonstrates that, depending on the context, conservation program spillovers may or may not occur. Furthermore, if they exist, they can have either positive or negative effects. Negative spillovers occur when the project increases deforestation among non-participants as a result of market equilibrium effects typically or when a forest-owner shifts planned deforestation activities from a PES-enrolled plot to a non-PES-enrolled plot (Dyer et al., 2012), for example. Positive spillovers occur when the project decreases deforestation among non-participants. This positive impact may arise from multiple channels, such as learning effects among non-participants upon contact with participants, social norms in communities with participants or employment opportunities generated by participants in favor of non-participants (Pfaff and Robalino, 2017). Moreover, even in cases where the additionality of the program can be demonstrated, there is no guarantee that this effect will be permanent, as shown by (Carrilho et al., 2022). Finally, it appears that the question of the effectiveness of REDD+ programs, which simultaneously covers additionality, permanence and spillovers, is above all empirical and must be dealt with using reliable data.

4 Material and Methods

Reconstructing forest loss on individual plots

We use farmholds' boundaries from the CAR. We delineate a 80-kilometer buffer around the Transamazonian highway for the Altamira, Senador Jose Porfirio, Anapu and Pacaja municipalities in order to delimit the farmholds that would be included in our initial sample. Georeferenced deforestation data and registered private rural properties are overlapped to enable identification of patches cleared inside property boundaries. We use information from GFC and PRODES to determine the location of forest clearings on an annual basis. All geographical datasets are re-projected to a common spatial reference (SIRGAS 2000/UTM 22S). Our sample covers the 2008-

2018 period. Since we did not have information about changes in property borders during our sample period, we assume that they were constant throughout this period. For the GFC tree cover layer, we use a threshold of 75 percent of vegetation cover as a definition of the forest, which is the average threshold used in previous studies run in the Amazonian context (Baker and Spracklen, 2019; Gasparini et al., 2019).

Identification strategy for the impact assessment

To identify the causal effect of the SSA program on the participants, referred to as the Average Treatment effect on the Treated (ATT), we use a matching approach that uses pre-treatment outcomes to construct a valid control group from non-participating plots (Imbens and Wooldridge, 2009). The ATT measures the difference in mean (average) outcomes between farms assigned to the treatment group (participants in our case) and farms assigned to the control group (matched non-participants in our case). This econometric method, widely used in economics, allows to distinguish the effects of enrolling some specific farms in a REDD+ program from the effects of the program itself (Millimet and Alix-Garcia, 2021).

Estimating treatment effects using observational data indeed brings the problematic of selection bias, since participants self-select into the program, the treated and untreated units may be different for many reasons other than the treatment itself. This bias occurs because some of the factors that influence the selection of participants also determine the outcomes of interest (forest loss in our case study). Observations of pre-treatment outcomes might help to correct for selection bias because they contain information on these confounding factors. Thus, matching treated and untreated groups on pre-treatment deforestation outcomes allows us to correct for selection bias (Abadie et al., 2010). Note that matching on the pre-treatment outcomes amounts to performing a difference-in-difference matching, bringing the pre-treatment difference to zero.

In addition to pre-treatment outcomes, we select a number of covariates likely to drive both the participation in the SSA project and decisions regarding deforestation, in order to improve the matching procedure. These covariates include farm size, distance to the main road (Transamazon highway), distance from the main navigable river (the Xingu river), distance from the main market (Altamira city), and distance from the nearest small village (local market).

We perform an estimation for the ATT using two nearest neighbor matching estimators: the Mahalanobis distance matching and the propensity score matching estimators. The outcome variables (forest loss) and covariates used in this analysis are measured at the farm level; the unit of observation is therefore the farm. In practice, we first run balancing tests to determine if the matching procedure was successful in achieving balance on the observed covariates. We then compare the average level of outcomes in the two matched groups. The analysis concerns the years 2008 to 2018, where 2008-2012 corresponds to the pre-treatment period and 2013-2018 to the post-treatment period. The SSA program was implemented between 2013 and 2017. The data used therefore allows us to assess the impact of the program up to one year after its official closure.

The stable unit of treatment value assumption

A key assumption for the validity of the identification strategy 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 or SUTVA (Rubin, 1978). SUTVA could be violated if some individuals were influenced by the exposure assignment of other individuals. For example, in the present case, one may fear that the beneficiaries of PES have organized certain arrangements with their direct neighbors, so as to be able to extend the pastures while respecting the terms of their PES contract. If so, these neighboring untreated plots would not be valid matched counterparts for the impact evaluation. For SUTVA to hold, we thus exclude from the untreated group those plots that are less than three kilometers distant from a treated plot, thus creating a buffer zone between treated farmholds and potential control ones (Figure 3). By doing so, we end up with 11,897 observations. Each of the 350 treated polygons is clearly delimited in the cadastral database. It may have happened that some of the 350 plots overlapped neighboring plots, but in all cases, none of the neighboring plots were eligible for the control group. Therefore the overlaps had no consequences in our analysis and did not require any particular procedure.

Strategy for addressing potential spillovers

In any conservation program targeting individuals, the possible presence of spillover effects, i.e., an impact of the program on individuals who were not initially targeted by the program but were exposed to it, must be considered. To test for the presence of such effects in the present case, we focus on farms not participating in the PES program but located within a radius of one kilometer from a participating farm. However, in the present case, it should be specified that if it were possible to detect any change in the deforestation of the plots surrounding the participating farms, it would not be possible to say whether these are indirect effects of the project – what are usually called spillovers – or rather direct effects of the project, which offered ranchers the possibility of training in new types of agricultural activities, even if they did not wish to enter into a PES contract, since these individuals have not been registered in any database.

Since we have to deal with SUTVA in this case too, we again create a buffer zone between the spillover zone and potential control farms, by excluding from the sample of untreated plots those farm-holds located between one and three kilometers from an enrolled plot. This identification strategy is illustrated in Figure 3.

Estimate of program cost-effectiveness

Following Jayachandran et al. (2017) and Simonet et al. (2018b), we calculate the value of the carbon benefit over the 2013 to 2018 period, using the social cost of carbon (SSC), and compare this value to the program's costs. The SCC is a metric that helps quantify the costs of climate change related to carbon emissions in terms of dollars per metric ton of carbon dioxide (CO_2) emitted. It can also be used to quantify the benefits of reducing CO_2 emissions. Policy recommendations for the SCC ranged from 11 to 116 USD/ton of CO_2 over the 2013 to 2018 period (IWG, 2016). The benefits of the SSA project are computed using the estimates of the total number of hectares of forest saved as a result of the program.

5 Results

Statistical and spatial consistency

The purposes and methodologies of PRODES and GFC are quite divergent (Table 1). Firstly, GFC records forest changes in every type of vegetation greater than 5 m in height (including primary and secondary forests), while PRODES only captures 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), while

GFC's methodology is grounded on pixel-based classifications (i. e., automated decision tree). As such, there is no a priori reason for forest-loss-related information provided by the two products to coincide. To check this assumption, we run a paired t-test of annual differences in deforestation as measured in the two datasets. The results reveal significant differences between the PRODES and GFC data for the years 2008 to 2018 (SI Appendix, Table S1). Furthermore, GFC detected higher rates of deforestation than PRODES in all years except 2010 and 2011.

Also, several spatial differences emerge when comparing the GFC and PRODES data. To highlight these differences, we aggregate deforestation pixels for the 2008-2018 period into binary raster layers. To measure the spatial consistency between the two RS products, we overlap both layers and perform validation samples of the areas of consistency and inconsistency (SI Appendix, Figure S2). We find that the datasets have a 39 percent concordance at the municipality scale, a 36 percent concordance at the settlement scale and a 27 percent concordance at the SSA plot scale.

Annual additionality of the REDD+ initiative

The low spatial agreement between the two products suggests that one or both may not be suitable for monitoring individual-level deforestation under REDD+ programs. However, this does not necessarily call into question the interest of these products for evaluating the effectiveness of REDD+ programs in curbing deforestation. Indeed, it is possible that the precision level of forest loss measurement is sufficient to detect any significant differences between the participating and control plots. In other words, it is possible to detect a statistically significant difference in forest loss between participating farms and control farms, even though the level of forest loss itself is imprecisely measured on each farm.

The results of the balancing tests are presented in Table 2. They show that, before matching, the participant group is significantly different from the non-participants for most covariates and that after matching, these differences drop below 0.25 standard deviations, suggesting that the matching procedure performed well. This result is also illustrated with Figure 4. The results of the ATT estimates for each year between 2013 and 2018 are displayed in Table 3. Looking at the first years of the program and using GFC data, the ATT ranges between -0.40 (SE=0.14) and -0.60 (SE=0.20) hectares for the year 2013, between -0.84 (SE=0.33) and -1.06 (SE=0.32) hectares for the year 2014, and between -0.31 (SE=0.18) and -0.63 (SE=0.22) hectares for the year 2015. Similarly, we find significant negative point estimates using PRODES data: the ATT ranges between -0.33 (SE=0.11) and -0.61 (SE=0.24) hectares for the year 2014, between -0.64 (SE=0.25) and -1.13 (SE=0.26) hectares for the year 2015, and between -0.43 (SE=0.17) and -0.72 (SE=0.23) hectares for the year 2016.

These results are also shown graphically on Figure 1. Regardless of the data source used, we can visually confirm that participants and matched individuals have nearly identical pre-treatment deforestation rates (i.e., the parallel trend assumption holds) while unmatched individuals have not. Then, according to the GFC dataset, the participant group deviates significantly from the trajectory of the control group from 2012 until 2015. The same phenomenon is demonstrated with the PRODES data, with a one-year lag, due to the difference in the observation period (Table 1). Under the hypotheses that we made when constructing the control groups, this clear break in the deforestation trend among participants can be attributed to the SSA program. To test the robustness of this result, we rerun the estimations using an alternative set of covariates in the matching procedure model. We include two additional pre-treatment covariates (pasture and forest area as measured in 2012) to the set of matching covariates. Pasture and forest area are obtained from the MapBiomas project (https://mapbiomas.org). Same results hold. The balancing tests and ATT estimates are displayed in Tables S2 and S3 in the SI Appendix. In addition, following Ferraro and Miranda (2017) we run a fixed effect model regression using the matched dataset and main results hold as well. These results are provided in Table S4 in the SI Appendix.

Permanence of the effects of the REDD+ initiative

The lowest part of Table 3 gives the estimates of the impact during the last years of the program. We fail to detect a significant impact of the program for the years 2016, 2017 and 2018, using GFC data, and for the years of 2017 and 2018, using PRODES data. The fact that the ATT becomes non-significant as the program ends indicates that the treated group, whose trajectory had diverged from that of the control group during three years, goes back to its business-as-usual behavior thereafter, i.e. the same deforestation rate as controls. In Figure 1, the disappearance of the effect of the program is illustrated by the overlap of the deforestation curves of the two groups, from 2015 according to GFC data and 2016 according to PRODES data. Taking for example GFC data provided in Table 2, this means that participants and matched controls both recorded the same forest loss before the program starts (1.55 hectares in 2008, 2.22 hectares in 2019, 0.91 hectares in 2010, 0.71 hectares in 2011, and 1.49 in 2012). Thereafter, from 2013 to 2015, the treated group cuts significantly less forest than the control group. The participants cut 1.01 hectares in 2013, 2.22 hectares in 2014, and 0.75 hectares in 2015, while the control group cuts 1.41 hectares in 2013, 3.05 hectares in 2014, and 1.06 hectares in 2015 (taking the smallest ATT estimates provided in Table 3). Finally, the two groups display again the same deforestation pattern from 2016 to 2018 (2.49 hectares in 2016, 3.39 in 2017, and 1.74 in 2018).

These results suggest that the gains achieved by the program until 2018 represent a three-year delay in the deforestation that would have occurred in the absence of the program. This means that the program participants consented to modifying their behavior for the duration of the program, only to return to their business-as-usual behavior after the end of the program, suggesting that the intervention was not sufficient to trigger long-lasting changes in farmers' behavior. Nevertheless, it is important to mention that we do not detect a higher rate of deforestation by the participating group than by the control group after the end of the program, meaning that participants did not catch up on their postponed deforestation. Thus, the environmental gain generated during the first three years of the program is not subsequently lost, but lasts at least until 2018 (when our analysis ends).

Total effect of the REDD+ initiative

In order to obtain a single point estimate of the impact of the program over the whole period (rather than by year), we look at the impact on total forest loss during the post-treatment period, using the same identification strategy as before. Results are displayed in Table 4. They are consistent with annual additionality estimates, since we obtain a total number of hectares saved over the period which roughly corresponds to the sum of the hectares saved each year. Column 1 gives the ATT expressed in hectares. It ranges between -1.71 (SE=0.57) and -2.66 (SE=0.74) using PRODES data and -2.21 (SE=0.92) and -3.47 (SE=0.74) using GFC data. Note that the estimates obtained for the two datasets do not differ statistically, as shown by the confidence intervals which overlap very widely (Column 2). We can therefore conclude that the smallest estimates both converge on a total effect of about two hectares saved on average on each farm. To get a sense of the magnitude of this impact, we then report the ATT to the mean forest area of participants provided by MapBiomas for the year 2012, i.e. 48.5 hectares (SE=52.73). The smallest impact estimate using PRODES data would therefore represent 3.5 percent of the initial forest area, while that using GFC data would represent 4.5 percent.

When it comes to expressing impact as a proportion of forest loss, the story is of course different. As shown previously, forest loss estimates produced by PRODES and GFC differ greatly. Proof of this is the considerable difference between the total number of hectares cut on average by the participants over the period according to PRODES (3.5 hectares) and GFC (12.9 hectares). The ratio of the ATT and the counterfactual forest loss (the average loss among the participants plus the estimated value of the ATT) now ranges between -32.8 and -43.2 percent using PRODES data and -14.6 and -21.2 percent using GFC data. Here the confidence intervals do not overlap at all and it can therefore be concluded that the estimates diverge. Without being able to say which dataset is more relevant than the other, one can only conclude that the program would have reduced deforestation by at least 15 percent on average, possibly up to 43 percent. These estimates are significantly lower than those reported by the project implementer, which are based on a before and after comparison. This is consistent with the findings of West et al. (2020), which demonstrate that REDD+ projects have exaggerated baselines, which can result in hot air being traded in offset markets. However, this is not the case in the present study, as the SSA project was fully funded by the Amazon Fund and did not sell carbon credits in voluntary carbon markets.

Impact of the REDD+ project on neighboring farmholds

We then applied our identification strategy to farmholds likely to have been impacted indirectly by the PES program, focusing on any deforestation that may have occurred in the plots surrounding participating farms. The results are displayed in Table 5, while balancing tests can be found in the SI (Table S5). We find that tree cover loss on plots surrounding participating farms was lower than forest loss on control plots, suggesting that the program indeed had a positive effect on neighboring farmholds, at least during the first years of the program. Note that this result is not robust across the datasets, since using PRODES data leads to a 2-year impact while using GFC data rather suggests a one-year impact. In all cases however, the effect disappears after 2015. Therefore, the total impact on neighboring farmholds is significantly less than that on participants, which spans several years.

Cost effectiveness of the REDD+ initiative

We scale up yearly point estimates to the 350 farmholds enrolled in the project, by multiplying the estimated ATT (Table 3) by the total number of participants. We obtain a total number of hectares of forest, saved thanks to the program, ranging from 490 to 861 hectares using PRODES data, and from 543 to 802 hectares using GFC data (See Table 6, Column 1). Next, we compute the average stock of carbon in the study area, using the estimates of biomass provided by the World Resources Institute, i.e., 116 tons of carbon (C) above-ground per hectare of forest with at least 50 percent tree cover (Simonet et al., 2018a). We then calculate the impact of the forestland conserved in tons of CO_2. Since one CO_2 molecule weighs 3.67 times as much as a carbon atom, this means that 426 metric tons of CO_2 are stored in one hectare of land covered by the PES contracts. Therefore, we find that the program avoided between 208,603 and 366,545 tons of CO_2 emissions using PRODES data, and from 230,953 to 341,215 tons of CO_2 using GFC data (See Table 6, Column 2).

The costs of the SSA project's PES component are computed using the amount disbursed to participants from 2014 to 2017 (i.e. 626 USD per participant), which came to 838,849 USD of discounted costs (using a 3 percent discount rate). By relating this expenditure to the emissions avoided, we find that the cost of the project was between 2.29 and 4.02 USD per ton of CO_2 emissions avoided using PRODES data, and from 2.46 to 3.63 using GFC data. We then calculate the value of the carbon benefits using three SSC rates of return (5%, 3%, and 2.5%) and find that the discounted benefit of avoided emissions ranges between 408,159 and 1,905,362 USD using PRODES data, and between 588,385 and 2,245,703 USD using GFC data (See Table 6, Columns 4, 6 and 8). This gives us a benefit/cost ratio that ranges between 0.5 and 2.3, using PRODES data, and between 0.7 and 2.7, using GFC data (See Table 6, Columns 5 and 9). Focusing on the 3% discount rate (Columns 7), which is most often used (IWG, 2016), we find that the ratio is almost always greater than one, regardless of the data and ATT estimate used.

6 Discussion

Remote-Sensing products

The divergence that we find between the two RS datasets can be partially explained by methodological differences in the construction of the products. First, small levels of deforestation are not incorporated within PRODES estimates (because deforestation activities are only reported if they accumulate beyond the 6.25-hectare threshold), while these can be detected more easily with GFC. Second, GFC quantifies global tree cover as any vegetation taller than 5 meters in the year 2000, therefore it can detect secondary forest clearings while PRODES does not. Third, some of the cover loss reported in the GFC dataset may be due to forest degradation (e.g., forest fires and selective logging), something that is less likely to be captured with PRODES estimates. All this may explain why GFC often detects higher rates of deforestation than PRODES.

This result calls for at least two comments. The first is that neither of the two products seems to completely outperform the other. PRODES estimates are validated in the field but are not able to account for small deforestation operations. GFC, on the other hand, can detect small patches of deforestation, but sometimes does so when an area is not, in fact, strictly deforestation. This should encourage REDD+ project evaluators to cross-validate their results using multiple datasets when available. The second comment relates to the suitability of PRODES and GFC products for the evaluation of REDD+ programs. A number of studies use RS data to evaluate farm-level REDD+ interventions. Yet their suitability has often been questioned since they have limitations, for instance in their spatial resolution or the definition of forest areas they use. Some studies like Cunningham et al. (2019) or Kinnebrew et al. (2022) discussed those limitations and biases, comparing the GFC product with their own land cover maps of the Amazon, and showed how critical it is to take into account those biases when using RS-based deforestation products. Similar observations were made by Sannier et al. (2016) regarding the use of GFC product for national reporting of forest cover change in Gabon. Does this mean that these products are of no use in properly estimating the impact of PES programs targeting smallholders? Although these products do not seem suitable for the fine monitoring of this type of program, our analysis nevertheless suggests that they make it possible to assess the effectiveness of a PES program. This can be done provided that (i) the impact of the program is large enough to be detected despite the lack of precision of the RS products, and (ii) the noise caused by the imprecision of the RS product estimates is distributed between the treated and control plots so that it is netted out through the comparison between the two groups. There is no reason, a priori, for the second condition not to be fulfilled, since inaccuracies can appear on a participating farm as well as on a farm in the control group.

Local REDD+ effectiveness

We assess the impact of an SSA project over 2013-2018 and estimate that about 2 hectares of forest, i.e. about 4 percent of the initial forest area, were saved on average on each participating farm during the early years of the project, regardless of the source of deforestation data used. The size of the estimated effect is smaller than that estimated using survey data by Simonet et al. (2018a), which is consistent with the idea that survey data would overestimate the impact of the program when participants tend to overestimate their effort to curb deforestation. On the contrary, our estimate is quite similar in magnitude to those found for other PES-based forest conservation programs run elsewhere in Latin America (Robalino and Pfaff, 2013; Alix-Garcia et al., 2012).

We fail to detect a positive impact of the program during its last year (the difference between participants and the counter-factual group vanishes even before the end of the program), suggesting that the program's effects were primarily realized in its initial years. Evidence thus suggests that the SSA project may have failed to prompt a transition to more sustainable agricultural practices in the years following. Similarly, Giudice et al. (2019) and Fiorini et al. (2020) find 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. One possible explanation for this is that the opportunity costs of complying with the program requirements increased during the period when the program was in place, leading farmers to return to their business-as-usual practices even before the end of the program. As we can see in SI Appendix, Fig. S2, the price of cattle sharply increased from 97 BRL per arroba (or 15 kilograms) in January 2013 to 144 BRL in January 2015. This abrupt increase in cattle prices may have played a determining role on the decision to deforest, by increasing the relative profitability of expanding pastures compared to that of complying with the program requirements (Caviglia-Harris, 2018).

We also find lower deforestation on farmholds surrounding treated plots, compared to the control group, suggesting that the project had a positive effect on the farmholds located near the beneficiaries of the PES program, at least in the early years of the program. One possible explanation for this is that non-participants may have learned about environmental legislation or the profitability of new practices promoted by the program. Furthermore, the new practices supported by the program may have increased demand for labor from neighboring farmers, shifting deforestation efforts to more sustainable activities. Also, the constant presence of the NGO in the communities may have a discouraging effect on the strategic behavior of participants. It should also be stressed that the SSA program had several components, other than the PES, which may have played a role in the effects we estimated. Unfortunately, it is not possible to know precisely which farmholds are likely to have benefited from the information campaigns and other sustainable activities (while the farms having received a PES are clearly identified). We are therefore not able to disentangle the roles of each of these components in the detected impact on deforestation and thus cannot exclude that non-monetary components of the program were also at work.

7 Conclusion

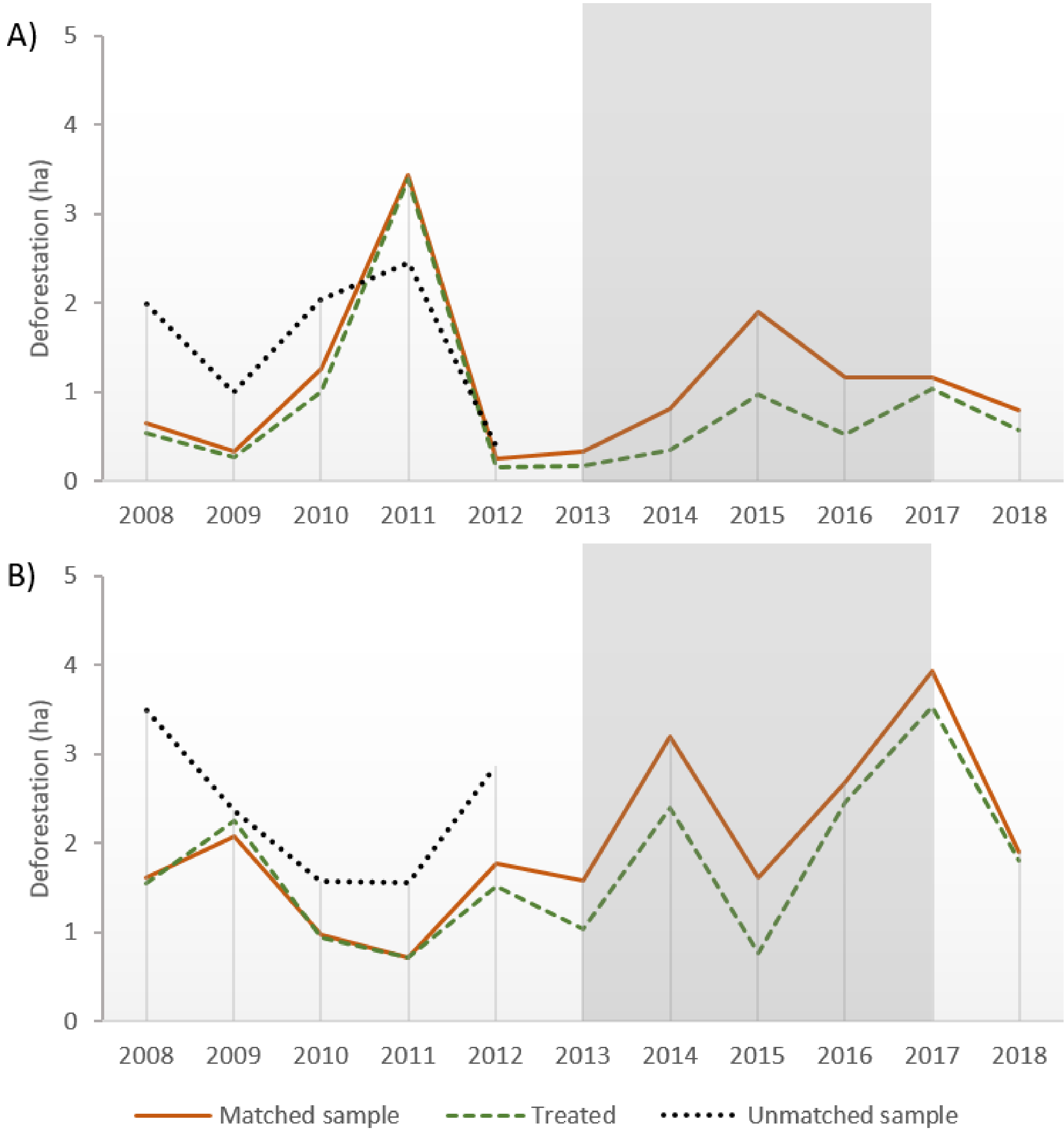
To summarize, the four key messages one can take away from this analysis relate to (i) the suitability of RS products for evaluating conservation program effectiveness, (ii) the likely short- and long-term effectiveness of PES programs, (iii) the likely spillover effects of such programs and ultimately (iv) their cost-effectiveness. Overall, our findings suggest that, despite the disagreement between GFC and PRODES on forest cover loss estimates at the individual plot-level, such datasets represent a valuable source of data to evaluate forest conservation projects.

We find evidence that the local REDD+ initiative was effective in reducing deforestation during its early years of implementation in the Transamazon region, an area with historically high deforestation rates. This suggests that PES programs targeting smallholders in the Brazilian Amazon may well be effective, at least in the short-run. Moreover, we find evidence that non-enrolled farm-holds located close to enrolled ones were somehow impacted by the program, as they also decreased deforestation during the early years of program implementation. This suggests that PES programs may change the behavior of farmers who are not the primary beneficiaries of the program - although we are not able to determine through which channel.

In addition, we find that the participants resumed their normal rate of deforestation even before the end of the program. Our findings suggest that the SSA project failed to generate a permanent effect on farmers' decisions about deforestation or to induce more sustainable agricultural practices in years subsequent to the program. Despite this, we value the three-year delayed CO_2 emissions highlighted by the impact assessment and find that the SSA program benefits were greater than its costs.

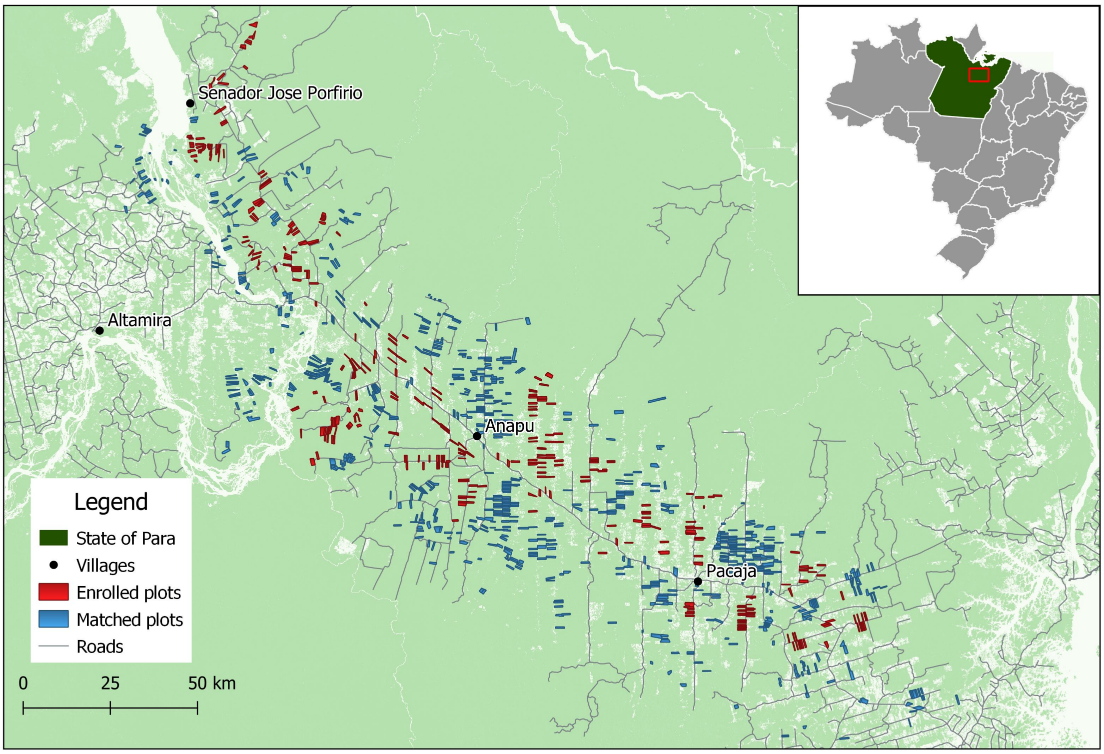
Figures

Figure 1: Deforestation on enrolled and non-enrolled farms for the 2008–2018 period



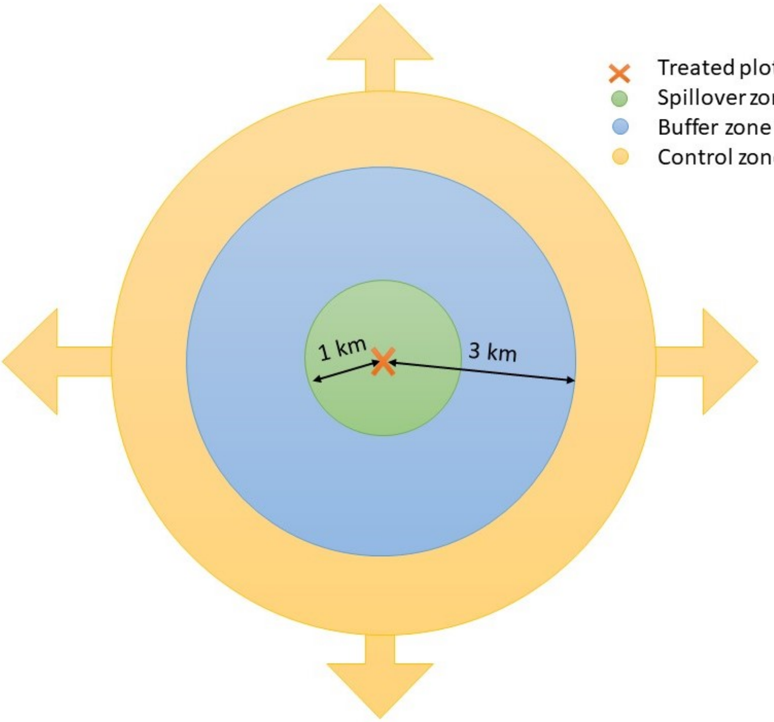
Note: (A) Nearest neighbor matching (NNM) estimates using PRODES dataset. (B) NNM estimates using GFC dataset. The REDD+ project was implemented from 2013 to 2017 (grey panel). The difference between treated and controls is significant for the early years of program implementation.

Figure 2: Localization of treated and matched plots used for estimating counterfactual levels of forest loss.



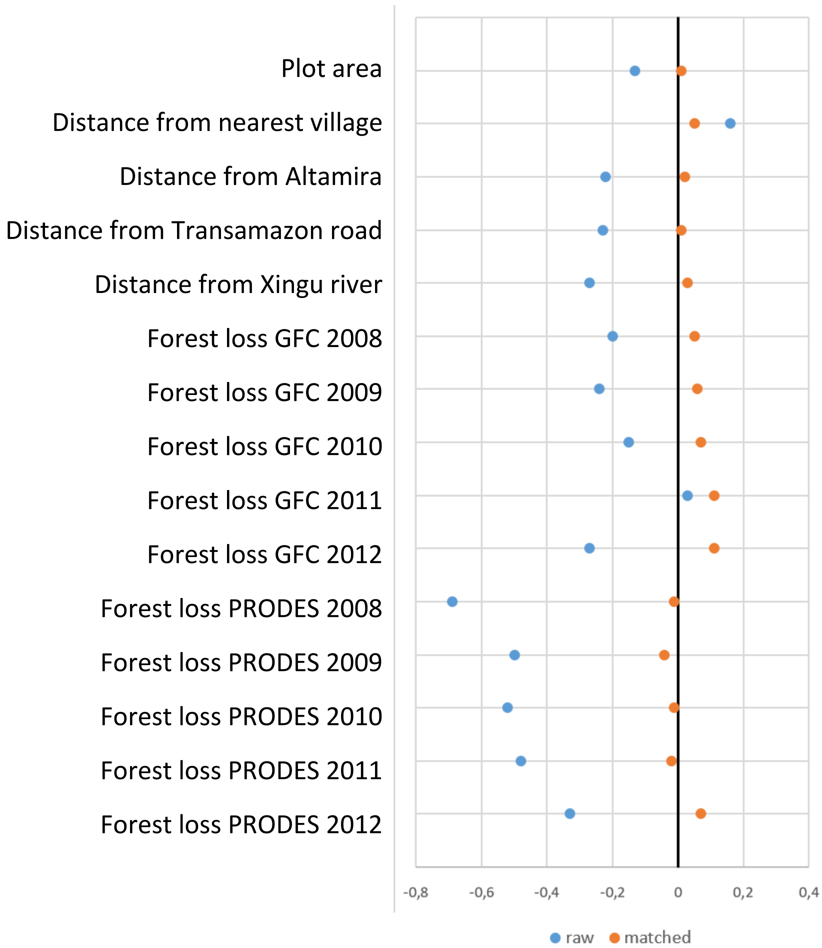
Note: We matched each treated household (red plots) to two of the most similar control households (blue plots).

Figure 3: Study design to address the Stable Unit Treatment Value Assumption (SUTVA) and spillovers



Note: To deal with SUTVA, we build a buffer zone around treated units (3 km) and excluded the farmholds located in this zone from the donor pool. When testing for spillovers, we included the farmholds that would be more likely to experience spillovers due to proximity (less than 1 km from a treated unit).

Figure 4: Standardized differences for baseline covariates comparing treated to untreated farms in the original and the matched sample



Tables

Table 1: Comparison between GFC and PRODES datasets

	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

Table 2: Summary statistics and balancing tests for participants and comparison groups

Pre-treatment variables	Non-participants (n=10,962)		Participants (n=350)		Standardized differences			
					GFC		PRODES	
	Mean	Std. Dev.	Mean	Std. Dev.	Raw	Matched	Raw	Matched
Plot area (ha)	97.38	77.81	77.21	37.00	-0.33	0.10	-0.33	0.07
Distance from nearest village	29.33	14.74	23.09	11.24	-0.48	-0.04	-0.48	-0.02
Distance from Altamira	164.57	98.20	122.60	56.75	-0.52	-0.04	-0.52	-0.01
Distance from Transamazon road	20.13	13.87	13.88	10.82	-0.50	-0.04	-0.50	-0.04
Distance from Xingu river	111.88	84.06	63.76	52.80	-0.69	-0.04	-0.69	-0.01
Forest loss GFC 2008	3.06	7.32	1.55	3.14	-0.27	0.11		
Forest loss GFC 2009	2.08	5.16	2.22	3.27	0.03	0.11		
Forest loss GFC 2010	1.42	4.18	0.91	2.62	-0.15	0.07		
Forest loss GFC 2011	1.41	3.55	0.71	1.97	-0.24	0.06		
Forest loss GFC 2012	2.43	5.72	1.49	3.68	-0.20	0.05		
Forest loss PRODES 2008	1.94	7.05	0.55	2.30			-0.27	0.03
Forest loss PRODES 2009	0.97	4.16	0.27	1.48			-0.23	0.01
Forest loss PRODES 2010	1.97	6.08	0.93	3.15			-0.22	0.02
Forest loss PRODES 2011	2.37	6.05	3.36	6.60			0.16	0.05
Forest loss PRODES 2012	0.40	2.05	0.17	1.50			-0.13	0.01
Post-treatment variables								
Forest loss GFC 2013	1.65	3.75	1.01	1.96				
Forest loss GFC 2014	2.55	4.89	2.22	2.82				
Forest loss GFC 2015	1.35	3.86	0.75	1.57				
Forest loss GFC 2016	2.49	5.02	2.30	3.42				
Forest loss GFC 2017	3.45	5.62	3.39	4.03				
Forest loss GFC 2018	2.27	4.49	1.74	2.82				
Forest loss PRODES 2013	0.46	2.17	0.18	1.19				
Forest loss PRODES 2014	0.62	2.69	0.35	1.52				
Forest loss PRODES 2015	1.31	4.07	0.86	3.00				
Forest loss PRODES 2016	0.95	3.45	0.53	2.02				
Forest loss PRODES 2017	1.01	3.38	0.83	2.70				
Forest loss PRODES 2018	0.79	2.88	0.59	2.22				

Note: This table presents descriptive statistics and balancing tests of the two groups before and after the matching procedure. The output indicates that the covariates were not balanced in the raw data. After matching, however, the standardized differences are all close to zero, which suggest that the matching procedure performed well.

Table 3: Impact of the REDD+ project on participants (by year)

Year	estimator	ATT PRODES		SE	ATT GFC		SE
2013	NNM (4X)	-0.153		0.095	-0.553	***	0.161
	NNM (2X)	-0.174		0.113	-0.603	***	0.203
	NNM (1X)	-0.169		0.149	-0.474	**	0.224
	PSM (4N)	-0.005		0.073	-0.399	***	0.142
	PSM (2N)	0.011		0.078	-0.488	***	0.168
	PSM (1N)	0.082		0.076	-0.528	***	0.198
2014	NNM (4X)	-0.401	***	0.128	-1.044	***	0.266
	NNM (2X)	-0.402	**	0.157	-0.931	***	0.306
	NNM (1X)	-0.613	**	0.243	-0.835	**	0.335
	PSM (4N)	-0.328	***	0.113	-1.043	***	0.235
	PSM (2N)	-0.471	***	0.144	-1.046	***	0.266
	PSM (1N)	-0.575	***	0.192	-1.058	***	0.324
2015	NNM (4X)	-1.134	***	0.260	-0.635	***	0.224
	NNM (2X)	-1.061	***	0.285	-0.307	*	0.180
	NNM (1X)	-1.043	***	0.373	-0.402	*	0.240
	PSM (4N)	-0.760	***	0.214	-0.557	***	0.145
	PSM (2N)	-0.642	**	0.251	-0.504	***	0.184
	PSM (1N)	-0.338		0.267	-0.417	*	0.216
2016	NNM (4X)	-0.430	**	0.174	-0.521	*	0.287
	NNM (2X)	-0.491	**	0.208	-0.405		0.325
	NNM (1X)	-0.458	*	0.264	-0.187		0.320
	PSM (4N)	-0.659	***	0.166	-0.359		0.242
	PSM (2N)	-0.573	***	0.180	-0.176		0.252
	PSM (1N)	-0.721	***	0.231	-0.094		0.294
2017	NNM (4X)	-0.328		0.212	-0.690	**	0.324
	NNM (2X)	-0.240		0.223	-0.858	**	0.387
	NNM (1X)	-0.332		0.270	-0.605		0.441
	PSM (4N)	-0.514	***	0.188	-0.321		0.280
	PSM (2N)	-0.375	*	0.209	-0.307		0.307
	PSM (1N)	0.016		0.208	-0.227		0.346
2018	NNM (4X)	-0.033		0.152	-0.024		0.185
	NNM (2X)	-0.106		0.175	-0.142		0.203
	NNM (1X)	-0.044		0.217	-0.245		0.240
	PSM (4N)	-0.122		0.145	0.126		0.187
	PSM (2N)	-0.167		0.171	0.216		0.201
	PSM (1N)	-0.138		0.197	0.223		0.231

Note: The average treatment effect on the treated (ATT) is the mean difference in forest loss (hectares) between participants and the control group. ***, **, and * denote rejection of the null hypothesis of no impact at the 1%, 5% and 10% level. NNM(4X) (resp. 2X and 1X) refers to the nearest neighbor estimator using 4 (resp. 2 and 1) matched observations as controls. PSM(4N) (resp. 2N and 1N) refers to the propensity score matching estimator using 4 (resp. 2 and 1) matched observations as controls.

Table 4: Impact of the REDD+ project on participants (whole period)

Dataset	Estimator	(1) ATT	(2) CI		(3) ATT (%)	(4) CI (%)	
PRODES	NNM (4X)	-2.480*** (0.504)	-3.468	-1.492	-41.5	-49.8	-29.9
	NNM (2X)	-2.474*** (0.558)	-3.569	-1.380	-41.5	-50.5	-28.3
	NNM (1X)	-2.658*** (0.743)	-4.113	-1.203	-43.2	-54.1	-25.6
	PSM (4N)	-2.402*** (0.450)	-3.284	-1.519	-40.8	-48.5	-30.3
	PSM (2N)	-2.240*** (0.507)	-3.233	-1.246	-39.1	-48.1	-26.3
	PSM (1N)	-1.708*** (0.570)	-2.825	-0.591	-32.8	-44.7	-14.5
Mean in treated	3.492 hectares						
GFC	NNM (4X)	-3.467*** (0.740)	-4.926	-2.009	-21.2	-27.6	-13.5
	NNM (2X)	-3.245*** (0.860)	-4.922	-1.568	-20.1	-27.6	-10.8
	NNM (1X)	-2.748*** (0.950)	-4.617	-0.879	-17.6	-26.4	-6.4
	PSM (4N)	-2.698*** (0.430)	-3.551	-1.846	-17.3	-21.6	-12.5
	PSM (2N)	-2.481*** (0.720)	-3.892	-1.069	-16.1	-23.2	-7.7
	PSM (1N)	-2.206** (0.920)	-4.014	-0.398	-14.6	-23.7	-3.0
Mean in treated	12.890 hectares						

Note: The average treatment effect on the treated (ATT) is the mean difference in forest loss (hectares) between participants and the control group between 2012 and 2018. ***, **, and * denote rejection of the null hypothesis of no impact at the 1%, 5% and 10% level. NNM(4X) (resp. 2X and 1X) refers to the nearest neighbor estimator using 4 (resp. 2 and 1) matched observations as controls. PSM(4N) (resp. 2N and 1N) refers to the propensity score matching estimator using 4 (resp. 2 and 1) matched observations as controls. Standard errors are given in parentheses.

Table 5: Impact of the REDD+ project on non-participants (by year)

Year	estimator	ATT PRODES		SE	ATT GFC		SE
2013	NNM (4X)	-0.094	*	0.051	-0.312	***	0.093
	NNM (2X)	-0.113	**	0.057	-0.262	**	0.103
	NNM (1X)	-0.150	**	0.067	-0.293	**	0.119
	PSM (4N)	-0.019		0.045	-0.184	**	0.079
	PSM (2N)	0.001		0.044	-0.207	**	0.090
	PSM (1N)	0.028		0.047	-0.145		0.110
2014	NNM (4X)	-0.452	***	0.095	-0.369	*	0.205
	NNM (2X)	-0.466	***	0.104	-0.361		0.232
	NNM (1X)	-0.486	***	0.122	-0.314		0.263
	PSM (4N)	-0.405	***	0.089	-0.038		0.182
	PSM (2N)	-0.412	***	0.105	-0.027		0.195
	PSM (1N)	-0.410	***	0.121	-0.028		0.226
2015	NNM (4X)	-0.673	***	0.193	-0.253		0.181
	NNM (2X)	-0.653	***	0.206	-0.167		0.205
	NNM (1X)	-0.732	***	0.238	-0.234		0.233
	PSM (4N)	-0.300	**	0.121	-0.157		0.113
	PSM (2N)	-0.358	**	0.152	-0.153		0.127
	PSM (1N)	-0.414	**	0.184	-0.133		0.147
2016	NNM (4X)	-0.149		0.120	-0.145		0.206
	NNM (2X)	-0.139		0.141	-0.162		0.225
	NNM (1X)	-0.167		0.170	-0.078		0.241
	PSM (4N)	-0.102		0.106	-0.001		0.176
	PSM (2N)	-0.143		0.123	-0.129		0.202
	PSM (1N)	-0.113		0.069	0.063		0.220
2017	NNM (4X)	-0.235		0.176	-0.357		0.220
	NNM (2X)	-0.240		0.184	-0.576	**	0.253
	NNM (1X)	-0.306		0.199	-0.659	**	0.296
	PSM (4N)	-0.077		0.115	-0.242		0.239
	PSM (2N)	-0.115		0.121	-0.276		0.225
	PSM (1N)	-0.089		0.139	-0.129		0.254
2018	NNM (4X)	0.060		0.080	-0.235	*	0.142
	NNM (2X)	0.046		0.093	-0.334	*	0.174
	NNM (1X)	0.025		0.109	-0.435	**	0.203
	PSM (4N)	-0.057		0.064	-0.039		0.134
	PSM (2N)	-0.084		0.086	-0.158		0.146
	PSM (1N)	-0.086		0.100	-0.142		0.159

Note: The average treatment effect on the treated (ATT) is the mean difference in forest loss (hectares) between neighboring farms and the control group. ***, **, and * denote rejection of the null hypothesis of no impact at the 1%, 5% and 10% level. ATT is the Average Treatment effect on the Treated. NNM(4X) (resp. 2X and 1X) refers to the nearest neighbor estimator using 4 (resp. 2 and 1) matched observations as controls. PSM(4N) (resp. 2N and 1N) refers to the propensity score matching estimator using 4 (resp. 2 and 1) matched observations as controls.

Table 6: Cost effectiveness of the REDD+ initiative for different discount rates

Dataset	Number of hectares	Avoided CO_2 emissions	Cost PES	SCC 5%		SCC 3%		SCC 2.5%	
				Benefits	(B/C)	Benefits	(B/C)	Benefits	(B/C)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PRODES	490	208,603	838,849	408,159	0.49	830,981	0.99	1,076,923	1.28
	861	366,545	838,849	722,241	0.86	1,470,127	1.75	1,905,362	2.27
GFC	543	230,953	838,849	588,385	0.70	1,185,874	1.41	1,542,051	1.84
	802	341,215	838,849	856,594	1.02	1,727,281	2.06	2,245,703	2.68

Note: This table displays the costs of the PES component of the SSA program (Column 3) compared with the benefit of delayed CO_2 emissions under different SCC values (Columns 4, 6 and 8). The annual benefit of delayed emissions equals $\frac{r}{r+1}.SCC$, where r is 2.5, 3 and 5%

References

Abadie, A., Diamond, A., and Hainmueller, J. (2010). Synthetic control methods for comparative case studies: Estimating the effect of california's tobacco control program. *Journal of the American statistical Association*, 105(490):493–505. 4

Alix-Garcia, J. and Wolff, H. (2014). Payment for ecosystem services from forests. *Annu. Rev. Resour. Econ.*, 6(1):361–380. 1

Alix-Garcia, J. M., Shapiro, E. N., and Sims, K. R. (2012). Forest conservation and slippage: Evidence from mexico's national payments for ecosystem services program. *Land Economics*, 88(4):613–638. 1, 6

Alix-Garcia, J. M., Sims, K. R., and Yañez-Pagans, P. (2015). Only one tree from each seed? environmental effectiveness and poverty alleviation in mexico's payments for ecosystem services program. *American Economic Journal: Economic Policy*, 7(4):1–40. 1

Arriagada, R. A., Ferraro, P. J., Sills, E. O., Pattanayak, S. K., and Cordero-Sancho, S. (2012). Do payments for environmental services affect forest cover? a farm-level evaluation from costa rica. *Land Economics*, 88(2):382–399. 1

Assunção, J., Gandour, C., and Rocha, R. (2015). Deforestation slowdown in the brazilian amazon: prices or policies? *Environment and Development Economics*, 20(6):697–722. 1

Assunção, J. and Rocha, R. (2019). Getting greener by going black: the effect of blacklisting municipalities on amazon deforestation. *Environment and Development Economics*, 24(2):115–137. 1

Baker, J. and Spracklen, D. (2019). Climate benefits of intact amazon forests and the biophysical consequences of disturbance. *Frontiers in Forests and Global Change*, 2:47. 4

BenYishay, A., Heuser, S., Runfola, D., and Trichler, R. (2017). Indigenous land rights and deforestation: Evidence from the Brazilian Amazon. *Journal of Environmental Economics and Management*, 86:29–47. 1

Blackman, A. (2013). Evaluating forest conservation policies in developing countries using remote sensing data: An introduction and practical guide. *Forest Policy and Economics*, 34:1–16. 1

Börner, J., Baylis, K., Corbera, E., Ezzine-de Blas, D., Honey-Rosés, J., Persson, U. M., and Wunder, S. (2017). The Effectiveness of Payments for Environmental Services. *World Development*, 96(April):359–374. 1

Bos, A. B., De Sy, V., Duchelle, A. E., Herold, M., Martius, C., and Tsendbazar, N.-E. (2019). Global data and tools for local forest cover loss and redd+ performance assessment: Accuracy, uncertainty, complementarity and impact. *International Journal of Applied Earth Observation and Geoinformation*, 80:295–311. 1

Bowman, M. S. (2016). Impact of foot-and-mouth disease status on deforestation in brazilian amazon and cerrado municipalities between 2000 and 2010. *Journal of Environmental Economics and Management*, 75:25–40. 1

Câmara, G., Valeriano, D. d. M., and Soares, J. V. (2006). Metodologia para o cálculo da taxa anual de desmatamento na amazônia legal. *São José dos Campos: INPE*. 2

Carrilho, C. D., Demarchi, G., Duchelle, A. E., Wunder, S., and Morsello, C. (2022). Permanence of avoided deforestation in a transamazon redd+ project (pará, brazil). *Ecological Economics*, 201:107568. 1, 3

Caviglia-Harris, J. L. (2018). Agricultural innovation and climate change policy in the brazilian amazon: Intensification practices and the derived demand for pasture. *Journal of Environmental Economics and Management*, 90:232–248. 6

Cisneros, E., Börner, J., Pagiola, S., and Wunder, S. (2022). Impacts of conservation incentives in protected areas: The case of bolsa floresta, brazil. *Journal of Environmental Economics and Management*, 111:102572. 1

Correa, J., Cisneros, E., Börner, J., Pfaff, A., Costa, M., and Rajão, R. (2020). Evaluating redd+ at subnational level: Amazon fund impacts in alta floresta, brazil. *Forest Policy and Economics*, 116:102178. 1

Costedoat, S., Corbera, E., Ezzine-de Blas, D., Honey-Rosés, J., Baylis, K., and Castillo-Santiago, M. A. (2015). How effective are biodiversity conservation payments in mexico? *PloS one*, 10(3):e0119881. 1

Cromberg, M., Duchelle, A. E., Simonet, G., and de Freitas, A. (2014). Sustainable settlements in the amazon, brazil. 3

Cunningham, D., Cunningham, P., and Fagan, M. E. (2019). Identifying biases in global tree cover products: A case study in costa rica. *Forests*, 10(10):853. 6

de Sá, S. A., Palmer, C., and di Falco, S. (2013). Dynamics of indirect land-use change: Empirical evidence from brazil. *Journal of Environmental Economics and Management*, 65(3):377–393. 1

dos Reis, M., de Alencastro Graça, P. M. L., Yanai, A. M., Ramos, C. J. P., and Fearnside, P. M. (2021). Forest fires and deforestation in the central amazon: Effects of landscape and climate on spatial and temporal dynamics. *Journal of Environmental Management*, 288:112310. 1

Dyer, G. A., Matthews, R., and Meyfroidt, P. (2012). Is there an ideal redd+ program? an analysis of policy trade-offs at the local level. *PLoS One*, 7(12):e52478. 3

Engel, S., Pagiola, S., and Wunder, S. (2008). Designing payments for environmental services in theory and practice: An overview of the issues. *Ecological Economics*, 65(4):663 – 674. Payments for Environmental Services in Developing and Developed Countries. 1

Ferraro, P. J., Lawlor, K., Mullan, K. L., and Pattanayak, S. K. (2012). Forest figures: Ecosystem services valuation and policy evaluation in developing countries. *Review of Environmental Economics and Policy*, 6(1):20–44. 1

Ferraro, P. J. and Miranda, J. J. (2017). Panel data designs and estimators as substitutes for randomized controlled trials in the evaluation of public programs. *Journal of the Association of Environmental and Resource Economists*, 4(1):281–317. 5

Fiorini, A. C. O., Mullally, C., Swisher, M., and Putz, F. E. (2020). Forest cover effects of payments for ecosystem services: Evidence from an impact evaluation in brazil. *Ecological Economics*, 169:106522. 6

Garbach, K., Lubell, M., and DeClerck, F. A. (2012). Payment for ecosystem services: the roles of positive incentives and information sharing in stimulating adoption of silvopastoral conservation practices. *Agriculture, ecosystems & environment*, 156:27–36. 1

Gasparini, K. A. C., Silva Junior, C. H. L., Shimabukuro, Y. E., Arai, E., Silva, C. A., Marshall, P. L., et al. (2019). Determining a threshold to delimit the amazonian forests from the tree canopy cover 2000 gfc data. *Sensors*, 19(22):5020. 4

Giudice, R., Börner, J., Wunder, S., and Cisneros, E. (2019). Selection biases and spillovers from collective conservation incentives in the peruvian amazon. *Environmental Research Letters*. 6

Guizar-Coutiño, A., Jones, J. P., Balmford, A., Carmenta, R., and Coomes, D. A. (2022). A global evaluation of the effectiveness of voluntary redd+ projects at reducing deforestation and degradation in the moist tropics. *Conservation Biology*. 1

Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., Thau, D., Stehman, S., Goetz, S. J., Loveland, T. R., et al. (2013). High-resolution global maps of 21st-century forest cover change. *science*, 342(6160):850–853. 2

Harding, T., Herzberg, J., and Kuralbayeva, K. (2021). Commodity prices and robust environmental regulation: Evidence from deforestation in brazil. *Journal of Environmental Economics and Management*, 108:102452. 1

Herrera, D., Pfaff, A., and Robalino, J. (2019). Impacts of protected areas vary with the level of government: Comparing avoided deforestation across agencies in the brazilian amazon. *Proceedings of the National Academy of Sciences*, 116(30):14916–14925. 1

Hill, J. and Su, Y.-S. (2013). Assessing lack of common support in causal inference using bayesian nonparametrics: Implications for evaluating the effect of breastfeeding on children's cognitive outcomes. *The Annals of Applied Statistics*, pages 1386–1420. 1

Honey-Rosés, J., Baylis, K., and Ramirez, M. I. (2011). A spatially explicit estimate of avoided forest loss. *Conservation biology*, 25(5):1032–1043. 1

Imbens, G. W. and Wooldridge, J. M. (2009). Recent developments in the econometrics of program evaluation. *Journal of economic literature*, 47(1):5–86. 4

INPE (2019). Coordenação geral de observação da terra. projeto prodes: Monitoramento da floresta amazônica brasileira por satélite. 1, 2

IWG (2016). Technical support document of the interagency working group: technical update of the social cost of carbon for regulatory impact analysis under executive order 12866. *Environmental Protection Agency*, pages 2016–12. 4, 5

Jayachandran, S., Laat, J. D., Lambin, E. F., Stanton, C. Y., Audy, R., and Thomas, N. E. (2017). Reduce Deforestation. *Science*, 357(6348):267–273. 1, 4

Jones, K. W., Holland, M. B., Naughton-Treves, L., Morales, M., Suarez, L., and Keenan, K. (2017). Forest conservation incentives and deforestation in the ecuadorian amazon. *Environmental Conservation*, 44(1):56–65. 1

Jones, K. W. and Lewis, D. J. (2015). Estimating the counterfactual impact of conservation programs on land cover outcomes: The role of matching and panel regression techniques. *PLoS ONE*, 10(10):1–22. 1

Kalamandeen, M., Gloor, E., Mitchard, E., Quincey, D., Ziv, G., Spracklen, D., Spracklen, B., Adami, M., Aragão, L. E., and Galbraith, D. (2018). Pervasive rise of small-scale deforestation in amazonia. *Scientific reports*, 8(1):1–10. 2

Kinnebrew, E., Ochoa-Brito, J. I., French, M., Mills-Novoa, M., Shoffner, E., and Siegel, K. (2022). Biases and limitations of global forest change and author-generated land cover maps in detecting deforestation in the amazon. *PloS one*, 17(7):e0268970. 6

Kugler, T. A., Grace, K., Wrathall, D. J., de Sherbinin, A., Van Riper, D., Aubrecht, C., Comer, D., Adamo, S. B., Cervone, G., Engstrom, R., et al. (2019). People and pixels 20 years later: the current data landscape and research trends blending population and environmental data. *Population and Environment*, 41(2):209–234. 1

Maurano, L. E. P., Escada, M. I. S., and Renno, C. D. (2019). Padrões espaciais de desmatamento e a estimativa da exatidão dos mapas do PRODES para amazônia legal brasileira. *Ciência florestal*, 29:1763–1775. 2

Millimet, D. L. and Alix-Garcia, J. (2021). Introduction to causal inference in environmental and resource economics: Challenges, developments, and applications. *Journal of the Association of Environmental and Resource Economists*, 8(2):193–198. 4

Moffette, F., Skidmore, M., and Gibbs, H. K. (2021). Environmental policies that shape productivity: Evidence from cattle ranching in the amazon. *Journal of Environmental Economics and Management*, 109:102490. 1

Mohebalian, P. M. and Aguilar, F. X. (2018). Beneath the Canopy: Tropical Forests Enrolled in Conservation Payments Reveal Evidence of Less Degradation. *Ecological Economics*, 143:64–73. 1

Mullan, K., Caviglia-Harris, J. L., and Sills, E. O. (2021). Sustainability of agricultural production following deforestation in the tropics: Evidence on the value of newly-deforested, long-deforested and forested land in the brazilian amazon. *Land Use Policy*, 108:105660. 1

Neeff, T., Steel, E. A., Kleinn, C., Hung, N. D., Bien, N. N., Cerutti, P. O., and Moutinho, P. (2020). How forest data catalysed change in four successful case studies. *Journal of Environmental Management*, 271:110736. 1

Nepstad, D., Mcgrath, D., Stickler, C., Alencar, A., Azevedo, A., Swette, B., Bezerra, T., Digiano, M., Shimada, J., Seroa, R., Armijo, E., Castello, L., Brando, P., Hansen, M. C., Mcgrath-horn, M., Carvalho, O., and Hess, L. (2014). Slowing Amazon deforestation through public policy and interventions in beef and soy supply chains. *Science Magazine*, 344(6188). 1

Nolte, C., Agrawal, A., Silvius, K. M., and Soares-Filho, B. S. (2013). Governance regime and location influence avoided deforestation success of protected areas in the brazilian amazon. *Proceedings of the National Academy of Sciences*, 110(13):4956–4961. 1

Ollivier, H. (2012). Growth, deforestation and the efficiency of the redd mechanism. *Journal of Environmental Economics and Management*, 64(3):312–327. 2010 Monte Verita Conference on Sustainable Resource Use and Economic Dynamics(SURED). 1

Pagiola, S., Honey-Rosés, J., and Freire-González, J. (2016). Evaluation of the permanence of land use change induced by payments for environmental services in quindío, colombia. *PloS one*, 11(3):e0147829. 1

Pailler, S. (2018). Re-election incentives and deforestation cycles in the brazilian amazon. *Journal of Environmental Economics and Management*, 88:345–365. 1

Pattanayak, S. K., Wunder, S., and Ferraro, P. J. (2010). Show me the money: do payments supply environmental services in developing countries? *Review of environmental economics and policy*, 4(2):254–274. 1

Pfaff, A. and Robalino, J. (2017). Spillovers from conservation programs. *Annual Review of Resource Economics, Volumen 9 (2017), pages 299-315.* 3

Pinto de Paulo Pedro, E. (2016). O papel do pagamento por servicos ambientais conforme a realidade de diferentes perfis de agricultores familiar da amazonia. Master's thesis, MS Thesis, University of Brasilia, Center for sustainable development. 3

Robalino, J. and Pfaff, A. (2013). Ecopayments and Deforestation in Costa Rica: A Nationwide Analysis of PSA's Initial Years. *Land Economics*, 89(3):432–448. 1, 6

Roopsind, A., Sohngen, B., and Brandt, J. (2019). Evidence that a national redd+ program reduces tree cover loss and carbon emissions in a high forest cover, low deforestation country. *Proceedings of the National Academy of Sciences*, 116(49):24492–24499. 1

Rubin, D. B. (1978). Bayesian inference for causal effects: The role of randomization. *The Annals of statistics*, pages 34–58. 4

Samii, C., Lisiecki, M., Kulkarni, P., Paler, L., Chavis, L., Snilstveit, B., Vojtkova, M., and Gallagher, E. (2014). Effects of payment for environmental services (pes) on deforestation and poverty in low and middle income countries: a systematic review. *Campbell Systematic Reviews*, 10(1):1–95. 1

Sanchez-Azofeifa, G. A., Pfaff, A., Robalino, J. A., and Boomhower, J. P. (2007). Costa rica's payment for environmental services program: intention, implementation, and impact. *Conservation biology*, 21(5):1165–1173. 1

Sannier, C., McRoberts, R. E., and Fichet, L.-V. (2016). Suitability of global forest change data to report forest cover estimates at national level in gabon. *Remote Sensing of Environment*, 173:326–338. 6

Scullion, J., Thomas, C. W., Vogt, K. A., Perez-Maqueo, O., and Logsdon, M. G. (2011). Evaluating the environmental impact of payments for ecosystem services in coatepec (mexico) using remote sensing and on-site interviews. *Environmental Conservation*, 38(4):426–434. 1

Sills, E. O., Atmadja, S. S., de Sassi, C., Duchelle, A. E., Kweka, D. L., Resosudarmo, I. A. P., and Sunderlin, W. D. (2014). *REDD+ on the ground: A case book of subnational initiatives across the globe*. Cifor. 1

Simonet, G., Bos, A. B., Duchelle, A. E., Pradnja Resosudarmo, I. A., Subervie, J., and Wunder, S. (2018a). Forests and carbon : The impacts of local REDD+ initiatives. *Transforming REDD+*, pages 117–130. 1, 5, 6

Simonet, G., Karsenty, A., de Perthuis, C., Newton, P., and Schaap, B. (2015). REDD+ projects in 2014: an overview based on a new database and typology. *Les Cahiers de la Chaire Economie du Climat - Information and debates Series*, (32):34. 1

Simonet, G., Subervie, J., Ezzine-de Blas, D., Cromberg, M., and Duchelle, A. E. (2018b). Effectiveness of a REDD+ Project in Reducing Deforestation in the Brazilian Amazon. *American Journal of Agricultural Economics*, 101(1):211–229. 1, 3, 4

Sims, K. R. and Alix-Garcia, J. M. (2017). Parks versus pes: Evaluating direct and incentive-based land conservation in mexico. *Journal of Environmental Economics and Management*, 86:8–28. Special issue on environmental economics in developing countries. 1

Sims, K. R., Alix-Garcia, J. M., Shapiro-Garza, E., Fine, L. R., Radeloff, V. C., Aronson, G., Castillo, S., Ramirez-Reyes, C., and Yañez-Pagans, P. (2014). Improving environmental and social targeting through adaptive management in mexico's payments for hydrological services program. *Conservation Biology*, 28(5):1151–1159. 1

Smith, N. J., Falesi, I. C., Alvim, P. d. T., and Serrão, E. A. S. (1996). Agroforestry trajectories among smallholders in the brazilian amazon: innovation and resiliency in pioneer and older settled areas. *Ecological economics*, 18(1):15–27. 3

Soares-Filho, B. S., Nepstad, D. C., Curran, L. M., Cerqueira, G. C., Garcia, R. A., Ramos, C. A., Voll, E., McDonald, A., Lefebvre, P., and Schlesinger, P. (2006). Modelling conservation in the amazon basin. *Nature*, 440(7083):520–523. 3

Tropek, R., Sedláček, O., Beck, J., Keil, P., Musilová, Z., Šímová, I., and Storch, D. (2014). Comment on: High-resolution global maps of 21st-century forest cover change. *Science*, 344(6187):981–981. 2

Villoria, N., Garrett, R., Gollnow, F., and Carlson, K. (2022). Demand-driven efforts to stop deforestation in brazil's soy sector are unlikely to be offset by cross-border leakage. 1

West, T. A., Börner, J., Sills, E. O., and Kontoleon, A. (2020). Overstated carbon emission reductions from voluntary redd+ projects in the brazilian amazon. *Proceedings of the National Academy of Sciences*, 117(39):24188–24194. 1, 5

Wunder, S. et al. (2005). Payments for environmental services: some nuts and bolts. 1