Beyond reducing deforestation: impacts of conservation programs on household livelihoods

Gabriela Demarchi, Caue D Carrilho, Thibault Catry, Stibniati Atmadja, Julie Subervie

CEE-M
CENTER FOR ENVIRONMENTAL ECONOMICS - MONTPELLIER

Beyond reducing deforestation: impacts of conservation programs on household livelihoods

Gabriela Demarchi
Caue D. Carrilho
Thibault Catry
Stibniati Atmadja
&
Julie Subervie

CEE-M Working Paper 2022-09

INRAE

Beyond Reducing Deforestation: Impacts of REDD+ projects on Household Livelihoods

Gabriela Demarchi* Caue D. Carrilho† Thibault Catry‡ Stibniati Atmadja§
Julie Subervie¶

September 2022

Abstract

Understanding why forest conservation initiatives succeed or fail is essential to designing cost-effective programs at scale. In this study, we investigate direct and indirect impact mechanisms of a REDD+ project that was shown to be effective in reducing deforestation during the early years of its implementation in the Transamazon region, an area with historically high deforestation rates. Using counterfactual impact evaluation methods applied to survey and remote-sensing data, we assess the impact of the project over 2013-2019, i.e., from its first year until two years after its end. Based on the Theory of Change, we focus on land use and socioeconomic outcomes likely to have been affected by changes in deforestation brought about by the initiative. Our findings highlight that forest conservation came at the expense of pastures rather than cropland and that the project induced statistically greater agrobiodiversity on participating farms. Moreover, we find that the project encouraged the development of alternative livelihood activities that required less area for production and generated increased income. These results suggest that conservation programs, that combine payments conditional on forest conservation with technical assistance and support to farmers for the adoption of low-impact activities, can manage to slow down deforestation in the short term are likely to induce profound changes in production systems, which can be expected to have lasting effects.

Keywords: REDD+, CO2 emissions, impact evaluation, livelihood, Brazilian Amazon.

*CIFOR, CEE-M. Univ. Montpellier, CNRS, INRAE, SupAgro, Montpellier, France
†PROCAM, USP, São Paulo, Brazil.
‡Espace-Dev, IRD, Montpellier, France.
§CIFOR, Montpellier, France
¶CEE-M. Univ. Montpellier, CNRS, INRAE, SupAgro, Montpellier, France

1 Introduction

More than 15 years have passed since REDD+ entered the climate policy arena, but evidence about the effectiveness of this promising mechanism remains scarce (Duchelle et al., 2018). Indeed, we still know little about the ability of these initiatives to mitigate climate change while also safeguarding the people whose livelihoods depend upon tropical forests. Of the few rigorous impact evaluations from the REDD+ literature, some suggest that the initiatives are effective in reducing deforestation (Jayachandran et al., 2017; Simonet et al., 2018a; Roopsind et al., 2019; Coutiño et al., 2022), while others find null or mixed impacts (Correa et al., 2020; West et al., 2020). However, most evaluations of REDD+ local initiatives focus on environmental impacts and do not measure their effects on other land use activities or socioeconomic outcomes (Jack and Santos, 2017), which does not allow conclusions to be drawn as to the reasons for the success or failure of these programs.

Even in cases where the primary environmental objective has been achieved, it is important to understand how and to consider the implications for other land uses and for the livelihoods of program participants who agreed to reduce their rate of deforestation. In some cases, it is crucial to evaluate to what extent a program that succeeds in preserving the native forest also guarantees sustainable livelihoods of local populations (Blundo-Canto et al., 2018), because even when conservation programs are voluntary and offer financial compensation to participants in exchange for forest conservation, certain unanticipated exogenous shocks may ultimately reduce the profitability of participation. Evaluating the direct and indirect effects of conservation programs can also tell us about the potential sustainability of the results of these programs once they end. There is thus a need for rigorous assessment of all the likely impacts beyond forest outcomes of local REDD+ initiatives (Sills et al., 2017). Understanding why REDD+ pilot initiatives succeed or fail is essential both for the improvement of this mechanism to fight climate change and for designing upscale cost-effective programs in the future (Wunder et al., 2020).

In this study, we carried out a comprehensive evaluation of the impacts of the Sustainable Settlements in the Amazon (SSA) program, a REDD+ initiative whose objective was to reduce deforestation in the Brazilian Amazon by improving local agricultural systems. The smallholders who entered the program benefited from a mixed approach of Payments for Environmental Services (PES) and Integrated Conservation and Development Projects (ICDP). This study builds on previous analyses that have evaluated the effectiveness of the SSA program (Simonet et al., 2018a; Carrilho et al., 2022; Demarchi et al., 2020). In particular, Demarchi et al. (2020) showed that the SSA project prevented, on average, almost two hectares of forest from being cleared on each participating farm during the first three years of the program. The results also suggest that the participants resumed their normal rate of deforestation thereafter, without catching up on their postponed deforestation, thus maintaining a significant gap with non-participants in the program, even after its end. In this study, we aim at understanding how this reduction in deforestation was achieved and how the program impacted participants. We also examine whether other project objectives, initially considered secondary, were achieved, in what time frame, and with what chance of having lasting effects over time.

Using the available literature and project documentation, survey data collected from a sample of participants and non-participants, and remotely-sensed data on the land-use of all the participants and those of their non-participating neighbors, we evaluated the impact of the SSA program on a series of environmental outcomes, agricultural practices, and livelihood indicators. As much as possible, we used the same analytical tools used in previous studies that highlight the the SSA project's environmental performance. We applied matching estimators to panel data on participating and non-participating farms, using matched non-participants to establish counterfactual participant levels.

Results suggest that the decrease in deforestation occurred mainly at the expense of the slowdown in the extensions of pasture areas. Moreover, we investigated whether the number of cattle per hectare increased on the farms benefiting from the program, and our findings suggest that there was in fact an intensification in cattle ranching activities. Furthermore, our results indicate that the program had a positive impact on farmers' gross income and on alternative livelihood production activities that require less area for production than extensive livestock farming and slash-and-burn agriculture, the two main drivers of deforestation in the study region. These findings demonstrate that REDD+ projects that combine PES with technical assistance and support for the adoption of low-impact activities can be effective in the fight against climate change, without jeopardizing the livelihood of local populations. They also suggest that the effort made to curb deforestation mechanically resulted in a lower extension of pastures (not herds) but did not prevent the participants from simultaneously developing new agricultural activities, which can be expected to have lasting effects, even if deforestation returns to a normal rate.

The remainder of the paper proceeds as follows. Section 2 describes the content of the SSA project and the Theory of Change that frames our empirical analysis. Section 3 describes the data used in the analysis. Section 4 presents the identification strategy. Section 5 reports the results and robustness checks. Section 6 discusses the main results and Section 7 summarizes the key messages of the study.

2 The SSA program

REDD+ was envisioned and designed to be implemented by governments at national and jurisdictional levels (Wunder et al., 2020). However, most initiatives that have been implemented and are subject to detailed evaluations today have been undertaken at the local scale by non-governmental organizations (NGOs) and the private sector (Sills et al., 2014; **?**). Although PES schemes were originally envisioned as the first choice of intervention in local REDD+ programs, non-conditional incentives to adopt sustainable livelihood alternatives have been adopted more frequently by proponents of local initiatives (Duchelle et al., 2017). These local projects aim to implement a mix of interventions to reduce deforestation and promote alternative production activities that require less land to achieve a given production/income level. This is the case of the SSA program which was implemented by the *Instituto de Pesquisa Ambiental da Amazonia* (IPAM), a Brazilian NGO dedicated to environmental research which has played an important role in designing and implementing REDD+ in Brazil (Gebara et al., 2014). IPAM started operating the program in 2012 and ended it in 2017, after its refinancing request was denied by the Amazon Fund[1] (Carrilho et al., 2022).

2.1 Program content to support alternative agricultural production

The primary goal of SSA was to reduce deforestation rates, mainly by promoting alternative livelihood activities, which were expected to generate better profits than traditional land-use, while being associated to lower deforestation practices. On aggregate, IPAM targeted approximately

[1] A results-based funding program created in 2008 that allocated international REDD+ donations to Brazilian projects (Correa et al., 2019).

2,700 smallholders from the western part of the Pará state (Brazil) (IPAM, 2016). The main economic activities of target smallholders were slash-and-burn agriculture and extensive cattle ranching (Cromberg et al., 2014). In this study, we focused on 350 smallholders who benefited from the whole package of interventions offered by IPAM, including PES.

Alternative livelihood activities were defined by IPAM's technicians together with farmholders in customized property management plans (Simonet et al., 2018a). IPAM then made a selection of the activities they wanted to promote, based on a market study that identified the agricultural products with the greatest commercialization potential in the nearest larger cities (IPAM, 2017; Souza et al., 2020). The objective was to implement activities that require less area for production but provide higher economic returns. These included new livelihood activities (e.g., fish-farming, horticulture, fruit pulp and cocoa production) as well as alternative *practices* for current agricultural production - in this case, the transition from extensive to more intensive cattle ranching, and from slash-and-burn to mechanized agriculture (IPAM, 2017; Stella et al., 2020; Carrilho et al., 2022).

To promote these new/alternative activities, IPAM offered technical assistance and free agricultural inputs in addition to PES (Carrilho et al., 2022). The PES component was designed to provide participants additional income (up to 1,600 BRL per year) until the new livelihood activities took off. The payments were conditional on preserving forest on at least 50 percent of the farm[2], the preservation of riparian forests along water courses, and the adoption of a fire-free production system (IPAM, 2016; Simonet et al., 2018a). In addition, IPAM provided support with transportation and market infrastructure to farmers selling vegetables in cities (Carrilho, 2021).

Participants also benefited from information meetings designed to raise awareness about the Brazilian Forest Code, which requires farmholds to retain a legal reserve of forest[3] and permanent preservation areas (PPA) along streams and rivers and around water springs. Participants also benefited from administrative support to register their proprieties under the Rural Environmental Registry (*Cadastro Ambiental Rural* or CAR) (Simonet et al., 2018a). It is worth mentioning that CAR is a mandatory digital registration for all Brazilian rural properties in which landholders must document their property's boundaries, including the location of all native vegetation that must be protected according to the Brazilian Forest Code.

[2]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

[3]The legal reserve consists in a fixed proportion of land covered with native vegetation that varies between 50% and 80% of the farmhold in the Amazon biome.

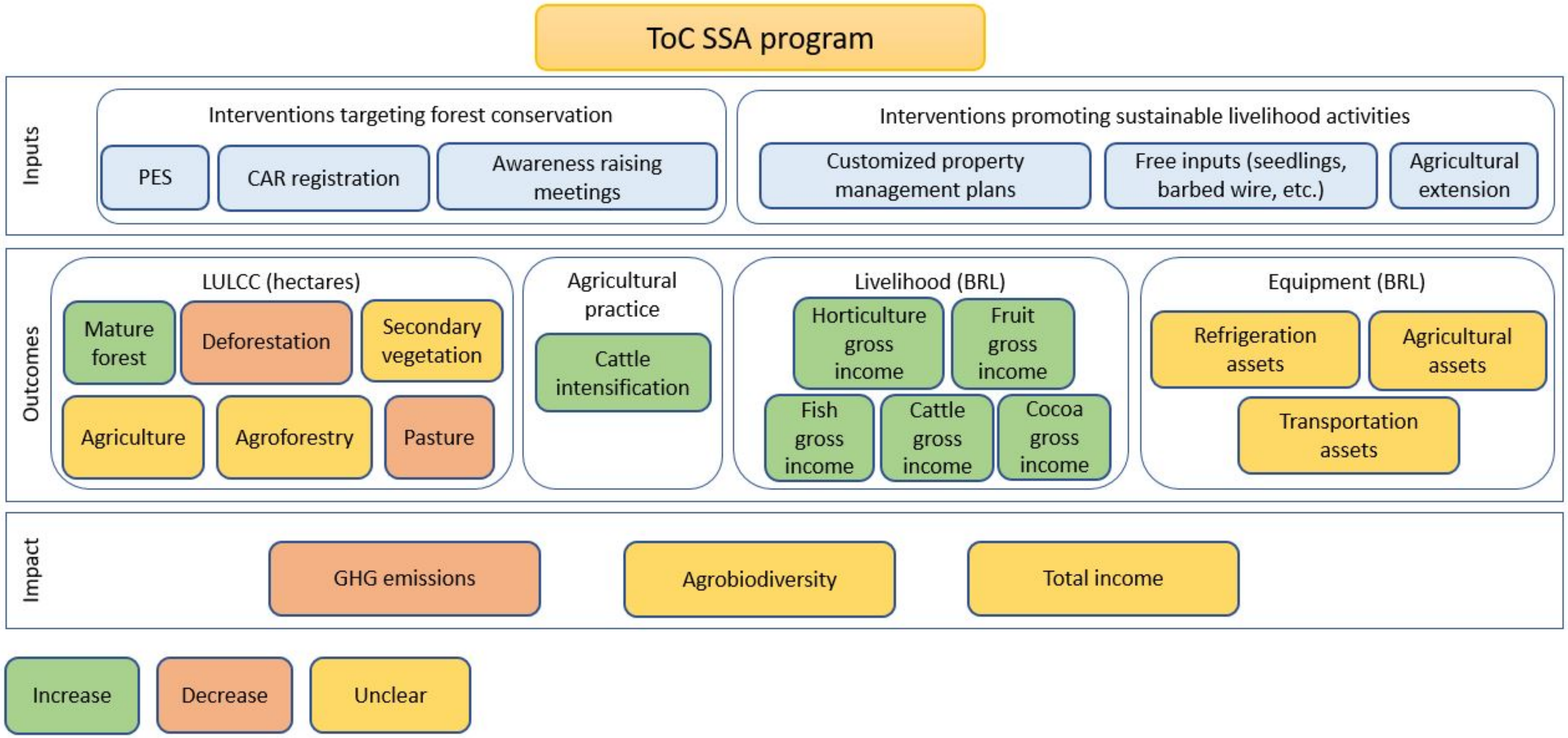
2.2 Expected and unexpected outcomes (Theory of Change)

To understand how the interventions proposed by IPAM could achieve both expected and unexpected outcomes on forests and livelihoods, we built a Theory of Change (ToC) of the SSA program, as represented in Figure 1. The diagram is divided into three parts: program inputs, program outcomes (which can also be seen as intermediary impacts), and (final) program impacts. The color code corresponds to the sign of the expected effect, when it is possible to envisage it, at least theoretically. Since we are interested in the 350 participants who received all the interventions offered by IPAM, and decisions about deforestation and land use are simultaneous, it is difficult to establish a priori a causal link between a given intervention and a given outcome. However, in order to organize the description of the ToC in a simple way, we first describe the interventions that were designed by IPAM, mainly with the objective of curbing deforestation in the short term. We then present the interventions, whose main objective was to develop sustainable alternative production systems over time in order to reduce deforestation in the long term after the PES ended.

2.2.1 Interventions targeting forest conservation

At the top left of Figure 1, there are three interventions whose primary objective was to reduce deforestation in the short term, i.e., as soon as the household had signed its commitment to comply with the program requirements, namely the PES, the registration at the CAR, and attendance of the information meetings. Starting with PES, the rationale is that direct payments are expected to induce forest conservation by providing landholders higher economic returns from conserving forests than they would receive from deforestation (World Bank, 2018). In other words, by making standing forests more profitable for landowners than economic activities that generate deforestation (e.g., slash-and-burn agriculture, extensive cattle ranching), payments should induce them to cooperate with forest conservation (Phelps et al., 2013). Therefore, to effectively attract participants to the program, payments should at least offset the opportunity cost of deforestation, i.e., the yields lost by abandoning business-as-usual land uses (Wunder, 2008). In the case of the SSA program, according to IPAM, payments were defined based on the local yields from cattle ranching and agricultural activities (Pinto et al., 2020).

Figure 1: Representation of the SSA program Theory of Change



Note: This is a representation of the simplified theory of change linking the SSA intervention with intermediate outcomes and impact indicators. The color code corresponds to the hypothesized direction of the effect.

In small-scale PES-based pilot programs, participants' conservation actions are generally well monitored, and free-riding behaviors can easily be avoided (Pagiola et al., 2020). However, once farmers lose the financial incentive not to clear forests, business-as-usual deforestation becomes more economically attractive again (Swart, 2003). Thus, like payments offered in the SSA program, the PES are temporary by design (Pagiola et al., 2016) and expected to result in only temporary deforestation reduction (Wunder, 2008; World Bank, 2018). At least three recent studies have been able to highlight the change in deforestation that was induced by the PES offered as part of the SSA program (see Simonet et al. (2018a); Carrilho et al. (2022); Demarchi et al. (2020). On aggregate, their findings show that the program conserved, on average, between 2.24 to 8.45 hectares per farm while payments were ongoing. Moreover, PES was also probably the SSA intervention responsible for improving beneficiaries' perceived well-being during the program's initial years (Carrilho et al., 2022). Yet as predicted by theory, deforestation resumed after the temporary PES program ended. Still, according to Demarchi et al. (2020) and Carrilho et al. (2022), the program left a permanent environmental gain, since deforestation reduction achieved during the program was not offset by any catch-up behavior thereafter.

In the SSA ToC, both CAR and public information meetings were also expected to have a direct impact on deforestation reduction. These interventions were designed by IPAM with the goal of raising farmers' compliance with the Brazilian Forest Code. Indeed, CAR is one of the most important forest monitoring instruments of Brazilian environmental agencies such as IBAMA, and previous evidence indicates that registering properties on CAR might result in deforestation reduction (e.g., Alix-Garcia et al. (2018); Costa et al. (2018)). In addition, in the most isolated regions where households are not always well informed about forest conservation regulations, meetings such as those offered by IPAM can fill the information gap. In the present case, the information collected in the field suggests that the inhabitants of the study area (both in the treated and control communities) were generally well aware of the legal obligations of retaining a certain portion of native vegetation, the existence of forest monitoring by environmental agencies, and the risk of possible sanctions for non-compliance. In any case, it is important to emphasize that even if there were an impact of the CAR or the public information meetings on deforestation decisions, our empirical analysis framework would not allow us to highlight it, because in our data, both the participants and non-participants used as counterfactuals had a CAR and the meetings were open to the local community (while non-participants used as counterfactuals didn't receive PES, technical assistance nor free inputs).

To understand the broader picture of land-use changes, it is also important to analyze possible indirect impacts of the SSA program on other types of vegetation, which include not only mature forest, but also secondary forests and fallow vegetation. These outcomes are represented in the central left part of Figure 1. As farmers in the study area usually deforest mature and secondary forests to grow crops and raise cattle, it seems reasonable to expect that avoided deforestation will come at the expense of pasture or cropland (Simonet et al., 2018a). One might also expect that some of the participants displace part or all of their deforestation from mature forests to secondary forests and do not leave fallow vegetation aside to regenerate. If this were the case, participants would remain eligible for the payment, but there would be a trade-off between curbing deforestation and inducing forest regeneration. Thus, by sparing mature forests, PES are also likely to induce a negative impact on forest regeneration and, consequently, on carbon sequestration. According to Demarchi et al. (2020), the SSA program reached the REDD+ goals of reducing deforestation and avoiding carbon emissions by 309,746 tCO2. However, this estimate does not take into account the likely impact of the SSA program on secondary vegetation. In this paper, we attempt to understand if avoided deforestation emissions were somehow negatively compensated by a reduction of secondary forests.

2.2.2 Interventions targeting household livelihoods

At the top right of Figure 1 is a representation of the package of non-conditional incentives designed to promote alternative livelihoods (i.e., customized property management plans, technical assistance, and free inputs) whose expected outcome are land uses less dependent on deforestation. This approach, not new, is based on the so-called Integrated Conservation and Development Project (ICDP) principle, which provides upfront subsidies and assistance to boost livelihoods likely to achieve the dual objective of poverty reduction and environmental conservation (Sanjayan et al., 1997). The assumption behind this strategy is that more environmentally-friendly land uses can provide higher economic returns than current, less sustainable, practices. Therefore, as long as the program incentives overcome obstacles to their adoption (e.g., startup costs, farmers' lack of technological knowledge, social approval and acceptance), one can expect that beneficiary farmers will switch from business-as-usual to sustainable practices over the long term (Pagiola et al., 2020). Such interventions are expected to support deforestation reduction even after the end of conditional payments.

For various reasons, however, the transition from a system dependent on deforestation to a sustainable one may not occur (Wright et al., 2016). First of all, the returns from the sustainable activities may actually be lower than those from current practices, at least for some of the beneficiaries. Remember that rural households are not homogeneous and are thus expected to vary in many aspects, including the opportunity costs of adopting more environmentally-friendly land uses (Piñeiro et al., 2020). If the proposed land uses are less profitable than business-as-usual activities, participants will not adopt them or, when adopting, will abandon the new activities after receiving frustrating results (Pagiola et al., 2020). Second, since these incentives are non-conditional, i.e., there are no requirements associated with receiving the package, certain diversion behaviors of the inputs offered may be observed (Pagiola et al., 2016). Typically, beneficiaries could use the free inputs to invest in business-as-usual activities instead of in sustainable land uses. Finally, the beneficiaries may adopt new activities without abandoning business-as-usual practices (Barrett et al., 2001). This combination of new and old activities could be possible, for example, (i) by reallocating time devoted to production activities among household members (Allison and Ellis, 2001), (ii) by reducing household members' leisure time (Epstein et al., 2022), and (iii) by distributing over the year the dedication to multiple activities in order to maximize economic returns, based on product seasonality and the variation of market prices (Van Vliet, 2010). Thus, whether ICDP-type incentives can be effective in reducing deforestation over the long term is difficult to anticipate. Previous evaluation of the impact of ICDP programs on conservation outcomes provides evidence of disappointing results (Roe et al., 2015).

In the case of the SSA program, however, the context appeared particularly favorable, since the sustainable activities were previously agreed upon between IPAM and the household heads themselves. According to Carrilho (2021), 48% of the sampled households self-declared that have implemented sustainable activities between 2014, when IPAM began providing technical assistance and free inputs, and 2019. When comparing this number to how many matched non-participants adopted alternative activities in the same period, the authors show the SSA program increased by approximately 40% the probability of households adopting new livelihood activities. Notably, the authors also show that participants who adopted new sustainable activities continued to have more self-declared forest cover than matched non-participants, even after the program ended. Yet the results suggest that this was insufficient to promote long-term deforestation avoidance in average terms. Moreover, the authors show that the SSA program increased beneficiaries' agricultural productivity and annual farm income (approximately 3,200 BRL per cultivated hectare more in the participating farms than in their matched counterparts). However, the authors do not investigate if the program positively impacted the agricultural production generated by the sustainable activities, which we, therefore, address in this article. We also investigate potential SSA impacts on households' physical assets necessary to agricultural production and transportation of the products for sale. We posit that beneficiaries might have used REDD+ transfers to accumulate longer-lasting assets, which could have contributed to maintaining the alternative activities and enhancing participants' well-being.

The bottom right of Figure 1 shows two outcomes assumed to be affected by the package of incentives to adopt sustainable production systems. First is total gross income, a measure of household well-being. We estimated SSA impacts not only on total income, but also on the income from salary and family business, taken separately. Despite Carrilho (2021) finding improvements in farm income, it would still be possible that beneficiaries faced some trade-off between income sources. As household members were supposed to dedicate time to the sustainable activities IPAM wanted to promote, they might have had to reduce time devoted to other economic activities. For instance, in the Transamazon region, it is common for farmers to do some daily-wage work on neighbor farms, in addition to working on their own property. Time devoted to these daily-wage jobs may have been reallocated to the new activities. In this case, if the returns from the new activities did not overcome those from the abdicated daily-wage work, contrary to what the participants had hoped, the SSA program might have led to negative impacts on total income. This could help explain why Carrilho et al. (2022) detected that participants' perceived that their well-being declined after the program ended.

The second final outcome that we can assume will be affected by the SSA program is a measure of agrobiodiversity on the farm. By diversifying livelihoods, the SSA program may have promoted unplanned increases in the agrobiodiversity of participant farms, which could have potential benefits to farmers' food access. On the other hand, since the payments were conditional on activities not dependent on deforestation, it is quite possible that landholders decreased the production of cassava, corn, banana, beans, and other crops (that are dependent on deforestation). Therefore, on the one hand, incentives to adopt new subsistence crops may have increased agrobiodiversity, while on the other hand, the impediment to clearing new areas may have decreased the number of crops that were commonly cultivated in the area prior to the program.

3 Data sources and variables

3.1 Land Use and Land Cover (LULC) remote-sensing data

The map with the localization of the farmholds enrolled in the SSA program is publicly available on IPAM's website (http://www.pas-simpas.org.br/). We used it to geolocalize the boundaries of the farms enrolled in the program. In order to build a control group, we also used property boundaries from the CAR of 11,457 farmholds in our study area. Land Use and Land Cover (LULC) annual maps were obtained from the MapBiomas project. These maps are produced based on the classification of Landsat imagery mosaics. The mosaics are then used to produce a map with land cover classes (forest, agriculture, pasture, urban area, water, etc.) using the random forest algorithm. All data are publicly available at the MapBiomas website (https://mapbiomas.org). Detailed information on the processing and validation of this dataset is provided in Souza and Azevedo (2017).

The spatial resolution of the dataset did not allow us to assess land use classes that cover small areas (< 1 ha). In our case, this means that MapBiomas does not typically provide data on the area covered by crops and agroforestry. Hence, we focused our analysis on pasture cover, mature forest, and secondary forest. We computed the surface of each LULC class for each farmhold by multiplying the number of pixels classified by the pixel area (0.09 hectares). At the time of the analyses, we only had access to data on pasture and mature forest cover up to 2019 and on secondary forest cover ending in 2017. The forest land use class includes both primary and secondary forest together. To be consistent with Demarchi et al. (2020), we built LULC maps starting in 2008. Therefore, we ended up with five observations for the period prior to the program start (2008-2012), five observations for secondary forest cover (2013-2017), and seven observations for pasture and forest (2013-2019) after the program began.

3.2 *Socioeconomic survey data*

We used household-level survey data from the Center for International Forestry Research (CIFOR)'s Global Comparative Study (GCS) on REDD+. Data were collected in eight communities (four intervention and four comparison) in three periods, one pre-treatment in 2010 (the baseline) and two post-treatment: 2014 (one year after the program began) and 2019 (two years after the program ended). Intervention communities were randomly chosen from a pool of twelve communities in which IPAM had planned to implement the SSA program. In turn, the comparison communities were selected based on a pre-matching procedure with another pool of fifteen communities located in the Transamazon region. The pre-matching procedure was to identify communities with a balanced distribution of characteristics that could influence the selection of SSA's target areas, e.g., forest cover, deforestation pressures, and market accessibility (Sunderlin et al., 2016).

A total of 240 households (30 in each community) were randomly selected for face-to-face interviews during the baseline period. There was considerable attrition of households between the three survey rounds. This includes households that moved, passed away, were traveling, or no longer wanted to participate in the study. The final sample of households for which we could obtain information from the three survey rounds thus includes 98 households: 52 treated farms (i.e., program participants) and 46 comparison farms (non-participants likely to be used as matched counterparts). Besides land use information, the GCS dataset includes socioeconomic characteristics of the households[4] (e.g., demographic data, sources of income, assets).

When looking at the alternative livelihoods, we focused on four variables measuring the farmer's involvement in sustainable activities: i) gross income from cocoa farming (*Theobroma cacao*); ii) gross income from horticulture (e.g., carrots - *Daucus carota*, parsley - *Petroselinum crispum*, lettuce - *Lactuca sativa*), iii) gross income from fruit pulp manufacturing (e.g., from açaí - *Euterpe oleracea*, cupuaçu - *Theobroma grandiflorum*, passion fruit - *Passiflora edulis*), and iv) gross income from fish farming. We also looked at cattle production and cattle intensification, measured as the change in the cattle stocking rate, i.e., the ratio between the number of adult cattle per hectare of pasture. The gross income of cattle, as well as the production of the five alternative livelihoods,

[4] GCS data also involve a number of interviews with IPAM and other key informants, such as government officials, local NGOs, and community associations. We used this information to better understand the SSA program and its target areas, to build the ToC, and to interpret the results of the impact analysis.

were estimated as the product of the production volume (consumed and traded) from the twelve months prior to the survey and the market prices.

In addition, we examined three asset categories: i) agricultural equipment (e.g., tractor, plow, water pump, wheelbarrow), ii) refrigeration equipment (i.e., refrigerator/freezer) since we consider them essential to store fish from psiculture and frozen fruit pulp, and iii) transportation equipment (e.g., automobile, truck). Survey data also allowed us to measure the total income of the households in the sample, i.e., all household yields obtained in the 12 months prior to the survey. This included the yields from farm activities (crop and animal production) and environmental income (i.e., income from products obtained from low or no management forest and non-forest areas), both for consumption and trade, added to the income from salary, wages, family business, government transfers, and other possible income sources (e.g., the renting out of land, remittances from relatives, inheritance, etc.). We also looked at income from salary, wages, and family business separately, since we suspected that households could have reduced these activities to invest time in the new livelihoods. Finally, we used survey data to construct a variable of crop richness, measured by the number of crops grown on the farm, divided by the total farm area. We used this as a proxy for agrobiodiversity.

4 Identification strategy

We estimated the impact of the SSA program on a series of variables that included LULC, agrobiodiversity, livelihood, and socioeconomic outcomes. To do so, we estimated the difference between the change in the level of the outcome observed on participating farmholds and that which would have been observed in those same farmholds if they had not been enrolled in the REDD+ initiative (i.e., the counterfactual scenario). This is the Average Treatment Effect on the Treated (ATT), $ATT = E(y^1 - y^0|D = 1)$, where y^1 denotes the change in the level of the outcome variable under the treatment, y^0 is the same variable in the absence of treatment, and D is a dummy that takes the value of one when the household has been treated and zero otherwise. Since we cannot observe y^0 when D equals 1, the counterfactual scenario has to be estimated (Ferraro, 2009).

This is not a straightforward task, since the intervention was not randomly assigned. Participation in the SSA program, like in most REDD+ projects, was indeed voluntary. Therefore, one can expect that farmers who chose to participate have different characteristics than those who declined (e.g., social preferences, environmental motivations, human and natural capital). If these pre-existing differences between participants and non-participants were correlated to the outcomes of interest, comparing the two groups directly would yield biased estimates of the program's impact (White and Raitzer, 2017). However, it is reasonable to assume that in comparison communities it is possible to find a number of farmholders who would have participated in the program, had they been offered to do so. Therefore, we used similar farmholders as matched counterparts of participants.

We used a Difference-in-Difference (DID) approach combined with a matching procedure, using a series of pre-treatment observable characteristics likely to affect both a farmer's decision to participate in the program and the outcomes of interest (Imbens and Wooldridge, 2009). We used the Nearest Neighbor matching (NNM) and the Propensity Score matching (PSM) estimators, which matches each treated farmhold to the most similar non-participant farmhold from the comparison group (Abadie et al., 2004). Insofar as the sample of farms for which we have LULC remote-sensing panel data is different and much larger than that for which we have survey panel data (more than 11,000 farmholds in the first case versus 98 farmholds in the second case), the vector of covariates used for the matching procedure was different in the two cases.

For the sample of 11,299 farmholds for which we have panel data on pasture areas, forest areas, and secondary forest areas, the set of covariates used for the matching procedure also included the farm size, the distance from the farm to: i) the main road, ii) the main navigable river, iii) the main market, and iv) the nearest village. Summary statistics and balancing tests are presented in the Appendix in Table 5. The results show that, before matching, the participant group was significantly different from the non-participants for most covariates and that after matching, these differences dropped below 0.25 standard deviations, suggesting that the matching procedure performed well. To deal with the Stable Unit Treatment Value Assumption (SUTVA), we excluded from the untreated group those farmholds that were less than three (3) kilometers distant from a treated plot, thus creating a so-called buffer zone between treated plots and potential control ones.

For the sample of 98 farms for which we have survey panel data on livelihoods and socioeconomic and agrobiodiversity outcomes, the set of covariates used for the matching procedure included five variables only extracted from the baseline survey[5]: i) the number of members in the family, ii) the

[5]Since we aimed to assess the SSA effects on multiple outcomes, including the pre-treatment values of each of the outcomes in the matching procedure would create different control groups for each estimation. However, including all

total area of the farm, iii) the share of the farm covered by forest, iv) the share of the farm under pasture, and v) the total household income. Summary statistics and balancing tests are presented in the Appendix in Table 6. The results show that before matching, the participant group was significantly different from the non-participant group and all normalized differences of the baseline covariates, except for household members, were higher than 0.25 standard deviations, while after matching, these differences dropped below 0.25 standard deviations, indicating that selection bias decreased and, therefore, a valid control group was constructed from non-participating households.

5 Results

5.1 Impacts on LULC outcomes

Table 1 displays the estimates of the impact of the SSA program on forest cover, each year, over the period 2013-2019, using six different matching estimators. In most cases, we failed to demonstrate a significant effect of the program over its first year of implementation. On the other hand, the results tend to show a positive impact of the program, i.e., a statistically larger forest area on the treated farms than on the control farms, each year from 2014 until 2019. The last row of Table 1 gives the average forest area in the treated group. The numbers show that the forest cover of the treated farms decreased every year, but it decreased less than in the control group, which is why the ATT is always positive. The ATT indeed ranged from 1.1 ha to 5.4 ha in 2014 and increased steadily every year, eventually ranging between 4.4 ha and 8.1 ha in 2019. This indicates that the effect of the program continued even two years after its end (2017). At the time the study was conducted, it had saved more than 4 ha of forest, on average, per farm (taking the smallest estimate).

Similarly, Table 2 displays the estimates of the impact of the SSA program on pasture area, each year, over the same period, using the same estimators. Again, results do not show any significant impact of the program in 2013. In most estimates, they also show no significant impact in the second year of the program (2014). From 2015, however, the results tend to show a negative impact of the program, i.e., a statistically smaller pasture area on the treated farms than on the control farms. The last row of Table 2 shows that the pasture cover of the treated farms increased every year on

of the pre-treatment values would have complicated the matching procedure, given the sample size. We thus chose to match on the same set of baseline covariates, without controlling for pre-treatment outcomes.

Table 1: Impact of the REDD+ project on forest cover each year between 2013 and 2019

Estimator	2013	2014	2015	2016	2017	2018	2019
NNM (4X)	0.310	1.125**	1.947***	2.596***	3.330***	3.700***	4.409***
	0.435	0.499	0.562	0.633	0.710	0.790	0.815
NNM (2X)	0.295	1.095**	2.082***	2.844***	3.680***	4.309***	5.004***
	0.397	0.503	0.588	0.677	0.759	0.833	0.877
NNM (1X)	0.539	1.531**	2.796***	3.592***	4.589***	5.296***	5.964***
	0.515	0.623	0.730	0.816	0.900	0.947	0.981
PSM (4N)	1.472	2.308	3.024**	3.642**	4.480***	4.822***	5.831***
	1.462	1.521	1.519	1.510	1.483	1.441	1.307
PSM (2N)	2.658**	3.531**	4.087***	4.708***	5.528***	5.559***	6.405***
	1.281	1.446	1.505	1.530	1.542	1.511	1.327
PSM (1N)	4.497**	5.378***	5.889***	6.399***	7.239***	7.224***	8.123***
	1.791	1.893	1.920	1.922	1.939	1.915	1.687
Mean in treated	49.479	48.575	47.655	46.275	45.611	44.111	40.992

Notes: This table displays the average treatment effect (ATT) on forest area in hectares. NNM(4X) (resp. 2X and 1X) refers to the DID nearest neighbor estimator using 4 (resp. 2 and 1) matched observations as controls. PSM(4N) (resp. 2N and 1N) refers to the DID propensity score matching estimator using 4 (resp. 2 and 1) matched observations as controls. ***, ** and * indicate that the estimated coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively. Standard errors are given in parentheses.

treated farms, but it increased less than in the control group. Thus, the ATT ranged from -3 ha to -1.6 ha in 2015 and (its absolute value) increased steadily every year, until 2019 when it ranged between -7.1 ha and -3.3 ha. This suggests that almost seven years after its launch, the program had prevented the establishment of more than 3 ha of pasture, on average, on each enrolled farm (taking the smallest estimate).

Finally, Table 3 displays the results of the estimates of the impact of the SSA program on secondary forest area, using the same identification strategy. Results show a quite clear impact of the program from 2015 to 2017 (our analysis stops in 2017). The secondary forest area of the treated farms slightly decreased between 2015 and 2017, but it decreased less than in the control group, which is why the ATT is positive: it represented more than half a hectare in 2015 and almost a hectare in 2017 (taking the smallest estimates). This suggests that there was actually not a trade-off between deforestation reduction and forest regeneration. Program participants therefore did not offset the reduction in mature forest cutting by an increase in secondary forest cutting or by impeding fallow regeneration. Quite the contrary, it would seem that they made an effort both on the mature forest and on the secondary forest. One possible explanation for this is the need for rural properties to comply with the Brazilian Forest Code and recover permanent preservation areas (PPA) in order to receive the PES. To comply with the law, the farmers indeed had to delimit the

PPA along streams and rivers and around water springs, isolating those areas with natural fences (namely trees) or physical barriers to avoid the entry of animals and human activity.

Table 2: Impact of the REDD+ project on pasture cover each year between 2013 and 2019

Estimator	2013	2014	2015	2016	2017	2018	2019
NNM (4X)	-0.232	-0.928**	-1.599***	-1.620***	-2.214***	-2.736***	-3.284***
	(-0.336)	(0.445)	(0.517)	(0.609)	(0.711)	(0.819)	(0.911)
NNM (2X)	-0.303	-1.433***	-2.185***	-2.431***	-3.253***	-3.902***	-4.657***
	(0.305)	(0.442)	(0.544)	(0.640)	(0.744)	(0.862)	(0.981)
NNM (1X)	-0.364	-1.497***	-2.479***	-2.552***	-3.339***	-4.032***	-4.673***
	(0.299)	(0.491)	(0.595)	(0.730)	(0.853)	(0.999)	(1.116)
PSM (4N)	-0.781	-1.824	-2.621	-3.133***	-4.155***	-4.590***	-5.795***
	(1.470)	(1.539)	(1.532)	(1.440)	(1.439)	(1.443)	(1.549)
PSM (2N)	-1.060	-2.070	-2.739***	-3.167***	-4.250***	-4.678***	-5.862***
	(1.287)	(1.255)	(1.210)	(1.107)	(1.094)	(1.130)	(1.382)
PSM (1N)	-1.304	-2.453	-3.008	-3.644***	-4.735***	-5.487***	-7.091***
	(1.557)	(1.606)	(1.580)	(1.460)	(1.475)	(1.541)	(1.821)
Mean in treated	28.352	29.300	30.254	31.705	32.458	34.055	37.196

Notes: This table displays the average treatment effect (ATT) on pasture area in hectares. NNM(4X) (resp. 2X and 1X) refers to the DID nearest neighbor estimator using 4 (resp. 2 and 1) matched observations as controls. PSM(4N) (resp. 2N and 1N) refers to the DID propensity score matching estimator using 4 (resp. 2 and 1) matched observations as controls. ***, ** and * indicate that the estimated coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively. Standard errors are given in parentheses.

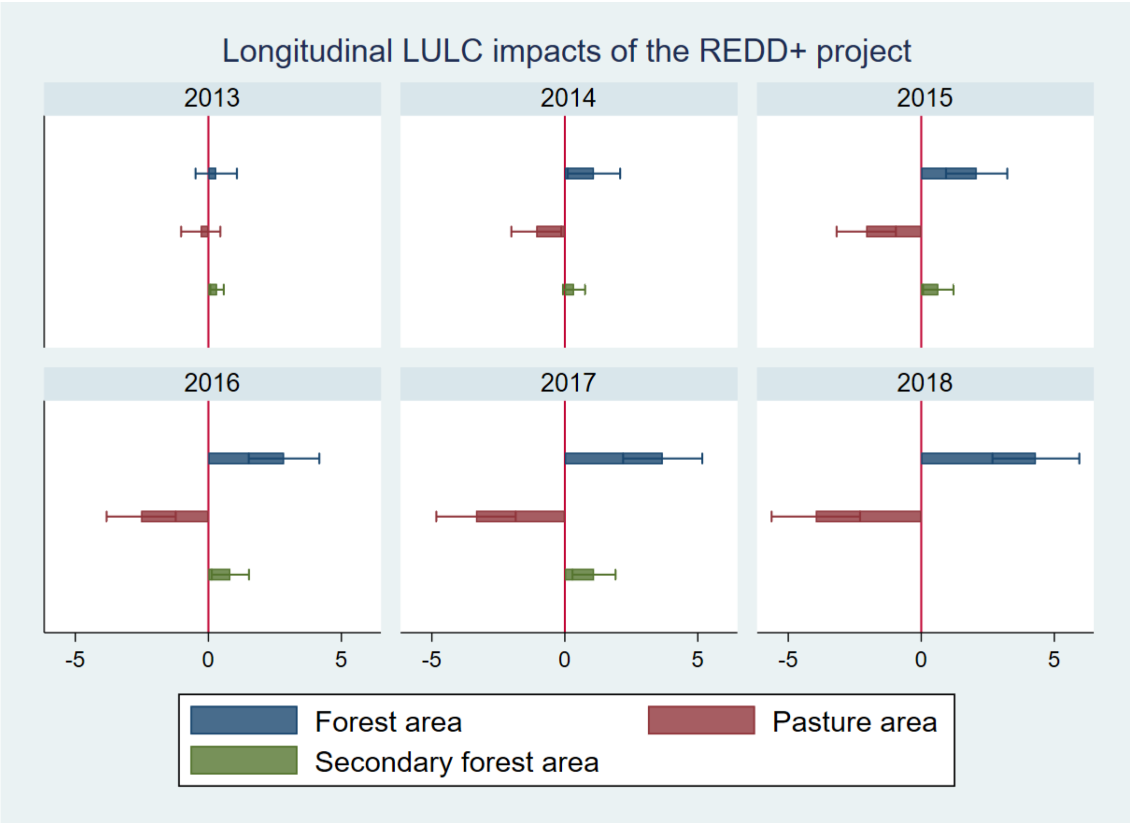
Table 3: Impact of the REDD+ project on secondary forest cover each year between 2013 and 2017

Estimator	2013	2014	2015	2016	2017
NNM (4X)	0.318**	0.364*	0.674**	0.773**	0.951**
	(0.126)	(0.201)	(0.269)	(0.321)	(0.379)
NNM (2X)	0.325**	0.348	0.639**	0.827**	1.097***
	(0.129)	(0.213)	(0.292)	(0.357)	(0.414)
NNM (1X)	0.337**	0.386	0.746**	0.992**	1.382***
	(0.161)	(0.256)	(0.367)	(0.433)	(0.510)
PSM (4N)	0.826	0.876	1.213*	1.190*	1.262*
	(0.652)	(0.670)	(0.660)	(0.644)	(0.650)
PSM (2N)	0.900	1.025	1.350*	1.361*	1.451**
	(0.738)	(0.749)	(0.738)	(0.705)	(0.698)
PSM (1N)	1.182	1.209	1.646*	1.584*	1.757**
	(0.877)	(0.875)	(0.853)	(0.811)	(0.805)
Mean in treated	10.364	10.436	10.709	10.209	10.178

Notes: This table displays the average treatment effect (ATT) on secondary forest area in hectares. NNM(4X) (resp. 2X and 1X) refers to the DID nearest neighbor estimator using 4 (resp. 2 and 1) matched observations as controls. PSM(4N) (resp. 2N and 1N) refers to the DID propensity score matching estimator using 4 (resp. 2 and 1) matched observations as controls. ***, ** and * indicate that the estimated coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively. Standard errors are given in parentheses.

Taken all together, these results suggest that the program was effective in curbing deforestation among participants one or two years after the start of the program and up to two years after its end. The magnitude of the estimated effects quite clearly suggests that the conservation effort made on the forest cover from 2015 resulted almost mechanically in a lesser increase in pasture. This result is illustrated by Figure 2, which shows the estimated ATT, positive for forests and negative of comparable magnitude for pasture.

Figure 2: Impact of the REDD+ project on LULC outcomes



Note: This graph displays the ATT estimates for the three LULC outcomes. Bars represent the ATT, estimated using the DID nearest-neighbor estimator that matches 4 observations as controls. Brackets represent 95 percent confidence intervals. Forest area includes both primary and secondary forests. Data for secondary forests is only available until 2017.

5.2 Impact on livelihood outcomes

Main findings on program impacts on variables measuring livelihoods from CIFOR surveys are displayed in Table 4 (robustness checks are presented in the Appendix in Tables 7–10). The first column of results presents the estimates made for the variables measured in 2014 (the short-term impact). The second column of results presents the estimates made for the variables measured in 2019 (the long-term impact). In general, the results regarding the adoption of more sustainable activities suggest that the program indeed boosted the production of alternative livelihoods, but only over the long run. No statistically significant impacts were found in the early project stage. However, looking at 2019, i.e., six years after the project began and two years after its end, we found significant impacts on the production of three of the four activities under study: i) fish production (almost 5,000 BRL more annual income among the treated than among the controls), ii) horticulture production (almost 1,900 BRL more), and iii) fruit pulp production (1,200 BRL more). Yet, we failed to detect significant impacts on cocoa income, whether short- or long-term. One possible explanation for such a result is that the cocoa tree takes a long time to produce, meaning that, even if the project had indeed triggered the adoption of this activity, the results would only be detectable over a longer time horizon.

Results also indicate that the project somehow contributed to the transition from extensive to more intensive cattle ranching systems. We indeed found a positive gap in the cattle stocking rate (i.e., the number of adult cattle per pasture area) between the two groups, which equaled 0.4 in the short run and 0.69 in the long run. Since our results on LULC outcomes indicate that the project had a negative impact on pasture expansion, this means that farmers simply raised more cattle using less pasture area because of the project. In the long run, we also found that the increase in the cattle stocking rate was followed by an increase of almost 22,000 BRL in annual gross income from cattle production.

The increase in the production of cattle, fish, horticulture, and fruit pulp was not followed by significant impacts on households' assets, except for refrigeration equipment (in the long run). Participating households were expected to use at least part of the payment received to accumulate the equipment required for new agricultural production and transportation. However, we found no evidence of this, whether in the short or long term. As for refrigeration assets, we found an increase of about 1,000 BRL, which could be related to the expansion of fish and fruit pulp production.

Looking at total household income, we found a negative impact (almost 1,500 BRL) on the income from salary, wages, and family business, in the short run only. As mentioned in the ToC section, the likely explanation is that households may have invested less time in business-as-usual activities to invest more time in the new activities promoted by the project. Moreover, this early negative impact seems to have then been compensated by positive impacts on the total income in the long run, since we found that participation in the project increased total income by an average of more than 40,000 BRL by 2019.

Finally, our results also suggest that the project had a positive impact on farms' agrobiodiversity. We found an increase in crop richness, as measured by the number of crops grown on the farm divided by the farm's total area that reached 0.08 in the short run and 0.09 in the long run. Considering that the average land area of the treatment group is about 80 ha (see summary statistics in Table 6), this indicates an average increase in the number of cultivated crops of 6.3 in the short run and 7.4 in the long run.

6 Discussion

6.1 No catch-up of postponed deforestation after end of payments

Our main results on the impact of the SSA project on forest cover are in line with and complement the findings of previous studies that evaluated the same program using different data. Using survey panel data on forest cover, Simonet et al. (2018b) estimated that, as of 2014, the program had saved, on average, about 4 hectares of forest on each participating farm, which is also found by Carrilho et al. (2022) using the same survey data. Using remote sensing panel data on annual forest loss, Demarchi et al. (2020) highlighted that the declarative data relating to deforestation practices may have somewhat overestimated the impact found by Simonet et al. (2018b) and that the program had more likely saved 2 hectares per farm, on average, during the first three years of the project.

Moreover, we showed in Demarchi et al. (2020) that this reduction in deforestation stopped before the end of the payments (or else became too low from 2017 to be detected using public data), meaning that the participants had resumed their usual rhythm of annual cutting. However, we provided evidence that no catch-up of postponed deforestation was observed thereafter. Using a satellite dataset different from that used in Demarchi et al. (2020), the present study corroborates this absence of catching-up, since it highlights the persistence of a gap in forest cover between the treated and control groups two years after the end of payments. Taken end to end, these works thus support the idea that the SSA program did indeed reduce deforestation during the period of

Table 4: Short- and long-term effects of the REDD+ project on livelihood outcomes

Alternative livelihoods	Short-run impact	Long-run impact
Cocoa gross income	517.53	7407.36
	(1393.54)	(8479.02)
Fish gross income	-1232.64	4597.091*
	(1781.98)	(2657.53)
Horticulture gross income	403.65	1876.85***
	(365.16)	(708.43)
Fruit pulp gross income	321.18	1200.23***
	(250.26)	(430.08)
Equipment		
Refrigeration assets	194.59	1059.1**
	(390.24)	(480.49)
Agricultural assets	320.47	133.21
	(526.14)	(502.42)
Transportation assets	1892.86	3429.12
	(1920.99)	(2319.32)
Cattle production		
Cattle stocking rate	0.4*	0.69**
	(0.21)	(0.29)
Cattle gross income	-3589.74	21974.23**
	(5614.88)	(10458.55)
Agrobiodiversity		
Crop richness	0.079**	0.092***
	(0.03)	(0.03)
Income		
Total income	-7816.63	40279.07**
	(13557.19)	(17096.00)
Salary + Business income	-1436.67**	-1254.58
	(557.98)	(3103.65)

Notes: This table displays the ATT of the SSA project on short-run (2014) and long-run (2019) outcomes obtained with the nearest neighbor estimator (NNM) using 2 matched observations as controls. The cattle stocking rate is expressed as the herd size divided by the pasture area. Crop richness is expressed as the number of different crops divided by the total area. ***, ** and * indicate that the estimated coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively. Standard errors are given in parentheses.

PES payments but not beyond and that the environmental gain generated during this short period was not subsequently canceled – at least until 2019, when our analysis ends.

6.2 The interplay of deforestation and the intensification of cattle ranching

Our results are also in line with previous findings from Simonet et al. (2018b) that used survey data to show that the decrease in deforestation occurred mainly at the expense of the slowdown in the expansion of pasture areas. We came to the same conclusion using satellite panel data on pasture areas of the whole population of participants. We investigated whether this decrease in pasture expansion had a negative impact on cattle herds and found that the number of cattle per hectare had increased on the farms benefiting from the program, suggesting that there had in fact been an intensification in cattle ranching activities. These findings add to the knowledge on the SSA project by pointing out that one of the mechanisms through which the conservation of primary and secondary forest was achieved was the intensification of cattle ranching.

A number of scholars have advocated that encouraging cattle ranching intensification in Brazil could decline greenhouse gas emissions by sparing land from deforestation (Nepstad et al., 2014; Cohn et al., 2014; Garrett et al., 2018). The idea is that intensification of cattle ranching could help ranchers use the already deforested land more efficiently and prevent them from clearing more land. More recently, however, the likely effects of land-use intensification on deforestation have been debated in the literature. Müller-Hansen et al. (2019) developed an agent-based model to study the interplay of deforestation and the intensification of cattle ranching in the Brazilian Amazon. The model shows that intensification can lower deforestation rates under certain conditions only, when the local cattle market is saturated. Indeed the model shows that in most scenarios intensification would not reduce deforestation rates and sometimes would even increase them. An evaluation of the SSA program in a few years would provide an empirical contribution to the debate.

6.3 The coexistence of sustainable and non-sustainable systems

Our results suggest that the implementation of sustainable activities under the SSA project seem to have created new means of subsistence for the participants and thus new sources of income. These effects, however, are noticeable only two years after the end of the program (2019). This suggests that when program participants voluntarily adopt new practices which require a greater mobilization of techniques, knowledge, and resources, it takes time for their effects to become observable through the data. Our results also show that participants simultaneously continued with more conventional and environmentally damaging systems and that cattle ranching continues to be one of their main sources of income.

Promoting a structural change in agricultural practices by stimulating the adoption of more sustainable activities and keeping deforestation rates permanently low at the same time, proves to be quite challenging. The relatively higher profitability of cattle ranching seems to be the most obvious explanation. However, recent studies have shown that livestock production yields the lowest per hectare incomes and still remains the most prevalent land use in remote areas of the Brazilian Amazon (Garrett et al., 2017). The literature presents several explanations as to why changes in agricultural practices are difficult to achieve, ranging from social preferences, the lack of technical assistance and rural extension services, the absence of clear land tenure, and lack of access to credit.

In the case of the SSA program, most of these bottlenecks were solved, or at least temporarily alleviated, but still, there was a relatively low uptake of the alternative livelihood activities (Carrilho, 2021). Qualitative data collected from the field suggest that one of the biggest obstacles to the adoption of alternative agricultural activities is poor access via unpaved roads, which gets worse every year during the rainy season, making it difficult not only for people to move around, but also for the outflow of agricultural production. According to several farmers' narratives, the lack of access makes it impossible to market the agricultural production most of the year (typically between November and May). This would be one of the main reasons why farmers continue to focus on cattle ranching, as cattle buyers come directly to the farms to buy the animals.

7 Conclusion

This study complements a series of recently carried out analyses aimed at evaluating the effectiveness of one of the first pilot PES programs implemented in the Brazilian Amazon. By combining satellite data never before used for this case study, covering all program participants (and thousands of non-participants who could be used as a control group), and survey data collected from a small but extremely rich and precise sample, we were able not only to corroborate or amend the findings of previous studies but also to complete the story of the project, namely the mechanisms by which the objective of reducing deforestation was achieved.

The key messages one can take away from this analysis relate to the likely short- and long-term effectiveness of REDD+ projects that aim at improving both forest conservation and household livelihoods. Overall, our findings suggest that the decrease in deforestation occurred mainly at the expense of the slowdown in the expansion of pasture areas. When we investigated whether this decrease in pasture expansion had a negative impact on cattle herds, we found that the number of cattle per hectare had increased on the farms benefiting from the program, suggesting that there was in fact an intensification in cattle ranching activities, something that can be observed in the short run. Our results further show that the program had a positive impact on the adoption of alternative production activities that require less area for production than extensive livestock farming and slash-and-burn agriculture, the two main drivers of deforestation in the region. The development of such activities, however, is not statistically observable in the short term, while they are designed to have lasting impacts, contrary to PES. Altogether, these results suggest that local REDD+ programs that combine PES with technical assistance and support to farmers for the adoption of sustainable activities can be effective in reducing deforestation in the short run, at least as long as the PES last, without jeopardizing the standard of living of participants. They also show that a number of households are ready to adopt new agricultural practices, while maintaining their traditional ones. The question of whether the coexistence of both types of production systems is sustainable over time or not remains open. In any case, the transmission of technical knowledge necessary for the development of environmentally sustainable activities was effective and it cannot be ruled out that the participants who have acquired this new knowledge during the program will use it in the future.

References

Abadie, A., Drukker, D., Herr, J. L., and Imbens, G. W. (2004). Implementing matching estimators for average treatment effects in stata. *The stata journal*, 4(3):290–311. 4

Alix-Garcia, J., Rausch, L. L., L'Roe, J., Gibbs, H. K., and Munger, J. (2018). Avoided Deforestation Linked to Environmental Registration of Properties in the Brazilian Amazon. *Conservation Letters*, 11(3):1–8. 2.2.1

Allison, E. H. and Ellis, F. (2001). The livelihoods approach and management of small-scale fisheries. *Marine policy*, 25(5):377–388. 2.2.2

Barrett, C. B., Reardon, T., and Webb, P. (2001). Nonfarm income diversification and household livelihood strategies in rural africa: concepts, dynamics, and policy implications. *Food policy*, 26(4):315–331. 2.2.2

Blundo-Canto, G., Bax, V., Quintero, M., Cruz-Garcia, G. S., Groeneveld, R. A., and Perez-Marulanda, L. (2018). The different dimensions of livelihood impacts of payments for environmental services (pes) schemes: A systematic review. *Ecological Economics*, 149:160–183. 1

Carrilho, C. (2021). *Forest conservation and well-being outcomes of a REDD+ initiative: A quasi-experimental assessment among smallholders in the Brazilian Amazon*. PhD thesis, Universidade de São Paulo. 2.1, 2.2.2, 6.3

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, 2, 2.1, 2.2.1, 2.2.2, 6.1

Cohn, A. S., Mosnier, A., Havlík, P., Valin, H., Herrero, M., Schmid, E., O'Hare, M., and Obersteiner, M. (2014). Cattle ranching intensification in brazil can reduce global greenhouse gas emissions by sparing land from deforestation. *Proceedings of the National Academy of Sciences*, 111(20):7236–7241. 6.2

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

Correa, J., van der Hoff, R., and Rajão, R. (2019). Amazon fund 10 years later: lessons from the world's largest redd+ program. *Forests*, 10(3):272. 1

Costa, M. A., Rajão, R., Stabile, M. C., Azevedo, A. A., and Correa, J. (2018). Epidemiologically inspired approaches to land-use policy evaluation: The influence of the Rural Environmental Registry (CAR) on deforestation in the Brazilian Amazon. *Elementa*, 6:1–17. 2.2.1

Coutiño, A. G., 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

Cromberg, M., Duchelle, A. E., Simonet, G., and de Freitas, A. (2014). Sustainable settlements in the amazon, brazil. 2.1

Demarchi, G., Julie, S., Catry, T., and Tritsch, I. (2020). Using publicly available remote sensing products to evaluate redd+ projects in brazil. 1, 2.2.1, 3.1, 6.1

Duchelle, A. E., de Sassi, C., Jagger, P., Cromberg, M., Larson, A. M., Sunderlin, W. D., Atmadja, S. S., Resosudarmo, I. A. P., and Pratama, C. D. (2017). Balancing carrots and sticks in redd+ implications for social safeguards. *Ecology and Society*, 22(3). 2

Duchelle, A. E., Simonet, G., Sunderlin, W. D., and Wunder, S. (2018). What is redd+ achieving on the ground? *Current Opinion in Environmental Sustainability*, 32:134–140. 1

Epstein, G., Alexander, S. M., Marschke, M., Campbell, D., and Armitage, D. (2022). The ambiguous impacts of alternative livelihoods on fisher wellbeing in a closed access fish sanctuary in port antonio, jamaica. *Coastal Studies & Society*, page 26349817211067052. 2.2.2

Ferraro, P. J. (2009). Counterfactual thinking and impact evaluation in environmental policy. *New directions for evaluation*, 2009(122):75–84. 4

Garrett, R. D., Gardner, T. A., Morello, T. F., Marchand, S., Barlow, J., de Blas, D. E., Ferreira, J., Lees, A. C., and Parry, L. (2017). Explaining the persistence of low income and environmentally degrading land uses in the brazilian amazon. *Ecology and Society*, 22(3). 6.3

Garrett, R. D., Koh, I., Lambin, E. F., De Waroux, Y. l. P., Kastens, J. H., and Brown, J. (2018). Intensification in agriculture-forest frontiers: Land use responses to development and conservation policies in brazil. *Global Environmental Change*, 53:233–243. 6.2

Gebara, M. F., Fatorelli, L., May, P., and Zhang, S. (2014). Redd+ policy networks in brazil: constraints and opportunities for successful policy making. *Ecology and Society*, 19(3). 2

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

IPAM (2016). Assentamentos sustentáveis.instituto de pesquisa ambiental da amazônia. 2.1

IPAM (2017). A assistência técnica e extensão rural diferenciada: a experiência do PAS. Informativo do Projeto Assentamentos Sustentáveis na Amazônia (PAS). 2.1

Jack, B. K. and Santos, E. C. (2017). The leakage and livelihood impacts of pes contracts: a targeting experiment in malawi. *Land Use Policy*, 63:645–658. 1

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

Müller-Hansen, F., Heitzig, J., Donges, J. F., Cardoso, M. F., Dalla-Nora, E. L., Andrade, P., Kurths, J., and Thonicke, K. (2019). Can intensification of cattle ranching reduce deforestation in the amazon? insights from an agent-based social-ecological model. *Ecological Economics*, 159:198–211. 6.2

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). 6.2

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. 2.2.1, 2.2.2

Pagiola, S., Honey-Rosés, J., and Freire-González, J. (2020). Assessing the permanence of land-use change induced by payments for environmental services: Evidence from nicaragua. *Tropical Conservation Science*, 13:1940082920922676. 2.2.1, 2.2.2

Phelps, J., Carrasco, L. R., Webb, E. L., Koh, L. P., and Pascual, U. (2013). Agricultural intensification escalates future conservation costs. *Proceedings of the National Academy of Sciences*, 110(19):7601–7606. 2.2.1

Piñeiro, V., Arias, J., Dürr, J., Elverdin, P., Ibáñez, A. M., Kinengyere, A., Opazo, C. M., Owoo, N., Page, J. R., Prager, S. D., et al. (2020). A scoping review on incentives for adoption of sustainable agricultural practices and their outcomes. *Nature Sustainability*, 3(10):809–820. 2.2.2

Pinto, E., Souza, M. L. d. L., Nascimento, D., and Stella, O. (2020). Pagamento por Serviços Ambientais na Agricultura Familiar. In Souza, M. L. and Alencar, A. S., editors, *Assentamentos Sustentáveis na Amazônia. Agricultura Familiar e Sustentabilidade Ambiental na maior floresta tropical do mundo*, chapter 5, pages 147–161. Instituto de Pesquisa Ambiental da Amazônia (IPAM). 2.2.1

Roe, D., Booker, F., Day, M., Zhou, W., Allebone-Webb, S., Hill, N. A., Kumpel, N., Petrokofsky, G., Redford, K., Russell, D., et al. (2015). Are alternative livelihood projects effective at reducing local threats to specified elements of biodiversity and/or improving or maintaining the conservation status of those elements? *Environmental Evidence*, 4(1):1–22. 2.2.2

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

Sanjayan, M., Jansen, M., and Shen, S. (1997). *Experiences with integrated-conservation development projects in Asia*, volume 23. World Bank Publications. 2.2.2

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. 2

Sills, E. O., de Sassi, C., Jagger, P., Lawlor, K., Miteva, D. A., Pattanayak, S. K., and Sunderlin, W. D. (2017). Building the evidence base for REDD+: Study design and methods for evaluating the impacts of conservation interventions on local well-being. *Global Environmental Change*, 43:148–160. 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, 2.1, 2.2.1

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. 6.1, 6.2

Souza, C. and Azevedo, T. (2017). Mapbiomas general handbook. *MapBiomas: São Paulo, Brazil*, pages 1–23. 3.1

Souza, M. L. d. L., Pereira, C., Stella, O., Cardoso, A., Nascimento, D., Carvalho, E., Pinto, E., Bentes, A. J., and Nascimento, D. (2020). Estratégias para uma Agricultura Familiar Sustentável na Amazônia. In Souza, M. L. and Alencar, A. S., editors, *Assentamentos Sustentáveis na Amazônia. Agricultura Familiar e Sustentabilidade Ambiental na maior floresta tropical do mundo*, chapter 3, pages 44–123. Instituto de Pesquisa Ambiental da Amazônia (IPAM). 2.1

Stella, O., Pereira, C., Soave Jr., M., Balzani, C., Piontekowski, V., and Martenexen, F. (2020). O Projeto Assentamentos Sustentáveis (PAS). In Souza, M. L. and Alencar, A., editors, *Assentamentos Sustentáveis na Amazônia. Agricultura Familiar e Sustentabilidade Ambiental na maior floresta tropical do mundo*, chapter 2, pages 42–62. Instituto de Pesquisa Ambiental da Amazônia (IPAM), Brasília. 2.1

Sunderlin, W. D., Larson, A. M., Duchelle, A. E., Sills, E. O., Luttrell, C., Jagger, P., Pattanayak, S. K., Cronkleton, P., Ekaputri, A. D., de Sassi, C., et al. (2016). *Technical guidelines for research on REDD+ subnational initiatives*. CIFOR. 3.2

Swart, J. A. (2003). Will direct payments help biodiversity? *Science*, 299(5615):1981–1982. 2.2.1

Van Vliet, N. (2010). Participatory vulnerability assessment in the context of conservation and development projects: a case study of local communities in southwest cameroon. *Ecology and Society*, 15(2). 2.2.2

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

White, H. and Raitzer, D. A. (2017). *Impact evaluation of development interventions: A practical guide*. Asian Development Bank. 4

World Bank (2018). Evaluating the permanence of forest conservation following the end of payments for environmental services in Uganda. 2.2.1, 2.2.1

Wright, J. H., Hill, N. A., Roe, D., Rowcliffe, J. M., Kümpel, N. F., Day, M., Booker, F., and Milner-Gulland, E. (2016). Reframing the concept of alternative livelihoods. *Conservation Biology*, 30(1):7–13. 2.2.2

Wunder, S. (2008). Necessary conditions for ecosystem service payments. 2.2.1, 2.2.1

Wunder, S., Duchelle, A. E., Sassi, C. d., Sills, E. O., Simonet, G., and Sunderlin, W. D. (2020). Redd+ in theory and practice: how lessons from local projects can inform jurisdictional approaches. *Frontiers in Forests and Global Change*, 3:11. 1, 2

Appendix

Table 5: Summary statistics of LULC variables for participants and comparison groups

	Participants (n=348)		Comparison (n=10,950)		N.D.	
Pre-treatment variables	Mean	Std. Dev.	Mean	Std. Dev.	Raw	Matched
Total area (ha)	77.209	37.002	97.410	77.828	-0.335	0.210
Distance from nearest village (km)	23.092	11.245	29.327	14.736	-0.478	-0.039
Distance from Altamira (km)	122.601	56.746	164.546	98.194	-0.502	-0.085
Distance from Transamazon highway (km)	13.875	10.821	20.133	13.863	-0.690	-0.074
Distance from Xingu river (km)	63.761	52.797	111.857	84.054	-0.527	-0.072
Pasture area in 2008 (ha)	28.158	21.386	46.530	53.312	-0.454	0.174
Pasture area in 2009 (ha)	29.116	21.749	47.605	53.587	-0.453	0.175
Pasture area in 2010 (ha)	29.326	21.797	49.057	53.686	-0.483	0.172
Pasture area in 2011 (ha)	29.706	21.775	49.532	53.446	-0.488	0.173
Pasture area in 2012 (ha)	28.207	21.451	48.460	52.725	-0.505	0.162
Forest area in 2008 (ha)	49.906	29.043	51.513	54.012	-0.048	0.129
Forest area in 2009 (ha)	48.946	29.000	50.432	53.175	-0.045	0.125
Forest area in 2010 (ha)	48.730	29.004	48.985	52.281	-0.017	0.128
Forest area in 2011 (ha)	48.361	29.275	48.478	51.938	-0.013	0.128
Forest area in 2012 (ha)	49.853	29.730	49.509	52.436	-0.002	0.137
Secondary forest area in 2008 (ha)	6.433	9.127	6.406	10.226	0.002	0.138
Secondary forest area in 2009 (ha)	7.006	9.422	6.860	10.633	0.013	0.149
Secondary forest area in 2010 (ha)	7.204	9.685	7.107	10.944	0.008	0.146
Secondary forest area in 2011 (ha)	8.062	10.199	7.444	11.419	0.055	0.164
Secondary forest area in 2012 (ha)	8.594	10.678	8.123	11.960	0.040	0.167
Post-treatment variables						
Pasture area in 2013 (ha)	28.327	21.928	49.623	53.052		
Pasture area in 2014 (ha)	29.241	22.118	50.384	52.984		
Pasture area in 2015 (ha)	30.148	22.076	51.479	52.729		
Pasture area in 2016 (ha)	31.522	22.232	52.695	52.871		
Pasture area in 2017 (ha)	32.177	22.179	53.452	52.594		
Pasture area in 2018 (ha)	33.680	22.366	55.247	52.665		
Pasture area in 2019 (ha)	36.822	23.725	57.843	53.407		
Forest area in 2013 (ha)	49.479	29.790	48.453	52.445		
Forest area in 2014 (ha)	48.575	29.428	47.590	52.316		
Forest area in 2015 (ha)	47.655	28.790	46.382	51.612		
Forest area in 2016 (ha)	46.275	28.787	44.754	50.835		
Forest area in 2017 (ha)	45.611	29.065	43.904	50.512		
Forest area in 2018 (ha)	44.111	29.094	42.215	49.684		
Forest area in 2019 (ha)	40.992	28.100	40.286	48.300		
Secondary forest area in 2013 (ha)	10.330	11.356	9.265	12.954		
Secondary forest area in 2014 (ha)	10.397	11.170	9.406	13.323		
Secondary forest area in 2015 (ha)	10.666	11.592	9.987	13.835		
Secondary forest area in 2016 (ha)	10.162	11.177	9.701	13.855		
Secondary forest area in 2017 (ha)	10.125	11.287	9.712	13.975		

Notes: N.D.: normalized differences between the two groups. Forest area includes mature and secondary forests area.

Table 6: Summary statistics for participants and comparison groups from GCS survey dataset

Variables	Participants (n=52)		Comparison (n=46)		N.D.	
Pre-treatment variables	Mean	Std dev.	Mean	Std dev.	Raw	Matched
Household head age in 2010 (years)	48.73	11.42	53.91	11.42	-0.45	-0.07
Household members in 2010 (number)	5.59	2.45	5.33	2.63	0.10	0.03
Total area in 2010 (ha)	80.02	35.29	91.61	54.39	-0.25	-0.02
Forest cover (%)	69.62	15.80	0.59	0.22	0.55	0.09
Pasture cover (%)	20.09	15.75	0.33	0.23	-0.66	-0.16
Total income in 2010 (BRL)	49546.02	37734.36	61086.10	44547.24	-0.28	0.07
Salary + Business income in 2010 (BRL)	9502.25	14806.32	3049.56	5277.59		
Cocoa gross income in 2010 (BRL)	6392.20	9189.18	5087.53	13894.69		
Fish gross income in 2010 (BRL)	579.56	3685.89	43.94	298.02		
Cattle gross income in 2010 (BRL)	15458.57	20658.29	31836.80	31077.65		
Horticulture gross income in 2010 (BRL)	255.43	557.93	274.50	393.58		
Fruit pulp gross income in 2010 (BRL)	295.03	889.39	154.11	324.30		
Refrigeration assets in 2010 (BRL)	1143.47	1017.43	963.26	956.97		
Agricultural assets in 2010 (BRL)	1249.53	2048.27	853.89	979.94		
Cattle stocking rate in 2010	0.50	0.56	0.91	0.81		
Transportation assets in 2010 (BRL)	5925.98	12295.62	6501.63	11567.66		
Crop richness in 2010	0.17	0.11	0.17	0.11		
Post-treatment variables						
Total income in 2014 (BRL)	75227.36	59943.44	99891.39	120464.00		
Total income in 2019 (BRL)	111688.90	101528.30	92466.84	85108.62		
Salary + Business income in 2014 (BRL)	7167.41	11168.19	2300.24	3980.81		
Salary + Business income in 2019 (BRL)	8637.71	16915.89	3047.57	6469.20		
Cocoa gross income in 2014 (BRL)	6807.00	10137.32	4416.73	10281.47		
Cocoa gross income in 2019 (BRL)	16698.63	60282.37	4079.65	10411.12		
Fish gross income in 2014 (BRL)	1244.94	4909.81	757.57	5058.78		
Fish gross income in 2019 (BRL)	7162.55	18506.81	3084.35	15151.92		
Cattle gross income in 2014 (BRL)	23878.09	30616.69	43955.45	46145.65		
Cattle gross income in 2019 (BRL)	45955.12	58378.01	47383.80	60036.40		
Horticulture gross income in 2014 (BRL)	1756.95	2270.51	1168.04	2063.74		
Horticulture gross income in 2019 (BRL)	2385.83	5241.03	405.33	660.45		
Fruit pulp gross income in 2014 (BRL)	609.53	1498.88	173.12	281.08		
Fruit pulp gross income in 2019 (BRL)	1429.16	3222.57	181.99	349.03		
Refrigeration assets in 2014 (BRL)	1712.64	1539.57	1253.66	1494.76		
Refrigeration assets in 2019 (BRL)	2257.35	2595.53	1088.22	854.81		
Agricultural assets in 2014 (BRL)	2011.45	2616.53	1162.43	1089.75		
Agricultural assets in 2019 (BRL)	1890.69	1992.62	1185.00	1337.15		
Transportation assets in 2014 (BRL)	8517.18	15594.03	5862.49	7456.84		
Transportation assets in 2019 (BRL)	11721.57	21243.73	7734.78	11140.42		
Cattle stocking rate in 2014	0.51	0.52	0.69	0.82		
Cattle stocking rate in 2019	0.60	0.64	0.50	0.47		
Crop richness in 2014	0.27	0.19	0.19	0.11		
Crop richness in 2019	0.23	0.16	0.15	0.11		

Notes: N.D.: normalized differences between the two groups. Cattle stocking rate is expressed by the herd size divided by the pasture area. Crop richness is expressed by the number of different crops divided by the total area.

Table 7: Short- and long-term effects on alternative livelihood outcomes

Estimator	Cocoa gross income		Fish gross income		Horticulture gross income		Fruit pulp gross income	
	Short run	Long run	Short run	Long run	Short run	Long run	Short run	Long run
NNM (2X)	517.53	7407.36	-1232.64	4597.09*	403.65	1876.85***	321.18	1200.23***
	(1393.54)	(8479.02)	(1781.98)	(2657.53)	(365.16)	(708.43)	(250.26)	(430.08)
NNM (1X)	16.67	6681.80	-1049.74	4187.32	89.04	1813.00**	371.55	1244.46***
	(1356.82)	(8379.15)	(1668.03)	(3187.27)	(443.32)	(704.81)	(261.75)	(433.77)
PSM (2N)	2002.45	13468.73	391.61	4900.29**	434.64	1884.20***	322.44	1150.67***
	(2776.67)	(9448.38)	(485.59)	(2197.70)	(388.21)	(699.52)	(226.68)	(408.83)
PSM (1N)	2195.89	14977.77	-11.70	6043.38***	828.06**	1897.64***	391.68 *	1253.23***
	(3142.01)	(9956.69)	(764.74)	(1920.88)	(386.20)	(695.74)	(234.23)	(408.98)

Notes: This table displays the average treatment effect (ATT) on alternative livelihood outcomes. NNM refers to the DID nearest neighbor estimator using 2 (1) matched observations as controls. PSM refers to the DID propensity score matching estimator using 2 (1) matched observations as controls. ***, ** and * indicate that the estimated coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively. Standard errors are given in parentheses.

Table 8: Short- and long-term effects on cattle production and agrobiodiversity

Estimator	Cattle gross income		Cattle stocking rate		Crop richness	
	Short run	Long run	Short run	Long run	Short run	Long run
NNM (2X)	-3589.74	21974.23**	0.26*	0.81***	0.08**	0.09***
	(5614.88)	(10458.55)	(0.21)	(0.29)	(0.03)	(0.03)
NNM (1X)	-5726.41	18888.24	0.35*	0.77***	0.09**	0.10***
	(5849.01)	(11658.40)	(0.19)	(0.27)	(0.04)	(0.03)
PSM (2N)	-6179.31	26136.31***	0.35*	0.47*	0.07*	0.08***
	(4964.67)	(8049.49)	(0.18)	(0.25)	(0.04)	(0.03)
PSM (1N)	-3255.55	27556.42***	0.38*	0.25	0.07*	0.11***
	(5856.31)	(8357.34)	(0.20)	(0.24)	(0.04)	(0.03)

Notes: This table displays the average treatment effect (ATT) on cattle production and agrobiodiversity. NNM refers to the DID nearest neighbor estimator using 2 (1) matched observations as controls. PSM refers to the DID propensity score matching estimator using 2 (1) matched observations as controls. ***, ** and * indicate that the estimated coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively. Standard errors are given in parentheses.

Table 9: Short- and long-term effects on physical assets

Estimator	Refrigeration equipment		Agricultural equipment		Motorized vehicles	
	Short run	Long run	Short run	Long run	Short run	Long run
NNM (2X)	194.59	1059.10**	320.47	133.21	1892.86	3429.12
	(390.24)	(480.49)	(526.14)	(502.42)	(1920.99)	(2319.32)
NNM (1X)	-25.37	1097.27**	30.84	-100.25	2796.88	3523.40
	(469.50)	(512.34)	(556.35)	(502.31)	(1935.96)	(2721.13)
PSM (2N)	215.27	1191.67***	406.36	371.08	1342.70	1571.32
	(325.12)	(395.38)	(533.65)	(416.91)	(1842.10)	(3138.64)
PSM (1N)	217.17	1246.08***	532.95	651.32	2186.71	1651.96
	(345.15)	(393.34)	(600.89)	(462.70)	(1859.30)	(3486.67)

Notes: This table displays the average treatment effect (ATT) on physical assets value. NNM refers to the DID nearest neighbor estimator using 2 (1) matched observations as controls. PSM refers to the DID propensity score matching estimator using 2 (1) matched observations as controls. ***, ** and * indicate that the estimated coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively. Standard errors are given in parentheses.

Table 10: Short- and long-term effects on gross income

Estimator	Off farm income		Salary + Business income		Total income	
	Short run	Long run	Short run	Long run	Short run	Long run
NNM (2X)	96.60	-604.33	-1436.67**	-1254.58	-7816.63	40279.07**
	(5399.18)	(3296.25)	(557.98)	(3103.65)	(13557.19)	(17096.00)
NNM (1X)	-2240.59	363.80	-1229.07**	-1163.37	-20810.26	36737.23**
	(6100.79)	(3320.66)	(582.50)	(3100.28)	(17612.01)	(18531.58)
PSM (2N)	1406.47	-576.09	-1510.50***	-2182.00	-5927.572	50886.33***
	(4742.16)	(3906.19)	(554.17)	(3067.00)	(12337.14)	(13761.76)
PSM (1N)	2405.97	1519.51	-1593.89***	-107.64	3311.78	55908.98***
	(5120.92)	(3825.88)	(569.55)	(3020.74)	(11174.23)	(13873.16)

Notes: This table displays the average treatment effect (ATT) on income. NNM refers to the DID nearest neighbor estimator using 2 (1) matched observations as controls. PSM refers to the DID propensity score matching estimator using 2 (1) matched observations as controls. ***, ** and * indicate that the estimated coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively. Standard errors are given in parentheses.

CEE-M Working Papers[1] - 2022

WP 2022-01	Denis Claude & **Mabel tidball** « Taking firms' margin targets seriously in a model of competition in supply functions »
WP 2022-02	Cauê D. Carrilhoa, **Gabriela Demarchi**, Amy E. Duchelle, Sven Wunder, & Marla Morsello « Permanence of avoided deforestation in a Transamazon REDD+ initiative (Pará, Brazil)functions »
WP 2022-03	Francisco Cabo, Alain Jean-marie & **Mabel tidball** « Positional effects in public good provision. Strategic interaction and inertia »
WP 2022-04	**Fabien Prieur**, Weihua Ruan & Benteng Zou « Optimal lockdown and vaccination policies to contain the spread of a mutating infectious disease »
WP 2022-05	**Claudia Kelsall**, Martin F. Quaas & **Nicolas Quérou** « Risk aversion in renewable resource harvesting »
WP 2022-06	**Raphaël Soubeyran, Nicolas Quérou** & Mamadou Gueye « Social Preferences and the Distribution of Rewards »
WP 2022-07	**Antoine Pietri** « Plus de voiture pour davantage de vélo ? Une étude sur la ville de Tours »
WP 2022-08	**Sebastien Desbureaux**, Frederic Mortier, Esha Zaveri, Michelle van Vliet, Jason Russ, Aude Sophie Rodella & Richard Damania « Mapping global hotspots and trends of water quality (1992-2010): a data driven approach »
WP 2022-09	**Gabriela Demarchi**, Caue D. Carrilho, Thibault Catry, Stibniati Atmadja & **Julie Subervie** « Beyond reducing deforestation: impacts of conservation programs on household livelihoods »

[1] **CEE-M Working Papers / Contact** : laurent.garnier@inrae.fr

- RePEc https://ideas.repec.org/s/hal/wpceem.html
- HAL https://halshs.archives-ouvertes.fr/CEE-M-WP/