Redesigning payments for ecosystem services to increase cost-effectiveness*

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July 2024

Abstract

Payments for Ecosystem Services (PES) are a widely used approach for forest conservation through which people are paid to avoid deforesting land they enroll in the program. We present findings from a randomized trial in Mexico that tested whether a PES contract that requires enrollees to enroll all of their forest is more effective than the traditional PES contract that allows them to exercise choice. The modification's aim is to prevent landowners from enrolling only parcels they planned to conserve anyway while leaving aside other parcels to deforest. We find that the full-enrollment treatment reduces deforestation by 41% compared to the traditional contract. This extra conservation occurs despite the full-enrollment provision reducing the compliance rate due to its more stringent requirements. The full-enrollment treatment more than quadrupled cost-effectiveness, highlighting the potential to substantially improve the efficacy of conservation payments through simple contract modifications.

Keywords: *Deforestation, Payments for Ecosystem Services, financial incentives, contract design, Mexico*

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*Juan David Ramirez, Santiago Fernandez and Juliana Sanchez Ariza provided excellent research assistance. We are grateful to Natura y Ecosistemas Mexicanos A.C. (Natura Mexicana), Innovations for Poverty Action Mexico, and Comisión Nacional Forestal (Conafor) for support implementing this project. We are also grateful for feedback from audiences at Universidad Nacional Autónoma de México (UNAM) and from Rebecca Dizon-Ross and Kelsey Jack. This project was funded by the King Climate Action Initiative at J-PAL and pre-registered in the American Economic Association trial registry (AEARCTR-0007693). This project received IRB approval from Northwestern University (STU00214258) and Université du Québec Outaouais (2021-1527).

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1 Introduction

Human-driven tropical deforestation is a significant contributor to greenhouse gas emissions (Seymour and Busch, 2016) and biodiversity loss (Giam, 2017; Hansen et al., 2013; Gibson et al., 2011; Pendrill et al., 2022). Tropical deforestation often occurs in high-poverty areas with limited government capacity to enforce bans. Consequently, Payments for Ecosystem Services (PES) programs have emerged as a promising policy to achieve forest conservation without exacerbating poverty (Wunder et al., 2018; Jayachandran, 2023). PES programs offer cash or in-kind incentives to participating landowners or communities, with payments conditional on specific natural resources management activities, such as forest protection (Wunder, 2005; Engel, Pagiola and Wunder, 2008). A recent review recorded 550 active PES programs globally with around US$40 billion in annual transactions (Salzman et al., 2018).

Whether and in what contexts PES programs are effective in achieving desired outcomes has received considerable scholarly attention (Wunder, 2013; Börner et al., 2017; Wunder et al., 2018). Much less work has tested how contract design affects program outcomes. The importance of program design has been discussed conceptually (Börner et al., 2017; Wells et al., 2020; Engel et al., 2016) and empirically (Izquierdo-Tort et al., 2021; Wunder et al., 2018), and prior studies have used lab-in-the-field or framed field experiments to examine the effects of PES design on outcomes such as participation (Rudolf, Edison and Wollni, 2022), equity perceptions (Cook, Grillos and Andersson, 2023), and collective action (Kaczan et al., 2017; Midler et al., 2015). While randomized controlled trials (RCTs) that assess environmental outcomes of actual PES schemes have emerged in recent years, these have mostly evaluated program effects against a no-program scenario (Wilebore et al., 2019; Adjognon, Van Soest and Guthoff, 2021; Wiik et al., 2019; Grillos et al., 2019; Pynegar et al., 2018; Jayachandran et al., 2017; Martin et al., 2014), as opposed to isolating the effects of design variations. One exception is a study of PES to reduce agricultural burning in India that experimentally varied payment levels, conditionality, and upfront versus ex-post payments (Jack et al., 2022).

We test a design variation aimed at reducing inframarginal payments in PES for forest protection. PES effectiveness depends crucially on the extent to which payments are inframarginal, or made for protecting forest that would have been protected even without the financial incentive (Wunder, 2005). We focus on an important source of inframarginality: participants' strategic selection of which land to enroll (Izquierdo-Tort, Ortiz-Rosas and Vázquez-Cisneros, 2019). If eligible landowners systematically enroll the subset of their lands that they were unlikely to deforest, many of the payments will be for conservation that would have happened anyway.

Reducing inframarginal payments is especially important because the policy objective for PES is not just effectiveness but cost-effectiveness, e.g., additional forest cover per dollar of program expenditures. Inframarginal payments add to program costs without generating benefits so depress cost-effectiveness. Improving cost-effectiveness is critical given under-funding of conservation initiatives (Cosma, Rimo and Cosma, 2023) and a recent trend of PES program downsizing or discontinuation in some contexts (Hayes et al., 2022; Rode, 2022; Etchart et al., 2020), including Mexico, our study's setting.

In this paper, we conduct the first randomized trial to test the impacts of requiring PES participants to enroll all of their eligible forest landholdings ('full-enrollment'). The primary outcome is avoided deforestation, measured using satellite imagery. The study takes place in Selva Lacandona, Chiapas, Mexico.

We compare the full-enrollment "treatment" group to a "control" group offered a PES contract that gives participants the flexibility to enroll some lands for conservation while leaving other lands outside the program ('standard PES' or 'partial enrollment'). Since payments are conditional on maintaining only the enrolled parcels, under standard

PES, participants can be in compliance yet continue their business-as-usual deforestation by clearing non-enrolled lands. The partial enrollment provision is used in Mexico's national Pago Por Servicios Ambientales (PSA) program and other major PES programs worldwide such as the Conservation Reserve Program in the US (Chang and Boisvert, 2009). Our standard contract closely follows PSA, but with a one-year rather than five-year duration.

To see why full-enrollment might be a valuable modification, suppose the owner of 20 forest hectares wants to clear 4 hectares during the contract period. With a standard PES scheme, she can enroll the other 16 hectares, keep them intact, deforest the left-out 4 hectares, and receive payment, despite not having reduced her deforestation at all. She is paid for 16 hectares of conservation, but the payments are entirely inframarginal. In contrast, a full-enrollment scheme offers her the choice of not participating or enrolling all 20 hectares she owns. Now she cannot receive payment without reducing her deforestation. If she complies, she will generate more additional forest cover under full-enrollment (4 hectares versus 0 hectares). However, another implication is that, due to the more demanding contract terms, full-enrollment reduces the likelihood that she chooses to comply. Combining these two predicted effects, the net effect on forest cover is ambiguous, though full-enrollment should outperform standard PES on forest cover per dollar spent, or cost-effectiveness. We test all of these predictions.

We found that full-enrollment led to 5.7 percentage points less annual deforestation than the control group, or 41% less deforestation. As predicted, the extra conservation is on parcels that individuals were not planning to enroll if given the choice. Drawing on prior estimates of the effectiveness of standard PES in our study context (Costedoat et al., 2015), we calculate that our contract modification more than quadrupled the cost-effectiveness of PES. Many PES programs worldwide give participants the latitude to choose which parcels to enroll, so the modification we introduce has wide applicability.

Our study is the first to empirically compare full-enrollment against standard, partial-enrollment PES. We build on a previous study that evaluated the impact of full-enrollment PES in Uganda relative to a no-PES control group (Jayachandran et al., 2017). That study found less inframarginality and more cost-effectiveness than is typical for PES. Based on that result, we hypothesized that requiring full-enrollment among PES participants in Mexico would increase cost-effectiveness and likely the amount of forest preserved.

2 Conceptual Framework

The predictions about the effects of full-enrollment can be seen more formally through a stylized model. Consider a landowner i that owns a one-dimensional continuum of forest parcels, (OL) in Figure 1. The parcels are ordered along the horizontal axis based on the net benefits of deforesting them, with higher net benefits on the right. Each parcel j would produce a private benefit b_j if deforested, the red line passing through A, B and C. For simplicity, we assume the cost of deforesting each parcel is identical and equal to d. The blue line passing through F, A and E is the cost to deforest each parcel.

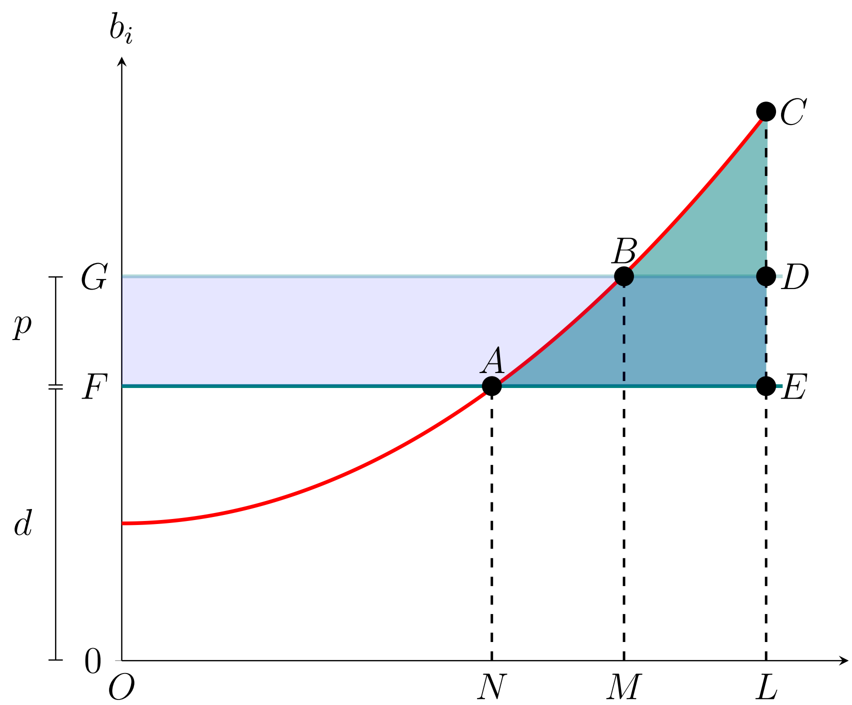
Scenario without PES

Without a PES program, the landowner would deforest all grids with $b_j > d$. That is, the landowner would deforest the parcels in the line segment NL in Figure 1. The net benefits to her from this deforestation are represented by the triangle ACE. For the segment ON, it is in her private interests to conserve this land, even without PES.

Standard PES scenario

Assume now there is a PES program that pays p per enrolled grid. With a traditional PES program that allows the landowner to choose which grids to enroll, the farmer would

Figure 1: Theoretical avoided deforestation with modified contract



Notes: Theoretical representation of the standard PES program and the modified full-enrollment PES assessed in this study. The red line passing through A, B and C represents the benefits of deforesting each parcel. The blue line passing through F, A and E represents the private costs of deforesting the parcel. Consequently, without PES the farmer would deforest NL. With standard PES that pays p, the landowner enrolls OM and deforests the segment ML. With the modified PES, she will need to enroll and preserve ML to be in compliance. She will choose to comply if the rectangle of total PES payments ($DEFG$) is larger than the area of net benefits of deforestation (ACE) she would enjoy without PES.

enroll all grids with $b_i < p + d$. These are the parcels on the segment OM. The avoided deforestation is (NM), and she is also receiving inframarginal payments for parcels (ON) she would not have deforested anyway.

As long as there is some parcel where $b_j < d + p$ and a landowner can partially enroll land, in this simple model, she will choose to enroll and comply with PES. There will be additionality as long as there exist some parcels where $d < b_j < d + p$, which in our example, is the segment NM.

Full-enrollment PES scenario

Consider now the modified program where the farmer has to enroll all her forest land (OL). That would require the farmer not deforesting the grids ML that she would not have chosen to enroll under the standard contract. The avoided deforestation is (NL). She is also receiving inframarginal payments for the land she would not have deforested anyway (ON). A first prediction is that avoided deforestation is higher for someone who complies with full-enrollment PES than with standard PES. A second prediction is that this extra avoided deforestation is on the parcels that the landowner would exclude from the PES program if given the choice.

A third prediction is that the likelihood of taking up and complying with the PES program is weakly lower under full enrollment. As explained above, with our assumptions, everyone complies with standard PES. With full-enrollment PES, the landowner will comply if the rectangle of total PES payments ($DEFG$) is larger than the area of net benefits of deforestation (ACE) without PES. This condition may or may not hold. To see this, note that as $p \to 0$, the area of $DEFG$ becomes 0, and when p is high enough that the line GBD intersects or is above the point C then the triangle ACE that represents the net benefits of deforesting is a strict subset of the payments rectangle $DEFG$.

3 Study Context

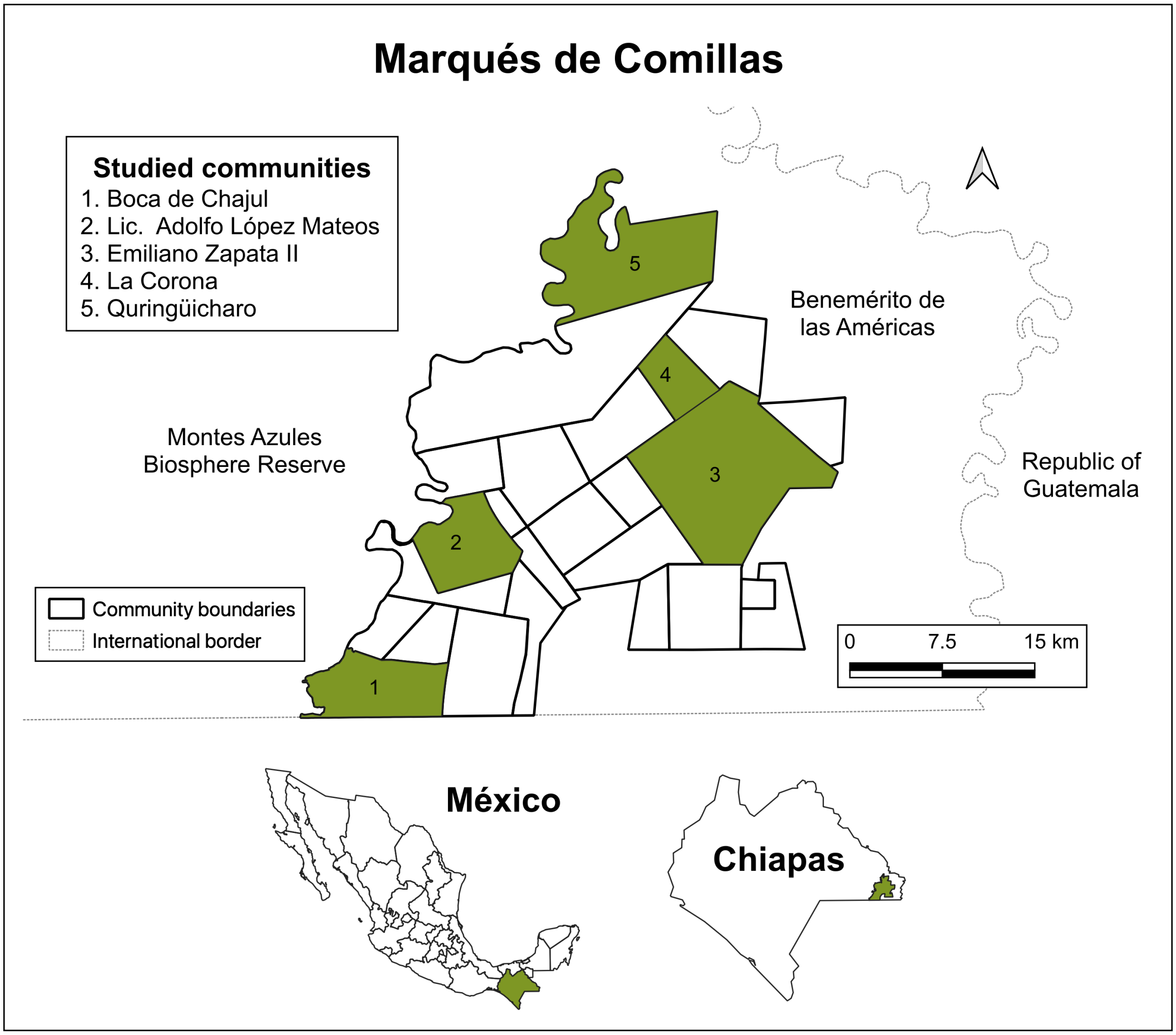
Mexico has one of the oldest and largest government-funded PES programs worldwide, in terms of both area enrolled and public spending (Shapiro-Garza, 2020). Since 2003, it has been implemented nationally by the national forest commission (Conafor) and has focused on preventing land cover change, particularly deforestation, in critical ecosystems (Sims and Alix-Garcia, 2017; Muñoz-Piña et al., 2008). Mexico's PES (or PSA in Spanish) provided annual payments of MX$1,000 (approximately US$50) per hectare in the study area in 2021. The conditions for payment are maintaining forest cover and performing forest management activities on enrolled lands. Program compliance is monitored through periodic field visits and remote sensing. Most applications are made at the ejido (community) level, bundling individual and sometimes collectively-managed landholdings (Izquierdo-Tort et al., 2021).[1] Local implementation is facilitated by Conafor-appointed intermediaries who help communities prepare applications and oversee program activities. Our implementing partner, the non-profit Natura Mexicana, is a Conafor intermediary.

Many but not all studies find that PSA has been effective at reducing deforestation (Sims and Alix-Garcia, 2017; Alix-Garcia, Sims and Yañez-Pagans, 2015; Costedoat et al., 2015; Charoud et al., 2023). However, PSA's funding has declined. From 2015-2019, Conafor's annual budget was cut by 70% in real terms (Provencio and Carabias, 2019). Although demand for PSA has exceeded available funding since the program's outset (Muñoz-Piña et al., 2008), the shrinking budget has recently made access considerably harder for interested communities (Izquierdo-Tort et al., 2021).

We study five *ejidos* in Marqués de Comillas (MdC) municipality in Chiapas state (see Figure 2). MdC is an agricultural frontier region within Selva Lacandona, which is the largest high-canopy tropical rainforest remnant in Mexico and a biodiversity hotspot (Carabias, De la Maza and Cadena, 2015), but also a region of high deforestation for cattle ranching and agricultural production (Fernández-Montes de Oca, Gallardo-Cruz and Martínez, 2015). Landholders in MdC manage individual endowments of 30-50 hectares, which they allocate to a combination of pastures, agricultural fields, and forest reserves. Many households face economic poverty (Izquierdo-Tort, 2020). The five communities have previously participated in several PSA contracts since the late 2000s.

[1] An *ejido* is a legally recognized communal land governance entity that comprises plots that are individually managed by landholders and common-resource areas that are managed collectively.

Figure 2: Map of study location



Notes: The top panel depicts the municipality of Marques de Comillas (MdC), with the five ejidos in the study shaded in green. The shading in the bottom panel indicates the location of MdC within Chiapas and the location of Chiapas within Mexico.

Previous research in MdC finds that PSA has reduced deforestation on enrolled lands (Costedoat et al., 2015; Charoud et al., 2023) and yielded socio-economic co-benefits (Izquierdo-Tort, 2020; Izquierdo-Tort et al., 2022). However, prior research finds that most landholders enroll only a fraction of their eligible property, and deforestation rates are high on non-enrolled lands, which participants consider more productive for ranching and agriculture (Izquierdo-Tort, Ortiz-Rosas and Vázquez-Cisneros, 2019).

4 Data and Empirical Strategy

4.1 Sample selection

We recruited landholders from the five ejidos Marqués de Comillas, Chiapas who had applied to PSA in 2021 with individual landholdings but were rejected due to Conafor having insufficient funding.[2] Of the 118 landholders who met this criterion, We attempted to enroll 96 of them, excluding those who had requested to enroll more than 90 hectares (for project budget reasons). We successfully enrolled 64 of them. We were unable to contact 13 of them, and 19 chose not to participate (reasons included having alternative land use plans and not wanting to have landholdings measured or answer survey questions).

4.2 Data collection

Study participants completed a baseline survey in May-June 2021. As part of the baseline, enumerators walked around the participants' plots to record the exact polygons for the deforestation analysis using GPS software on smartphones.

We conducted an endline survey in August 2022 and successfully resurveyed 58 of the 64 study participants, though the response rate was lower on several questions, such as income. We use the baseline data to ensure the study arms are balanced, and we

[2] They met all requirements for participation but did not score high enough in Conafor's ranking system. Although Conafor does not disclose the ranking evaluations, Natura Mexicana staff attribute the rejections to the lands not being within a federal natural protected area and the communities having participated in PSA during the five preceding years and lacking forestry certification, all of which lower priority.

use the endline survey for supplementary analysis of impacts on satisfaction with the modified PES program.

We measure deforestation using the participants polygons, satellite data and a machine learning algorithm. Specifically, we Planet-NICFI data, which provide monthly cloud-free images with a resolution of 4.59m by 4.56 m. We train a random forest algorithm to classify each pixel as forest-covered or not, using hand-classified images as training data. See the appendix for details.

4.3 Description of PES contracts and random assignment

In June-July 2021, Natura Mexicana held meetings in each community and offered each study participant one of two PES contracts: (a) a contract to enroll the same forested lands that she had previously submitted to PSA in 2021 (standard PES, or control group) or (b) a contract that required her to enroll all of her forested lands (full enrollment, or treatment group). We determined participants' contract type based on a random number generator in Stata, with the randomization stratified by ejido. There is no "pure control" group that was not offered PES; the study is designed to measure the *relative* performance of full enrollment, compared to standard PES.

To determine the enrolled area for the control group, we use the shapefiles that ejidos submitted with their 2021 PSA application indicating the forest parcels they wanted to enroll. We also have this information for the treatment group, so we know the parcels they would have enrolled had they been offered standard PES. Similarly, because we mapped all of the forest owned by a landholder, we have the polygons for forest area left out of the PES contract for the control group. Thus, we can compare the treatment and control groups' deforestation rate overall for their forest and also separately for the parcels they would have included versus excluded if given the partial-enrollment option. On average, landowners left out 49% of their forest area from their PSA application.

At the community meeting, participants chose whether to enroll (sign the contract); the contract took effect immediately. The control and treatment contracts were identical except for the land enrollment requirement. The payment rate was set at the level used by PSA, MX$1,000 per year per hectare of forest. Payment disbursal at the end of the one-year contract was conditional on maintaining forest cover on all of the enrolled land, which was determined based on satellite imagery and, if needed, in-person verification. Our monitoring and sanctioning of non-compliance differs from Conafor's methods in PSA in two key ways: i) our contracts are signed at the individual as opposed to the community-level, which facilitates enforcement; ii) participants on whose land non-compliance was detected receive zero payment, as opposed to Conafor's more lenient approaches where non-compliant participants can still receive partial payments (Izquierdo-Tort, Ortiz-Rosas and Vázquez-Cisneros, 2019). For the satellite verification, we developed a random-forest model to analyze high-resolution Planet imagery, classifying pixels as forested or not. We use the same model to estimate the treatment impacts reported in the next section. Our implementing partners, Natura Mexicana and Innovations for Poverty Action, disbursed payment to those who complied. We then administered an endline survey to study participants in August 2022.

4.4 Summary statistics

Table 1 presents summary statistics for the study sample. Each row presents the mean and then the standard deviation in parentheses. Column 1 presents statistics for the whole sample, column 2 for the treatment group (full enrollment) and column 3 for the control group (partial enrollment). Column 4 reports the standardized difference between the two groups (difference divided by the pooled standard deviation). 62% of study participants are male, average education is 7 years, and average household expenditures was MX$3,500 in the previous month (around US$175). 60% had been enrolled in Conafor's PSA in the past. Study participants, on average, own 42 hectares of land of which 19 are forest.

Table 1: Balance at baseline

Variable	Total (1)	Treatment (2)	Control (3)	Standardized diff (4)
Male	0.625 (0.488)	0.645 (0.486)	0.606 (0.496)	0.080
Years of school completed	7.127 (4.054)	6.710 (4.391)	7.531 (3.724)	-0.203
Household expenditure in last month (Ln)	8.157 (0.751)	8.097 (0.797)	8.210 (0.715)	-0.150
Has been or is enrolled in a PSA program	0.603 (0.493)	0.645 (0.486)	0.562 (0.504)	0.168
Land area across all plots (hectares)	42.019 (20.976)	46.932 (21.056)	37.404 (20.129)	0.454
Distance to road (minutes)	15.581 (14.559)	16.245 (15.499)	14.957 (13.830)	0.088
Previous def. % Conafor area	0.007 (0.019)	0.009 (0.022)	0.006 (0.016)	0.158
Previous def. % Non- Conafor area	0.232 (0.194)	0.186 (0.186)	0.279 (0.193)	-0.479
Primary forest area total across all plots (hectares)	18.812 (14.093)	22.790 (15.658)	15.076 (11.464)	0.547
Number of observations	64	31	33	

Notes: for each variable, each row presents the mean and below the standard deviation in parenthesis. Column 1 for the whole sample, column 2 for the treatment group and column 3 for the control group. Column 4 presents the standardized difference.

The only statistically significant difference between study arms is for previous-year deforestation in the forest land that participants had not chosen for enrollment in their 2021 PSA application (i.e. non-Conafor areas). Our main results are robust to controlling for this variable, as shown in Table A.1.

4.5 Regression model

As treatment was randomized, we can estimate the effect of the program by comparing outcomes in the treatment and control groups. We do this by estimating the regression model shown in equation (1):

$$y_{pie} = \beta Treatment_i + \alpha_e + \varepsilon_{pie} \tag{1}$$

where y_{pie} is the outcome (deforested) for a pixel p owned by individual i, residing in ejido e. $Treatment_i$ is a binary variable that equals 1 if individual i was offered the full-enrollment contract. Finally, α_e are ejido fixed effects, the stratification unit for the treatment. When each observation is a pixel, we cluster standard errors at the individual level, allowing for arbitrary non-independence of the error term ε_{pie}, within an individual's pixels.

We can also conduct the deforestation analysis at the individual level and study heterogeneity by forest at baseline.

$$y_{ie} = \beta_1 Treatment_i + \beta_2 Treatment_i \times Z_i + \beta_3 Z_i + \alpha_e + \varepsilon_{ie} \tag{2}$$

where y_{ie} is deforestation of individual i, belonging to ejido e. And Z_i is a characteristic of individual i, for example whether individual had a large area of forest at baseline (above the median). ε_{ie} is the error term. We allow for heteroskedasticity-robust standard errors.

Table 2: Treatment effects on deforestation

	Deforestation May 2021 - August 2022		
	Property area	Conafor area	Non-Conafor area
	(1)	(2)	(3)
Treat	-0.057	-0.004	-0.135
	(0.021)***	(0.008)	(0.036)***
Control mean	0.142	0.019	0.288
N	779451	382350	397101

Notes: Each observation is a 4.59 m by 4.56 m pixel within the landholding of a study participant, that was forest-covered at baseline. All regressions include ejido fixed effects. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5 Results

5.1 Treatment effect on deforestation

Table 2 reports the effects on deforestation of the full enrollment contract (treatment), relative to standard PES. Specifically, we examine how much of the forest that existed at baseline was deforested over the PES contract period. The outcome is a binary variable that equals 1 if the pixel is non-forest at the end of the study period.[3]

We first analyze deforestation within each participant's entire forest area, enrolled or not (column 1). In the standard contract arm, 14% of the forest area was deforested over the year. The treatment group deforests 5.7 percentage points (pp) less (p-value=0.01), equivalent to 41% less deforestation. Figure A.1 presents this treatment effect in the context of deforestation trends from 2017 to 2023. The treatment years of 2021 and 2022 are the only years when the deforestation rate is significantly lower in the treatment group than control group.

Column 2 restricts the sample to forest pixels the individuals were planning to enroll

[3]The baseline month is May 2021 (because the first contracts started in June 2021), and the endline month is August 2022 (because the last contracts ended in July 2022).

in Conafor's PSA ("Conafor area"). This area is covered by our PES contract for both treatment and control groups. The number of observations (pixels) in column 2 is 49% of the observations in column 1, indicating the proportion of their forest that landowners enrolled when given choice. For this land, the deforestation rate is relatively low (1.9%) in the control group and nearly identical in the treatment group.

We next examine the forest that the participant had not wanted to enroll in PSA (column 3).[4] The control group was in compliance with their contract regardless of what they did on these parcels, while the treatment group had to conserve them to be in compliance. Deforestation is very high in the control group for these parcels, at 28.8%. In the treatment group, the deforestation rate is 13.5 pp lower (p-value=0.000), equivalent to 47% less deforestation on these parcels.

As an alternative analysis, Table 3 presents the results at the individual level instead of pixel level. Odd columns present average treatment effects, while even columns study heterogeneity by the amount of forest at baseline. Column 1 shows that, weighting each landowner equally, there is no significant difference in deforestation between the contracts. This pattern can be reconciled with the result in Table 2 if the treatment reduced deforestation more for owners of large amounts of forest. Column 2 shows that this heterogeneity indeed is present. The treatment reduces deforestation among those who own above-median forest (by 8.2 pp on net, p-value=0.005), but not among those with below-median forest. Columns 3 to 6 show results for the Conafor and non-Conafor parcels, and, as expected, the improved performance of the treatment contract is because of lower deforestation in the non-Conafor area.

[4] Five people included all of their forest in their 2021 PSA application so have no non-Conafor area.

Table 3: Treatment effects at the individual level, including heterogeneity by baseline forest area

	Deforestation May 2021 - August 2022					
	Property area		Conafor area		Non-Conafor area	
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	-0.039	0.011	-0.007	-0.009	-0.126	-0.091
	(0.025)	(0.039)	(0.018)	(0.026)	(0.041)***	(0.070)
Treat × Above-median forest area at baseline		-0.093		0.013		-0.063
		(0.050)*		(0.029)		(0.081)
Above-median forest area at baseline		0.023		-0.030		-0.001
		(0.043)		(0.035)		(0.062)
Control mean	0.138	0.138	0.031	0.031	0.311	0.311
p-val: Treat + Treat × Above-median forest area at baseline = 0		.005		0.767		0.001
N	64	64	64	64	59	59

Notes: Each observation is a landowner. All regressions include ejido fixed effects. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2 Treatment effect on compliance

In the control group, 30 out of 33 individuals (91%) complied. In the treatment group, 22 out of 31 (71%) complied.[5] The lower compliance rate in the treatment group (p-value=0.04) is consistent with the stricter requirements of the full-enrollment contract. Despite the lower compliance rate, the treatment reduced total deforestation because it led to much higher averted deforestation per person who complied.

5.3 Cost-effectiveness

Our finding that the treatment reduced deforestation by 5.7% of total forest area relative to standard PES (Table 2, column 1), is one input into a cost-effectiveness calculation. We also need the absolute amount of avoided deforestation under each contract type. For this, we need to make an assumption about how much averted deforestation was caused

[5]One landowner in each arm chose not to enroll in the PES program. The other non-compliers enrolled but deforested some of their enrolled land.

by standard PES relative to a scenario with no PES. Based on the previous literature, we assume standard PES led to 2.2% less deforestation per year on enrolled land, which implies 1.1% less deforestation on total land Costedoat et al. (2015). This assumes no impacts on non-enrolled land, which is a generous assumption for standard PES: deforestation might have shifted from enrolled to non-enrolled land. This assumption choice yields a conservative estimate of the gains in cost-effectiveness from our treatment.

Full-enrollment PES therefore prevented 6.8% of forest area being lost relative to no PES (1.1% + 5.7%). This implies 65.8 hectares of avoided deforestation with full-enrollment PES and 7.3 hectares with standard PES.

The treatment increased hectares of forest enrolled and payments. In the standard PES group, we paid in total MX$313,400 and in the treatment group, MX$591,000. This implies MX$42,932 (US$2143) per hectare of avoided deforestation for standard PES versus MX$8,982 (US$448.29) for full-enrollment PES.[6] Thus, our treatment increased PES cost-effectiveness by a factor of 4.8.

To quantify the carbon benefits of full-enrollment PES, we use prior estimates that the Lacandona forest stores 550 metric tons of CO_2 per hectare Saatchi et al. (2011). The environmental benefits of a short-term PES program derive from *delaying* deforestation. We assume that after the contract period ends, landowners revert to their business-as-usual deforestation: they do not continue with their higher conservation rate, but they also do not deforest at a higher catch-up rate Jayachandran et al. (2017). Using a 3% discount rate, we can express the delayed emissions in terms of the equivalent permanently avoided emissions. This calculation yields that full-enrollment PES's cost is US$4.76 per metric ton of permanently averted CO_2.

[6] We use the mid-July 2021 exchange rate of MX$20.036 = US$1. Administrative costs are low relative to payments; they reduce the relative cost-effectiveness of the treatment because they are also incurred for non-compliers.

6 Conclusions

Because tropical deforestation rates are high – contributing to climate change and biodiversity loss – while conservation funding is limited, there is a pressing need for design improvements in conservation policies (Wunder et al., 2018). Our findings from a proof-of-concept PES experiment in Mexico suggest that simple contract design changes can enhance the cost-effectiveness of conservation payments.

We found that introducing a requirement for PES participants to enroll all their forest led to 5.7 percentage points less annual deforestation than what is achieved with a standard PES contract that allows for strategic land selection, or 41% less deforestation. As predicted, the extra conservation is on parcels that individuals were not planning to enroll if given the choice. Drawing on prior estimates of the effectiveness of standard PES in our study context (Costedoat et al., 2015), we calculate that our contract modification more than quadrupled the cost-effectiveness of PES. Many PES programs worldwide give participants the latitude to enroll a subset of their land, so the modification we introduce has wide applicability.

Importantly, the improvement in PES performance did not require a sophisticated market mechanism to elicit the landowner's private information about their opportunity costs and planned land decisions (Kang et al., 2019; Layton and Siikamäki, 2009) or a prediction model to identify where additionality and ecological benefits would likely be high (Mayfield et al., 2020; Havinga et al., 2020; Aspelund and Russo, 2023), as have been suggested to improve spatial targeting. Our improvement came from amending a clause in the contract and essentially closing a loophole that allowed landholders to continue business-as-usual deforestation but receive PES payments.

Moreover, we document a high rate of landowner satisfaction with the program: 100% of endline respondents in the full enrollment arm and 90% in the standard PES arm expressed satisfaction and interest in participating in a program like ours again. If we assume those who did not complete the endline survey were unsatisfied, the satisfaction rates were 84% for full-enrollment and 82% for standard PES — still quite high and, notably, as high among those offered the full-enrollment contract.

Yet our results also highlight the potential trade-offs when tweaking policy design. Adding a more stringent land enrollment requirement generated more additional forest cover among those who complied but also reduced the compliance rate. Theoretically, the net effect of our design change on total averted deforestation could have been positive or negative, depending on the magnitude of each effect. We attribute the observed net positive effect to how the design change interacted with contextual and implementation factors (Börner et al., 2017), namely i) large land endowments, leading to widespread 'partial enrollment' among participants; ii) high deforestation rates driven by cattle expansion in the region, which created significant scope for reducing land conversion; iii) a high degree of trust and local legitimacy towards our procedures, as reflected by participant satisfaction; and iv) our ability to monitor and sanction non-compliance effectively.

We note, however, that some of our study innovations relative to Conafor's PSA, such as mapping of total landholdings and more stringent enforcement, would be challenging to achieve at a large scale from technical and political standpoints. In addition, our contract duration was only one year, and with a longer contract period, landowners may be less willing to comply with the more demanding full-enrollment contract. One needs to be cautious in extrapolating our results to a more typical five-year contract duration. Two additional study limitations are that the results are based on a small sample, and we focused on effects on deforestation; our study does not analyze socio-economic effects. Thus, we view our results as demonstrating the possibility of very large gains from using a full-enrollment contract design, with more evidence needed to understand the gains that would be achieved at larger scale and over a longer duration.

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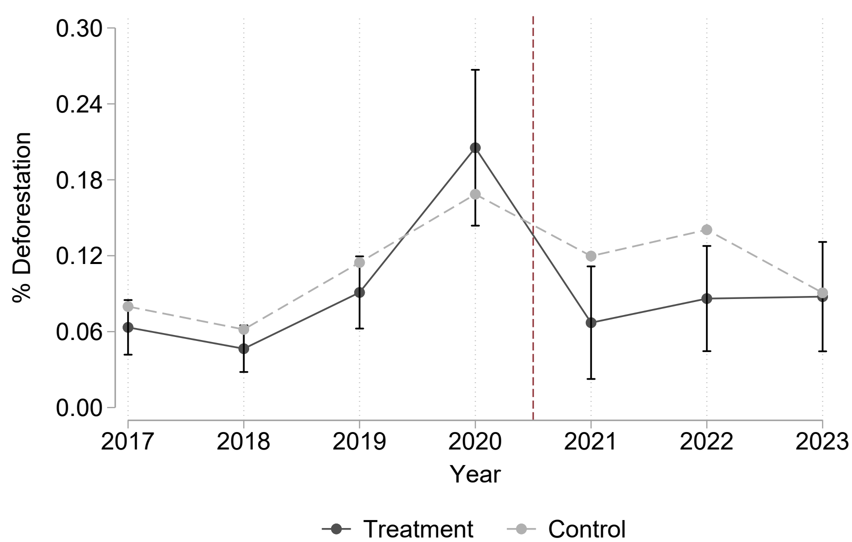
A Appendix

Table A.1: Robustness: Controlling for past deforestation

	Deforestation May 2021 - August 2022		
	Property area	Conafor area	Non-Conafor area
	(1)	(2)	(3)
Treat	-0.049	-0.010	-0.107
	(0.019)**	(0.008)	(0.037)***
Control mean	0.142	0.019	0.288
N	779451	382350	397101

Notes: This table repeats the main specification, reported in Table 2, but adding a control variable for past deforestation. Each observation is a 4.77 m by 4.77 m pixel within the landholding of a study participant, that was forest-covered at baseline. All regressions include ejido fixed effects. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A.1: Treatment effect and trends in deforestation rates



Notes: Percentage deforestation (y-axis) by year (x-axis) for treatment (dark line) and control (gray dashed line) groups. The helix represents the 95% confidence interval for the difference between the two groups. Note that the imagery is available as a semester cloudless composite before 2020, instead of monthly, so the image is cleaner and the predictions have less noise, making the errors smaller.

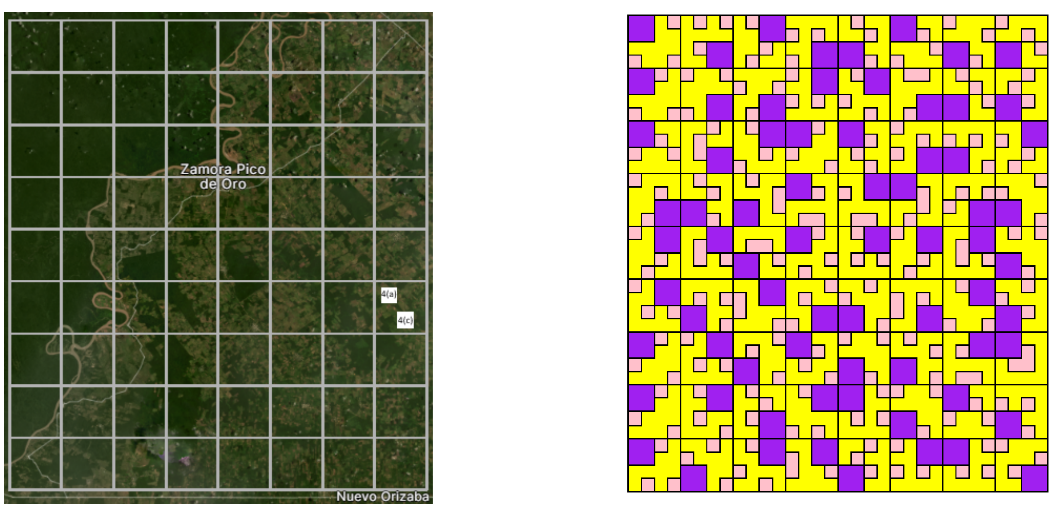
Remote sensing measure of deforestation

We trained a random forest algorithm to automatically classify each pixel in satellite imagery of our study area as forest or not. We used the algorithm, applied to imagery from the end of the PES contract period, to determine if individuals complied with the contract. We also use the model output to construct the study's main outcome variable: deforestation. We use the sample of pixels with forest at baseline, according to the model, and the outcome variable is an indicator that equals 1 if the pixel was no longer forest cover at endline, according to the model.

We use satellite imagery from Planet-NICFI (Norway's International Climate and Forest Initiative). These images provide a monthly cloud-free image with a resolution of pixels 4.59m x 4.56m (the date(s) within the month for the specific images is not provided). We then created the smallest rectangle that contains all the polygons of individuals participating in the study. We divided the rectangle into regions of 100 x 100 pixels. Each region is divided randomly into training (56.25%), validation (18.75%) and testing data (25%). Where the yellow, pink and purple squares in Figure A.2 represent the training, validation and testing data, respectively.

For the training data, we use hand-classified data from baseline that labeled whether each pixel in study participants' land was forest or not. Specifically, we use the polygons collected in the baseline survey, extract the imagery, and visually inspect each pixel, classifying it as forest or no forest. This manual labeling is what we used to determine the forest land to enroll in the PES contracts for both treatment and control groups.

Figure A.2

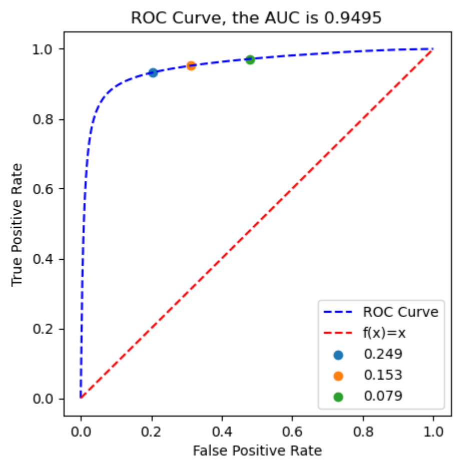


(a) (b)

Notes: The study area on the left is divided into 4.59km x 4.56km regions. Then each region is randomly divided into yellow, pink and purple squares representing the training, validation and testing data respectively, as shown on the right.

For each pixel, there are four variables that are used as predictors: the red band, the green band, the blue band and the infrared band. We tried several models and parameters and the best-performing was a random forest using 100 trees, a maximum depth of each tree of 50 (i.e., maximum 50 binary splits of the data in each decision tree), and two variables at each node (mtry parameter). The receiver operating characteristic (ROC) curve of the model with the performance of the model is shown in Figure A.3.

Figure A.3



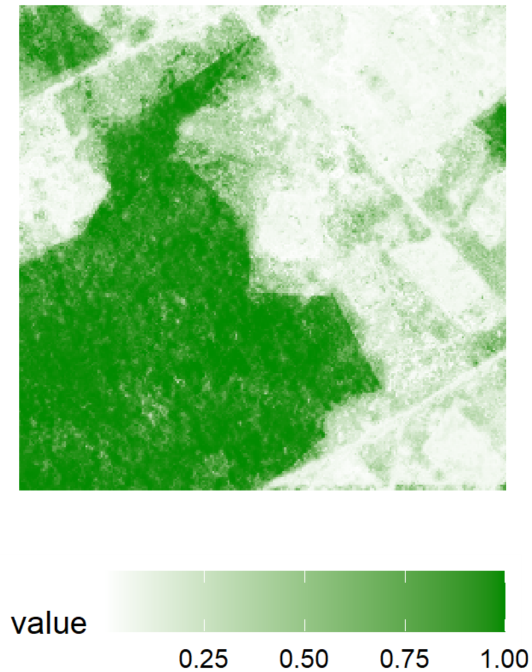
Notes: The receiver operating characteristic (ROC) curve of the model plots the true positive rate (TPR) against the false positive rate for different cutoffs. The TPR is the proportion of forest pixels accurately classified as forest. The FPR is the fraction of no forest pixels incorrectly classified as forest. As we lower the cutoff we increase the TPR and the FPR.

Figure A.4 presents two examples of the satellite imagery and the predictions of the model.

In the regression analysis, we define a pixel as deforested if the model predicts it to be deforested in that month and the subsequent month (to reduce the rate of false positives).

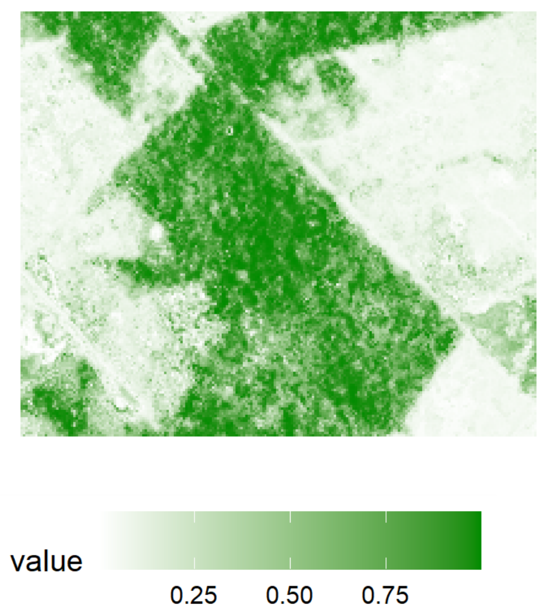
Figure A.4

(a)



(b)

(c)



(d)

Notes: Panels (a) and (c) show raw satellite imagery of examples of land owned by study participants. Panels (b) and (d) show the corresponding remote sensing model output classifying the pixel's likelihood of being forest, on a scale from 0 to 1. Figure A.2a shows the location of these areas in the map.