# The Long Run Effects of Forest Incentives on Forest Cover and Carbon Storage: Evidence from Guatemala

N. Borchers-Arriagada[*] A. Bragança[†] M. Conte Grand[‡]

July 2024

[*]University of Tasmania, e-mail: nicolas.borchers@utas.edu.au.
[†]World Bank, e-mail: aamorimbraganca@worldbank.org.
[‡]World Bank, e-mail: mcontegrand@worldbank.org.

# 1 Introduction

Guatemala is the largest economy in Central America, with the agroindustrial sector - one of the main sectors of the economy - representing approximately 20% of the country's GDP. The primary agricultural sector represents half of this and generates highly competitive products. Guatemala is the world's largest exporter of cardamom, the fifth largest exporter of sugar and the seventh largest producer of coffee (World Bank, 2024).

However, like elsewhere, economic activities seem to interact with forests in a non-sustainable way. From 2000 to 2020, Guatemala experienced a net change (gains + loss) of -6% in tree cover (Global Forest Watch, 2024). According to the Inter American Development Bank (2020), the primary cause of deforestation in the country is land-use change, mainly driven by: (i) expansion of medium and large-scale ranching activities (35% of deforestation); (ii) production of staple crops by small farmers, particularly in the western and eastern regions (31%); and (iii) production of coffee, cardamom, and rubber by small farmers and agroindustry (24%).[1]

One way to improve forest management, with the aim of increasing forest conservation, reforestation, carbon sequestration, and in general increase the provision of environmental (ecosystem) services, is through what is known as payment for environmental (ecosystem) services (PES). This happens when a provider (i.e., landowners) of an environmental (ecosystem) service is paid by users or beneficiaries (i.e., government, general population) of that service (Fripp, 2014). PES and forest incentives for land management practices (not necessarily ecosystem services) are usually considered jointly, as they are both financial mechanisms for improving forests.

Conceptually, forest incentives of this sort aim to align private use of resources with social

[1] According to Devine et al. (2020), illegal cattle ranching linked to drug trafficking in the Maya Biosphere in Petén is responsible for most of the reserve's deforestation, ranging from 59 to 87%. Similar assessments on the ecological impact of drug traffickers' activities are made for Guatemala in Tellman et al. (2020), among others.

interest. As programs are voluntary, a necessary condition for them to work is that payments cover the opportunity cost of other activities that could be undertaken in the same land. Therefore, a beneficiary will choose to participate, because the economic return under those circumstances is at least equal to the one obtained through alternative activities on that land. Hence, the design and implementation of these policies requires careful consideration of stakeholders' incentives to avoid adverse selection (i.e., enrolling only those actors that would comply even without payments) and moral hazard (i.e., when beneficiaries end up "cheating" on the program by not complying with the conditions agreed).[2]

Since 1996, Guatemala has enacted three forest incentives programs with the main aim of increasing forest conservation and reforestation (PINFOR, PINPEP and PROBOSQUE).[3] These programs offer payments for different land management practices, but not specifically for ecosystem services. Nevertheless, it is reasonable to expect that better management would result in an overall improvement of these. Tree restoration is considered one of the most effective carbon draw-down solutions to date (Bastin et al., 2019; Duncanson et al., 2023; Baumbach et al., 2023), as well as to maintain forests as habitats for biodiversity (Baumbach et al., 2023).

Many forest incentives programs have been implemented worldwide, and specially in Latin America. Recent work shows that payments in Guatemala are consistently the highest when compared to other five countries in the region (Cristales et al., 2022). According to the authors, the present value [4] of reforestation payments per tree are the lowest in Mexico and the highest for PROBOSQUE in Guatemala. Similarly, the lowest present value of disbursements for agroforestry correspond to Colombia and the highest to Guatemala PROBOSQUE. Finally, the present value of payments for conservation are the lowest amount in Peru and the highest in Guatemala (PROBOSQUE).

[2]See Wunder et al. (2020) for an interesting discussion on these and other conceptual aspects of forest incentives.

[3]More detail on forest incentive programs in Guatemala is presented in the next section

[4]The discount rate used for all present value calculations is 4%, and they account for years in which payments are given, which varies per program and per country.

Moreover, the impact of several forest incentive programs has been assessed (Perevochtchikova et al., 2021; Börner et al., 2020; Wunder et al., 2020; Patrick, Butsic and Potts, 2023). For example, Jayachandran et al. (2017) studied the effects of payments for forest conservation in 121 Ugandan villages, 60 of which were randomly selected to participate in a program which took place between 2011 and 2013. Using satellite imagery, the study showed convincingly that tree cover (i.e., share of the village with tree cover) loss near those villages was only half of that observed around the other villages: 4.2 percent on average, instead of 9.1 percent.

In Latin America, most impact analyses focus on Brazil and Mexico, the largest countries in the region, but programs in Colombia, Costa Rica, Ecuador, and to a lower extent in Bolivia, Peru, Nicaragua, and Guatemala, have also been assessed. A literature review by Börner et al. (2020) was able to identify 136 estimates with counterfactual based treatment effects of conservation mechanisms. From those estimates, many are for Latin America (57). Brazil is the single most analyzed country (16) despite being a relatively latecomer to these types of programs (Cisneros et al., 2022). This is arguably because Brazil has several forest incentives mechanisms and given the great interest in conserving the Amazon. The statistical methods and forest indicators used to assess the effectiveness of these programs vary considerably. According to Börner et al. (2020), most studies estimated the average treatment effect on the treated using some type of covariate matching (111 out of 136 studies), followed by matching combined with difference-in-difference (DID) (11 out of 136 studies). Some of the most used forest indicators include forest cover, deforestation, and normalized difference vegetation index (NDVI) (Börner et al., 2020; Wunder et al., 2020).

As expected, the impacts of different programs vary by country or region, by method, and by outcome variable. For forest cover, for example, high effects (5.56 pp) are found for payments of hydrological services in a region of Mexico (Von Thaden et al., 2019). The authors show that there is a significantly lower decrease in forest cover (0.76% loss) in plots receiving payments compared to control areas (6.29%) between 2003 and 2013. A lower but also significant effect was obtained by incentive programs in Brazil. Fiorini et al. (2020) evaluate forests incentives in the region of Rio de Janeiro and find that the program results in a net change in forest cover of 1.54 pp from 2010 to 2016, equivalent to 2.4% of the beneficiaries' forest area. Also for Brazil, Ruggiero et al. (2019) analyze the effects of two incentive programs to promote native forest conservation in the Brazilian Atlantic Forest and find that average annual net forest change on enrolled farms increased from 0.43 to 0.98% after implementation (an additional 2.8% of farm area forest coverage) whereas for unenrolled farms, it decreased from 0.38 to 0.01%. Hence, the difference in difference results in a net forest change as a result of the enrollment of 0.9 pp over the course of 5 years.

For the specific case of Guatemala, a recent study assessed the impact of forest incentives programs (Patrick, Butsic and Potts, 2023). The authors analyze the impact of over 16000 projects, from the two largest programs (PINFOR and PINPEP) on forest cover and height change from 2000 to 2020 and forest cover loss after enrollment. The authors estimate the impact of these programs by generating a counterfactual using the synthetic controls methodology. Alternatively, the authors use matching with difference-in-differences to compare their main results. Depending on the program, the treatment effect (treated versus untreated) on forest cover was 3.2% for PINPEP and 8.3% for PINFOR, with the largest effect found for restoration projects within PINFOR (15%). [5] The study also highlights some differences per project type (i.e., restoration projects appear as more effective than plantation and agroforestry ones). Moreover, a recent publication for Guatemala, in a more specific analysis including two townships and based on in situ carbon measurements (VonHedemann, 2023), finds a higher carbon capture for plots that receive payments versus control.

[5] The effect on forest height was 2% for PINPEP (not statistically significant) and 5.7% for PINFOR with the highest effect found for natural forest management production projects in PINPEP (7.5%) and restoration projects in PINFOR (12.5%). Forest loss decreased 3.4% for PINPEP and increased 1.6% for PINFOR.

However, existing assessments of forest incentive programs in Guatemala have some limitations and are not able to capture the overall impact of these programs. In particular, the assessment done by Patrick, Butsic and Potts (2023) does not include all projects and for those included, the available spatial information consisted on project centroids and not polygon data. Also, the most recent program, PROBOSQUE, was not included in this assessment. Furthermore, only forest indicators were included, and two of them (forest cover and height) only had data for the years 2000 and 2020. The estimation of treatment effects with only two points in time may not allow for an adequate evaluation of the impact of these programs. Ideally, annual data should be used. To our knowledge, there are no further systematic assessments of the impacts of forest incentives programs for Guatemala.

Given the existing gaps in knowledge, our work aims to further improve existing evidence and assess the long run effects of forest incentives in Guatemala on tree cover and above and below ground biomass carbon, and based on these, perform an analysis of the costs and benefits of these programs. The remainder of this work is structured as follows: section 2 briefly reviews the main characteristics of forest incentives programs in Guatemala, section 3 presents the methods and materials used for our analysis, section 4 presents the results, and finally, discussion and conclusions are presented in section 5.

## 2 Forest Incentive Programs in Guatemala

Reforestation and conservation of Guatemala's forest is at the highest level in the country's legal framework since the 1985 Constitution itself (art. 126) highlights their importance.[6] After the creation of the National Institute of Forests (INAB, for its initials in Spanish,

[6] Even before that, in 1974, Guatemala had a tax incentives system that aimed to provide stimulus for the development of a robust commercial forestry industry for national economic development by Decree 58-74 Larrazábal Melgar et al. (2009). It allowed a deduction of income tax and, later, vehicle circulation tax for 10 years based on costs invested in reforestation on plantations of more than 5 ha, up to 50% of the tax burden. The companies that were involved in this program were mostly large ones.

https://www.inab.gob.gt/) in the forest law (Decree 101-1996), Guatemala enacted three forest incentive programs: PINFOR, PINPEP, and PROBOSQUE.

The first of these programs, the Forest Incentives Program (PINFOR, for its initials in Spanish), was created in 1996 (Decree 101-1996) and gave priority to productive forests to boost the economic activity of the nation, with the added benefit of provision of ecosystem services. As a result of the focus on forestry production, 80% of the program funds were assigned for reforestation or natural regeneration, with only 20% allocated to natural forests conservation. Beneficiaries needed to have at least 2 ha of land, which excluded 45% of landowners (vonHedemann, 2020). As time passed, some small beneficiaries joined efforts with the support of their respective municipalities to ask for PINFOR benefits and were successful. However, most funds (75.7% in the 1998-2016 period) were assigned to rather large private landowners or companies, not to smallholders (vonHedemann, 2020).

In 2010 (Decree 51-2010), the Incentive program for owners of small extensions of forestry or agroforestry land (PINPEP) Law was passed. The origin of PINPEP, in 2006, was a Dutch financing program for small landowners (Aguilar-Støen, 2018), which was financially absorbed by the Guatemalan government in 2010. Unlike PINFOR, this program is directed towards small landholders and has the additional objective (besides economic growth and provision of ecosystem services) of fostering rural development. Several NGOs advocated for a similar source of funds that would allow access to forest incentives that were denied under PINFOR, and in part, that allowed for the creation of the PINPEP law in 2010.

Finally, in 2016, PINFOR was reformulated into the Promotion of the Establishment, recovery, management, production, and protection of Forests in Guatemala (PROBOSQUE, Decree 2-2015) Law. This shifted the focus towards provision of ecosystem services as the dominant discourse justifying the program (VonHedemann, 2023). This program extended beyond the scope of PINFOR including agroforestry services. It is also a more inclusive program, since minimum land area requirements changed to 0.5 ha and while those lands must hold titles in the National Property Register, INAB can also accept ancestral titles of indigenous communities' land.

To apply for these programs, the interested party must submit a management plan certified by a forestry technician. If approved, INAB would evaluate enrolled parcels along time. The following streams are (were) available: 1) management of natural forest for production; 2) management of natural forest for protection; 3) forestry plantation; 4) restoration of degraded forest; and 5) agroforestry systems.

The standing forest incentive programs in Guatemala, as in other countries, give different amounts and for a different number of years depending on the activity they support. Within PINPEP, average amounts per year and per hectare are: over 10 years, USD 398 for management of natural forest for production if the plot has between 0.1 and 5 ha, and USD 1,991 for the first 5 ha and USD 111 for the remaining ones when the plot has more than 5 ha; over 10 years, USD 372 for management of natural forest for protection in the case of the smallest plots and 1,861 for the first 5 has and 96 for the remaining ones in the case of the largest plots; over 6 years, between USD 296 and 394 from the largest to smallest forestry plantations; and, over 6 years, between USD 148 and 197 from the largest to smallest agroforesty systems. [7] Beneficiaries of PROBOSQUE projects receive average amounts per year and per hectare of: over 10 years, USD 181 and 322 as a base for management of natural forest for production depending on the type of production, and additional amounts if the plot has more than 15 ha; over 10 years USD 350 for forest protection (manglar forest); over 5 or 6 years, USD 490 to 578 for forestry plantation depending on its destination; USD 290 to 320 over 10 years for restoration of degraded forest, depending on its type; and USD 211 to 320 over 6 years depending for agroforestry systems, depending

[7] https://www.inab.gob.gt/index.php/component/content/article/112-servicios/183-pinpep?Itemid=437para-manejo-de-bosques

on its original forest density (i.e., if lower density, receive lower amounts).[8]

Note that, from an INAB/WB document: Within PINPEP, beneficiaries receive the following amounts by category on average: USD 406 per ha for the first 5 ha and additional USD 113 per ha for management of productive natural forests: USD 379 per ha for the first 5 ha and additional USD 97 per ha for protection of natural forests; USD 2,061 per ha for forest plantations and maintenance; and USD 1,030 per ha for the establishment and maintenance of agroforestry systems. Beneficiaries of PROBOSQUE projects receive on average USD 2,175 per ha over 6 years for plantations; USD 684 per ha for 6 years when doing agroforestry; USD 394 per ha for the first 15 ha and US 71 for the rest during 10 years of natural forest management; and USD 2,433 per ha for 10 years of restoration of degraded forest land.[9]

In addition to targeted environmental impacts, Guatemala forest incentives aim to generate social benefits as number of jobs created and also consider women participation. Forest incentives generated on average 2.1, 2.8 and 2.2 million of jobs per year for PINFOR, PINPEP and PROBOSQUE respectively. Women participate in those programs actively. For example, they represent 47% of beneficiaries of PINPEP since its entry in operation. [10]

# 3 Materials and Methods

## 3.1 Study Area (PENDING for article)

## 3.2 Modelling Framework

We estimate the dynamic effects of Guatemala's forest incentives on four different outcome variables following the process summarized below, illustrated in Figure 1, and fur-

[8] https://www.inab.gob.gt/images/servicios/probosque/8formularios/Trifoliar$_{P}ROBOSQUE.pdf$

[9] https://www.inab.gob.gt/images/pre/documentos/seccion1-descripcion-del-programa/Plan%20de%20Distribuci%C3%B3n%20de%20Beneficios%20PDB.pdf

[10] Sistema de Información Forestal de Guatemala, SIFGUA, https://www.sifgua.org.gt/SIFGUAData/PaginasEstadistica forestales/

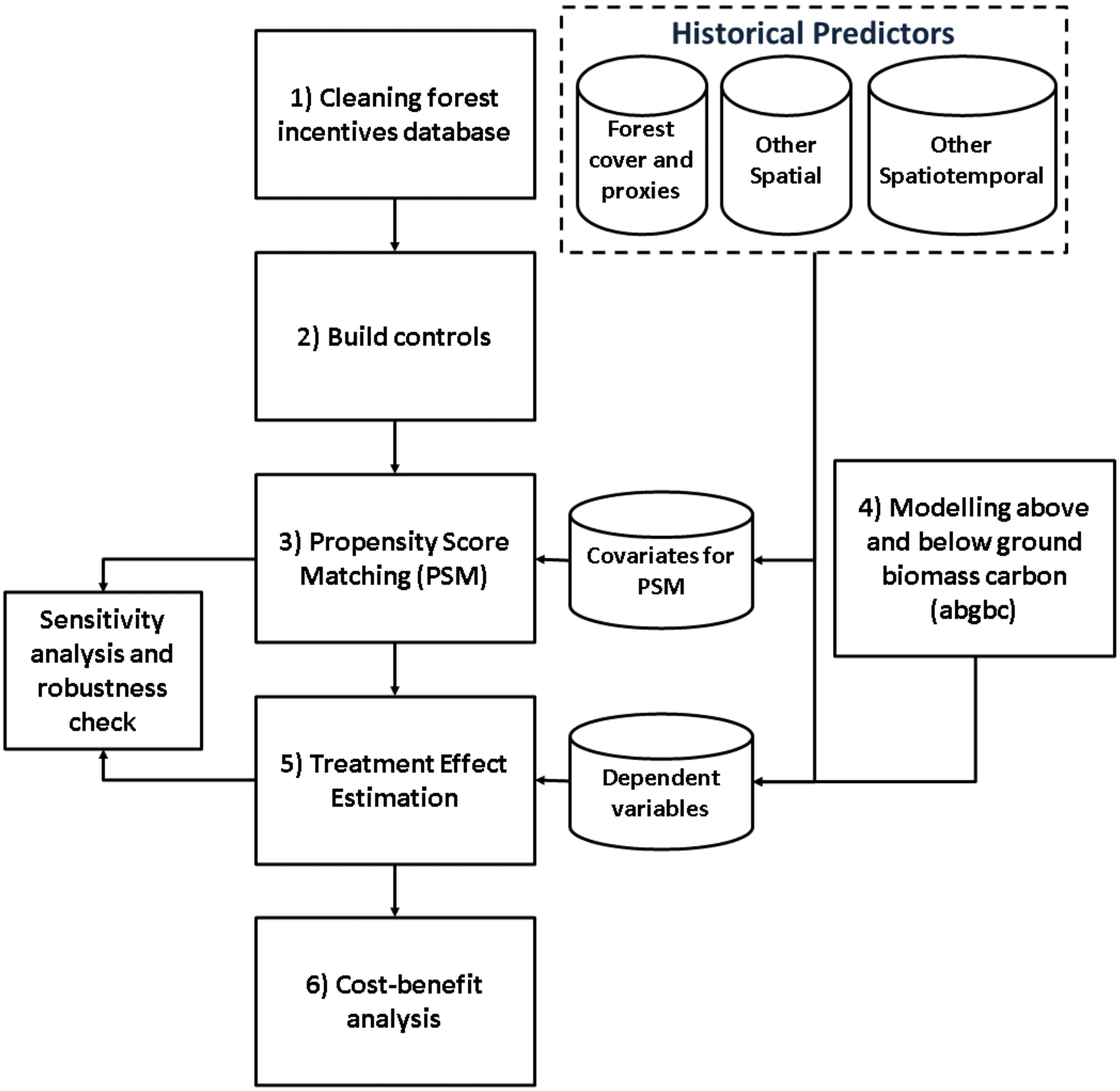
ther detailed in the appendix. Our modelling uses a series of variables from different sources, which are summarised within each subsection below, but further described in Appendix A.

1. We analyzed and cleaned a forest incentives database obtained from INAB.
2. We randomly created 3.1 ha (100m radius) controls across Guatemala, where there were no forest incentives projects and no protected areas.
3. We extracted selected covariates for treated and untreated sites, and used propensity score matching (PSM) to construct a dataset with comparable groups of treated and untreated plots.
4. We developed a random forest model to predict annual above and below ground biomass carbon between 2001 and 2023 since that information was not available for the whole period.
5. We calculated the treatment effect of forest incentive programs on the following outcomes: a) tree cover, b) above and below ground biomass carbon (abgbc), c) fractional vegetation cover (FVC), and d) normalized difference vegetation index (NDVI). We used a differences-in-differences (DID) approach to estimate the treatment effect. As a sensitivity analysis we also calculated the event study estimator developed by De Chaisemartin and d'Haultfoeuille (2024).[11] For both strategies (main analysis and sensitivity), we used the matched dataset developed in 3).
6. Finally, we did a cost-benefit analysis to evaluate and compare the economic costs and environmental benefits of Guatemala's forest incentives programs. We did the assessment for an average plot overall, an average plot for each type of program

[11] Goodman-Bacon (2021) shows that differences-in-differences estimators obtained using two-way fixed effects (TWFE) regressions are a weighted mean of all 2x2 differences-in-differences estimators that can be computed in the sample. If there is heterogeneity in treatment timing (e.g., plots start receiving forest incentives at different periods) and effects (the effects of forest incentives change over time), these weights can be negative, biasing the differences-in-differences estimators obtained through TWFE regressions.

(PINFOR, PINPEP, PROBOSQUE) and an average plot by program and project type. We considered as costs the unitary payments (USD/ha) the forest incentives programs are offering and we calculated two types of environmental benefits: a) carbon storage, and b) ecosystem services.

Figure 1: Schematic diagram showing the modelling framework used to estimate the impact of forest incentives programs in Guatemala



### 3.3 Cleaning and analyzing forest incentives database (treatment units)

The main source of data used throughout this paper is geo-referenced data on the plots enrolled in Guatemala's forest incentive programs – treatment units – obtained from INAB. [12] For each treatment unit, this database contains information on the program (*PINFOR*, *PINPEP* or *PROBOSQUE*), the modality or project type (e.g., restoration, conservation, agro-forestry), the type of owner (individual, municipality, business, NGO, etc.), location (region, department, municipality), and the period it received financial incentives (different phases for each project, with first year and last year for each one of them).

The process used to clean the dataset was as follows:

1. We checked if there were any relevant overlaps between plots. If overlapping area between two plots was small (<1% on area of plots), these plots remained in the database. Otherwise, plots were flagged and assessed further for exclusion in the analysis.

2. We checked consistency of reported location and geo-spatial information, mainly, the assigned Department within Guatemala. We flagged those plots with wrong Department and excluded from our analysis.

3. We extracted predictors to apply the propensity score matching algorithm, but flagged those plots with missing data and excluded from our analysis.

It should be noted that some plots were flagged more than once (i.e., wrong department and overlap of at least 1%, or wrong department and missing data)

### 3.4 Building control (untreated units)

INAB's dataset only contains information of plots that enrolled in Guatemala's forest incentive programs. Thus, we created our own control units. To do this, we randomly

[12] It contains information from the beginning of each program up to August 2023.

created 100 meters (100m) radius plots located outside protected areas[13] (and outside forest incentives programs areas) throughout Guatemala. In total, we were able to create 500,663 plots (roughly six times the number of original treated plots). Appendix B further describes this procedure.

### 3.5 Propensity Score Matching

To ensure that control plots were comparable to treatment plots, we used propensity score matching (PSM). We used a series of variables in our PSM algorithm to characterize baseline conditions (i.e., conditions before the forest incentive programs began). Elevation, aspect, and slope were obtained from the NASA Shuttle Radar Topographic Mission (SRTM) digital elevation data (Jarvis et al., 2008). Forest cover and forest height for 2000 were obtained from the Global Land Analysis and Discovery lab (GLAD) (Potapov et al., 2022). Travel time to cities with a population larger than 20k was obtained from (Nelson et al., 2019). Distance to rivers and streams was obtained from the HydroSHEDS dataset (Lehner and Grill, 2013). Finally, mean annual precipitation, mean annual temperature, and precipitation during the driest month were obtained from the Worldclim dataset (Hijmans et al., 2005). Appendix C presents the details of the estimation of the propensity score, the matching procedure used, more details on the matching variables, and the various sensitivity analysis that were performed.

### 3.6 Modelling above and below ground biomass carbon

To estimate annual above and below ground biomass carbon, we obtained above and below ground biomass carbon (abgbc) density (MgC/ha) for the year 2010 at a 300m spatial resolution from Spawn et al. (2020). We developed a random forest model to predict abgbc for other years (i.e., 2001 to 2009, 2011 to 2023), based on a series of spatial

[13] 349 protected areas covering 32% of the territory according to the *Sistema Guatemalteco de Área Protegidas (SIGAP)*

and spatio-temporal predictors. Spatial only variables (e.g., that do not vary in time) included the x and y coordinates calculated from the plot centroids, and the mean (2000 and 2020) forest cover and height from GLAD (Potapov et al., 2022). We also used spatiotemporal variables for years 2001-2023. We estimated land surface temperature (LST), fractional vegetation cover (FVC), emissivity, and normalised difference vegetation index (NDVI) from Landsat 7 images using an algorithm developed by Ermida et al. (2020). We also used the MOD44B Version 6.1 Vegetation Continuous Fields (Dimiceli, Sohlberg and Townshend, 2022) yearly product to calculate percent tree cover, percent non-tree vegetation cover, and percent non-vegetation cover. Appendix D presents the details on model development and performance.

### 3.7 Treatment effect estimation

To estimate the treatment effect We compute a 2×2 differences-in-differences estimator comparing the difference in outcomes in period 0 (before all plots were treated) and from 10 years before to 10 years after each plot was treated between treatment and control groups. This estimator identifies the effects of the forest incentive programs under hypotheses of parallel trends and no anticipation. We also explore if there are any differences when comparing the difference in outcomes with period -1 (instead of 0). To do this we use the marginal effects package in R (Arel-Bundock, 2024). To calculate the treatment effect we control for all covariates that were previously used in the matching procedure.

As a sensitivity analysis, we use the event study estimator developed by De Chaisemartin and d'Haultfoeuille (2024). This estimator generalizes event study estimators robust to heterogeneity in treatment timing such as Callaway and Sant'Anna (2021) and De Chaisemartin and d'Haultfoeuille (2020) to settings in which treatment might be reversed.[14] It

[14] De Chaisemartin and d'Haultfoeuille (2020) and Callaway and Sant'Anna (2021) introduce consistent estimators for the ATT(g,t) – the treatment effects for cohort $g$ and period $t$ – for setting in which there is heterogeneity of treatment time. They also show how these estimators can be aggregated to compute the dynamic effects of policies. However, these estimators do not allow for the case in which treatment is reversed.

is thus ideal to our setting as farmers/ranchers enter in forest incentives programs at different moments and exit forest incentives programs after some time. The event study estimator developed by De Chaisemartin and d'Haultfoeuille (2024) has the same identification hypotheses of the differences-in-differences estimator described earlier. In our application, these hypotheses imply that outcome of interest should have evolved comparably between treatment and control units in the absence of the forest incentive programs and that farmers/ranchers should not have made changes because they expected to enroll in forest incentives programs in the future.

The treatment effect was calculated using the matched dataset as detailed previously.

### Outcome data (dependent variables)

For our assessment we considered four outcomes of interest. Our main analysis focuses mainly on the impact of forest incentives programs on tree cover and above and below ground biomass carbon (a proxy for carbon stock). These results will help us perform an analysis of the costs and benefits of these programs. Additionally, as a sensitivity analysis and to assess how our results change when using spatial data with a finer spatial resolution, we explore the impact of these programs on two other variables: Landsat 7 fractional vegetation cover (FVC) and normalized difference vegetation index (NDVI). For all variables, we extracted annual mean values for each plot (treated and untreated) for the years 2001-2023.

To estimate tree cover, we used the MOD44B Version 6.1 Vegetation Continuous Fields (Dimiceli, Sohlberg and Townshend, 2022) which has a spatial resolution of 250m. We calculated the carbon stock for each treated and untreated plot using the methods summarised earlier (section 3.6 and further detailed in Appendix D). We estimated annual fractional vegetation cover (FVC) and normalized difference vegetation index (NDVI) from Landsat 7 images using a Google Earth Engine algorithm developed by (Ermida et al., 2020). FVC represents the ratio between the vertical projected area of above-ground green vegetation and the total vegetation area (Yang et al., 2017). Values of FVC range from 0 (no green vegetation) to 1 (only green vegetation). NDVI is a vegetation index with values that range from -1 to 1. Values indicate: below 0, water and other non-vegetated features, between 0 and 0.3, no vegetation cover; between 0.3 and 0.6, sparse vegetation cover; between 0.6 and 0.9, dense and healthy vegetation cover; above 0.9, very dense vegetation as rainforest. For our analysis, FVC was calculated at 30m spatial resolution while NDVI was calculated at 100m spatial resolution.

## 3.8 Heterogeneity and subgroup analysis

To assess heterogeneity we did subgroup analysis on the following:

1. **by program**
   (a) *PINFOR*
   (b) *PINPEP*
   (c) *PROBOSQUE*
2. **by project type**
   (a) *Agroforestry*
   (b) *Forestry plantations*
   (c) *NFM Production*
   (d) *NFM Protection*
3. **by Location**
   (a) *Regions*
   (b) *Departments*

   (c) *Ecoregions*

4. **Initial conditions:** here we subset our data set into two groups using two different classifications: 1) <50th and >=50th percentiles, and 2) <=10th and >=90th percentiles.

   (a) *Slope*

   (b) *Area*

   (c) *Distance to cities*

   (d) *Forestation rate*: calculated as the slope during the previous 5 years before starting treatment (t = 0)

   (e) *Tree cover*: calculated before starting treatment (t = 0)

   (f) *Above and below ground biomass carbon*: calculated before starting treatment (t = 0)

   (g) *Landsat FVC*: calculated before starting treatment (t = 0)

   (h) *Landsat NDVI*: calculated before starting treatment (t = 0)

## 3.9 Cost-benefit analysis

We use the estimates obtained in the previous sections to monetize the benefits of Guatemala's forest incentive programs in terms of ecosystem services and carbon storage. We convert changes in tree cover into changes in ecosystem services using data from Bank (2021). This data reports that a typical hectare of forests in Guatemala generates USD 32.7 per year in benefits from the production of non-timber forest products, USD 24.1 per year in benefits from watershed protection, and USD 319.5 per year in benefits from recreation, hunting, and fishing. We monetize changes in carbon storage assuming a price of USD 20 per ton of $CO_2$ equivalent and a discount rate of 5%.[15] We assumed that benefits were permanent (i.e., they continued after the project duration).

We calculated the project costs based on payments from the different programs and project types.

We did the analysis for an average plot across all programs and project types, for an average plot per program, and an average plot per program and project type.

## 3.10 Robustness checks

To assess the robustness of our analysis and results, we did the following:

1. **Propensity Score Matching**
   (a) *We tested different matching algorithms*
   (b) *We tested the final balance of our dataset when varying the number of potential controls*
   (c) *We used different methods to evaluate our matching procedure*
2. **Treatment effect estimation**: we used two methods to calculate treatment effect
   (a) *PSM + DID: with two references (-1 and 0)*
   (b) *PSM + Event Study Estimator*
3. **Outcomes assessed**: we calculated the treatment effect on 4 outcomes, all related to forest and tree cover, and all with different spatial resolutions ranging from 30m to 300m.
   (a) *Tree cover*
   (b) *Above and below ground biomass carbon*
   (c) *Landsat 7 FVC*

[15] Alternatively, it is possible to convert changes in tree cover directly into changes in carbon storage using data on carbon storage in Guatemala's forests. We find similar results using this approach.

(d) *Landsat 7 NDVI*

# 4 Results

## 4.1 General results

The original INAB dataset contains a total of 83,677 plots receiving forest incentives comprising 434,184. A substantial number of plots present overlap between them – there is some overlap in 30,696 plots (roughly 37% of the plots), but the intersection area is low and accounts for just under 5% of the total forest incentives area (21,121 hectares). We flagged and excluded a total of 1,064 plots (25,417 hectares) that had an overlap of more then 1% of area in each plot. We also found some inconsistency in the assigned location of plots within Guatemala. We flagged and excluded a total of 3,035 plots (15,071 hectares) that had an inconsistent Department assigned. Finally, and after extracting data for the matching procedure, we flagged and excluded a total of 609 plots (10,030 hectares) with missing data. The final dataset of treatment plots had 79,156 plots (94.6% of original number of plots) with a total of 394,636 hectares (90.6% of original area).

The most common program (Table 1) is PINPEP (52,515 plots), followed by PROBOSQUE (16,902 plots), and PINFOR (9,739 plots). However, in terms of area, the largest program is PINFOR (mean = 10.6 ha, SD = 88.4 ha), followed by PROBOSQUE (mean = 7.9 ha, SD = 35 ha), and PINPEP (mean = 3 ha, SD = 2.9 ha). This is coherent with the characteristics of each of the programs. For example, the mean area is highest for PINFOR and lowest for PINPEP as is the minimum area required in each case (i.e., 2 ha for the former and 0.1 ha for the latter). The average treatment plot has 5 hectares and received payments for an average of 4.8 years.

Table 1: Descriptive statistics by program

| Program | Legal period | Legal minimum area | Number of plots | Area* (hectares) | Time active* (years) |
|---|---|---|---|---|---|
| PINFOR | 1996-2005 | 2 ha | 9,739 | 10.6 (88.4) | 6 (2.4) |
| PINPEP | 2010-present | 0.1 ha | 52,515 | 3 (2.9) | 5.2 (2.7) |
| PROBOSQUE | 2016-present | 0.5 ha | 16,902 | 7.9 (35) | 2.9 (1.8) |
| **TOTAL** | | | **79,156** | **5 (35.2)** | **4.8 (2.7)** |

* mean (standard deviation)

Prior to applying the propensity score matching, we also excluded control plots with missing data, ending up with a total of 494,087 potential control plots. Figure 2 shows the spatial distribution of treated (panel A) and untreated (panel B) plots. Descriptive statistics presented in 2 for selected variables show how the mean values for variables used in the propensity score matching algorithm are adequately balanced between treated and untreated plots. This can be further observed in B.1 which shows a summary of the region of common support and an estimate of the standardized mean difference and the Kolmogorov-Smirnov statistic before and after matching, as well as mean values for the final matched dataset for covariates used in the PSM algorithm.

Figure 2: Location (distribution) of (A) selected treated and (B) untreated plots

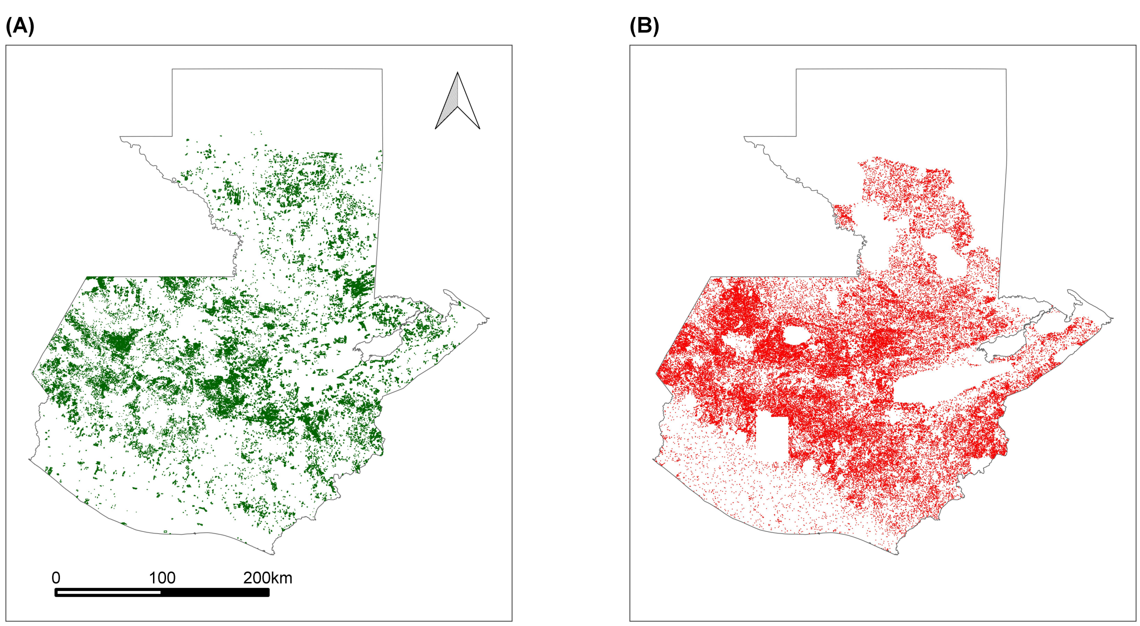


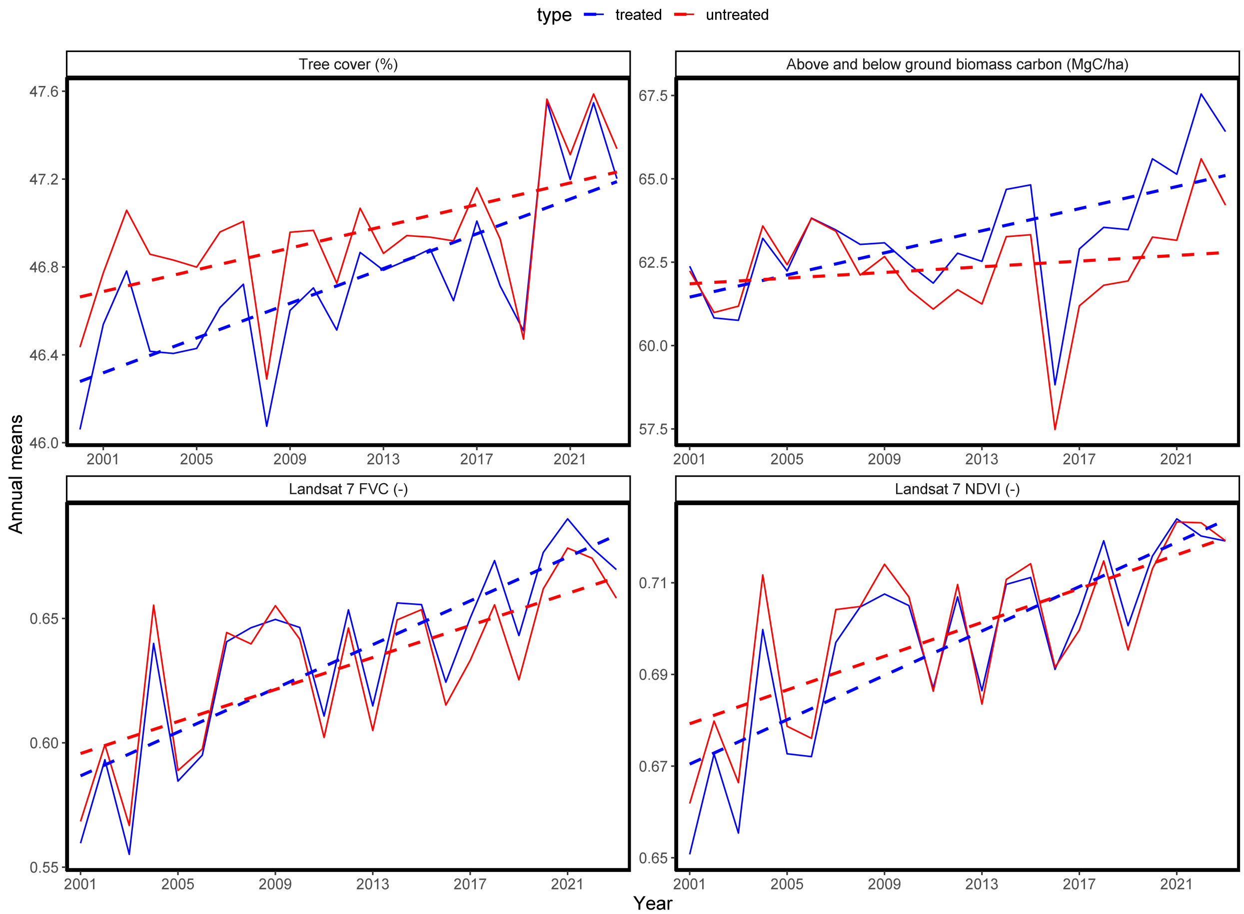
Table 2: Descriptive statistics for selected variables

| Variable | All | Treated* PINFOR | PINPEP | PROBOSQUE | Untreated* All |
|---|---|---|---|---|---|
| ***Space*** | | | | | |
| Above and below ground biomass carbon 2000 (MgC/ha) | 147.2 (68.3) | 137.5 (75.8) | 142.6 (66.2) | 166.9 (66.5) | 149 (59.6) |
| Forest Cover 2000 (share) | 0.9 (0.2) | 0.8 (0.3) | 0.9 (0.2) | 0.9 (0.3) | 0.9 (0.2) |
| Forest height 2000 (meters) | 13.4 (7.2) | 11.3 (7.1) | 13.5 (7) | 14.4 (7.5) | 13.2 (6.4) |
| Tree cover 2001 (%) | 44.7 (20.2) | 44.4 (21.2) | 42.8 (20) | 51 (18.9) | 45.1 (18.8) |
| ***Threat*** | | | | | |
| Orientation of slope (degrees 0 to 360) | 15.3 (8.5) | 11.2 (8.8) | 17.2 (7.9) | 11.8 (8.2) | 15.4 (9) |
| Travel time to cities with population above 20k (mins) | 83.8 (98.7) | 78.1 (89.9) | 76.4 (93.2) | 110.2 (114.4) | 80.8 (104.4) |
| Distance to rivers and streams 2010 (meters) | 255.8 (470.7) | 320.7 (529.7) | 256.3 (467.1) | 216.6 (440.4) | 248.4 (493.8) |

* mean (standard deviation) for treated and matched untreated plots

Figure 3 shows the annual mean values for the four outcome variables for treated and matched untreated plots. A linear trend line was fitted to each time series, and the figure suggests that overall treated plots have an average higher improvement in all variables in time (slope in treated plots is higher than in untreated plots). Table A.2 presents descriptive statistics for outcome variables for 2001, 2023 and change between 2001-2023 for treated and matched untreated plots. Results reinforce the argument that treated plots might be having a positive treatment effect compared to untreated plots, as the change between 2001-2023 is higher for treated than untreated for all variables.

Figure 3: Annual means for outcome variables for treated and matched untreated plots




## 4.2 Treatment effects

Figure 4 shows the dynamics of tree cover and above and below ground biomass carbon in treated/untreated plots over time, with a window of 10 years before and after the treatment. Here, we focus on the overall effects (all programs), and can see how before treatment there were minor differences (treated vs. untreated) in trends, at least up to 5 years pre-treatment. After treatment, both tree cover and above and below ground biomass carbon begin to increase in treated plots relative to untreated 1-2 years after enrollment in the forest incentive programs. Figure 4 also shows how these dynamics change when using a different reference point (i.e., the year chosen as the last period before treatment change), with consistent patterns for year 0 and -1. The results show a consistent increase in treatment effect for both outcomes reaching more than 2.5 p.p. ($p$-value<0.001) for tree cover and almost 2.7 (MgC/ha) ($p$-value<0.001) for above and below ground biomass carbon.

These effects, and by program and project type, are reported in Table 3. Figure E.1 in the appendix shows these results for all four outcome variables. The chosen reference year does not seem to have a big influence in these results, and although all four present different patterns before treatment - particularly Landsat 7 FVC and NDVI compared to tree cover and above and below ground biomass carbon - in all cases a consistent increase in treatment effect is observed until 10 years after treatment.

As discussed previously (subsection 3.7), we also used an event study design to investigate the dynamics of land use in treated/untreated plots in more detail. Figure E.2 shows how results compare when using DID w/matching vs. event study estimator developed by (De Chaisemartin and d'Haultfoeuille, 2024). Some differences are observed when comparing results estimated using DID w/matching compared to the event study estimator, particularly for years further away (before and after) from treatment, but increasing trends in time are consistent in all cases after treatment. Differences in magnitudes are likely due to not controlling for matching covariates with the event study estimator as we did with DID w/matching. Table E.1 in appendix shows a summary of treatment effects for the four outcome variables, 5 and 10 years after treatment, when using DID w/matching and the event study estimator.

Figure 4: The dynamic effects of Forest Incentives on Tree Cover(%) and Above and Below Ground Biomass Carbon (MgC/ha)

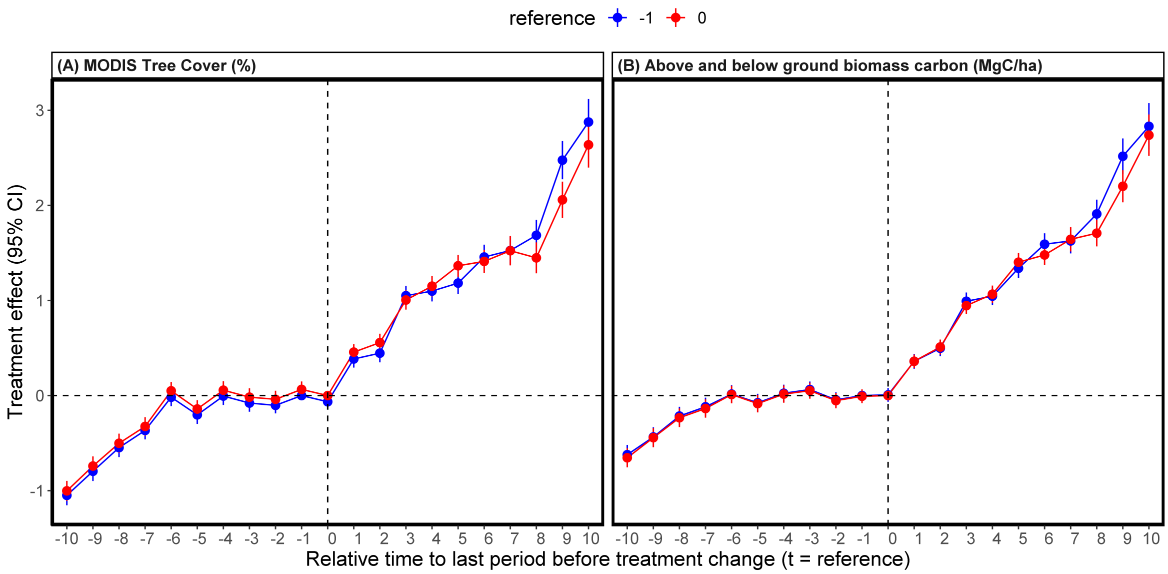



Table 3 reports the effects of forest incentives on tree cover and above and below ground biomass carbon, 5 and 10 years after treatment, using differences-in-differences with matching. We estimate that forest incentives increase tree cover by 1.37 p.p. (95% CI, 1.25 - 1.48) after 5 years of treatment and by 2.64 p.p. (95% CI, 2.4 - 2.88) after 10 years of treatment. By program, the 10-year effect is of 1.69 p.p. (95% CI, 1.4 - 1.98) for PINPEP and 4.34 p.p. (95% CI, 3.86 - 4.81) for PINFOR. For PROBOSQUE, which has been active for less time, we estimate an effect of 3.16 (95% CI, 2.64 - 3.68) after 5 years of treatment. The relative magnitudes of the treatment effect estimates for above and below ground biomass carbon are largely comparable to those for tree cover. The 10-year effect for PINPEP and PINFOR is of 1.58 (95% CI, 1.33 - 1.84) and 4.87 (95% CI, 4.42 - 5.31) (MgC/ha) respectively, while the 5-year effect for PROBOSQUE is of 2.2 (95% CI, 1.77 - 2.62). In appendix E, we evaluate the effect in time by program and project type (Figure **??** and Figure **??**). By program, we observe how PINFOR consistently performs best, followed by PROBOSQUE albeit only being assessed for 5 years after treatment. By project type, the largest effects are observed for forestry plantations, followed by Agroforestry which presents similar treatment effects to all project types combined. We did not estimate consistent positive treatment effects for NFM Production and NFM Protection.

Table 3: Effects on Tree Cover (%) and Above and Below Ground Biomass Carbon (MgC/ha): DID w/ matching

| **Program/ Project type** | **Years since treatment** | **Tree cover (%)** | **Above and below ground biomass carbon (MgC/ha)** |
|---|---|---|---|
| All | 5 | 1.37 (1.25 - 1.48)*** | 1.4 (1.31 - 1.5)*** |
| | 10 | 2.64 (2.4 - 2.88)*** | 2.74 (2.52 - 2.96)*** |
| **Program** | | | |
| PINPEP | 5 | 0.62 (0.49 - 0.76)*** | 0.83 (0.72 - 0.93)*** |
| | 10 | 1.69 (1.4 - 1.98)*** | 1.58 (1.33 - 1.84)*** |
| PINFOR | 5 | 2.17 (1.86 - 2.49)*** | 2.85 (2.56 - 3.14)*** |
| | 10 | 4.34 (3.86 - 4.81)*** | 4.87 (4.42 - 5.31)*** |
| PROBOSQUE | 5 | 3.16 (2.64 - 3.68)*** | 2.2 (1.77 - 2.62)*** |
| **Project type** | | | |
| Agroforestry | 5 | 0.76 (0.3 - 1.23)** | 1.2 (0.85 - 1.55)*** |
| | 10 | 1.95 (0.96 - 2.94)*** | 1.74 (0.92 - 2.55)*** |
| Forestry plantations | 5 | 2.89 (2.58 - 3.19)*** | 3.75 (3.49 - 4.02)*** |
| | 10 | 4.96 (4.45 - 5.47)*** | 5.5 (5.02 - 5.99)*** |
| NFM Production | 5 | 1.6 (0.74 - 2.45)*** | 2.01 (1.15 - 2.87)*** |
| | 10 | -0.66 (-2.04 - 0.72) | 0.06 (-1.41 - 1.53) |
| NFM Protection | 5 | 0.8 (0.65 - 0.94)*** | 0.47 (0.34 - 0.59)*** |
| | 10 | 1.18 (0.88 - 1.49)*** | 0.71 (0.43 - 0.99)*** |
| Other | 5 | 0.83 (-0.82 - 2.48) | 3.07 (1.76 - 4.38)*** |
| | 10 | 10.02 (7.76 - 12.27)*** | 11.53 (9.83 - 13.24)*** |

**Notes:** *** $p<0.01$; ** $p<0.05$; * $p<0.10$.

There is high heterogeneity in our results by location and biophysical characteristics of plots prior to treatment. All regions (Figure 5) show positive treatment effects for tree cover (%) 10 years after treatment ranging from 1.4% (95% CI, 0.79-2.01) in the Northeast to 5.52% (95% CI, 3.10-7.93) for Guatemala. 5 out of 8 regions present mid estimates higher than the national estimate of 2.64% (95% CI, 2.4-2.88). Trends are consistent for tree cover and above and below biomass carbon.

By Department (Figure E.5 in appendix) and Ecoregion (Figure E.6) there seems to be higher heterogeneity but some locations have very wide confidence interval ranges given the low number of plots considered for that analysis. Figure E.7 shows a map of the mid estimates for tree cover (%) by Region, Department and Ecoregion.

We also explored how these estimates varied by different initial plot conditions (Figure 6). Higher treatment effects were estimated for plots that were further away from cities with a population of 20k or more and with a lower slope, area, and initial mean values for all four outcome variables. With respect to forestation rate, although our results show that those plots with higher forestation rate had a higher treatment effect, these are quite similar. Figure E.8 shows how plots with lower forestation rate (<= 10th percentile) had a higher treatment effect than those with a higher forestation rate (>= 90th percentile). These results align with those from initial conditions from the four outcome variables (i.e., those plots with worst tree/forest-related conditions had a higher treatment effect).

Figure 5: The Effects of Forest Incentives on Tree Cover (%) and Above and below ground biomass carbon (MgC/ha) by Region - 10 years since treatment

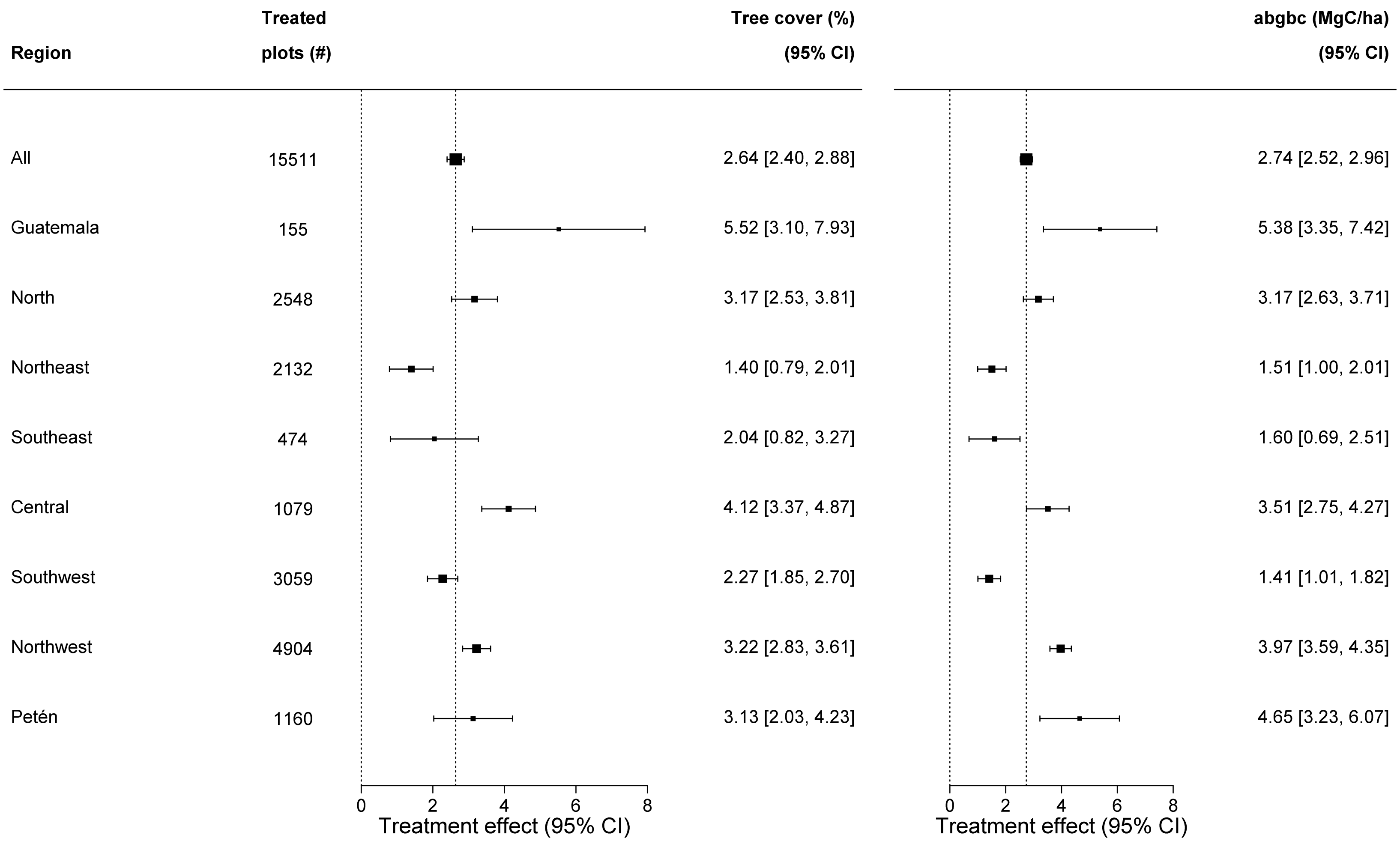
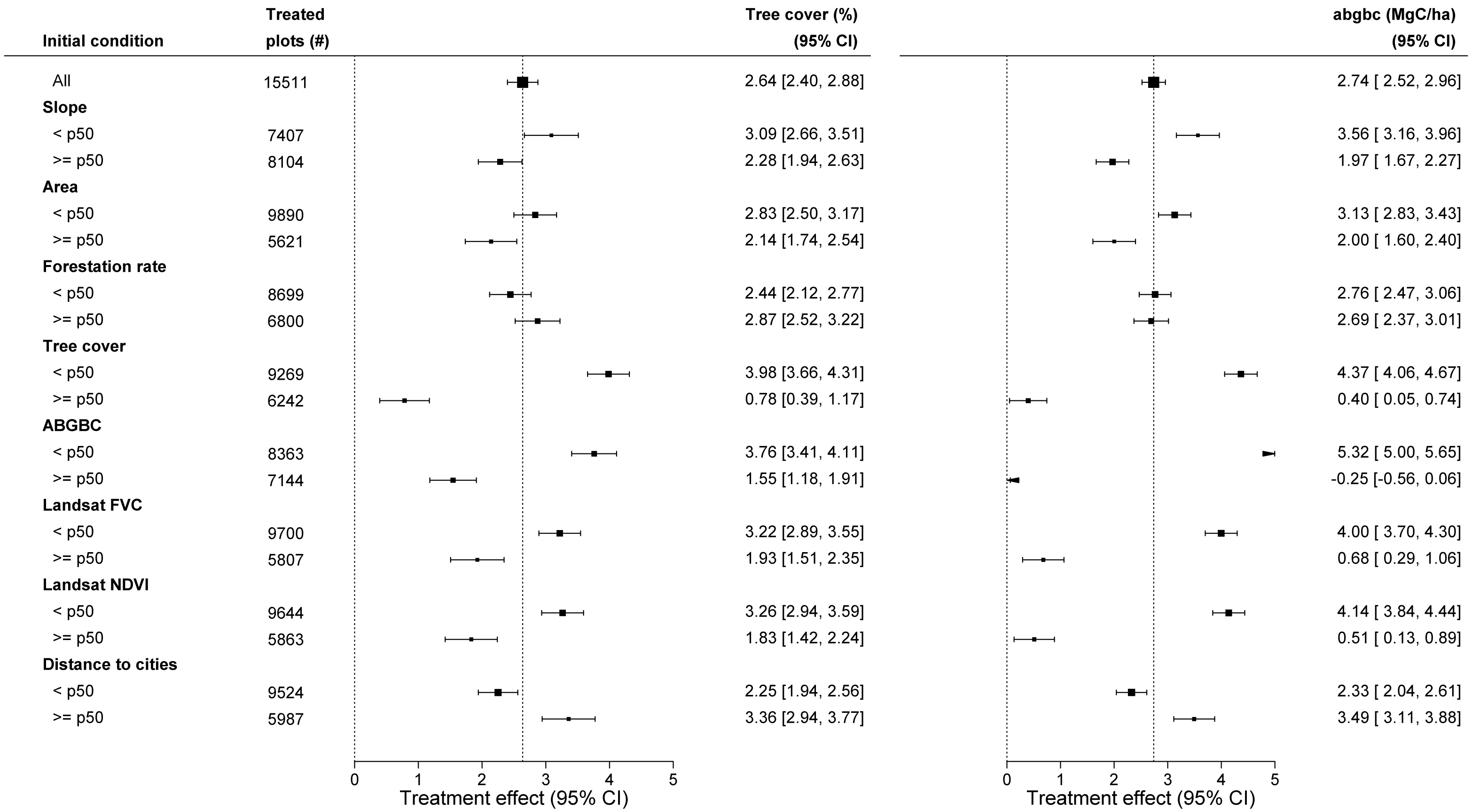


Figure 6: The Effects of Forest Incentives on Tree Cover (%) and Above and below ground biomass carbon (MgC/ha) by initial plot conditions - 10 years since treatment



### 4.3 Cost-benefit analysis

Assuming permanence of benefits (benefits do not disappear over time), our results indicate a total benefit (ecosystem services and carbon) of 565-659 USD/ha for all project combined, 330-390 USD/ha for PINPEP and 996-1150 for PINFOR/PROBOSQUE. By project type, forestry plantations (1,126-1,302 USD/ha] and restoration projects (2,352-2,707 USD/ha) have higher benefits per hectare. For most cases except for restoration projects, the net present value of costs exceeds the environmental benefits (even in the less conservative estimate). The benefit cost ratio ranges between negative values for Native Forest Management (production) projects to 1.48 for restoration projects.

Table 4: Results for cost-benefit analysis

| | Net Present Value: Benefits (USD/ha) | | | | | |
|---|---|---|---|---|---|---|
| | Eco-system services (low) | Eco-system services (high) | Carbon | Total | Net Present Value: Costs (USD/ha) | Ratio |
| All | 62 | 156 | 503 | [565, 659] | 1818 | [0.31, 0.36] |
| PINPEP | 40 | 100 | 290 | [330, 390] | 1617 | [0.2, 0.24] |
| PROBOSQUE | 102 | 256 | 894 | [996, 1,150] | 1,949 | [0.51, 0.59] |
| PINPEP, Agroforestry | 46 | 115 | 319 | [365, 434] | 715 | [0.51, 0.61] |
| PINPEP, Forestry plantations | 117 | 293 | 1,009 | [1,126, 1,302] | 1,430 | [0.79, 0.91] |
| PINPEP, Native Forest Management (Production) | -16 | -39 | 11 | [-5, -28] | 2,086 | [0, -0.01] |
| PINPEP, Native Forest Management (Protection) | 28 | 70 | 130 | [158, 200] | 1,656 | [0.1, 0.12] |
| PROBOSQUE, Agroforestry | 46 | 115 | 319 | [365, 434] | 501 | [0.73, 0.87] |
| PROBOSQUE, Forestry plantations | 117 | 293 | 1,009 | [1,126, 1,302] | 2,312 | [0.49, 0.56] |
| PROBOSQUE, Native Forest Management (Production) | -16 | -39 | 11 | [-5, -28] | 657 | [-0.01, -0.04] |
| PROBOSQUE, Native Forest Management (Protection) | 28 | 70 | 130 | [158, 200] | 1,933 | [0.08, 0.1] |
| PROBOSQUE, Restoration | 236 | 591 | 2,116 | [2,352, 2,707] | 1,831 | [1.28, 1.48] |

## 4.4 Discussion

The previous sections document relatively modest impacts – aggregating the effects of all programs indicates an aggregate impact of just over 11,000 hectares, representing an increase of only 5.9% in tree cover (i.e., 2.64 over 44.7% tree cover for all programs) relative to the baseline (i.e., t = 0). Our analysis also shows that the effects continue growing after typical duration of the forest incentives, indicating that the effects are persistent. And, although there is concern that forest incentive programs might induce landholders to replace high-quality native forests for low quality planted forests (i.e., reducing ecosystem services provided), our analysis shows that at least for carbon storage this is not the case. We estimate that the treatment effects on carbon storage (abgbc) area quantitatively similar to the effects reported for tree cover. We estimate aggregate effects of 4 million tCO2eq ten years after plots entered the program, which represent which represents an increase of 4.3% in carbon storage (i.e., 2.74 over 63 MgC/ha abgbc for all programs) relative to the baseline.

There is considerable heterogeneity in the effects of Guatemala's forest incentive programs. Results show that the treatment effect for PINFOR and PROBOSQUE are larger than those estimated for PINPEP. And although, we could only calculate the effect for PROBOSQUE up to 5 years, trends show that effects produced through this scheme might be even higher than PINFOR. We estimated that tree cover has increased 4.34% (95% CI, 3.86-4.81) 10 years since treatment for PINFOR and 3.16% (95% CI, 2.64-3.68) 5 years since treatment for PROBOSQUE, in both cases, the effect is higher than the overall estimate after 10 years. Heterogeneity across programs is largely explained by differences in the activities supported by each of them. A larger proportion of projects (31.9%) in PINFOR and PROBOSQUE are forestry plantations compared to PINPEP (12.3%), which is the project type with one of the highest treatment effects, almost doubling the overall estimate after 10 years. Finally, there is also substantial heterogeneity depending on the location of beneficiaries and their characteristics. There are particular subregions of the country that show effects three times the mean effects, and plots with relatively more "negative" characteristics (e.g., lower forestation rate, lower tree cover prior to treatment, further away from cities, etc.) tend to show higher treatment effects (more than double) compared to those plots with more "positive" characteristics.

Regardless of the positive effects that we have found under the many different configurations of plots that have participated or are currently participating under a forest incentive scheme in Guatemala, we find that the costs of these programs are relatively high compared to the modest environmental benefits. We estimate that the ratio of environmental benefits to costs ranges between 0-1.48, with only one project type having a ratio above 1 (benefits higher than costs), and these number reflect two important aspects. Firstly, Guatemala's forest incentives are quite generous, as generous as the most generous programs in the region (Costa Rica for agroforestry, Colombia for conservation, Chile for restoration). Secondly, the effects of these incentives on tree cover, are slightly below the average effect of comparable programs reported in the literature. The Cohen d, a measure of effect size, is 0.13 in Guatemala and 0.19 in the studies reviewed by Wunder et al. (2020). Even if evidence is very scattered, other forest incentives programs yield similar results in terms of the benefit/cost ratio. For example, R. and Borner (2021) for Peruvian Amazon estimates that costs exceed environmental benefits by a factor of 12. Regardless, there are also exceptions in the opposite direction in other parts of the world. For example, et al. (2017) for a forest incentives program in Uganda, under which landowners are paid not to cut their trees, the benefit for delayed carbon emissions is 2.4 times the costs of the program.

#### 4.4.1 Strengths and Limitations

Although the analysis presented here provides valuable insights on the environmental effects (and benefits) of Guatemala's forest incentives programs, several limitations must be acknowledged.

Firstly, while our intention was to assess the effect in time of these programs on forests, we were not able to incorporate an annual forest cover indicator. We used tree cover, as a proxy for forest cover, and above and below ground biomass carbon as a proxy for carbon storage. Both of these datasets were available at relatively coarse spatial resolutions (250m and 300m). Furthermore, abgbc data was not available for every year, and we had to develop a model to predict this variable from 2001-2009 and 2011-2023. Regardless, our analysis shows that these two variables behaved in a very similar pattern and magnitude, further supporting our findings. We also explored the effect of these programs on two other commonly used variables which have finer spatial resolution (Landsat 7 FVC and NDVI). Results with this variables align with our findings for tree cover and abgbc. Nevertheless, it is likely that future analysis may be improved by using more detailed data on forest cover that distinguishes between primary and secondary forests and using more detailed data on ecosystem services other than carbon. This would undoubtedly enable a better assessment of the effects of forest incentives on forest quality.

It seems that, according to our analysis, only considering the environmental benefits included in our assessment (i.e., carbon and ecosystem services), might not be enough to justify the programs costs. However, we acknowledge that the analysis is silent on the impacts of the forest incentives either on farm-level indicators such as investments, profits, labor demand, input demand or municipality-level outcomes such as employment, income, and poverty. Including these dimensions in future evaluations is key to better understand the multiple impacts of these programs.

Another limitation of the analysis is the lack of investigation of spillovers between neighboring plots. Comparisons across datasets with different resolutions suggests that negative spillovers do not seem to be influencing the analysis, and the analysis done by Patrick, Butsic and Potts (2023) found that there seem to be positive impacts on forest height and cover in surrounding plots. Nevertheless, a more detailed investigation is crucial for ensuring that these programs do not inadvertently cause harm to surrounding areas.

Throughout all of our analysis we carried out a series of sensitivity analyses and robustness checks to ensure that our assessment was as replicable and defensible as possible. We explored multiple approaches to the propensity score matching procedure, we calculated the effect of forest incentive programs on four different outcomes with different levels of spatial resolution using two different methods, and we performed a series of subgroup analyses to explore heterogeneity in our estimates.

### 4.4.2 Policy recommendations

Guatemala's forest incentive programs are among the largest forest incentive programs in the world. Ensuring that these programs generate positive results for people and the environment is key to ensure their long-term viability. Our analysis indicates there is substantial scope for improving the design of these programs.

Guatemala's forest incentive programs have multiple goals such as stimulating economic growth, promoting rural development, and increasing the provision of ecosystem services. However, there is not a proper translation of these goals into measurable indicators, negatively impacting the monitoring of these programs. Establishing clear and quantifiable indicators for each of the programs' objectives is therefore imperative to improve the monitoring of these programs and allow for regular assessment of the programs' impacts, ensuring they respond to changing conditions and outcomes.

There is currently no effort to target the forest incentives to regions and property types where the impacts of forest incentives on environmental and socioeconomic outcomes are more significant. Introducing targeting could increase substantially the effectiveness of the programs. However, it is important to pay close attention to potential trade-offs between environmental and economic impacts to ensure the programs achieve their multiple goals effectively.

Our analysis shows that the environmental effects vary considerable for different activities. Adjusting payments to better reflect the heterogeneity of these benefits for different activities (or even locations) could help increase the effectiveness of these programs.

As it currently stands, Guatemala's forest incentives programs are amongst the most generous in the region. This translates into high costs in exchange for modest environmental benefits. Proper targeting and better calibration of payments (e.g., aligning costs with those of comparable programs in the region) could help reduce the costs without negatively affecting the environmental benefits. Furthermore, lower costs per hectare could eventually end up increasing the total number of beneficiaries.

# 5 Conclusion

This paper studies the environmental effects of forest incentive programs in Guatemala. It finds that forest incentives have a positive impact on tree cover and carbon storage, with the effects becoming more pronounced over time. However, albeit significant, the results are quantitatively modest – the three programs evaluated increase tree cover and carbon storage between 4-6%.[16] This translates into monetary benefits (ecosystem services and carbon storage) between USD 13-41/hectare/year depending on the specific program evaluated. Although a complete cost/benefit exercise is not possible with the existing data, these benefits are unlikely to exceed program costs.

The findings have important implications for the design and implementation of forest incentives programs in Guatemala and other similar regions. First, it shows the importance of evaluating the impacts of forest incentive programs as it is often the case that plots that enroll in these programs would have engaged in forest conservation or restoration activities without incentives. Second, it shows the importance of tailoring forest incentives to

[16] This carbon estimate is rather small but it is on the positive side, and that is not always the case. For example, Heilmayr, Echeverría and Lambin (2020) for Chile shows evidence which indicates that forest subsidies increased tree cover through expansion of exotic species plantation but decreased the area of native forest, without increasing total carbon stored in above the ground biomass.

regions with high deforestation pressure.

We study here payments that are designed as direct incentives for forest sustainability, but there are also other indirect instruments that have the same goal Tedesco et al. (2023). For example, despite that the IDB Agrimonitor shows that support estimate for the agriculture sector in Guatemala as a share of GDP is low when compared to most of the other countries in the region (for example, TSE in Guatemala is equivalent to 0.6% of GDP when for its neighbor, Belize, it accounts for 2.59% of the gross domestic product for the last 10 years for which data are reported,i.e., 2012-2021), the linkages between forest and the sector could make worth revising if that support is oriented toward sustainability. Another indirect instrument that may affect forest sustainability is access to carbon trading. In that same direction could be international funds and grants for forest.

# References

**Aguilar-Støen, Mariel.** 2018. "Social forestry movements and science-policy networks: The politics of the forestry incentives program in Guatemala." *Geoforum*, 90: 20–26.

**Arel-Bundock, Vincent.** 2024. "marginaleffects: Predictions, Comparisons, Slopes, Marginal Means, and Hypothesis Tests." R package version 0.18.0.9.

**Bank, World.** 2021. "The changing wealth of nations 2021: managing assets for the future."

**Bastin, Jean-Francois, Yelena Finegold, Claude Garcia, Danilo Mollicone, Marcelo Rezende, Devin Routh, Constantin M Zohner, and Thomas W Crowther.** 2019. "The global tree restoration potential." *Science*, 365(6448): 76–79.

**Baumbach, Lukas, Thomas Hickler, Rasoul Yousefpour, and Marc Hanewinkel.** 2023. "High economic costs of reduced carbon sinks and declining biome stability in Central American forests." *Nature Communications*, 14(1): 2043.

**Börner, Jan, Dario Schulz, Sven Wunder, and Alexander Pfaff.** 2020. "The effectiveness of forest conservation policies and programs." *Annual Review of Resource Economics*, 12: 45–64.

**Callaway, Brantly, and Pedro HC Sant'Anna.** 2021. "Difference-in-differences with multiple time periods." *Journal of econometrics*, 225(2): 200–230.

**Cisneros, Elías, Jan Börner, Stefano Pagiola, and Sven Wunder.** 2022. "Impacts of conservation incentives in protected areas: The case of Bolsa Floresta, Brazil." *Journal of Environmental Economics and Management*, 111: 102572.

**Cristales, René Zamora, Maggie Gonzalez, Victoria Rachmaninoff, Maria Franco Chuaire, Walter Vergara, Ronnie De Camino, Andriana Miljanic, Marioldy Sanchez, Luis Hilton, Claudio Cabrera Gaillard, et al.** 2022. "Healing the Wounded Land: The Role of Public Economic Incentives in Scaling Up Restoration Efforts in Six Latin American Countries."

**Daniel Baston.** 2020. "exactextractr: Fast Extraction from Raster Datasets using Polygons." R package version 0.5.0.

**De Chaisemartin, Clément, and Xavier d'Haultfoeuille.** 2024. "Difference-in-differences estimators of intertemporal treatment effects." *Review of Economics and Statistics*, 1–45.

**De Chaisemartin, Clément, and Xavier d'Haultfoeuille.** 2020. "Two-way fixed effects estimators with heterogeneous treatment effects." *American economic review*, 110(9): 2964–2996.

**Devine, Jennifer A, Nathan Currit, Yunuen Reygadas, Louise I Liller, and Gabrielle Allen.** 2020. "Drug trafficking, cattle ranching and Land use and Land cover change in Guatemala's Maya Biosphere Reserve." *Land Use Policy*, 95: 104578.

**Dimiceli, C, R Sohlberg, and J Townshend.** 2022. "MODIS/Terra Vegetation Continuous Fields Yearly L3 Global 250m SIN Grid V061 [Data set]." *NASA EOSDIS Land Processes Distributed Active Archive Center*.

**Duncanson, L., M. Liang, V. Leitold, J. Armston, S. M. Krishna Moorthy, R. Dubayah, S. Costedoat, B. J. Enquist, L. Fatoyinbo, S. J. Goetz, M. Gonzalez-Roglich, C. Merow, P. R. Roehrdanz, K. Tabor, and A. Zvoleff.** 2023. "The effectiveness of global protected areas for climate change mitigation." *Nature Communications 2023 14:1*, 14(1): 1–13.

**Ermida, Sofia L., Patrícia Soares, Vasco Mantas, Frank M. Göttsche, and Isabel F. Trigo.** 2020. "Google Earth Engine Open-Source Code for Land Surface Temperature Estimation from the Landsat Series." *Remote Sensing 2020, Vol. 12, Page 1471*, 12(9): 1471.

**Fiorini, Ana Carolina Oliveira, Conner Mullally, Marilyn Swisher, and Francis E Putz.** 2020. "Forest cover effects of payments for ecosystem services: Evidence from an impact evaluation in Brazil." *Ecological Economics*, 169: 106522.

**Fripp, Emily.** 2014. "Payments for Ecosystem Services (PES): A practical guide to assessing the feasibility of PES projects." Bogor, Indonesia:CIFOR.

**Global Forest Watch.** 2024. "Dashboard for Guatemala." *https://www.globalforestwatch.org/dashboards/country/GTM/?map=eyJjYW5Cb3VuZCI6dHJ1ZX0*

**Goodman-Bacon, Andrew.** *2021. "Difference-in-differences with variation in treatment timing."* Journal of econometrics*, 225(2): 254–277.*

**Heilmayr, Robert, Cristian Echeverría, and Eric F Lambin.** *2020. "Impacts of Chilean forest subsidies on forest cover, carbon and biodiversity."* Nature Sustainability*, 3(9): 701–709.*

**Hijmans, Robert J., Susan E. Cameron, Juan L. Parra, Peter G. Jones, and Andy Jarvis.** *2005. "Very high resolution interpolated climate surfaces for global land areas."* International Journal of Climatology*, 25(15): 1965–1978.*

**Ho, Daniel E., Kosuke Imai, Gary King, and Elizabeth A. Stuart.** *2011. "MatchIt: Nonparametric Preprocessing for Parametric Causal Inference."* Journal of Statistical Software*, 42(8): 1–28.*

**Hui, Bronson, Wenyue Ma, and Nicolas Hübner.** *2023. "Alternatives to traditional outcome modelling approaches in applied linguistics: A primer on propensity score matching." 2(3): 100066.*

**Inter American Development Bank.** *2020. "Guatemala SUSTAINABLE FOREST MANAGEMENT PROJECT."* https://pubdocs.worldbank.org/en/962621571172386122/6428-XFIPGT033A-Guatemala-Sustainable-Forest-Management-Project-Document.pdf*.*

**Jarvis, A., E. Guevara, H.I. Reuter, and A.D. Nelson.** *2008. "Hole-filled SRTM for the globe : version 4 : data grid." Published by CGIAR-CSI on 19 August 2008.*

**Jayachandran, Seema, Joost De Laat, Eric F Lambin, Charlotte Y Stanton, Robin Audy, and Nancy E Thomas.** *2017. "Cash for carbon: A randomized trial of payments for ecosystem services to reduce deforestation."* Science*, 357(6348): 267–273.*

**Larrazábal Melgar, LB, E Oliva Hurtarte, Muhammad Ibrahim, and Guillermo Detlefsen.** *2009. "Programa de incentivos forestales (PINFOR) de Guatemala."* Buenas prácticas agrícolas para la adaptación al cambio climático*.*

**Lehner, Bernhard, and Günther Grill.** *2013. "Global river hydrography and network routing: baseline data and new approaches to study the world's large river systems."* Hydrological Processes*, 27(15): 2171–2186.*

**Nelson, Andy, Daniel J. Weiss, Jacob van Etten, Andrea Cattaneo, Theresa S. McMenomy, and Jawoo Koo.** *2019. "A suite of global accessibility indicators."* Scientific Data 2019 6:1*, 6(1): 1–9.*

**Patrick, Evan, Van Butsic, and Matthew D Potts.** *2023. "Using payment for ecosystem services to meet national reforestation commitments: impacts of 20+ years of forestry incentives in Guatemala."* Environmental Research Letters*, 18(10): 104030.*

**Perevochtchikova, Maria, Ricardo Castro-Díaz, Alfonso Langle-Flores, and Juan José Von Thaden Ugalde.** *2021. "A systematic review of scientific publications on the effects of payments for ecosystem services in Latin America, 2000–2020."* Ecosystem Services*, 49: 101270.*

**Potapov, Peter, Matthew C. Hansen, Amy Pickens, Andres Hernandez-Serna, Alexandra Tyukavina, Svetlana Turubanova, Viviana Zalles, Xinyuan Li, Ahmad Khan, Fred**

**Stolle, Nancy Harris, Xiao Peng Song, Antoine Baggett, Indrani Kommareddy, and Anil Kommareddy.** *2022. "The Global 2000-2020 Land Cover and Land Use Change Dataset Derived From the Landsat Archive: First Results."* Frontiers in Remote Sensing*, 3: 856903.*

**QGIS Development Team.** *2024. "QGIS Geographic Information System." QGIS Association.*

**R Core Team.** *2018. "R: A Language and Environment for Statistical Computing."*

**R., Giudice, and J. Borner.** *2021. "Benefits and costs of incentive-based forest conservation in the Peruvian Amazon."* Forest Policy and Economics*, 131: 102559.*

**Ruggiero, Patricia GC, Jean Paul Metzger, Leandro Reverberi Tambosi, and Elizabeth Nichols.** *2019. "Payment for ecosystem services programs in the Brazilian Atlantic Forest: Effective but not enough."* Land use policy*, 82: 283–291.*

**Spawn, Seth A., Clare C. Sullivan, Tyler J. Lark, and Holly K. Gibbs.** *2020. "Harmonized global maps of above and belowground biomass carbon density in the year 2010."* Scientific Data 2020 7:1*, 7(1): 1–22.*

**Tedesco, Anazelia M, Pedro HS Brancalion, Michelle L Hak Hepburn, Khalil Walji, Kerrie A Wilson, Hugh P Possingham, Angela J Dean, Nick Nugent, Katerina Elias-Trostmann, Katharina-Victoria Perez-Hammerle, et al.** *2023. "The role of incentive mechanisms in promoting forest restoration."* Philosophical Transactions of the Royal Society B*, 378(1867): 20210088.*

**Tellman, Beth, Steven E Sesnie, Nicholas R Magliocca, Erik A Nielsen, Jennifer A Devine, Kendra McSweeney, Meha Jain, David J Wrathall, Anayasi Dávila, Karina Benessaiah, et al.** *2020. "Illicit drivers of land use change: Narcotrafficking and forest loss in Central America."* Global Environmental Change*, 63: 102092.*

**UNEP-WCMC.** *2024. "Protected Area Profile for Guatemala from the World Database on Protected Areas."*

**vonHedemann, Nicolena.** *2020. "Transitions in payments for ecosystem services in Guatemala: Embedding forestry incentives into rural development value systems."* Development and Change*, 51(1): 117–143.*

**VonHedemann, Nicolena.** *2023. "The importance of communal forests in carbon storage: Using and destabilizing carbon measurement in understanding Guatemala's payments for ecosystem services."* The Canadian Geographer/Le Géographe canadien*, 67(1): 106–123.*

**Von Thaden, Juan, Robert H Manson, Russell G Congalton, Fabiola López-Barrera, and Jacob Salcone.** *2019. "A regional evaluation of the effectiveness of Mexico's payments for hydrological services."* Regional Environmental Change*, 19: 1751–1764.*

**World Bank.** *2024. "World Development Indicators Database."* https://databank.worldbank.org/source/world-development-indicators*.*

**Wunder, Sven, Jan Börner, Driss Ezzine-de Blas, Sarah Feder, and Stefano Pagiola.** *2020. "Payments for environmental services: Past performance and pending potentials."* Annual Review of Resource Economics*, 12: 209–234.*

**Yang, Linqing, Kun Jia, Shunlin Liang, Xiangqin Wei, Yunjun Yao, Xiaotong Zhang, Linqing Yang, Kun Jia, Shunlin Liang, Xiangqin Wei, Yunjun Yao, and Xiaotong Zhang.** *2017. "A Robust Algorithm for Estimating Surface Fractional Vegetation Cover from Landsat Data."* RemS*, 9(8): 857.*

**et al., Seema Jayachandran.** *2017. "Cash for carbon: A randomized trial of payments for ecosystem services to reduce deforestation."* Science*, 327: 267–273.*

# FOR ONLINE PUBLICATION

# Appendix to "The Long Run Effects of Forest Incentives on Forest Cover and Carbon Storage"

**Table of Contents**


A Datasets and variables used 1

B Building Controls 4

C Propensity Score Matching (PSM) 6

D Modelling Above and Below-Ground Biomass Carbon Density 9

E Additional Results 11

# A Datasets and variables used

Table A.1 summarizes the datasets and variables used in our analysis for propensity score matching and to model above and below-ground biomass carbon density. Table A.2 presents descriptive statistics for the four outcome variables used in this assessment (tree cover, above and below ground biomass carbon, Landsat 7 FVC, and Landsat 7 NDVI) for treated and matched untreated plots.

Table A.1: Summary of data used for modelling

| Name | Concept | Units | Time coverage | Spatial resolution | Data source |
|---|---|---|---|---|---|
| agbc | Above ground biomass carbon | MgC/ha | 2010 | 300m | Spawn et al. (2020) |
| bgbc | Below ground biomass carbon | MgC/ha | 2010 | 300m | Spawn et al. (2020) |
| y | y coordinate of plot centroid | degrees | - | - | Calculated with R based on data provided by INAB |
| x | x coordinate of plot centroid | degrees | - | - | Calculated with R based on data provided by INAB |
| landsat_ndvi | annual mean normalised difference vegetation index (NDVI) | - | 2001-2023 | 100m(*) | Ermida et al. (2020) |
| landsat_lst | annual mean land surface temperature | Kelvin | 2001-2023 | 100m(*) | Ermida et al. (2020) |
| landsat_fvc | annual mean fractional vegetation cover | fraction | 2001-2023 | 100m(*) 30m(**) | Ermida et al. (2020) |
| landsat_em | annual mean emissivity | fraction | 2001-2023 | 100m(*) | Ermida et al. (2020) |
| glad_forest_cover | mean forest cover | fraction | 2000, 2020 | 30m | Potapov et al. (2022) |
| glad_forest_height | mean forest height | meters | 2000, 2020 | 30m | Potapov et al. (2022) |
| elevation | distance above sea level | meters | - | 90m | Jarvis et al. (2008) |
| slope | measure of steepness | degrees | - | 90m | Jarvis et al. (2008) |
| aspect | orientation of slope in degrees from 0 to 360 | degrees | - | 90m | Jarvis et al. (2008) |
| modis_perc_tree | tree cover | % | 2001-2023 | 250m | Dimiceli, Sohlberg and Townshend (2022) |
| modis_perc_nontree_veg | non-tree cover | % | 2001-2023 | 250m | Dimiceli, Sohlberg and Townshend (2022) |
| modis_perc_nonveg | non-vegetation cover | % | 2001-2023 | 250m | Dimiceli, Sohlberg and Townshend (2022) |
| ttc_20k | Travel time to cities with a population larger than 20k | minutes | - | 100m | Nelson et al. (2019) |
| dist_to_river_2010 | Distance to rivers and streams | meters | 2010 | - | Lehner and Grill (2013) |
| annualPrecip | Mean annual precipitation | mm | average 1970-2000 | 100m | Hijmans et al. (2005) |
| annualMeanTemp | Mean annual temperature | °C | average 1970-2000 | 100m | Hijmans et al. (2005) |
| precipDriestMonth | Precipitation during driest month | mm | average 1970-2000 | 100m | Hijmans et al. (2005) |

(*) Original resolution at 30m, but calculated at 100m due to resource restriction
(**) additionally calculated at 30m to estimate treatment effect

Table A.2: Descriptive statistics for outcome variables (2001, 2023, and change)

| Variable | Treated All | Treated PINFOR | Treated PINPEP | Treated PROBOSQUE | Untreated* All |
|---|---|---|---|---|---|
| *Tree cover (%)* | | | | | |
| 2001 | 44.7 (20.2) | 44.4 (21.2) | 42.8 (20) | 51 (18.9) | 45.1 (18.8) |
| 2023 | 48.2 (18.9) | 47.4 (18) | 46.9 (19.1) | 52.9 (18) | 46.6 (18) |
| Change between 2001 and 2023 | 3.5 (11.4) | 3 (14) | 4.1 (10.4) | 1.8 (12.5) | 1.5 (12.9) |
| *Above the ground biomass carbon (MgC/ha)* | | | | | |
| 2001 | 61.9 (24.5) | 57.5 (27.8) | 61.7 (23.8) | 64.9 (24.2) | 61.4 (23) |
| 2023 | 66.4 (21.4) | 62.9 (22.4) | 67 (21.3) | 66.6 (21) | 64.2 (21.4) |
| Change between 2001 and 2023 | 4.5 (10.8) | 5.4 (14.8) | 5.3 (9.3) | 1.6 (11.8) | 2.8 (12.2) |
| *Landsat 7 FVC (-)* | | | | | |
| 2001 | 0.56 (0.238) | 0.583 (0.263) | 0.519 (0.223) | 0.674 (0.229) | 0.568 (0.231) |
| 2023 | 0.67 (0.186) | 0.694 (0.171) | 0.648 (0.191) | 0.723 (0.166) | 0.658 (0.172) |
| Change between 2001 and 2023 | 0.11 (0.184) | 0.11 (0.191) | 0.129 (0.18) | 0.049 (0.176) | 0.09 (0.19) |
| *Landsat 7 NDVI (-)* | | | | | |
| 2001 | 0.651 (0.137) | 0.672 (0.138) | 0.628 (0.132) | 0.71 (0.13) | 0.662 (0.134) |
| 2023 | 0.719 (0.103) | 0.734 (0.089) | 0.707 (0.108) | 0.748 (0.091) | 0.719 (0.094) |
| Change between 2001 and 2023 | 0.068 (0.111) | 0.062 (0.101) | 0.079 (0.11) | 0.037 (0.112) | 0.057 (0.113) |

* mean (standard deviation) for treated and matched untreated plots

# B Building Controls

Following methods used by Patrick, Butsic and Potts (2023) we created 500,663 non-overlapping 100m radius (3.1ha) potential control plots using the Open Source Geographic Information System QGIS (version 3.22.8-Białowieża) (QGIS Development Team, 2024). We used the following procedure:

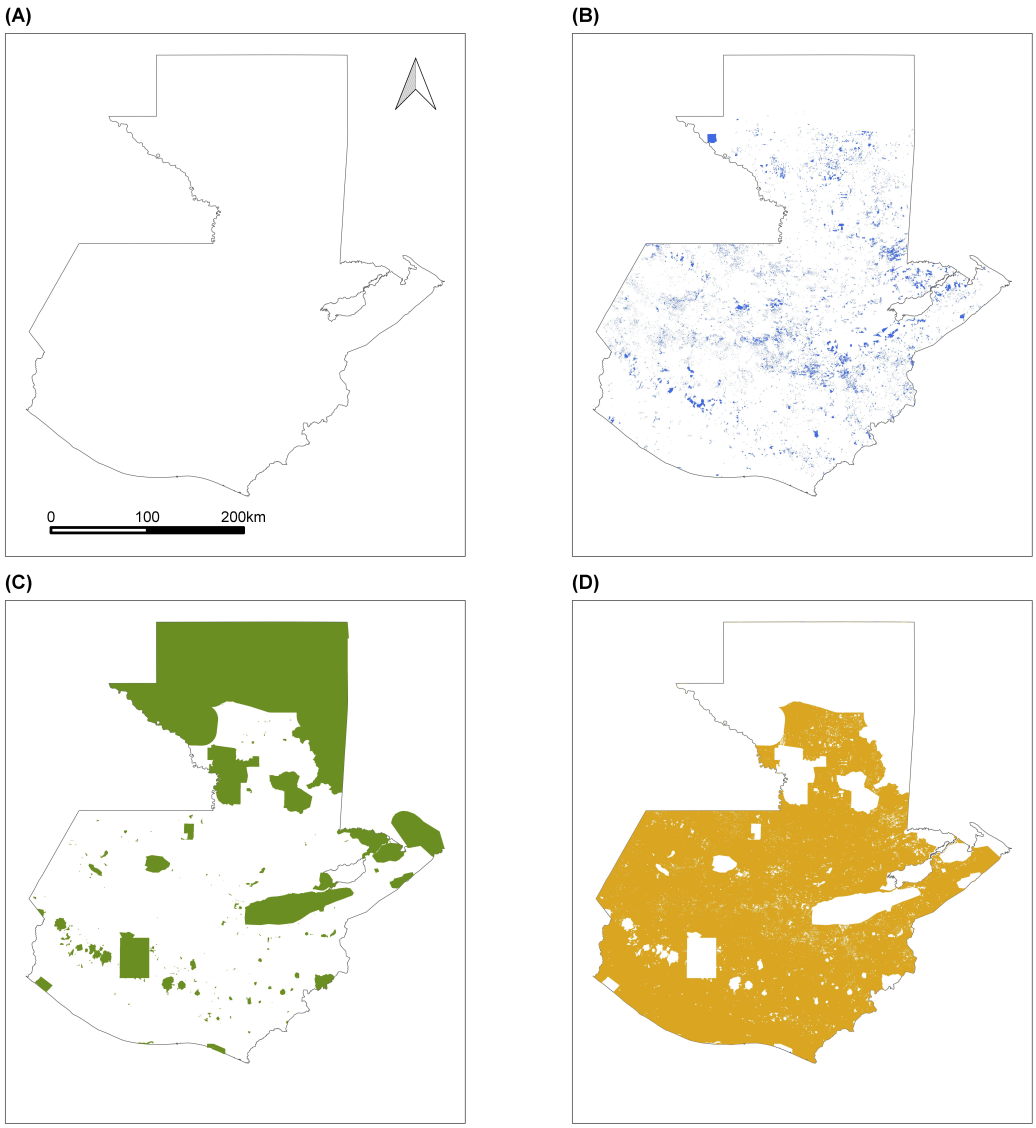
1. We identify the area within Guatemala that doesn't contain any forest incentive projects (INAB's database) nor any protected areas (UNEP-WCMC, 2024). We do this by using the "Difference" algorithm in combination with the country, forest incentives and protected areas shapefiles.

2. We generate a 350m x 350m grid using the "create grid" algorithm (rectangle) for the extent of the area identified in 1). A total of 1,607,148 grid cells were generated.

3. We use the "Extract by location" algorithm to extract grid cells from 2) that 'are within' the area identified in 1). A total of 500,663 grid cells are extracted.

4. We use the "Geometry by expression" algorithm to generate circular plots of 100m radius ( 3.1 hectares) centered on grid cells extracted in 3).

Figure B.1: Maps of (A) Guatemala, (B) INAB's forest incentives, (C) Protected Areas, and (D) Search area for controls




After this, we used propensity score matching to select one control plot for each treated plot. This procedure is detailed in appendix C.

# C Propensity Score Matching (PSM)

We used propensity score matching to select 1 control for each treated plot. The process we used, adapted from Hui, Ma and Hübner (2023), is as follows:

1. **Choose relevant covariates**: following methods used by Patrick, Butsic and Potts (2023) we selected the following covariates: (1) elevation, (2) aspect, (3) slope, (4) GLAD forest cover 2000, (5) GLAD forest height 2000, (6) travel time to cities with a population larger than 20k, (7) distance to rivers and streams, (8) mean annual precipitation (mean of 1970-2000), (9) mean annual temperature (mean of 1970-2000), and (10) precipitation of driest month (mean of 1970-2000).

2. **Extraction of covariates**: we used the 'exact_extractr' function from the 'exactextracr' R package (Daniel Baston, 2020) to extract the mean values for the selected covariates for each of the treated and untreated (or control) plots. After this process, we dropped all plots (treated and untreated) that had missing data, ending up with 79020 treated plots and 489061 potential control plots.

3. **Estimate the propensity score**: We modelled the propensity score using the MatchIt package (Ho et al., 2011) in the R statistical software (R Core Team, 2018). Treated plots were assigned a value of 1 while control plots were assigned a value of 0. For our main analysis, we used a logistic regression with no replacement and all controls (489,061 controls with complete data on covariates). We performed the following sensitivity analyses:

   (a) *function for calculating the propensity score* - we used the following alternative functions or methods to calculate the propensity score: probit, gam, lasso, ridge, glmnet, bart, and randomforest.

   (b) *replacement of controls* - we calculated with and without replacement of controls.

   (c) *number of potential controls* - we tested allowing the algorithm to select from the following number of controls: 97800, 195600, 293400, 391200, or 489061 (all potential controls).

4. **Match treated and untreated**: After modelling, we used the 'match.data' function from the MatchIt package, which matches treated and untreated plots minimising the distance between them (i.e., the propensity score).

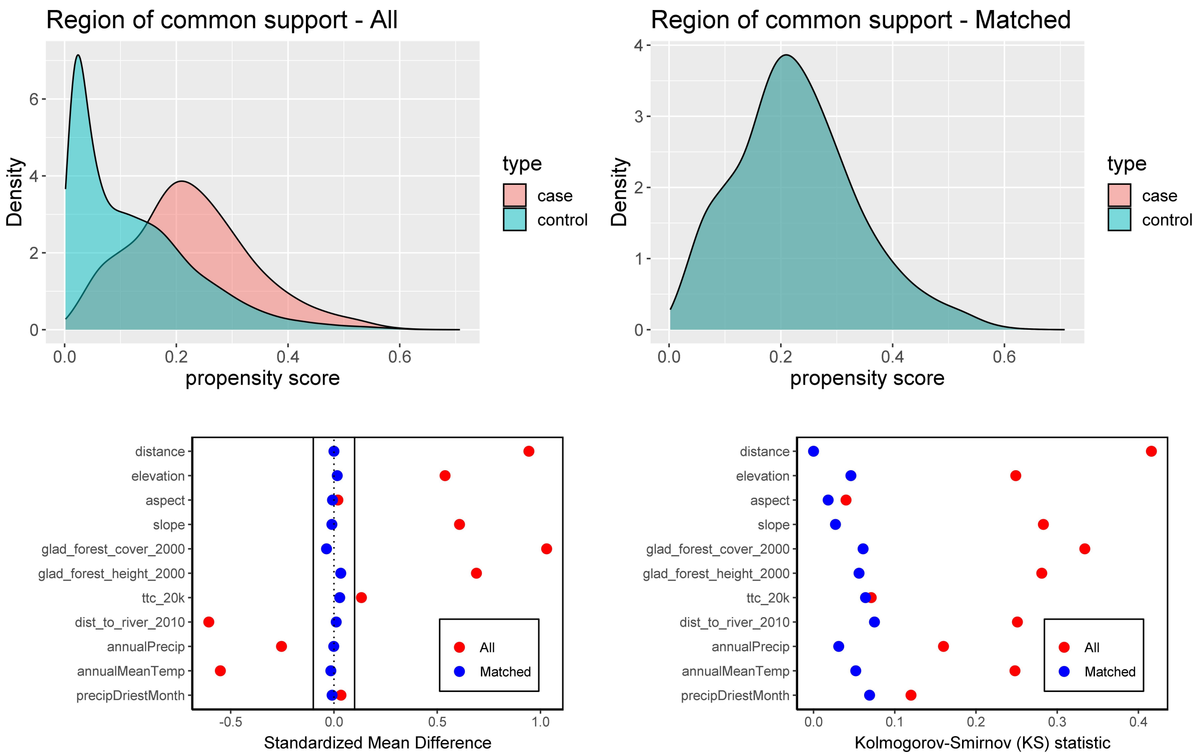
5. **Evaluate matches**: We evaluate our matching procedure using different methods:

   (a) *visual inspection*: we look at the region of common support before and after matching, and different density plots to check covariate balance.

   (b) *t-test*: we calculate t-test to test for differences in means between treated and untreated plots after matching

   (c) *Kolmogorov–Smirnov test*: we apply the Kolmogorov-Smirnov Goodness of Fit Test (K-S test) to compare if covariates from treated and untreated plots have the same distribution.

Figure C.1: Summary for main matching model




| | Means Treated | Means Control | Std. Mean Diff. | t_stat | p_value_t | ks_stat | p_value_ks |
|---|---|---|---|---|---|---|---|
| *distance* | 0.23 | 0.23 | 0 | 0 | 0.9977 | 0 | 1 |
| *elevation* | 1336.9 | 1322.14 | 0.016 | 3.37 | 0.0008 | 0.046 | 0 |
| *aspect* | 177.72 | 178.32 | -0.007 | -1.45 | 0.1471 | 0.018 | 0 |
| *slope* | 15.31 | 15.4 | -0.01 | -1.9 | 0.0574 | 0.027 | 0 |
| *glad_forest_cover_2000* | 0.89 | 0.9 | -0.036 | -7.66 | 0 | 0.061 | 0 |
| *glad_forest_height_2000* | 13.45 | 13.22 | 0.033 | 6.79 | 0 | 0.056 | 0 |
| *ttc_20k* | 83.89 | 81.1 | 0.028 | 5.45 | 0 | 0.064 | 0 |
| *dist_to_river_2010* | 255.17 | 250.16 | 0.011 | 2.06 | 0.0396 | 0.075 | 0 |
| *annualPrecip* | 1902.57 | 1903.35 | -0.001 | -0.18 | 0.8569 | 0.031 | 0 |
| *annualMeanTemp* | 19.92 | 20 | -0.015 | -3.19 | 0.0014 | 0.052 | 0 |
| *precipDriestMonth* | 36.64 | 36.95 | -0.009 | -1.68 | 0.0925 | 0.069 | 0 |

# D Modelling Above and Below-Ground Biomass Carbon Density

We trained a random forest model to predict above and below ground biomass carbon (abgbc) density for years 2001-2009 and 2011-2023. We modelled abgbc as a function of: (1) x coordinate, (2) y coordinate, (3) elevation, (4) aspect, (5) slope, (6) GLAD forest cover (mean of 2000 and 2020), (7) GLAD forest height (mean of 2000 and 2020), (8) mean annual precipitation (mean of 1970-2000), (9) mean annual temperature (mean of 1970-2000), and (10) precipitation of driest month (mean of 1970-2000), (11) MODIS tree cover (%), (12) MODIS non-tree vegetation cover (%), (13) MODIS non-vegetation cover (%), (14) LANDSAT land surface temperature, (15) LANDSAT fractional vegetation cover, (16) LANDSAT emissivity, (17) LANDSAT NDVI. In our model, the independent variable was abgbc for 2010 from Spawn et al. (2020), which was calculated as the sum of above- and below-ground biomass carbon density. A full dataset for 2010 was used to train our model. Variables (1)-(10) were kept constant for all years, while MODIS (11-13) and LANDSAT (14-17) variables varied each year.

To develop our model we first split our dataset (2010 data) into a training (90% of dataset) and a validation set (10% of dataset). We tested the performance of our model with the out-of-bag (OOB) R-squared and the R-squared calculated on the validation set (unseen data). Our model obtained similar performance values for OOB and validation with an R-squared of 81.5% and a root mean squared error (RMSE) of 13.8. Figure D.1 shows a scatter plot of predicted vs. original values from (Spawn et al., 2020) for the validation set (i.e., 10% of left out data).

The top 5 most important variables (Figure D.2) were: (1) GLAD forest height, (2) GLAD forest cover, (3) MODIS tree cover, (4) MODIS non-tree vegetation cover, and (5) LANDSAT FVC.

Figure D.1: Predicted vs. (Spawn et al., 2020) above and below ground biomass carbon density: (A) out-of-bag, (B) validation set

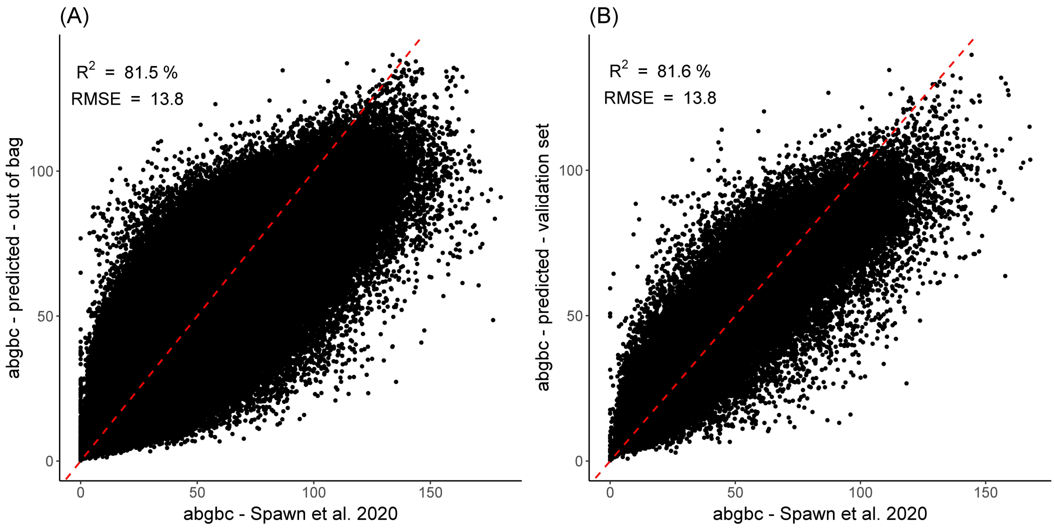
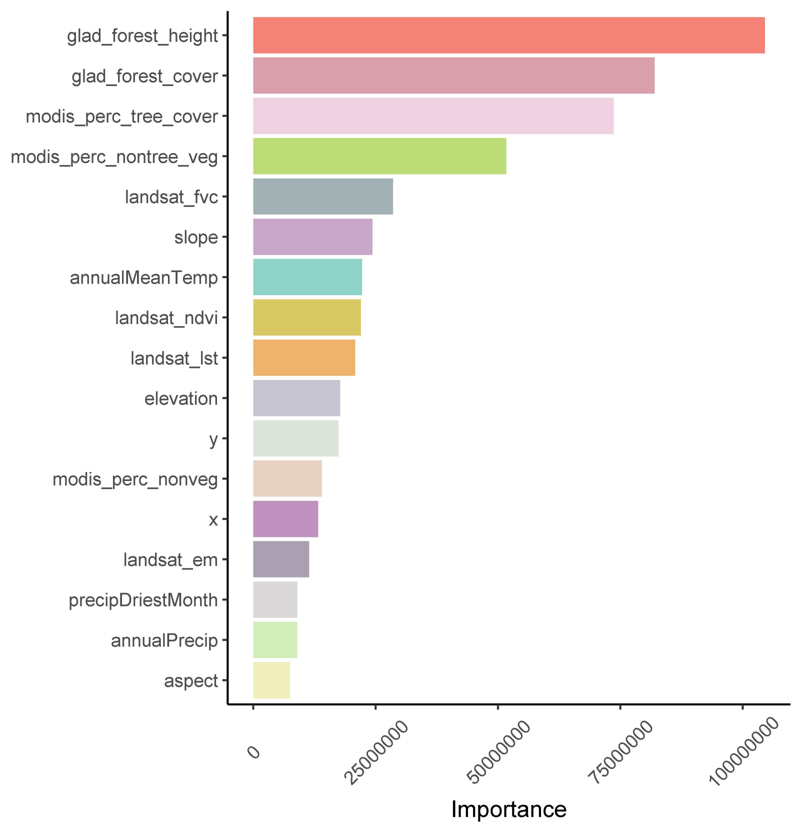



Figure D.2: Variable importance of random forest model



# E Additional Results

Figure E.1: The Effects of Forest Incentives on tree cover (%), abgbc (Mg/ha), FVC (-), and NDVI(-): DID w/matching

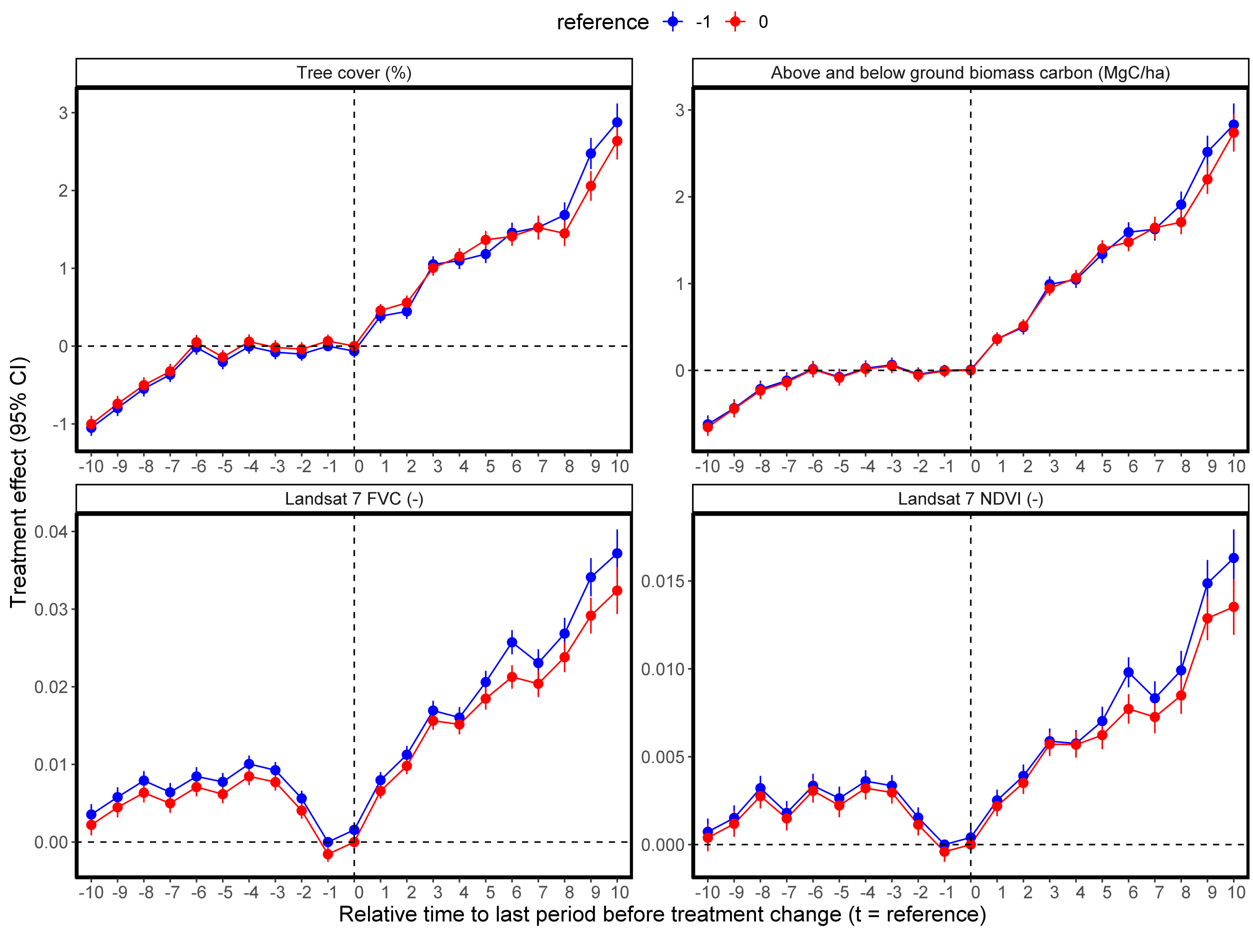


Figure E.2: The Effects of Forest Incentives on tree cover (%), abgbc (Mg/ha), FVC (-), and NDVI(-): DID w/matching vs. event study

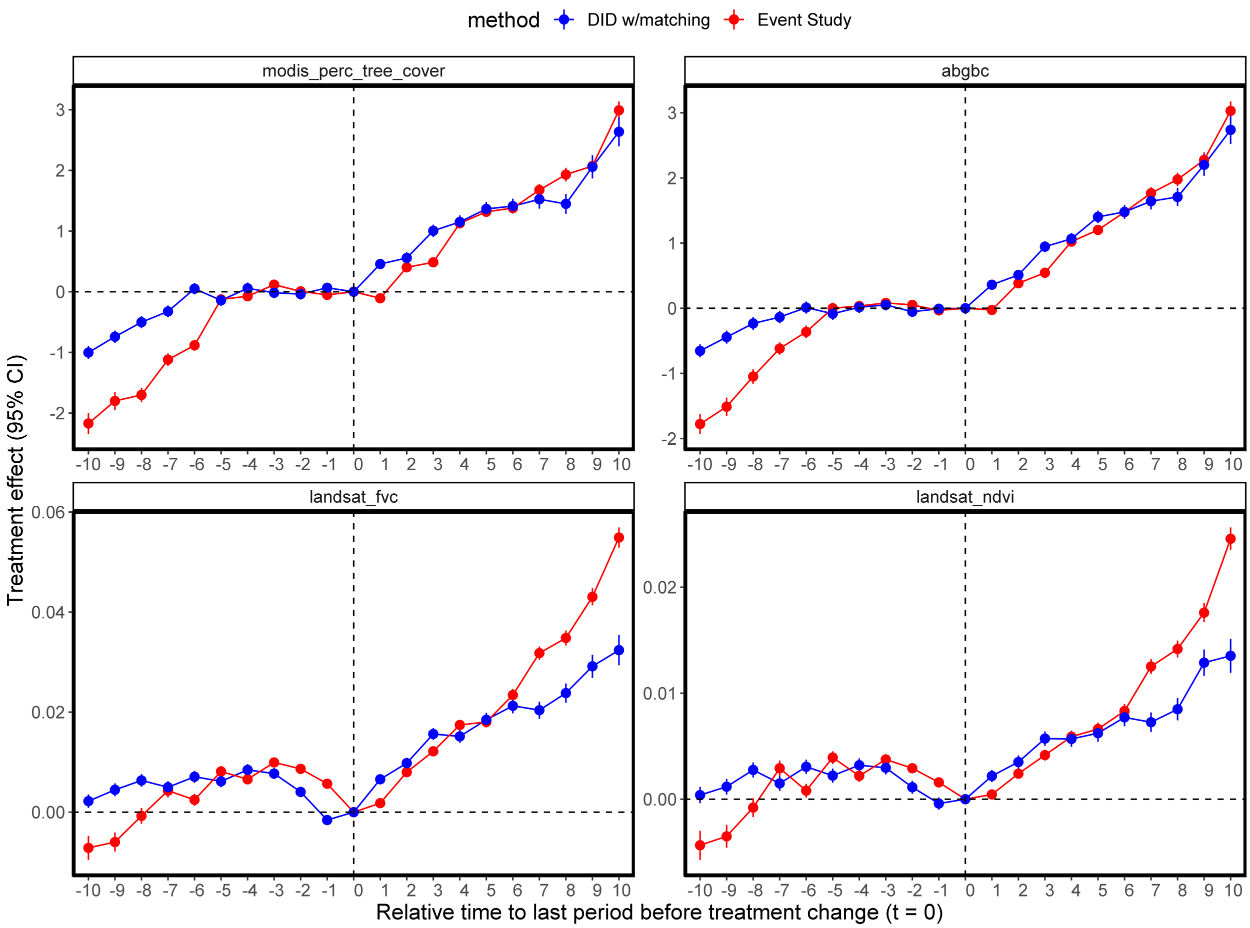



Table E.1: Treatment effect by outcome variable and assessment method

| **Outcome variable** | **Years since treatment** | **DID w/matching** | **Event study estimator** |
|---|---|---|---|
| Tree cover (%) | 5 | 0.81 (0.69 - 0.92)*** | 1.32 (1.23 - 1.4)*** |
| | 10 | 2.51 (2.27 - 2.76)*** | 2.99 (2.84 - 3.14)*** |
| Above and below ground biomass carbon | 5 | 1.01 (0.91 - 1.11)*** | 1.2 (1.13 - 1.28)*** |
| | 10 | 2.69 (2.46 - 2.92)*** | 3.03 (2.88 - 3.17)*** |
| Landsat 7 FVC | 5 | 0.02 (0.02 - 0.02)*** | 0.02 (0.02 - 0.02)*** |
| | 10 | 0.03 (0.03 - 0.04)*** | 0.05 (0.05 - 0.06)*** |
| Landsat 7 NDVI | 5 | 0.01 (0.01 - 0.01)*** | 0.01 (0.01 - 0.01)*** |
| | 10 | 0.01 (0.01 - 0.02)*** | 0.02 (0.02 - 0.03)*** |

**Notes:** *** p<0.01; ** p<0.05; * p<0.10.

Figure E.3: Treatment effect by program and years of treatment (DID w/matching) - Tree Cover (%) and Above and Below Ground Biomass Carbon (MgC/ha)

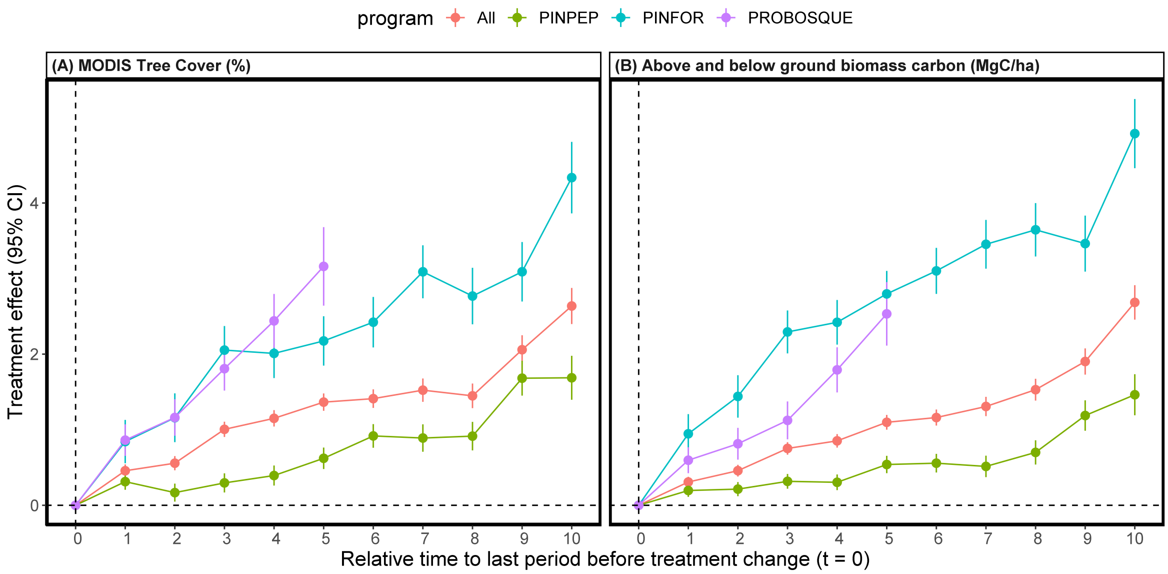



Figure E.4: Treatment effect by project type and years of treatment (DID w/matching) - Tree Cover (%) and Above and Below Ground Biomass Carbon (MgC/ha)

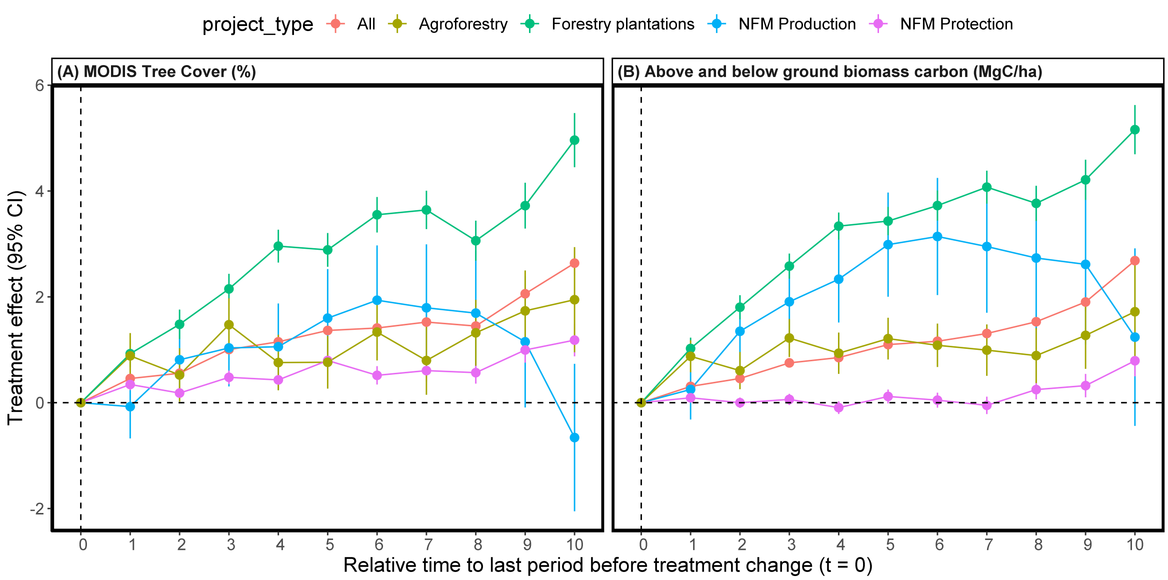


Figure E.5: The Effects of Forest Incentives on Tree Cover (%) and Above and below ground biomass carbon (MgC/ha) by Department - 10 years since treatment

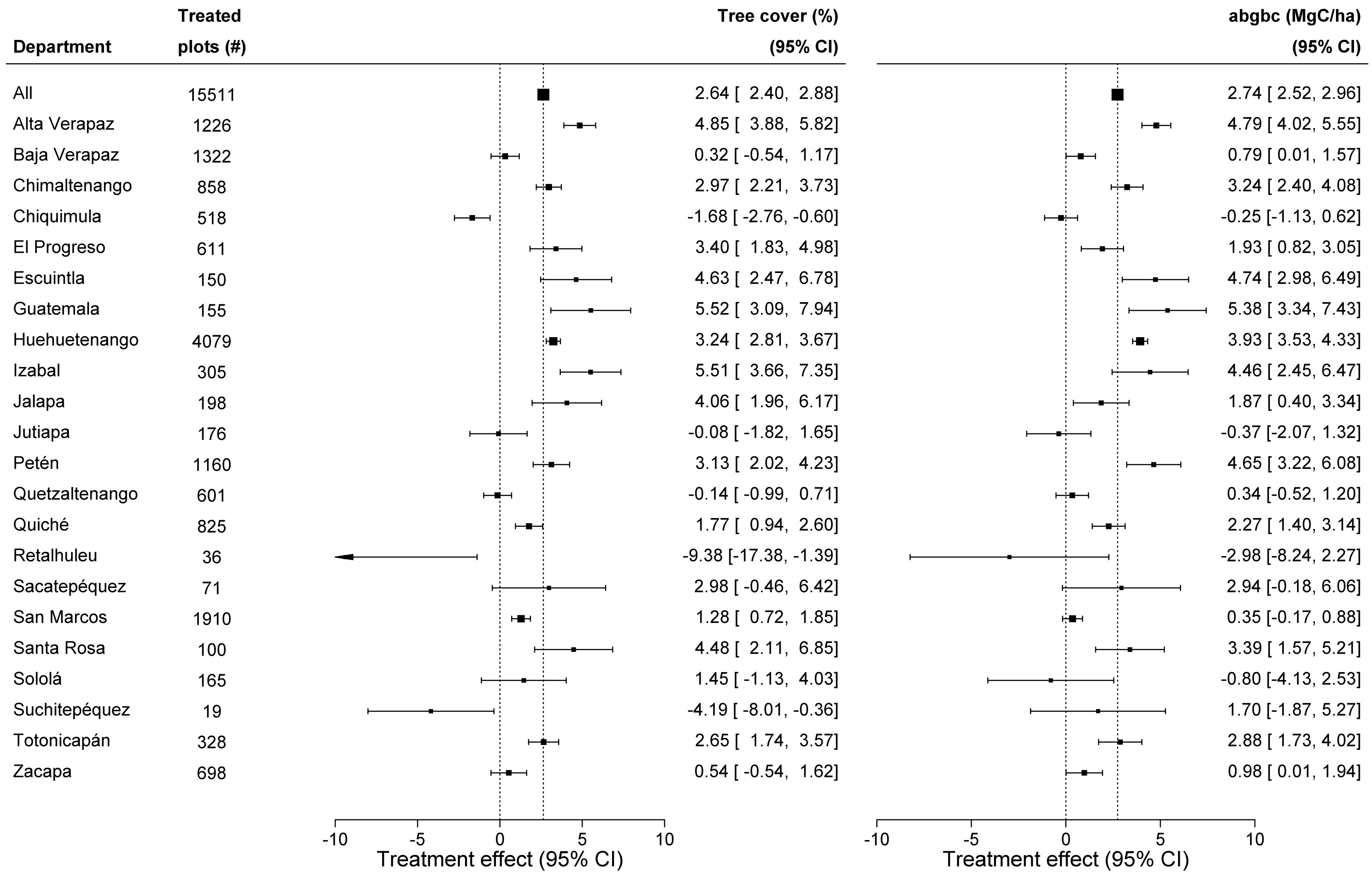


Figure E.6: The Effects of Forest Incentives on Tree Cover (%) and Above and below ground biomass carbon (MgC/ha) by Ecoregion - 10 years since treatment

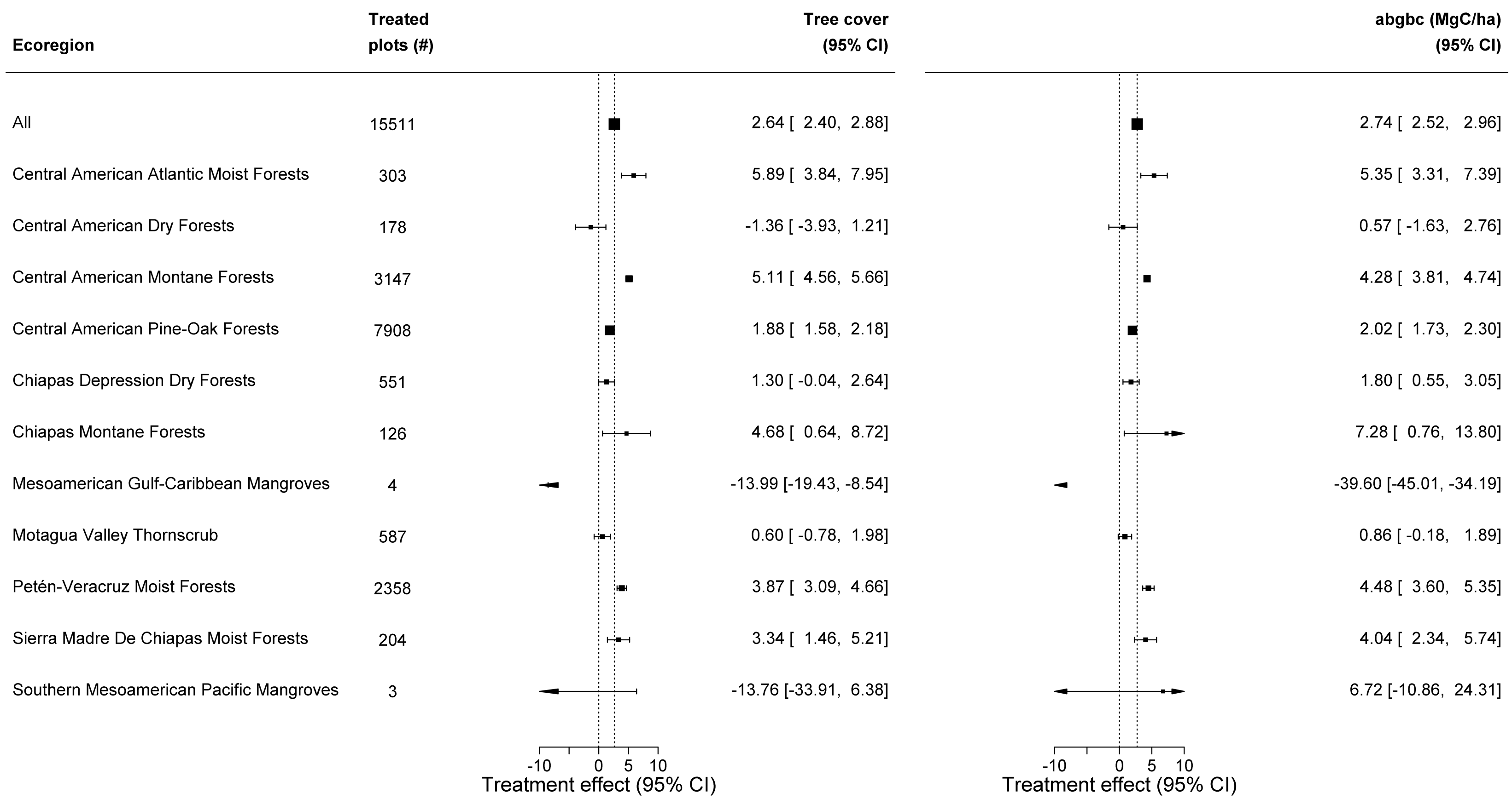


Figure E.7: Treatment effect by (A) Region, (B) Department and (C) Ecoregion (DID w/matching) - Tree Cover (%) - 10 years after treatment

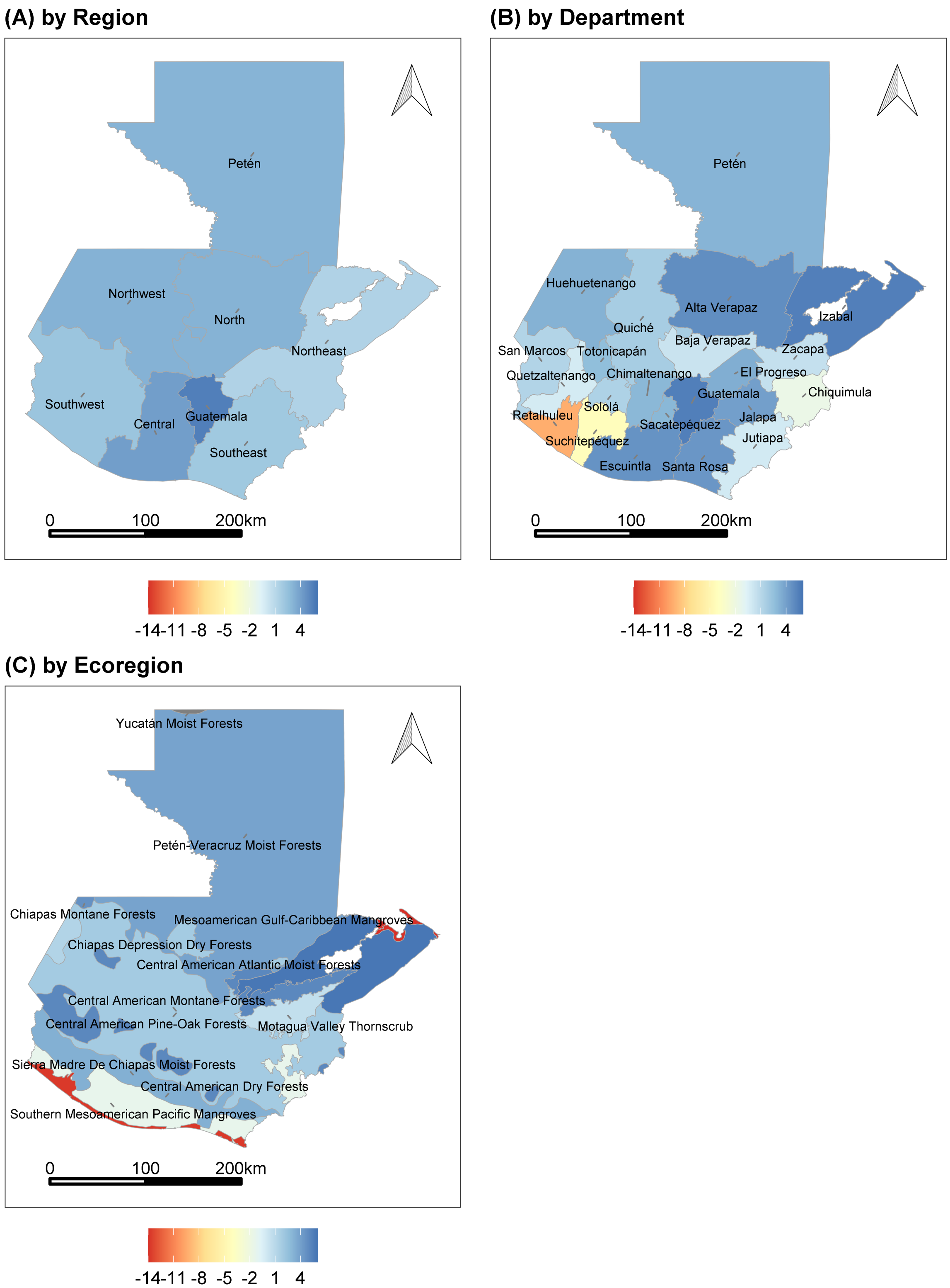


Figure E.8: Treatment effect by initial conditions (10th and 90th percentiles) after 10 years by model used for matching - DID w/matching

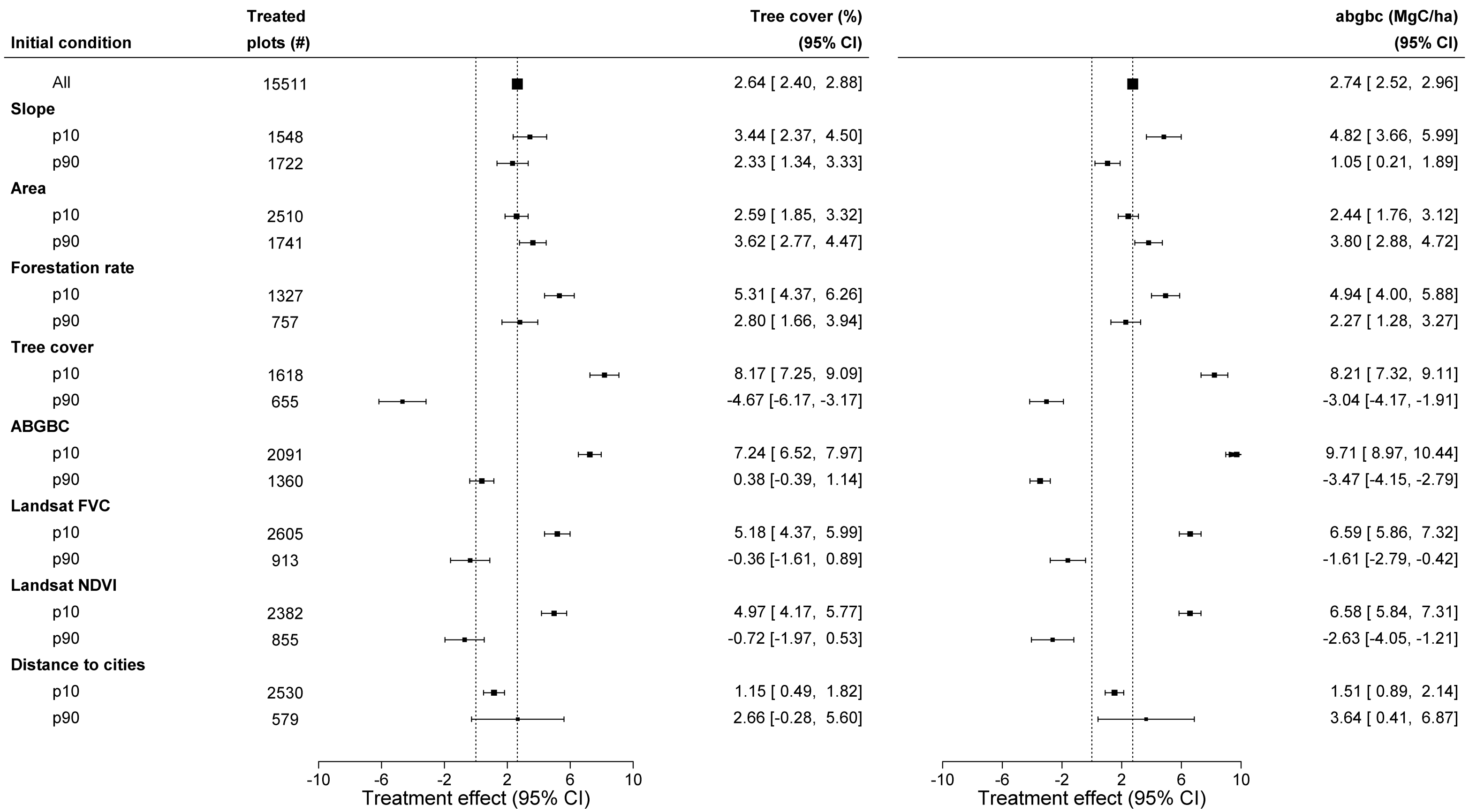


Figure E.9: Treatment effect (all programs) after 10 years by model used for matching - DID w/matching