Three Essays on the Economics of Tropical Deforestation

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Abstract

This thesis examines how policy instruments and agricultural productivity factors influence deforestation in the Colombian Amazon, a region where environmental, poverty, and national security concerns intersect. Forest loss remains one of the most pressing environmental and development challenges, driven by both illicit activities—particularly coca cultivation—and legal agricultural expansion along the forest frontier.

The thesis comprises three chapters, each addressing one of the following research questions: (i) How do anti-drug policies affect deforestation? (ii) Can military enforcement curb illegal deforestation? and (iii) How are agricultural incentives correlated with farmers' land-clearing decisions at the forest frontier?

To address the first question, we investigate whether supply-side anti-drug enforcement generates ancillary environmental benefits. Exploiting a policy-induced discontinuity created by the suspension of the anti-drug program along the Colombian–Ecuadorian border (2008–2013), we provide causal evidence that anti-drug enforcement had no measurable effect on forest loss, challenging the assumption that drug enforcement can serve as an effective conservation tool.

The second question is addressed by assessing the impact of militarised, place-based interventions on illegal deforestation hotspots in Amazon protected areas. As a case study, we evaluate Operation Artemis (2019–2022), the largest anti-deforestation military intervention in Colombia. Using a quasi-experimental design in a staggered difference-in-differences framework, we find short-term reductions in illegal deforestation, alongside a potentially high cost-effectiveness ratio.

Finally, to address question (iii), we investigate whether agricultural productivity is correlated with deforestation and estimate the opportunity cost of conservation across Colombian Amazon farms. We model farmers' land-clearing decisions using data from over 39,000 Amazon farms and satellite imagery and find that opportunity costs vary widely across farms and are positively associated with crop profitability. Furthermore, our results suggest that improving access to credit and technical assistance can strengthen environmental and agricultural policies.

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Introduction

> *"The Absent Feedback Loop: Latin America does adjust by types of reform, by writing new laws and constitutions, but not based on feedback from the realities of implementation. Instead, it relies on an alternative Utopian/Ideal project, which it adds to the failed one."*
>
> — James A. Robinson, Nobel Memorial Prize in Economic Sciences

Tropical deforestation is a major driver of climate change and a first-order contributor to biodiversity loss (Achard et al., 2014; Bradshaw et al., 2009). Despite costly policy efforts, forest clearance in the Amazon biome remains one of the most pressing environmental and development challenges in Latin America, as land-use dynamics are closely linked to both legal and illegal economies that fuel conflict, poverty, and violence across the region (UNODC, 2025, 2023*a*; Davalos et al., 2021). Policies have been developed, reinstated, and modified, yet empirical evaluations remain scarce, limiting the understanding of the "realities of implementation." This thesis addresses this gap by providing empirical evidence on how policy interventions and agricultural factors influence deforestation in the Amazon rainforest.

The Colombian Amazon, which accounts for more than 40% of the country's territory, has served as a vital carbon sink for the world and is well known for its biological richness and cultural heritage (Garzón and Valánszki, 2019). Yet, it is also a region with historically limited state presence and high levels of poverty, both facilitating conditions for the emergence and continued operation of powerful organised criminal groups that control the world's highest concentration of coca cultivation (UNODC, 2023*b*). Deforestation linked with these criminal activities, a phenomenon known as narco-deforestation (Devine et al., 2021; Sesnie et al., 2017), has prompted the implementation of different enforcement strategies to curb cocaine production and mitigate its environmental externalities (Ministerio de Defensa Nacional, 2022). However, constraints on enforcement capacity in remote areas have driven a wedge between the initial *de iure* design of forest management policies and their *de facto* implementation, with no evaluation to assess the magnitude of this divergence.

In Colombia, environmental targets have become closely tied to national security concerns, as organised crime is concentrated in natural resource-rich areas (Clerici et al., 2020). Moreover, land conflicts arising from the coexistence of licit and illicit activities in the region have promoted the combination of conservation strategies with military interventions to recover natural forest from illicit uses (Ministerio de Defensa Nacional, 2022). Since the signing of the Peace Agreement in 2016, several anti-narcotics policies have been reformed and new conservation strategies implemented. Anti-drug policies shifted toward interdiction efforts and voluntary crop substitution rather than forced coca eradication. Meanwhile, post-conflict conservation strategies focused on expanding the extent of legally protected natural areas and incentivising forest preservation through payments compensating farmers for forgone agricultural revenues (Rodríguez-de Francisco et al., 2021). However, the recent resurgence of coca cultivation and illegal deforestation (UNODC, 2025; IDEAM, 2025) has renewed interest in reinstating forced aerial eradication as a central tool for drug control, alongside the militarisation of protected areas as a key strategy to curb narco-deforestation.

The spatial overlap between deforested areas and placed-based enforcement strategies targeting criminal organisations is widely recognised in the Colombian Amazon, yet its underlying causal mechanisms remain poorly understood. In previous literature, there is limited attention to the endogeneity arising from the fact that narco-deforestation campaigns have tended to target areas already experiencing elevated rates of deforestation, introducing policy selection bias that complicates causal interpretation.

(i) How do anti-drug policies affect deforestation? This question is addressed in Chapter 1, titled ”Conservation by Eradication? Lessons from Drug Enforcement and Deforestation in Colombia”. The study engages with the debate over whether supply-side drug control policies can generate ancillary environmental benefits. In particular, we examine the impact of the region’s most ambitious anti-narcotics initiative, Plan Colombia, whose core strategy involved aerially spraying herbicides over coca crops, on forest conservation. The original aim of Plan Colombia in 2000 was to reduce the production and trafficking of illegal drugs (mainly cocaine) by 50 percent within six years. However, the intuition behind the environmental co-benefits of this strategy was that by reducing the attractiveness and potential returns of coca cultivation, eradication campaigns may limit new coca plantations and slow the expansion of the agricultural frontier (Davalos and Morales, 2019). We were concerned that areas targeted for aerial spraying tended to overlap with regions of high coca crop density, which are also prone to elevated levels of deforestation, thereby potentially confounding the causal interpretation. (Davalos et al., 2021; Roa and Núñez, 2014; Negret et al., 2019).

Exploiting a policy-induced enforcement discontinuity created by the suspension of aerial spraying along the Colombian–Ecuadorian border between 2008 and 2013, Chapter 1 provides causal evidence on the effects of eradication campaigns on forest cover. Our analysis reveals that aerial spraying campaigns had no measurable effect on tree loss, challenging the notion that supply-side drug enforcement can serve as an effective conservation strategy. Furthermore our findings suggest that to address the environmental consequences of narco-deforestation tailored interventions grounded in the specific drivers of deforestation might be more effective for forest conservation goals.

Having identified that a policy instrument designed to address a single market failure—such as crime or drug trafficking—was not effective in mitigating environmental externalities (Tinbergen, 1952), we proceed to examine a policy intervention explicitly tailored to reduce illegal deforestation in protected areas.

In 2019, the Colombian government launched Operation Artemis tha was the largest anti-deforestation military initiative recorded in the Colombian Amazon, deploying more than 23,000 soldiers across approximately 21,000 hectares of illegal deforestation hotspots. The original aim of Operation Artemis was to achieve zero deforestation by 2030. Since the military is not typically trained to protect the environment, we question whether military enforcement can effectively curb deforestation. This question is addressed in Chapter 2, titled ”Can Military Enforcement Curb Illegal Deforestation? Evidence from Colombia's Largest National Parks”. This study examines whether place-based militarised intervention in protected areas of the Amazon can deter illegal deforestation. Concentrating military resources in urban areas with high criminality has increased in recent years and has proven to be an effective mechanism for deterring crime (Braga et al., 2019; United Nations Office on Drugs and Crime, 2025). Yet, the effectiveness of similar operations in protected natural areas remains unclear, as the literature on rural contexts is extremely limited, information on military activities is often restricted, and causal identification is challenging given that enforcement areas are rarely assigned at random.

To provide evidence of the effectiveness of rural place-based military intervention on illegal deforestation, we focus on Operation Artemis, which implemented targeted interventions in Protected Areas (PAs) of the Colombian Amazon between 2019 and 2022. Using the words of the former Colombian Ministry of Environment, this study aims to respond to the following questions: *What would have happened if they had not carried out the mission of Operation Artemis? Would the amount of deforestation in the national natural parks have been higher? It is plausible, although it is very difficult to judge. The problem is that there are no objective evaluations for the results of the operation* (Tarazona and Parra De Moya, 2023).

Our empirical strategy to address the research question rests on a staggered difference-in-differences (DiD) framework and relies on two complementary methods. First, we exploit a quasi-natural experiment arising from the fact that the hotspots targeted with the military intervention were legally restricted to enforce illegal deforestation within the administrative boundaries of PAs. Second, we examine the military's selection process and show that the assignment of enforcement to eligible hotspots was not driven by the level of illegal deforestation. Consistent with this, we show that the DiD results from the quasi-natural experiment hold under different sets of temporal and spatial eligible controls. We find that areas targeted by the military intervention experienced a 3.9% reduction in the number of early deforestation alerts, corresponding to a 12% reduction in the area of tree loss. However, the effects of the intervention persist for only up to one year and appears to be costly to enforce. With this in mind, is there a more cost-efficient way to reduce deforestation?

Incentives to clear forestland in the Colombian Amazon vary substantially across stakeholders and are not limited to illicit activities (Davalos et al., 2021; Lapola et al., 2023). Legal economic activities produce more than 327 different agricultural products and sustain the livelihoods of over 40,000 farms DANE (2016). However, these activities have also been recognized as poverty-driven drivers of deforestation, as the expansion of subsistence agriculture is frequently associated with the clearing of natural forests (Barbier, 1997). In an attempt to reconcile this trade-off, the Colombian government has introduced the Payment for Environmental Services (PES) legislation (República de Colombia Decreto 1076, 2018), promoting subsidies offering constant per-hectare payments to compensate farmers who agree to conservation measures for forgone agricultural profit. The country's most ambitious PES initiative, Vision Amazonia, aimed to achieve zero net deforestation by 2020. Deforestation had not ceased by 2020, and new evidence suggests that the scheme's success in curbing deforestation was limited relative to the level of investment (Ministerio de Ambiente y Desarrollo Sostenible, 2025; Rodríguez-de Francisco et al., 2021).

While the optimal design of PES contracts remains an active area of research, several authors agree that the effectiveness of PES schemes depends critically on how accurately payments reflect landowners' opportunity costs of conservation (Assunção et al., 2015; Rodríguez-de Francisco et al., 2021). Furthermore, a clear understanding on the correlation between a land parcel's deforestation risk and the wealth of the landowner is essential for designing PES programs that can achieve anti-poverty and conservation aims simultaneously (Alix-Garcia et al., 2015). Previous literature has focused on understanding the spatial land-use changes that drive deforestation (Davalos et al., 2021; Clerici et al., 2020; Armenteras et al., 2019). However, spatial models alone are insufficient to directly test the economic incentives underlying agents' land-clearing decisions.

How are agricultural incentives correlated with farmers' land-clearing decisions at the forest frontier? This question is addressed in Chapter 3, titled "Frontiers of Conservation: The Economic Trade-offs of farming in the Amazon". This study engages with the legal economies of Colombian Amazon farmers and identifies the economic drivers that are correlated with deforestation to inform the design of policy instruments. In particular, we focus on the agricultural factors that may affect the level of compensation that landholding agents receive in exchange for not engaging in agricultural activities to inform the design of cost-efficient Payment for Environmental Services (PES) programs.

Building on the land conversion model proposed by Barbier and Cox (2004), the empirical analysis of chapter three is guided by a profit-maximising agent who clears forestland for agricultural production. We model the land-clearing decisions of farmers and test them using the revealed choices of 39.175 farms surveyed in the Colombian Amazon by the 2014 Colombian National Agricultural Census (CNAC) as well as. We complement this data with satellite land use measures and market prices for 127 different agricultural goods. Our findings indicate that higher crop productivity is correlated with increased deforestation. Furthermore, we find that receiving technical assistance and having access to financial credit for agricultural purposes are associated with a decrease in the likelihood of deforestation. These findings highlight feasible channels to support PES policy to pursue forest conservation.

Moreover, as PES in this region are framed as both anti-poverty and conservation programs, we provide spatially explicit estimates of landowners' opportunity costs of conservation at the lowest administrative unit level available. If the forgone values of crop profitability are used as a proxy of the farmer opportunity cost preserving the forest vary widely across farms, ranging from US \$25 to US\$1381 per hectare. Such results suggest that conservation strategies based on constant per-hectare payments (Flat-rates) may under- or overcompensate farms for their agricultural opportunity costs, thereby limiting both the achievement and cost-effectiveness of environmental and development targets (Bateman et al., 2024).

The main contributions of this thesis are twofold. First, it causally analyses the implicit selection bias in targeting highly deforested areas for the implementation of enforcement policies. Second, it models agents' behaviour and empirically tests the micro-level foundations that correlated with farmers' land-clearing choices. Overall, our main findings indicate that environmental policy instruments are more effective when they focus on a specific market failure and provide incentives consistent with the opportunity costs (legal or illegal) of land use. Furthermore, we support the adoption of a decision-support framework grounded in cost–benefit or cost-effectiveness analysis of policy that adequately accounts for the full social costs of implementation. Taken together, we hope to provide evidence that addresses empirical gaps in the literature on the economics of tropical deforestation and to inform policy design in an effort to break the *absent feedback loop* between ecological outcomes and environmental policy instruments.

Chapter 1

Conservation by Eradication? Lessons from Drug Enforcement and Deforestation in Colombia

Abstract

Most of the Amazon deforestation is associated with lucrative forms of organized crime, including drug production and trafficking. Addressing these dynamics require coordinated policies that integrate environmental protection with criminal justice. In this paper, we examine the impact of drug eradication policies on forest conservation leveraging the introduction of an exclusion zone along the Colombian's frontier with Ecuador. Within a regression discontinuity design framework, we show – contrary to previous contributions – that aerial spraying of coca crops had no impact on forest conservation. Our findings challenge the notion that anti-drug policies contribute to conservation targets and the assertion that eradication campaigns are primary drivers of deforestation in the Amazon.

1.1 Introduction

Tropical deforestation represents one of Colombia's most pressing environmental and development challenges. As a megadiverse country with over half of its lowland territory covered by the Amazon Rainforest (UNDP, 2018), Colombia has lost nearly three million hectares of forest in the past decade alone, with deforestation reaching a historic peak in 2017 just one year after the signing of the Peace Agreement (Prem et al., 2020; Global Forest Watch, 2025). This surge in forest loss has coincided with a dramatic resurgence in coca cultivation across the Colombian Amazon, effectively reversing nearly two decades of costly drug enforcement efforts (Prem et al., 2021; UNODCa, 2023). By 2020, the United Nations estimated that approximately 44% of Amazonian deforestation in Colombia was directly or indirectly associated with coca production (UNODC, 2022). By 2023, coca cultivation reached record highs, driven partially by surging global demand for cocaine, making it the world's fastest-growing illicit drug market (UNODC, 2025). The intersection of illicit economies and environmental degradation is referred as narco-deforestation (Devine et al., 2021; Sesnie et al., 2017) and has emerged as a defining challenge not only for Colombia but also across much of South and Central America (UNODC, 2025; UNODCb, 2023).

In the context of narco-deforestation, Plan Colombia stands out as one of the most ambitious and externally supported anti-narcotics initiatives in the region. Launched in the early 2000s with substantial U.S. funding and political backing, the program combined military operations, crop eradication, and state-building efforts aimed at curbing coca production and weakening armed groups. Between 2000 and 2015, its core strategy for reducing illegal plantations involved aerially spraying herbicides over coca crops in an effort to disrupt the supply of cocaine. Rozo (2014); Mejía et al. (2017) examined the effectiveness of aerial spraying in reducing coca cultivation in Colombia, reporting a statistically significant but modest impacts.[1] In 2016, following the signing of the Colombian Peace Agreement, the government suspended aerial coca eradication campaigns due to legal and public health concerns (CNE, 2015). However, the recent surge in coca cultivation has prompted renewed interest to reinstate aerial spraying as a central tool in drug control policy.

[1] Rozo (2014), for instance, estimates that a 1-percentage-point increase in the likelihood of aerial spraying led to a reduction of just 0.07 hectares of coca cultivation per square kilometer between 2000 and 2010. Similarly, Mejía et al. (2017) find that a 10-percentage-point increase in spraying probability reduced coca cultivation by 0.35 hectares per square kilometer between 2006 and 2010. Both studies conclude that, given these limited effects, aerial eradication is unlikely to be a cost-effective strategy for significantly reducing cocaine production in Colombia.

A key issue in the debate over resuming aerial spraying is its potential to benefit forest conservation (ANLA, 2021). The intuition behind this approach is that by reducing the attractiveness and the potential returns from coca cultivation, eradication campaigns may limit new coca cultivation and slow the advance of the agricultural frontier (Davalos and Morales, 2019). However, implications of aerial spraying for deforestation remain ambiguous. While suppression efforts may reduce cultivation in already-degraded areas, they may simultaneously incentivize displacement into ecologically sensitive regions, thereby accelerating forest loss in biodiversity-rich zones (Rincón-Ruiz and Kallis, 2013). Furthermore, given that coca crops in Colombia can be harvested four to six times annually (WOLA, 2008), the economic losses from eradication may be recuperated within a single production cycle, potentially limiting the deterrent effect and reducing the necessity for spatial relocation (UNODC, 2006).

While much of the existing research on the war on drugs has centred on the effectiveness of enforcement policies, the ancillary environmental impacts and unintended consequences of aerial spraying remain relatively understudied. Previous studies have explored the relationship between anti-drug efforts and deforestation, particularly focusing on the environmental consequences of aerial spraying campaigns, but the evidence remains inconclusive.[2] Furthermore,in the previous literature there is limited attention to the endogeneity arising from non-random policy implementation. In particular, aerial spraying campaigns have tended to target areas already experiencing elevated rates of deforestation, introducing policy selection bias that complicates causal interpretation.

The contribution of this study is to causally analyse the implicit selection bias in choosing high-deforested areas for the implementation of the anti-drug policy. We leverage a policy shock that offers a natural experiment in enforcement patterns. Following diplomatic tensions between Colombia and Ecuador over the alleged cross-border harms of aerial spraying, Colombian authorities established a 10-kilometer exclusion zone along the border from 2008 to 2013. Within this buffer,

[2] Davalos et al. (2021) find that while aerial fumigation did not directly influence deforestation rates, coca cultivation and its eradication through fumigation intensified armed conflict, thus indirectly contributing to forest loss through displacement and violence. In contrast, Rincón-Ruiz and Kallis (2013); Rincon-Ruiz et al. (2016) provide evidence that aerial spraying has directly contributed to deforestation by displacing coca cultivation from already-degraded areas into biodiversity-rich regions, thereby accelerating the destruction of intact forest ecosystems. Several authors discuss the impact of anti-drug enforcement on deforestation elsewhere in South America. McSweeney et al. (2014), for example, notes that eradication policies often push coca (and opium poppy and marijuana) growers into ecologically sensitive zones, with substantial environmental impacts across several Latin American countries. Bradley and Millington (2008) and Salisbury and Fagan (2013) found similar effects in Bolivia and Peru, respectively.

aerial spraying was formally suspended —- creating a sharp, policy-driven discontinuity in treatment exposure. Drawing on the empirical strategy of Mejía et al. (2017), we exploit this boundary within a regression discontinuity design and a conditional difference in difference strategy to causally identify the effects of aerial eradication on forest outcomes, comparing adjacent areas that differ only in their exposure to spraying due to the enforced exclusion. Different from Mejía et al. (2017) our paper assesses the impact of eradication campaigns on deforestation as well as expand the period of analysis.

More broadly, this paper contributes to a growing body of literature examining the effectiveness of policy instruments in tackling narco-deforestation and forest conservation targets in regions affected by organized crime and state fragility (Goulder and Parry, 2008; Merkus, 2024). In recent decades, particularly in developing countries, militarized interventions targeting illicit activities tied to natural resource exploitation – such as illegal mining, logging, and coca cultivation – have increasingly been framed as producing ancillary environmental benefits (Dethier et al., 2024; UNODC, 2025). Economic literature offer a limited evidence that a policy instrument designed to address one market failure –such as crime or drug trafficking – could also effectively mitigate environmental externalities (Tinbergen, 1952; Landry and Bento, 2020). The logic of optimal policy design suggests that each externality requires its own targeted intervention.

Using Plan Colombia as a case study and high-resolution satellite imagery, we estimate the causal impact of aerial coca eradication on forest cover in the Colombian Amazon's border with Ecuador. Our analysis reveals that, between 2008 and 2013, aerial spraying campaigns had no measurable effect on tree loss, challenging the notion that supply-side drug enforcement can serve as an effective conservation strategy. Our results contribute to the economic insight that in complex governance environments, where illicit economies and ecological degradation are deeply intertwined, narrowly focused instruments are unlikely to generate broad-based policy synergies.

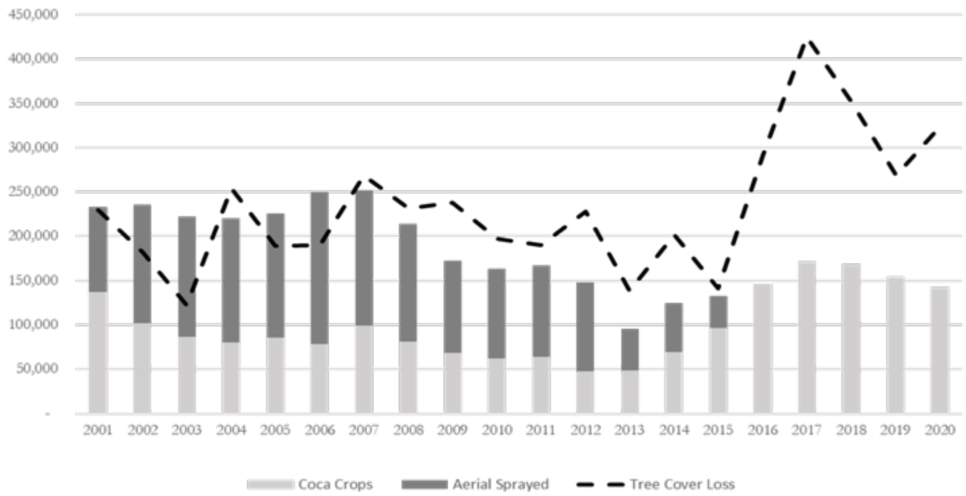
The rest of this article is organised as follows: Section 1.2 discusses the institutional framework and the literature regarding the Colombian 'war on drugs' campaign and its socio-environmental impacts. Section 1.3.1 describes the identification strategy and our empirical methodology. In section 1.3.2, we present the data and provide an overview of the relevant summary statistics. Section 1.3.3 contains the empirical results, while section 1.4 concludes.

1.2 Background: Plan Colombia and aerial spraying

In 1999, the Colombian and US Governments jointly launched the biggest anti-drug program ever implemented in a drug-producing country, known as Plan Colombia. The original aim was to reduce the production and trafficking of illegal drugs (mainly cocaine) by 50 percent within six years.

The supply-reduction strategy focused on manual and aerial eradication of coca plantations by spraying high doses of herbicides. Between 2000 and 2015, aerial spraying of glyphosate (herbicide) over coca crops represented the main enforcement policy, taking place in over 300 Colombian municipalities (27 percent of the total). By 2015, the total cost of the program in Colombia had reached approximately US$9.6 billion (DNP, 2016), complemented by an estimated US contribution of just over US$9 billion (CRS, 2021). Combined, these expenditures represented roughly 1.2% of Colombia's GDP (Mejía et al., 2017). Figure 1.1 plots the trends over time of tree cover loss, coca crops area, and surface subject to aerial spraying between 2000 and 2020. Notably, deforestation increased significantly after 2015, coinciding with the suspension of aerial coca eradication campaigns. This surge in forest loss is frequently cited by proponents of aerial spraying as the evidence that environmental benefits are associated with drug eradication efforts.

Figure 1.1: Hectares of coca crops, tree loss, and aerial spraying Colombia (2000-2020)



Source: Author's illustration using data from Hansen et al. (2013), UNODC and Ministry of Defence

Because significant aerial spraying took place close to the Ecuador border, the

Ecuadorian government was worried about the possible negative effects of spraying on the environment, agricultural production and population health on its side of the border. Therefore, in 2006, the Ecuadorian government claimed that since the beginning of Plan Colombia, "the spraying has caused serious damage to people, crops, animals, and the natural environment on the Ecuadorian side of the international frontier with Colombia and posed a grave risk of further damage over time" (ICJ, 2009). Despite promises to avoid spraying areas closer than 10 km from the border, Colombia continued its aerial campaigns. In light of this, in 2008 Ecuador filed an Application instituting proceedings against Colombia at the International Court of Justice in The Hague (ICJ, 2009).

Following the filing of the lawsuit on March 31, 2008, the Colombian Government stopped all spraying within a 10 km band of its territory along the international frontier with Ecuador. This state of affairs continued until 2013, when the Ecuadorian Government notified the Court that an Agreement had been reached between the two countries; which included the creation of an exclusion zone within 2 km from the border, in which Colombia will not conduct aerial spraying operations (Colombia and Ecuador, 2013). This Agreement lasted until 2015, when, following the signing of the Colombian Peace Agreement, and with the support of the International Agency for Research on Cancer, the Colombian government banned aerial spraying campaigns.

As in Figure 1.1 just after the prohibition of aerial fumigation in 2015, deforestation in Colombia reached the highest point ever recorded. Some members of the Congress took advantage of these developments to push for the resumption of aerial spraying, claiming that the data showed that the previous campaigns conducted to control coca crops had helped reduce deforestation (Roa and Núñez, 2014; Huezo, 2019).

In 2019, the Colombian National Police proposed a plan to resume aerial spraying for coca eradication. By 2021, the National Environmental Licensing Authority (ANLA) had approved the program's reactivation. However, in 2022, the Constitutional Court suspended the environmental permit before operations could begin, citing inadequate consultation and insufficient dissemination of information to communities potentially affected by the spraying. As of now, the environmental permit for aerial fumigation remains suspended. Nevertheless in response to a sharp and unprecedented increase in coca cultivation, the government has authorized the purchase of 22,000 litres of glyphosate to scale up manual eradication efforts and is studying the possibility to use drones for spraying (CEMA, 2025).

1.3 Drug eradication and tropical deforestation

Despite a growing body of literature on deforestation and drug enforcement, few studies explicitly attempt to isolate the causal impact of anti-drug campaigns on forest loss from other drivers of deforestation. A key challenge lies in the fact that areas targeted for aerial spraying tend to overlap with regions of high coca crop density areas that are also prone to elevated levels of deforestation (Davalos et al., 2021; Roa and Núñez, 2014; Negret et al., 2019). As a result, conventional estimations of the effect of aerial spraying on forest cover loss are likely to suffer from upward bias.

In what follows, we use a Regression Discontinuity Design (RDD) that leverages the geographical and temporal variation induced by the creation of the exclusion zone along the Ecuador-Colombia border to identify the causal impact of aerial spraying.

1.3.1 Identification strategy

Our identification strategy relies on the fact that, given the arbitrary nature of the size and position of the exclusion area, the assignment into the treatment and control groups of areas just inside and outside of the restriction zone can be considered as good as random. Absent the diplomatic frictions, these areas would have been indistinguishable from each other in terms of coca production, aerial spraying, and deforestation. Our RDD, therefore, allows us to causally attribute any difference in tree loss across the border of the exclusion zone to the impact of treatment, i.e. being exposed to (the possibility of) aerial spraying.

Given the exogenous creation of the 10km exclusion zone on the Colombian side of the Ecuador-Colombia border between 2008 and 2013, we test the impact of aerial spraying on deforestation in the Amazon. Mejía et al. (2017) use a similar approach to gauge the effectiveness of the spraying program in reducing coca production between 2006 and 2010. They conclude that the aerial campaign was effective, but that the size of its impact was minimal, estimating that overall spraying one additional hectare of coca crops led to a reduction in coca cultivation of around 0.03 hectares. Our work expands their analysis to the period 2008-2013 and asses the existence of environmental impacts of aerial spraying.

Our dataset combines satellite and geo-referenced data on 1-square-km (10 ha) grid cells between 2001 and 2015. We focus on the discontinuity in outcomes at the 10 km threshold between the exclusion and the spraying zone for the years when the prohibition became effective, i.e. 2008-2013. Notice that, since we do not have access to the confidential, geo-referenced data on the actual spraying activity carried out in Colombia, our approach is to estimate the impact of the initial treatment assignment and therefore estimate Intention To Treat effects. Furthermore, as we are interested in the effect of coca aerial eradication on deforestation, our RDD regressions are restricted to cells that were reported to contain coca cultivations.

Letting R_i be the nearest Euclidean distance from the centroids of each cell to the Ecuadorian international frontier, we denote the normalised distance from the threshold as $D_i = (R_i - 10\text{km})$. By construction, D_i takes on negative values if the cell's centroid is in the exclusion zone, and a positive value otherwise. The assignment to treatment, therefore, follows $T_i = \mathbb{1}_T(D_i > 0)$, where $\mathbb{1}_T$ is an indicator function that takes on the value 1 if the distance from the border exceeds 10 km.[3]

We indicate the potential outcomes in terms of tree cover loss for grid cell i as $Y_i(T_i)$, so that $Y_i(1)$ denotes tree loss in a cell outside of the exclusion zone, whereas $Y_i(0)$ indicates the same outcome variable for a cell within the exclusion zone. The empirical challenge we face in this context is to estimate the average treatment effect at the threshold, τ, given by

$$\tau = \mathbb{E}\left[Y_i(1) - Y_i(0)|D_i = 0\right], \tag{1.1}$$

without observing either value at the threshold. Indeed, Cattaneo et al. (2020) argue that the crucial feature of a sharp RDD is that there are no observations for which the value of the running variable is exactly equal to the cutoff value, so that the RDD analysis relies fundamentally on extrapolation towards this cutoff. The goal of empirical RDD analyses is thus to adequately perform this local extrapolation to compare control and treatment units.

Following the current best-practice in the literature, we estimate the (local, RD) average Intension To Treat (ITT) effect via local-linear regressions with bias correction (Calonico et al., 2014; Cattaneo et al., 2020, 2024); and select the optimal bandwidth by minimising the mean square error of the local linear estimator (Imbens and Kalyanaraman, 2012). Observations are weighted with a triangular kernel, to put the greatest weight on the closest cells to the 10km cutoff (Cattaneo et al., 2020). Finally, we adopt the bias-correction algorithm developed by Calonico et al.

[3]Some cells straddling the 10-km cut-off line might have their centroid in the exclusion zone and the remaining of their surface in the spraying area. To avoid erroneous the attribution of such cells to either the treatment or control group, in our estimations we exclude all observations whose centroid falls within 500 meters of the cut-off. We perform robustness checks including the cells that had their centroid in the first 500m around the cutoff. Results are qualitatively similar and available from the authors upon request.

(2014) to estimate the bias due to the estimation close to the threshold and to correct the RD point estimates accordingly.

While the estimation of the ITT at the threshold does not in general require the addition of other covariates, it may be argued that tree loss depends on a number of factors, such as the geography and ease of access to the area. In what follows, we also present results that account for some selected variables, such as the distance to the nearest main road, the distance to the nearest settlement, the altitude, as well as the longitude and latitude coordinates at the cell to control for differences across grid cells.

1.3.2 Data

We assemble our dataset from three main sources. The United Nations Office for Drugs and Crime (UNODC) provides information about the location and size (on a 1 km x 1 km grid) of coca cultivations identified from satellite images in Colombia between 2001 and 2015.

Our second source of data is a dataset provided by the Ministry of Justice in Colombia, which reports the intensity of aerial spraying activity at the municipality level. The dataset does not contain the precise location of the spraying, but it reports the number of hectares sprayed for each municipality for each year between 2001 and 2015.

The third set of spatial information comes from the Global Land Analysis and Discovery (GLAD) laboratory at the University of Maryland Department of Geographical Sciences. Their Global Forest Watch dataset contains forest loss data collected from 2001 to 2015 on a 30 m cell size grid.[4]

Finally, we extract geographical information on the remaining variables related to potential causes of deforestation, such as slope of the terrain, altitude, distance to the nearest road and distance to the nearest urban/rural centre from the National Statistics Administrative Department (DANE), the Geographical Institute Agustín Codazzi (IGAC), the Hydrologic adn Meteorologic Institute of Colombia (IDEAM), and the Open Street Map platform. Table 1.5 summarises the source and availability for each variable.

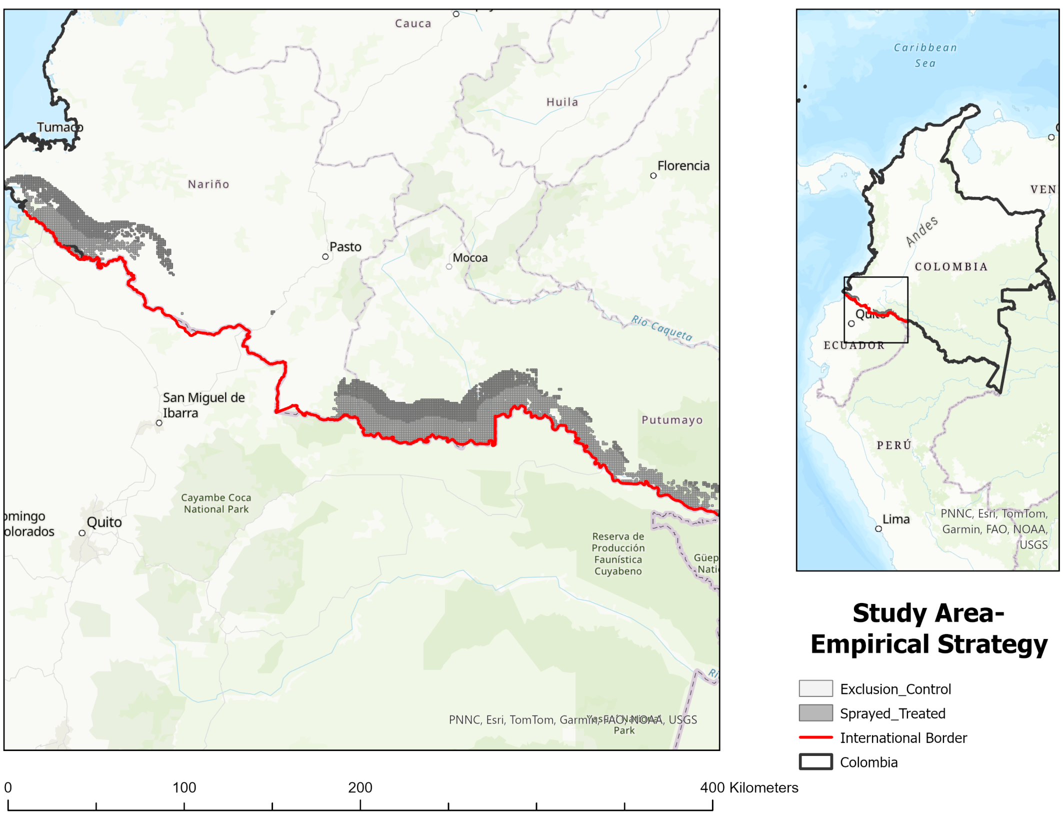
All ours variables fit a grid of 1 km x 1 km. We restrict our sample to the cells within a 20 km band of the Ecuador-Colombia international frontier that had been reported as

[4] For more details, please see `https://www.globalforestwatch.org/`, as well as Hansen et al. (2013).

having coca crops at any point in time between 2001 and 2015. Our dataset includes 5,137 cells; 3,109 cells are within the exclusion zone, 2,028 in the (potentially) sprayed area. Each cell contains yearly information on tree loss, area planted with coca, the average intensity of the spraying campaigns per hectare at the municipality level and the socio-geographical information mentioned above. Figure 1.2 reports our study area with the (lighter) 10 km and (darker) 20 km bands along the Ecuador border.

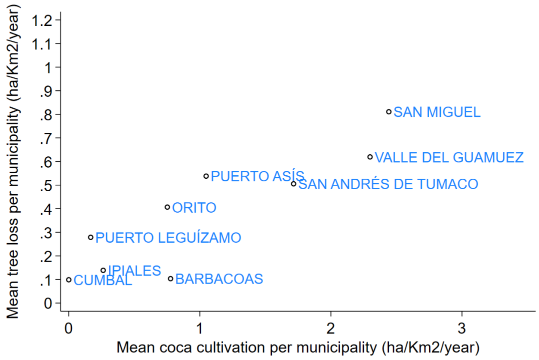
The 10 km exclusion zone overlaps with eleven municipalities. Since the beginning of the 21st century, these municipalities are jointly responsible for around 25% of Colombia's coca production. Figure 1.3 plots the mean yearly area of tree cover lost in each municipality between 2001 and 2015 against the average area of coca cultivations (left panel) and the area sprayed per year (right panel). As shown in Figure 1.3b, the areas with the largest density of coca crops are also those that tend to experience the highest level of deforestation. Clearly, however, since the same areas tend to be subject to more intense aerial fumigation campaigns, a positive correlation emerges

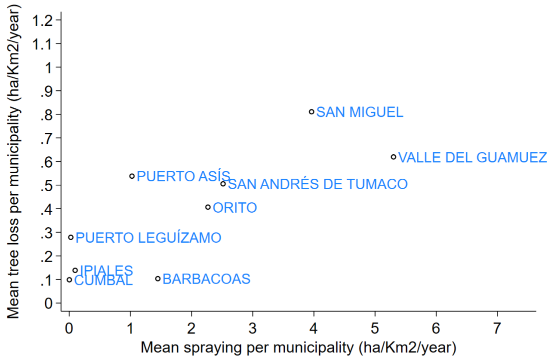
Figure 1.2: Study area: Coca crops in the area 20km from the frontier that includes the exclusion zone (0-10km) and the spraying region (¿10-20km)



Source: Author's illustration from UNODC data

Figure 1.3: Yearly average of tree loss, coca crops, and spraying campaigns for the Municipalities included in the exclusion zone (2001-2015)





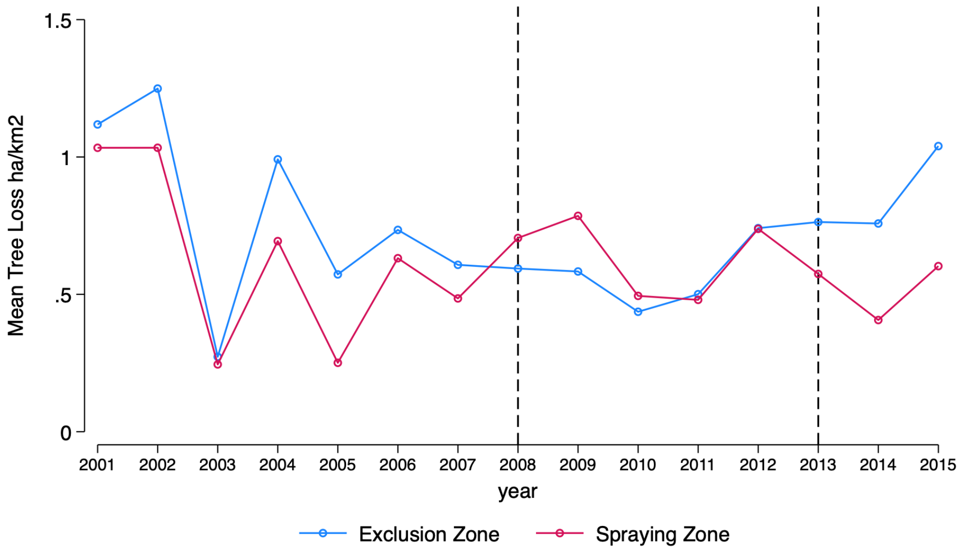
Source: Author's elaborations on Hansen et al. (2013), Colombian Ministry of Justice and UNODC data.

between aerial fumigation and tree loss. The evidence in Figure 1.3b support the positive correlation between spraying and tree-loss found in the literature to estimate the impact of aerial spraying on deforestation but without properly accounting for the endogeneity that links targeted spraying and high-density of coca crops, results are bias(Rincón-Ruiz and Kallis, 2013; Rincon-Ruiz et al., 2016; Bradley and Millington, 2008; Salisbury and Fagan, 2013).

Our empirical design responds to the need of providing causal inference about the impact of spraying on tree loss, explicitly accounting for the endogeneity. For our sharp RDD to be valid, we need to assume that, in the absence of the diplomatic tensions leading to the introduction of the exclusion zone, the areas immediately abutting the 10-km lines would be indistinguishable. We start by looking at some descriptive statistics – see in the appendix Table A. 1.6. The summary statistics reports that both coca cultivation and tree loss are larger in the exclusion zone; the exclusion zone is, not surprisingly, also more remote, being on average further away from access roads. The geography of the two areas is broadly similar, although the spraying zone has a slightly higher average altitude.

Figure 1.4 shows the average annual area of tree loss between 2001 and 2015 in the exclusion and spraying zones. From 2001 to 2007, the exclusion zone exhibited higher deforestation rates than the spraying area. This is quite possibly linked to the more remote nature of the regions closer to the international border. Following the entry into force of the exclusion zone in 2008, the tree loss in the treatment area exceeded tree loss in the exclusion zone; this trend reversed again in 2013, after the resolution

Figure 1.4: Average yearly density of tree loss for the exclusion and the spraying zones (2001-2015).



Source: Author's elaborations on Hansen et al. (2013) and UNODC data. The vertical lines indicate the time-window of our study.

of the international dispute, when deforestation was once again higher closer to the international frontier.

As a more formal test of the validity of our approach, we conduct a regression discontinuity estimation across the 10 km threshold for our case study, before the entry into force of the exclusion zone. *A priori*, we would expect to find no discontinuity, suggesting that the area immediately inside and outside the exclusion zone can be considered identical before the diplomatic tension. Indeed, Table 1.1 and the corresponding graphs in Figure 1.5 support our priors and show no evidence of a discontinuity in tree loss for any of the specifications detailed in the table.

A potential challenge to our identification strategy comes from the fact that a rational response of coca farmers to the introduction of the exclusion zone could be to relocate their illegal activities away from the spraying area and into the exclusion zone. This would result in an endogenous sorting of units around the cut-off, thus violating the non-manipulability assumption in RDDs and invalidating our causal identification (e.g. McCrary, 2008). If this were the case, however, we would observe a discontinuity in the grid units with coca plantations across the discontinuity. To assess whether the design is vulnerable to such manipulability, we follow Cattaneo et al. (2020) and estimate the density of the observation of coca crops across the 10 km threshold. The plot in Figure 1.6 suggests continuity of the density across the threshold, and neither the conventional

Table 1.1: Estimates of the discontinuity at the threshold for tree loss (Pooled RD, 2001-2007)

	Linear		Quadratic	
	(I)	(II)	(III)	(IV)
Conventional	0.03	0.02	0.08	0.05
	(0.07)	(0.07)	(0.10)	(0.09)
Robust	0.05	0.04	0.09	0.06
	(0.08)	(0.08)	(0.12)	(0.10)
Bandwidth est.	2.86	2.69	3.18	3.59
Observations	35,784	35,784	35,784	35,784
Effective obs. est.	9,317	8,617	10,318	11,655
Covariates	✗	✓	✗	✓

Notes: This table reports the estimated coefficients from non-parametric RD estimations of the discontinuity at the threshold. The coefficients are estimated following Calonico et al. (2014). Columns (I) and (III) are estimated without covariates, using linear and quadratic polynomials, respectively. Columns (II) and (IV) are estimated with the inclusion of covariates for both the linear and quadratic approximations. The estimates include municipality-year fixed effects. Standard errors are reported in parentheses.
*, **, *** indicate 10%, 5% and 1% statistical significance, respectively.

nor the robust, bias-corrected tests à la Cattaneo et al. (2019) provide any evidence of sorting (see Table 1.2). Thus, it seems plausible that eradication enforcement does not incentivize coca farmers to grow new illicit crops in the exclusion zone.

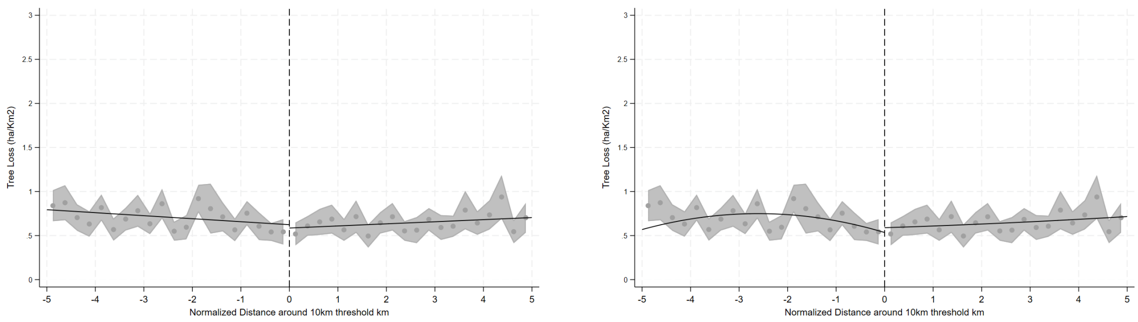
Table 1.2: Non-manipulability tests (2008-2013)

	RD manipulation test
Conventional	0.01
	(0.99)
Robust	0.01
	(0.99)
Bandwidth estimation	2.70-3.369
Observations	30822
Effective obs. estimation	8532

Notes: This table reports the results of the conventional and robust, bias-corrected RD manipulation tests, using local polynomial density estimations based on Cattaneo et al. (2019). The parentheses report p-values.
*, **, *** indicate 10%, 5% and 1% statistical significance, respectively.

The final step to validate our sharp regression discontinuity approach is to claim that no spraying took place in the exclusion zone between 2008 and 2013. As mentioned above, we do not have access to the geo-referenced spraying data used in Mejía et al. (2017) and cannot, therefore, test directly whether any spraying activity might have spilled over into the exclusion zone. As a first piece of evidence, we rely on the results of Mejía et al. (2017), who show that the probability of spraying activity in

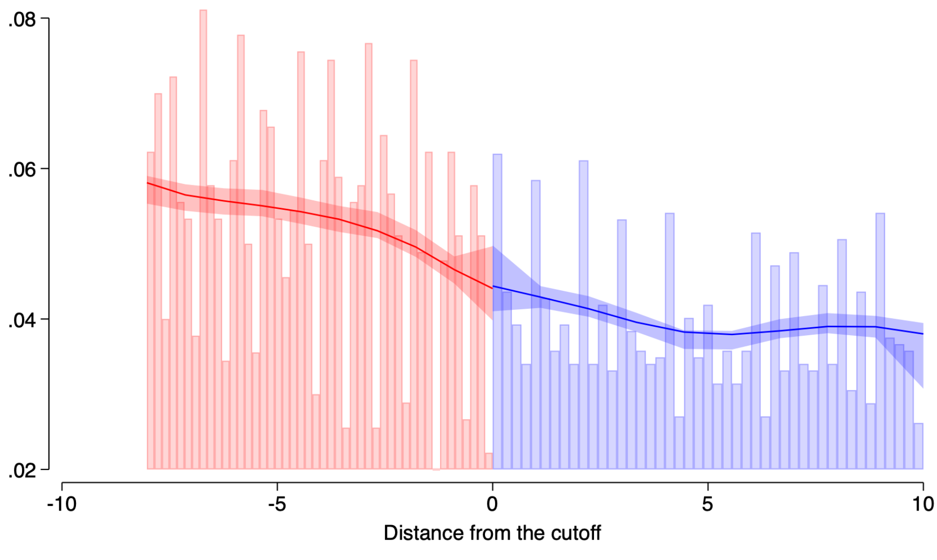
Figure 1.5: Pooled RD linear (left) and quadratic (right) estimates of tree loss around the threshold before the establishment of the exclusion zone (2001–2007).



Linear Quadratic

Note: Graphs are presented with bandwidth of 5km from the normalized distance in the 10 km threshold. Points represent bins of means tree loss separately for the treated spraying area (right) and the control exclusion observations (left). A linear degree polynomial function is fitted as the conditional expectation function for each side of the threshold, and 95 percent confidence intervals for each bin are displayed with shaded areas. Source: Author's illustration with data from UNDOC, Ministry of Justice, Hansen et al., 2013, DANE, IGAC, IDEAM and OpenStreetMap

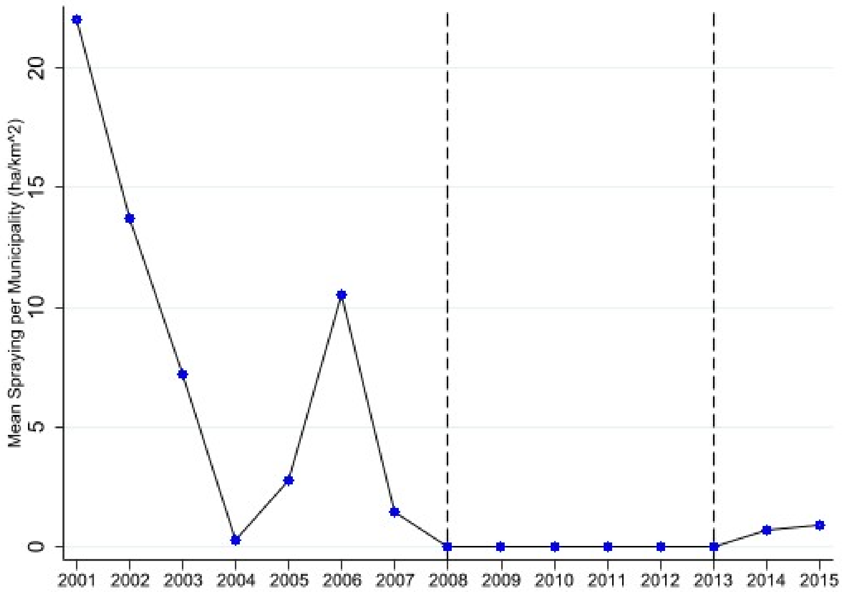
Figure 1.6: Distribution of grid cells with evidence of coca cultivation (2008-2013)



Note: The bars represent the number of observations within each bin. The shaded areas are 95% confidence intervals.

the exclusion zone between 2008 and 2010 dropped to zero. To further support the claim that the exclusion zone was indeed free from spraying activity, we use the open-access spraying reports released at the municipal level to gauge Colombia's compliance with the restrictions during 2008-2013. Unfortunately, no municipality is completely in the restricted area. The municipality of San Miguel comes closest, with over 97% of its area included in the exclusion zone. Figure 1.7 plots the data recorded by the Colombian Ministry of Justice pertaining to spraying activity in San Miguel between 2001 and 2015. As can be clearly seen, no spraying took place during the period of our analysis, suggesting that a sharp RDD is indeed appropriate in this context.

Figure 1.7: Aerial spraying campaigns per square kilometre, San Miguel (2001-2015)



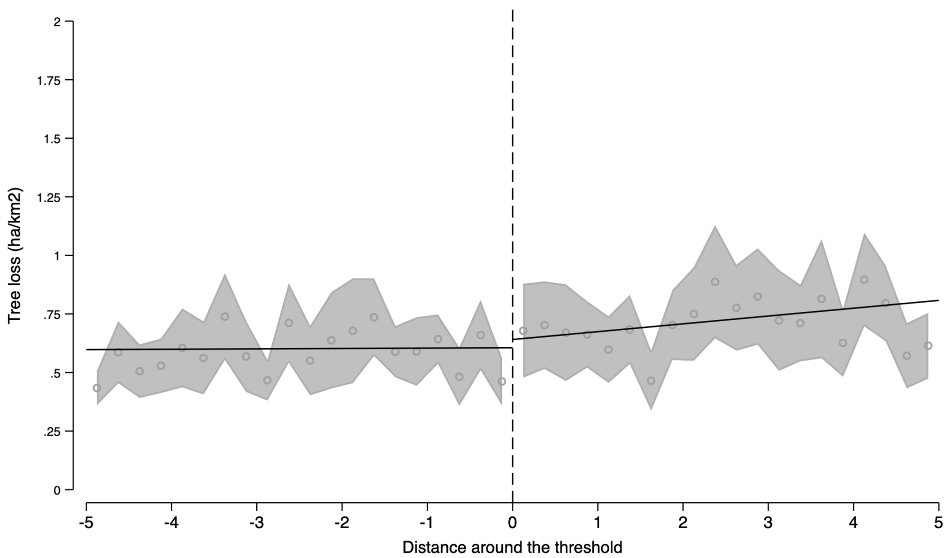
Source: Author's elaborations on Colombian Ministry of Justice and UNODC data. The vertical lines indicate the time window of our study.

1.3.3 Results

Having verified that the introduction of the exclusion zone can be treated as a natural experiment and the sharp RD approach is appropriate for our research question, we are now ready to present the results of our RDD analysis.

Table 1.3 reports the estimated average treatment effect using the local polynomial RD point estimators with robust bias-corrected confidence intervals and inference procedures developed in Calonico et al. (2014, 2018, 2019, 2020). Estimates are obtained using data for the entire period when the exclusion zone was in place, i.e. between 2008 and 2013. We offer two different specifications of the RD, the first one, which is our preferred one, assumes a linear polynomial; the second, which assumes a quadratic polynomial is included for robustness, as advised by Cattaneo et al. (2020). Furthermore, for each specification, we present results from regressions with do not include any co-variates in the estimation – columns (I) and (III) – followed by results obtained by including year and municipality fixed effects, together with controls for a cell's altitude, the slope of the terrain, as well as its distance to the nearest road and settlement. The latter specifications are run to control for time-invariant differences amongst cells that might be driving the variation in deforestation rates. For each specification, the conventional and the bias-corrected estimates are reported in the first two rows. In the second row, the standard errors are rescaled to incorporate the contribution of the bias correction step to the variability of the bias-corrected point estimator, as detailed in Cattaneo et al. (2020). The bottom half of the table provides information on the optimal bandwidth selection as well as the overall and effective observations used for each estimation. Figure 1.8 shows a graphical representation of our preferred specification from column (I).

Figure 1.8: Pooled RD estimates of tree loss around the threshold (2008-2013)



Note: The plot presents the RD estimation of the discontinuity at the threshold. A linear polynomial is fitted as the conditional expectation function at each side of the threshold. The mean of tree loss within each bin and shown. The shaded area represents the 95% confidence interval within each bin.

The results of the regressions in Table 1.3 show that we cannot reject the null hypothesis that there is no discontinuity at the border of the exclusion zone and suggest that the aerial spraying makes no difference in terms of deforestation rate.

For completeness, and to rule out that the lack of significance might be due to averaging out positive and negative effects across years, we run the same analysis for each year individually (see Table 1.7 in the Appendix). None of the yearly estimates shows a significant discontinuity at the threshold, confirming the results from the pooled data.

Table 1.3: Pooled RD estimates: Average intention- to-treat effects, tree loss (2008-2013)

	Linear		Quadratic	
	(I)	(II)	(III)	(IV)
Conventional	-0.03	0.05	0.25	0.30
	(0.13)	(0.12)	(0.28)	(0.26)
Bias-corrected, robust	-0.06	0.02	0.29	0.33
	(0.15)	(0.14)	(0.34)	(0.31)
Bandwidth est.	3.00	2.83	3.32	3.16
Observations	29,244	29,244	29,244	29,244
Effective obs. est.	7,104	6,558	7,980	7,416
Covariates	✗	✓	✗	✓

Notes: This table reports the estimated coefficients from non-parametric RD estimations of the effect of exposure to the possibility of aerial spraying on tree loss. The coefficients are estimated following Calonico et al. (2014). Columns (I) and (III) are estimated without covariates, using linear and quadratic polynomials, respectively. Columns (II) and (IV) are estimated with the inclusion of covariates for both the linear and quadratic approximations. The estimates include municipality-year fixed effects. Standard errors are reported in parentheses. *, **, *** indicate 10%, 5% and 1% statistical significance, respectively. Source: Author's calculations with data from UNDOC, Ministry of Justice, Hansen et al., 2013, DANE, IGAC, IDEAM and OpenStreetMap

Our findings contradict the claim that eradication campaign is a conservation policy. In fact, aerial spraying exerts no statistically significant effect on deforestation and, in particular, does not contribute to a reduction in tree loss in our case study area.

Furthermore, since the 10 km threshold was not physically demarcated on the ground, it is plausible that the effective exclusion zone may have been implemented at a shorter distance from the international border—such as 9 or even 8 km— to align with Colombian interests[5].

While it is unlikely that aerial spraying may lead to any reduction of deforestation, one potential concern is that the uncertainty in the threshold might rather push coca cultivations, and therefore deforestation further inside the exclusion zone. To investigate this possibility and to provide a more in-depth assessment of the impact of the spraying campaigns at at alternative thresholds near the original one, we run additional (RDD) analyses around the 10 km threshold. Further analysis, reported in the Appendix (Figure 1.10), implemented pooled ITTs using 12 different alternative threshold, at 0.25 kilometre intervals from the international border (7 km up to a

[5] In the lawsuit pledge at the International Court of Justice, no technical instructions were provided for estimating the 10 km buffer zone applied within Colombian territory (ICJ, 2009) Since geographic distances on Earth are measured over a curved surface rather than a flat plane, naïve Euclidean calculations between geographic coordinates can significantly overestimate true geodesic distances. Banerjee (2005).

9.75 km distance from the international border, i.e. -3 and-0.25 km in 'normalized distance' respectably) and show that none of the estimates are statistically significant.

1.3.3.1 Robustness Checks: Semiparametric Difference-in-Difference estimator

To account for the limitation of the local nature of the sharp RDD estimates (Cattaneo et al., 2020) and a potential attenuation bias causing by an imperfect compliance of the spraying campaigns close to the threshold, we present complimentary estimates of a difference in difference strategy (DnD) in the spirit of Mejía et al. (2017) and Guadalupe et al. (2012). Different from our RDD desing that initially explode the spatial discontinuity of ever-coca cells around the 10 km cutoff, the DnD strategy relayed on exploiting the temporal within-cell variation of grid-cells that where in the spraying and the exclusion zones, before and after 2008. Formally, our DnD specification is defined as:

$$Y_{it} = \alpha + \beta \left(Spraying_i \times Post_t \right) + \gamma_i + \delta_t + \varepsilon_{it} \tag{1.2}$$

where Y_{it} is the number of hectare of tree loss per squared kilometre in cell i in year t. $Spraying_i$ is a binary indicator equal to one if cell i is located in the spraying zone and zero if it is located within the exclusion zone. $Post_t$ is a binary indicator equal to one for the period 2008-2013, when the exclusion zone was in force, and zero otherwise. γ_i denotes cell fixed effects to control for the selection of time/invariant characteristics (e.g. altitude, slope), and δ_t denotes year fixed effects. Standard errors are robust and clustered at the cell level to account for heteroscedasticity. The coefficient of interest, β, measures the intention to treatment effect of the change in Y_{it} after 2008 in the spraying area compare with the exclusion zone.

As previously mentioned in Section 1.3.2, the presence of pre-existing differences in coca cultivation and tree loss documented in Table 1.6 suggest differential behaviour between the two areas, which may violate the parallel trends assumption of the DiD estimator. To address this concern and ensure that the estimates of β reflect the change in potential deforestation from 2008 onward, we use a propensity score estimator to reweight grid cells to reflect differences in the probability of being exposed to aerial spraying based on predetermined characteristics measured prior to 2008.

For each year before the establishment of the exclusion zone, we treat coca cells located in the spraying zone as intention-to-treat observations and cells in the exclusion zone as controls. We pool treated and control observations across these pre-intervention years to estimate the probability that a coca cell was exposed to spraying as a function of a set of predetermined characteristics. We estimated the propensity score $\hat{p}$, using a logit model. The characteristics used to obtain $\hat{p}$ are: lagged coca cultivation, lagged tree cover, altitude, slope, precipitation, wind speed, and distance to the nearest anti-narcotic military base, road, and human settlement.

Following Abadie (2005) and Mejía et al. (2017), we adopt a two-step semiparametric DiD strategy to address the imbalance in pre-treatment characteristics between the spraying and exclusion zones. Specifically, we use the conditional DiD version $E[Y^1(1) - Y^0(1) \mid X_k, D = 1]$, where $Y^1(t)$ and $Y^0(t)$ denote the potential outcomes in the presence and absence of treatment at time t, respectively, D is a binary indicator equal to one if the coca grid cell is located in the spraying zone and X_k is a function of covariates X. The weighting scheme is directly based on the propensity score $\hat{p} = \hat{p}(X) = P(D = 1 \mid X)$. Specifically, grid cells in the spraying area are weighted by $1/\hat{p}$, while grid cells in the exclusion area are weighted by $1/(1 - \hat{p}_i)$.

Table 1.4 reports the results of weighted specification in Eq.(1.2) across four increasingly demanding specifications. Column (I) includes grid-cell fixed effects. Column (II) adds year fixed effects to account for common annual shocks affecting all areas simultaneously. Column (III) use year FE and include time-varying climatological controls — precipitation and wind speed. Column (IV) includes grid-cells effects and municipality-year fixed effects, which control any municipality-specific yearly shocks that could simultaneously affect all grid cells within a given municipality.

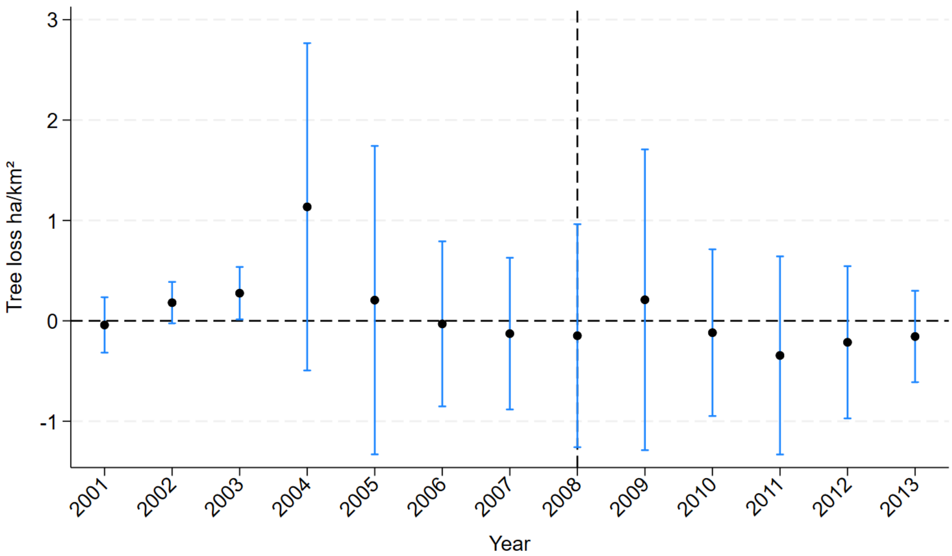
Panel A in Table 1.4 restricts the sample to grid cells with coca cultivation — the cells most directly exposed to the spraying campaigns and the main sample for our RDD estimates — while Panel B includes the full set of grid cells within the 20km band around the Ecuador-Colombia border. Across both panels and all four columns, the coefficient on the treatment indicator — defined as the interaction between being located in the spraying zone and the post-2008 period — are not statistically significant. To show the year by year estimates Figure 1.9 presents the estimates in an event-study format of column 4 Panel B and provides evidence supporting the parallel trends assumption after conditioning on pre-treatment characteristics. Overall, the DiD results confirm the null effect of aerial spraying on tree loss found in our main RDD analysis and suggest that the difference in tree loss between the spraying and exclusion zones — whether identified through a smooth function of geographic location around the 10km cutoff or through within-cell variation conditioning on pre-treatment characteristics — is statistically indistinguishable from zero. Across all specifications and both sample definitions, the DiD estimates suggest that imperfect compliance is unlikely to be driving our RDD results through attenuation bias.

Table 1.4: Estimates Semiparametric Difference-in-Difference: Average intention-to-treat effects, tree loss (2008–2013)

Differences in Tree loss (ha/km^2)	(I)	(II)	(III)	(IV)
Panel A: Ever-Coca Grid Cells				
Spray zone × Post (2008–13)	−0.366	−0.150	−0.684	−0.265
	(0.262)	(0.262)	(0.637)	(0.317)
Observations	73,110	73,110	73,110	73,095
Panel B: All Grid Cells				
Spray zone × Post (2008–13)	−0.366	−0.260	−0.691	−0.306
	(0.262)	(0.262)	(0.585)	(0.300)
Observations	160,665	160,665	160,665	160,665
Grid Fixed Effects	✓	✓	✓	✓
Year Fixed Effects	✗	✓	✓	✗
Time-Varying Covariates	✗	✗	✓	✓
Municipality-Year FE	✗	✗	✗	✓

Notes: All specifications are estimated with inverse propensity score weights and a donut hole of 0.5 km around the 10 km cutoff. Column (I) includes cell fixed effects only. Column (II) adds year fixed effects. Column (III) adds time-varying covariates (precipitation and wind speed). Column (IV) controls municipality-year fixed effects and includes covariates. Robust standard errors are clustered at the grid-cell level in parentheses. *, **, *** indicate significance at the 10%, 5% and 1% levels respectively.

Figure 1.9: Event study Estimates Semiparametric Difference in Difference. Average Intention-to-treat effects, tree Loss (2001-2013)



Source: Author's elaborations based on data from UNODC and Hansen et al. (2013).

1.4 Conclusions

One of the main challenges facing Central and South American countries in addressing narco-deforestation is integrating criminal policies with environmental strategies to reduce pressures on tropical forests. The recent expansion of the cocaine market has led regional governments to intensify military enforcement against illegal drug activities. Environmental protection is often presented as an ancillary benefit of these interventions, framing the 'war on drugs' as a simultaneous 'war on deforestation'

Using Plan Colombia as a case study, this paper provides causal evidence that the largest anti-drug policy in the Amazon – now under consideration for reinstatement – was not a conservation policy. Our findings challenge earlier studies that interpreted spatial correlations between military interventions and forest loss as evidence of causation. We show instead that eradication campaigns neither drove deforestation nor displaced coca cultivation in ways that caused further tree loss.

Our empirical strategy exploits a quasi-experiment created by an international lawsuit between Colombia and Ecuador, which restricted aerial spraying on coca crops along the border. This design mitigates endogeneity concerns arising from coca eradication targeting high-deforestation areas. Drawing on spatial data for coca crop locations and densities between 2008 and 2013, we find no statistically significant impact of enforcement eligibility on forest clearance in coca-growing areas.

These results undermine the narrative that anti-drug policies serve as conservation strategies and reject the hypothesis that eradication campaigns are a primary cause of deforestation in the Amazon. More broadly, they indicate that enforcement measures aimed solely at suppressing coca cultivation are ill-suited to address the narco-deforestation problem. Given the high costs, negligible environmental benefits, and continued resilience of coca production, any renewed aerial eradication strategy is unlikely to deliver meaningful gains for either drug control or rainforest conservation.

1.A Appendix – Additional tables and figures

Table 1.5: List of variables, by availability and source

Variable name	Unit of Measure	Period available	Source
Coca cultivation	ha/km^2	2001-2015	UNODC
Tree loss	ha/km^2	2001-2015	Hansen et al. (2013)
Area aerially sprayed	ha/Municipality	2001-2015	Ministry of Justice
Distance to nearest road	km	2010	OpenStreetMap
Distance to nearest human settlement	km	2012	IDEAM
Altitude	m	2010	IGAC
Municipality area	km^2	2005	DANE

Table 1.6: Descriptive statistics by area type 2001 to 2007.

Variable	All	Obs.	Spraying	Obs.	Exclusion	Obs.
Tree Loss	0.73	35,959	0.62	14,196	0.80	21,763
	(1.75)		(1.44)		(1.93)	
Coca cultivation	1.77	35,959	1.40	14,196	2.01	21,763
	(3.94)		(3.63)		(4.12)	
Altitude	266.43	35,959	289.76	14,196	251.22	21,763
	(157.01)		(220.24)		(92.24)	
Slope	4.25	35,959	4.52	14,196	4.08	21,763
	(3.31)		(3.94)		(2.81)	
Distance to nearest road	2.85	35,959	2.06	14,196	3.35	21,763
	(4.52)		(3.53)		(5.00)	
Distance to nearest settlement	6.99	35,959	7.85	14,196	6.43	21,763
	(4.96)		(5.42)		(4.56)	

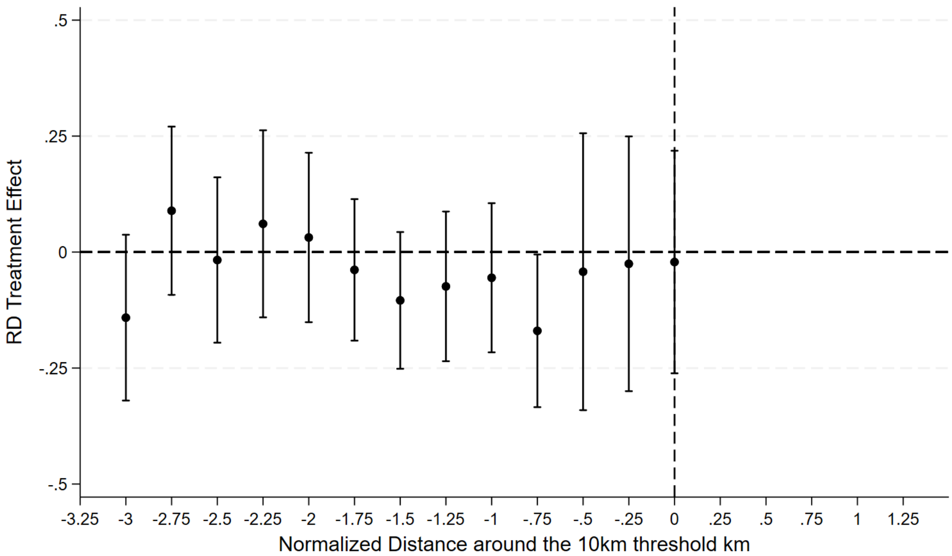
Notes: This table reports means and standard deviations (in parentheses) for each variable, by area type. All variables are computed at the 1 km^2 grid cell level. Tree loss and coca cultivation are measured in hectares per square kilometre. Distances are in kilometres and slope in degrees. Distance to Roads and Human Settlements refers to the shortest Euclidean distances from the cell centroid.

Table 1.7: Yearly RD estimates: Average treatment effect, tree loss (2008-2013)

	Linear		Quadratic	
	(I)	(II)	(III)	(IV)
	2008			
Bias-corrected, robust	0.34	0.62	0.53	0.82
	(0.59)	(0.55)	(0.82)	(0.77)
Bandwidth est.	1.450	1.383	2.377	2.335
Effective obs. est.	407	363	837	837
	2009			
Bias-corrected, robust	0.45	0.55	0.91	1.00
	(0.69)	(0.61)	(1.11)	(1.01)
Bandwidth est.	2.021	2.079	3.003	2.986
Effective obs. est.	704	704	1184	1145
	2010			
Bias-corrected, robust	-0.58	-0.54	-0.51	-0.46
	(0.40)	(0.38)	(0.42)	(0.40)
Bandwidth est.	2.094	2.054	4.174	4.138
Effective obs. est.	704	704	1716	1716
	2011			
Bias-corrected, robust	0.01	0.05	0.36	0.33
	(0.35)	(0.29)	(0.68)	(0.65)
Bandwidth est.	2.594	2.987	3.078	3.127
Effective obs. est.	937	1145	1184	1236
	2012			
Bias-corrected, robust	0.28	0.37	0.22	0.29
	(0.37)	(0.36)	(0.52)	(0.52)
Bandwidth est.	2.584	2.542	3.942	3.774
Effective obs. est.	937	937	1621	1511
	2013			
Bias-corrected, robust	-0.06	0.15	0.32	0.33
	(0.30)	(0.35)	(0.53)	(0.50)
Bandwidth est.	2.593	2.133	3.382	3.351
Effective obs. est.	937	741	1330	1330
Covariates	✗	✓	✗	✓

Notes: The coefficients are estimated following Calonico et al. (2014). Columns (I) and (III) are estimated without covariates, using linear and quadratic polynomials, respectively. Columns (II) and (IV) are estimated with the inclusion of covariates for both the linear and quadratic approximations. Standard errors are reported in parentheses. *, **, *** indicate 10%, 5% and 1% statistical significance, respectively.

Figure 1.10: Pooled Linear RD estimates at different integer cutoffs (2008-2013)



Note: The graph presents the RD unbiased point estimates and the 95% confidence intervals for alternative thresholds at 0.25 km intervals.

Source: Author's elaborations from UNODC data and Hansen et al. (2013).

Chapter 2

Can Military Enforcement Curb Illegal Deforestation? Evidence from Colombia's Largest National Parks

Abstract

This article evaluates the effectiveness of military interventions in deterring illegal deforestation. We focus on Operation Artemis, an intervention conducted between 2019 and 2022, which used military units to target illegal deforestation hotspots in protected areas of the Colombian Amazon. To identify causal effects, we use a novel approach that exploits geographic and temporal variation of hotspot policing strategies, along with legal restrictions on enforcement. We show that the military interventions were able to reduce illegal deforestation. However, our evidence suggests that rural hotspot policing may have limited effectiveness in deterring offenders and appears to be costly to enforce. Results are robust to two complementary staggered difference-in-difference strategies using alternative specifications and controls.

2.1 Introduction

Illegal activities that affect the environment are among the most lucrative forms of organised crime and have grown substantially over the last decade in the tropic rainforest (Maloney et al., 2025; United Nations Office on Drugs and Crime, 2025). Weak governance and institutions have contributed to the rise of criminal organisations involved simultaneously in illegal deforestation, drug trafficking, illegal mining and land grabbing (Maloney et al., 2025). Such criminal presence is common in the Amazon basin, where most deforestation is illegal, and occurs in areas where property rights are weakly defined, costly to administer, and often poorly enforced (Assunção et al., 2023). While technological advancements, particularly in remote sensing, enable the monitoring of forest loss and fire outbreaks in near real time, the management of environmental resources in the rainforest remains challenging given the vastness and remoteness of the areas at risk of agricultural conversion and lucrative illegal activities (Barbier, 2019).

Actions to strengthen the monitoring and enforcement of illegal activities that affect the environment have been prioritized as a key strategy to promote economic growth in many low- and middle-income countries [1] (United Nations Office on Drugs and Crime, 2025). The use of military actors, techniques, technologies, and partnerships as a conservation strategy is known as "green militarisation," a concept first introduced by Lunstrum (2014) to describe militarized anti-poaching strategies aimed at fighting the illegal wildlife trade in Africa. Recently, military operations against illegal deforestation have taken place in Brazil [2], Peru, Colombia, and Indonesia (Baretta, 2023; Corredor-Garcia and Lopez Vega, 2023; Ministerio de Defensa Nacional, 2022; Jong, 2025). Yet, the effectiveness of these operations remains unclear, as most information about military operations is restricted, official policy evaluations are rare, and causal identification proves challenging, given that enforcement areas are rarely assigned at random.

In this article, we attempt to study the effectiveness of military interventions to reduce illegal deforestation in the Amazon by focusing on hotspot policing, one of the

[1] The creation of the Law Enforcement Assistance Programme to Reduce Tropical Deforestation (LEAP) by UN is the most recent attempts for strengthening capacities to prevent and combat organized crime in the Amazon. LEAP is the result of a partnership between the Norwegian International Climate and Forest Initiative, the Container Control Program, INTERPOL, the Global Program against Money Laundering and the UNODC Global Program Crimes.

[2] One of the most prominent cases was Brazil's Operation Green Brazil under President Bolsonaro. The operation lasted for around one year (2020-2021) and mobilized about 2,000 soldiers per day to combat Amazon Forest fires Baretta (2023). According to official sources, Green Brazil contributed to a 15% reduction in deforestation between August 2020 and April 2021 (Ministério da Defesa, 2022). It also resulted in criminal charges against roughly 500 individuals and fines exceeding US$632 million.

most common strategies used by armed forces in this context. Concentrating law enforcement resources in areas with high criminality has been shown to be an effective mechanism for deterring crime in urban settings (Braga et al., 2019; Chainey et al., 2024). However, evidence from rural contexts remains extremely limited and is concentrated in developed countries (Weisburd and Telep, 2014; Sherman and Weisburd, 1995). To provide evidence of the effectiveness of hotspot policing in a rural context, we focus on Operation Artemis (Operacion Artemisa) - a hotspot policing intervention conducted in National Parks in the Colombian Amazon– as our case study. To the best of our knowledge, this is the first study to evaluate the effectiveness of hotspot policing in rural areas, with a specific focus on environmental offenses in developing countries.

Since 2016, national parks and other protected areas (PAs, henceforth) in Colombia have experienced a dramatic surge in illegal deforestation, typically overlapping with the presence of armed groups, illicit cropping, and land-grabbing organizations (Prem et al., 2020; Davalos et al., 2021). Illegal forest clearance has been concentrated in deforestation hotspots located along the administrative borders of PAs. In response to the alarming increase in illegal deforestation between 2019 and 2022, the Colombian government launched Operation Artemis–an inter-institutional initiative that deployed more than 23,000 soldiers in around 21,000 hectares deforested by criminal organizations in different PAs of the Colombian Amazon.

Official figures reported that Operation Artemis contributed to a 34% reduction in deforestation during the first semester of 2021 (Ministerio de Defensa Nacional, 2022). However, these results have been contested by independent journalistic investigations. In an interview cited by Tarazona and Parra De Moya (2023), Colombia's former Minister of the Environment, Manuel Becerra, raised concerns about the effectiveness of the operation: *The question is: What would have happened if they had not carried out the mission of Operation Artemis? Would the amount of deforestation in the national natural parks have been higher? It is plausible, although it is very difficult to judge. The problem is that there are no objective evaluations for the results of the operation.* In what follows, we try to answer this question.

Our analysis relies on combining a set of official and secondary datasets to create a unique panel dataset that covers the period 2019–2022 and includes data on deforestation. Importantly, our data records the location and timing of all deforestation hotspots, both those that were targeted by military interventions and those that were not, allowing us to identify the causal impact of the interventions

Given the design of Operation Artemis, our empirical strategy rests on a staggered difference-in-differences (DiD) framework and relies on two complementary methods. First, we exploit a quasi-natural experiment arising from the fact that the hotspots targeted with the military intervention were legally restricted to enforce illegal deforestation within the administrative boundaries of PAs. Second, we examine the military's selection process and show that the assignment of enforcement to eligible hotspots was not driven by the level of deforestation. Consistent with this, we show that after controlling for pre-treatment characteristics, treated areas and those that were eligible but not treated were similar. Based on criminal, geographical and logistical information that military forces had before any intervention, we predict which hotspots will be military targets and assess, using a propensity score reweighting estimator, whether our DiD results from the quasi-natural experiment hold under different sets of temporal and spatial eligible controls.

Consistent with the economic view that enforcement mechanisms increase the probability of conviction and therefore deter offenders (Becker, 1968), we find statistically significant negative impacts of military interventions on illegal deforestation. Our results suggest that areas targeted by Artemis experienced a 3.9% reduction in the number of early deforestation alerts. Using satellite-based measures that results potentially translate into a 12% reduction in the area of tree loss. Contrary to previous findings by Assunção et al. (2023), we found that the effect of the military intervention was short-lived. Our results show that the effects lasted only up to one year and appear to be localised in specific areas. Results are consistent across our two different specifications, and on average, both methodologies suggest that military interventions had a limited deterrent effect on illegal deforestation. By contrast, the enforcement did not have any detectable effect on forest fire incidence.

Our paper contributes to the literature on the economics of crime and that on tropical deforestation (Balboni et al., 2023). Studying law enforcement and criminal activity commonly implies a classic simultaneous equation model characterised by strong endogeneity (Draca et al., 2011; Chimeli and Soares, 2017; Assunção et al., 2023). The article proposes a novel strategy to overcome endogeneity based on the design of hotspot policing strategies and the state's legal restrictions on criminal enforcement. In addition, our paper extends the literature on policing and crime, particularly on the effectiveness of hotspot policing strategies in rural areas[3], to the

[3] A recent systematic review of hotspot policing by Braga et al. (2019), identified 65 studies on hotspot policing interventions, yet only three were conducted in major Latin American cities. In Colombia, two randomised controlled trials have assessed hotspot policing in the country's largest cities – Bogotá and Medellín (Collazos et al., 2021; Blattman et al., 2021). Both studies find that increased state presence can deter crime, although the magnitude of the effect varies by offence type.

context of environmental crimes (Weisburd and Telep, 2014; Sherman and Weisburd, 1995; Braga et al., 2014, 2019). Given that the majority of police agencies worldwide serve small to mid-size municipalities, we belived that this is a major contribution since criminal organizations that affect the environment are highly active in rural areas, threatening over two billion people with severe natural and human costs (Nellemann et al., 2018).

The rest of the paper is organized as follows: Section 2.2 illustrates the institutional framework of natural protected areas in Colombia, reviews the literature on the post-conflict upsurge in deforestation, and describes the design of Operation Artemis. Section 2.3 describes our unique panel dataset that records the process of militarized intervention along with the information recorded by the Colombian Forest Monitoring System. Section 2.4 outlines our identification strategy, presenting the quasi-natural experimental design and the complementary inverse probability weighted estimator that supports the main estimates by capturing the decision-making process behind the military intervention decisions. Section 2.5 explore the policy cost. Finally, Section 2.6 concludes.

2.2 Institutional Background

2.2.1 Protected Areas and Property Rights

The National System of Protected Areas in Colombia is a long-established and complex institutional framework, formally created in 1959 with the enactment of Law 2 (Congreso de la República de Colombia, 1959). Under this law, approximately 35% of the country's continental territory was designated for environmental protection. Since then, institutional reforms have led to the creation of more than 1,800 legally recognized PAs. By 2025, PAs cover approximately 50% of the country's total continental territory – an area comparable to the size of France. Most of these continental PAs are located in the Amazon region, where around 90% of the land is protected under environmental legislation.

Although most territories designated as protected areas (PAs) in the Colombian Amazon are formally under state management and jurisdiction, in practice, they often function as de facto open-access areas and are vulnerable to unauthorized occupation. This common-pool resource dynamic has contributed to numerous

However, these findings are limited to urban settings, and little is known about the effectiveness of hotspot policing in rural municipalities – particularly in natural parks.

conflicts between private individuals – who, over time, have acquired legal property rights – and the government. However, regardless of the land legal tenure status, within the administrative boundaries of most protected areas (PAs), special environmental protection laws grant the government discretionary authority to revoke private ownership if land use is found to conflict with the legally-established conservation objectives (Congreso de la República de Colombia, 1959).

2.2.2 Post-Conflict Deforestation in the Amazon Protected Areas

Since the signed of the peace agreement in 2016 (Comisionado para la Paz, 2016), Colombia's largest national parks were heavily affected by illegal deforestation (Clerici et al., 2018). Among Colombia's national parks, those located in the Amazon region experienced the highest tree loss, with a sharp increase during 2016–2018 compared with 2013–2015, accounting for 25% of the country's total deforestation (Clerici et al., 2020). The illegal forest clearance has been concentrated in deforestation hotspots both inside and outside the administrative limits of protected areas (PAs), particularly in 10 kilometers buffer zones around them. Evidence from 39 continental PAs indicates a substantial 177% increase in deforestation in the three years before and after Colombia's Peace Agreement in 2016 (Clerici et al., 2020).

According to Davalos et al. (2021), illegal armed groups engaged in deforestation to promote cattle ranching and coca cultivation with violence and human displacement. Negret et al. (2019) attributed the post-conflict deforestation to a lack of governance following the peace accords. In addition to illegal deforestation, illegal forest fires, largely driven by human activity, increased sixfold in protected areas (PAs) following guerrilla demobilization between 2017 and 2018 (Armenteras et al., 2019). In response to rising illegal deforestation, in 2019 the Colombian government launched Artemis Operation, a ”green militarization” strategy that prosecuted deforestation offenders and imposed penalties of up to 15 years of imprisonment (Corredor-Garcia and Lopez Vega, 2023).

2.2.3 Artemis: Military enforcement and hotspot policing in rural areas

Artemis Operation was explicitly designed as a hotspot policing strategy [4] and was carried out through staggered missions between 2019 and 2022 in deforestation hotspots located within PAs of the Colombian Amazon. Artemis intervention was divided into twenty missions implemented over over the four years. Sixteen of these missions took place within PAs located in the most extensive Colombian region that acts as a natural corridor knowing as the Andes-Amazon Transition Belt[5]. This region encompasses Colombia's largest national parks–including the world's largest tropical park–and spans the administrative boundaries of four departments (Caquetá, Guaviare, Meta, and Putumayo) and ten municipalities across the region[6]. Official figures from the Ministry of National Defence revealed that Artemis employed approximately 23,000 members of the armed forces in 21,000 hectares within Colombia's PAs (Corredor-Garcia and Lopez Vega, 2023; Ministerio de Defensa Nacional, 2022). The same reports indicate that most missions resulted in the apprehension and penalization of individuals involved in these crimes, as well as the blockage of illegally constructed routes within PAs (Ministerio de Defensa Nacional, 2021).

Artemis initiative aimed to curb the rise in illegal deforestation within the PAs of the Colombian Amazon. According to official sources, armed criminal organizations were primarily responsible for the forest loss, transforming these PAs into critical deforestation "hotspots" (Corredor-Garcia and Lopez Vega, 2023). To implement Operation Artemis, the Colombian government established a legal framework and an inter-institutional Environmental Protection Force, involving the Ministry of National Defence and the Ministry of the Environment – under whose forest authority the Instituto de Hidrología, Meteorología y Estudios Ambientales (IDEAM) operates – alongside other governmental actors (Ministerio de Defensa

[4]Hotspot policing is a widely studied mechanism for reducing crime, which focuses law enforcement resources on geographically concentrated areas with high crime rates. Given the spatial clustering of illegal activity in specific settings, this approach has been implemented globally to target locations where crimes are most likely to occur. Systematic reviews of studies conducted in large cities suggest that hotspot policing yields modest but statistically significant reductions in crime, typically ranging from 6 to 13 percent (Sherman and Weisburd, 1995; Braga et al., 2014)

[5]"This area is represented by three contiguous National Natural Parks: Cordillera de los Picachos, Tinigua, and the Sierra de la Macarena. This group of national parks, established respectively in 1977, 1989, and 1971, represent an ecological connection between the mountainous Páramo province in the South American Transition Zone and the Imerí province in the Boreal Brazilian dominion" (Clerici et al., 2018)

[6]Colombia's political–administrative division consists of departments, municipalities, and veredas, the latter being the smallest administrative units

Nacional, 2022).

Inter-institutional coordination in Operation Artemis functioned in parallel, with agencies sharing information that enabled the armed forces to intervene in deforestation hotspots. First, the deforestation hotspots were detected and reported by the Ministry of Environment to the Ministry of National Defence (MND). Using this geographic data, the MND, in alliance with other governmental entities, assessed the security and governance risks of a possible intervention. The risk assessment monitored current criminal activity in the areas, analysed the jurisdictional status of the land, and calculated the logistical requirements for military deployment to determine where to intervene. Once the risk assessment was completed, the armed forces targeted specific hotspot within the PAs (Ministerio de Defensa Nacional, 2022).

2.3 Data

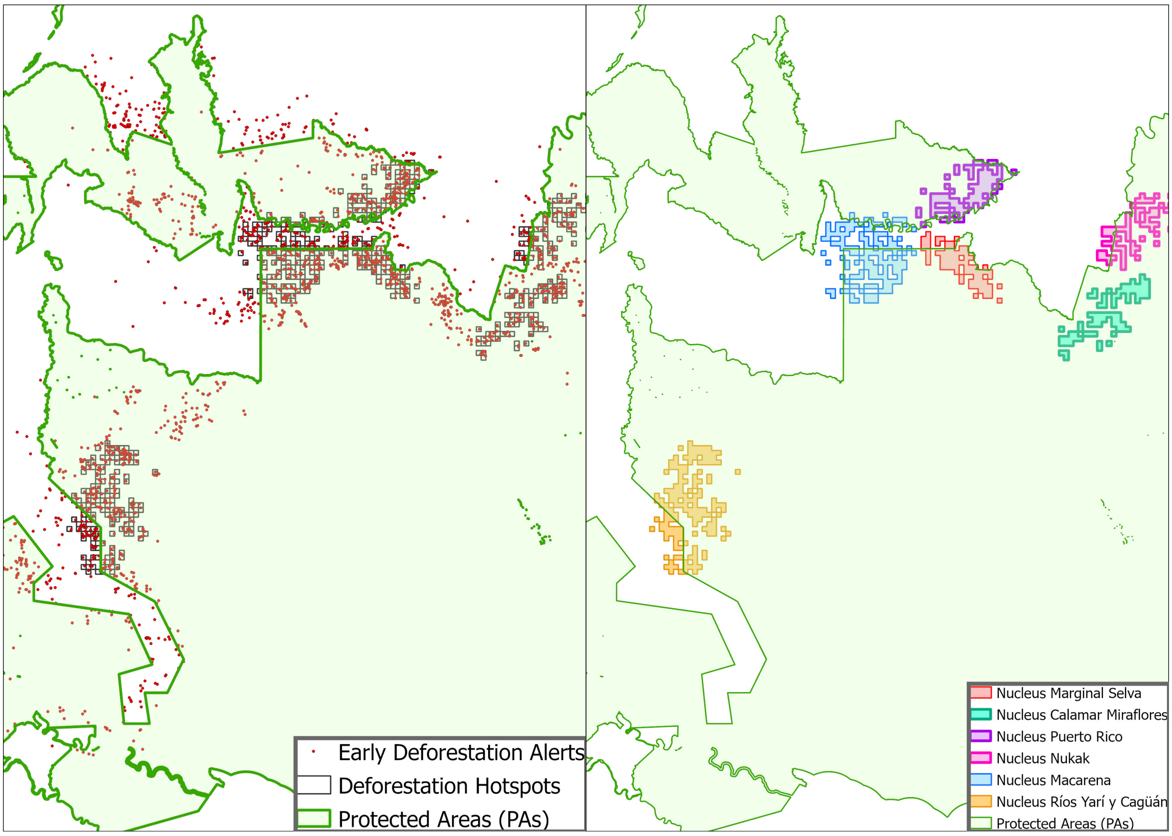
2.3.1 Deforestation Hotspot and Nuclei in the Colombian Forest Monitoring System

In Colombia, the Instituto de Hidrología, Meteorología y Estudios Ambientales (IDEAM) is the National Forest Authority, responsible for managing the Forest and Carbon Monitoring System, which quantifies forest cover loss due to deforestation (Cabrera et al., 2019). Since 2017, IDEAM has reported the exact coordinates of early deforestation alerts (EDAs) on a quarterly basis and monitors active fire alerts generated by NASA (Schroeder et al., 2024). EDAs are recorded as geographical points (with specific longitude and latitude coordinates) when IDEAM detects a change in tree cover over an area larger than 0.5 hectares[7] (Galindo, 2024; Cabrera et al., 2019) Once satellites have mapped the full distribution of EDAs across Colombian territory, IDEAM estimates the density of EDAs per area using a defined grid of 6.25 square kilometres. The cells of 6.25 square kilometres with the highest density of EDAs are classified as deforestation hotspots. Based on the spatial proximity of these hotspots are aggregated into clusters, officially referred to as

[7] Area of deforestation data is not used as primary dependent variable because their yearly official release frequency does not allow us to exploit the spatial and temporal variation in seasonal deforestation patterns and the timing of military deployments that define our identification strategy. Instead, we rely on quarterly early deforestation alerts (EDAs), which align with the recording period of military interventions. A forecasting transformation from EDAs to annual tree cover loss using data from Hansen et al. 2013 is performed in our back-of-the-envelope cost-effectiveness analysis of the operation presented in Section 2.5.

deforestation nuclei. Each nucleus is named after a municipality or geographical landmark (e.g., rivers, mountains) and is reported quarterly by IDEAM. Figure 2.1 presents the EDA points, the 6.25 square kilometre grid-based deforestation hotspots, and the official deforestation nuclei reported by IDEAM for the first quarter of 2019. As showed in Figure 2.1, deforestation nuclei were located around the administrative boundaries of protected areas covering the 10-km buffers zones around them.

Figure 2.1: Early Deforestation Alerts (left), Deforestation hotspots - 6.25km^2- (left) and Deforestation Nuclei in the first quarter in 2019 (right)



Note. Source: Author's illustration with data from IDEAM and the Ministry of Environment.

2.3.2 Military interventions and deforestation hotpots

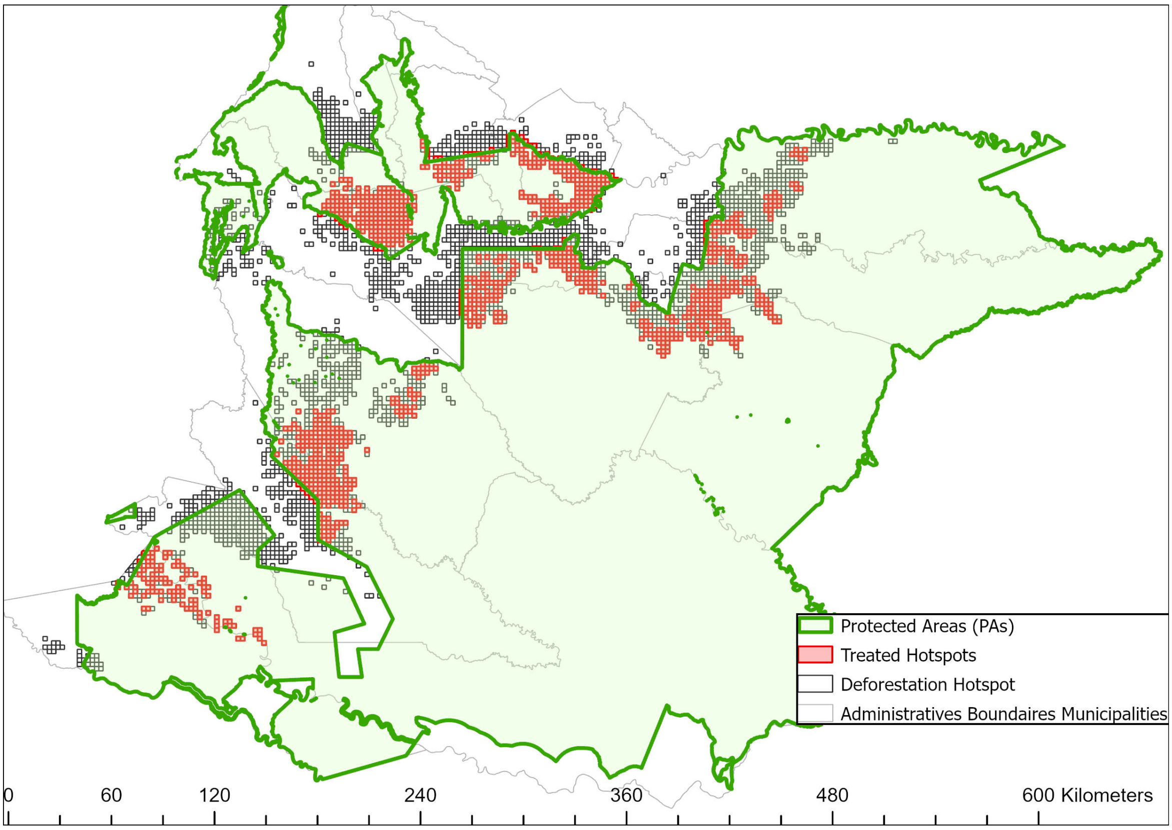
Details of Operation Artemis were compiled over a two-year period through a combination of official communications and interviews with personnel from the Colombian Military Forces, the Ministry of National Defence , the National Police, the Ministry of Environment, and IDEAM.

First, using information from the Ministry of National Defense (MND), we identified the ten municipalities in the Colombian Amazon where Operation Artemis was implemented and defined these as our study area. Using data from IDEAM, we identified the full set of deforestation hotspots that formed the official deforestation nuclei between 2019 and 2022, when Operation Artemis was in place. We then located the exact coordinates of Early Deforestation Alerts (EDAs) reported quarterly between 2017[8] and 2022. Based on information from the MND and IDEAM, we identified the number of active nuclei in each quarter and those "targeted" by the operation. However, since the military operation was restricted to protected areas (PAs), only the hotspots of targeted nuclei located within the administrative boundaries of PAs were treated. As a result, our dataset records 3,361 hotspots belonging to 52 active nuclei from 2019 to 2022, of which 11 nuclei — formed by 1,401 hotspots — were militarily targeted, but only 1,148 hotspots were treated as they were the units contained within the administrative boundaries of PAs.

Figure 2.2 presents our dataset, which aggregates all deforestation hotspots that formed the officials active nuclei between 2019 and 2022, when operation Artemis was deployed. As can be seen from Figure 2.2, nuclei were spatially distributed inside and outside the administrative boundaries of protected areas.

[8]2017 was the earliest year in which EDAs were reported on a quarterly basis by IDEAM.

Figure 2.2: Deforestation hotspots that formed the deforestation Nuclei officially identified by the IDEAM 2017–2022



Note. Source: Author's illustration with data from IDEAM and the Ministry of Environment.

2.4 Identification Strategy

2.4.1 Sources of identification and model specifications

Our identification strategy relies on two complementary differences in differences approaches that exploit different sources of spatial variation in the assignment of military enforcement to deter illegal deforestation.

In the first strategy, we exploit a quasi-natural experiment arising from the legal restriction of Operation Artemis to operate within the administrative boundaries of protected areas. We focus on the 11 nuclei "targeted" by the operation and use the hotspots belonging to those nuclei located outside the PA boundaries — in the buffer zones — as control units. Our design exploits the fact that the legal restriction partitions each targeted nucleus into treated and control hotspots. The key identifying assumption is that the administrative boundaries of PAs, established before Operation Artemis, were exogenous to the deforestation behaviour of criminal organisations but did affect the intervention decision. Our preferred model specification uses the staggered difference-in-differences (DiD) outcome regression estimator of Callaway and Sant'Anna (2021), but we corroborate our results using the staggered DiD two-way fixed effects (TWFE) model Guadalupe et al. (2012). To account for the potential overestimation of our results due to deforestation leakage, we implement a second identification strategy that compares treated hotspots against control units that are more spatially distant.

The second source of identification analyses the intervention decisions among the hotspots of 44 nuclei that were eligible — that is, hotspots located within PAs — but did not receive Operation Artemis. First, we show that when comparing the density of early deforestation alerts between treated and eligible but untreated hotspots, the military decision was not driven by active levels of criminal activity. We corroborate this with interviews with military officials who participated in the design of the operation. Following the conditional independence assumption that all differences between treated and eligible but untreated hotspots are captured by observed variables revealed by military officials — including the history of deforestation and observed logistical, social, and geographic characteristics — we exploit a conditional inverse probability weighted DiD estimator (Callaway and Sant'Anna, 2021) and a TWFE to assess whether the results of the quasi-natural experiment hold under a completely different set of controls and are not driven by leakage outside the PA boundaries.

We acknowledge the potential for spatial displacement — whereby illegal clearing relocates to areas adjacent to those targeted by Operation Artemis — which represents a common limitation of spatially concentrated enforcement policies (Collazos et al., 2021) and a major challenge for causal inference with observational data (DiTraglia et al., 2023).

In this paper, we address this concern, to some extent, in two ways: First, we present two different sets of specifications that evaluate different potential spatial directions of displacement. If leakage were severe, we expect the first strategy — which uses geographically proximate controls — to produce larger estimates than the second systematically. Similar magnitudes across both strategies suggest that the effect is attributable to within-cell variation in deforestation among treated hotspots, compared with relatively stable deforestation rates in the control areas over time. Two, we present event-time estimates to assess the temporary nature of the deterrent effect. We expect that a short-lived treatment effect is consistent with the interpretation that criminal organisations return to the same hotspots once the probability of convictions decreases, reducing the likelihood of permanent spatial displacement. By contrast, a long-run deterrent effect would support the hypothesis that enforcement permanently relocates criminal organisations away from the targeted hotspots. We acknowledge that distinguishing between these two mechanisms would require data on convictions and criminal mobility at a finer spatial and individual resolution, which is beyond the scope of the current paper but represents an important avenue for future research.

2.4.2 A hotspot quasi-natural experiment

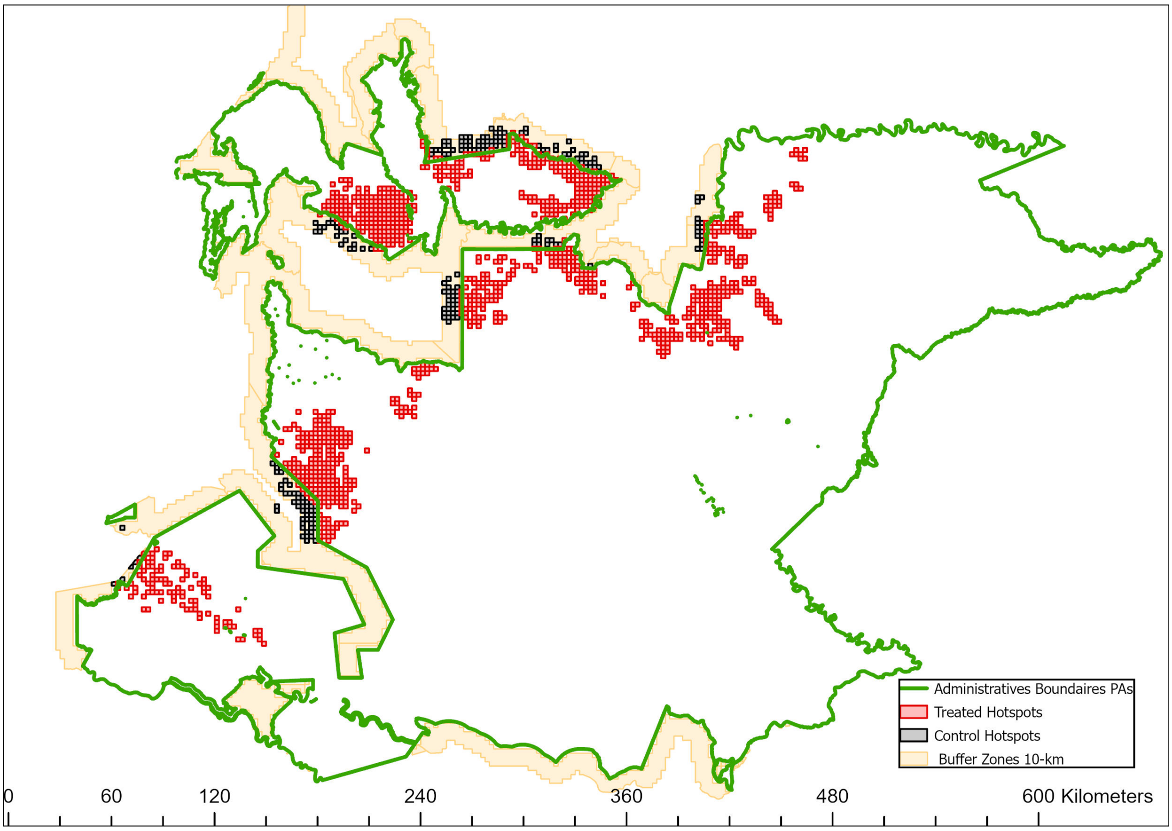
Having identified the entire sample of 3,361 hotspots that belonged to nuclei recorded by the IDEAM from 2017 to 2022, we decided to focus only on the nuclei (sets of hotspots) that were targeted by Operation Artemis.

We found that in approximately 88% of the missions (15 out of 17), the area of the targeted nuclei was located both inside and outside the administrative boundaries of protected areas (PAs). We used the definition by Clerici et al. (2020) and defined buffer zones (BZs) as areas within 10 km of the administrative boundaries, since around 97% of the hotspots outside the PAs fell within this threshold. Our final spatial dataset contains 1,401 hotspots (6.25 km^2) that shaped the nuclei targeted by Artemis. However, of the 1,401 targeted hotspots, only 1,148 were treated, and 253 were located in the surrounding BZs, which serve as controls. Figure 2.3 displays the assembled grid of the study area.

Our analysis exploits the spatial and temporal variation of areas defined by IDEAM as deforestation nuclei and their intersection with the administrative boundaries of PAs. As previously discussed, Operation Artemis was designed to operate within the boundaries of PAs, partly due to the special protected status of these areas, which grants the government discretionary authority to revoke private ownership. However, this discretionary authority is not clearly defined in areas adjacent to the administrative boundaries of PAs (Presidencia de la República de Colombia, 1974). In these regions, government efforts to assert such authority–even in the presence of criminal activity–may face legal challenges, as they risk being perceived as administrative overreach into private property.

We consider the administrative boundaries of PAs exogenous to deforestation, yet they influenced the intervention strategy by partitioning the same deforestation nuclei into treated and untreated hotspot cells. We base our claim on four main points: (i) the existence of administrative boundary does not implies different deforestation behaviour

Figure 2.3: Deforestation hotspots targeted by Artemis Operation



Note. *Source*: Author's illustration with data from IDEAM, the Ministry of Defence, and the Ministry of Environment.

among offenders, (ii) Enforcement was restricted to PAs as the risk to the military to be sued was higher in the Buffers zones, iii) PA boundaries in our study area were established prior to the intervention, and (iv) Apart from the legal restriction, the intervention decisions between hotspots of the same nucleus inside and outside PAs followed a quasi-random assignment (Tobón, 2022) that was arguably uncorrelated with unobserved grid-cell characteristics.

To explain our first point, we begin by comparing the number of EDAs reported per square kilometre before the first intervention (2019Q2) for our treated and control hotspots. Table 2.1 presents the pre-intervention (2017Q1–2019Q1) summary statistics on various characteristics of hotspots in both treated hotspots within protected areas (PAs) and control hotspots in buffer zones (BZs). Before the military interventions, the number of EDAs was statistically identical between treated and control hotspots, as were the climatological conditions. This suggests that criminal behaviour, detected by early deforestation alerts, was not different in the treated and control hotspots.

In addition, the results from Table 2.1 align with our second claim that enforcement was deployed in areas where the government faced lower legal risk of individual lawsuits concerning administrative overreach on private property. Using cadastral information as a proxy for private ownership, Table 1 shows that while only 2% of the hotspots within PAs had a cadastral register, the proportion in BZs exceeded 30%.

Table 2.1: Descriptive statistics Hotspot in Protected Areas and Buffer Zones pre-intervention.

	Protected Areas		Buffer Zones			
	Mean (1)	S.D. (2)	Mean (3)	S.D. (4)	Diff (5)	pvalue. (6)
Deforestation Characteristic - Depend Variable						
Early Deforestation Alerts (#/Km^2)	0.083	0.276	0.079	0.223	0.004	0.55
Geographic Characteristics						
Slope	3.824	3.161	3.701	2.796	0.122	0.11
Precipitation (mm)	192.755	91.316	195.015	89.029	-2.260	0.318
Socioeconomic Characteristics						
Population Density-Vereda (#/km^2)	0.394	1.113	0.334	0.696	0.060^{*}	0.019
% Area with Land-Cadastral Register	0.019	0.137	0.316	0.465	-0.297^{***}	0.000
Observations	7092	7092	2079	2079		

Columns 1 and 2 report the quarterly mean and Standard Deviation for Deforestation Hotspots within the Protected Areas (PAs). Columns 3 and 4 report the same summary statistics for Deforestation Hotspots in the Buffer Zones (BZs). Column 5 reports the mean difference of PAs-BZs and Column 6 reports pvalue. Values with *** are significant at 1%, ** at 5% and * at 10%.

To explain our third point, we refer to Section I-A, in which we describe that most of the administrative boundaries in the Colombian Amazon were established in 1959 under Law 2. No PAs were created during the period in which Artemis operated.

For our four point, we leverage two characteristics of the procedure used by the Colombian Forest Authority (IDEAM) to designate deforestation nuclei. First, according to IDEAM, the protected status of the land does not influenced the denomination of hotpots or nuclei (see Section 3.1). Second, the definition of a hotspot and a nucleus can vary over time. According to IDEAM, nuclei are composed by aggregating the hotspots that fall within the three categories with the highest density of deforestation alerts at the national level in a specific quarter. Since deforestation is not constant across quarters or regions in Colombia, the highest density categories change throughout the year. For instance, national reports indicate that the category with the highest density in the fourth quarter of 2019 was approximately four times larger than the category with the highest density in the second quarter, which exhibited a range of 27–43 EDAs per grid compared to 52–120 EDAs per grid.

The dynamic nature of hotspot classification is consistent with the view of the

Director of the Forest and Carbon Monitoring System at IDEAM, who noted that nationwide variability in meteorological conditions and continuous shifts in the socioeconomic drivers of deforestation make it extremely difficult to predict where the next deforestation hotspots will emerge. This unpredictability reinforces the no-anticipation assumption underlying our identification strategy, as neither criminal organisations nor military forces could have foreseen which hotspots would be classified as active — and therefore eligible for intervention — in subsequent quarters.

A potential concern for our four point, is that the dynamic classification of deforestation hotspots by IDEAM — whereby the set of active hotspots and their aggregation into nuclei varies across quarters depending on the national distribution of deforestation alerts — could affect our results. We address this concern in three ways. First, since treated and control hotspots belong to the same targeted nucleus by construction, any quarter-specific changes in the national classification threshold affect both groups equally and are differenced out by our DiD estimator. Second, we use a seasonal differencing operator that removes time-invariant classification differences across hotspots by comparing each hotspot to itself in the same quarter of the previous year, ensuring that our estimates reflect the changes in deforestation activity rather than changing of the classification system. Third, our preferred specification controls for treatment effect heterogeneity across cohorts and over time using the group-time average treatment effects estimator of Callaway and Sant'Anna (2021).

To define our identification strategy, it is helpful to consider the supply function of illegal deforestation, based on targeted deforestation nuclei that aggregate the deforestation hotspots i (grids of 6.25 km^2) distributed across protected areas (PAs) and buffer zones (BZs) over time.

$$D_{it} = \beta M_{it} + \delta X_{it} + \tau_i + \rho_t + \varepsilon_{it} \tag{2.1}$$

where D_{it} is the number of deforestation alerts per square kilometre for a hotspot i in time t, that is measured in quarters. M_{it} is a dummy variable that becomes 1 if i is within the boundaries of PAs. X_{it} is a vector of observable elements at the hotspot level that affect illegal deforestation such as population, slope, altitude, precipitation and nearest distance to road, human settlements. In our panel data structure τ_i captures the grid fixed effect and ρ_t control for time fixed effect attributable to some quarter year variation. Finally, we denote ε_{it} as a random error term.

We consider a seasonally differenced version of Eq.(2.1), where the dependent variable is the change in the number of deforestation alerts relative to the level in the same quarter of the previous year. This is critical in our case, as deforestation in the Amazon rainforest exhibits strong seasonal variability driven by weather patterns throughout the year and shows persistence across some deforestation nuclei over time. Eq.(2.2) presents the year-on-year change form of Eq.(2.1), yielding:

$$\Delta_q D_{it} = \Delta_q M_{it} + \delta \Delta_q X_{it} + \Delta_q \rho_t + \Delta_q \varepsilon_{it} \tag{2.2}$$

Where Δ is a difference operator, with q indexing the order of seasonal differencing between quarter t and its corresponding quarter in the previous year $(t-4)$. $\Delta_q D_{it}$ reflects the quarterly difference in the number of early deforestation alerts in hotspot i. $\Delta_q M_{it}$ is a dummy variable that captures the shift in military enforcement for the hotspot located within the PAs. As it is possible for a hotspot i to be identified for enforcement at both time t and $t-4$, we discard hotspots that were eligible for more than one intervention[9]. Under this condition, our staggered adoption variable $\Delta_q M_{it}$ will take the value of 1 only once and will remain constant once the unit becomes treated[10]. $\Delta_q \rho_t$ represents the year-on-year change in factors common across all areas. Due to the high precision of our data, our deforestation controls rely on precipitation changes measured on a year-quarterly basis at the hotspot level[11]. Finally, the estimates of $\varepsilon_{it} - \varepsilon_{i(t-4)}$ are presented with robust standard errors clustered at the grid level to correct for heteroscedasticity and time autocorrelation.

As Artemis had an staggered adoption of military interventions, following Baker et al. (2021) we denote a two-way fixed effect difference in difference model (TWFE DiD) with event-time indicators that will takes the following form:

$$\Delta_4 D_{it} = \Delta_4 \rho_t + \sum_k \delta_k I[t - g_i = k] + \theta_3 \Delta_4 X_{it} + \Delta_4 \varepsilon_{it} \tag{2.3}$$

Where $\Delta_4 D_{it}$ is presented using both the levels and logarithm forms by using the inverse hyperbolic sine (IHS) transformation[12] as many of our panel data reports 0

[9] To avoid compare units with different intensity of treatments we exclude all the grids (hotspots) that were treated more than once.

[10] In our staggered treatment adoption specification, the quarterly difference of a dummy variable will always remain constant once a unit becomes treated. See Irreversibly Assumption in Callaway and Sant'Anna (2021).

[11] It is relevant to notice how Δ differencing eliminates τ_i as grid fixed effects are time-invariant variables, such as geological conditions and distances to roads, human settlements, rivers, and military bases.

[12] The inverse hyperbolic sine (IHS) transformation is defined as $\text{IHS}(x) = \text{arcsinh}(x) =$

for some periods of study. g is the time period where treatment begins for unit i and $I[t - g_i = k]$ is an indicator for being k years of treatment started capturing event time relative to the treatment[13]. δ_k our average treatment effects estimate ATT is the coefficient on event time that measures the treatment effect k periods after (or before, if $k < 0$, to test the parallel trend assumptions) the treatment.

We incorporated the Callaway and Sant'Anna (2021) estimator to control for treatment effect heterogeneity[14]. We use the outcome matching regressions estimator (OR) between treated units and never-treated (with no anticipation), initially proposed by Heckman et al. (1997, 1998) We choose the OR estimand based on the concerns that due to the treatment effect heterogeneity, the parallel trends assumption holds only after condition on observed covariates that affect both military interventions and deforestation outcomes. Our DiD estimator is the group-time average treatment effects (GT–ATT) that computes average effects across all positive lengths of exposure in an "event study" form (Callaway and Sant'Anna, 2021). If we aggregated all the hotspots treated i per year-quarter in a group-time variable g and re-centre ATT around g, we have ATT(g, k) where $t = g + k$ [15]. Thus ATT(g, k) after k periods of being treated is defined:

$$\text{GT–ATT}^{nev}_{OR}(g, k) = E\left[\frac{G_g}{E[G_g]}\left((Y_k - Y_{g-1}) - [Y_k - Y_{g-1} \mid X]\right)\right] \tag{2.4}$$

Where GT–ATT$^{nev}_{OR}(g, k)$ is a group-time weighted average treatment effects of all hotspots treated compare with never treated units. G_g is a binary variable that is equal to one if a hotspot i is first treated in group-time g. $Y_k - Y_{g-1}$ is the difference outcomes $(\Delta_4 D_{it})$ of a treated g between relative time period k of being treated and the reference time period $g - 1$. $[Y_k - Y_{g-1} \mid X]$ are population outcome regression for the never treated hotspots, conditional on X $(\Delta_4 X)$ using the same relative and reference time periods k and $g - 1$. Standard errors of the relative event period ATTs are calculated using bootstrap procedure following Callaway and Sant'Anna (2021)[16]

Lastly, it is worth mentioning that despite the high precision of our military data, geographically speaking, our estimates still rely on Intention to Treat (ITT) estimates.

$\ln\left(x + \sqrt{x^2+1}\right)$ (Bellemare and Wichman, 2020).

[13]The possibility of dynamic treatment effects is implemented by including leads and lags of the treatment variable instead of a single binary indicator variable (Baker et al., 2021).

[14]Baker et al. (2021) found that staggered treatment timing and treatment effect heterogeneity, either across groups or over time, leads to biased TWFE DiD estimates for the sample-average ATT.

[15]Thus, the ATT for a cohort in the first year-quarter of treatment is denoted as ATT$(g, 0)$.

[16]In section 2.4.3, we use the Callaway and Sant'Anna (2021) variation of Eq.(2.4) using inverse propensity weighting, formally presented as:

All our results are presented in this form. The exact coordinates where military forces recovered the 23,000 hectares of deforested land remain confidential, so we rely on the total area of the treated nuclei. However, we consider this a strength of our empirical analysis. Regardless of the precise location of the recovered area, our interest lies in evaluating the deterrent effect of Artemis on the broader administrative region potentially affected by the intervention. Including the entire area of the deforestation nuclei allows us to define socio-economic units for the analysis. Focusing only on the exact coordinates of the recovered area would assess outcomes in places that have already been deforested.

2.4.2.1 Results using quasi-natural experiment

Our empirical strategy allows us to address the following research questions: (a) What was the average treatment effect of being eligible for Operation Artemis across all groups that received the intervention between 2019 and 2022? and (b) How did the average treatment effects vary with the length of exposure to the treatment?

Table 2.2 presents the ITT results using Equation (3) in columns 1 and 2, and Equation (4) in columns 3 and 4, for the change in the number of early deforestation alerts (EDAs). Panel A presents the results in levels, while Panel B shows estimates using the inverse hyperbolic sine transformation of EDAs between hotspots that were enforced in protected areas (PAs) and the never-treated controls in buffer zones (BZs). We report the results excluding hotspots that intersect the administrative boundaries of PAs and partially overlap with BZs. In addition to the inclusion of time-varying controls in columns 1, 2, and 4, and quarterly fixed effects in columns 1 and 2, we present results obtained by excluding hotspots with a cadastral register (a proxy for private property) in columns 2 and 4. In columns 3 and 4, our group-time average treatment effect (GT-ATT) estimates are computed using the ordinary least squares kernel-based matching method (OR), conditional on changes in precipitation, for the nine group-time (year-quarter) periods during which we were able to track Artemis interventions. Aggregate estimates are weighted by the area of the hotspots and reported using fixed effects in the regressions in columns 1 and 2. Time-varying controls include quarterly changes in precipitation. We refer to column 4 as our benchmark specification, showing the results of the intervention in levels (Panel A) and using the hyperbolic sine transformation

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$$\text{GT–ATT}^{nev}_{IPW}(g,t;\delta) = \mathbb{E}\left[\left(\frac{G_g}{\mathbb{E}\left[G_g\right]} - \frac{\frac{p_g(X)\cdot C}{1-p_g(X)}}{\mathbb{E}\left[\frac{p_g(X)\cdot C}{1-p_g(X)}\right]}\right)(\Delta_4 D_t - \Delta_4 D_{g-\delta-1})\right] \tag{2.5}$$

.

(Panel B).

Table 2.2: Average treatment effects (Intention to treat–ITT–estimates) of Artemis operation on illegal deforestation

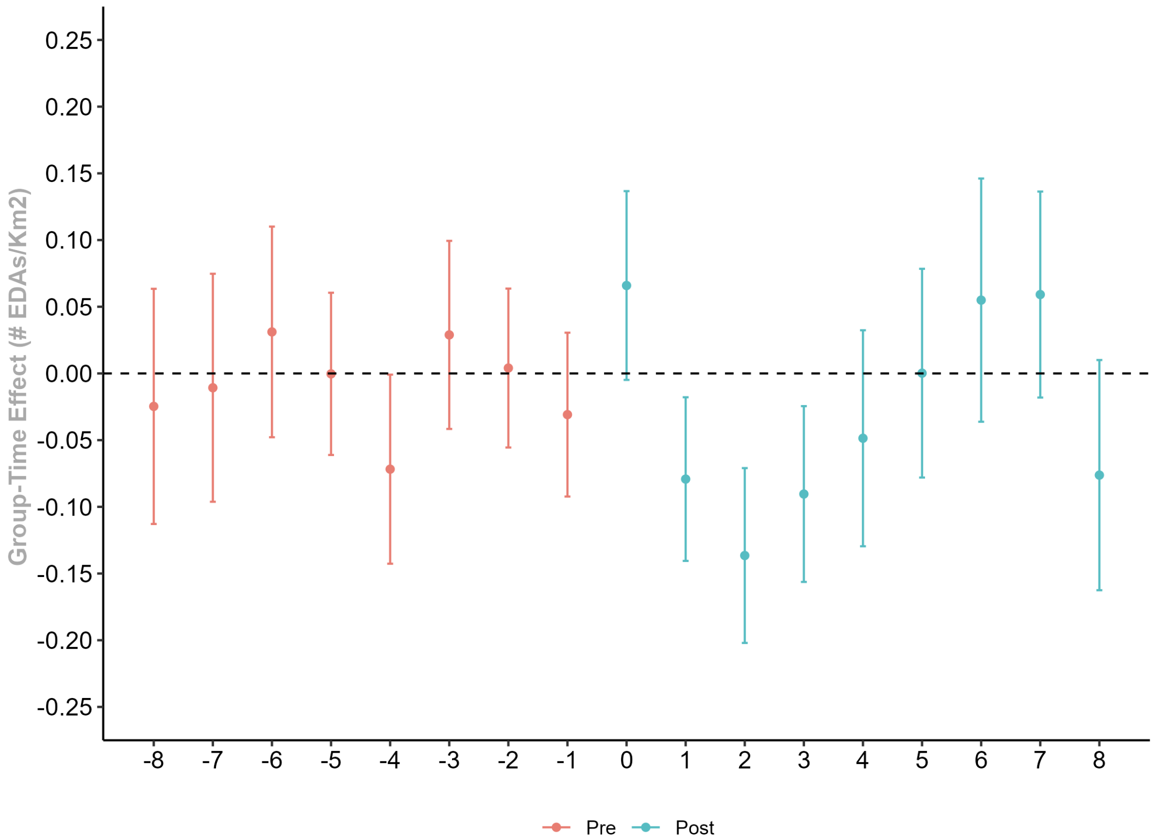
Differences among deforestation hotspots within and outside Protected Areas	TWFE		OR Conditional	
	(1)	(2)	(3)	(4)
Panel A				
Levels (#EDAs/Km^2)	-0.0425^{***}	-0.0398^{***}	-0.0382^{*}	-0.0392^{*}
	(0.008)	(0.008)	(0.0147)	(0.0186)
Panel B				
Inverse Hyperbolic Sin Transformation EDAs	-0.0385^{***}	-0.0359^{***}	-0.0573^{*}	-0.0422^{*}
	(0.006)	(0.007)	(0.0147)	(0.0186)
Time-Varying Controls	Yes	Yes	Yes	Yes
Time Fixxed Effects	Yes	Yes	No	No
Restricting Units without Cadastral Register	No	Yes	No	Yes
Observations	18140	16620	35270	35270

Notes: All specifications are weighted by the area of the grid. Panel A presents estimates in levels for the quarterly change in the number of Early Deforestation Alerts (EDAs), and Panel B shows the results when using Inverse Hyperbolic Sin Transformation EDAs. Column 1 presents estimates of Equation 3 with the panel fixed effect weighted regression, including the quarterly change of precipitation as a control and time fixed effect for every quarter. Column 2 presents the estimates of equation 3 when restricting to hotsposts without Cadastral register information. Column 3 presents estimates of Equation 4 and computes the ordinary least squares kernel-based matching method (OR) conditional on covariates following Callaway and Sant'Anna (2021). Column 4 presents the estimates of equation 4 when restricting to hotsposts without Cadastral register information. Standard errors are clustered in parentheses at the 6.25 squared kilometres cell level and robust against heteroskedasticity and serial correlation. For columns 1 and 2, values with *** are significant at 1%, ** at 5% and * at 10%. For columns 3 and 4 (bootstrapped standard errors), estimates with * indicate that confidence intervals do not cover 0. Source: Author's estimates with data from IDEAM, Ministry of Justice, Ministry of National Defence, DANE, IGAC and OpenStreetMap.

Overall, the results indicate a significant impact of Operation Artemis in reducing the number of early deforestation alerts (EDAs). Estimates suggest that hotspots eligible for enforcement reported 0.04 fewer deforestation alerts per square kilometre than areas that were not treated. Similarly, the results show a comparable and statistically significant reduction in deforestation alerts per square kilometre when excluding hotspots with a cadastral register. Using the inverse hyperbolic sine transformation, we estimate that being eligible for treatment led to a reduction of approximately 4% in the number of EDAs. In general, the estimates confirm the deterrent effect of hotspot military intervention on EDAs.

Figure 2.4 shows the event-study results from column 4, corresponding to the estimates of Equation (4), Panel A. For visualization purposes, we restrict the lag and lead effects of the operation to eight periods, as the trend follows a similar pattern in both pre- and post-treatment periods. The results are based on aggregating the GT-ATT estimates from the Artemis missions, grouped by the year-quarter of intervention. It is worth noting that the graphic serves as a pre-test of the parallel trends assumption in our staggered DiD model. We observe that the differences between treated and control units in all pre-treatment periods are statistically indistinguishable from zero. The GT-ATT estimates support the view that during the first year of the operation, being eligible for Artemis enforcement led to a greater reduction in EDAs compared to the never-treated hotspots located in buffer zones. The effect increases with the length of exposure immediately following the intervention but appears to dissipate after one year of treatment.

Figure 2.4: Average treatment effects on levels of Early Deforestation Alerts in an Event study aggregation



Note. Source: Author's illustration with data from IDEAM, DANE, IGAC, OpenStreetMap, the Ministry of National Defence, and the Ministry of Environment.

Overall, our empirical strategy suggests that the observed decline in EDAs is unlikely to be driven by weather conditions or by the inclusion of control units that had already experienced complete forest clearance, since both treated and control units maintained an average post-intervention forest cover of 50%. These results indicate that, in the year following the intervention, offenders became more aware of the likelihood of in situ punishment and adjusted their behavior in response to a higher perceived probability of conviction.

2.4.3 The military intervention decision. An alternative approach using eligible but not treated hotspots.

Having established that military forces were restricted to intervene within protected areas (PAs), we sought to understand what guided the intervention decision in a particular nucleus among the broader set of eligible but untreated deforestation nuclei located within the administrative boundaries of PAs. In this part of the paper, we argue that the intervention decision among eligible hotspots was primarily driven by predetermined characteristics of the areas. If this is the case, our results should hold when comparing treated hotspots with other eligible but untreated hotspots.

To begin our analysis, we constructed a new dataset containing information on all nuclei and hotspots that were simultaneously eligible for treatment under Operation Artemis from 2019 to 2022. The dataset includes 3,361 hotspots, each measuring 6.25 square kilometres, of which 2,517 were located within protected areas (PAs). Of these, 1,148 were treated, while 1,369 serve as the new control group. Figure 2.5 displays the assembled grid (2,517 cells) of treated and control hotspots located within the boundaries of PAs.

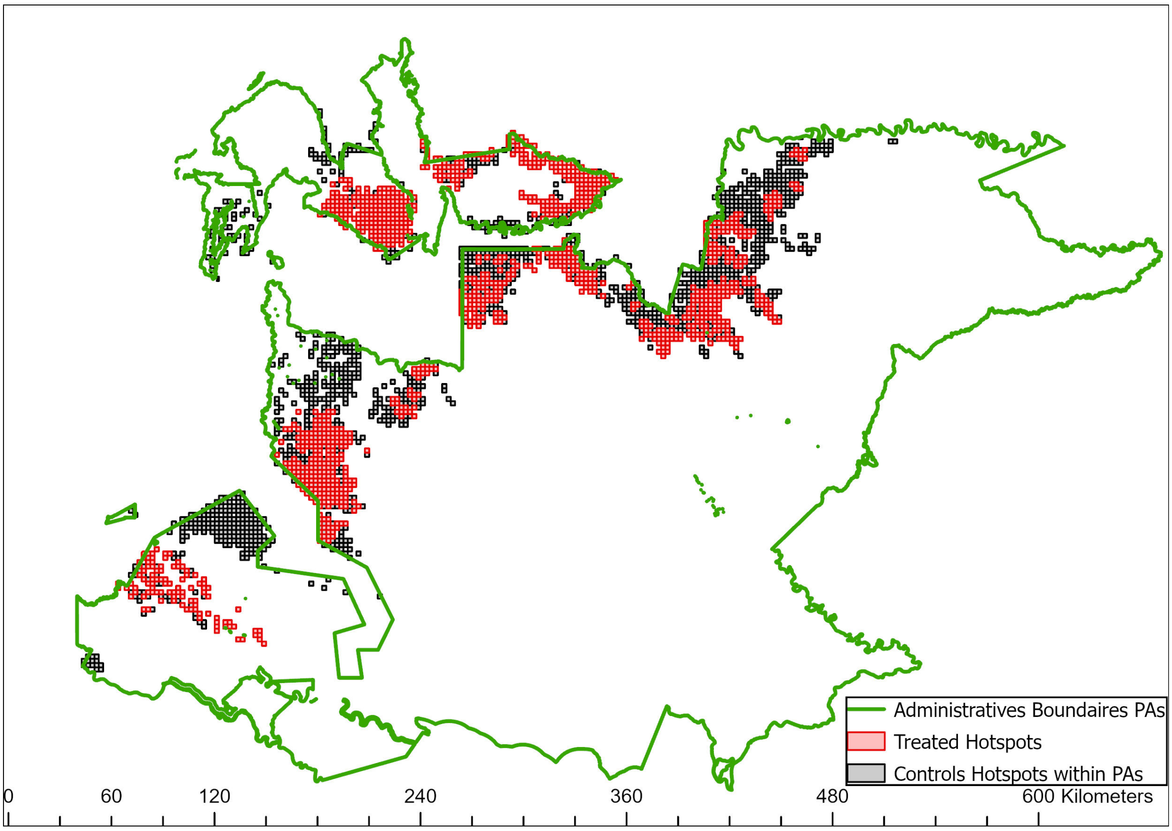
2.4.3.1 The enforcement decision on eligible hotspots

As we explain in Section III, our main concern regarding the causal identification of enforcement effects on EDAs is that only areas with high deforestation rates were treated by Operation Artemis. However, members of the military forces informed us that, after identifying all active deforestation hotspots, the decision to intervene was primarily driven by the criminal record associated with the hotspot, the security conditions for armed forces to carry out the intervention, and other socioeconomic and political characteristics of the municipality that influence the national government's perception[17].

To examine whether the decision for Artemis to intervene was primarily driven by the initial density of EDAs, Figure 2.6 presents the density of EDAs for all deforestation

[17]Some national and independent newspaper suggested that variables such as the presence of indigenous communities or associated farmers (Zonas de Reserva Campesina) were important socioeconomic variables that affected the deployments of the troops (Bautista, 2022; Tarazona and Parra De Moya, 2023)

Figure 2.5: Hotspots located within the administrative boundaries of Protected Areas

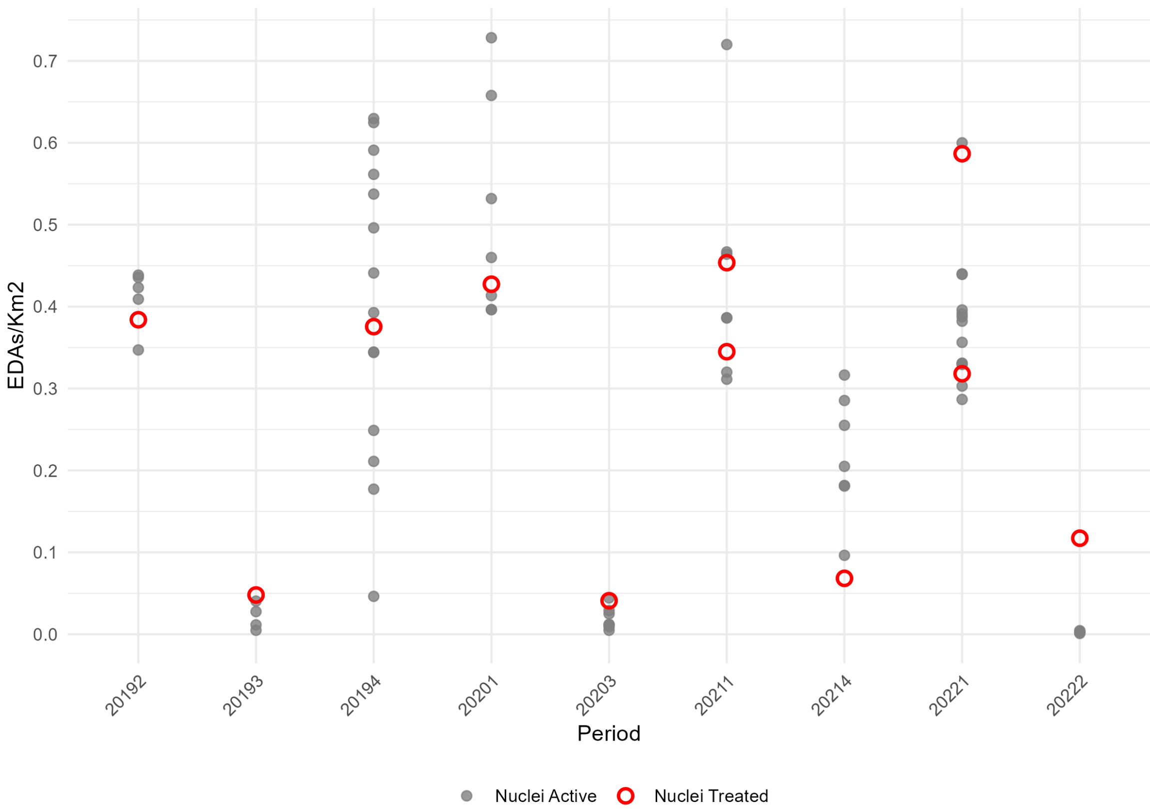


Note. Source: Author's illustration with data from IDEAM, the Ministry of National Defense and the Ministry of Environment.

nuclei that were active in a given year-quarter within hotspots located in protected areas (PAs). As shown in Figure 2.6, in most quarters, among the set of active nuclei, military forces did not target those with the highest density of early deforestation alerts (EDAs). A simple t-test of the means across hotspots yields a p-value of 0.338, with a mean density of 0.070 EDAs/km^2 for treated units compared to 0.073 EDAs/km^2 for hotspots within PAs that were not treated. Our main conclusion from this analysis is that, conditional on comparing similar hotspots eligible for treatment, the final assignment decision was not mainly driven by the density of early deforestation alerts.

But if the initial number of EDAs was not the main driver of the intervention decision, what variables did influence it? To answer this question, we combined the strategy of Guadalupe et al. (2012) and Prem et al. (2023) and constructed a model to predict the probability that an eligible deforestation hotspot will be targeted by Operation Artemis, based on lagged EDAs and other pre-treatment characteristics, as shown in Equation 5.

Figure 2.6: Density of Early Deforestation Alerts in active nuclei during Artemis Operation



Note. Source: Author's illustration with data from IDEAM, the Ministry of National Defence, and the Ministry of Environment.

$$P_{itm} = \alpha_0 + \alpha_1 D_{i(t-1)} + \alpha_2 X_{i(t-1)} + \rho_t + \lambda_m + \nu_{it} \tag{2.6}$$

Where P_{it} at time t in hotspot cell i located at municipality m, is a variable that depends on the historical number of EDAs $D_{(it-j)}$ and a set of predeterminate covariates $X_{(it-1)}$. We used j from 1 to 4 to account for the seasonality of deforestation. The set of $X_{(it-1)}$ contains population density at the rural district level (Vereda) in 2015, the nearest distance to: Military bases, roads, human settlements, administrative boundaries of PAs and rivers, measured before 2019 and a dummy variable that identifies if the area is categorized as an Indigenous Reservoir. Finally, we controlled for year-quarter fixed effect ρ_t and municipalities fixed effects λ_m. Results of a logit[18] specification of equation 5 are shown in Table 2.3.

In general, the coefficients in Table 3 are consistent with the behavior of a rational

[18] Probit results are similar and available upon request

Table 2.3: The intervention decision: Logit model for the probability of being treated in hotspot within Protected areas

	(1)	(2)	(3)
Lag Early Deforestation Alerts (#/Km^2)	0.0195	-0.0373	0.498***
	(0.0472)	(0.0487)	(0.0730)
Lag2 Early Deforestation Alerts (#/Km^2)	0.289***	0.243***	0.697***
	(0.0464)	(0.0450)	(0.0702)
Lag3 Early Deforestation Alerts (#/Km^2)	0.429***	0.444***	0.723***
	(0.0518)	(0.0518)	(0.0760)
Lag4 Early Deforestation Alerts (#/Km^2)	0.374***	0.379***	0.581***
	(0.0513)	(0.0514)	(0.0650)
Population Density-Vereda 2015 (#/km^2)		-0.178***	-0.132***
		(0.0469)	(0.0442)
Indigenous Reservoir		-0.641***	-0.596***
		(0.107)	(0.163)
Distance from the nearest Human Settlement (Km)		0.0156	0.148***
		(0.0104)	(0.0165)
Distance from the nearest Military Base (Km)		-0.0128***	-0.0245***
		(0.00148)	(0.00241)
Distance from the nearest River (Km)		0.00152	0.000296
		(0.00649)	(0.00808)
Municipality Fixed Effects	No	No	Yes
Time fixed Effects	No	No	Yes
Pseudo R2	0.0049	0.0338	0.2539
Observations	42920	42920	32085

Notes: Standard errors are clustered in parentheses at the 6.25 squared kilometres cell level and robust against heteroskedasticity and serial correlation. Values with *** are significant at 1%, ** at 5% and * at 10%. Source: Author's estimates with data from IDEAM, Ministry of Justice, Ministry of National Defense, 2013, DANE, IGAC and OpenStreetMap.

economic agent. First, it is important to note that the inclusion of municipality and time fixed effects in column 3 substantially improves the model fit, increasing the pseudo R^2 from 3% to more than 25%. In this specification, the lagged number of EDAs plays a major role in the intervention decision[19]. Moreover, the estimates indicate that hotspots located farther from military bases were less likely to be targeted.

Interestingly, hotspots located within Indigenous Reserves and those with higher population density were also less likely to receive military intervention. These results contradict some claims in the independent literature suggesting that Operation Artemis primarily targeted areas inhabited by Indigenous communities.

2.4.3.2 Results Interventions decision: Inverse probability weighted Difference in Difference estimator

Having established that the intervention decisions in hotspots within protected areas (PAs) were mainly driven by predetermined characteristics, we now test whether the level of EDAs in treated hotspots followed a parallel pre-intervention trend compared to other detected hotspots that did not receive the operation. Empirically, to estimate the causal effect of military enforcement on EDAs for hotspots within PAs, we use a propensity score estimator from Eq. (2.6) to reweight hotspots in Eq.(2.3) and Eq.(2.4), reflecting differences in the probability of being intervened. We transform the propensity score estimates into inverse probability weights (IPW) and run a reweighted sample of EEq.(2.3) and Eq.(2.4). To remain consistent with Section III, we run the reweighted DiD sample in the Callaway and Sant'Anna (2021) framework Eq.(2.5) and validate our estimates using the canonical TWFE model (Eq.(2.3)), including time fixed effects and weather controls.

Table 4 presents the results of the weighted event-study regressions for both the TWFE and the Callaway and Sant'Anna (2021) specifications combined. Estimates in Panel A are presented using the inverse hyperbolic sine transformation, excluding hotspots that intersect administrative boundaries. Panel B shows the density levels for the same sample. Overall, the results in Table 4 align closely with those presented in Table 2, reinforcing the significant impact of Operation Artemis in reducing early deforestation alerts (EDAs). Estimates from both the two-way fixed effects (TWFE) model—shown in columns 1 and 2—and the group-time average treatment effects

[19] If we include the initial value of EDAs, there is no improvement in the pseudo R2 of our estimation, remaining at 0.25. This result supports the anecdotal view that on a set of active deforestation hotspots eligible to be treated, the current number of EDAs was not the main driver for the intervention.

(GT-ATT) approach from Callaway and Sant'Anna (2021)—shown in columns 3 and 4—are consistent. Notably, the GT-ATT estimates conditioned on covariates (column 4) yield slightly larger effects. Specifically, treated areas report approximately 0.06 fewer deforestation alerts per square kilometre compared to untreated hotspots within protected areas (PAs). This effect remains robust and statistically significant across all specifications. Using the inverse hyperbolic sine transformation, we estimate that eligibility for enforcement led to a reduction of approximately 5.5% in the number of EDAs.

Table 2.4: Average treatment effects Early Deforestation Alerts in hotspots within protected Areas

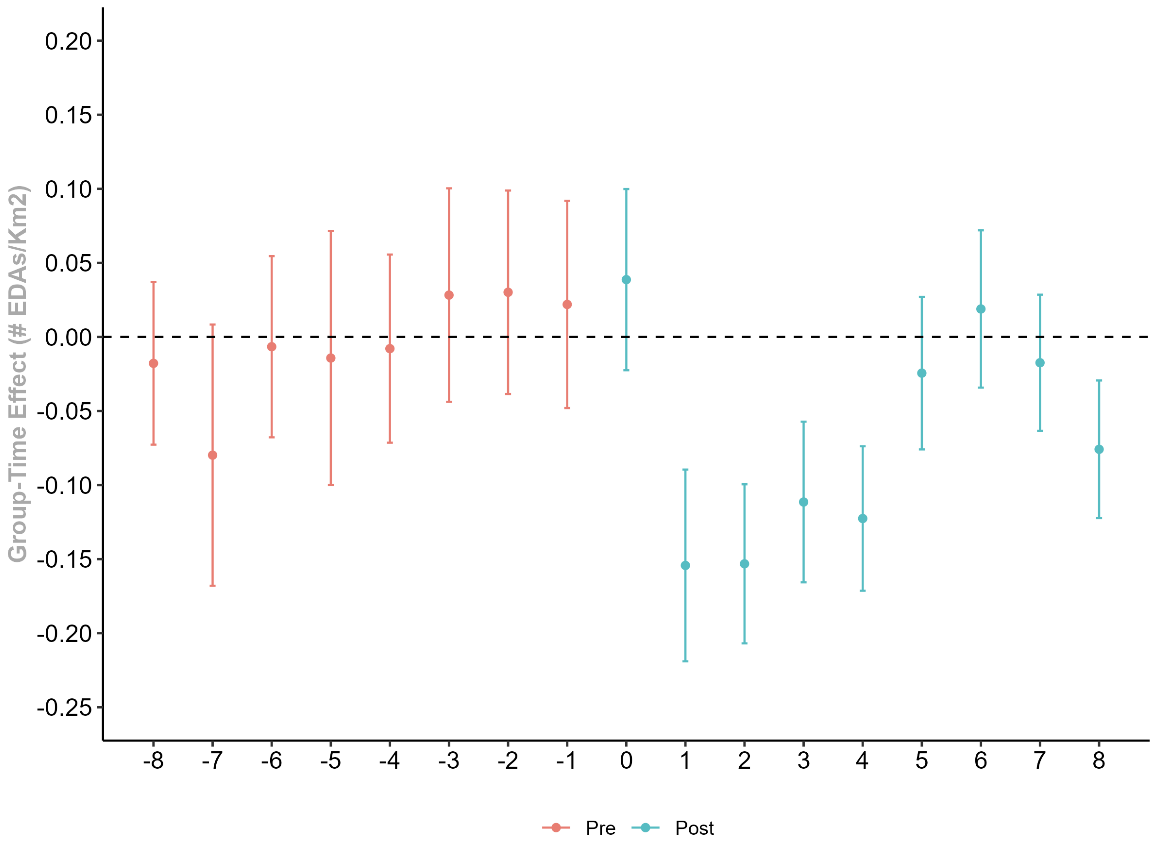
Differences among deforestation hotspots within Protected Areas	TWFE		OR Conditional	
	(1)	(2)	(3)	(4)
Panel A				
Inverse Hyperboilc Sin Transformation ETAs	-0.0507^{***}	-0.0373^{***}	-0.0490^{*}	-0.0841^{*}
	(0.00549)	(0.00589)	0.010	0.0131
Panel B				
Levels (#EDAs/Km^2)	-0.0537^{***}	-0.0387^{***}	-0.0782^{*}	-0.0841^{*}
	(0.00658)	(0.00708)	0.0095	0.01314
Time-Varying Controls	Yes	Yes	No	Yes
Time Fixxed Effects	No	Yes	No	No
Observations	35270	35270	35270	35270

Notes: All specifications are weighted by inverse propensity Score. Column 1, presented the panel fixed effect weighted regression, including the quarterly change of precipitation as control. Column 2 includes a time fixed effect for every quarter. Column 3 computes ordinary least squares with never-treated units compared with treated units. Column 4 shows the ordinary least squares kernel-based matching method (OR) conditional on covariates following Callaway and Sant'Anna (2021). Standard errors are clustered in parentheses at the 6.25 squared kilometres cell level and robust against heteroskedasticity and serial correlation. For columns 1 and 2 Values with *** are significant at 1%, ** at 5% and * at 10%. For columns 3 and 4 (Bootstrapping Standard errors) estimates with * indicates that confidence Intervales does not cover 0. Source: Author's estimates with data from IDEAM, Ministry of Justice, Ministry of National Defence, DANE, IGAC and OpenStreetMap.

Figure 2.7 presents the results from column 4, Panel A, in an event-study format grouped by the quarter of intervention. As with Figure 2.4, Panel A, we find evidence supporting the parallel trends assumption after conditioning on pre-treatment characteristics for treated and control units located exclusively within protected areas (PAs). The GT-ATT estimates in Figure 2.7 reinforce the view that the effect of military intervention persisted for up to one year following treatment.

One notable result from Figures 2.4 and 2.7 in our event-study analysis is the

Figure 2.7: Average treatment effects in an Event study aggregation for treated and controls hotspots that were located within Protected Areas



Note. *Source*: Author's illustration with data from IDEAM, the Ministry of National Defence, and the Ministry of Environment.

"instantaneous growth effect" observed at time 0, where the number of early deforestation alerts (EDAs) increased in both treated and control areas. Although this effect is not statistically significant, a plausible explanation for this parallel rise in EDAs lies in two factors endogenous to the design of the intervention. As discussed in Section I, Operation Artemis was conceived as a reactive mission——meaning that by the time the military forces were deployed, deforestation had already occurred, as indicated by the deforestation alarms. This implies that both treated and control units experienced a seasonal increase in EDAs, since at time t–1, none of the areas had yet been identified as deforestation nuclei. Secondly, the immediate differences between treated and control units may be attributed to uncontrolled fires ignited during the intervention period, which could not be contained by the military forces. However, in the Amazon rainforest, fires are not always temporally correlated with deforestation alerts, as the two phenomena follow distinct patterns. This sequence is largely explained by the "slash-and-burn" deforestation pattern commonly practiced in tropical forests, where vegetation is first cleared and left to dry before being burned (Tinker et al., 1996). To see a placebo study with fire alerts of our two empirical strategies please refer to appendix.

2.5 Cost-Effectiveness Analysis

Overall, our estimates indicate a significant reduction in Early Deforestation Alerts (EDAs) due to military enforcement. This raises two key questions: how many hectares of forest were saved, and was Operation Artemis a cost-effective policy for deterring illegal deforestation in Colombia?

To answer the first question, we estimate the relationship between EDAs and tree loss, using annual data from Hansen et al. (2013). We fit a yearly fixed-effects model in which forest loss, measured in hectares per square kilometre, is the dependent variable and the number of EDAs is the main explanatory variable, with year fixed effects included. We find that, on average, each EDA was significantly associated with approximately 3 hectares of tree loss per square kilometre per year.

Using this value, we multiplied the number of EDAs to simulate the quarterly size of avoided deforestation. Based on Equations (3) and (4) in the hyperbolic sine transformation form, we estimate an elasticity of approximately 12% in the size of avoided deforestation with respect to military enforcement (see results in Table A.2). This effect translates into an average reduction of 0.15 hectares of tree loss per square kilometre. Using the highest and lowest predicted values from Table A.2 (columns 3 and 4), the quarterly avoided deforestation per square kilometre, and the total area of treated nuclei (5,000 km^2), we estimate that Operation Artemis was able to save between 581 and 1,002 hectares of tropical forest. Combining this with official data on militarised areas—over 17,000 hectares from the military missions we were able to track—our estimates imply that, to avoid the loss of one hectare of rainforest in a given year, between 17 and 30 hectares of tropical forest would need to be militarised. Extending these findings to the deployment of approximately 23,000 armed forces personnel involved in Artemis, this suggests that between 22 and 44 soldiers would need to be sent to the rainforest to save a single hectare.

To estimate the cost of militarising one hectare of rainforest in Colombia, we combine publicly available data from the Defence Sector Budget with information reported in national newspapers regarding the cost of the operation. According to official data provided by the Ministry of National Defence to one of Colombia's most renowned newspapers, along with independent journalism sources, the total cost of Operation Artemis from 2019 to 2020 was approximately USD $750,000 (Rojas, 2021; Tarazona and Parra De Moya, 2023). During this period, Artemis intervened over 6,000 hectares, yielding an estimated financial cost of about USD $125 per hectare militarized. Based on the estimated effect of the operation in terms of tree loss, saving one hectare of tropical forest may cost between USD $2,550 and $4,500 with an average of $3,320/ha.

Finally, using official values for carbon stocks in aboveground and belowground biomass, dead organic matter, and soil in tropical rainforests, the conservation of one hectare avoids an estimated average emission of 114 tC/ha/year (equivalent to 410 tCO_2/ha/year) (IDEAM et al., 2018). Taking an average cost of militarization of $3,320/ha, this corresponds to approximately $8 per ton of CO_2 avoided. This figure is substantially higher than the estimate reported by Assunção et al. (2023) for enforcement efforts against deforestation in Brazil ($0.69/$tCO_2$). Since our results indicate that the effectiveness of militarization is limited to the first year of recovery, the total cost would need to be reinvested annually.

2.6 Concluding Remarks

Given the growing concern over illegal deforestation, strengthening monitoring and military enforcement against criminal organizations in rural areas has been promoted as a key strategy to foster economic growth in countries of the Amazon basin. However, the effectiveness of military interventions on the tropical forest remains unclear, as most information is restricted, and enforcement zones are rarely assigned randomly. This paper presents a novel modelling approach to assess the impact of militarized initiatives on curbing illegal deforestation, based on the design of hotspot policing strategies and constraints in administrative enforcement capacity.

In the last decade, the Colombian Amazon rainforest experienced a dramatic surge in illegal deforestation, concentrated in specific hotspots. Due to weak administrative capacities, the vast size of these areas, and the presence of armed non-state actors, hotspot policing strategies, based on early satellite deforestation detection, has been implemented. Our research question investigates whether these military interventions can effectively reduce illegal deforestation in the Colombian Amazon and represent a cost-effective climate policy. We focus on Operation Artemis, a military intervention on the Colombina largest national park, which was structured into multiple missions, staggered and implemented between 2019 and 2022. The initiative focused on illegal deforestation hotspots in protected areas (PAs) and deployed approximately 23,000 military personnel to recover more than 21,000 hectares deforested by criminal organizations.

We were concerned about the endogeneity problem that arises when the level of enforcement is at least partially determined by the prevalence of criminal activity. Criminal records are measured by the number of early deforestation alerts (EDAs) that were detected within official deforestation hotspot areas. To address the selection bias, we leveraged two strategies: i) a quasi-natural experiment created by the spatial and temporal variation in deforestation hotspots and the administrative boundaries of PAs ii) a propensity score reweighting estimator that predicts, among eligibles hotspots which areas will be target by the military intervention.

The overall evidence from both strategies suggests that being eligible for Operation Artemis is associated with an approximate 5% reduction in deforestation alerts, that translates into a 12% reduction in forest loss. This effect is temporally localized, lasting up to one year after the intervention. Our estimates imply that, to avoid the loss of one hectare of tropical forest during a given year, at least 17 hectares would need to be militarized, requiring the deployment of at least 22 soldiers. When compared with the reported costs, these figures indicate that militarized hotspot enforcement may cost between USD $2,550 and $4,500.

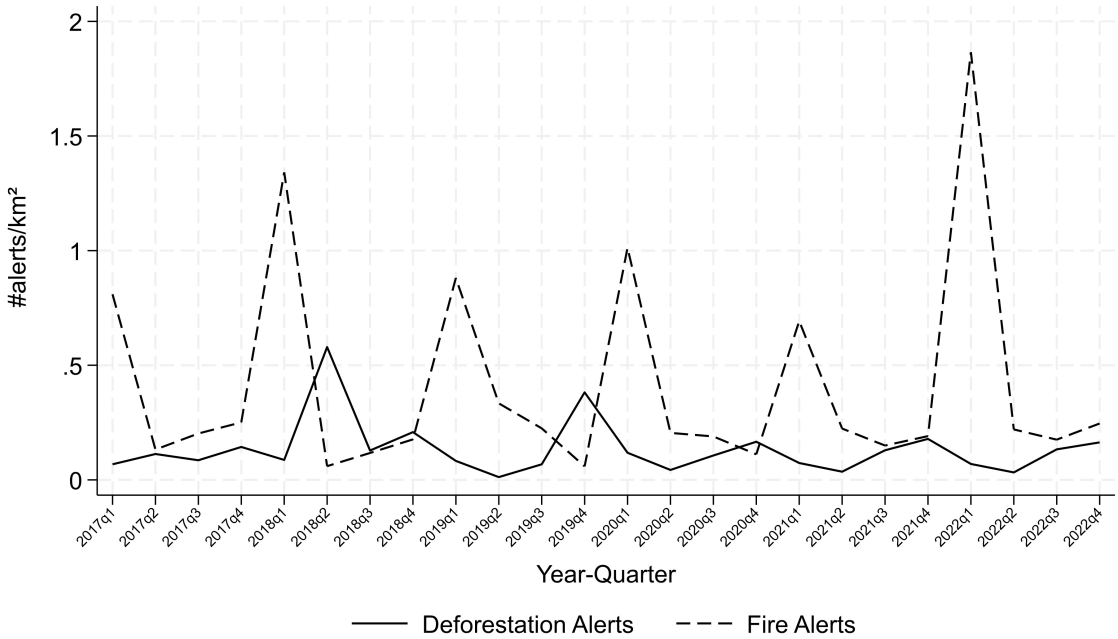
While our findings are just representative for the geographical area of the study, the evidence indicates that military interventions can produced costly time-limited effects in curbing illegal deforestation. This suggests that, given the reported cost of the operation, the marginal increase in the likelihood of prosecution following the interventions may be insufficient, over time, to outweigh the incentives for criminal organizations to continue illegal deforestation in the rainforest.

2.A Appendix – Additional tables and figures

2.A.1 A Placebo Study with Fire Alerts

According to the Instituto de Hidrología, Meteorología y Estudios Ambientales (IDEAM), deforestation alerts in the Amazon region tend to peak prior to fire alerts Galindo (2024). This sequence is largely explained by the "slash-and-burn"[20] deforestation pattern commonly practiced in tropical forests, where vegetation is first cleared and left to dry before being burned (Tinker et al., 1996) . Using the information of NASA (Schroeder et al., 2024), Figure 2.8 shows the difference in peaks between fire alerts and deforestation alerts for our area of study.

Figure 2.8: Deforestation Alerts and Fire Alerts in the Amazon-Andes Transitional Belt



Note. Source: Author's illustration with data from IDEAM and NASA.

To test if fire alerts (FAs) followed the same pattern of EDAs we run equation 5 for our both approaches: the natural experiment presented in section IV that uses hotspot inside the PAs and outside in Buffers Zones (BZs) and the inverse propensity weighted

[20] In this method, trees are initially cut down and the valuable timber is extracted for sale. As the rainy season approaches, the remaining biomass is left on the land to dry. Once the dry season begins, the accumulated biomass is burned, enriching the soil with nutrients and creating temporarily fertile land. However, after a few years, soil productivity declines due to nutrient depletion, prompting farmers to clear nearby untouched forest areas and repeat the cycle.

regression in Section V that compares just hotspots that were within PAs. Results are presented in Table A1 for our two preferred specification in each approach. Panel A presents the IHS and Panel B Levels of fire alerts.

Contrary to our deforestation results, fire alerts did not significantly decrease following Artemis enforcement. This suggests that, although direct forest clearing may have been curbed, the incidence of fire—often used in land preparation and associated with ongoing deforestation practices—persists or even intensifies in zones under formal environmental protection.

Table 2.5: Average treatment effects with Forest Fire Alerts

Differences of Fire Alerts	Comparing Hotspots inside and outside the Protected Areas (Quasi-natural experiment)		Comparing Hotspots inside the Protected Areas (IPW)	
	TWFE (1)	OR Conditional (2)	TWFE (3)	OR Conditional (4)
Panel A				
Inverse Hyperbolic Sin Transformation	-0.0014	-0.0441	-0.0105	0.0170
	0.009	0.0489	0.0100	0.0241
Panel B				
Levels (#FAs/Km^2)	0.0195	-0.111	0.0170	-0.0452
	0.025	0.058	0.019	0.07510
Time-Varying Controls	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	No
Restricting Units without Cadastral Register	Yes	Yes	No	No
Observations	18140	18140	35720	35720

Notes: All specification are weighted by inverse propensity Score. Column 1, presented the panel fixed effect weighted regression including the quarterly change of precicpitaion as control. Column 2 includes time fixed effect for every quarter. Column 3 computes ordinary least squares with never-treated units compared with ftreated units. Column 4 shows ordinary least squares kernel-based matching method (OR) conditional on covariates. Standard errors are clustered in parentheses at the 6.25 squared kilometres cell level and robust against heteroskedasticity and serial correlation. For columns 1 and 2 values with *** are significant at 1%, ** at 5% and * at 10%. For columns 3 and 4 (bootstrapped standard errors) estimates with * indicates that confidence intervals do not cover 0. Source: Author's estimates with data from IDEAM, Ministry of Justice, Ministry of Defense., 2013, DANE, IGAC and OpenStreetMap.

2.A.2 From Early deforestation alerts to area of Tree loss

Table 2.6: Average treatment effects of predicted quarterly tree loss 2019-2022

Differences in Tree Loss	Comparing Hotspost inside and outside the Protected Areas (Quasi-natrual experiment)		Comparing Hotspost inside the Protected Areas (IPW)	
	TWFE (1)	Callaway and Sant 'Anna (2021) (2)	TWFE (3)	Callaway and Sant 'Anna (2021) (4)
Panel A				
Levels (ha/km^2)	-0.1274***	-0.1708***	-0.1162***	-0.2005***
	0.023	0.0543	0.0212	0.0383
Panel B				
Inverse Hyperboilc Sin Transformation	-0.0919***	-0.1504***	-0.0946***	-0.1541***
	0.013	0.0321	0.0128	0.0245
Time-Varying Controls	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	No
Restricting Units without Cadastral Register	Yes	Yes	No	No
Observations	18140	18140	35720	35720

Notes: All specification are weighted by inverse propensity Score. Column 1, presented the panel fixed effect weighted regression including the quarterly change of precicpitaion as control. Column 2 includes time fixed effect for every quarter. Column 3 computes ordinary least squares with never-treated units compared with ftreated units. Column 4 shows ordinary least squares kernel-based matching method (OR) conditional on covariates. Standard errors are clustered in parentheses at the 6.25 squared kilometers cell level and robust against heteroskedasticity and serial correlation. For columns 1 and 2 Values with *** are significant at 1%, ** at 5% and * at 10%.. For columns 3 and 4 (Bootstrapping Standard errors), estimates with * indicate that confidence Intervales does not cover 0. Source: Author's estimates with data from IDEAM, Ministry of Justice, Ministry of National Defence, 2013, DANE, IGAC and OpenStreetMap.

Chapter 3

Frontiers of Conservation: The Economic Trade-offs of farming in the Amazon

Abstract

This paper identifies agricultural factors correlated with deforestation and estimates the private opportunity cost of conserving natural forest on Colombian Amazon farms. Building on a land conversion model and using the revealed choices of 39,175 farmers, satellite land cover data, and productivity measures of 125 agricultural products, we report that crop productivity is positively correlated with an increase in the probability of deforestation. Using the forgone values of crop profitability, opportunity costs for preserving the forest vary widely across farms, ranging from US$25 to US$1,381 per hectare. Our results suggest that anchoring forest conservation subsidies to the opportunity cost of crop production, while improving access to credit and technical assistance, can strengthen environmental and agricultural policies to protect the Amazon forest.

3.1 Introduction

Since 2000, the conversion of tropical forests to crop agriculture and pasture has been the dominant driver of deforestation in the Amazon Basin (Curtis et al., 2018). This conversion has been particularly pronounced in the Colombian Amazon, where agriculture is the main productive sector of the region, and the multidimensional poverty levels are among the highest in the country (DANE, 2025). Current deforestation rates and projected scenarios suggest that continued agricultural expansion will fragment the Colombian Amazon and irreversibly harm ecosystem connectivity by the mid–21st century (IDEAM, 2025; González-González et al., 2021). However, in a region experiencing such high poverty rates, important questions remain regarding potential trade-offs between conservation and development goals.

In an attempt to reconcile this trade-off, the Colombian government has introduced the Payment for Environmental Services (PES) legislation (República de Colombia Decreto 1076, 2018), promoting subsidies offering constant per-hectare payments to compensate farmers who agree to conservation measures for forgone agricultural profits. In particular, one of the most ambitious PES initiatives in the country, Vision Amazonia (VA), provided quarterly PES payments to 2,573 farms at a constant quarterly rate of approximately US$250 per farm between 2018 and 2023. The VA program aimed to preserve 120,263 hectares of natural forest (Ministerio de Ambiente y Desarrollo Sostenible, 2025). However, evidence suggests that the deforestation effects of VA were small relative to the policy's cost, as it avoided a net loss of 1,152 hectares compared with counterfactual areas, at an estimated total investment of US$87.3 million. [1] (Ministerio de Ambiente y Desarrollo Sostenible, 2025). While the optimal design of PES contracts remains an active area of research, several authors agree that the effectiveness of PES schemes depends critically on how accurately payments reflect landowners' opportunity costs of conservation (Assunção et al., 2015; Rodríguez-de Francisco et al., 2021). Furthermore, given that incentives to clear forestland in the tropics vary substantially across stakeholders (Lapola et al., 2023), a clear understanding on the correlation between a land parcel's deforestation risk and the wealth of the landowner is essential for designing PES programs that can achieve antipoverty and conservational aims simultaneously (Alix-Garcia et al., 2015). In what follows, we aim to provide empirical evidence of the correlation to inform the design of cost-efficient PES programs.

[1] For more budget details see: https://visionamazonia.minambiente.gov.co/remi-ejecucion-presupuestal/

Our research questions test 1) factors correlated with deforestation and 2) estimate the opportunity cost of conserving the remaining natural forest on Colombian Amazon farms. Literature on the relationship between agricultural productivity and deforestation remains ambiguous and is particularly limited for the Colombian Amazon. On the one hand, increased agricultural productivity may induce entry into farming on the extensive margin (Angelsen and Kaimowitz, 2001). On the other hand, increasing farm productivity per unit of area may have the potential to reduce deforestation, as farmers may choose to intensify and produce more output with less land (Phalan et al., 2016; Szerman et al., 2022).

Building on the land conversion model proposed by Barbier and Cox (2004), we contribute to this debate by providing empirical evidence on producers' decisions underlying the choice of expanding the agricultural frontier into natural forests to then determine the opportunity costs of forest conservation strategies. Our empirical analysis is guided by a profit-maximising agent who clears forest land for agricultural production. We model the probability of land-clearing and the opportunity costs using the revealed responses of 39.175 Agricultural Production Units (APUs) surveyed in the Colombian Amazon by the latest Colombian National Agricultural Census (CNAC) conducted in 2014. We complement this data with satellite land use measures and market prices for 127 different agricultural goods.

Using the reported attitudes toward clearing forested land in the Census, we model the probability of deforestation and find that crop productivity is correlated with increased deforestation. We find that forest loss is primarily associated with the expansion of land-intensive crops that do not necessarily yield the highest profitability per unit of land. Furthermore, we find that access to technical assistance and agricultural credit reduced the likelihood of deforestation, highlighting these factors as feasible channels for complementing environmental policy.

Our opportunity cost empirical model identifies the range of payments correlated for preserving natural forests. We provide these values for 783 veredas in the Amazon, which are the smallest administrative geographic units in Colombia. The spatial heterogeneity of crop production across farms suggests that uniform per-hectare payments may weaken economic incentives for conservation and may not represent the most cost-effective use of public funds. Our estimates support the implementation of differential rates for PES.

Our paper complements the literature on agricultural opportunity cost of tropical deforestation, mostly based on global meta-regression (Phan et al., 2014), where region-specific estimates are missing, and case-specific studies (Mullan et al., 2018), where limited sample sizes reduce the external validity of the results. To the best of our knowledge, we are the first to produce farm-level estimates that encompass the full universe of registered farms in the Colombian Amazon.

The rest of the paper is structured as follows: Section 3.2 provides background information on deforestation in the Colombian Amazon and reviews the literature on the opportunity cost of preserving natural forests. Section 3.3 describes the conceptual framework that guides our empirical strategy. Section 3.4 presents the data used in the analysis. Section 3.5 discusses our empirical strategy. Section 3.6 presents the main results and discusses their policy implications. Section 3.7 concludes.

3.2 Deforestation and Institutional Background in the Colombian Amazon

The Colombian Amazon accounts for more than 40% of the country's area and is well-known for its biological diversity and cultural richness (Garzón and Valánszki, 2019). Recent findings from the Colombian Institute of Hydrology, Meteorology and Environmental Studies show a 74% increase in deforestation in the Amazon region in 2024 (+32,850 hectares) compared with 2023 (IDEAM, 2025). The literature has identified crop expansion and cattle grazing as the main drivers of deforestation, with pasture growth being the strongest predictor of deforestation (Davalos et al., 2021; Van Dexter and Visseren-Hamakers, 2020).

González-González et al. (2021) provides one of the latest deforestation scenarios (2030-2050) for the Colombian Amazon. Results suggest that agricultural activities have a significant role in deforestation in Colombia. Most veredas[2] in the Colombian Amazon are projected to experience increased deforestation over the coming decades, with the highest rates concentrated in the northwestern region of the biome, where agricultural activity is nowadays more prevalent (IDEAM, 2025).

Incentives to clear forestland in the tropics vary substantially across stakeholders (Lapola et al., 2023). Some land-cover models emphasise the poverty-driven deforestation factor that associates the expansion of subsistence agriculture (Barbier, 1997) as a key driver. Other studies highlight the role of powerful actors in opening new forest frontiers through the promotion of economic activities in forests, such as

[2]Colombia's political–administrative division consists of departments, municipalities, and veredas, the latter being the smallest administrative units

commodity production and infrastructure development (Ferrante and Fearnside, 2020). According to Davalos et al. (2021), multiple factors of both models can potentially explain tropical deforestation in the Colombian Amazon. However, the economic drivers shaping these processes differ, and spatial models alone are insufficient to test the economic incentives underlying agents' land-clearing decisions directly.

In response to the alarming increase in deforestation, since 2014, the Colombian government has placed deforestation control and climate change mitigation at the centre of its National Development Plan. In 2016, it created a national carbon tax (approximately $4 tCO2e in 2025), allowing regulated entities to acquire national or international carbon credits to lower the deforestation trend. Furthermore, in 2018, the Colombian government introduced the Decreto 1007 of 2018 (República de Colombia Decreto 1076, 2018), a law that supports the Payment for Environmental Services (PES) in Colombia. Officially, PES are calculated based on the opportunity cost of land (República de Colombia Decreto 1076, 2018). For most areas of the Colombian Amazon, this opportunity cost is determined by agricultural activities; however, limited information on farmers' prices—since many crops are cultivated for subsistence or sold only in local markets—raises concerns regarding current payment levels.

Among PES schemes in Colombia, Vision Amazonia (VA) stands out as one of the main initiatives implemented in the Amazon, with a total budget of US$87.3 million between 2018 and 2023.[3]. During the 6 years, the VA promoted its conservation goals by paying a flat rate subsidy to 2573 households for the conservation of 120.263 hectares of natural forest(Ministerio de Ambiente y Desarrollo Sostenible, 2025). Families received an average quarterly payment of US$250 (Rodríguez-de Francisco et al., 2021), corresponding to approximately US$22 per hectare of natural forest preserved per year [4]. In 2025, the VA program reported that PES implementation resulted in the conservation of 1,152 hectares of natural forest compared with counterfactual areas. Considering only the direct cost of PES subsidies invested over the six-year period (US$2.5 million), the implied average annual cost is US$372 per hectare of forest conserved. When total program costs are included (US$87.3 million), the corresponding average annual cost rises to US$12,731 per hectare of forest conserved. Some evidence suggests that the effectiveness of VA in curbing deforestation has been limited because the incentives do not sufficiently address the

[3]See information at https://visionamazonia.minambiente.gov.co/en/remi-home/

[4]Using official estimates of carbon stocks of 410 tCO_2/ha (IDEAM et al., 2018), this translates into an implied opportunity cost of approximately US$0.10 per tonne of CO_2 avoided

main drivers of deforestation (Rodríguez-de Francisco et al., 2021). Moreover, as the opportunity cost of preserving natural forest varies across farmers [5] (Assunção et al., 2015), "Flat-Rate" payments may not reflect the landowner's opportunity cost of conservation (Bateman et al., 2024).

3.3 Conceptual framework

Our conceptual framework for explaining the relationship between tropical deforestation and agricultural expansion in the Amazon is based on the land-conversion framework of Barbier and Cox (2004). In this framework, the choice of agricultural activities is driven by their relative profitability, and land use change may be explained by the economic incentives facing the farm, indexed by $j \in J$, operating in the Colombian Amazon.

Given the initial endowment of land F_j, initially all covered by natural forest, the owner of farm j can choose the area $N_j \leq F_j$ to clear, in order to grow and sell one or more agricultural crops (e.g., corn, pineapple, sugar cane), indicated by the vector $\mathbf{I}_j$. Therefore, at any time t, the profit function of farm j is defined as:

$$\max_{N_j, \mathbf{X}_j} \mathbf{P}\, f_j(\mathbf{X}_j, N_j; \mathbf{Z}) - \mathbf{w}\mathbf{X}_j - w_N N_j, \tag{3.1}$$

where $\mathbf{X}_j$ denotes a vector of inputs, such as labour, fertilisers, and seeds used in the agricultural production of $\mathbf{I}_j$. Input prices are given and are represented by the vector $\mathbf{w}$. Selling prices of the agricultural products included in $\mathbf{I}_j$ are represented by $\mathbf{P}$. We consider other exogenous factors that might influence the profits of farm j, such as the access to credit and access to technical assistance (Balboni et al., 2023) and denote them by $\mathbf{Z}$. As deforestation can serve as an important source of liquidity, credit-constrained farms may be more likely to deforest when agricultural income is low (Ferraro and Simorangkir, 2020). In addition, technological improvement can decrease deforestation by reducing the total land area needed for agricultural production (Borlaug, 2007). Finally, N_j denotes the area of land allocated by farm j to agricultural production of $\mathbf{I}_j$, and w_N is the rental price of land. As each farm clears its own forest, w_N represents the implicit price or opportunity cost of land (e.g., Panayotou and Sungsuwan, 1994) [6]. Solving the

[5] The latest Agricultural Census reports that more than 327 different crops are cultivated in the Colombian Amazon (DANE, 2016).

[6] For Colombian Amazon farms, a lower bound of the opportunity cost can be associated with

problem in (3.1) returns $\mathbf{X}_j$ and N_j as a function of prices and exogenous factors only. In particular, the demand for land cleared by the j-th farm is:

$$N_j = N_j(\mathbf{P}, \mathbf{w}, w_N; \mathbf{Z}), \text{ with } \frac{\partial N_j}{\partial P} > 0, \tag{3.2}$$

so that the demand for cleared land is expected to increase as the prices of agricultural products rise, ceteris paribus. The farm-level demand in (3.2) can now be aggregated into the total demand for converting the natural forest by all J farms. We define N as the aggregate demand for cleared natural forest area within the Colombian Amazon farms:

$$N = N(\mathbf{P}, \mathbf{w}, w_N; \mathbf{Z}). \tag{3.3}$$

The principal input for clearing land is the labour L, which is paid some exogenously determined wage rate w_L. Following Barbier and Cox (2004), a cost function can be specified as the minimum cost incurred by the farm to produce a given level of cleared forest area, N_j, for a given level of w_L:

$$C_j = C_j(w_L, N_j). \tag{3.4}$$

As farms provide their own land N_j and labour L, forestland is cleared up to the point where the total revenues gained from converting N_j units of land, $w_N N_j$, equal the total costs represented by (3.4). Then w_N is the implicit "rental" price or opportunity cost of using additional converted forest land. In the equilibrium, the implicit price w_N ensures that the farm's cost of supplying its own land is equated with its derived demand for converting the natural forest into an agricultural area. Then, following the authors, the following cost conditions for supplying its own cleared land must hold:

$$w_N = C_j(w_L, N_j). \tag{3.5}$$

Together with the farm's derived demand for converted land (3.2), equation (3.5) determines the equilibrium level of natural forest clearing by the agricultural farms, as well as its implicit price w_N [7]. When substituting (3.5) for w_N in (3.2), we can solve

a potential fiscal benefit foregone: under Article 14 of Law 299 of 1996, privately owned land that conserves natural vegetation can be exempted from 100% of the land property tax. Preserving the forest, therefore, entitles the landowner to this tax exemption, while clearing the land implies its permanent loss

[7] Following Barbier and Cox (2004), w_N serves two roles in the model. On the demand side, Equation (3.1), it shapes how much cleared land the farmer demands, with $\partial N_j / \partial w_N < 0$. On the

the reduced form equation for the equilibrium level of cleared forestland. Rearranging the term yields:

$$N_j = N_j(\mathbf{P}, \mathbf{w}, w_N) = N_j(\mathbf{P}, \mathbf{w}, C_j(w_L)). \tag{3.6}$$

As the wage rate is also included in the vector of input prices w, we present the reduced form relationship for the aggregate equilibrium level of cleared forest in all farms J as:

$$N^* = N(\mathbf{P}, \mathbf{w}; \mathbf{Z}), \tag{3.7}$$

Following the idea that agricultural profitability is an underlying cause of tropical deforestation, we expect that the amount of forest converted would increase with the price of agricultural products and decrease with the price of inputs.

3.3.1 Monetary valuation of agricultural land

Given farmers' land-use conversion decisions, we assign a monetary value to agricultural land using the crops and livestock products produced on cropland and pastures, respectively, as proxies, as captured by the set of products included in $\mathbf{I}_j$. We estimate the average profit of agricultural land N_{j_I} as net revenues per agricultural hectare. Specifically, for a farm producing the set of goods $\mathbf{I}_j$ on a total agricultural area of N_{j_I}, average profit is defined as the sum of revenues minus production costs, divided by N_{j_I}. Formally, we represent profits per agricultural hectare for farm j as:

$$\pi_{N_{j_I}} = \frac{\sum_{i=1}^{I} \left(q_i p_i - q_i w_i\right)}{\sum_{i=1}^{I} \left(N_{j_i}\right)}, \tag{3.8}$$

where q_i is the quantity produced of farm good i and p_i and w_i are the respective selling prices and input costs.

supply side, in Equation (3.5), w_N is equated to the average cost of clearing land $C_j(w_L, N_j)$. Since the farmer clears their own forest rather than renting land from a market, w_N is an implicit shadow price determined in equilibrium rather than observed directly. The opportunity cost of land therefore restrict how much forest gets cleared through the equilibrium condition in Equation (3.6), but it remains outside the production function, consistent with the land conversion framework of Barbier and Cox (2004).

3.4 Data

3.4.1 Agricultural productivity

We use the information from the responses of 39,175 Agricultural production units (APU) surveyed in the Colombian Amazon by the 2014 Colombian National Agricultural Census (CNAC). A APU is defined as a single legal producer (either an individual or an entity) with an area that produces agricultural crops, and employs at least one production input—such as buildings, equipment, or labour. The APUs (farms, henceforth) surveyed in the Amazon are located in 1919 veredas, which are rural administrative subdivisions of municipalities, and cover a total area of 2.819.495 hectares, of which natural forest accounts for 58%, pastures for 24% and cropland for 18%.

From the CNAC, we recorded types of sown crops, initial area planted, the ultimately harvested area, and the quantities produced. In total, we observe 326 different crops, with plantain, cassava, yellow corn, and sugar cane among the most commonly cultivated by farms. From the same source, we also observe (i) information on whether farms have access to credit and technical assistance[8] for agricultural activities, (ii) details on land tenure status, (iii) the ethnicity of property owners, and (iv) the total population within each farms. Finally, CNAC also records the area allocated to pastures, natural forest and croplands per farm.

Input prices for crops were obtained from reports by the Ministry of Agriculture, its affiliated financial institution (Finagro), and the Colombian International Corporation, which provides credit and technical assistance to the agricultural sector (Ministerio de Agricultura y Desarrollo Rural, 2018). Selling prices for crops were obtained from the Colombian National Statistics Office (SIPSA, for its Spanish acronym). As not all the crops planted in the Colombian Amazon had available information on prices, we were able to collect prices from 125 crops that account for 78% of the total area planted. All prices correspond to average national market values and are expressed in 2024 US Dollars[9].

To estimate farms profits per hectare, we use Eq. (3.8), combining information on quantities produced and land allocated from CNAC with cost and price data from the above-mentioned sources. Our main productivity measures are profits in US dollars per agricultural hectare. In addition, we report a biophysical indicators of biomass

[8]This variable can be associated with receiving technical guidance in good agricultural practices, producer associativity, market access, soil management, and other forms of ancestral knowledge.

[9]We thank Erazo et al. (2021) for providing data access of agricultural prices.

productivity per unit area: crop yields (tons per hectare of cropland). Table 3.1 shows the mean and standard deviation of main variables collected, divided into three categories: Land Use characteristics, variables associated with productivity measures and Socioeconomic conditions for the farms.

Table 3.1: Summary Statistics of the collected variables at the Farm Level

Variable	Mean	SD
Productivity Measures		
Crop Yield (Tons/ha)	3.24	2.23
Crop Profit ($ per ha)	461.45	363.54
Area harvest over planted (%)	0.73	0.28
Land Use farms		
Area Crops (ha)	13.00	242.07
Area Pasture (ha)	17.01	119.02
Area Natural Forest (ha)	41.97	914.97
Socioeconomic Characteristics		
Technical Assistance (%)	0.15	0.35
Credit (%)	0.12	0.33
Indigenous (%)	0.26	0.44
Communal Ownership (%)	0.18	0.38
Population Density (Inds/km^2)	657.76	4309.61
Observations	39,175	

According to Table 3.1, the average farm size is 72 hectares, of which 58% and 42% correspond to natural forest and agricultural land, respectively (18% crops and 24% pasture). Crop productivity measures among the farms have a wide range, starting from areas with no low yield, to high returns, mostly driven by high price crops.

Average crop yield is 3.24 Tons per hectare, from which a farm can earn approximately US$461 per year. The proportion of the area harvested over the area planted is, on average, 73% as farmers may choose not to harvest a section of a field, or an entire field, if the crop has been damaged (e.g., pest or climate-related extreme events) or if market conditions make harvesting not profitable.

Regarding both human and capital factors of production, around 15% of farms reported receiving technical assistance. Financial inclusion for farm activities remains low, as only 12% of farms reported having access to credit from financial institutions.

Lastly, Indigenous farms represented about 26% of the sample, while communal ownership accounted for roughly 18% of farms.

3.4.2 Deforestation data at the vereda level

As the CNAC data at the farm level were not geo-referenced at the farm scale and did not include information on the amount of deforestation undertaken by individual farm, we aggregate farm-level information to the vereda level, which is the smallest administrative geographic unit available in Colombian rural statistics.

We quantify the amount of deforestation at the vereda level using data from the Global Forest Watch dataset, which provides information on forest loss for 2013 (Hansen et al., 2013). Given that land cover within veredas comprises multiple classes (such as forestland, cropland, grassland, wetlands, settlements, and other land) and deforestation occurs in Forestland, we use data from MapBiomas Colombia (MapBiomas et al., 2025) to identify the share of natural forest in each vereda in 2012. We then compute the average hectares of tree loss in 2013 per square kilometre of natural forest in 2012.

Table 3.2 shows the descriptive statistics of the variables included in our vereda dataset, including the tree loss, share of forest cover for 1,919 veredas.

Table 3.2: Summary Statistics: Vereda-Level Variables

Variable	Mean	SD
Tree Loss Area (ha/km^2 Natural forest)	1.44	2.06
Natural Forest Cover Share in a Vereda (%2013)	0.50	0.28
Vereda Area (ha)	13,375	75,539
Number of farms per Vereda	20.41	49.79
Average Tree loss in a farms (ha)	6.37	26.32
Observations	1,919	

Consistent with data from the CNAC, natural forest covers approximately 50% of the area in the average vereda, which contains around 20 farms. The mean tree loss of 1.44 hectares per square kilometre of natural forest implies that, at current rates, natural forest in the Colombian Amazon would be fully cleared in approximately 65 years.

3.5 Empirical strategy

3.5.1 Probability of clearing natural forest to expand the agricultural frontier

The reduced form relationship $N_j^* = N_j(P, w; Z)$ in Eq (3.7) directly motivates our empirical question: Are higher agricultural returns correlated with increased natural forest clearance on Colombian Amazon farms? From Eq (3.2) predictions $\partial N_j/\partial P > 0$, higher agricultural profitability should increase the area of forest land allocated to agricultural production. As data on forest clearance were not available at the farm level, we adopt two complementary strategies to test the prediction of the model. First, we use the survey responses of 39,175 farms from the 2014 Colombian National Agricultural Census (CNAC) regarding agricultural expansion decisions into natural forest. Second, we validate these responses against satellite-based measures of deforestation aggregated at the vereda level to assess whether self-reported land-use choices are consistent with observed land cover changes.

In our first strategy we use the responses to the following question: ”In 2013, for the establishment of your crops or forest plantations, did you transform, clear, or cut down natural forest?”

To define our empirical specification and test the prediction of the model, we aggregate all agricultural profits into a single variable represented by $Crop_j$. We then assess whether the probability of deforestation increases with agricultural productivity by estimating the following logit model:

$$\Pr(N_j) = \beta_1 \, Crop_j + \beta_2 \mathbf{Z}_j + \varepsilon_j, \tag{3.9}$$

where N_j is a dummy variable that takes the value of 1 if a farm j replies affirmatively to the above-mentioned question. $Crop_j$ is the crop's productivity variable expressed in monetary terms (US$) with the profits of crop (basket of crops) per hectare of area planted. $\mathbf{Z}_i$ is a vector of socioeconomic characteristics expressed by dummies that takes the values of 1 if the farm: i) had technical assistance for the production, ii) had access to credit, iii) had communal ownership, iv) was registered as an indigenous reservoir in 2013. Finally, we denote ε_i as a logistic/normal random error term and use robust standard errors.

As biomass productivity is not always associated with monetary profitability in agriculture, we additionally examine whether a biomass-based measure of agricultural productivity — crop yield per hectare of cropland — was correlated with the probability of deforestation, estimating a logistic model analogous to Equation (3.9). Further details are provided in the Appendix..

Among the 39,175 farms surveyed, 5,837 replied affirmatively to the question, revealing their choices for expanding the agricultural frontier into natural forest. It is important to acknowledge that farmers may have incentives to under report forest clearance, as higher levels of cleared land may increase the land tax on productive area, potentially inducing strategic negative responses. Although census respondents are aware that the information they share is legally protected and the Colombian National Statistics Office guarantees the confidentiality of individual responses under Colombian statistical law (Law 79 of 1993), we believe that estimates from Equation (3.9) are likely downward biased. To address this concern we validate the farm-level responses against satellite-based measures of tree cover loss from Hansen et al. 2013 at the vereda level (see Appendix 3.A.2 for details on the model construction).

3.5.2 The opportunity cost of saving the remaining natural forest in Amazon farms

Following Barbier and Cox (2004),the equilibrium condition $w_N = C_j(w_L, N_j)$, combined with the profit maximisation condition $P\partial f/\partial N_j = w_N$, implies that the implicit shadow price of land equals the marginal revenue product of cleared land. Therefore, if the profitability of agricultural activities drives deforestation, then the forgone profits from agriculture can be interpreted as an opportunity cost of conserving the remaining natural forest on Colombian Amazon farms.

We approximate this value by the average agricultural profit per hectare $\pi_{N_j^I}$ on an Amazon farm. Using CNAC data on the remaining natural forest area in farm j, denoted by F_j, we define the opportunity cost of preserving the natural forest (OC_j) as the product of the remaining forest area and agricultural profits per hectare, $OC_j = F_j \times \pi_{N_j^I}$. We then compute the marginal opportunity cost of conserving an additional hectare of natural forest as the ratio of cumulative opportunity cost across all farms, $\sum_{j=1}^{J} OC_j$, to the cumulative area of remaining natural forest, $\sum_{j=1}^{J} F_j$. Formally, we define the marginal opportunity cost of natural forest as:

$$MOC = \frac{\sum_{j=1}^{J} OC_j}{\sum_{j=1}^{J} F_j}. \tag{3.10}$$

3.6 Results

3.6.1 Probability of clearing natural forest to expand the agricultural frontier

Based on Eq. 3.9, Table 3.3 reports the marginal effects estimated at the average for the probability of deforestation with robust standard errors are reported in parentheses across the specifications.

Table 3.3: Probability of Clearing Natural Forest to Expand the Agricultural Frontier

	Marginal Effects
Crop profit (USD 100/ha)	0.016***
	(0.004)
Technical Assistance	-0.156***
	(0.043)
Agricultural Credit	-0.287***
	(0.051)
Indigenous	0.434***
	(0.039)
Communal ownership	0.286***
	(0.043)
Population density (1,000 ind./km^2)	-0.21***
	(0.07)
Observations	39,175

Notes: Reported coefficients are marginal effects. Standard errors are shown in parentheses. Source: Author's calculation with data from CNAC 2014, Ministry of Agriculture, DANE, and Fedegan. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Our estimates suggest that higher profitability per area planted is associated with a higher probability of deforestation. Using the predicted values for the probability of deforestation from column (1), we estimate that an average farm with cropland profitability of approximately US$460 per hectare is correlated with a deforestation probability of about 15%. Doubling cropland profits is associated with an increase in the likelihood of deforestation of roughly one percentage point. Validity of our estimates is assessed using satellite-based measures of deforestation from Hansen et al. (2013), reported in 2013 at the vereda level, where we find that a 10% increase in crop profits per hectare planted are correlated with an approximately 5% increase in tree loss per unit area of natural forest (see Appendix 3.A.2 for details on the model construction and results). Our results are aligned with the findings of Mullan et al. (2018), who report that a 10% increase in cleared area is associated with a 5.6% increase in household income for farms in the Brazilian Amazon.

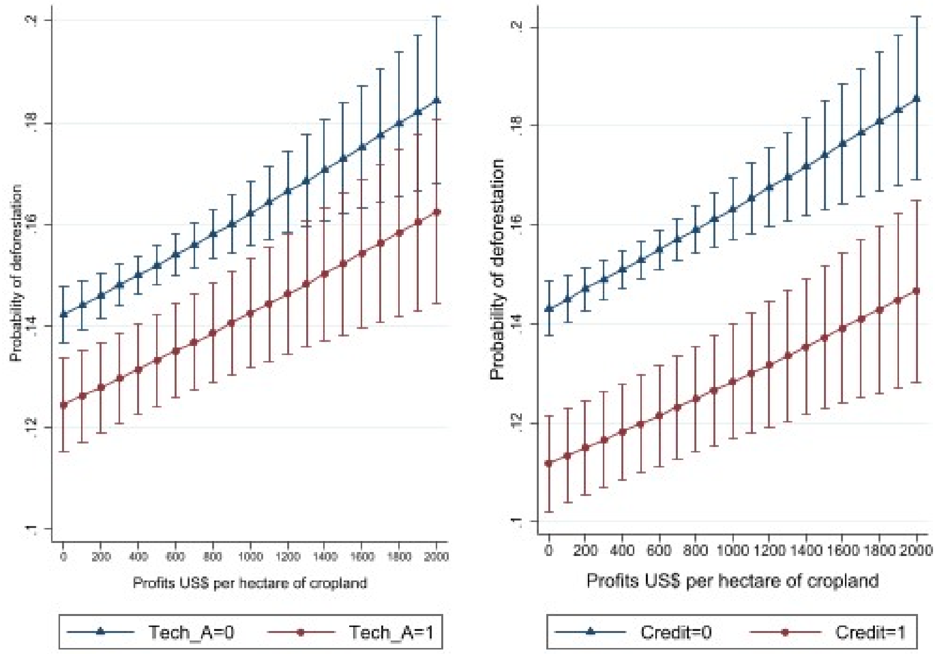
Regarding the institutional dummy variables in Eq. 3.9, denoted $\mathbf{Z}_j$ we find that farms that received technical assistance for sowing crops (TechA=1) exhibit a significantly lower correlation with the probability of deforestation. The left panel in Figure 3.1 indicates that, for a given level of cropland profitability below US$1000, a farm that received technical assistance is, on average, 1.6 percentage points less likely to expand the agricultural frontier by cutting natural forests [10].

Our estimates indicate that having access to rural credit is associated with a lower probability of deforestation. Estimates in Table 3.3 and the right panel in 3.1 show that a farm that had access to credit (Credit=1) is, on average, 3 percentage points less likely to cut natural forest. Our results align with Faria et al. (2025), who show that, in the Brazilian Amazon, rural credit resources allocated to investment activities contribute to reducing deforestation.

As expected, and consistent with the tragedy of the commons, communal ownership, relative to single ownership, is associated with an increase of approximately 3 percentage points in the probability of converting natural forest to agricultural land. Notably, farms designated as Indigenous territories (Dindi = 1) exhibit deforestation probabilities that are approximately 4 percentage points higher than those of non-Indigenous farms, even though profitability in Indigenous areas is significantly lower than in farms without ethnicity-based land-tenure statutes. Figure 3.2 illustrates these patterns: the left panel shows the difference in deforestation probabilities between communal (commons = 1) and non-communal ownership, while the right panel compares Indigenous (Dindi = 1) and non-Indigenous territories.

[10] Moreover, a simple t-test shows no statistically significant difference in crop profitability per hectare between units with and without technical assistance (p-value = 0.13), suggesting that the lower likelihood of deforestation among units that receive technical assistance is not driven by reduced crop profitability.

Figure 3.1: Probability of Deforestation as a Function of Crop Profits, by Technical Assistance (Left) and Credit Access (Right)



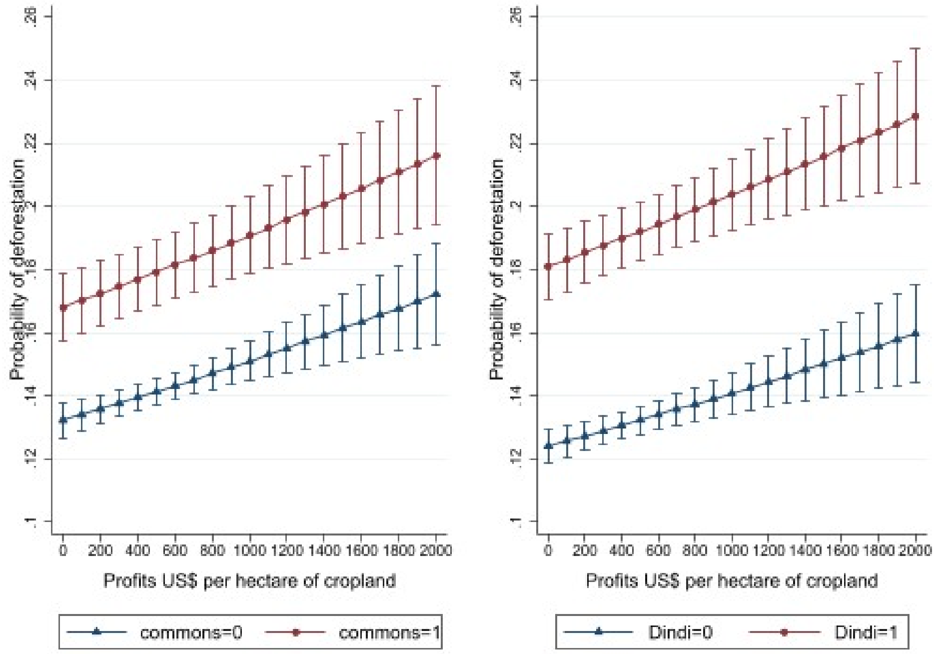
Note: Predictive margins are estimated from the baseline specification. Shaded areas represent 95% confidence intervals. *Source*: Author's calculations with data from CNCA 2014.

3.6.2 Results: Forgone Crop Profitability as the Opportunity Cost of Conserving the Natural Forest

Having identified that crop profitability is correlated with the probability of deforestation, we present the average profitability values of farms and associate them with the opportunity cost of preserving one additional hectare of natural forest. To present these values spatially, we aggregate farm-level crop profitability data to the *vereda* level and apply Eq. (3.10) to compute the corresponding forgone agricultural returns. We restrict our analysis to the 783 veredas that (i) reported positive crop profits, (ii) contain natural forest, and (iii) include at least one farm that reported having expanded the agricultural frontier by clearing natural forest in 2013. The total area of natural forest across the 783 veredas, located within the boundaries of 23,761 farms, amounts to 838,723 hectares. Figure 3.3 shows the results of Eq. (3.10), with *veredas* ordered from the lowest to the highest levels of crop profitability per hectare.

If the forgone values of crop profitability are used as the opportunity cost of conserving

Figure 3.2: Probability of Deforestation as a Function of Crop Profits, by Communal ownership (Left) and Indigenous Territory (Right)

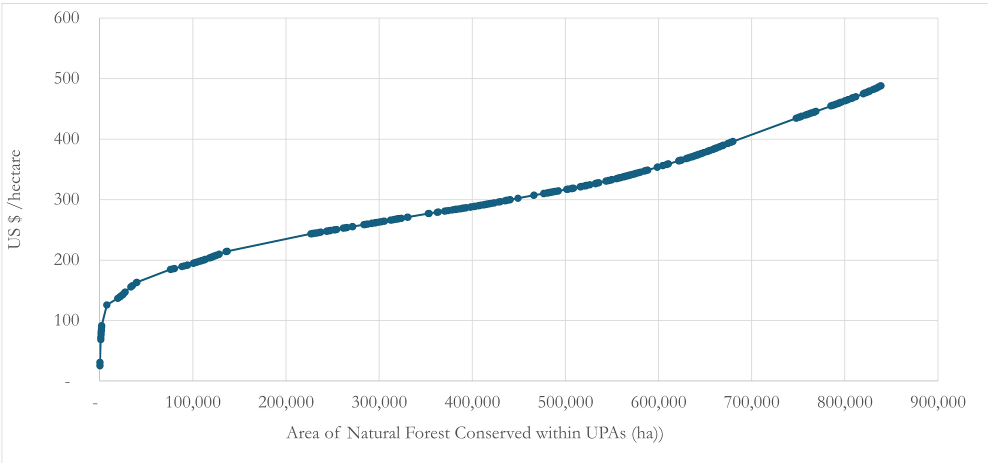


Note: Predictive margins are estimated from the baseline specification. Shaded areas represent 95% confidence intervals. *Source*: Author's calculations with data from CNCA 2014.

natural forest, as shown in Figure 3.3, preserving 838,723 hectares of natural forest within Colombian Amazon farms would entail an opportunity cost of approximately US$0.4 billion, corresponding to an average marginal value of US$488 per hectare. However, accounting for the spatial heterogeneity of the crop profitability among the farms, the opportunity cost of saving natural forest ranges between US $25 and US $1381. Figure 3.4 illustrates the spatial heterogeneity of opportunity costs across veredas that reveal preferences for expanding the agricultural frontier through forest clearing.

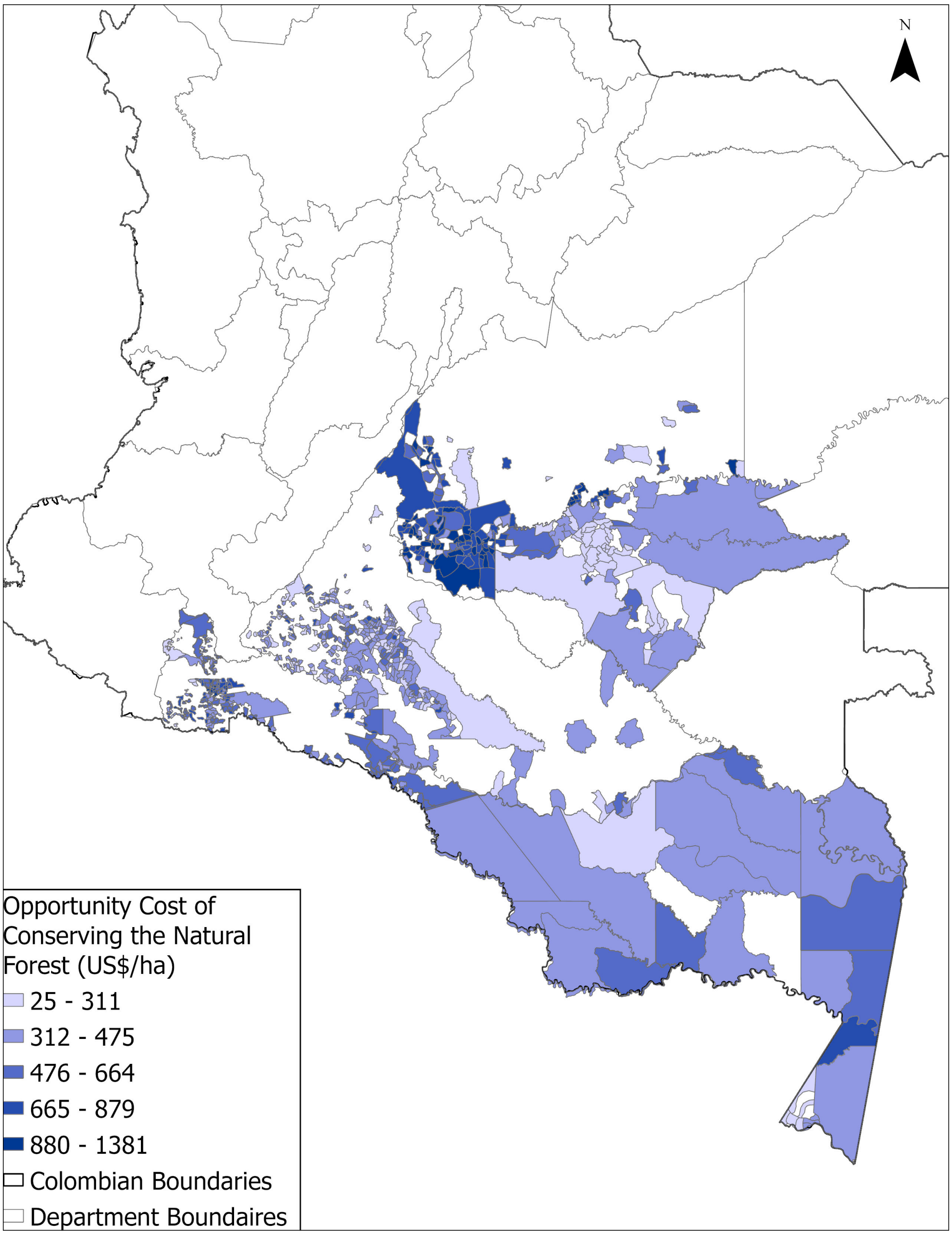
Using official values for carbon stocks in aboveground and below ground biomass, dead organic matter, and soil in tropical rainforests, the conservation of one hectare of forestland avoids an estimated average emission of 114 tC/ha/year (equivalent to 410 tCO_2/ha/year) (IDEAM et al., 2018). Taking the average opportunity cost of US$488/ha, this corresponds to approximately US$1.2 per ton of CO_2 avoided. These values are consistent with studies of avoided deforestation in Brazil, Mexico, and Peru, which report costs ranging between US$0.3 and US$2 per tCO2eq (Phan et al., 2014; Börner et al., 2016; Alix-Garcia et al., 2015; Ickowitz et al., 2017).

Figure 3.3: Forgone Crop profitability as the Opportunity Cost of Saving Natural Forest in Veredas that expanded the Agricultural frontier



Note: *Source*: Author's calculations with data from CNCA 2014, Minister of Agriculture, and DANE.

Figure 3.4: Forgone Crop profitability as the Opportunity Cost of Saving Natural Forest in Veredas with Amazon farms that revealed the expansion of the Agricultural frontier



Note: *Source*: Author's calculations with data from CNCA 201, Minister of Agriculture, and DANE.

3.7 Conclusions

PES instruments have been introduced to curb deforestation in the Amazon. Still, their impact has been limited because incentives often fail to align with the drivers of deforestation and local opportunity costs. This study contributes to filling this gap by employing a simplified land conversion model along with revealed preferences from 39,175 Amazonian farms and satellite land cover data. Our research question seeks to identify the agricultural factors associated with natural forest conversion on farms in the Colombian Amazon and to estimate the opportunity cost of conserving the remaining forest.

Our results suggest that higher crop productivity is associated with an increase in the likelihood of deforestation. This relationship is primarily driven by land-intensive crops that generate high biomass yields but do not necessarily exhibit the highest profitability per unit of land.

In addition, we find that receiving technical assistance and having access to financial credit for agricultural purposes are associated with a decrease in the likelihood of deforestation. These findings highlight feasible channels to support environmental policy to pursue forest conservation.

Our results show that if the forgone values of crop profitability are used as the opportunity cost of conserving natural forest, preserving 838,723 hectares of natural forest would require an investment of approximately US$0.4 billion, corresponding to an average compensation for forgone agricultural returns of US$488 per hectare.

Our analysis is subject to several limitations. First, our results should be interpreted as informative correlations rather than causal estimates. Second, in calculating the opportunity cost, we exclude the agricultural profitability of illicit crops — coca production is among the most common agricultural activities in the Colombian Amazon, however the 2014 Census did not collect information on this crop, precluding its inclusion in our estimates. Third, we do not account for the future benefits of land speculation, such as expected increases in rental values driven by land appreciation. Finally, our opportunity cost estimates do not include non-market values such as carbon storage, biodiversity, and ecosystem services.

Notwithstanding these limitations, our results have relevant implications for agricultural and environmental policymaking. Interventions that promote an increase in agricultural productivity can also lead to environmental benefits when they are accompanied by technical assistance and improved access to financial services. In this context, investments in human capital can play a key role in mitigating the risk of expanding the agricultural frontier driven by crop profitability. Moreover, the spatial heterogeneity in opportunity costs underscores the importance of geographically targeted interventions. Conservation strategies based on constant per-hectare payments may under- or overcompensate farms for their agricultural opportunity costs, thereby limiting both the achievement and cost-effectiveness of environmental and development targets.

3.A Appendix – Additional tables and figures

3.A.1 Probability of clearing natural forest to expand the agricultural frontier with biomass productivity measures

To assess whether the probability of deforestation increases with biomass agricultural productivity. Formally, we test the following logit model:

$$\Pr(N_j) = \lambda_1\, CropBio_j + \lambda_2 \mathbf{Z}_j + \varepsilon_j, \tag{3.11}$$

where N_j is a dummy variable that takes the value of 1 if a farm j replies affirmatively to the question:"In 2013, for the establishment of your crops or forest plantations, did you transform, clear, or cut down natural forest?". $CropBio_j$ is the crop's productivity variable expressed biomass levels (Tons) per hectare of area planted. $\mathbf{Z}_i$ is a vector of socioeconomic characteristics expressed by dummies that takes the values of 1 if the farm: i) had technical assistance for the production, ii) had access to credit, iii) had communal ownership, iv) was registered as an indigenous reservoir in 2013. Finally, we denote ε_i as a random error term and use robust standard errors.

Table 3.4 shows the results of Eq. (3.11) at the farm level. Biomass production in crops is positively associated with deforestation, as land-intensive crops —such as cassava and pineapple— tend to require additional land to achieve a financial break-even point compared with lower-yield crops, such as blackberries or strawberries. While doubling profits per hectare from US$1,000 to US$2,000 is associated with a two percentage point increase in the likelihood of deforestation, doubling yields from 10 to 20 tons per hectare is predicted to raise deforestation by approximately 6 percentage points. Figure 3.5 illustrates the relationship between monetary and biomass measures of crop productivity.

3.A.2 The Cross elasticity of cleared natural forest with respect to crop's profitability

One limitation of the 2014 Colombian National Agricultural Census (CNAC) is the absence of information on the amount of natural forest converted for agricultural expansion, as georeferenced data at the farm level are not publicly available.

Therefore, the farm-level survey responses do not allow us to quantify the magnitude of forest clearance in terms of area cleared — that is, the cross-elasticity of demand for cleared natural forest. As a second-best approach, we exploit the fact that the CNAC links farms to veredas — the smallest administrative units with georeferenced data available in Colombian rural statistics — and aggregate farm-level crop profit information to the vereda level to estimate average agricultural profit per unit of productive land. We restrict this analysis to the 783 veredas that include at least one farm that reported having expanded the agricultural frontier by cutting natural forest in 2013, encompassing a total of 5,837 such farms.

report positive crop profits, contain natural forest, and include at least one farm that reported having expanded the agricultural frontier by cutting natural forest in 2013, encompassing a total of 5,837 such farms.

To quantify the effect of changes in the price (profits) of crops on the quantity demanded of forest land, we model an ordinary least squares (OLS) regression of the natural logarithm of tree loss with respect to the natural logarithm of crop profitability. Taking from (3.9), and restricting to croplands our specification for estimating the cross elasticity λ of a cleared natural forest with respect to crop profitability is as follows:

$$\ln(N_v) = \lambda \ln(\text{Crops}_v) + \Omega \mathbf{Z}_v + \epsilon_v, \tag{3.12}$$

where for a vereda v, N_v is the average amount of tree loss, measured in hectares per square kilometer of natural forest. $[Crops_v]$ denotes the average profits of one hectare of cropland in v. $\mathbf{Z}_v$ represents the socioeconomic controls expressed as the share of farms in a vereda that report positively for the dummy variables relative to the total number of farms within the same vereda. In other words, if a vereda is composed of 20 farms and 10 received technical assistance, the corresponding value of this variable is 0.5. Finally, we use robust standard errors and express ϵ_v as the random error term.

3.A.3 Results: The Cross elasticity of cleared natural forest with respect to crop's profitability

Using profitability data aggregated at the vereda level, we estimate potential tree loss and normalise the results per square kilometre to ensure comparability across locations. Relying on satellite-based land-use measures described in Section 3.4.2, we define average deforestation in a vereda as the number of hectares of tree loss in

Table 3.4: Probability of Clearing Natural Forest to Expand the Agricultural Frontier

	Probability of Clearing Natural Forest
Crop yield (Tons/ha)	0.036***
	(0.006)
Technical Assistance	-0.153***
	(0.043)
Agricultural Credit	-0.286***
	(0.051)
Indigenous	0.433***
	(0.039)
Communal ownership	0.282***
	(0.043)
Population density (1,000 ind./km^2)	-0.21***
	(0.07)
Observations	39,175

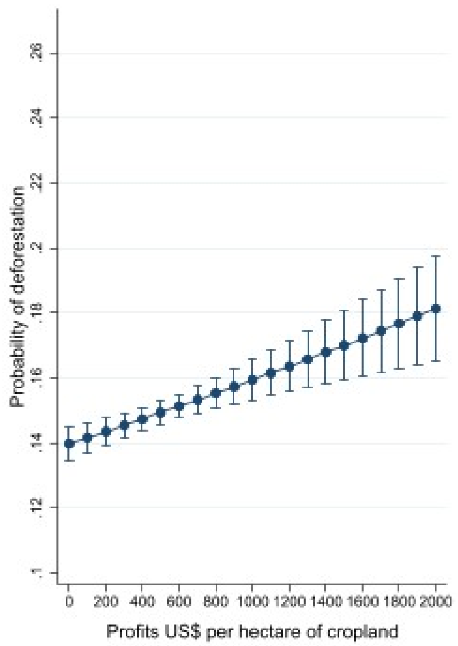
Notes: Reported coefficients are marginal effects. Standard errors are shown in parentheses. Source: Author's calculation with data from CNAC 2014, Ministry of Agriculture, DANE, and Fedegan. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

2013 relative to the total area (in square kilometers) of natural forest in 2012. This variable is expressed in natural logarithms, enabling elasticity-based interpretation of the results.

Table 3.5 presents the results of Eq.3.12. Column (1) includes only the natural logarithm of crop profits per hectare planted, while Column (2) adds crop profits as well as the full set of vereda-level socioeconomic controls (share of technical assistance, access to credit, indigenous population, communal ownership and population density).

Based on the coefficient estimates reported in Column (2) of Table 3.5, a 10% increase in crop profits per hectare planted is associated with a statistically significant increase of approximately 5% in tree loss per unit area of natural forest. This value is consistent with the findings of Mullan et al. (2018), who report that a 10% increase in cleared area is associated with a 5.6% increase in household income in the Brazilian Amazon.

Figure 3.5: Probability of Deforestation as a Function of Crop Profits (Left panel) and Yields (Right panel)



Note: Predictive margins are estimated from the baseline specification. Shaded areas represent 95% confidence intervals. *Source*: Author's calculations with data from CNCA 2014, Ministry of Agriculture and DANE.

Table 3.5: The Cross elasticity of cleared natural forest with respect to crop's profitability

	Dependent variable: ln(Tree loss)	
	(1)	(2)
ln(Crops)	0.586**	0.485**
	(0.259)	(0.226)
Controls		Yes
Observations	783	783

Note: The dependent variable is the natural logarithm of tree loss measured in hectares per square kilometer of natural forest. Column (1) includes only the natural logarithm of crop profits per hectare planted. Column (2) includes crop profits and the full set of vereda-level socioeconomic controls at the vereda level. Standard errors are reported in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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