Collateral damage: The impact of forced eradication of illicit crops on human capital*

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Abstract

The role of eradication policies in decreasing drug trade, insecurity, and ultimately fostering development remains largely debated. This paper examines the unintended consequences of aerial fumigation of coca on human capital accumulation and its medium-term socioeconomic impacts in Colombia. Employing a spatial regression discontinuity design and utilizing newly digitized data on the exact location subject of aerial spraying, we find that eradication increases school dropout and failure rates in the short term. A key mechanism of these impacts is the negative income shock experienced by households. Furthermore, we document that even after the ban on aerial spraying in 2015, villages exposed to aerial eradication exhibit worse socioeconomic outcomes, including lower schooling, higher child labor, increased early marriage, and deteriorating living conditions.

Keywords: Aerial spraying; Coca; Glyphosate; Human capital; Income shock.
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"The space where coca grows and the peasants who grow it - because they have nothing else to cultivate - is demonized. For you, my country is of no interest except to poisons its jungles, to put its men in jail and to throw its women into exclusion. You are not interested in a child's education, but rather in killing its forest." Gustavo Petro (Sep, 20, 2022)

1 Introduction

The recent UN World Drug Report for 2023 highlights how illicit drug trafficking and economies pose significant obstacles for countries to meet their Sustainable Development Goals (UNODC, 2023b). However, the policy solutions aimed at breaking the negative feedback loop between drug trade, conflict, and underdevelopment remain vastly opaque. One policy that has been frequently advocated for and used around the world – receiving major foreign investment e.g., by the U.S. – are efforts targeted at eradicating the production of illicit crops such as coca and poppy.

Whether these eradication policies help countries overcome the negative feedback loop is highly doubtful. Indeed, these policies may exacerbate underdevelopment and create conditions conducive to further illicit crop production – even if they might be successful at restricting supply in the short-run. This is primarily because eradication measures mainly harm small-scale farmers engaged in illegal crop production by destroying their crops and, consequently, their sources of income.. Evidence from Colombia suggests that farmers use these revenues mainly to meet their basic needs as well as to invest into their children's education (Gutiérrez Sanín, 2019). In turn, a lack of education has long been recognized as a factor contributing to underdevelopment, suggesting that eradication policies might even fail at achieving their fundamental goal in the medium- to long-term.

In this paper, we investigate the unintended impact of aerial fumigation of coca on human capital accumulation in Colombia and its socioeconomic implications in the medium term, along with the underlying mechanisms. Colombia is currently the world's leading producer of coca and cocaine; it alone furnishes more than 90 percent of the U.S. supply (O'Neil et al., 2022). Among the counter-narcotics policies implemented to curb this problem, aerial spraying with glyphosate standed out as the largest and more costly form of forced eradication (Mejia et al., 2017). Yet, despite its ban in 2015 for being "probably carcinogenic to humans" (IARC, 2017), aerial eradication remains at the center of a fierce debate on counter-narcotics policies not only in Colombia, but also in other producing countries, such as Afghanistan (SIGAR, 2018).

We exploit quasi-random variation from the eradication flights, as the planning and execution of aerial eradication were intricate and influenced by organizational and natural constraints, including weather conditions, proximity to airports, time limitations, and idiosyncratic decisions of the pilots. Leveraging the exogeneity in demarcating the sprayed areas, we employ a spatial regression discontinuity design (RDD). We digitized the precise geographical coordinates of 1293 sprayed areas from 2004 to 2015, and 767 manually eradicated polygons from 2006 to 2015, using the annual "Colombian Coca Cultivation Survey" published by the United Nations Office on Drugs and Crime (UNODC). This dataset is then combined with the geolocated universe of all schools in Colombia, allowing us to compare schools just inside sprayed areas with those just outside them.

We find that aerial spraying does worsen educational outcomes. Specifically, schools situated within sprayed areas experience an 11% increase in dropout rates and an 8.5% increase in failure rates when compared to schools just outside the eradication area, i.e., schools located just 5 and 8 kilometers away from the eradication boundary, respectively. Our results are robust to a number of tests and alternative specifications, including a sensitivity test for observations near the cutoff, using only schools for which more than 80% of the surrounding area was eradicated, introducing geographic controls, using quadratic polynomials, and applying different sample splits.

Importantly, we show that there were no significant differences in socioeconomic, geographic, or eradication-related characteristics prior to the start of the aerial spraying. Specifically, we document that the level of coca cultivation in the vicinity of schools was similar for both sprayed and non-sprayed schools in the year preceding eradication. We also find that the likelihood of these schools being subjected to alternative forced eradication programs, i.e., manual eradication, was the same. We found no statistically significant differences in slope, nighttime light density and the presence of landmines in the areas surrounding the schools in 1993. Additionally, using municipality-level data, we showed that the schooling characteristics were also the same across the eradication boundary. We only observed differences in elevation and the likelihood of having been sprayed in the previous year, for which we always control for.

We document that the plausible mechanism through which forced eradication affects human capital is the negative impact on farmers' income. First, we find that families respond to the eradication shock by reducing education expenses – i.e., withdrawing children who are not of working age – and potentially increasing labor force participation within the household – i.e., withdrawing children of working age. Second, we demonstrate that aerial eradication does have a significant negative impact on household income and economic activity by using nighttime light density.

Next, we rule out health as a potential mechanism for the observed negative effects on education, considering glyphosate's known impact on health (IARC, 2017; Camacho &

Mejía, 2017; Zhang et al., 2022; Dias et al., 2023). To investigate this, we employ manual eradication, which does not impact public health. In our analysis, we use an RDD, comparing schools inside areas subjected to manual eradication with those just outside. The findings indicate that manual eradication had a similar adverse effect on dropout and failure rates as aerial spraying, both in terms of magnitude and statistical significance. This suggests that, at least in the short term, health does not appear to be a primary factor contributing to the decline in educational outcomes. Additionally, we rule out conflict – proxied by landmines – and selective migration – using school transfer rates –as plausible mechanisms.

Having to dropout of or bad performance in school plausibly shapes individual outcomes throughout their whole life. To study the effects of aerial spraying on socioeconomic conditions and household dynamics on a longer term, we employ an RDD using 2018 census data at the rural section level and aggregating all the spraying areas from 2004 to 2015. We find that rural sections subjected to aerial spraying indeed have lower schooling rates –in primary, secondary and high school– among the adults who were exposed during their youth. Again, we do not find significant effects in self-reported health outcomes, nor do we identify selective migration as a potential long-term mechanism.

Instead, bolstering our short-term income effects, we observe that rural sections within aerial spraying areas exhibit higher child labor rates for boys, consistent with the observed increase in dropout rates for working-age children. Yet, we also find that girls are more involved in household chores.

We further investigate the gender differences in responses to the eradication shock by studying early marriage. A growing body of research indicates that early marriage can be a coping mechanism for impoverished households facing income shocks (Hoogeveen et al., 2011; Baird et al., 2011; Corno et al., 2020; Chort et al., 2022). Our findings show that the percentage of married girls aged 10 to 14, and 20 to 29, is higher in rural sections subjected to spraying. This suggests that the eradication shock may indeed influence marriage patterns among young women in these areas, shedding light on the societal consequences of eradication efforts.

Lastly, we document that the temporary eradication shock results in longer-term household impoverishment. Rural areas subjected to aerial spraying have, on average, less access to clean water, sanitation facilities, and waste disposal compared to unsprayed areas. Given the substantial magnitude of these effects, it is unlikely that they stem solely from the one-time income shock caused by the inability to sell eradicated crops in the eradication year. Instead, these effects are likely linked to lower levels of human capital, which subsequently lead to worse labor market outcomes for individuals, diminishing their lifetime earning potential.

This paper highlights the importance of assessing the downstream consequences on the civilian population during the formulation and execution of law enforcement policies. Particularly, when such policies have the potential to significantly affect the livelihoods of already marginalized communities. Forced eradication programs should not only aim to mitigate the adverse effects on communities engaged in coca cultivation but also provide sustainable economic alternatives.

Our paper is related to several strands of the literature. First, it speaks to research studying how law enforcement policies impact human capital accumulation (Kalsi, 2018; Ang, 2021; Cameron et al., 2021; Sviatschi, 2022). We study one of the longest and most expensive programs targeted at reduce coca supply that ever took place. Our findings highlights how anti-drug policy enforcement in producer countries can worsen human capital accumulation and increase impoverishment of rural communities. This effect is not just restricted to the short-run, but we find evidence of medium-term negative implications.

In particular our paper is related to previous research on forced eradication, using survey data survey data, in Peru (Dammert, 2008) and Colombia (Rodriguez, 2020). They document potential negative effects on child labor markets, but do not find implications for educational outcomes. The later being particularly important as it leads to long lasting negative consequences of the eradication programs. We are able to reconcile those findings having newly collected granular data on precise boundaries of eradicated areas and matching this information to the entire universe of schools. Further, apart from long-lasting negative educational and labour market outcomes we also document other negative seriocomic consequences, in particular an entrenchment of more conservative gender-role. We document an increase in (female) child marriages in areas that had been eradicated.

Second, our study relates to the literature on exposure to illegal markets and the subsequent implications for the labor market and educational prospects (Angrist & Kugler, 2008; Ibáñez, 2010; Sviatschi, 2022; Angulo, n.d.). The literature so far has highlighted how these illegal markets increase child labor in rural areas and through this having negative implications for human capital accumulation. However, our findings highlight that destroying illegal markets is not a solution to this problem, as we show that policies targeted at forcefully eradicating illegal agricultural activities simply contributed to the downward spiral in human capital accumulation and development. The reason for this seems to be that, at least in the case of coca eradication, the intervention reduces household incomes, which are commonly invested into education, and consequently these policies hinder overall development further and plausibly propagate the illegal market in the long-run.

The rest of this paper is structured as follows. Section 2 describes the institutional background. Section 3 describes the main data sources. In Section 4, we present the empirical strategy and results for the short-term analysis. Section 5 present the empirical strategy and results for the medium-term analysis. Section 6 concludes.

2 Institutional background

This section describes the dual role of coca cultivation in Colombia's rural regions, both as a source of income and opportunities, and its association with armed groups. We outline the functioning of forced eradication programs and the educational system in Colombia.

2.1 Coca and eradication programs

Coca has been part of the life of indigenous communities in the Andes for centuries (Thoumi, 2003). Yet, it is also the primary raw material used in the production of cocaine; and Colombia stands as the largest producer of both coca and cocaine in the world (UNODC, 2023a). In 2021, coca cultivation in Colombia increased by 43%, producing a total of 204.000 hectares, and the potential manufacture of cocaine increased by 14% compared to the previous year, reaching both global records to the highest levels ever register (UNODC-SIMCI, 2022).

The cultivation of coca is a remarkably stable crop as coca plants exhibit rapid year-round growth, allowing for frequent harvesting approximately every three months. In contrast, many other crops have less frequent harvest cycles and significantly longer initial growth periods. For example, a coca bush requires only six to seven months to yield its first harvest, whereas a coffee bush takes between 2 and 4 years to mature and produce its initial fruits. This rapid growth cycle contributes to relatively high revenues with minimal initial investment. The cultivation of coca is a remarkably stable crop as coca plants exhibit rapid year-round growth, allowing for frequent harvesting approximately every three months. In contrast, many other crops have less frequent harvest cycles and significantly longer initial growth periods. For example, a coca bush requires only six to seven months to yield its first harvest, whereas a coffee bush takes between 2 and 4 years to mature and produce its initial fruits. This rapid growth cycle contributes to relatively high revenues with minimal initial investment.

Furthermore, coca offers unique advantages within the Colombian agricultural landscape. It is the only agricultural product that offers a market capable of guaranteeing minimum prices and the sale of the entire harvest without incurring additional costs. Unlike legal agricultural products, coca buyers directly acquire the harvest from households, sidestepping the substantial transportation expenses (Crisis Group, 2021). This distinctive characteristic makes coca cultivation financially viable and stable for small-scale farmers, making it an appealing option for impoverished farmers who lack access to financial markets. In 2016, it was estimated that approximately 215,000 families were engaged in coca cultivation (Crisis Group, 2021).

However, while coca cultivation is easy to engage in for farmers, its illegality has negative externalities due non-state armed groups being key to facilitating its trade. The presence of these exacerbates violence and insecurity in rural areas. In response to this and due to international pressure, the Colombian government has undertaken significant efforts to reduce the cultivation of coca. Among the most important measures are aerial spraying of glyphosate and forced manual eradication.

2.1.1 Aerial spraying of glyphosate:

Glyphosate (commonly marketed as RoundUp) is the herbicide used for eradicating illicit crops in Colombia. When sprayed, this herbicide targets the leaves of the plants while leaving the soil unaffected, making it possible to replant a coca bush in the same location following eradication. The regrowth of coca is especially facilitated by glyphosate not impacting the coca plant's stem, allowing the affected plants to sprout new leaves as soon as six months after (UNODC-SIMCI, 2004). While the intended target of glyphosate spraying is primary coca leaves, it has also had affected other crops such as yuca, plantains, rice, and fruits (Corte Constitucional de Colombia, 2017).

Colombia has employed aerial spraying of herbicides since 1994.[1] The scale of this was considerably expanded in 1999 as the Colombian and U.S. governments launched Plan Colombia – the largest counter-narcotics intervention in a producer country with expenditures for the program exceeding \$10 billion. This decade-long program significantly expanded eradication and fumigation efforts, reaching its peak in 2006 with more than 172,025 hectares sprayed (see Figure 1). From 2000 to 2008, approximately 1.15 million hectares were eradicated through aerial spraying of glyphosate (O'Neil et al., 2022). Spraying continued after 2008, but on a lower scale. Aerial spraying was fully halted in October 2015 influenced by the World Health Organization's International Agency for Research on Cancer (IARC) classification of glyphosate as "probably carcinogenic to humans" (Huezo, 2017).

Despite the massive efforts and resources allocated to this policy, there is only limited evidence for it being successful in curbing coca supply. For instance, Bogliacino & Naranjo (2012), who employ a system of equations where aerial spraying and cultivation are determined simultaneously, and Reyes (2014), using the distance to the nearest airport as an instrument for spraying, find that aerial spraying actually increases land used for coca cultivation due to the reallocation of crops. Moya Rodríguez et al. (2005), employing matching on observables to address selection bias, does not observe any significant impact on coca

[1] Its use against cannabis and poppy crops dates back to 1978 (Vargas Meza, 1999).

cultivation. In contrast, Rozo (2013) – using distance to protected areas that cannot be sprayed and U.S. antinarcotics expenditures as instrument – find a significant negative effect reduction in coca cultivation. Mejia et al. (2017), leveraging quasi-experimental variation due to a diplomatic friction between the governments of Ecuador and Colombia, also document a negative effect on coca cultivation, but conclude that these are too small to justify the cost-effectiveness of aerial spraying as a policy.

The planning and execution of fumigation flights were complex, and influenced by two factors: organizational and natural constraints. The aerial spraying operations had to be planned by the Antinarcotics Police (DIRAN). The aircraft used included models such as the OV-10 Bronco, Air Tractor AT-802, or Turbo Thrush, that were adapted to carry fumigation equipment instead of weaponry (Reyes, 2014). This adaptions carried inherent risks due to attempts by non-state groups to shoot down these planes. To mitigate this threat, aircrafts were accompanied by armed helicopters (Huey II and UH-60 Black Hawk). In contrast to the airplanes, these helicopters had a range of only 80 miles from the airport. These operational limits to the geographic extent of eradication were further constrained by the fact that there were only eleven airports from which these operations could take place (Reyes, 2014).

Secondly, while the primary criterion for selecting areas for eradication was the density of coca crops – identified through satellite imagery and verification flights – there were several additional constraints that influence the exact location of sprayed areas. For instance, specific weather conditions had to align for spraying to occur. Wind speeds had to remain below 5 knots, and temperatures needed to be no higher than 35°C. Spraying operations were also suspended if there was a high likelihood of rainfall or if clouds were too close to the surface (Comité Técnico Interinstitucional Asesor del CNE (2003)). Lastly, the discretion of the pilot also played a significant role in determining when and where to halt eradication efforts. Pilots could choose to suspend spraying if they had doubts about the suitability of an area or in response to an attack on the aircraft (U.S Department of State, 2002). We argue that these constraints introduced a degree randomness in the demarcation of eradication areas that we will exploit later on.

Today, given the unprecedented surge in coca cultivation and mounting pressure from the U.S. administrations, aerial spraying has taken again a center stage in the ongoing debate surrounding strategies to counteract drug supply.[2] In 2021, former President Ivan Duque issued a decree regulating the possible return of aerial spraying of illicit crops with glyphosate. However, the Colombian Constitutional Court has prevented attempts to resume

[2]Particularly during the Trump administration, which repeatedly pressed the Colombian government to reinstate aerial fumigation and even threatened to blacklist the country for its perceived inaction in addressing the global drug trade (CBS, 2017).

aerial spraying (El Espectador, 2022).

2.1.2 Manual eradication:

The Eradication Mobile Groups (GME) strategy was established in 2004 as a complementary approach to the aerial spraying program.[3] These groups are comprised of around 30 members, most of them are farmers[4], often from different regions than where they operated. Their primary task involved venturing into the fields to uproot coca plants. These eradication teams typically spent 30 to a maximum of 45 days at a site, with protection provided by the police or army.

While this program boasted several advantages, such as relatively low implementation costs and minimal negative environmental and agricultural impacts – ensuring food security for local residents (Caballero Farfan, 2019) – it entailed higher risks than aerial spraying. Eradicators frequently fell victim to illegal armed groups, and clashes between these groups and the army and police heightened local violence.

Unlike the aerial spraying program, manual eradication fell under the Presidential Agency for Social Action, specifically managed by the Presidential Program Against Illicit Crops (PCI, in its Spanish acronym). Nevertheless, DIRAN continued to play a crucial role in planning and ensuring the safety of eradicators (Caballero Farfan, 2019).

2.2 Education system in Colombia

The Colombian education system is divided into five levels: pre-school (under six years old), primary (6 to 10 years old), middle school (10 to 14 years old), high school (15 to 16 years old), and tertiary education. Compulsory education, as mandated by Colombian law, encompasses ten years of study, starting at the age of 5 and concluding at 15. However, despite this theoretical minimum age when leaving school, in practice many students exit school much earlier.

The educational landscape in Colombia is characterized by significant disparities between rural and urban areas. While urban areas boasted an average of 9.3 years of schooling, their rural counterparts lagged behind with an average of just 6 years (both average below the minimum years of schooling). Ensuring access to education and retaining students in the education system, especially in rural areas, continue to be significant challenges in Colombia.

[3] Manual eradication of coca crops had been employed even prior to the 2000s to a very limited extent.

[4] At first, demobilized people were also included in the GME strategy, but due to some problems they stopped being used in the eradication programs (Caballero Farfan, 2019)

In 2015, the net enrollment rates in rural areas,[5] were approximately 50% in pre-school, 82% in primary school, 65% in middle school, and a mere 35% in high school (MEN, 2018). These discrepancies in educational access and attainment shed light on the persistent hurdles faced by rural students, who are disproportionately impacted by factors such as poverty, armed conflict, and limited access to essential public services.

In this context, some have argued that coca cultivation has to some extent improved opportunities for social mobility, access to education, and access to healthcare for impoverished farming households (Crisis Group, 2021). A survey conducted among 412 coca-growing households in southern Colombia, shows that 52% of the people interviewed considered education as their top investment priority, second only to investments in land (19%) (Gutiérrez Sanín, 2019). While this underscore some positive aspects of coca cultivation, it is important to note that coca cultivation has also boosted violence and conflict in these rural areas.

3 Data

This section describes our primary data sources and supplemental datasets utilized for exploring potential mechanisms and testing key identifying assumptions. Further information regarding the data can be found in Appendix A.1. Tables A.1 and A.2 present the summary statistics for the main variables.

Eradication Areas: Since 2004, the UNODC Global Illicit Crop Monitoring Programme (SIMCI, by its Spanish acronym), in collaboration with the Colombian Government, has conducted the Colombian Coca Cultivation Survey. These encompass a wide range of data, including information on regions engaged in illicit crop cultivation, estimations of the illicit drug market, and detailed maps outlining the areas subject to eradication (see Figure A.1). Aerial spraying maps are produced by UNODC with information provided directly by DIRAN[6], the institution responsible for the aerial spraying program. Manual eradication maps are produced with information from the PCI.

We have meticulously digitized and georeferenced these maps for all available years. Accordingly, our data covers the yearly-geographic extent of aerial spraying 2004–2015 and manual eradication 2006–2015. This has yielded fine-grained data on Colombia's regions that underwent eradication. Figure A.2 illustrates the digitized maps of aerial spraying from

[5]The net enrollment rate measures the percentage between the students enrolled in the corresponding level who are of the expected age for that level and the population of the theoretical age to attend that level.

[6]Geospatial information of the areas sprayed was done through a GPS located in the airplanes. This GPS system records the location when valves are open (Mejia et al., 2017)

2004 until 2015.

Our data collection has identified 1293 individual areas (polygons) that were sprayed with an average size of 777km^2. 767 polygons were manually eradicated with the average size being 483km^2.

School census: The annual school census is collected by the Statistics Bureau (DANE) and the Ministry of Education. This dataset is publicly available in DANE's web page. It contains school-level information such as enrollment, dropout, failure, and records of student transfers to other educational institutions[7]. These measures provide the main outcome variables of interest for our analysis. We link this data to eradication via information for the exact location of schools provided by DANE.

Figure 2 provides an example showing the extent of eradication that occurred in 2006 and school locations. In the average year, we observe 900 schools situated within sprayed areas. For comparison, on average 1175 schools are located just outside the sprayed areas (within a radius of 5 Km). We restrict our analysis to schools with enrollment exceeding 20 students. Outcomes for schools below this threshold are sensitive to random behaviour of individual students, i.e. observed outcomes are subject to considerable measurement error from year to year. We exclude these schools which account for less than 1% of the total student population from our baseline analysis.

Additional data sources:

- *Geographic characteristics:* To assess balance across geographic characteristics, such as elevation and slope, we rely on data from the United States Geological Survey (USGS), specifically utilizing the Shuttle Radar Topography Mission (SRTM) at a resolution of 1 arc-second (i.e., approximately 30 meters).

- *Coca Cultivation Density:* This data is derived from two sources: satellite images collected and processed by UNODC-SIMCI, and verification flights with GPS-equipped airplanes (UNODC-SIMCI, 2006). We use coca cultivation density to evaluate whether schools inside and outside eradicated areas exhibit similar levels of coca.

- *Nighttime light density:*To investigate potential mechanisms, we employ nighttime light density as a proxy for economic activity. This dataset is provided by the Defense Meteorological Satellite Program-Operational Linescan System (DMSP-OLS), spanning from 2004 to 2013. We calculate the average luminosity within different radii around each school location.

[7]Note that due to the absence of individual-level data, we cannot determine whether students return to studies after dropping out or identify the specific institutions to which they were transferred.

- *Landmines:* The data on anti-personnel landmines is sourced from the Information Management System for Mine Action (IMSMA) within the Geneva International Centre for Humanitarian Demining (GICHD). This dataset contains precise details regarding the coordinates of events[8] related to landmines. For our analysis spanning the years 2004 to 2015, we employ the average count of all events related to landmines in the vicinity of schools providing a proxy for the presence of conflict.

- *Population and household census 2018:* To analyze longer-term outcomes, we utilized the 2018 census data, which provide socioeconomic characteristics (e.g., dwelling conditions, education, labor force participation, etc.) for all Colombian households. Although we don't have the exact location of the households, we are able to locate them at the rural section level, which is a statistical division in rural areas, with an average size of approximately 20 square kilometers.

- *Data at the municipality level:* We got data from the Municipality Panel Dataset from CEDE, Universidad de los Andes (Acevedo & Bornacelly, 2014).

4 Short-term effects of aerial spraying

In this section, we examine the short-term impact of aerial spraying on educational outcomes. We find that schools located just inside the sprayed area exhibit, on average, poorer educational outcomes compared to schools located just outside of those areas. This effect is robust to different specifications, i,e., excluding observations near the cutoff, narrowing the treatment definition, introducing geographic controls, and applying different sample splits. We rule out migration, health, and conflict as drivers of this negative impact on education. Instead, we provide evidence that the decrease in household income is the primary mechanism behind this effect.

4.1 Empirical strategy

To estimate the causal effects of forced coca eradication on educational outcomes we use a regression discontinuity (RD) design, where we compare schools located just inside an area sprayed to schools located just outside them. We employ the following specification:

$$y_{i,t} = \beta Erad_{i,t} + f(location_{i,t}) + X_i + \lambda_t + \epsilon_{i,t} \quad for\ i \in bw \tag{1}$$

[8]These events include: explosions, stored arsenal, demining, seizures, unexploded ordnance, fabric of landmines and suspicion of presence of landmines.

where $y_{i,t}$ is our outcome of interest for school i in year t: dropout and failure rates. $Erad_{i,t}$ is dummy variable equal to one if the school is inside a sprayed area, and equal to zero otherwise. X_i is a school level vector of covariates (e.g. slope, elevation, eradication controls). λ_t denotes year fixed effects.[9] $f(location_{i,t})$ is an RD polynomial, which controls for smooth functions of location of school i. We use a linear polynomial of distance of school to the closest border of a sprayed area (see Gelman & Imbens, 2019; Cattaneo et al., 2019). Following Cattaneo et al. (2019), we compute the optimal bandwidth using the MSE-minimizing procedure and we use a triangular weighting kernel. $\epsilon_{i,t}$ is the error term with standard errors clustered at the school level, i.e., the treatment level.

Our coefficient of interest is β, which shows the effect of being just inside of an eradication area on educational outcomes. Importantly, we rely on the exogeneity of the sprayed area borders to interpret the effect as causal. As detailed in Section 2.1.1, the demarcation of sprayed areas is contingent on several criteria and conditions, including factors such as weather, distance to airports, time constraints, and idiosyncratic decisions of the pilots. Thus, it is unlikely that the areas that ended up just within the eradication border – along with the schools located within them – differ structurally from neighboring areas just outside. However, this reliance hinges on two identifying assumptions. First, schools had similar characteristics before the eradication took place. This assumption ensures that, in the absence of aerial eradication, non-sprayed schools serve as an appropriate counterfactual for those situated just inside the sprayed area. Second, there was not selective migration across the RD boundaries before treatment occurred, i.e., students from sprayed schools did not selectively out-migrate to non-sprayed areas due to them being able to anticipate aerial spraying occurring in the future.

To assess the first assumption, we estimate specification (1) for several pre-existing characteristics surrounding schools (elevation, slope, nighttime light density, and landmines) and coca-related characteristics in the preceding year of eradication (square kilometers of coca crops and eradication in previous years). We present the results using both an optimal bandwidth and a fixed bandwidth of approximately 6 kilometers – the optimal bandwidth for our primary outcome. Table 1 Panel A displays the results.

Overall, we observe that a number of relevant characteristics of both non-sprayed and sprayed schools do not exhibit discontinuous changes at the boundaries of sprayed areas. We find no statistical differences in pre-existing socioeconomic development around schools – proxied by nighttime light density (see Chen & Nordhaus, 2011; Henderson et al., 2012). Neither do we find differences in the occurrence of landmine events before the eradication

[9] For recent work using time-varying RD settings see Cellini et al. (2010); Grembi et al. (2016); Hsu & Shen (2021); Méndez & Van Patten (2022); Cattaneo & Titiunik (2022)

programs started – which serve as a proxy for conflict and presence of illegal armed groups. Importantly, we find no differences in the number of square kilometers of coca surrounding schools in the year preceding eradication. The probability of having been in an area subjected to manual eradication at time *t* or *t-1* is also not statistically different between treated and untreated schools. On average, schools are situated at the same slope. This provides empirical evidence supporting that the exact border of eradication was indeed exogenously defined by a multitude of idiosyncratic factors as discussed in Section 2.1.1.

We document only one statistically significant geographic difference between treated and non-treated schools, which is that the former are located at lower elevation. However, this difference is not big when considering that coca is cultivated in places between between 3,300 and 6,600 feet above the sea (1,000 to 2,000 meters above the sea) (U.S Department of State, 1991)). Then, we include altitude in our baseline controls to rule out that our results are driven by this difference rather than eradication. Further, we observe that the probability of having been treated at *t-1* is marginally associated with treatment at time *t* in a subset of balance checks. Out of caution we also include this variable in our baseline controls. Indeed it is interesting here that our evidence suggests that areas were neither targeted more or less based on previous spraying efforts (notably this is the case even without controlling for coca cultivation here). This seems to support that many idiosyncratic factors played a key role in defining the exact extent of the spraying efforts from year to year.

We continue our balance check by looking at pre-eradication educational characteristics. Unfortunately, school census data does not extend to pre-2004 – so that we are unable to observe education outcomes at the school-level before treatment started. We instead provide evidence for this using municipality-level from (Acevedo & Bornacelly, 2014). This data provides municipality characteristics from the 1993 census and administrative records from 1996. In this exercise, we maintain the school as our unit of observation, but we base our analysis on the outcomes associated with their respective municipalities. Similarly, we present evidence on the land suitability differences for three agricultural products commonly cultivated in those areas: oil palm, plantain, and coffee[10] (MJD & UNODC, 2012). This data comes from the Global Agro-Ecological Zones (GAEZ). Table 1, Panel B, displays the results.

We document no statistically significant differences in any of the pre-existing educational outcomes, including school-age population, population in primary and secondary education, years of schooling, illiteracy rate, and the number of teachers and students. Moreover, we do not observe disparities in land suitability for the three main agricultural products. We also conducted the balance check using the municipality as the observation unit and considering

[10]Please refer to subsection A.1.6 of the appendix for a detailed explanation of the suitability variables

the distance from its centroid to the spraying border. We obtained consistent results (see Table A.3).

Lastly, even as it seems unlikely that students can anticipate eradication considering the complexity of eradication flights, we provide supportive evidence for this second assumption (no selection into treatment) using transfer rates across schools. Accordingly, we estimate specification (1) studying the relationship between eradication (t) and transfer rates in the year preceding eradication (*t-1*). Reassuringly, Table 2 confirms that there is no statistically significant difference in past transfer rates between areas exposed to eradication and those that are not. This is the case when using baseline controls (in columns (1) and (2)), extended controls (in columns (3) and (4)), and different bandwidths.

4.2 Results

Before presenting the primary findings on education, we aim to examine whether aerial spraying achieves its core objective: the reduction of coca cultivation. Table 3 compares the coca presence around schools at *t+1* for both sprayed and non-sprayed schools at t. No statistically significant differences were observed, even when employing controls. This may be attributed to families choosing to retain their affected but recoverable coca plants or opting to cultivate new ones. However, the absence of significant differences does not negate the possibility of a negative income shock, a point we elaborate on in Section 4.7, while concurrently presenting the education-related results.

Table 4 presents the results of aerial spraying on human capital accumulation — dropout rate – and academic performance — failure rate.

Column (1) presents the effect of aerial eradication on the dropout rate controlling only for year fixed effects. We find that schools located within sprayed areas exhibit a 0.6 percentage point higher dropout rates compared to schools situated just outside these areas. We observe similar effects after accounting for our baseline controls (elevation and having been sprayed at *t-1*) in column (2). The magnitude of the estimate slightly increases to a one percentage point higher dropout rates. This translates to an 11.4% increase in dropout rates compared to non-treated schools as the mean dropout rate for non treated schools is 9.4 percentage points. For academic performance, in column (3), we observe a 0.4 percentage point increase in school failure rates within the aerial spraying polygons. Again the effect is slightly higher after including the baseline controls in column (4) suggesting a 0.6 percentage points increase in school failures. This suggests an 8.5% increase in the likelihood of students repeating a year compared to the non-sprayed schools average of 7.2 percentage point. Figure 3 illustrates the RD plot for our baseline results.

We do not find evidence of a persistent effect of aerial eradication on educational outcomes in the year following exposure to spraying, as shown in Table 5. This suggests a relatively short-term impact of this policy. However, it is important to note that even short-term effects can have significant long-term implications, especially in the context of dropout rates,when students temporarily leave school, they are at a high risk of permanently exiting the education system.

4.3 Robustness checks

Sensitivity to observations near the cutoff – We start our robustness analysis estimating results using the "donut hole" approach. We use specification (1) excluding observations around 100, 200, 300 400 and 500 mts from the RD cutoff. Table 6 presents the results. On average, we observe results consistent with our baseline findings, both in terms of magnitude and statistical significance. This analysis serves two key purposes: i) it allows us to show that our results are robust to potential inaccuracies in pinpointing the exact location of the aerial spraying borders. For example, an area might have been intended to be sprayed by an airplane but the herbicide actually eradicated crops further afield in closely neighbouring locations due to the herbicide being spread slightly more or less than anticipated by wind and other weather conditions. However, it seems unlikely here that this would affect areas more than 1km away from the intended target. ii) we can assess that there are not potential non-compliers near the cutoff driving the results. As we lack precise information regarding the locations of students' households, we rely on the assumption that school locations approximate the areas where households are situated. Again we can rule this out with our up to 500 mts donut approach as calculations using census data suggest that rural sections – plausibly the max extent of student's commute to school – are located no further than 1.3km away from the nearest school[11] and the average rural section has 4 schools.

Refining treatment and control group– We investigate the second point further making sure that results do reflect exposure to eradication by comparing treated schools for which 80% of the surrounding area within a 1 km radius was eradicated with non treated schools that were not sprayed within a 1 km radius. Table 7 presents the results which are similar to our baseline results.

Geographic controls – A potential concern is that the findings presented in Table 4 may be driven by spatial differences across eradication polygons or unobserved characteristics that vary over time and geographical areas. To address this concern, in Table 8 we

[11] This is the average distance between the rural section centroid to the nearest school

present the results of specification 1 including municipality fixed effects and the interaction of municipality and year fixed effects for both dropout and failure rate (see columns (1) and (3)). The results of this exercise demonstrate that, even with the inclusion of these large battery of fixed effects, the estimates remain similar to the baseline results. In columns (2) and (4) we performed a similar analysis using a larger geographic unit, i.e., departments, and once again, the results remained largely consistent with those of Table 4.

Quadratic polynomial and additional controls – In Table 9, we show that our results for dropout and failure rate are robust to using local quadratic polynomials, as shown in columns (1) and (3), respectively. In columns (2) and (4), we add extended control variables: slope, a binary indicator for whether the school was located within a manual eradication area, and the number of hectares of coca within a 1 km buffer in the preceding year. The results remain very similar to the ones presented in Table 4.

Sample restrictions – As outlined in section 3, we initially restricted our sample to schools with more than 20 students (representing $> 99\%$ of students). To provide evidence that our results hold even when varying enrollment of the sample, we use specification (1) for schools with enrollments ranging from 10 to 30 students. Figures 6 shows the results. Importantly, we show that the coefficients across these different specifications remains positive and significant throughout for dropout rates (sub-figure a) and failure rates (sub-figure b).

Two-way Fixed Effects – Finally, we use a simple two-way fixed-effects model where we consider all schools in rural municipalities with coca crops at any point between 1994 and 2015, rather than solely those schools in proximity to the border.[12] In this analysis, we include school and year fixed effects, effectively controlling for unobservable time-invariant school-specific factors and time-varying differences across years. In Table 10, columns (1) and (3), we use a binary variable of school i being within sprayed area in year t. Our findings confirm a significant increase in dropout and failure rates, respectively, due to schools being within the sprayed area. In columns (2) and (4), we use the continuous treatment variable, i.e., the percentage of eradicated area within a 5 km radius of the school. We again observe an increase in dropout and failure rate, respectively.

[12]We estimate the following equation:

$$y_{i,t} = \alpha + \beta Eradication\ treatment_{i,t} + \gamma_i + \lambda_t + \epsilon_{i,t} \tag{2}$$

4.4 Heterogeneity along education levels and gender

Education Levels – We investigate how the effects of aerial eradication differ along children' educational level. This analysis will not only highlight the most affected group but also sheds light on some of the underlying mechanisms driving these effects. Table 11 presents the results.

First, column (1) presents a significant and positive impact of aerial spraying on pre-school dropout rates, representing an increase of approximately 12% of the dropout rates when compared to the schools in the control group. This effect provides insights into how families adapt to such shocks without further implications in the child labor market – as the youngest children are typically not able to work. In this case, we document how families might simply opt to stop investing in the education of very young children or alternatively might no longer require these care services and lock after the child themselves. This should be solely a means to offset the income shock and maintain consumption levels (e.g. reducing time and monetary costs for transport to school and school meals), while children at this age are unlikely to be providing any additional labor.

Second, when child labor is a factor, we expect the largest impact at the primary school level. Indeed, we find a sizable effect on the dropout rates of children in primary education, with a 9% increase compared to schools located just outside the sprayed areas (column (2)). Primary represents a particularly vulnerable point in the education system, as it is common for children in rural areas to dropout right after, often because they transition into the labor market or assist with household chores. Children aged 6 to 12 are already integral to the labor force in coca-producing regions, engaging in various forms of work, including direct involvement in coca fields (e.g., picking coca leaves) and other agricultural activities (MJD & UNODC, 2012) Lastly, in column (3) we study the effect on secondary education. We have aggregated the educational outcomes of secondary and high school. While older students are plausibly also an important source of labor in rural households, we do not see any effect. A plausible reason for this is that rural areas generally have few secondary schools and lower enrollment rates in the first place. Accordingly, we might simply not be able to measure any effect as households relying on coca crops do not send their kids to that level of schooling.

Regarding school performance, we find that our results are entirely driven by students at the primary level. Specifically, being within a sprayed area leads to an increase in the failure rate of approximately 8% when compared to schools located just outside these areas.

Gender – In rural areas, traditional role models are still prevalent with boys and girls assuming different roles and responsibilities within households and communities. These roles are often shaped by cultural norms, socioeconomic factors, and traditional gender biases. For instance, girls are frequently tasked with domestic and caregiving duties such as cleaning chores, cooking, and childcare. In contrast, boys typically play a more active role in agricultural labor, as it is more physically demanding, such as farming and livestock care (Aspiazu & Labrunée, 2021). These deeply ingrained cultural norms can influence how families prioritize education and allocate their children's time in response to shocks (Løken (2010) and Dessy et al. (2023)). Thus, in Table 12, we study whether the eradication shock affects girls' and boys' educational outcomes differently. We do not observe gender differences in the effect of aerial eradication for dropout rates and academic performance. Aerial spraying negatively affects boys' and girls' educational outcomes equally. This again points towards child labor being not a key way of shaping the response – neither in the form of increasing or decreasing labor demand for boys in agriculture differently from the effect the shock had on girls.

4.5 Mechanisms

4.6 Selective migration

In section 4.1, we showed that students did not anticipate treatment and beforehand transferred to schools outside the sprayed areas. However, outmigration and school transfers might be a consequence of eradication and one type of coping mechanism. For instance, wealthier families might be able to out migrate from sprayed zones once they were treated as a coping mechanism. Alternatively, high transfers out of schools might reflect the movement of academically successful students to better schools or the movement of families from rural to urban areas.

We study the effect on transfer rates in Table 13. We observe that transfer rates decrease in the treated schools. First, this rules out that migration is used as a coping strategy to escape the negative consequences of aerial spraying. Second, this can be interpreted as further evidence of the negative effect of aerial spraying on students that are less likely to transfer out of schools in impoverished rural areas to better establishments than students from non-sprayed areas. This actually seems consistent with and a consequence of the income effects we document as the main mechanism. Sub-figure 7a presents the RD plot.

4.7 Income effect

Previous results have already suggested that one important way coca spraying negatively impacted educational outcomes is via the negative effect on farmers income. Plausibly, aerial spraying represents a substantial shock to the income of the thousands of families who rely on coca as their primary agricultural product. Small-scale coca farmers – while seeing only a fraction of the profits the illicit market for cocaine generates – do rely on selling their coca production to meet their basic needs (UNODC-SIMCI, 2006). And while criminal organisation are unlikely to be financially hit by eradication as demand for cocaine is inelastic and prices rise when supply is restricted, crop eradication does lead to small scale farmers losing their income as they no longer have anything to sell.

From a theoretical perspective the income shock can have positive and negative implications for education as either the income or substitution effects could dominate. On one hand, the income effect predicts that schooling will decrease following a negative income shock as families respond by withdrawing their children from school, either to alleviate the financial burden of education or to send children to work, to maintain their minimum consumption if credit constrained (see e.g., Beegle et al., 2006; Dammert, 2008; Cogneau & Jedwab, 2012). On the other hand, the substitution effect suggests a potential increase in schooling. If labor income derived from coca cultivation declines due to aerial spraying (e.g., by reducing work demanded for harvesting the leaves) the opportunity cost of attending school might also decrease if child labor is an important factor in coca production. This may result in an upturn in human capital accumulation as families opt for increased schooling rather than sending children to participate in labor activities (see e.g., Duryea & Arends-Kuenning, 2003; Shah & Steinberg, 2017). Considering the negative educational effects we focus on the former income shock effect, still this effect might be through the decline on spending for education or the need for increasing child labor to compensate the lower income.

In the heterogeneity analysis, we documented that families respond to the eradication shock by reducing education expenses – withdrawing their pre-school children– while also potentially increasing labor force participation in the household – withdrawing children of working age– to compensate for the income loss resulting from the eradication. To further confirm the income effect as mechanism we aim to demonstrate that the exposure to aerial spraying indeed exerts a significant negative impact on household incomes and economic activity. To do so, we rely on nighttime light density as a proxy for economic activity, which has been shown to be a useful measure in cases where subnational income data may be limited or unavailable (Chen & Nordhaus, 2011). We employ specification (1) to examine the luminosity within 1 km, 3 km, and 5 km radii around schools. As presented in Table 14, the results show a significant reduction in nighttime light density in areas located just inside the eradication zone. This effect remains consistent across the different radii. These findings suggest that the income shock is indeed one of the contributing factors to the decrease on human capital accumulation and academic performance. Sub-figure 7b presents the RD plot.

4.8 Health shock

Good health is a key determinant of education (Miguel & Kremer, 2004; Sorensen et al., 2019). Recent evidence points to the adverse effects of herbicides, especially glyphosate, on health outcomes. For instance, the International Agency for Research on Cancer has identified evidence linking glyphosate usage to an increased risk of cancer (IARC, 2017). Camacho & Mejía (2017) show a positive relation between aerial spraying of glyphosate and medical consultations with dermatological and respiratory diagnoses. Dias et al. (2023) find that the use of glyphosate in agriculture in Brazil has a negative impact on birth outcomes.

To assess whether health acts as an additional mechanism in the relationship between exposure to aerial spraying of glyphosate and adverse educational outcomes, we utilize manual eradication which has only a negative income effect for farmers but does not impact health. Therefore, if the coefficient for manual eradication closely mirrors the one for aerial eradication, it would suggest that health plays a minor role in the effects we have identified – at least in the short term for school age students. Conversely, if we observe a significantly larger coefficient for aerial eradication, it would point to a substantial role of health on the increase in dropout and poor academic performance.

In this analysis, we also employ a Regression Discontinuity (RD) design, comparing schools situated just inside areas subject to manual eradication with those just outside these areas. Table A.4 shows that geographic and economic characteristics on the border are not balanced. This makes it difficult to claim the randomness of the border. However, we did not come across any evidence that would suggest that manual eradication was targeted at areas based on their educational performance nor do we see significant differences in educational outcomes before eradication in 1993/1996 across the discontinuity.

Table 15 shows that manual eradication had a similar negative effect on dropout and failure rates as the one we observe for aerial spraying. This is the case even after including an extensive list of additional controls (pre-eradication socioeconomic conditions, eradication controls, and geographic characteristics). Sub-figures 7c and 7d present the RD plot of the results. These results suggest that health does not appear to be an important mechanism that can explain the negative effect on educational outcomes caused by aerial spraying. Instead, it further bolsters the evidence indicating that the income shock following forced eradication is the primary driver behind the increase in dropout and failure rates if coca plants get eradicated, at least in the short run.

4.9 Conflict exposure

As mentioned before, coca cultivation is deeply entwined with illegal armed groups. One of their strategies to protect coca crops involves the deployment of landmines (Crisis Group, 2021). While this tactic may be more prevalent in areas subjected to manual eradication, there is a concern that, even after experiencing aerial eradication, illegal armed groups might escalate the use of landmines to deter further military interventions in the regions. This poses a direct threat to the civilian population and can hinders human capital accumulation. It may result in children avoiding school due to the fear of falling victims of landmines, or they may become direct victims themselves. However, while eradication efforts might increase this type of conflict in general, it is not necessarily clear why eradicated areas would be mined more than coca producing areas that have not yet been eradicated (rather the opposite might be the case).

We assess whether aerial spraying is associated with an change in incidences of landmine events in Table 16. Utilizing geolocated data on landmines, we calculate the occurrences of landmine events within 1km, 3km, and 5km of the schools. We find that aerial spraying is associated with a decrease in these. This effect remains regardless the radius. Sub-figure 7e presents the RD plot. Thus, it does not appear to be the case that increased conflict due to eradication is what drives the increase of dropout and failure rates that we document.

5 Lifetime effects of aerial spraying

Having to drop out of or bad performance in school plausibly shapes individual outcomes throughout their whole life. In this section, we delve into whether the "short-term" educational effects have lasting implications for education, socioeconomic conditions, and household dynamics in areas that have once been eradicated.

5.1 Empirical strategy

To assess the causal effects of aerial spraying on longer-term outcomes, we aggregate all the spraying areas spanning from 2004 to 2015 – mapping the most extensive geographic extent of aerial spraying. We combine this with geocoded data from the 2018 census – conducted three years after the complete prohibition of aerial spraying.

We will compare rural sections that were fully within the area that has ever been sprayed (in the period 2004-2015) to those located just on the opposite site of this boundary and have never been sprayed (see figure 8). We employ the following specification:

$$y_r = \beta Erad_r + f(location_r) + \epsilon_r \quad for \; r \in bw \tag{3}$$

where y_r is our outcome of interest for rural section r. Our outcomes of interest are schooling, dwelling conditions, child labor market, health and early marriage [13]. $Erad_r$ is a dummy variable equal to one if the centroid of the rural section r is inside a sprayed area, and equal to zero otherwise. $f(location_r)$ is an RD polynomial, which controls for smooth functions of location for rural section r. We use a linear polynomial in distance of the centroid of the rural sections to the closest part of the border of a sprayed area. Following Cattaneo et al. (2019), we compute the optimal bandwidth using the MSE-minimizing procedure and we use a triangular weighting kernel. Standard errors are clustered at the rural section level, i.e., the treatment level.

Consistent with the yearly-changing extent of eradication the maximum extent of eradication appears as good as randomly assigned. We only find a discontinuity in the elevation, for which we control for in all the regressions.

5.2 Medium term results

Migration – For the interpretation of our results it is important that the composition of the population developed in the same way in treated and non-treated areas. Table 18 studies how aerial eradication influenced migration across rural sections. We observe that the inflow of migrants in the year prior to the census, as well as over the previous five years, is not significantly different between sprayed and non-sprayed rural sections. We do find that the proportion of individuals who have never left the municipality of their birth is notably higher in areas that were subjected to aerial spraying. This result aligns with the short-term findings and indicates the lower out-migration rate of individuals in sprayed areas while eradication occurred. Still considering that there is no evidence for differential migration between treated and non-treated areas over as much as the last 5 years is reassuring in that our results should reflect the effect on the population that was treated by aerial spraying.

Aerial Eradication reduces longer-term human capital – We examine whether the short-term adverse effects on education have lasting implications for human capital. Specifically, we estimate specification (3) for the proportion of individuals 25 to 29 years old, a group that has completed their education when we measure these outcomes in 2018, but has been affected by aerial spraying during their youth. The results in Table 19 indicate a lasting negative effect on human capital accumulation in areas subjected to aerial spraying. On

[13] See A.1.2 for a further information about the variables used in this section.

average, sprayed areas exhibit a 12pp decrease in the proportion of individuals with primary education, and a 10pp decrease for secondary education.

Child labor market effects – In section 4.4, we documented lower educational outcomes among working-age children, which plausibly lead to children entering the labor market. With the census data, we evaluate whether children in rural sections where eradication occurred were indeed more likely to have a job or do household chores[14], compared to neighboring areas. The results are presented in Table 20. In Column (1), we observe that the share of children between 10 and 19 years old with a job in sprayed rural sections is approximately 0.5 percentage points higher than those in non-sprayed areas. This result is primarily driven by boys, as indicated in Column (2). Interestingly, and in line with the short-term results, this does not imply that girls are unaffected. In contrast, in Column (6), we observe that girls are predominantly staying at home performing household chores. This effect is of approximately 27% in magnitude compared to the mean in non-sprayed areas.

Early marriage – In Colombia, the age of majority is 18. However, it is legal that girls between 14 and 17 years old get married, only if they had the approval of their parents. UNICEF (2022) has found that even if it is illegal, around 1.8% of girls between 10 to 14 years old was married or in a civil union in 2018. In our sample, we have found that around 5% of girls 10 to 14 years old were not single.

A growing body of literature has highlighted early marriage as a coping mechanism for impoverished households when they face income shocks (see Hoogeveen et al., 2011; Baird et al., 2011; Corno et al., 2020; Chort et al., 2022). However, limited research has explored whether this coping mechanism exists even in contexts without dowries (bride prices), as is the case in Colombia and Latin America more broadly. We investigate whether the eradication shock affects marriage rates among young women. We estimate specification 3 on the share of single[15] women within age cohorts. The results are presented in Table 21. On average, we observe a higher (though weakly significant) share of married women in rural sections that were subjected to aerial eradication. Although the percentage of married girls within the 10 to 14 age cohort (below the age of majority in Colombia[16]) is relatively low,

[14]The definition we used for having a job includes: 1) the individual worked at least 1 hour last week, and got a payment; 2) the individual worked or helped in a business at least one hour last week without payment; and 3) the individual didn't work last week but has a job or business, and receives a payment.

The definition we used for doing chores at home is whether the individual said that he/she did chores at home during last week. These two definitions are done using the 2018 census.

[15]Acording to the 2018 census, the individual is single if he/she is not in a civil union, married, divorced or widowed.

[16]Colombia is the only Latin American country that allows marriage from 14 years old (Semana (2022)).

our findings indicate that being inside a spraying area decreases the share of unmarried girls by 6pp compared to non-sprayed areas. We also find that marriage rates are generally higher for women aged 20 to 29 in sprayed areas compared to non-sprayed areas. This suggests that the eradication shock may indeed influence marriage patterns among young women in these regions, shedding light on the societal consequences of eradication efforts.

The income shock is persistent – Next, we investigate whether the temporary eradication shock results in longer-term household impoverishment. We employ specification (3) to analyze dwelling conditions three years after the end of the aerial spraying program. The results are presented in Table 22. We observe that households in rural sections subjected to aerial spraying have, on average, less access to drinkable water, sewage facilities, and garbage collection[17] compared to those that were not sprayed. This suggests that the income shock induced by eradication has a lasting impact on household living conditions. However, considering the large magnitude of these effects this plausibly is not due to the one time income shock due to being unable to sell the eradicated crops in the year of eradication, but plausibly due to the lower levels of human capital, and subsequently worse labour market outcomes of individuals reducing their life-time earning prospects.

Health in the medium term – Finally, some health issues related to glyphosate exposure may not exhibit immediate symptoms; rather, they may develop gradually over time due to prolonged exposure. Conditions such as cancer or respiratory problems, which can be linked to glyphosate exposure, often have a latency period, i.e., that it may take several years for symptoms to become noticeable. To examine the impact of glyphosate exposure on health in the medium-term, we use self-reported data on health[18] and disabilities[19] from the census. The results are presented in Table 23. Our analysis does not reveal a significant effect of aerial spraying exposure on the likelihood of falling ill before the census interview or having disabilities. It is important to note that one limitation of this approach is the lack of detailed information about the specific illnesses or disabilities experienced by the individuals.

[17] We measure the share of households that have each of these services: electricity, drinkable water, sewage and garbage collection. Having access to these services depends on the capacity of the state to provide them, but also on whether the households are able and willing to pay for them.

[18] We measure the percentage of people who had any health issue during the last 30 days and they didn't require hospitalization.

[19] Share of people who reported having a disability. We are not able to discern the type of disability

6 Conclusion

This paper presents evidence that exposure to aerial spraying of glyphosate diminishes human capital accumulation and educational performance in the short term, ultimately contributing to worsened socioeconomic outcomes for households in the medium term. These outcomes include lower schooling rates, increased child labor, early marriages, and deteriorated dwelling conditions. We document that the likely mechanism is the substantial income shock experienced by families residing in eradication areas. These households heavily depend on sources derived from coca cultivation, and the damage inflicted by glyphosate extends to legal crops, amplifying the economic impact.

To establish these effects, we employ a spatial regression discontinuity design, leveraging on the inherent exogeneity arising from the operational constraints of aerial spraying flights. Thus, we are able to compare units – schools or villages – located just inside an area sprayed to those located just outside.

While little evidence supports the success of forced eradication in reducing coca supply or violence, our study provides causal evidence that it diminishes development by further impoverishing households in the affected areas. This paper has broad policy implications. Firstly, it underscores the need to reconsider supply-center policies in a way that is tuned to local dynamics, as exemplified in Colombia, where thousands of households depend on coca cultivation as their sole viable source of income. Second, it highlights the importance of implementing alternative livelihood programs that provide viable economic options for households engaged in coca cultivation. Fostering sustainable alternatives can mitigate the negative impacts of eradication efforts. Lastly, our findings stress the importance of monitoring and evaluating anti-drug policies to assess their impact, make necessary adjustments, and ensure that unintended consequences are identified and addressed promptly.

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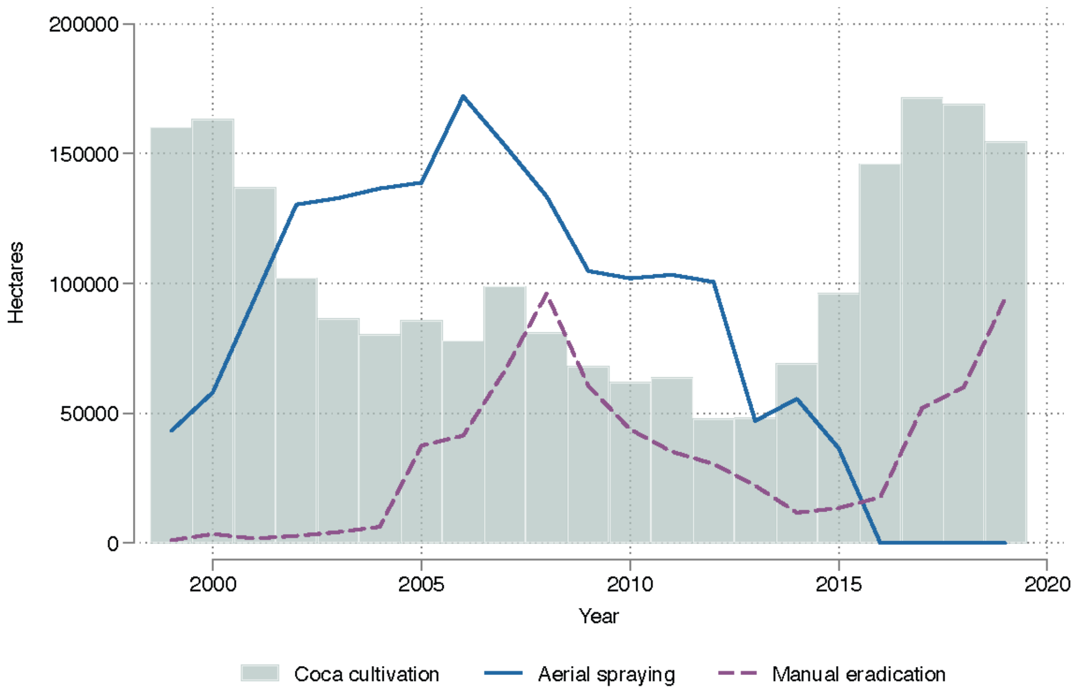
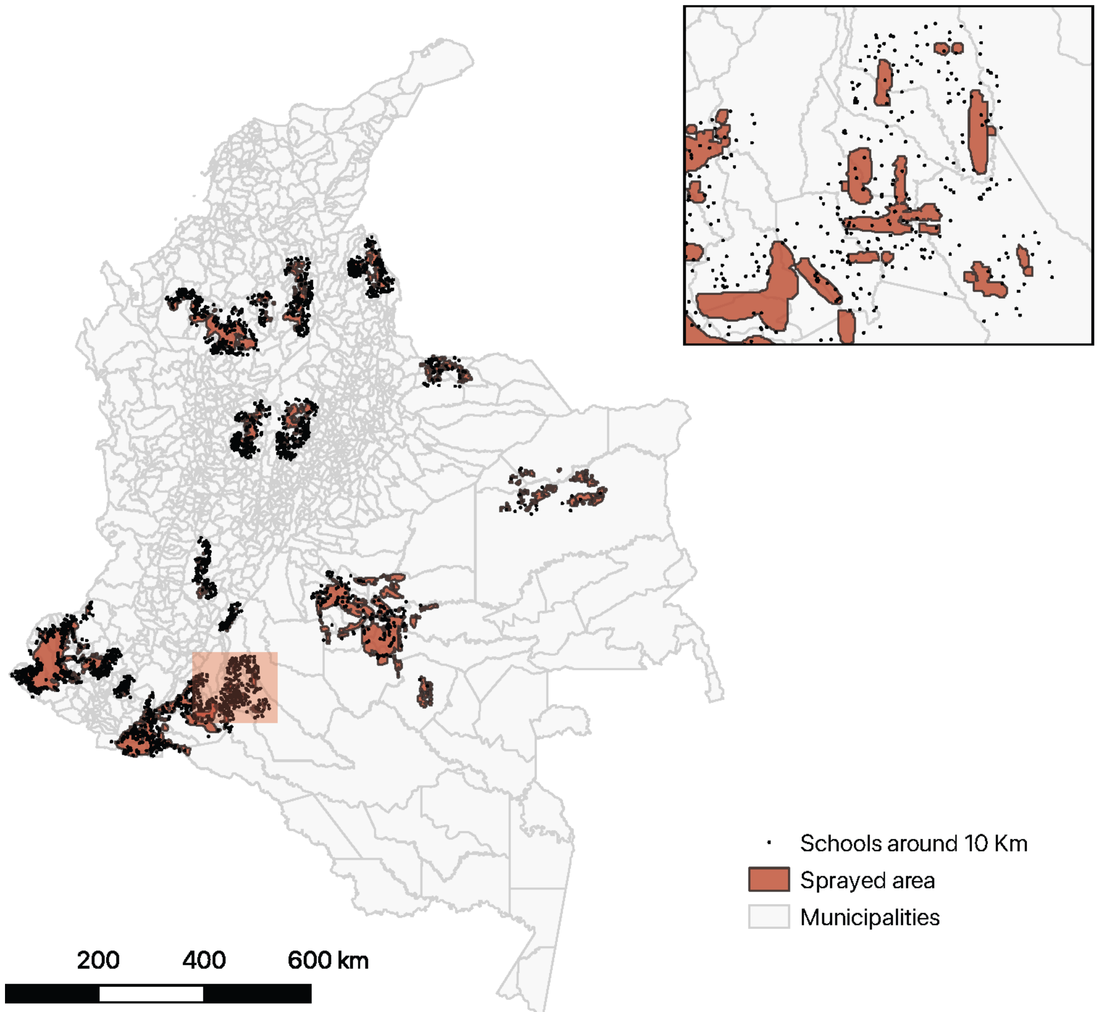
Figures

Figure 1: Coca cultivation and eradication programs across time



Note: This figure illustrates the hectares of coca cultivated, sprayed and manually eradicated from 1999 to 2019.

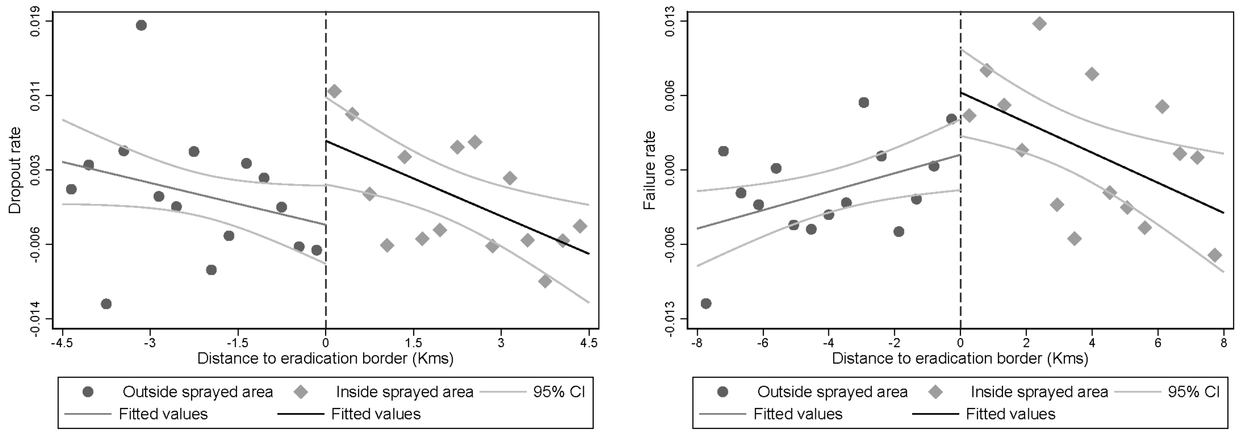
Figure 2: Digitized map of areas sprayed and schools location. 2006



Note: This map illustrates the eradication polygons in 2006 and the rural school located up to 10 Km around them.

Figure 3: Effect of aerial eradication on educational outcomes

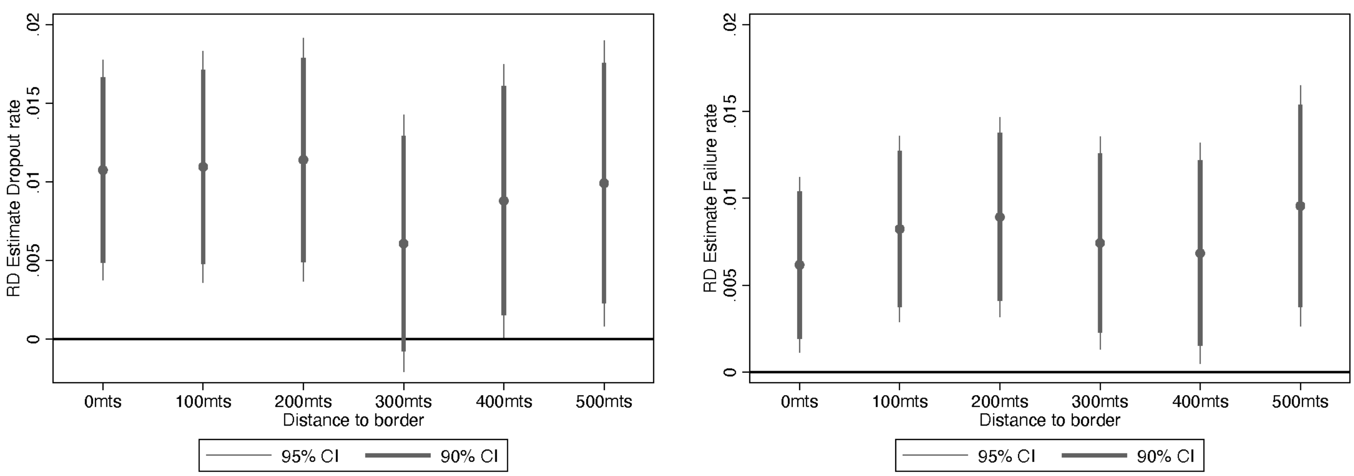
a) Dropout rate b) Failure rate



Note: These figures illustrate the results for dropout and failure rate. The vertical axis represents the mean residual of each outcome variable. The horizontal axis represents the distance to the nearest sprayed area border. Schools to the left are located in non-sprayed areas and schools to the right in sprayed areas. Regressions control for year fixed effects, elevation and a dummy indicating whether the school was inside a sprayed area in the preceding year. Optimal bandwidth is computed using the MSE-minimizing procedure following (Cattaneo et al., 2019). All regressions include a lineal polynomial and a triangular weighting kernel. Standard errors are clustered at the school level.

Figure 4: Effect of aerial eradication on educational outcomes - Donut Hole

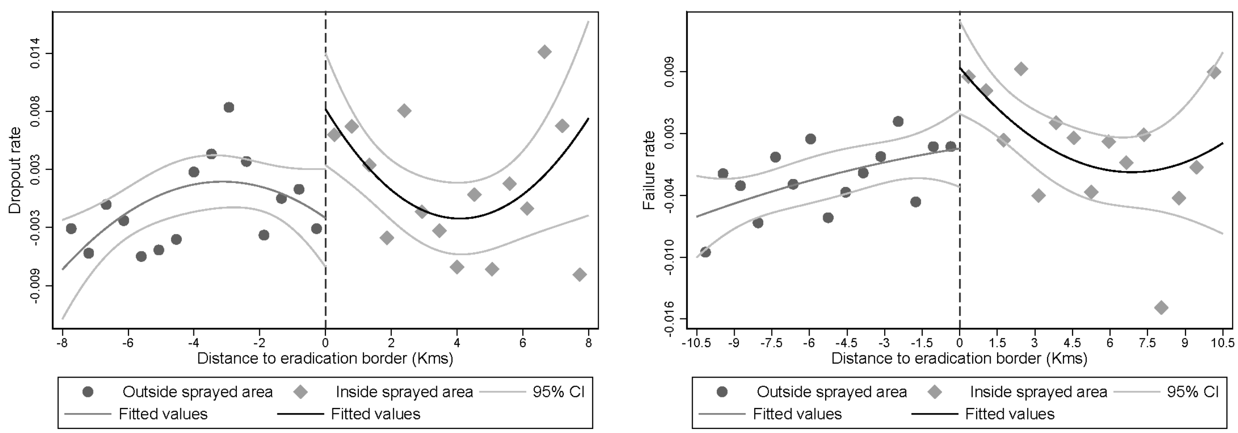
a) Dropout rate b) Failure rate



These figures present the point estimates for dropout and failure rate using the "donut hole" approach. Regressions control for year fixed effects, elevation and a dummy indicating whether the school was inside a sprayed area in the preceding year. We used the optimal bandwidth of the baseline estimation from Table 4. All regressions include a lineal polynomial and a triangular weighting kernel. Standard errors are clustered at the school level. It displays the 90% and 95% confidence intervals.

Figure 5: Effect of aerial eradication on educational outcomes - Quadratic polynomial

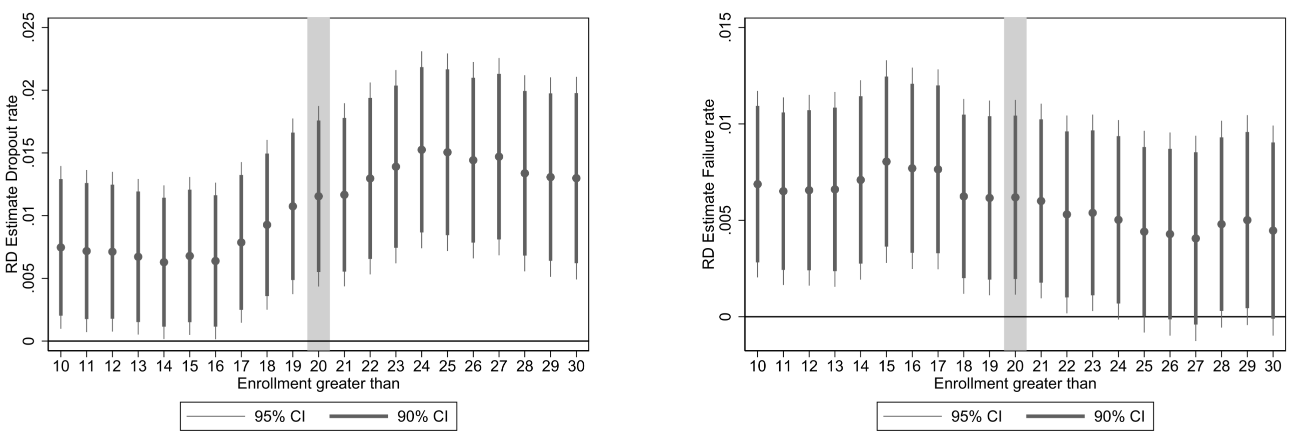
a) Dropout rate b) Failure rate



These figures illustrate the results for dropout and failure rate. The vertical axis represents the mean residual of each outcome variable. The horizontal axis represents the distance to the nearest sprayed area border. Schools to the left are located in non-sprayed areas and schools to the right in sprayed areas. Regressions control for year fixed effects, elevation and a dummy indicating whether the school was inside a sprayed area in the preceding year. Optimal bandwidth is computed using the MSE-minimizing procedure following (Cattaneo et al., 2019). All regressions include a quadratic polynomial and a triangular weighting kernel. Standard errors are clustered at the school level.

Figure 6: Effect of aerial eradication on educational outcomes - Sample restriction

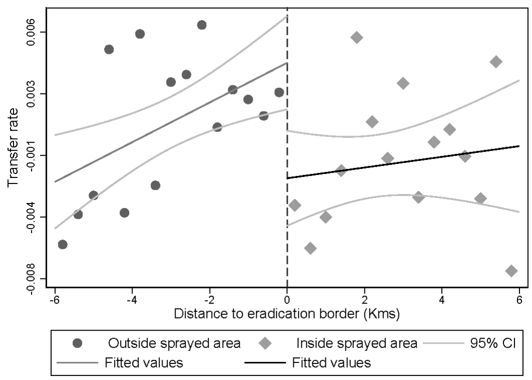
a) Dropout rate b) Failure rate



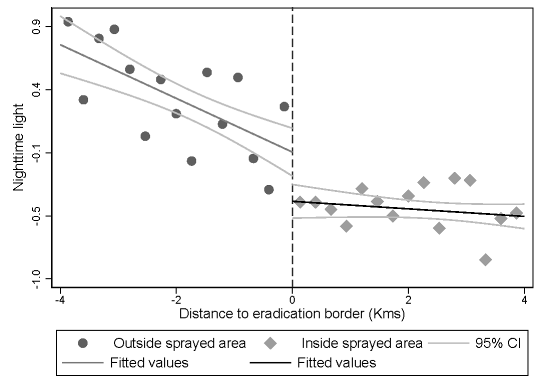
These figures present the point estimates for dropout and failure rate using different sample restrictions. Regressions control for year fixed effects, elevation and a dummy indicating whether the school was inside a sprayed area in the preceding year. Optimal bandwidth is computed using the MSE-minimizing procedure following (Cattaneo et al., 2019). All regressions include a lineal polynomial and a triangular weighting kernel. Standard errors are clustered at the school level. It displays the 90% and 95% confidence intervals.

Figure 7: Mechanisms through which aerial eradication affects educational outcomes

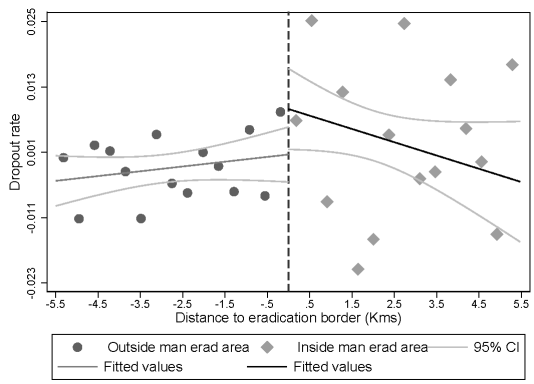
a) Effect of aerial spraying on Transfer rate



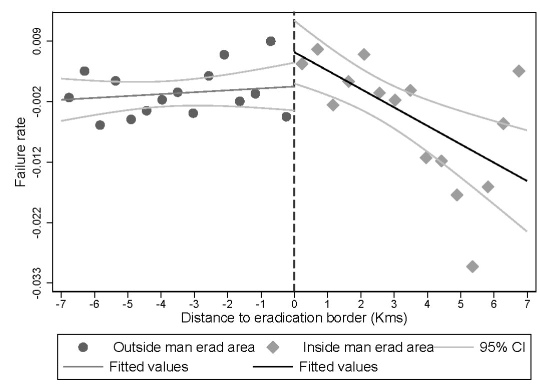
b) Effect of aerial spraying on NTL (1Km)



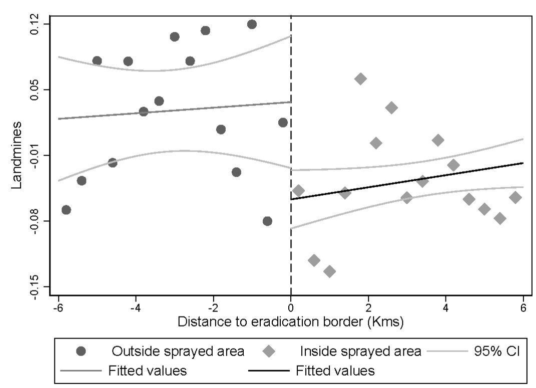
c) Effect of manual erad. on Dropout rate



d) Effect of manual erad. on Failure rate

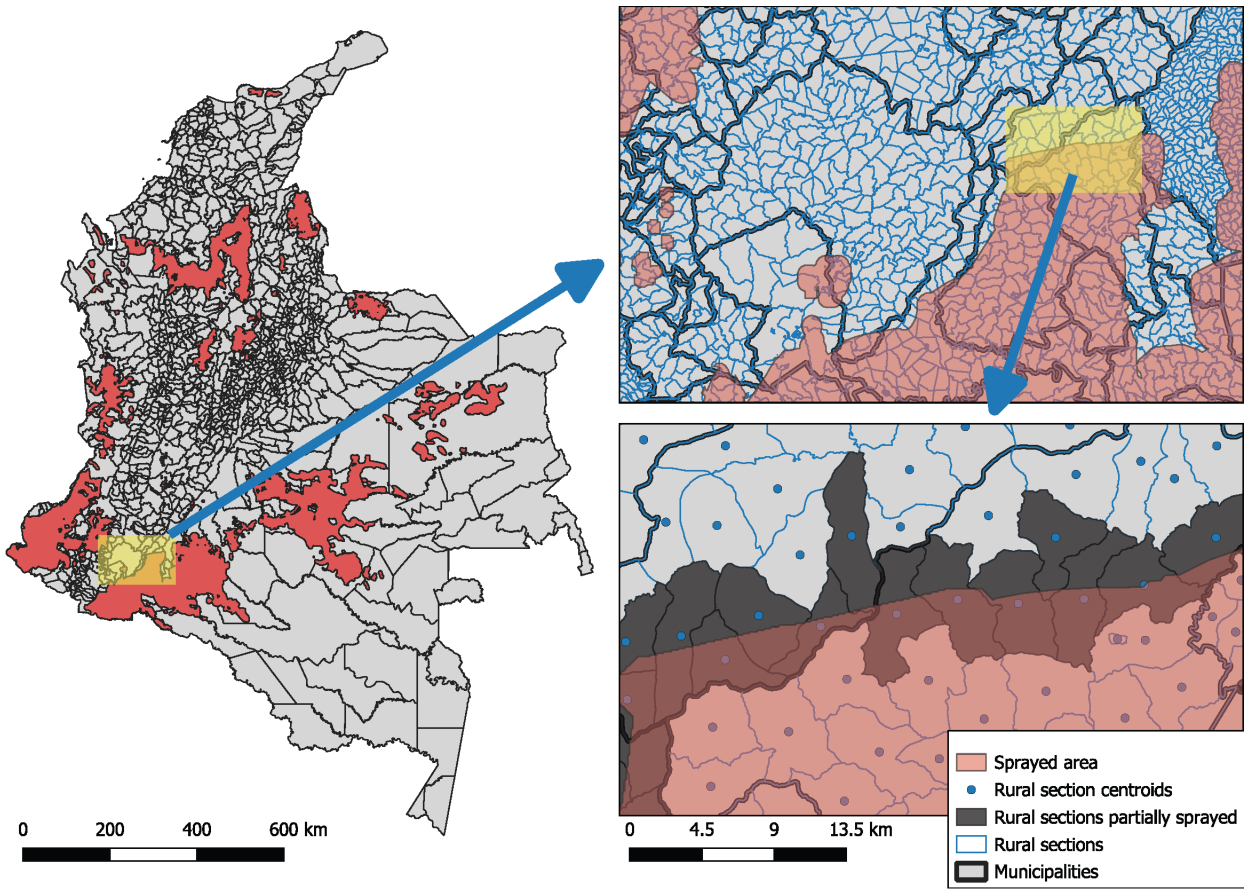


e) Effect of aerial spraying on Landmines (1Km)



Note: These figures illustrate the RD plot for the mechanism outcomes. The vertical axis represents the mean residual of each outcome variable. In subfigures a, b and e schools to the left are located in non-sprayed areas and schools to the right in sprayed areas. The horizontal axis in these subfigures represents the distance to the nearest sprayed area border. In subfigures c and d schools to the left are located in non-manually eradicated areas and schools to the right in manually eradicated areas. In these subfigures the horizontal axis represents the distance to the nearest manual eradication area border. Optimal bandwidth is computed using the MSE-minimizing procedure following (Cattaneo et al., 2019). All regressions include a lineal polynomial and a triangular weighting kernel. Standard errors are clustered at the school level.

Figure 8: Aerial spraying 2004 until 2015 and rural sections



Note: This map illustrates the areas sprayed between 2004 to 2015 and the rural sections

Tables

Table 1: Balance check aerial eradication

	Optimal bandwidth				Fixed bandwidth			
	RD Coefficient (1)	SE (2)	BW. (3)	No. (4)	RD Coefficient (5)	SE (6)	BW. (7)	No. (8)
Panel A: Characteristics at the school level								
-Geographic:								
Elevation	62.13527	14.2436***	5.84	24310	62.24343	14.1817***	5.93	24639
Slope	0.02701	0.0544	8.82	32765	0.05014	0.0638	5.93	24634
-Socioeconomic:								
Nighttime light rd 1Km 1993	-0.04493	0.1665	4.06	18712	0.11344	0.1465	5.93	24639
Nighttime light rd 3Km 1993	0.01983	0.1312	3.91	18114	0.14381	0.1132	5.93	24639
Nighttime light rd 5Km 1993	0.01714	0.0959	3.46	16356	0.11242	0.0786	5.93	24639
Landmines rd 1Km 1993	-0.00041	0.0109	6.59	26743	-0.00476	0.0107	5.93	24639
Landmines rd 3Km 1993	0.00380	0.0146	4.99	21790	0.02002	0.0150	5.93	24639
Landmines rd 5Km 1993	-0.00845	0.0197	4.88	21423	0.00909	0.0197	5.93	24639
-Eradication:								
Km2 coca rd 1Km at *t-1*	-0.03967	0.0326	3.24	12781	0.01475	0.0263	5.93	20706
Km2 coca rd 3Km at *t-1*	-0.23418	0.2211	3.59	14236	-0.09498	0.1861	5.93	20706
Km2 coca rd 5Km at *t-1*	-0.67355	0.5226	3.93	15362	-0.56578	0.4555	5.93	20706
Aerial eradication at *t-1*	-0.00232	0.0177	3.28	12946	0.02239	0.0135*	5.93	20706
Manual eradication at *t-1*	0.01407	0.0097	6.50	17090	0.01269	0.0101	5.93	15877
Manual eradication at *t*	0.00901	0.0081	6.83	22127	0.00864	0.0086	5.93	19850
Panel B: Characteristics with municipality-level data								
-Education:								
School-age population 1993	-0.59977	1.9806	12.80	38757	-0.85362	2.1292	5.93	22819
Population primary 1993	1.4e+02	2.0e+03	11.70	36851	5.3e+02	1.9e+03	5.93	22895
Population secondary 1993	93.96316	1.9e+03	11.60	36813	5.0e+02	1.9e+03	5.93	22895
Avg. schooling years 1993	-0.00742	0.1785	10.80	35261	0.05017	0.1899	5.93	22819
Illiteracy rate 1993	0.77663	1.7377	10.80	37681	0.24305	1.8329	5.93	24639
No. teachers 1996	15.41749	155.4715	11.00	37510	51.62922	153.1572	5.93	24228
No. students 1996	4.8e+02	3.4e+03	11.20	37738	1.3e+03	3.3e+03	5.93	24228
No. schools 1996	0.11508	19.6626	11.00	36426	6.73767	19.5542	5.93	23383
-Agriculture:								
Suitability index oil palm	-2.0e+02	521.2495	11.60	39201	-3.2e+02	528.3242	5.93	24639
Suitability index plantain	-2.6e+02	335.8092	10.60	37273	-3.8e+02	354.6768	5.93	24639
Suitability index coffee	-2.1e+02	242.5355	10.50	37171	-2.7e+02	261.1312	5.93	24639

Note: Panel A presents a balance test on several characteristics of schools. Some variables are computed around 1, 3 and 5 kms around schools. Panel B presents a balance test for pre-existing school and agricultural characteristics using municipality level data. Columns (1) to (4) present results using a fixed bandwidth of 5.93 Km (the optimal bandwidth of our main outcome). Columns (5) to (8) presents the result computing the optimal bandwidth following (Cattaneo et al., 2019). All regressions include year fixed effects, as well as a lineal polynomial and a triangular weighting kernel. Standard errors are clustered at the school level for Panel A and at the municipality level for Panel B. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table 2: Effect of aerial eradication on transfer rate

	Dep. var: Transfer rate t-1			
	(1)	(2)	(3)	(4)
Inside sprayed areas	-0.0028	-0.0018	-0.0023	-0.0014
	(0.0017)	(0.0019)	(0.0018)	(0.0020)
Year FE	yes	yes	yes	yes
Baseline controls	yes	yes	yes	yes
Extended controls	no	no	yes	yes
Bandwidth (Kms)	7.98	5.93	7.89	5.93
Bandwidth choice	Optimal	Fixed	Optimal	Fixed
Mean control	.032	.032	.032	.032
Observations	25873	20697	23043	18537

Note: This table presents the results of estimating specification (1) for transfer rate at (*t-1*). Base line controls include elevation and a dummy indicating whether the school was inside a sprayed area in the preceding year. Extended controls include slope, a dummy indicating whether the school was inside a manual eradication area, and square kms of coca around 1km from the school in the preceding year. All regressions include year fixed effects. Columns (1) and (3) present results using computing the optimal bandwidth following (Cattaneo et al., 2019). Columns (2) and (4) present results using a fixed bandwidth of 5.93 Km (the optimal bandwidth of our main outcome). All regressions include a lineal polynomial and a triangular weighting kernel. Standard errors are clustered at the school level. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table 3: Effect of aerial eradication on coca around schools in *t+1*

	Dep. var: Square kms of coca around 1km from school	
	(1)	(2)
Inside sprayed areas	0.0279	-0.0019
	(0.0292)	(0.0220)
Year FE	yes	yes
Baseline controls	yes	yes
Extended controls	no	yes
Bandwidth (Kms)	5.07	6.08
Bandwidth choice	Optimal	Optimal
Mean control	.349	.331
Observations	16310	16557

Note: This table presents the results of estimating specification (1) for square kms of coca around schools at (*t+1*). Base line controls include elevation and a dummy indicating whether the school was inside a sprayed area in the preceding year. Extended controls include slope, a dummy indicating whether the school was inside a manual eradication area, and square kms of coca around 1km from the school in the preceding year. All regressions include year fixed effects. We use the optimal bandwidth following (Cattaneo et al., 2019). All regressions include a lineal polynomial and a triangular weighting kernel. Standard errors are clustered at the school level. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table 4: Effect of aerial eradication on educational outcomes

	Dep. var: Dropout rate (1)	Dropout rate (2)	Failure rate (3)	Failure rate (4)
Inside sprayed areas	0.00605**	0.0107***	0.00474*	0.00616**
	(0.0030)	(0.0036)	(0.0025)	(0.0026)
Year FE	yes	yes	yes	yes
Baseline controls	no	yes	no	yes
Bandwidth (Kms)	5.93	4.61	9.22	8.68
Mean control	.092	.094	.072	.072
Observations	24640	17216	33825	27406

Note: This table presents the estimated effect of aerial eradication on dropout and failure rate using specification (1). Base line controls include elevation and a dummy indicating whether the school was inside a sprayed area in the preceding year. All regressions include year fixed effects. Optimal bandwidths are computed using the MSE-minimizing procedure following (Cattaneo et al., 2019). All regressions include a lineal polynomial and a triangular weighting kernel. Standard errors are clustered at the school level. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table 5: Effect of aerial eradication on educational outcomes in the following year

	Dep. var: Dropout rate at *t+1* (1)	Dropout rate at *t+1* (2)	Failure rate at *t+1* (3)	Failure rate at *t+1* (4)
Inside sprayed areas	-0.00216	0.000186	0.00154	0.00401
	(0.0028)	(0.0031)	(0.0027)	(0.0026)
Year FE	yes	yes	yes	yes
Baseline controls	no	yes	no	yes
Bandwidth (Kms)	7.44	6.99	7.10	9.35
Mean control	.091	.091	.073	.072
Observations	25852	20839	25019	25563

Note: This table presents the estimated effect of aerial eradication on dropout and failure rate in the following year of eradication (*t+1*) using specification (1). Base line controls include elevation and a dummy indicating whether the school was inside a sprayed area in the preceding year. All regressions include year fixed effects. Optimal bandwidths are computed using the MSE-minimizing procedure following (Cattaneo et al., 2019). All regressions include a lineal polynomial and a triangular weighting kernel. Standard errors are clustered at the school level. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table 6: Effect of aerial eradication on educational outcomes -Donut Hole

	Excluding schools near the border				
	100 mts	200 mts	300 mts	400 mts	500 mts
	(1)	(2)	(3)	(4)	(5)
Panel A: Dropout rate					
Inside sprayed area	0.0110***	0.0114***	0.00607	0.00879**	0.00991**
	(0.0037)	(0.0039)	(0.0042)	(0.0044)	(0.0046)
Year FE	yes	yes	yes	yes	yes
Baseline controls	yes	yes	yes	yes	yes
Bandwidth (Kms)	4.61	4.61	4.61	4.61	4.61
Bandwidth choice	Baseline	Baseline	Baseline	Baseline	Baseline
Mean control	.094	.094	.094	.094	.094
Observations	16832	16405	15914	15503	15085
Panel B: Failure rate					
Inside sprayed area	0.00806***	0.00823***	0.00996***	0.00892***	0.00895***
	(0.0027)	(0.0027)	(0.0029)	(0.0029)	(0.0030)
Year FE	yes	yes	yes	yes	yes
Baseline controls	yes	yes	yes	yes	yes
Bandwidth (Kms)	8.68	8.68	8.68	8.68	8.68
Bandwidth choice	Baseline	Baseline	Baseline	Baseline	Baseline
Mean control	.072	.072	.072	.072	.072
Observations	27022	26594	26103	25692	25274

Note: This table presents the estimated effect of aerial eradication on dropout (Panel A) and failure rate (Panel B) using specification (1). In columns (1), (2), (3), (4) and (5) we exclude schools 100, 200, 300, 400 and 500 mts near the sprayed border respectively. Base line controls include elevation and a dummy indicating whether the school was inside a sprayed area in the preceding year. We use the optimal bandwidth of baseline results from Table 4. All regressions include a lineal polynomial and a triangular weighting kernel. Standard errors are clustered at the school level. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table 7: Effect of aerial eradication on educational outcomes - Treatment refining

	Dep. var:			
	Dropout rate		Failure rate	
	(1)	(2)	(3)	(4)
Inside sprayed area	0.0105*	0.0103*	0.0179***	0.0122***
	(0.0057)	(0.0055)	(0.0045)	(0.0032)
Year FE	yes	yes	yes	yes
Baseline controls	yes	yes	yes	yes
Bandwidth (Kms)	4.41	4.61	4.86	8.68
Bandwidth choice	Optimal	Baseline	Optimal	Baseline
Mean control	.095	.095	.072	.072
Observations	13420	13870	14601	24060

Note: This table presents the estimated effect of aerial eradication on dropout and failure rate using specification (1). We only consider treated schools if at least 80% of their 1km buffer area was sprayed, and control schools those that didn't have aerial spraying around 1 km. Base line controls include elevation and a dummy indicating whether the school was inside a sprayed area in the preceding year. All regressions include year fixed effects. All regressions include year fixed effects. We use the optimal bandwidth of baseline results from Table 4. Optimal bandwidths are computed using the MSE-minimizing procedure following (Cattaneo et al., 2019). All regressions include a lineal polynomial and a triangular weighting kernel. Standard errors are clustered at the school level. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table 8: Effect of aerial eradication on educational outcomes - Geographic controls

	Dep. var:			
	Dropout rate		Failure rate	
	(1)	(2)	(3)	(4)
Inside sprayed area	0.00788**	0.00738**	0.00457*	0.00450*
	(0.0037)	(0.0034)	(0.0025)	(0.0025)
Year FE	yes	yes	yes	yes
Baseline controls	yes	yes	yes	yes
Geographic controls	Mun.	Dept.	Mun.	Dept.
Bandwidth (Kms)	4.61	4.61	8.68	8.68
Bandwidth choice	Baseline	Baseline	Baseline	Baseline
Mean control	.094	.094	.072	.072
Observations	17130	17206	27326	27394

Note: This table presents the estimated effect of aerial eradication on dropout and failure rate using specification (1). Base line controls include elevation and a dummy indicating whether the school was inside a sprayed area in the preceding year. Columns (1) and (3) include municipality FE and its interaction with Year FE. Columns (2) and (4) include department FE and its interaction with Year FE. All regressions include year fixed effects. We use the optimal bandwidth of baseline results from Table 4. All regressions include a lineal polynomial and a triangular weighting kernel. Standard errors are clustered at the school level. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table 9: Effect of aerial eradication on educational outcomes - Robustness

	Dep. var:			
	Dropout rate		Failure rate	
	(1)	(2)	(3)	(4)
Inside sprayed area	0.0130***	0.00730**	0.00577*	0.00636**
	(0.0039)	(0.0034)	(0.0033)	(0.0029)
Year FE	yes	yes	yes	yes
Baseline controls	yes	yes	yes	yes
Extended controls	no	yes	no	yes
Polynomial	2	1	2	1
Bandwidth (Kms)	8.32	5.60	10.5	7.30
Mean control	.090	.093	.071	.073
Observations	26629	17699	31367	21776

Note: This table presents the estimated effect of aerial eradication on dropout and failure rate using specification (1). Base line controls include elevation and a dummy indicating whether the school was inside a sprayed area in the preceding year. Extended controls include slope, a dummy indicating whether the school was inside a manual eradication area, and square kms of coca around 1km from the school in the preceding year. All regressions include year fixed effects. Optimal bandwidths are computed using the MSE-minimizing procedure following (Cattaneo et al., 2019). Columns (1) and Columns (3) include a quadratic polynomial. Columns (2) and Columns (4) include a lineal polynomial. All regressions include triangular weighting kernel. Standard errors are clustered at the school level. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table 10: Two-way fixed effects model

	Dep. var:			
	Dropout rate		Failure rate	
	(1)	(2)	(3)	(4)
Inside sprayed area	0.00655***		0.00262*	
	(0.0014)		(0.0014)	
% Sprayed area (5km Radius)		0.00255***		0.00113**
		(0.0005)		(0.0005)
Year FE	yes	yes	yes	yes
School FE	yes	yes	yes	yes
Mean dep. var	.083	.083	.077	.077
Observations	104912	104912	104912	104912

Note: This table presents the estimated effect of aerial eradication on dropout and failure rate using specification 2. The independent variable in columns (1) and (3) is a dummy variable indicating whether a school was inside a spraying area at time t. The independent variable in columns (2) and (4) is the percentage of area sprayed within a 5 km radius of the school at time t. All regressions include schools and year fixed effects. Standard errors are clustered at the school level. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table 11: Effect of aerial eradication on educational outcomes - Education level

	Dep. var:					
	Dropout rate			Failure rate		
	Pre-school (1)	Primary (2)	Secondary (3)	Pre-school (4)	Primary (5)	Secondary (6)
Inside sprayed areas	0.0113*	0.00848**	0.00246	0.00147	0.00616**	-0.00392
	(0.0059)	(0.0036)	(0.0042)	(0.0025)	(0.0029)	(0.0055)
Year FE	yes	yes	yes	yes	yes	yes
Baseline controls	yes	yes	yes	yes	yes	yes
Bandwidth (Kms)	6.55	5.20	13.5	11.8	8.37	12.2
Mean control	.092	.092	.058	.079	.079	.064
Observations	16104	18009	4224	24348	25623	3923

Note: This table presents the estimated effect of aerial eradication on dropout and failure rate by level of education using specification (1). We have aggregated the educational outcomes of secondary and high school education. Base line controls include elevation and a dummy indicating whether the school was inside a sprayed area in the preceding year. All regressions include year fixed effects. Optimal bandwidths are computed using the MSE-minimizing procedure following (Cattaneo et al., 2019). All regressions include a lineal polynomial and a triangular weighting kernel. Standard errors are clustered at the school level. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table 12: Effect of aerial eradication on educational outcomes - Gender

	Dep. var:			
	Dropout rate		Failure rate	
	Girl (1)	Boy (2)	Girl (3)	Boy (4)
Inside sprayed areas	0.0104***	0.0106***	0.00680***	0.00518*
	(0.0036)	(0.0039)	(0.0026)	(0.0030)
Year FE	yes	yes	yes	yes
Baseline controls	yes	yes	yes	yes
Bandwidth (Kms)	4.93	4.92	9.31	8.32
Mean control	.087	.100	.064	.064
Observations	18120	18138	28661	26612

Note: This table presents the estimated effect of aerial eradication on dropout and failure rate by gender using specification (1). Base line controls include elevation and a dummy indicating whether the school was inside a sprayed area in the preceding year. All regressions include year fixed effects. Optimal bandwidths are computed using the MSE-minimizing procedure following (Cattaneo et al., 2019). All regressions include a lineal polynomial and a triangular weighting kernel. Standard errors are clustered at the school level. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table 13: Effect of aerial eradication on transfer rate

	Dep. var: Transfer rate		
	(1)	(2)	(3)
Inside sprayed areas	-0.0062***	-0.0073***	-0.0075***
	(0.0019)	(0.0021)	(0.0022)
Year FE	yes	yes	yes
Baseline controls	no	yes	yes
Extended controls	no	no	yes
Bandwidth (Kms)	6.19	6.28	6.42
Mean control	.032	.032	.032
Observations	25495	21675	19703

Note: This table presents the estimated effect of aerial eradication on transfer rate using specification (1). Base line controls include elevation and a dummy indicating whether the school was inside a sprayed area in the preceding year. Extended controls include slope, a dummy indicating whether the school was inside a manual eradication area, and square kms of coca around 1km from the school in the preceding year. All regressions include year fixed effects. Optimal bandwidths are computed using the MSE-minimizing procedure following (Cattaneo et al., 2019). All regressions include a lineal polynomial and a triangular weighting kernel. Standard errors are clustered at the school level. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table 14: Effect of aerial eradication on nighttime light

	Dep. var: Nighttime Lights around		
	1Km	3Kms	5Kms
	(1)	(2)	(3)
Inside sprayed area	-0.461***	-0.369***	-0.386***
	(0.1278)	(0.1121)	(0.1067)
Year FE	yes	yes	yes
Baseline controls	yes	yes	yes
Bandwidth (Kms)	3.82	3.47	3.19
Mean control	4.77	4.50	4.25
Observations	13385	12266	11193

Note: This table presents the estimated effect of aerial eradication on nighttime light density around schools using specification (1). Base line controls include elevation and a dummy indicating whether the school was inside a sprayed area in the preceding year. All regressions include year fixed effects. Optimal bandwidths are computed using the MSE-minimizing procedure following (Cattaneo et al., 2019). All regressions include a lineal polynomial and a triangular weighting kernel. Standard errors are clustered at the school level. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table 15: Effect of manual eradication on educational outcomes

	Dep. var:			
	Dropout rate		Failure rate	
	(1)	(2)	(3)	(4)
Inside manual eradication	0.0100**	0.00910*	0.00545+	0.00625*
	(0.0048)	(0.0049)	(0.0037)	(0.0038)
Year FE	yes	yes	yes	yes
Baseline controls	no	yes	no	yes
Bandwidth (Kms)	5.62	5.70	7.84	7.36
Mean control	.086	.086	.065	.065
Observations	10280	9652	14227	12343

Note: This table presents the estimated effect of manual eradication on dropout and failure rate using specification (1). Base line controls include slope, square kms of coca around 1km from the school in the preceding year, an indicator of whether the school was subject of aerial spraying in t, nighttime light density around school in 1993 and the number of landmines around 1km from school in 1993. Optimal bandwidths are computed using the MSE-minimizing procedure following (Cattaneo et al., 2019). All regressions include a lineal polynomial and a triangular weighting kernel. Standard errors are clustered at the school level. $+p < 0.15, *p < 0.1, **p < 0.05, ***p < 0.01$.

Table 16: Effect of aerial eradication on landmines

	Dep. var: Landmines around		
	1Km	3Km	5Km
	(1)	(2)	(3)
Inside sprayed area	-0.0952***	-0.159***	-0.208***
	(0.0347)	(0.0505)	(0.0780)
Year FE	yes	yes	yes
Baseline controls	yes	yes	yes
Bandwidth (Kms)	5.87	4.56	5.12
Mean control	.252	.610	1.06
Observations	20475	17124	18607

Note: This table presents the estimated effect of aerial eradication on landmines around schools using specification (1). Base line controls include elevation and a dummy indicating whether the school was inside a sprayed area in the preceding year. All regressions include year fixed effects. Optimal bandwidths are computed using the MSE-minimizing procedure following (Cattaneo et al., 2019). All regressions include a lineal polynomial and a triangular weighting kernel. Standard errors are clustered at the school level. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table 17: Balance check aerial eradication - Rural Section

	RD Coefficient (1)	SE (2)	BW. (3)	No. (4)
Panel A: Characteristics of rural sections				
-Geographic:				
Elevation	-180.518	58.339***	10.60	3909
Slope	0.183	0.332	7.14	2343
-Socioeconomic:				
Nighttime light. 1993	-0.252	0.324	7.41	2465
Landmines.1993	-0.008	0.014	15.40	5674
-Coca cultivation:				
Perc of area with coca. 2003	0.001	0.001	5.24	1348
Perc of area with coca. 2016	0.000	0.002	7.32	2417
Panel B: Characteristics with municipality-level data				
-Education:				
School-age population. 1993	0.839	3.201	11.10	3806
Population primary. 1993	1195.823	4310.152	10.20	3482
Population secondary. 1993	978.400	4885.616	10.10	3451
Avg. schooling years. 1993	0.067	0.477	9.34	3077
Illiteracy rate. 1993	-0.250	2.377	7.00	2283
No. teachers. 1996	51.729	452.256	10.20	3637
No. students. 1996	1036	9277	10.10	3603
-Agriculture:				
Suitability index oil palm. 1961-1990.	153.893	671.618	14.40	5308
Suitability index plantain. 1961-1990.	-111.144	490.783	9.18	3287
Suitability index coffee. 1961-1990.	-208.547	378.679	9.67	3501

Note: Panel A presents a balance test on several characteristics at the rural section level. Panel B presents a balance test for pre-existing characteristics using municipality level data. Optimal bandwidths are computed using the MSE-minimizing procedure following (Cattaneo et al., 2019). All regressions include a lineal polynomial and a triangular weighting kernel. Standard errors are clustered at the rural section level for Panel A and at the municipality level for Panel B. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table 18: Medium term effect of aerial eradication on migration

	Dep. var: Share of people who were in the municipality		
	1 year ago	5 years ago	At birth
	(1)	(2)	(3)
Inside sprayed areas	-0.00298	0.0127	0.0861**
	(0.0162)	(0.0167)	(0.0379)
Bandwidth (Kms)	8.81	10.0	8.01
Mean control	.926	.786	.556
Observations	2891	3361	2523

Note: This table presents the estimated effect of aerial eradication on migration outcomes using specification 3. In column (1), the dependent variable is the share of individuals residing in the same municipality one year ago. In column (2), it pertains to individuals residing in the same municipality five years ago, and in column (3), it relates to those born in the same municipality. These variables were computed using the 2018 census. Optimal bandwidths are computed using the MSE-minimizing procedure following (Cattaneo et al., 2019). All regressions include a lineal polynomial and a triangular weighting kernel. Standard errors are clustered at the rural section level. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table 19: Effect of aerial eradication on schooling rates

	Dep. var: Schooling rate	
	Primary	Secondary
	(1)	(2)
Inside sprayed areas	-0.124**	-0.106**
	(0.0606)	(0.0529)
Bandwidth (Kms)	6.09	8.58
Mean control	.910	.535
Observations	1362	2232

Note: This table presents the estimated effect of aerial eradication on the schooling rates using specification 3. The dependent variable in column (1) is the percentage of people, 25 to 29 years old with at least primary education. The dependent variable in column (2) is the percentage of people, 25 to 29 years old with at least secondary education. All regressions include elevation. Optimal bandwidths are computed using the MSE-minimizing procedure following (Cattaneo et al., 2019). All regressions include a lineal polynomial and a triangular weighting kernel. Standard errors are clustered at the rural section level. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table 20: Medium term effect of aerial eradication on child labor

	Dep. var: Share of children 10 to 19 years old					
	Had a job			Household chores		
	All	Boy	Girl	All	Boy	Girl
	(1)	(2)	(3)	(4)	(5)	(6)
Inside sprayed areas	0.0564***	0.0779***	0.00608	0.0143	-0.0398*	0.0556**
	(0.0198)	(0.0287)	(0.0094)	(0.0258)	(0.0220)	(0.0279)
Bandwidth (Kms)	10.7	10.6	13.5	8.17	6.89	12.5
Mean control	.129	.204	.042	.120	.042	.208
Observations	3304	3087	3882	2380	1769	3594

Note: This table presents the estimated effect of aerial eradication on the share of children who had a job in last week and who engaged in unpaid household chores at home instead of studying. The definition we used for having a job includes: 1) the individual worked at least 1 hour last week, and got a payment; 2) the individual worked or helped in a business at least one hour last week without payment; and 3) the individual didn't work last week but has a job or business, and receives a payment. The definition we used for doing chores at home is whether the individual said that he/she did chores at home during last week. We used the 2018 census to compute these shares. We use specification 3. All regressions include elevation. Optimal bandwidths are computed using the MSE-minimizing procedure following (Cattaneo et al., 2019). All regressions include a lineal polynomial and a triangular weighting kernel. Standard errors are clustered at the rural section level. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table 21: Medium term effect of aerial eradication on early marriage

	Dep. var: Share of single women			
	10 - 14	15 - 19	20 - 24	25 - 29
	(1)	(2)	(3)	(4)
Inside sprayed areas	-0.0597*	-0.0294	-0.0561+	-0.117**
	(0.0316)	(0.0414)	(0.0381)	(0.0498)
Bandwidth (Kms)	6.89	10.3	11.4	8.04
Mean control	.947	.702	.355	.205
Observations	1582	2570	2740	1730

Note: This table presents the estimated effect of aerial eradication on the share of single women using specification 3. The individual is single if he/she is not in a civil union, married, divorced or widow. In column (1) we compute the share of single girls who are 10 to 14 years old. In column (2) we do it for girls 15 to 19 years old. In column (3) for women 20 to 24 years old, and in column (4) for women 25 to 29 years old. All regressions include elevation. Optimal bandwidths are computed using the MSE-minimizing procedure following (Cattaneo et al., 2019). All regressions include a lineal polynomial and a triangular weighting kernel. Standard errors are clustered at the rural section level. $+p < 0.15 * p < 0.1, **p < 0.05, ***p < 0.01$.

Table 22: Medium term effect of aerial eradication on socioeconomic conditions

	Dep. var: Share of households with utilities			
	Electricity	Drinkable Water	Sewage	Garbage Collection
	(1)	(2)	(3)	(4)
Inside sprayed areas	-0.0440	-0.119**	-0.0607*	-0.105**
	(0.0378)	(0.0513)	(0.0358)	(0.0528)
Bandwidth (Kms)	10.0	6.73	7.85	6.86
Mean control	.469	.150	.056	.095
Observations	3669	2157	2649	2213

Note: This table presents the estimated effect of aerial eradication on dwelling conditions using specification 3. We measure the share of households that have each of these services: electricity, drinkable water, sewage and garbage collection. All regressions include elevation. Optimal bandwidths are computed using the MSE-minimizing procedure following (Cattaneo et al., 2019). All regressions include a lineal polynomial and a triangular weighting kernel. Standard errors are clustered at the rural section level. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table 23: Medium term effect of aerial eradication on health

	Dep. var: Share of people with health issues			
	All	5 - 9	10 - 14	15 - 19
	(1)	(2)	(3)	(4)
Panel A: Have fallen sick lately				
Inside sprayed areas	0.00638	-0.0320	0.0199	-0.00711
	(0.0125)	(0.0236)	(0.0240)	(0.0143)
Bandwidth (Kms)	6.48	6.73	6.56	9.13
Mean control	.045	.057	.048	.053
Observations	1862	1683	1629	2535
Panel B: With disabilities				
Inside sprayed areas	0.0101	0.00969	0.00378	0.00969
	(0.0073)	(0.0074)	(0.0108)	(0.0154)
Bandwidth (Kms)	8.31	11.7	12.1	8.06
Mean control	.039	.028	.032	.031
Observations	2661	3353	3526	2154

Note: This table presents the estimated impact of aerial eradication on the percentage of individuals who had any health issue during the last 30 days and they didn't require hospitalization (Panel A) or have any disability (Panel B).In column (1) we compute these shares for all people. In column (2) we only do it for children who are 5 to 9 years old, in column (3) 10 to 14 years old, and in column (4) 15 to 19 years old. In panel B the dependent variable is the share of people who have any type of disability. We use specification 3. All regressions include elevation. Optimal bandwidths are computed using the MSE-minimizing procedure following (Cattaneo et al., 2019). All regressions include a lineal polynomial and a triangular weighting kernel. Standard errors are clustered at the rural section level. $*p < 0.1, **p < 0.05, ***p < 0.01$.

A Online Appendix

A.1 Data and Variables

A.1.1 Distance from schools to the nearest part of eradication border

The UNODC has published reports since 2004 until 2015 (2006-2015 for manual eradication) with maps of eradicated areas. We used QGIS to 1) georeference these maps and 2) get the coordinates of the eradicated areas. Then we use the location of schools that was provided by DANE to compute the distance from the school to the nearest part of the eradication border and to create the treatment variable, which is whether the school is inside or outside the eradication area.

A.1.2 2018 census and rural sections

For the living conditions estimations, we aggregated areas sprayed across all years into a single layer. Subsequently, we computed the distance from the centroid of each rural section to the border of the sprayed areas, as explained in the following lines.

A rural section is a statistical division in rural areas, each averaging 20 km^2 and with precise coordinates. There are approximately 47,134 rural sections acording to the 2018 Geostatistical Information System shapefiles (Marco Geoestadistico Nacional. 2018.) on DANE's website.

Using the *centroids* geoprocessing tool in QGIS, we obtained the centroid of each rural section. We then calculated the distance from each centroid to the nearest point on the eradication borders, determining whether the centroid falls inside or outside each eradication polygon.

The *overlap analysis* geoprocessing tool was utilized to determine the percentage of each rural section subjected to spraying. We considered only rural sections with eradication coverage at either 100% or 0%, ensuring perfect compliance for a precise RD estimator. Figure 8 illustrates this.

The 2018 census provides household-level socioeconomic data. Although household locations are not exact, each one has an identifier corresponding to the rural section. The next step involved linking this identifier with the one from the Geostatistical Information System (Marco Geoestadistico Nacional. 2018.).

Using the 2018 census, we aggregated socioeconomic variables at the rural section level, reporting only the shares. For instance, the rate of employed children aged 10 to 19 is calculated as the number of employed children in that age range over the total number of children of that age range in the rural section. Another example is the percentage of households with electricity, calculated as the number of electrified households over the total households in the rural section.

These are the definitions and computations of the socioeconomic variables computed for the results using rural sections.

The share of people who were in the same municipality one year ago in Table 18 is computed as the total number of people who were in the same municipality one year ago over the total number of people in the rural section. Similarly, the share of people who were in the same municipality five years ago is computed as the total number of people who were in the same municipality five years ago over the total number of people in the rural section, and the share of people who were in the same municipality at birth is computed as the total number of people born in the same municipality over the total number of people in the rural section.

The share of people with primary education in Table 19 is computed as the total number of people older than 25 years old with at least primary education over the total number of people older than 25 years old in the rural section. The same computation procedure applies to the share of people with at least secondary education and at least high school.

The share of children aged 10 to 19 with a job in Table 20 is computed as the total number of children in that age range with a job over the total number of children in that age range in the rural section. The same computation procedure applies to the share of children who did chores at home. The definition used for having a job includes: 1) working at least 1 hour last week with payment; 2) working or helping in a business at least one hour last week without payment; and 3) not working last week but having a job or business and receiving payment. The definition used for doing chores at home is whether the individual said they did chores at home during the last week. These definitions are from the 2018 census.

The share of single women in Table 21 is computed as the total number of single women of the respective age range over the total number of women of the respective age range in the rural section. The definition used for being single is whether the individual is not in a civil union, married, divorced, or widowed.

The share of households with utilities associated with socioeconomic conditions in Table 22 is computed as the total number of households with access to the respective service over the total number of households in the rural section.

The share of people with health issues in Panel A of Table 23 is computed as the total number of people of the respective age range with any health issue in the last 30 days without hospitalization over the total number of people of the respective age range in the rural section. Column 1 does this computation for all people regardless of their age. A similar procedure is followed in Panel B. In this case, the definition of having a disability is whether the individual says they have a disability. The 2018 census published by DANE does not distinguish the type of illness or the type of disability, although the questionnaire asks about the type of disability.

A.1.3 Schools buffers

We use the location of schools that was provided by DANE. The we used the *buffer* geo processing tool from QGIS to create buffers around schools: 1 km, 3 kms and 5km.

A.1.4 Coca around schools

We downloaded the dataset on coca from the Colombian open data portal (https://datos.gov.co/). The dataset is called "Densidad de cultivos de coca". This dataset has information of the coordinates of the polygons with coca, and the number of hectares of coca of each polygon. We had to make some modifications on this dataset to be able to use it in QGIS.

Then we used the *overlap* geoprocessing tool from QGIS to compute the amount of coca around schools. The buffers we used for schools are the same we computed in subsection A.1.3

A.1.5 Night light around schools

We downloaded the tif files from 1992 until 2013. The web site is https://eogdata.mines.edu/products/dmsp/. We downloaded specifically the files under the section "Version 4 DMSP-OLS Nighttime Lights Time Series". We also downloaded those tif files in which there is information from two different satellites. These files have a resolution of 30 arc second. They don't report the values as radiance, but as digital numbers whose range is 1-63, where 63 is the highest night light registered.

We used the *zonal statistics* geo processing tool in QGIS that takes the average night light inside the respective school buffer. For those years in which there is information from two satellites we took the average night light. These years are: 1994, and from 1997 until 2007. For the rest of years we only took the night light provided by the respective satellite.

A.1.6 Average suitability index at municipality

We download the suitability index range of current cropland for banana, coffee and oil palm[20]. This information is produced by the Global Agro-Ecological Zones (GAEZ) modelling framework, which is a project from the Food and Agriculture Organization of the United Nations (FAO) and the International Institute for Applied Systems Analysis (IIASA). The resolution of the files is 30 arc-second (9 x 9 km) and the range goes from 0 to 10000 (0 to 100 times 100), where 10000 means that the grid is very suitable for the specific crop and 0 means that it is not suitable.

We also use the shapefile of municipalities in Colombia published in the Geostatistical information system for 2018 (Marco Geoestadistico Nacional. 2018.). Therefore we utilized the *zonal statistics* geo processing tool in QGIS to get the average suitability index at the municipality level for each crop.

A.1.7 Digital elevation model

We downloaded the Digital Elevation Model (DEM) files from the United States Geological Survey (USGS) web page. Then we used the *merge* geo processing tool from QGIS to merge all tif files. We also used the *slope* geo processing tool from QGIS to get the slope.

Finally, we used the *raster values* geo processing tool from QGIS to get the elevation and slope at school.

A.1.8 Land mines

Information about land mines events is published by the Information Management System for Mine Action (IMSMA) of the Geneva International Centre for Humanitarian Demining

[20]These are the respective web sites:
https://s3.eu-west-1.amazonaws.com/data.gaezdev.aws.fao.org/res05/CRUTS32/Hist/6190H/suHa_ban.tif
https://s3.eu-west-1.amazonaws.com/data.gaezdev.aws.fao.org/res05/CRUTS32/Hist/6190H/suHa_cof.tif
https://s3.eu-west-1.amazonaws.com/data.gaezdev.aws.fao.org/res05/CRUTS32/Hist/6190H/suHa_olp.tif

(GICHD). This is a registry of events related to land mines by year. These events include: 1) explosions, 2) demining, 3) seizures, 4) fabrics, 5) suspicion of land mines, 6) unexploded ordnance and 7) arsenal storage. There is information from 1984.

This registry also has the coordinates of the events, so we are able to compute the number of events around schools, using the school buffers explained in A.1.3.

A.2 Additional Tables

Table A.1: Summary statistics of schools

	Mean	SD	Observations	Source
Panel A: Eradication areas				
Aerial spraying (Km2)	777.25	7453.88	1293	UNODC-DIRAN
Manual eradication (Km2)	482.92	9252.95	767	UNODC-DIRAN
Panel B: School census				
Enrollment, 2004-2015	129.13	223.74	35755	Form C-600
Dropout rate, 2004-2015	0.09	0.07	35755	Form C-600
Failure rate, 2004-2015	0.07	0.07	35755	Form C-600
Transfer rate, 2004-2015	0.03	0.04	35755	Form C-600
Panel C: Characteristics around schools				
Elevation	435.26	512.43	35755	USGS-SRTM
Slope	89.13	1.76	35742	USGS-SRTM
Km2 coca rd 1Km, 2004-2015	0.48	0.86	35755	UNODC
Km2 coca rd 3Km, 2004-2015	4.49	6.35	35755	UNODC
Km2 coca rd 5Km, 2004-2015	12.44	15.95	35755	UNODC
Nighttime light rd 1Km, 2004-2013	5.41	6.19	33097	DMSP-OLS
Nighttime light rd 3Km, 2004-2013	5.23	5.81	33097	DMSP-OLS
Nighttime light rd 5Km, 2004-2013	5.07	5.60	33097	DMSP-OLS
Landmines rd 1Km, 2004-2015	0.20	1.31	35755	IMSMA
Landmines rd 3Km, 2004-2015	0.52	2.02	35755	IMSMA
Landmines rd 5Km, 2004-2015	0.95	2.80	35755	IMSMA

Note: This table present the summary statistics of the variables used in the estimations at the school level.

Table A.2: Summary statistics of rural sections

	Mean	SD	Observations	Source
-Share of people older than 25 with				
At least primary	0.81	0.19	5723	2018 Census
At least secondary	0.26	0.20	5723	2018 Census
At least high school	0.15	0.17	5723	2018 Census
-Share of kids 10 to 19 years old who				
Attended school	0.62	0.25	5418	2018 Census
Had a job	0.14	0.15	5812	2018 Census
Did chores at home	0.14	0.15	5812	2018 Census
-Share of people				
Sick	0.05	0.06	5934	2018 Census
With a disability	0.04	0.05	5934	2018 Census
Born in the municipality	0.54	0.26	5934	2018 Census
-Share of households with service of				
Electricity	0.41	0.33	6442	2018 Census
Drinkable water	0.11	0.19	6442	2018 Census
Sewage	0.04	0.12	6442	2018 Census
Garbage Collection	0.06	0.16	6442	2018 Census

Note: This table present the summary statistics of the variables used in the estimations at the rural section level.

Table A.3: Balance check aerial eradication - Municipality

	Optimal bandwidth				Fixed bandwidth			
	RD Coefficient (1)	SE (2)	BW. (3)	No. (4)	RD Coefficient (5)	SE (6)	BW. (7)	No. (8)
-Education:								
School-age population 1993	0.54614	0.9216	15.10	1255	0.52779	1.0821	5.93	717
Population primary 1993	-6.9e+02	549.0277	11.80	969	-7.1e+02	641.7049	5.93	624
Population secondary 1993	-7.4e+02	580.1055	11.60	954	-7.4e+02	644.6281	5.93	624
Avg. schooling years 1993	-0.00763	0.1300	18.20	1383	-0.04555	0.1597	5.93	697
Illiteracy rate 1993	-0.27274	0.5923	13.90	1204	-0.43148	0.6451	5.93	717
No. teachers 1996	-4.9e+01	50.4438	12.10	1049	-5.2e+01	55.4188	5.93	667
Enrollment 1996	-1.1e+03	1.1e+03	12.70	1084	-1.0e+03	1.2e+03	5.93	667
No. schools 1996	-7.19575	8.5113	15.90	1223	-1.1e+01	8.4503	5.93	667
-Agriculture:								
Suitability index oil palm	-1.7e+02	548.3480	14.70	1238	33.78803	696.5585	5.93	717
Suitability index plantain	1.6e+02	330.6056	15.80	1296	3.3e+02	411.2089	5.93	717
Suitability index coffee	72.51679	288.5334	15.10	1256	22.68969	350.7223	5.93	717

Note: This table presents a balance test for pre-existing characteristics using municipality level data. The unit of observation is the municipality. Columns (5) to (8) present results using a fixed bandwidth of 5.93 Km (the optimal bandwidth of our main outcome). Columns (1) to (4) presents the result computing the optimal bandwidth following (Cattaneo et al., 2019). All regressions include year fixed effects, as well as a lineal polynomial and a triangular weighting kernel. Standard errors are clustered at municipality level. $*p < 0.1, **p < 0.05, ***p < 0.01$.

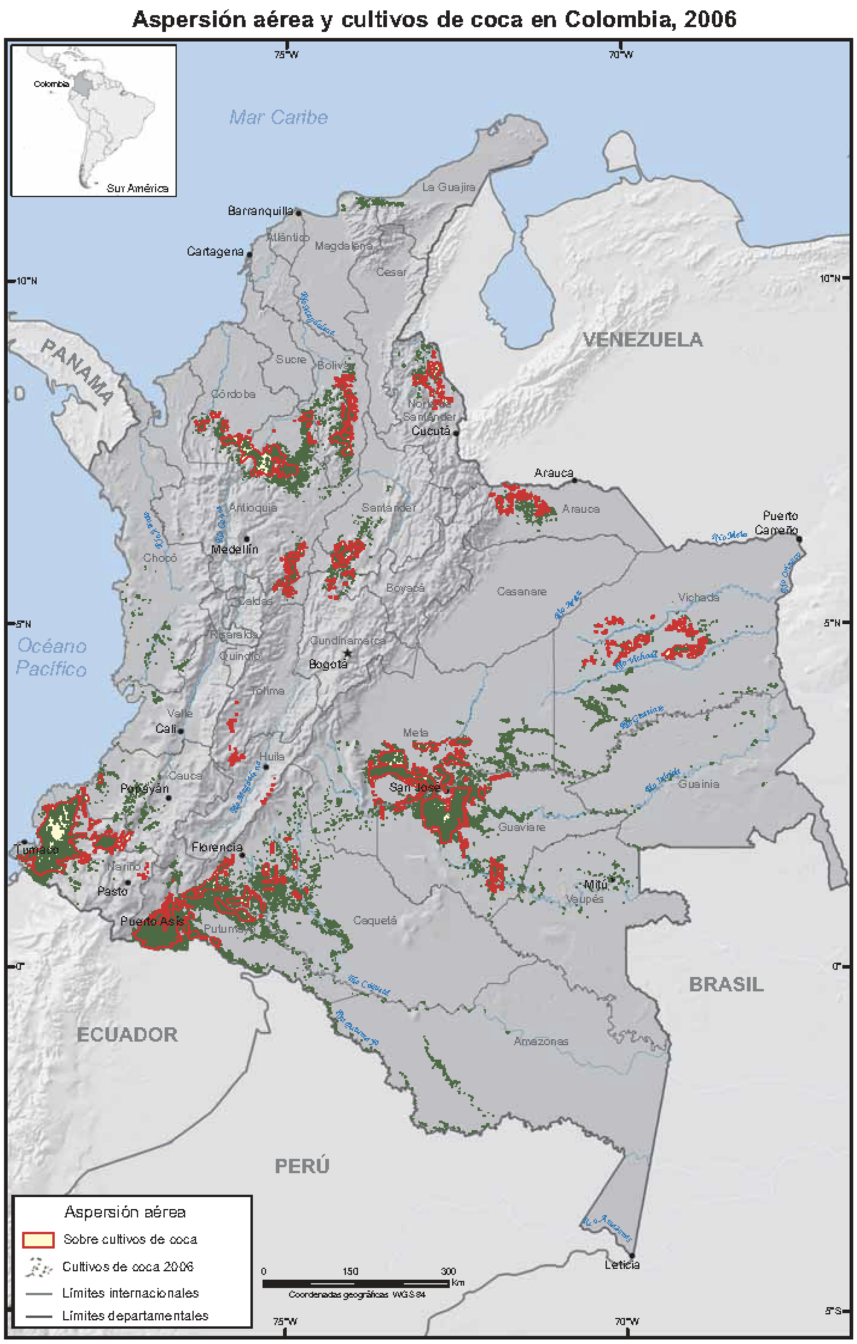
Table A.4: Balance check manual eradication

	Optimal bandwidth				Fixed bandwidth			
	RD Coefficient (1)	SE (2)	BW. (3)	No. (4)	RD Coefficient (5)	SE (6)	BW. (7)	No. (8)
Panel A: General characteristics at the school level								
-Geographic:								
Elevation	-3.7e+01	26.8853	4.64	8727	-3.7e+01	25.7840	5.50	10056
Slope	-0.39215	0.0587***	4.72	8839	-0.38854	0.0563***	5.50	10054
-Socioeconomic:								
Nighttime light rd 1Km 1993	0.39479	0.1437***	3.15	6288	0.49672	0.1238***	5.50	10056
Nighttime light rd 3Km 1993	0.28238	0.1007***	3.41	6717	0.40971	0.0906***	5.50	10056
Nighttime light rd 5Km 1993	0.13230	0.0759*	3.08	6121	0.25072	0.0640***	5.50	10056
Landmines rd 1Km 1993	0.00993	0.0099	4.20	8044	-0.00239	0.0089	5.50	10056
Landmines rd 3Km 1993	0.02565	0.0130**	4.42	8390	0.01131	0.0122	5.50	10056
Landmines rd 5Km 1993	0.02518	0.0149*	7.44	13494	0.03066	0.0160*	5.50	10056
-Eradication:								
Km2 coca rd 1Km at *t-1*	-0.12145	0.0535**	3.20	5939	-0.07543	0.0439*	5.50	9349
Km2 coca rd 3Km at *t-1*	-1.06882	0.4469**	2.95	5431	-0.49085	0.3440	5.50	9349
Km2 coca rd 5Km at *t-1*	-2.38090	1.1672**	2.97	5508	-1.28631	0.9019	5.50	9349
Aerial eradication at *t-1*	0.02441	0.0206	7.45	12495	0.02092	0.0225	5.50	9349
Manual eradication at *t-1*	-0.00467	0.0227	4.73	6562	-0.00232	0.0213	5.50	7520
Aerial eradication at *t*	0.05095	0.0195***	6.81	12412	0.04879	0.0209**	5.50	10056
Panel B: Characteristics at the municipality level								
-Education:								
School-age population 1993	0.83657	2.2910	7.68	13000	0.75315	2.2762	5.50	9328
Population primary 1993	1.3e+03	2.5e+03	7.49	12762	1.0e+03	2.3e+03	5.50	9389
Population secondary 1993	1.0e+03	2.7e+03	7.66	13046	8.5e+02	2.5e+03	5.50	9389
Avg. schooling years 1993	0.06280	0.2322	7.11	12041	0.07080	0.2233	5.50	9328
Illiteracy rate 1993	0.39363	1.9829	9.76	17167	0.95036	2.1259	5.50	10056
No. teachers 1996	41.13272	223.9371	7.75	13751	28.57860	195.3353	5.50	9875
No. students 1996	1.5e+03	4.9e+03	7.58	13475	1.3e+03	4.4e+03	5.50	9875
No. schools 1996	15.72196	26.0718	7.78	13643	13.29339	24.6517	5.50	9750
-Agriculture:								
Suitability index oil palm	5.5e+02	864.6669	8.69	15454	6.1e+02	864.4227	5.50	10056
Suitability index plantain	96.36074	423.2435	9.62	16923	1.9e+02	435.5299	5.50	10056
Suitability index coffee	-8.3e+01	258.7189	7.25	13179	-1.38182	261.5009	5.50	10056

Note: Panel A presents a balance test on several characteristics surrounding schools. Panel B presents a balance test for pre-existing school and agricultural characteristics using municipality level data. Columns (5) to (8) present results using a fixed bandwidth of 5.93 Km (the optimal bandwidth of our main outcome). Columns (1) to (4) presents the result computing the optimal bandwidth following (Cattaneo et al., 2019). All regressions include year fixed effects, as well as a lineal polynomial and a triangular weighting kernel. Standard errors are clustered at the school level for Panel A and at the municipality level for Panel B. $*p < 0.1, **p < 0.05, ***p < 0.01$.

A.3 Additional Figures

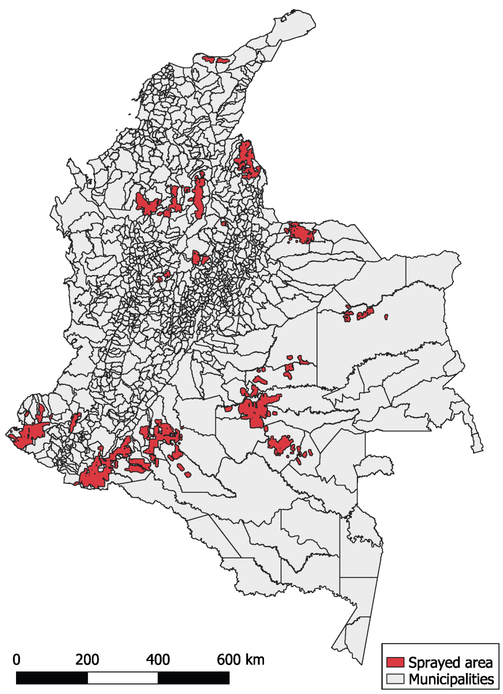
Figure A.1: Map Aerial spraying UNODC



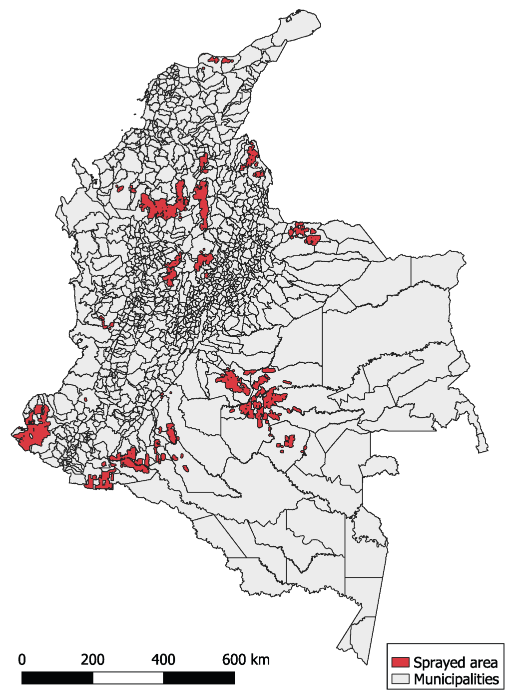
Fuentes: para cultivos ilícitos: Gobierno de Colombia - Sistema de monitoreo apoyado por UNODC; para aspersión aérea: DIRAN
Los límites, nombres y títulos usados en este mapa no constituyen reconocimiento o aceptación por parte de las Naciones Unidas

Figure A.2: Digitized maps of areas sprayed

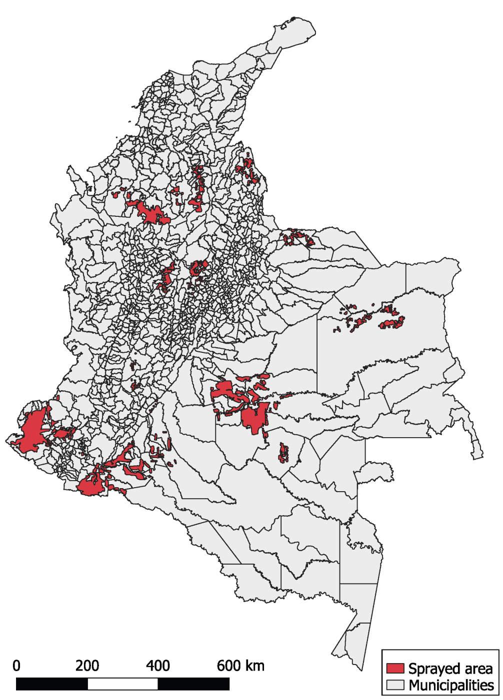
a) 2004



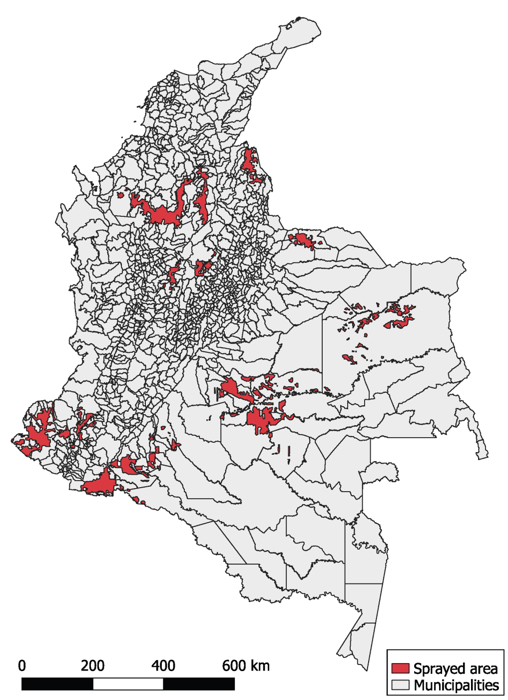
b) 2005



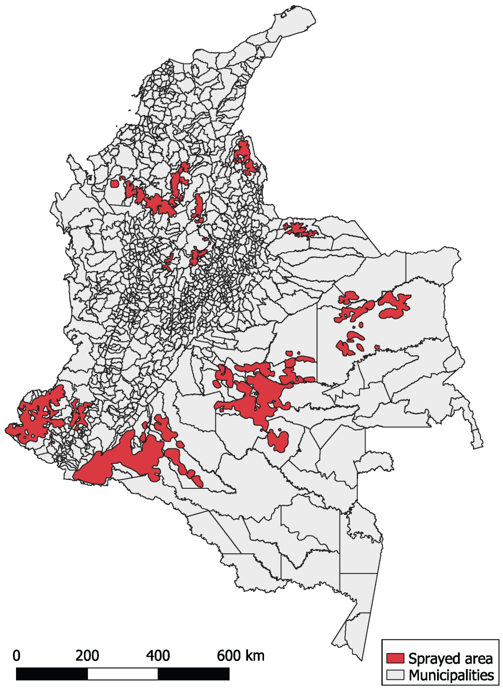
c) 2006



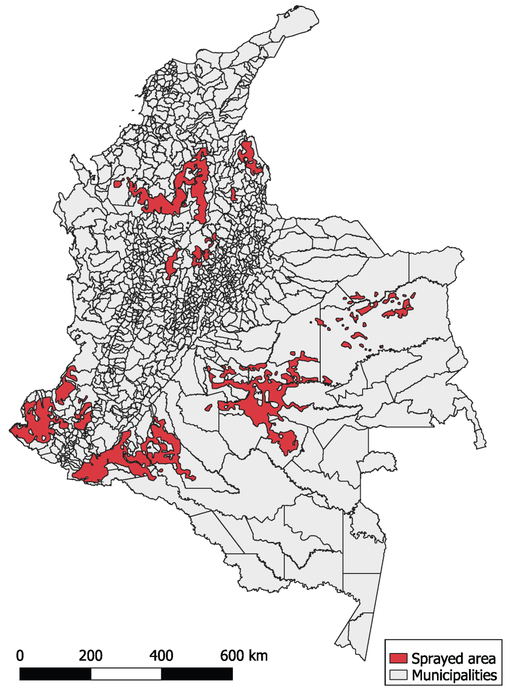
d) 2007



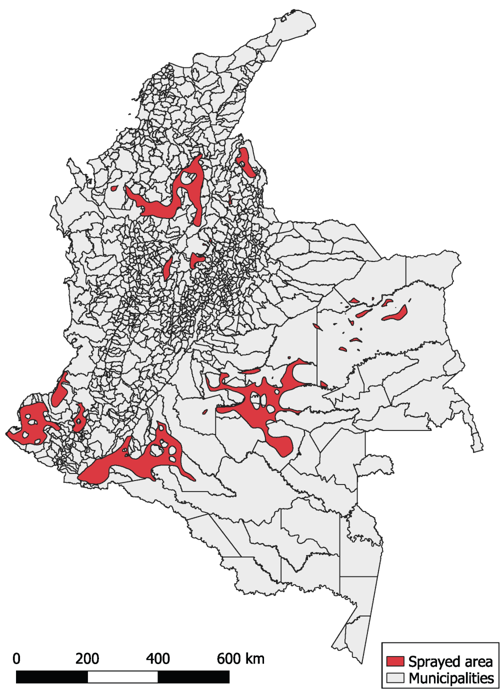
e) 2008



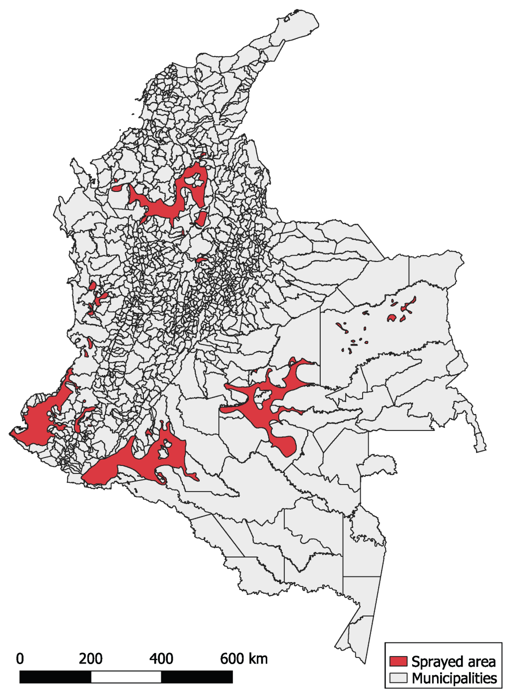
f) 2009

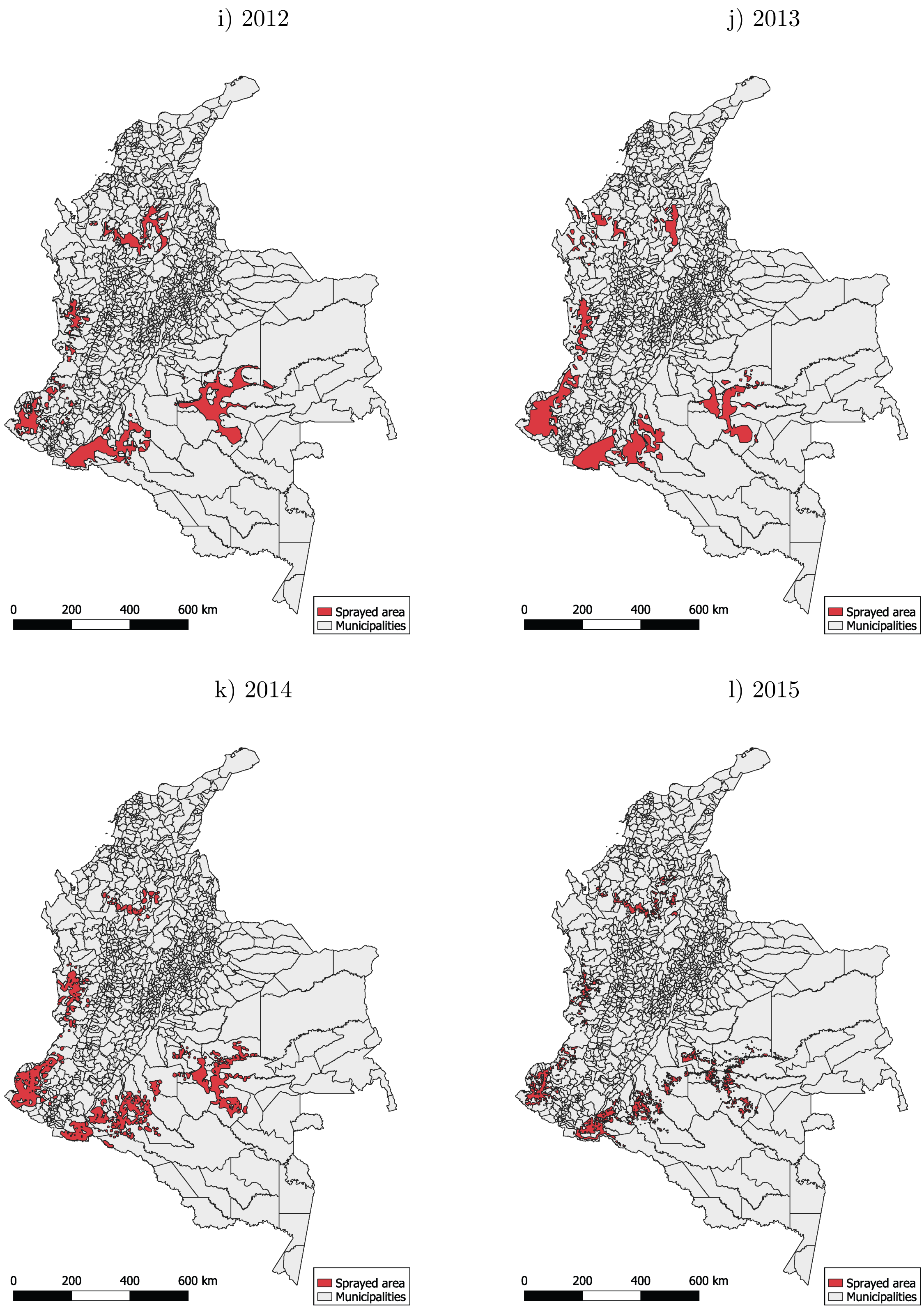


g) 2010



h) 2011





Note: These maps illustrate the sprayed areas.