Off-Target Impacts of Targeted Policy:

Evidence from Colombia *

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Abstract

Spatially targeted policies risk causing collateral damage to non-targeted areas, but evidence on these spillovers is scarce. This paper documents the off-target effects of the world's largest place-based drug eradication effort—Colombia's aerial glyphosate spraying of coca fields—on legitimate agricultural production. Using a novel atmospheric dispersion model to construct a measure of wind-borne herbicide exposure, we show that glyphosate drift reduces legal crop harvests by 13 percent in non-targeted municipalities. The damage is persistent and adaptation is minimal in the medium run. After the 2015 fumigation ban, we show that legal crop production in previously-exposed municipalities recovers only modestly, and where production does not recover, land use transitions toward grassland and shrubland. As Colombia considers reinstating aerial spraying, our policy simulations show that targeting only the largest coca hotspots could avoid $USD 611 million in spillover damages, equivalent to 3.7% of agricultural GDP.

Keywords: Spillovers, herbicide spraying, dispersion model, enforcement, agriculture
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1 Introduction

Geographic targeting is a common policy tool to curb undesirable activities by focusing enforcement on hotspots rather than individuals. From protected areas to urban crime-reduction zones, such interventions are attractive because they allocate funds where the marginal impact of enforcement is the highest (Gray and Shimshack, 2011). However, geographic targeting introduces a fundamental policy trade-off: it simplifies enforcement while risking spillovers into neighboring areas (Hanson and Rohlin, 2013, 2021). These externalities, whether economic, environmental, or social, often cross jurisdictional boundaries and can dilute or even reverse policy objectives (Neumark and Simpson, 2015; Englander, 2023). Measuring them is therefore crucial for evaluating whether place-based enforcement delivers net welfare gains or unintended harm.

The tradeoff between direct and indirect (spillover) effects is particularly salient in agricultural enforcement. Spatially targeted efforts to curb unwanted vegetation can unintentionally affect the livelihoods of households in nearby, non-targeted places (Camacho and Mejía, 2017). Yet little is known about how far, and to what extent, geographic targeting affects agricultural outcomes beyond targeted areas. Answering this question is important for low- and middle-income countries where rural communities rely heavily on small-scale agriculture for subsistence and income.

In this paper, we examine the off-target effects of the world's largest place-based drug eradication effort: Colombia's aerial spraying of coca, the primary input in cocaine production. Backed by U.S. funding under an initiative known as Plan Colombia, national authorities sprayed glyphosate—a widely used and potent herbicide—from aircraft over coca fields for over two decades. While glyphosate kills unwanted vegetation (Benbrook, 2016), it can also cause harmful externalities as wind drift and water runoff carry the chemical beyond intended targets (Rivas-Garcia et al., 2022; Dias et al., 2023).[1] At its peak, glyphosate was sprayed over an area roughly the size of Los Angeles (Camacho and Mejía, 2017). After two decades, and amid mounting health concerns, aerial spraying was suspended in 2015.

We use this setting as a natural experiment to answer two research questions: (i) to what extent does glyphosate drift damage legal crop production in areas that were not targeted? (ii) did agricultural production in previously-exposed areas recover after coca spraying was banned? By answering these questions, we quantify the spatial spillovers of place-based enforcement as well as the dynamics of agricultural recovery.

The main empirical challenge in quantifying spatial spillovers is that coca spraying is not random. Fumigation targeted coca-abundant areas, which systematically differ in terms of

[1] While some genetically modified (GM) varieties are less sensitive to glyphosate, adoption of GM crops in Colombia during our study period was very low ($< 1\%$ of cultivated land) (Section 2.4)

cartel violence, institutions, and poverty. Naive comparisons between municipalities more- and less-exposed to spraying would therefore confound off-target effects with these underlying differences. Estimating the causal effects of off-target spraying requires isolating variation in exposure that is orthogonal to place-based determinants of spraying.

We address this empirical challenge by computing a plausibly exogenous measure of wind-driven exposure to spraying using a novel air particle transport model. We start by digitizing maps from the UN Office on Drugs and Crime (UNODC) that contain all coca plantations targeted by aerial glyphosate spraying between 2011 and 2015. We then deploy the dispersion model to simulate 3D wind pathways of tracer particles emanating from each sprayed area at the same altitude as the actual aircraft. The fraction of tracer particles landing in a grid cell provides a continuous measure of a location's wind-driven exposure to herbicide drift. We run the model on a coca plantation-by-month basis for five years and aggregate to the municipality-year level. This yields a plausibly exogenous measure of municipalities' wind-driven exposure to aerial fumigation in a given year.

To estimate off-target damages from targeted spraying, we link our model-generated exposure measure to panel data on legitimate crop production from municipal agriculture surveys. This matched panel enables a credible two-way fixed effects (TWFE) design that gives rise to credible control groups for municipalities exposed to aerial spraying: other municipalities sharing similar characteristics, located equidistant to sprayed areas, but less exposed due to plausibly random differences in wind drifts. In addition to estimating average treatment effects, we also estimate spillovers across crop types, test whether higher soil quality and crop diversity buffer against glyphosate exposure, and characterize the dynamics of adaptation using data on the adoption of glyphosate-resilient GMO crops.

Our main analysis yields three key findings. First, we document extensive damage to legitimate, non-targeted crops from wind-driven exposure to aerial coca spraying. Municipalities more exposed to glyphosate drift experience 13% lower harvests (acres) compared to less exposed municipalities, with similar reductions in crop output (tons) and revenue ($USD). We document a similar pattern of off-target crop damage in satellite-derived measures of vegetation quality. In a back-of-the-envelope calculation using these estimates, we document that Colombia's agricultural GDP growth was held back by half a percent due to off-target crop damages from aerial fumigation.

Second, we document rich heterogeneity in spillover damages. Higher soil quality appears to cushion spillover damages from aerial spraying, whereas diversifying one's crop portfolio offers limited effectiveness as a stabilizer. We also document substantial heterogeneity across crop types. Spillover damages are largest for oilseeds, fibers, plantains, and tree crops. However, when grouping crops into annuals versus perennials, we detect no meaningful differences in spillover damages across the two groups.

Third, we find no evidence of adaption among farmers exposed to glyphosate drift in the medium run. If farmers adopted herbicide-resistant varieties or showed other adaptive behaviors, damages would diminish over time, producing a U-shape in lagged coefficients. Instead, cumulative lag estimates show that damages to off-target crops are unchanged three years later. We confirm this with municipality-level data on farm loans, using the idea that farmers may adapt by allocating credit to adaptive investments. Yet we find no impact of exposure to aerial spraying on farm credit. Lastly, we show the lack of adaptation more directly using data on GMO crop adoption, although data is only available at the coarser department level. We nevertheless find no correlation between exposure and GMO crop shares. All three pieces of evidence point to limited adaptation.

To demonstrate robustness of our findings, we design a placebo test that simulates particle paths from *non-sprayed* coca farms. If our estimates were driven by pollution sources other than coca spraying, then this would be captured by the placebo. Yet placebo exposure has zero impact on legitimate agriculture, suggesting that our main estimates are driven by glyphosate drift and not by other nearby pollution sources. Results are also stable when controlling for the aerial fumigation of *legitimate* crops (e.g., bananas, rice), which we measure by obtaining fumigation flight permits.[2] Our estimates of negative spillovers also hold under alternative administrative and remotely-sensed data sources. Lastly, the extent of negative spillovers is unchanged when we drop coca-growing municipalities from the sample altogether, which ensures estimates are only identified off of wind-driven exposure rather than place-based determinants of spraying.

Taken together, our findings from the Plan Colombia era provide new evidence that aerial coca eradication imposed widespread negative externalities on the legitimate agricultural sector. These adverse effects are especially concerning given that spraying was largely ineffective at reducing coca cultivation, as growers developed adaptive techniques to shield crops from herbicide exposure (Mejía, 2016). Large external costs and no private benefits underscore clear inefficiencies in policy design. In 2015, President Juan Manuel Santos terminated aerial spraying (in defiance of the U.S.), citing a World Health Organization declaration about the harms of glyphosate exposure (New York Times, 2015). Ten years later, it remains unclear whether undoing the policy reversed the damage already done.

In the second part of the paper, we extend the study period to 2018 and use a difference-in-differences design to study whether the 2015 policy reversal led to agricultural recovery, or whether collateral damage from Plan Colombia persisted even after aerial spraying ended. Treatment intensity is measured by cumulative pre-policy exposure to glyphosate and computed from the dispersion model. The intuition is that municipalities that were

[2] Standard agricultural fumigation differs from coca eradication in both flight altitude and herbicide concentration, which reduces the risk of glyphosate drift. See Section 2.1 for details.

highly-exposed (treated) to spraying during Plan Colombia have more "room for recovery" once spraying stops, whereas non-exposed (control group) municipalities have nothing to recover from. A positive coefficient therefore implies that harvested area rebounded at a faster rate in previously-exposed (treated) municipalities than control municipalities.

Our difference-in-difference estimates show that the ban on aerial spraying caused a differential *increase* in harvested area of legitimate crops, implying a process of agricultural recovery in treatment municipalities. However, and perhaps more importantly, point estimates are small and insufficient to reverse the damage already inflicted. Crop harvests in treated municipalities increase by 2% after glyphosate spraying stopped, compared to the 13% decline in harvests during our study period. The magnitude of recovery remains small even five years after the ban on spraying. Our estimates therefore imply that halting aerial spraying reduced negative spillovers on legitimate agriculture, but that agricultural recovery is slow and collateral damage on crops persisted well into the post-policy era.

Given the persistence of agricultural damages from the Plan Colombia era, the question arises: what happened to the damaged cropland that failed to recover? We investigate this using high-resolution land use classifications and estimate our difference-in-difference model with the share of municipality land under various land types as the outcome. We find that municipalities with higher prior exposure to glyphosate drift partly transition into grassland and shrubland after spraying stops.

The paper concludes with a timely policy analysis. In April 2025, under renewed U.S. pressure, the Colombian government announced plans to resume aerial fumigation (Tactics Institute, 2025) after its decade-long ban. Using our retrospective estimates, we simulate how much aggregate spillover crop damage can be avoided through smarter targeting the second time around. We find that $USD 611 million of collateral damage on legitimate crops can be avoided compared to business-as-usual if spray campaigns only target the largest coca hotspots, all else equal. These savings are equivalent to roughly 3.7% of Colombia's agricultural GDP, representing substantial gains from simple policy changes.

Our main contribution to the literature is to credibly estimate externalities from spatially targeted policy. A handful of studies have documented *nearby* spillovers from spatially targeted policies to reduce crime (Blattman et al., 2021), overfishing (Englander, 2023), and deforestation (Assunção et al., 2023). We extend this work by documenting *nationwide* spillovers from a related policy targeting illicit coca cultivation. Given that the direct effect of this policy was ineffective at eradicating coca (Mejia and Restrepo, 2016), quantifying indirect effects (externalities) is important for informing optimal policy design.

Our second contribution speaks to the literature on the effects of pesticide exposure. While the scientific literature (Agostini et al., 2020) and a growing body of economics literature (Camacho and Mejía, 2017; Frank and Taylor, 2022; Dias et al., 2023; Calzada et al., 2023;

Skidmore et al., 2023; Frank, 2024; Reynier and Rubin, 2025) document negative impacts of pesticide exposure on human health, this paper is among the first to provide causal evidence on crop health. In particular, we advance recent work on pesticide externalities, which has emphasized behavioral and adoption responses (Larsen et al., 2024; Missirian, 2024; Coinon, 2025). In contrast, we quantify crop damages arising from off-target glyphosate drift.[3] These results are important in the Colombian context, where agriculture employs 7.5% of the workforce and smallholders grow 70% of domestic food (OECD, 2015).

We also depart from prior work by studying a distinct herbicide application method: aerial spraying via aircraft at substantially higher altitudes and concentrations than conventional agricultural use. The two closest studies from Colombia, Camacho and Mejía (2017) and Horta-Sáenz and Tami-Patiño (2024), study *direct* impacts of aerial coca spraying on health and education, respectively, within sprayed areas. We instead focus on crop health and, more crucially, quantify spatial spillovers on non-targeted areas, extending the literature beyond direct impacts.

Our third contribution is methodological. We use recent advances in atmospheric modeling to measure crop exposure to glyphosate via wind drift. In doing so, we join an emerging literature that uses dispersion models to trace particle drift (Heo et al., 2023; Morehouse and Rubin, 2021; Hernandez-Cortes and Meng, 2023; Wen et al., 2023; Abman et al., 2024). While this literature mainly models air pollution dispersion, we are the first in the applied economics literature to use dispersion modeling to quantify spillovers of herbicide spraying on non-targeted crops.

The next section provides necessary background. Section 3 describes the data and dispersion model. Section 4 outlines the empirical strategy for evaluating spillovers from aerial spraying and Section 5 presents the results. Section 6 presents difference-in-difference estimates of the impact of banning aerial spraying. Section 7 simulates avoided damages from better targeting, and Section 8 concludes.

2 Background

This section discusses illicit coca cultivation in Colombia and the country's main policy response, known as Plan Colombia. We outline the key component of the Plan—aerial glyphosate spraying—and associated risks of herbicide drift on non-targeted crops.

[3] Young et al. (2023) study yield losses and seed adoption responses to dicamba drift using a structural network diffusion model informed by agronomic field trials, focusing on a different herbicide, crop, and setting.

2.1 Coca Cultivation and Eradication

Coca cultivation is the world's largest illicit agribusiness (Rincón-Ruiz and Kallis, 2013), with Colombia as the top supplier of coca leaves, the key input in cocaine production. In 2023, coca cultivation in Colombia reached 254,000 ha., roughly the size of Tokyo and the highest level in two decades (UNODC, 2024). Despite domestic and international eradication efforts, coca farming remains persistent, prompting militarized state-led intervention.

Multiple factors explain coca's resilience. Agronomically, the coca plant thrives in Colombia's fertile soils and favorable climate. Economically, the crop offers rural households a rare combination of short cultivation cycles (6 to 7 months), stable market demand, and on-farm sale to traffickers. In remote regions where infrastructure is sparse and state capacity limited, coca remains one of the few reliable sources of household income.

Successive Colombian administrations have experimented with a wide range of coca eradication policies, from voluntary crop substitution to forced manual removal. By the late-1990s, aerial herbicide spraying became the dominant strategy (Tokatlian, 1995, 1998). This approach was scaled up dramatically under Plan Colombia, a U.S.-backed counter-narcotics and defense program launched in 1999. During the program, roughly $11.6 billion was directed toward eradicating coca through large-scale fumigation campaigns and strengthening the Colombian military and police. The National Antinarcotics Police (DIRAN) led fumigation missions, with logistical and security support from the military. Large aircraft such as the T-65 Thrush and Air Tractor AT-802 (Solomon et al., 2005) sprayed herbicides, while armed helicopter escorts deterred insurgent groups such as the FARC and ELN.

Glyphosate served as the primary input in aerial eradication campaigns. Chemically known as N-(phosphonomethyl) glycine, glyphosate is a broad-spectrum, non-selective herbicide widely used in commercial agriculture (PAN, 2016; Benbrook, 2016). It works by disrupting key biological pathways necessary for plant growth (Giesy et al., 2000; Tzanetou and Karasali, 2020). Commercial formulations, such as Roundup, combine glyphosate salts with surfactants to improve leaf absorption. In Colombia, the sprayed mixture included Cosmo-Flux 411F (U.S. Department of State, 2002; Nivia, 2002; Hewitt et al., 2009), a surfactant blend designed to enhance penetration through waxy leaf cuticles (Solomon et al., 2005). While effective at increasing herbicidal potency, this formulation also raises the potential for unintended uptake by non-target crops and increases the likelihood of collateral damage.

2.2 Wind Drift and Off-Target Damages

Herbicide drift occurs through three mechanisms: i) primary (spray) drift, when droplets are carried by wind during application, (ii) vapor drift, resulting from post-application volatilization; and (iii) particle-bound drift, arising by post-application environmental pro-

Table 1: Comparison of Glyphosate Application Rates

Source	Liters/ha	Concentration (g/L)	Total Glyphosate (Kg/ha)
Producer's suggested dose	2.5	2.5	0.00625
Dose in spraying coca			
Vargas et al. (2003)	23.65	158	3.73
Solomon et al. (2005)	10.40	480	4.99
Marshall et al. (2009)	10.45	354	3.70
MinAmbiente and MinSalud (2014)	23.65	211	4.99

cesses such as wind erosion (van den Berg et al., 1999; Bish et al., 2020). Although glyphosate is non-volatile and therefore not subject to vapor drift (Franz et al., 1997), it remains susceptible to spray drift during application and may also become airborne when attached to soil or dust particles (Tzanetou and Karasali, 2020).

Several factors influence the extent of glyphosate drift: droplet size, nozzle height, wind speed, atmospheric stability, and soil moisture (Jordan et al., 2009; Fritz et al., 2010; Bish et al., 2020). Fine droplets ($<$ 200 microns) are particularly prone to being carried downwind, while dry soils exacerbate dispersion by promoting dust-bound glyphosate movement (Meftaul et al., 2021). Under intense precipitation events, rainfall can remove up to 97% of airborne glyphosate, redistributing it onto non-target surfaces (Chang et al., 2011). In aerial applications, operational parameters also matter: higher aircraft speeds generate smaller droplets (Hewitt et al., 2009), and doubling nozzle height can triple downwind deposition (Butts et al., 2022). Field evidence indicates that low-altitude spraying (2-3 meters above canopy) produces 3 to 8 times more drift than ground-based methods (Butts et al., 2022).[4]

Colombian fumigation operations exhibited conditions highly conducive to drift. Aircraft often flew approximately 30-50 meters above ground (Solomon et al., 2005; DIRAN, 2020; U.S. Department of State, 2003), far higher than the 2-3 meter spraying altitudes in conventional agricultural spraying. Although official protocols restricted spraying under adverse conditions[5] and required coarse droplets, compliance proved difficult in practice (Nivia, 2002). Moreover, despite GPS navigation and real-time weather monitoring, pilots retained final discretion over mission parameters (Solomon et al., 2005).

Glyphosate application dosages also far exceeded conventional agricultural guidelines.[6] Colombian technical assessments indicate that aerial fumigation involved effective discharges

[4] Despite mitigation efforts such as low-altitude flight and coarse droplets (>300 microns), glyphosate residues have been detected up to 800 meters from target areas (PAN, 2016; Ravier et al., 2019).

[5] Protocols prohibit spraying after rainfall, wind speeds >2 m/s, and humidity $<75\%$ (Solomon et al., 2005)

[6] Marshall et al. (2009) shows that low glyphosate doses provide poor control of coca.

of up to 23.6 L/ha of RoundUp Ultra (Table 1), corresponding to a glyphosate concentration roughly 26 times higher than manufacturer-recommended use. The addition of surfactants[7] further amplified biological efficacy by up to a factor of four (Nivia, 2002), implying an effective biological impact exceeding conventional recommendations by more than two orders of magnitude. The combination of exceptionally high application rates and elevated flight altitudes makes it critical to understand the extent to which airborne glyphosate drifted beyond its intended target and caused off-target damage in receiving regions.

2.3 The End of Aerial Spraying

Despite intensive fumigation campaigns under Plan Colombia, coca cultivation remains persistent, casting doubt about the long-term effectiveness of chemical eradication policies. While operationally effective in delivering herbicide to targeted coca plots, mounting complaints by rural households highlighted substantial risks (Defensoría del Pueblo, 2014). Documented concerns included off-target herbicide exposure, excessive dosages, and significant harm to rural communities. These issues fueled public opposition and policy debate, prompting skepticism about the strategy's viability as a counter-narcotics tool.

Starting in the mid-2000s, accumulating evidence began linking glyphosate spraying to a range of environmental and health impacts. Research documents contamination of drinking water (Myers et al., 2016), damages to soil micro-biota (Dewar et al., 2000; Sanderson et al., 1999), disruption of pollinator behaviors (Delkash-Roudsari et al., 2020), and impaired plant nutrient uptake and seed germination (Blackburn and Boutin, 2003).

These growing concerns culminated in 2015, when Colombia officially banned aerial coca spraying. The decision followed the World Health Organization's classification of glyphosate as a probable human carcinogen (International Agency for Research on Cancer, 2015). Whether the ban reversed the damages accrued over more than a decade of intensive fumigation remains an empirical question. We answer this question in Section 6 and show that damages persist several years after the policy ends.

2.4 Agriculture in Colombia

With this background, the remainder of the paper quantifies off-target effects of glyphosate spraying on Colombia's legal agricultural sector. We focus on agriculture for two reasons: first, there is already a crowded literature documenting spillovers on human health (see Literature Review), whereas evidence on damages to crop health is limited. Second, agriculture makes up 40% (44 million hectares) of Colombia's land area, contributes 15% of GDP, and

[7] Cosmo-Flux 411F in Colombia.

employs roughly 7.4% of the workforce (OECD, 2015, 2023).

Colombia's diverse landscapes feature a variety of crop systems potentially affected by glyphosate drift. In the tropical lowlands, banana, cotton, soybeans, rice, and sugarcane thrive. In mid-elevation temperate areas, farmers grow coffee, citrus fruits, papaya, flowers, and beans, many of which are critical for the country's (legal) agricultural exports. Cooler highlands support cereals (e.g., wheat, barley, oats), vegetables, tubers (e.g., potatoes, yucca), and fruit trees. In Section 5.4 we estimate spillover damages separately by crop type to understand which are more vulnerable.

The risk of glyphosate drift into non-targeted fields is especially acute because coca is frequently inter-cropped with legal crops or grown adjacent to subsistence plots (Nivia, 2002; Rincón-Ruiz and Kallis, 2013). Smallholders typically operate on narrow margins, and off-target herbicide exposure can result in substantial yield losses. Field and community reports document damage from fumigation campaigns to staple crops, such as plantains, yucca, and rice, sometimes hundreds of meters beyond targeted coca fields (Nivia, 2002; Rincón-Ruiz and Kallis, 2013; Defensoría del Pueblo, 2014; Consejo de Estado, 2021). In the empirical analysis that follows, we use an atmospheric dispersion model to quantify spillovers from aerial spraying onto non-targeted crops across the country.

While genetically modified (GM) crop varieties exhibit low sensitivity to glyphosate, adoption is negligible during our study period and concentrated mainly in cotton (introduced in 2003) and maize (introduced in 2007) (Brookes, 2020). In Section 5.5, we provide evidence in that farmers did not adapt to glyphosate exposure by adopting GM varieties.

3 Data

We assemble several novel datasets to quantify spillovers from aerial coca spraying, including locations of illegal plantations, digitized maps of sprayed fields, and municipal agricultural surveys. Wind drift from aerial spraying is measured via an atmospheric dispersion model. This section provides an overview of the data and dispersion model.

3.1 Main Data Sources

3.1.1 Illicit Coca and Aerial Spraying

We obtained 1km resolution maps of illicit coca plantations between 2011-2015 from the UNODC Integrated Illicit Crops Monitoring System (SIMCI in Spanish). UNODC processes and verifies raw imagery to distinguish coca from other crops. The final dataset measures hectares of coca in a gridcell. Figure 1A (green) maps coca in the baseline year. About 20%

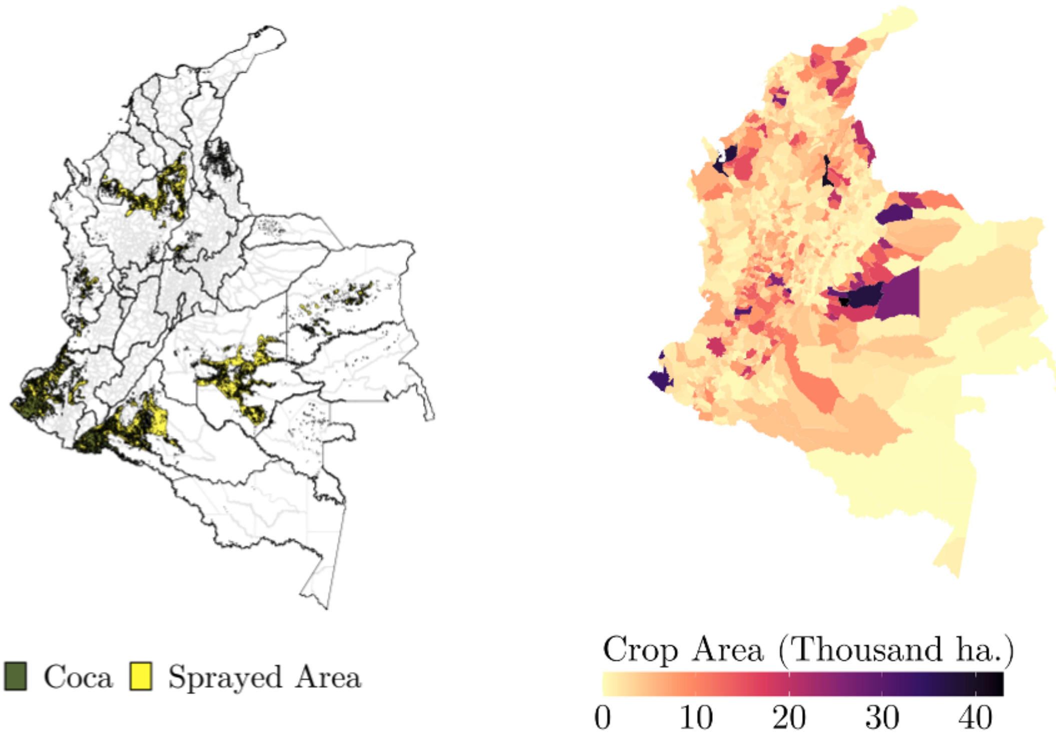

Figure 1: Coca Plantations, Aerial Spraying, and Legitimate Agriculture (2011)
Note: Data are from 2011. In Panel A (left), green areas are coca and yellow are sprayed areas—all sprayed areas had coca planted. Panel B (right) shows harvested area of legitimate crops across municipalities.

of municipalities grow coca, mainly in the North, West, and Central regions. The average municipality cultivates about 3,300 ha. per year of coca (Table A1).

To measure aerial spraying, we digitized SIMCI's annual Coca Cultivation Survey maps of sprayed areas from 2011 until 2015 (UNODC and Government of Colombia, 2011-2015).[8] Shapefiles demarcate polygons sprayed during the year, but not the exact date of spraying. Since our concern is wind drift from aerial spraying, these polygons serve as the point source for our dispersion model (Section 3.2.1). Figure 1A (yellow) shows sprayed areas in the baseline year: roughly 5,600 ha. per year was sprayed in the typical municipality, implying that 60% of sprayed area was covered by coca fields (Table A1). Also note that not all coca fields are sprayed, implying strategic targeting.[9] We account for this "place-based endogeneity" by measuring the distance from each municipality to the nearest sprayed area and controlling for this in all regressions (Section 3.1.3).

[8]In 2015, the Colombian government suspended the aerial fumigation program (see Section 6).

[9]The underlying variables used to select targeting areas are not publicly available, as the criteria employed by the National Anti-Narcotics Police are classified.

3.1.2 Legitimate Crop Production

To quantify spillovers from targeted herbicide spraying onto non-targeted crops, we use detailed municipal-level agricultural data from the Ministry of Agriculture's Evaluaciones Agropecuarias Municipales (EVA) annual survey. This dataset reports planted area, harvested area, and output for 223 crops at the crop-municipality-year level, making it the most granular and comprehensive sub-national agricultural dataset for Colombia. Figure 1B maps harvested crop area: the typical municipality produces 44,000 tonnes of crops on 4,000 ha. of land (Table A1). The figure also shows that most coca grows outside agricultural hubs, consistent with coca's illicit status which pushes production to remote, hard-to-monitor areas. Yet, as we show in Section 3.2.1, coca hubs are connected to agricultural hubs via wind drifts, exposing productive farmland to glyphosate through aerial coca spraying.

We calculate the economic value of agriculture using crop price data from FAOSTAT. This database provides prices received by farmers in $USD/tonne at the national level. First, we identify 51 crop categories grown in Colombia for which FAOSTAT price data are available. For each category-year, we compute annual revenue by multiplying its 2011 price (to express values in constant USD) by total production in tons. Next, we aggregate crop revenues at the municipal level to obtain total agricultural revenue per municipality per year.

To validate our survey-based estimates, we complement the administrative crop data described above with satellite measures of crop productivity. First, we use the Normalized Difference Vegetation Index (NDVI), a widely used measure of vegetation health, obtained from MODIS at 1km resolution (Didan et al., 2015).[10] Second, we use remotely-sensed land classification maps at 300m resolution from the European Space Agency (ESA). We use the cropland layer, which indicates if a pixel has rainfed, irrigated, or mosaic crops (small-scale agriculture interspersed with natural vegetation). To obtain a municipality-level measure, we extract means over cells within a municipality, weighted by cell overlap fraction.

3.1.3 Covariates

We include two sets of covariates in all our regressions. The first set accounts for the endogenous spraying decision and includes coca area and distance to the nearest sprayed area. Coca area (Section 3.1.1) accounts for the fact that places with more coca are more likely to be sprayed. The straight-line distance from the centroid of each municipality to the nearest sprayed area thus controls for other unobserved determinants of spraying.

The second set of covariates include temperature and rainfall, which partially guide wind drifts and can affect agriculture directly (Yuan et al., 2023). Annual temperature (°C) and

[10] Since NDVI also captures forests, we control for forest cover in all regressions with NDVI using forest cover data from the Vegetative Continuous Fields (VCF) gridded data product (Townshend et al., 2017).

rainfall (mm) are from the ERA5 product at 0.125° resolution (Hoffmann et al., 2019). In a robustness test (Section 5.3), we augment this set with additional meteorological controls, including energy flux, planetary boundary layer height, humidity, and velocity, and find no changes in our estimates. For all gridded data, we extract means over cells within a municipality, weighted by cell overlap fraction.

3.2 Measuring Wind-Driven Exposure to Aerial Herbicide Spraying

Our task is to measure the exposure of a municipality to aerial spraying. Our starting point is the fact that aerial pesticide spraying is prone to particle drift and volatilization once applied (Boonupara et al., 2023; Cederlund, 2017; Gandhi et al., 2021). To measure the movement of airborne pesticides, we use an atmospheric dispersion model that simulates the most likely drift pathways from a source location.

3.2.1 The HYSPLIT Dispersion Model

We use the Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) model developed by NOAA (Draxler and Hess, 1998; Draxler et al., 2020) to measure municipalities' exposure to aerial spraying via wind drift. The model simulates three-dimensional movement of tracer particles released from a point source—in our case, the location sprayed. Trajectories are primarily driven by wind, but also incorporate other meteorological data.[11] As described in the next subsection, we measure a municipality's exposure to aerial spraying by the share of tracer particles originating from sprayed areas landing within its borders.

The primary advantage of measuring exposure in this way is that we can precisely measure spillovers from aerial spraying. Since tracer particle paths from sprayed locations can pass over and deposit in municipalities that were not directly sprayed, these non-sprayed municipalities are exposed to glyphosate entirely through wind-driven spillovers. Whether these spillovers lead to legitimate crop damage is the central question of this paper.

There are several related advantages of using a dispersion model. First, the shape, size, and diffusion rate of dispersion plumes are entirely model-generated. In contrast, traditional wind direction vectors require assuming an arbitrary length and plume, often a 45° cone around the vector. Second, our measure can be cumulated to any spatial or temporal level without loss of information, which becomes important when defining treatment and control groups in our difference-in-difference design (Section 6.1). Conventional wind vectors capture seasonal variation in wind direction, which loses explanatory power when averaged over multiple years. Lastly, since our exposure measure is continuous, we can

[11] HYSPLIT also uses temperature, planetary boundary height, surface pressure, velocity, surface roughness, heat flux, short wave flux, humidity, convective energy, and precipitation (Draxler and Hess, 1998).

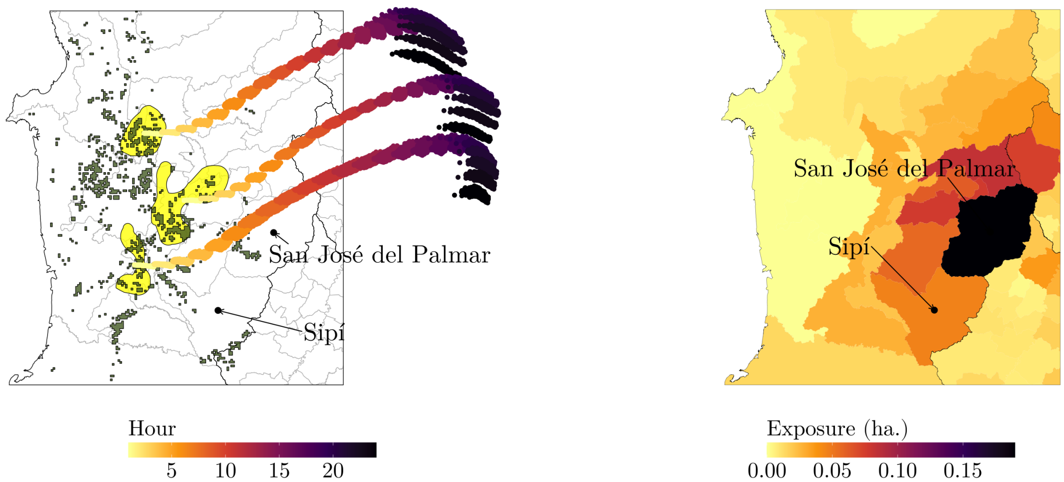

Figure 2: HYSPLIT Output (January 2011)

Note: Panel A shows HYSPLIT particle trajectories on January 1st, 2011 from three example sprayed areas (yellow). Colors denote where particles end up in each hour. Panel B shows municipality exposure (E_{mt} in Equation 2) to coca eradication in 2011.

group similar values into "plumes" and correct for spatial error correlation by clustering at the plume level. This enables more precise estimation of standard errors.

3.2.2 Measuring Exposure to Aerial Spraying

Step 1: Dispersion The first step for computing exposure to aerial spraying is to measure wind drift from each sprayed area. We generate a 0.1° grid over Colombia and set the centroid of each sprayed area (Figure 1A) as the point source.[12] Next, from each point source, we set HYSPLIT to emit a default number of tracer particles from 50m height for 24 hours, once a month, from 2011-2015.[13] We do this in the absence of data on the exact days that spraying took place. Running the model once a month enables us to calculate average statistics of wind drift over the year. While less precise than if we knew the day of spraying, using annual averages of wind direction is commonplace in the literature.

Figure 2A shows hourly tracer particle locations from an example spray in 2011. Note that these particles do not represent glyphosate per se—they are tracers that draw the mostly likely path that any particle from the point source would take given HYSPLIT meteorology assumptions. We implement placebo tests in Section 5.2 to rule out other emission sources in the sprayed area, strengthening the case that particle paths trace glyphosate drift. After each model run, we measure exposure of a gridcell as the downwind count of tracer particles, $ParticleCount_{ijt}$, landing in receptor grid cell i, originating from spray location j at time t.

[12]For big spray areas (>95th pctile), we randomly sample 5 points on the polygon as the point sources.
[13]50m is the typical height at which aircrafts drop glyphosphate (U.S. Department of State, 2003)

Step 2: Normalization The second step is to normalize $ParticleCount_{ijt}$ to one and then sum over model runs j in each year, adjusting for differences in sprayed area, $SprayArea_{jt}$:

$$CellExposure_{it} = \sum_{j \in \mathcal{J}_t} \left(\frac{ParticleCount_{ijt}}{\sum_i ParticleCount_{ijt}} \cdot SprayArea_{jt} \right) \tag{1}$$

Since we sum over all sprayed areas j in a year t, $CellExposure_{it}$ measures the *total modeled exposure* of gridcell i to aerial spraying in that year. This measure also accounts for the fact that larger spray zones pose greater potential for exposure. $CellExposure_{it}$ can be interpreted in ha., since $SprayArea_{jt}$ is effectively distributed across gridcells according to cell i's exposure intensity, which ranges from zero to one. For example, if the area sprayed is 100 ha., and the exposure of far-away grid cell i is 0.01, then it is *as if* 1 ha. of coca was sprayed in gridcell i, even though it may have no coca. This is how we capture spillovers.

Step 3: Aggregation The third step aggregates at the municipality-year level. Municipality m's exposure to spraying in year t is the sum of modeled exposure across gridcells $i \in m$:

$$E_{mt} := \sum_{i \in m} CellExposure_{it} \tag{2}$$

E_{mt} is the main explanatory variable in the first part of the empirical analysis. Figure 2B visualizes this variable in 2011. Again, note that E_{mt} does not measure exposure to glyphosate per se, but rather wind drift into municipality m from locations where coca was sprayed with glyphosate. Since sprayed coca fields are often in very remote places with little other economic activity, it is unlikely that E_{mt} captures exposure to any other airborne pollutant besides glyphosate. We confirm this with several placebo tests in Section 5.2.

The underlying variation in E_{mt} arises from three sources. First, *spatial variation* arises from physics formulae for gas movement and diffusion as modeled by HYSPLIT. A second source of *spatial variation* comes from the size of the area sprayed. Holding meteorology constant, the spraying of larger coca plantations generates greater exposure due to the area-weighting in Equation 1. Third, *temporal variation* arises from embedded formulae that describe the dynamics of particle transport. Importantly, both spatial and temporal variation depend on the location sprayed and can change when new plantations are targeted or previous spray campaigns are halted. This means that exposure is only plausibly exogenous *conditional on spraying*, since the choice to spray a location is strategic. To account for this, we control for distance from a municipality to the nearest sprayed area in all our regressions.

4 Empirical Strategy

This section describes our research design for estimating spillovers from aerial coca spraying. We use a two-way fixed effects (TWFE) design to compare agricultural outcomes within municipalities at varying levels of wind-driven exposure to aerial coca spraying, controlling for strategic targeting of coca plantations. This design exploits rich cross-sectional and temporal variation, giving rise to credible control groups for municipalities exposed to spraying: other municipalities with similar geographic characteristics, located equidistant to sprayed areas, but less exposed to them due to plausibly random differences in wind drifts.

Figure 2 provides visual intuition for our empirical strategy. Consider the experience of San José del Palmar and Sipí, two remote municipalities near the West coast. Both grow coca (Panel A, green), yet neither experienced aerial eradication in 2011 (Panel A, yellow). Moreover, they are both equidistant to the nearest sprayed area, meaning that they likely share similar determinants of spraying. Despite similar exposure *potential*, proximity, and geography, the two municipalities face drastically different exposure to the nearby spray campaign. San José lies directly in the exposure path of the southernmost sprayed area, whereas Sipí is completely unexposed. These differences can be seen even when aggregating exposure at the annual level (Figure 2B). Because differences in exposure arise from plausibly random wind patterns *conditional on the decision to spray*, we can use this variation to estimate the causal impact of downwind exposure to aerial eradication.

4.1 Main Estimating Equation

Our estimation strategy generalizes the visual intuition described above. We quantify spillovers from targeted coca spraying on off-target crops with the following equation:

$$\text{Log } Y_{mt} = \beta \cdot E_{mt} + \mathbf{X}'_{mt}\Omega + \alpha_m + \gamma_t + \epsilon_{mt} \tag{3}$$

where m indexes municipalities and t indexes years between 2011-2015. Y_{mt} denotes the logarithm of the harvested area in municipality m at time t. We also estimate versions where Y_{mt} measures output, revenue, and satellite measures of crop health. E_{mt} measures m's exposure to aerial herbicide spraying during year t (Equation 1). $\mathbf{X}'_{mt}$ is a vector of covariates including temperature, rainfall, and distance from m to the nearest sprayed area. The distance control is crucial and ensures comparisons are made between municipalities with similar characteristics that determine the choice to spray it (Section 3.1.3). All specifications include municipality and year fixed effects, α_m and γ_t, respectively.

The coefficient of interest is β, which captures the percentage change in agricultural outcomes from an additional hectare of wind-driven glyphosate exposure. $\beta < 0$ indicates negative spillovers, consistent with targeted aerial coca spraying harming off-target crops via wind-driven glyphosate drift.

We cluster ϵ_{mt} at the plume level. We choose this level of clustering since gridded values of $CellExposure_{it}$ are likely to be spatially correlated through unobserved formulae used by HYSPLIT that govern gas movement. Plumes are demarcated using a k-means clustering algorithm that groups cells with similar exposure values. Municipalities spanned by the same plume are assigned a common cluster ID and those spanned by multiple plumes are assigned the cluster with the largest overlap. We demarcate 50 plumes in the main analysis and test robustness to alternative numbers of clusters in Section 5.3. We also document robustness of our results to the computation of Conley standard errors.

4.2 Identification

Identification of β relies on the assumption that exposure is orthogonal to unobserved determinants of crop output, once we control for municipality and year fixed effects. There are four key threats to this assumption. First, the decision to spray a coca field is endogenous. We therefore control for distance to the nearest sprayed area to account for the determinants of spraying. Second, conditional on distance to the nearest sprayed area, differences in weather between treatment and control municipalities may affect particle trajectories as well as crop yields directly. We thus include temperature and rainfall in $\mathbf{X}'_{mt}$ to avoid potential omitted variable bias. Third, since our exposure measure is based on wind paths, it may inadvertently capture pollution from other nearby sources such as energy, vehicles, or biomass burning. To rule out these alternative pathways, we provide robustness checks that show null impacts of exposure on $PM_{2.5}$, SO_2, and NO_2 (Section 5.3). Lastly, some municipalities might be coca hotspots, crowding out legitimate agriculture and making the municipality more exposed to drift. We drop sprayed municipalities in a robustness check and show that our identification is based only on our measure of indirect exposure; our estimates are qualitatively unchanged.

β is estimated via OLS in a TWFE setup with continuous treatment. This estimator suits our context because some municipalities receive continuous "doses" of exposure in each period, whereas others are untreated. β thus represents a dose response to exposure at the municipality level and is best interpreted as the slope of the dose-response curve. A key concern with continuous treatment is that treatment intensity may itself be an endogenous choice by units, which can bias the TWFE estimand (Callaway et al., 2024). In our context, exposure intensity is not chosen by municipalities or farmers. Conditional on the decision of the government to spray a coca field (which we control for), municipalities' exposure to the resulting glyphosate drift is determined by atmospheric processes. Municipalities thus do

Table 2: Agricultural Spillovers from Coca Eradication

	(1) Area	(2) Area	(3) Output	(4) Revenue	(5) NDVI
Exposure (ha.)	-0.131**	-0.132**	-0.125**	-0.139***	-0.014**
	(0.055)	(0.057)	(0.050)	(0.039)	(0.005)
Coca Controls	No	Yes	Yes	Yes	Yes
Climate Controls	Yes	Yes	Yes	Yes	Yes
Forest Cover	No	No	No	No	Yes
Municipality FEs	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓
Observations	5610	5610	5610	5610	5610

* $p < .1$, ** $p < .05$, *** $p <.01$. Data are at the municipality-year level. Outcomes are in logs. "Coca Controls" include distance to nearest sprayed area and hectares of coca. "Climate Controls" include temperature and rainfall. "Exposure" to aerial spraying is measured in hectare-equivalents. All specifications include municipality and year fixed effects. Standard errors clustered at the plume level.

not select into higher or lower doses, nor can they adjust behavior to influence exposure.[14]

5 Results: The Plan Colombia Years

This section quantifies off-target impacts of targeted aerial coca spraying. We find that aerial spraying damages off-target crops via glyphosate drift, resulting in large revenue losses for farmers. We first present our main estimates and then investigate whether crop health rebounded after aerial spraying was banned in Section 6.

5.1 Main Results

Table 2 presents estimates of Equation 3. We explore a variety of agricultural outcomes from administrative data and then validate our estimates with satellite data. The primary outcome is log harvested area (column 1 and 2). We find $\beta < 0$: wind-driven exposure to targeted aerial coca spraying damages off-target crops. This result is robust to controlling for proximity to the nearest sprayed area and weather (column 2), implying that our estimates are not driven by endogenous determinants of spraying nor by direct effects of weather. The point estimate in column 2 implies that an additional unit of exposure to aerial spraying during the year causes a 13.2% reduction in harvested crop area.

[14]Still, we assess whether our results could be driven by comparisons across different exposure intensities, as cautioned by Callaway et al. (2024). The resulting effects are qualitatively consistent with our baseline estimates. See Appendix B.

To put this estimate in perspective, consider the fact crop harvests in the average municipality increased by 273 ha. during the study period, implying a pattern of agricultural growth across Colombia. At the same time, the average municipality was exposed to an equivalent of 0.067 ha. of airborne glyphosate via wind drifts, translating into $e^{(0.067\times -0.132)} =$ 0.99 ha. in crop damages. Therefore, agricultural expansion suffered a $0.99/273 \approx 0.4\%$ setback due to spillovers from coca eradication between 2011-2015.

Columns 3 and 4 explore sensitivity to alternative outcomes: log output (tonnes) and log revenue, respectively. Revenue is a weighted average of individual crop output and corresponding national prices (Section 3.1.3). Exposure to aerial spraying reduces output and revenue by magnitudes similar to the decline in harvested area. Column 5 validates our estimates with satellite-derived NDVI, a measure of vegetation health based on light absorbed by plants. Since NDVI measures both crops and forests, we control for forest cover in this specification to isolate effects on crop health. We continue to observe negative spillovers of aerial spraying on crop health, reinforcing our main estimates and providing reassurance that they are not driven by biases in administrative data collection.

5.2 Falsification Tests: Does Exposure Capture Glyphosate Drift?

Recall that modeled exposure (Equation 1) is based on *wind drifts* from areas sprayed with glyphosate, not actual glyphosate concentrations. We thus present two falsification tests to validate that observed damages to off-target crops (Table 2) are driven specifically by glyphosate exposure and not exposure to other airborne pollutants.

First, we simulate wind drifts from 200 randomly selected coca farms that were *not sprayed* with glyphosate[15], following the same modeling approach in Section 3.2. This generates a placebo measure of municipality m's exposure to non-sprayed coca farms in time t. If our main estimates are driven by glyphosate drift from aerial spraying, then exposure to *non-sprayed* areas should have no impact on off-target crops since there is no glyphosate drift associated with the placebo. On the other hand, if our main exposure measure captures other nearby emission sources (e.g. power plants, coca processing), then we should see negative spillovers on agriculture even through placebo exposure.

Table A2 presents estimates where we directly control for placebo exposure in the baseline equation. Both exposure measures are reported in standard deviations to account for differences in measurement. The placebo coefficient is near-zero and statistically insignificant for all outcomes, whereas the main coefficient of interest remains negative and significant. This exercise validates our exposure measure and builds confidence that our main

[15]We sample 200 placebo farms to balance computational time and statistical precision. HYSPLIT is run on each farm using the steps in Section 3.2, with coca area as weights (Equation 1) instead of spray area.

estimates are not driven by other emissions sources or air pollutants.

Second, we provide additional evidence that our exposure measure does not entangle other pollutants by directly estimating impacts on SO_2 (associated with energy generation), NO_2 (associated with vehicle emissions), and $PM_{2.5}$ (associated with biomass burning). Anecdotally, this endogeneity concern is minimal since coca plantations are set up far from human activity. Econometrically, if exposure is orthogonal to concentrations of these three pollutants, we can rule out alternative pollution pathways and become more confident that glyphosate drift is the key mechanism driving spillover crop damage.

Columns 1-3 of Table A3 show a near-zero and statistically insignificant impact of wind-driven exposure to aerial spraying on ambient $PM_{2.5}$, SO_2, and NO_2 levels[16]. Since the dispersion model measures wind paths from the exact locations sprayed, and there is no relationship between exposure to these locations and ambient pollution, it is hard to imagine any other reason driving crop damage in Table 2 besides glyphosate drift.

5.3 Additional Robustness Checks

Table A4 tests robustness to alternative specifications (column 1-4), alternative data sources (columns 5-6), and sample restrictions (columns 7-8).

A key concern is that factors other than coca eradication could drive both glyphosate exposure and agricultural outcomes. One possibility is that legitimate crop fumigation for rice, bananas, and other crops, could independently affect agriculture while correlating spatially with our exposure measure. Column 1 addresses this by controlling for the number of non-coca fumigation flights potentially crossing each municipality, constructed from AeroCivil permit data on flight dates and airport coordinates.[17] The coefficient is virtually unchanged, consistent with legal agriculture fumigation usually being conducted at substantially lower altitudes and with smaller doses than aerial coca eradication (Section 2.2).

Another concern is that the meteorological conditions determining particle paths may also affect crops directly. Column 2 addreses this by augmenting our baseline controls with energy flux, planetary boundary layer height, wind velocity, and humidity.[18] The coefficient remains the same, suggesting that weather conditions are not confounding our estimates.

Columns 3 and 4 investigate whether unobserved spatial or temporal heterogeneity drives our results. Column 3 adds department-year fixed effects to account for differential agricultural trends across departments. The coefficient remains within the confidence interval

[16]Gridded PM2.5 is obtained from Van Donkelaar et al. (2016). Gridded SO2 and NO2 is obtained from the MERRA-2 and HAQSTAT reanalysis products, respectively.

[17]We assume that legal fumigation is carried out on similar aircrafts as coca fumigation. Through discussions with Antinarcotics officers, Reyes (2014) find that fumigation planes have a range of 80 miles.

[18]These data are from the MERRA-2 reanalysis product M2T1NXFLX files.

of the baseline estimate, which is unsurprising since exposure is plausibly orthogonal to department characteristics. Column 4 adds linear municipality time trends to control for unobserved factors that vary at a constant rate over time. The coefficient is very similar.

Column 5 documents robustness to an alternative satellite-derived measure of cropland extent to complement NDVI. Cropland percent is measured from ESA maps (Section 3.1.2) and include irrigated crops, rainfed crops, or small-scale cropland interspersed with natural vegetation. The coefficient remains negative and statistically significant.

Another important threat to the identification strategy is place-base endogeneity: coca rich-areas are more likely to be sprayed and thus mechanically more likely to be exposed, potentially confounding wind-driven exposure with unobserved characteristics of coca-growing regions. We address this concern in columns 6 and 7. Column 6 applies a 30km mask around the centroid from which the dispersion model is run.[19] This removes places in the vicinity of the sprayed area which may feature unobserved characteristics that co-determine spraying, exposure, and agriculture, thereby helping isolate wind-driven exposure. Column 7 adopts a more extreme approach by excluding all sprayed municipalities from the sample, which leaves the coefficient to be identified solely off of wind drift rather than endogenous coca eradication. We continue to find strong evidence of negative spillovers in both cases.

Finally, table A5 reports estimates from alternative methods of inference. Recall that our baseline estimates cluster at the plume level using machine learning to demarcate 50 plumes (Section 4.2). While also arbitrary, column 1 tests robustness to demarcating 30 plumes instead. Column 2 clusters by municipality, the same level as the treatment. Columns 3-6 investigate spatial correlation more systematically by estimating Conley (1999) standard errors for kernel cut-off distances ranging from 200km to 500km.[20] Statistical precision of our estimates are robust to these alternative methods of accounting for spatial correlation.

5.4 Treatment Heterogeneity: Soil Quality and Crop Diversity

We next investigate whether better soil quality and greater crop diversity can minimize spillover damages to off-target crops. While both of these offer a "nature-based solution" for reducing climate-driven risks of crop failure (Renard and Tilman, 2019; Renard et al., 2023), there is little evidence on their success as a stabilizer against other extremes such as glyphosate drift. We estimate treatment heterogeneity with the following equation:

$$Y_{mt} = \beta_1 \cdot E_{mt} + \beta_2 \cdot (E_{mt} \cdot S_m) + \mathbf{X}'_{mt}\Omega + \alpha_m + \gamma_t + \epsilon_{mt} \quad (4)$$

where m and t are indices for municipality and year, respectively. We estimate one ver-

[19]The mask deletes grid cells within 30km of the point source during calculation of E_{mt} (Equation 1)

[20]We use the Colella et al. (2019) implmenetation with the acreg stata package.

Table 3: Heterogeneity by Soil Quality

	(1) Area	(2) Output	(3) Revenue	(4) NDVI
Exposure (ha.)	-0.964**	-1.030**	-0.906***	0.006
	(0.459)	(0.421)	(0.302)	(0.017)
Exposure (ha.) $\times$ Soil Quality	0.027*	0.029**	0.025**	-0.001
	(0.015)	(0.014)	(0.010)	(0.001)
Coca + Climate Controls	Yes	Yes	Yes	Yes
Forest Cover	No	No	No	Yes
Municipality FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓
Observations	5610	5610	5610	5610

* $p < .1$, ** $p < .05$, *** $p < .01$. Data are at the municipality-year level. Outcomes are in logs. "Coca Controls" include distance to nearest sprayed area and hectares of coca. "Climate Controls" include temperature and rainfall. "Exposure" to aerial spraying measured in hectare-equivalents. All specifications include municipality and year fixed effects. Standard errors clustered at the plume level.

sion of this equation where S_m measures baseline soil quality using gridded data on soil clay percentage for Colombia[21], and another version where S_m measures the Shannon Diversity Index, which we calculate from the EVA data as the number of crop species weighted by relative planted area. All other terms are the same as Equation 3. β_2 is the coefficient of interest and is positive if soil quality or crop diversity buffers against glyphosate drift.

Table 3 presents estimates of β_2 for soil quality. Higher soil quality cushions the damage from glyphosate drift on off-target crops. The point estimate implies that a one percentage point increase in clay composition mitigates the adverse impact of aerial spraying on harvested area by $0.027/0.964 \approx 3\%$ (column 1). Soil quality exhibits a similar mediating effect for output (column 2) and revenue (column 3). We find no heterogeneous effects for NDVI.

Table A6 presents estimates of β_2 for crop diversity. Qualitatively, crop diversity buffers against negative spillovers from aerial spraying, but estimates are imprecise. Table A7 tests robustness using species richness, an alternative diversity metric measured as the number of unique crops without weighting each one by relative planted area. Again, we document a moderating role of crop diversity, but precision remains low. These results suggest that, while crop diversity has been shown to increase resilience against climate-driven extremes, diversification may not work against other extremes such as glyphosate exposure.

Lastly, we test whether annual or perennial crops are more resilient. Annual crops have seasonal lifecycles and may be more vulnerable to short-term stressors, whereas perennials

[21] Data accessible here: https://essd.copernicus.org/articles/14/4719/2022/.

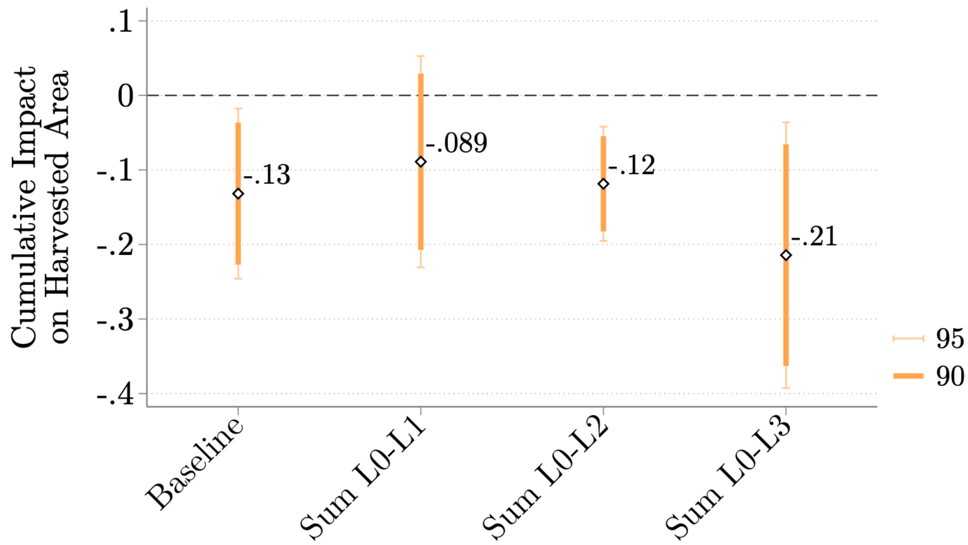

Figure 3: Dynamic Estimates

Note: The outcome is log harvested area. "Baseline" repeats the main result. "Sum L0-L1" adds the first lag of exposure to the main specification and reports the sum of coefficients on the first lag and baseline effect. "Sum L0-L2" sums up to the second lag, and so on. Bars are confidence intervals. All regressions control for distance to nearest sprayed area, hectares of coca, temperature, rainfall and municipality and year fixed effects. Standard errors clustered at the plume level.

grow over multiple years and have better regenerative capacity. Table A8 presents estimates of Equation 3 for nine types of annual crops, with log harvested area as the outcome. Damages from glypohsate spillovers are most pronounced for oil seeds, fibers, and an "other" category defined by EVA that we are unable to unbundle. Table A9 shows estimates for perennials: negative spillovers are strongest for plantains and tree crops. Yet, when categories are combined (column 1), effects on both crop groups are small and insignificant. These results suggest limited heterogeneity; both annuals and perennials appear susceptible to damage from glyphosate drift.

5.5 Adaptation: Dynamics, Farm Credit, and GMO Varieties

Our estimates thus far reflect off-target crop damage from aerial coca spraying *within the year*. They are also net of adaptation, which occurs if exposure prompts the adoption of herbicide-resistant crops. However, adaptation would bias β upwards, counter to the idea of negative spillovers. In other words, the fact that we find $\beta < 0$ in Table 2 means that our estimates hold in spite of adaptation and not because of it.

Although adaptation is not widespread enough to overturn our result, we can still diagnose the extent of adaptive behavior by studying dynamic effects. Figure 3 presents estimates of Equation 3 with lags up to three years. White diamonds are the sum of baseline and lagged coefficients, which measures net impacts of exposure to aerial spraying several periods later. If exposure prompts adaptive investments, then a U-shape should arise as negative effects become muted over time.

Instead of a U-shape, we find that damages to off-target crops are persistent. Cumulative damages two years later (Sum "L0-L2") are nearly equal to the baseline effect. While the extent of negative spillovers increases three years later, we cannot reject the null hypothesis that coefficients are equal since confidence intervals overlap point estimates across all periods. The more important takeaway is that negative spillovers are persistent and adaptation appears minimal in the medium run.

Table A10 investigates whether the lack of adaptation is reflected in farmers' investment behavior using farm credit data from EVA. Since adaptation requires upfront expenses, increased credit uptake in exposed municipalities can signal adaptation. Each column reports estimates of Equation 5 where the outcome measures credit disbursed to small, medium, and large farm operators in a municipality. While exposure weakly increases total credit provision (column 1), there are no impacts on individual producer groups (columns 2-4). These results suggest that farmers may be unable to adapt due to limited microcredit access.

The most direct test of adaptation is whether farmers shift to glyphosate-tolerant GMO crops. In the absence of municipality-level data, we obtained coarser department-year data on GMO maize and cotton through a Freedom of Information Request. Table A11 presents estimates of Equation 3 at the department level, where the outcome is GMO crop share. Since exposure is at the department level, we lose the ability to exploit plausibly exogenous variation in wind drift across similar municipalities. We find no correlation between exposure to aerial spraying and GMO crop adoption, suggesting limited adaptation at the department level. This aligns with the dynamic estimates and farm credit results.

6 The Ban on Aerial Spraying

Having established clear negative externalities from aerial spraying, the logical policy prescription is to ban the practice and find alternative ways to curb illegal coca production. Indeed, the Government of Colombia suspended aerial spraying in May 2015, citing the protection of population health and environmental conservation (El Consejo Nacional de Estupefacientes, 2015). This section evaluates whether the policy was effective at revitalizing the agricultural sector by reducing damage to off-target crops.

6.1 Policy Evaluation: Difference-in-Differences

We use a difference-in-differences design to study the impact of banning aerial spraying in 2015. Treatment is defined as a continuous variable measuring pre-policy cumulative exposure to aerial spraying, $E_m := \sum_{2011}^{2015} E_{mt}$, where E_{mt} is defined in Equation 1. Interacting E_m with a post-policy indicator generates two sources of variation that we exploit for identification: (i) geographic variation in pre-policy exposure to aerial coca spraying across municipalities (Figure A1), and (ii) time variation in crop production before and after the ban. Our difference-in-difference strategy thus compares crop health across previously exposed and less-exposed municipalities, before and after the ban with the following equation:

$$Y_{mt} = \theta \cdot (E_m \cdot \mathbb{1}_{t>2015}) + \mathbf{X}'_{mt}\Omega + \alpha_m + \gamma_t + \epsilon_{mt} \tag{5}$$

where m and t are indexes for municipality and year, respectively. Agricultural outcomes of interest are the same as Equation 3. E_m denotes the treatment, i.e., cumulative exposure of municipality m to aerial spraying during the pre-period. This enters interacted with $\mathbb{1}_{t>2015}$, a pre-post indicator that switches on in 2015 when aerial spraying was banned. As before, α_m and γ_t are municipality and year fixed effects, respectively.

The coefficient of interest is θ, the impact of banning aerial spraying on crop health in municipalities that were more exposed to glyphosate drift during Plan Colombia compared to those that were less-exposed. Since these control municipalities were minimally exposed in the first place, they have little to recover from and thus form the counterfactual agricultural growth trend. $\theta > 0$ thus implies that agriculture in previously-exposed areas grew faster post-ban, diverging from the counterfactual trend and signaling agricultural recovery. Standard errors are clustered by plume.

Identification of θ requires three assumptions: first, the treatment must be continuous, which is the case since E_m is measured in hectare-equivalents. The second assumption is no anticipation, meaning that farmers do not change their behavior before the ban. The third assumption is parallel trends, which assumes that the evolution of agricultural outcomes that municipalities with any exposure level, E_m, would have experienced without treatment is the same as the evolution of outcomes that units in the untreated group actually experienced. We test for parallel trends with an event study design next.

6.2 Dynamic Equation

To investigate the dynamic relationship between policy exposure and agricultural production, as well as explore pre-existing agricultural trends in treated municipalities, we present

Table 4: Difference in Differences Results

	(1) Area	(2) Output	(3) Revenue	(4) NDVI
Exposure$_m$ x $\mathbb{1}_{t>2015}$	0.023***	0.022***	0.004	0.001
	(0.006)	(0.008)	(0.012)	(0.000)
Coca + Climate Controls	Yes	Yes	Yes	Yes
Forest Cover	No	No	No	Yes
Municipality FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓
Observations	8976	8976	8976	8976

* $p < .1$, ** $p < .05$, *** $p < .01$. Data are at the municipality-year level. $Exposure_m$ is pre-policy cumulative exposure. $\mathbb{1}_{t>2015}$ is a dummy that switches on in 2015. "Coca Controls" include distance to nearest sprayed area and ha. of coca. "Climate Controls" include temperature and rain. Standard errors clustered by plume.

results from an event study version of the main equation:

$$Y_{mt} = \sum_{\tau \in \mathcal{T}^{pre}} \theta_\tau (E_m \cdot \gamma_t) + \sum_{\tau \in \mathcal{T}^{post}} \theta_\tau (E_m \cdot \gamma_t) + \mathbf{X}'_{mt}\Omega + \alpha_m + \gamma_t + \epsilon_{mt} \tag{6}$$

where all terms are the same as in Equation 5. Importantly, $\mathbf{X}'_{mt}$ includes distance from m to the nearest sprayed area. The coefficients of interest are θ_τ, where $\theta_{\tau=2014}$ is omitted so that coefficients are measured relative to the year before the policy. If farming activity in treatment and control districts were on similar trends prior to the spraying ban, then θ_τ should be statistically indistinguishable from zero when $\tau \in \mathcal{T}^{pre}$. When $\tau \in \mathcal{T}^{post}$, the θ_τ's identify the effect of the ban on agricultural outcomes in year τ.

6.3 Impacts of the Ban on Aerial Spraying

6.3.1 Limited Recovery of Agriculture

Estimates of Equation 5 are in Table 4. Column 1 is our preferred specification, where the outcome is log harvested area. We find $\theta > 0$, implying that agricultural production in municipalities previously exposed to glyphosate drift begin to rebound once aerial spraying is banned. Point estimates suggest that the ban increased harvested area by about 2.3% over the next four years. To contextualize this recovery, compare it with the estimated spraying-induced damage prior to the ban (Table 2). The modest 2.3% rebound from this lower baseline implies that only about 15% of the initial 13.2% loss (Table 2) in harvested area was recovered during the four years following the ban.[22] This suggests that most of the agricul-

[22] A 13.2% decline lowers harvested area to 0.868 of its original level. A 2.3% increase from this base yields $0.023 \times 0.868 \approx 0.020$, meaning that $0.020/0.132 \approx 0.15$ (15%) of the initial loss is recovered.

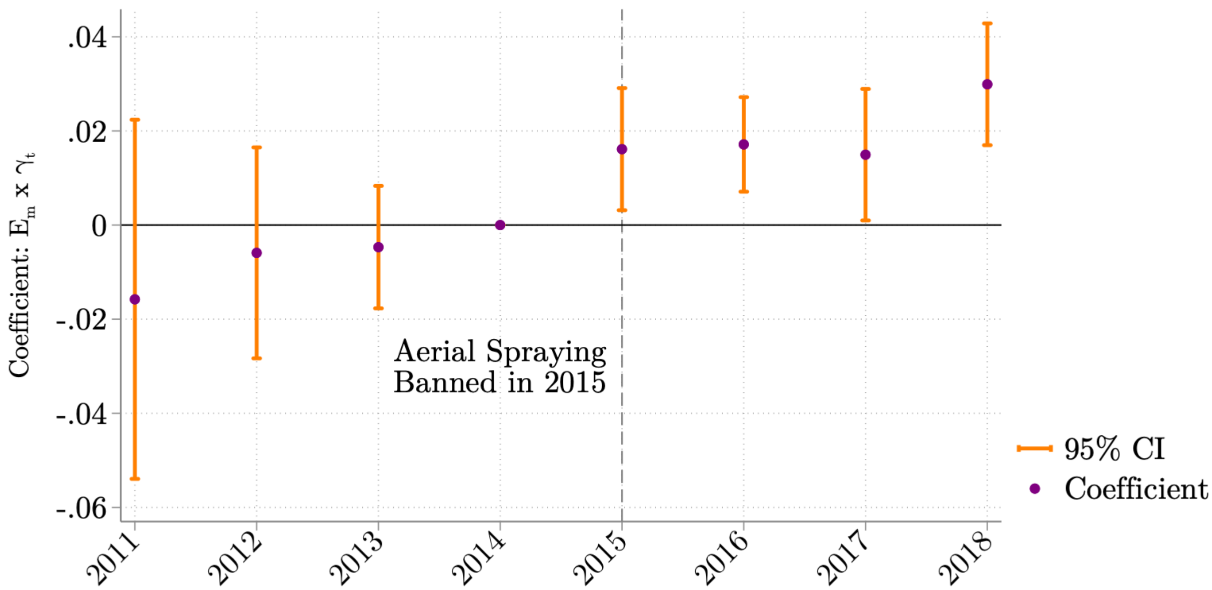

Figure 4: Event Study

Note: Purple circles are coefficients from Equation 6. The omitted period is 2014. Bars are 95% confidence intervals. The regression includes municipality and year fixed effects as well as controls for distance to the nearest sprayed area, coca area, temperature, and rainfall. Standard errors clustered by plume.

tural damage from aerial spraying persisted well after the spraying was discontinued.

Remaining columns explore sensitivity to alternative outcomes. Column 2 documents robustness to using log crop output (tonnes). The magnitude of recovery is the same as crop area. By contrast, we find no revenue response (column 3). Given higher output and fixed prices, the attenuation of revenue may be explained by a post-ban shift toward lower-value crops. Column 4 uses NDVI as the outcome and finds no effect. One explanation is that, although we control for forest cover, residual variation may still capture other natural vegetation which regenerates slower than managed agriculture.

Event study estimates are presented in Figure 4. Prior to the ban on aerial spraying, exposed and non-exposed municipalities are on statistically similar trends and coefficient estimates are near-zero. Once aerial spraying is banned in 2015, the coefficient turns sharply positive and significant for the next four years. Overall, lack of pre-trends support the parallel trends assumption. It also supports the no-anticipation assumption, which requires that farmers do not alter their behavior prior to policy.

6.3.2 Robustness of Difference-in-Difference Estimates

Table A12 shows results from robustness tests designed to improve confidence in our difference-in-difference estimates. The first test addresses overlap in the timing of the ban on aerial spraying and the FARC peace deal, a landmark accord that ended decades of armed conflict and aimed to promote rural development in conflict-affected areas of Colombia. Econometrically, this policy overlap is only a concern if FARC conflict is correlated with wind drift. Although it is hard to imagine why this would be the case, we control for $FARC_m \times \mathbb{1}_{t>2015}$ in column 1, where $FARC_m$ is an indicator for whether municipality m was affected by conflict before 2015. The interaction coefficient is statistically indistinguishable from zero, while the coefficient of interest, θ, remains positive, significant, and virtually unchanged in magnitude. Our main estimate is thus uncontaminated by the peace deal timing.

Columns 2-4 test sensitivity to alternative specifications, data sources, and sample restrictions. Column 2 controls for aerial fumigation of legitimate crops such as rice and bananas (see Section 5.3 for data details). Column 3 controls for five meteorology covariates (Section 3.1.3) which partially determine treatment intensity and, potentially, the rate of agricultural recovery. The coefficient remains virtually the same. Lastly, column 4 restricts the sample to municipalities that were never sprayed during Plan Colombia, ensuring that treatment variation is based only on *exposure* rather than any endogenous determinants of spraying. The main coefficient remains stable.

6.3.3 What Happened to Damaged Cropland?

We have shown that (i) wind drift from glyphosate spraying damaged off-target cropland, and (ii) minimal recovery of damaged cropland four years after spraying was banned. This raises the question: what became of the damaged cropland that failed to recover? We investigate this by examining land use change in our difference-in-difference framework.

Table A13 reports estimates of θ from Equation 5, where the outcome is the percent of municipality m classified as grassland, shrubland, forest, or bare area in year t. Data are from ESA land cover maps (Section 3.1.2).[23] We find a positive and statistically significant effect for grassland (column 1) and shrubland (column 2), suggesting that municipalities more exposed to glyphosate drift prior to the ban transitioned toward these land types. The transition of previously-exposed cropland into grassland and shrubland is consistent with either lasting damage to productivity, or land abandonment by farmers, though distinguishing between these channels is beyond the scope of the present analysis.

7 Policy Simulation: Reinstatement of Aerial Spraying

In April 2025, Colombia announced plans to reinstate aerial fumigation (Tactics Institute, 2025). Our findings thus take on new urgency, not only revealing the scale of past spillovers

[23] There are 36 land classes provided. We subsume these into fewer categories using IPCC classifications.

Table 5: Avoided Damages under Different Spraying Regimes

	BAU	Top 50	Top 25	Top 10
Revenue (USD Billions)	60.33556	60.94708	60.94775	60.94901
Avoided Damage (USD Millions)	0	611.5119	612.1846	613.4511

Note: Rows denote total harvest ($TotY^s$) and avoided crop loss ($AvoidedDamage^s$) under each policy scenario. Column 1 is business as usual. Column 2 only sprays areas with above-median coca area. Columns 3-4 target hotspots where coca area is in the top 25th and 10th percentile. Values are means over 1000 bootstrap draws.

but also informing how future spraying campaigns might be designed to reduce collateral damage. In this section, we use our retrospective estimates to simulate how alternative targeting strategies could mitigate spillover crop damage.

Consider three targeting rules that spray coca hotspots only: (i) target coca areas above the median of coca area distribution ("Top 50"), (ii) in the top quartile ("Top 25"), or (iii) in the top decile ("Top 10"). Under each scenario, spray campaigns targeting smaller coca plantations are dropped, and municipality exposure is recomputed according to Equation 2. Then, for each municipality m and year t, we use our coefficient estimates from Equation 3 to predict crop revenue in (constant) dollars, Y^s_{mt}, under scenario $s \in \{\text{Top 50, Top 25, Top 10}\}$:

$$\hat{Y}^s_{mt} = \hat{\beta} \cdot E^s_{mt} + \mathbf{X}'_{mt}\hat{\Omega} + \alpha_m + \gamma_t$$

where E^s_{mt} denotes realizations of exposure to spraying under scenario s. These predictions capture the partial-equilibrium effect of alternative coca targeting on spillover damage, holding other factors constant. We then sum local predicted values, $\hat{Y}^s_{mt}$, across all municipalities and years to construct counterfactual measures of national crop revenue under scenario s, denoted by $TotY^s$. Comparing these totals to the in-sample aggregate fitted values $TotY^{BAU}$ (business as usual) yields a simple metric of damage abated under each scenario:

$$\text{DamageMitigation}^s = \text{TotY}^s - \text{TotY}^{BAU} \qquad \text{for } s \in \{\text{Top 50, Top 25, Top 10}\} \tag{7}$$

To account for uncertainty in the predicted values, we bootstrap the prediction and aggregation procedure with 1000 draws and report the mean. Table 5 reports mean aggregate crop revenue and damage mitigation under each scenario. Restricting spraying to coca plantations above the median size would have avoided $USD 611 million of spillover crop damage relative to BAU. These savings amount to 3.7% of Colombia's average agricultural GDP during our study period (World Bank, 2026). Further restricting spraying to the largest coca plantations (top decile) yields additional savings of roughly $USD 2 million.

Three mechanisms could drive damage mitigation under our proposed targeting rules.

First, restricting spraying to large plantations reduces the total number of spray campaigns, lowering overall herbicide release (extensive margin). Second, small coca plots may be more likely to be embedded within mixed agricultural landscapes; excluding them therefore would reduce drift onto nearby legal crops. Lastly, if legitimate crops near small coca plantations are more vulnerable or more valuable, excluding these areas from spraying would yield additional benefits. Although we cannot separately identify these channels, our estimates quantify the total avoided damages implied by simple policy changes.

We acknowledge that reinstatement of aerial spraying has been announced but not yet initiated at the time of writing, creating a narrow window to incorporate evidence-based design into the upcoming policy. Our simulations suggest that, while aerial fumigation may remain undesirable, smarter spatial targeting can mitigate its unintended consequences.

8 Conclusion

This paper shows that spatially targeted enforcement policies can generate large and persistent externalities. Using aerial herbicide spraying to eradicate illicit crops in Colombia as an empirical setting, we document that enforcement technologies operating locally but dispersing across space can impose large costs on non-targeted units. Moreover, we find that the effects of these spillovers are not transitory and persist long after the intervention ends.

To quantify these effects we combine eradication data with a novel atmospheric dispersion model that simulates wind-driven glyphosate drift from sprayed coca fields. This approach yields a plausibly exogenous measure of herbicide exposure across municipalities. Our analysis reveals substantial negative spillovers: municipalities more exposed to glyphosate drift experienced a 13.2% reduction in crop output during the period of active spraying, with negative effects persisting for up to four years after exposure. In aggregate, our estimates imply that agricultural growth in Colombia was held back by nearly half a percentage point due to off-target crop losses.

A central feature of our findings is the persistence of off-target damages. We find little evidence of short-run adaptation through credit uptake or GMO crop adoption. Moreover, exploiting the 2015 ban on aerial spraying, our difference-in-differences analysis finds little crop recovery in previously exposed areas. Instead, we document a transition of damaged cropland into grassland and shrubland, indicating that enforcement-induced shocks can lead to longer-run changes in land use rather than temporary production disruptions. Taken together, we paint a picture of a place-based enforcement policy that inflicted collateral damage that far outlasted the policy itself.

In April 2025, Colombia announced plans to reinstate aerial spraying. Our estimates of off-target crop damage, along with prior evidence that spraying did not eradicate coca the first time around, implies that the policy should not be reinstated. However, if it is, our policy simulations help guide a second-best approach that minimizes externalities. We estimate that spraying only coca hotspots (plantations > median plot size) would have avoided roughly $USD 611 million in crop loss from spillover damages, equivalent to 3.7% of Colombia's agricultural GDP.

The policy implications of our findings extend beyond Colombia. As governments worldwide increasingly rely on spatially targeted interventions—whether to combat illicit activity, manage land use, or enforce environmental regulation—our study highlights the importance of accounting for unintended spillovers. And when rollback is politically infeasible, we show that better spatial targeting can reduce harm: even modest adjustments to the "place" component of place-based policy design can avert substantial collateral damage.

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A Online Appendix

A.1 Appendix Tables

Table A1: Summary Statistics (2011-2015)

	Obs.	Mean	Std. Dev.
A: Agriculture (2011-2018)			
Planted Area (ha.)	8976	4548.61	6701.46
Harvested Area (ha.)	8976	3879.96	5745.71
Production (tons)	8976	44333.85	182055.90
NDVI	8976	0.69	0.08
B: Aerial Spraying (2011-2015)			
Exposure (ha.)	5610	0.07	0.34
Sprayed Area (ha.)	5610	5639.88	30045.02
C: Covariates (2011-2018)			
Km to nearest sprayed area	5610	107.94	83.36
Coca (=1)	8976	0.18	0.38
Coca Area (ha.)	8976	3314.38	14302.80
Rain (mm)	8976	9.17	6.45
Temperature (° C)	8976	19.87	5.16

Note: Summary statistics of main outcome variables (Panel A), explanatory variables (Panel B), and covariates (Panel C). Aerial spraying data is available until 2015. All other data until 2018.

Table A2: Placebo Estimates: Impact of Exposure to Non-sprayed Coca Plantations

	(1) Area	(2) Output	(3) Revenue	(4) NDVI
Exposure (std. dev.)	-0.044**	-0.042**	-0.046***	-0.005**
	(0.019)	(0.017)	(0.013)	(0.002)
Placebo Exposure (std. dev.)	-0.007	-0.011	-0.008	-0.001
	(0.008)	(0.007)	(0.006)	(0.001)
Coca + Climate Controls	Yes	Yes	Yes	Yes
Forest Cover	No	No	No	Yes
Municipality FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓
Observations	5610	5610	5610	5610

* $p < .1$, ** $p < .05$, *** $p < .01$. Data are at the municipality-year level. Outcomes are in logs. "Exposure" to aerial spraying is measured in hectare-equivalents. "Placebo Exposure" is exposure to *unsprayed* coca plantations. "Coca Controls" include distance to nearest sprayed area and hectares of coca. "Climate Controls" include temperature and rainfall. Both explanatory variables are measured in standard deviations. All specifications include municipality and year fixed effects. Standard errors clustered at the plume level.

Table A3: Impacts on Ambient Pollution

	(1) log(PM2.5)	(2) log(SO2)	(3) log(NO2)
Exposure (ha.)	0.003	0.009	0.004
	(0.009)	(0.008)	(0.007)
Coca + Climate Controls	Yes	Yes	Yes
Municipality FEs	✓	✓	✓
Year FEs	✓	✓	✓
Observations	5610	5610	5600

* $p < .1$, ** $p < .05$, *** $p < .01$. Data are at the municipality-year level. "Exposure" to aerial spraying measured in hectare-equivalents. "Coca Controls" include distance to nearest sprayed area and hectares of coca. "Climate Controls" include temperature and rainfall. All specifications include municipality and year fixed effects. Standard errors clustered at the plume level.

Table A4: Robustness Checks – TWFE Estimates

	(1) Area	(2) Area	(3) Area	(4) Area	(5) Crop %	(6) Area	(7) Area
Exposure (ha.)	-0.131**	-0.131**	-0.093*	-0.091***	-0.087***	-0.254**	-0.341*
	(0.057)	(0.056)	(0.050)	(0.030)	(0.028)	(0.097)	(0.174)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Legal Spray	Yes	No	No	No	No	No	No
Meteorology	No	Yes	No	No	No	No	No
Municipality FEs	✓	✓	✓	✓	✓	✓	✓
Department × Year FEs			✓				
Year FEs	✓	✓		✓	✓	✓	✓
Linear Trend	No	No	No	Yes	No	No	No
Data Source	EVA	EVA	EVA	EVA	ESA	EVA	EVA
Mask	No	No	No	No	No	30km	No
Sample Restricted	No	No	No	No	No	No	Yes
Observations	5610	5610	5605	5610	5610	5610	4480

Note: Data are at the municipality-year level. "Exposure" to aerial spraying measured in hectare-equivalents. The outcome in columns 1-4 and 7-8 are log harvested area. The outcome in column 5 is cropland percent. Column 1 controls for legal crop spraying. Column 2 controls for energy flux, planetary boundary layer, velocity, humidity, and surface roughness. Column 3 includes department-year fixed effects. Column 4 adds a linear municipality trend. Column 5 uses alternative crop data from ESA. Column 6 adds a 30km mask around the point source before calculating exposure. Column 7 drops sprayed municipalities from the sample. All specifications control for distance to nearest sprayed area, ha. of coca, temperature, and rain. Standard errors clustered by plume.

Table A5: Robustness of TWFE Estimates: Standard Errors

	Standard Error Boundary		Conley Spatial Error Cutoff		
	(1) Plume	(2) Municipality	(3) 200km	(4) 300km	(5) 500km
Exposure (ha.)	-0.132**	-0.132**	-0.132***	-0.132**	-0.132***
	(0.057)	(0.059)	(0.048)	(0.058)	(0.051)
Controls	Yes	Yes	Yes	Yes	Yes
Municipality FEs	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓
Clustering	Plume (30)	Municipality	Conley	Conley	Conley
Observations	5610	5610	5610	5610	5610

* $p < .1$, ** $p < .05$, *** $p < .01$. Data are at the municipality-year level. Coefficient estimates and standard errors are from baseline equation (Equation 3) with alternative error clustering. Column 1 clusters at the plume level with 30 demarcated plumes. Column 2 clusters at the municipality level. Columns 3-6 implement Conley (1999) standard errors for four different values of the kernel cut off distance (in km)

Table A6: Heterogeneity by Crop Diversity

	(1) Area	(2) Output	(3) Revenue	(4) NDVI
Exposure (ha.)	-0.234	-0.246	-0.215	0.013
	(0.255)	(0.222)	(0.177)	(0.016)
Exposure (ha.) × Shannon Index	0.049	0.058	0.037	-0.013
	(0.135)	(0.120)	(0.089)	(0.008)
Coca + Climate Controls	Yes	Yes	Yes	Yes
Forest Cover	No	No	No	Yes
Municipality FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓
Observations	5610	5610	5610	5610

* $p < .1$, ** $p < .05$, *** $p < .01$. Data are at the municipality-year level. "Exposure" to aerial spraying is measured in hectare-equivalents. "Coca Controls" include distance to nearest sprayed area and hectares of coca. "Climate Controls" include temperature, and rainfall. All specifications include municipality and year fixed effects. Standard errors clustered at the plume level.

Table A7: Heterogeneity by Crop Diversity (Species Richness)

	(1) Area	(2) Output	(3) Revenue	(4) NDVI
Exposure (ha.)	-0.260	-0.224	-0.262**	0.006
	(0.155)	(0.144)	(0.103)	(0.012)
Exposure (ha.) × Number of Crops	0.013	0.010	0.013	-0.002
	(0.018)	(0.018)	(0.011)	(0.001)
Coca + Climate Controls	Yes	Yes	Yes	Yes
Forest Cover	No	No	No	Yes
Municipality FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓
Observations	5610	5610	5610	5610

* $p < .1$, ** $p < .05$, *** $p < .01$. Data are at the municipality-year level. "Exposure" to aerial spraying measured in hectare-equivalents. "Coca Controls" include distance to nearest sprayed area and hectares of coca. "Climate Controls" include temperature, and rainfall. All specifications include municipality and year fixed effects. Standard errors clustered at the plume level.

Table A8: Impacts of Exposure on Annual Crops

	(1) All	(2) Oilseeds	(3) Fibers	(4) Cereals	(5) Flower	(6) Veggies	(7) Legumes	(8) Spices	(9) Other
Exposure (ha.)	-0.150	-0.281**	-0.023*	-0.085	0.001	0.004	-0.161	0.025	-0.016***
	(0.110)	(0.129)	(0.012)	(0.099)	(0.005)	(0.058)	(0.177)	(0.019)	(0.005)
Coca + Climate Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	5478	5478	5478	5478	5478	5478	5478	5478	5478

* $p < .1$, ** $p < .05$, *** $p < .01$. Data are at the municipality-year level. "Exposure" to aerial spraying measured in hectare-equivalents. "Coca Controls" include distance to nearest sprayed area and hectares of coca. "Climate Controls" include temperature, and rainfall. All specifications include municipality and year fixed effects. Standard errors clustered at the plume level.

Table A9: Impacts of Exposure on Perennial Crops

	Annual Crops				
	(1) All	(2) Fruits	(3) Plantains	(4) Tree Crops	(5) Other
Exposure (ha.)	-0.058	0.037	-0.078**	-0.297*	-0.116
	(0.041)	(0.083)	(0.034)	(0.158)	(0.082)
Coca + Climate Controls	Yes	Yes	Yes	Yes	Yes
Municipality FEs	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓
Observations	5478	5478	5478	5478	5478

* $p < .1$, ** $p < .05$, *** $p < .01$. Data are at the municipality-year level. "Exposure" to aerial spraying measured in hectare-equivalents. "Coca Controls" include distance to nearest sprayed area and hectares of coca. "Climate Controls" include temperature, and rainfall. All specifications include municipality and year fixed effects. Standard errors clustered at the plume level.

Table A10: Adaptation: Farm Credit

	(1) All Farms	(2) Small Farms	(3) Medium Farms	(4) Large Farms
Exposure (ha.)	0.315*	-0.164	0.058	-0.088
	(0.165)	(0.115)	(0.070)	(0.143)
Coca + Climate Controls	Yes	Yes	Yes	Yes
Municipality FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓
Observations	5610	5610	5610	5610

* $p < .1$, ** $p < .05$, *** $p < .01$. Data are at the municipality-year level. Outcome is log(farm credit + 1) for different farm operations. "Exposure" to aerial spraying measured in hectare-equivalents. "Coca Controls" include distance to nearest sprayed area and ha. of coca. "Climate Controls" include temperature, and rain. All specifications include municipality and year fixed effects. Standard errors clustered at the plume level.

Table A11: Adaptation: GMO Crop Adoption

	(1) GMO Cotton	(2) GMO Maize
Exposure (ha.)	-0.107	-0.447
	(0.076)	(0.264)
Coca + Climate Controls	Yes	Yes
Department FEs	✓	✓
Year FEs	✓	✓
Observations	125	125

* $p < .1$, ** $p < .05$, *** $p < .01$. Data are at the department-year level. The outcome is share of harvested area planted with GMO cotton or maize. "Exposure" to aerial spraying is measured in hectare-equivalents. "Coca Controls" include distance to nearest sprayed area (department-year mean) and ha. of coca (department-year total). "Climate Controls" include temperature, and rain (department means). All specifications include department and year fixed effects. Standard errors clustered at the department level.

Table A12: Robustness: Difference-in-Difference Estimates

	(1) Area	(2) Area	(3) Area	(4) Area
$\text{Exposure}_m \times \mathbb{1}_{t>2015}$	0.021***	0.022***	0.021***	0.223***
	(0.007)	(0.006)	(0.006)	(0.042)
$\text{FARC}_m \times \mathbb{1}_{t>2015}$	0.026			
	(0.058)			
Controls	Yes	Yes	Yes	Yes
Legal Spray	No	Yes	No	No
Meteorology	No	No	Yes	No
Municipality FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓
Data Source	EVA	EVA	EVA	EVA
Sample Restricted	No	No	No	Yes
Observations	8976	8976	8976	7258

* $p < .1$, ** $p < .05$, *** $p < .01$. Note: Data are at the municipality-year level. $Exposure_m$ is the pre-policy total exposure of municipality m. $\mathbb{1}_{t>2015}$ is a dummy that switches on in 2015. $FARC_m$ is a dummy for whether m experienced FARC-related conflict in the pre-period. Column 2 controls for legal crop spraying. Column 3 controls for energy flux, planetary boundary layer, velocity, humidity, and surface roughness. Column 4 drops sprayed municipalities from the sample. All specifications control for distance to nearest sprayed area, ha. of coca, temperature, and rain. Errors clustered by plume.

Table A13: Difference in Differences Results: Land Use Transitions

	(1) Grassland	(2) Shrubland	(3) Forest	(4) Bare
Exposure$_m$ x $\mathbb{1}_{t>2015}$	0.003**	0.006*	-0.016	-0.000
	(0.001)	(0.003)	(0.011)	(0.000)
Coca + Climate Controls	Yes	Yes	Yes	Yes
Municipality FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓
Observations	8976	8976	8976	8976

* $p < .1$, ** $p < .05$, *** $p < .01$. Data are at the municipality-year level. Outcomes are the percent of land under each land use type. $Exposure_m$ is the pre-policy total exposure of municipality m. $\mathbb{1}_{t>2015}$ is a time dummy that switches on in 2015. "Coca Controls" include distance to nearest sprayed area and hectares of coca. "Climate Controls" include temperature and rainfall. Standard errors clustered by plume.

A.2 Appendix Figures

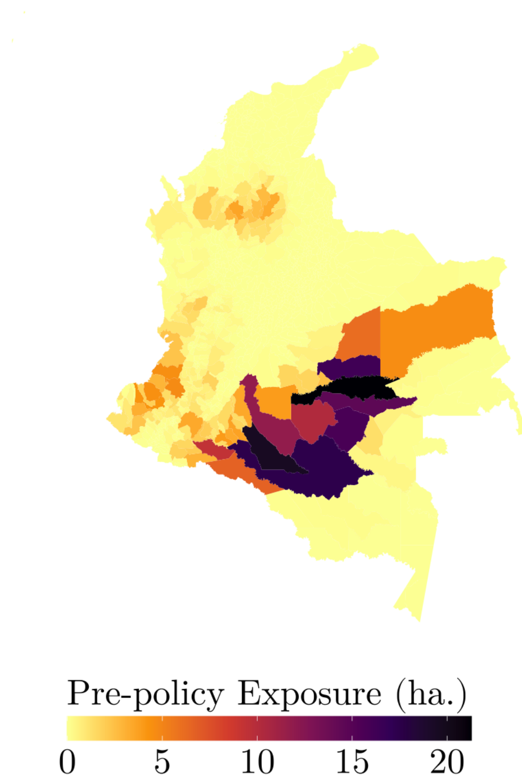

Figure A1: Treatment Distribution: Pre-policy Exposure

Note: Treatment is cumulative exposure during the pre-policy period.

B Robustness to Continuous-Treatment DiD Concerns

Table A14 shows estimates after we discretize exposure into high and low intensity regimes to assess whether our results could be driven by comparisons across different exposure intensities, as cautioned by Callaway et al. (2024). This approach restricts identification to exposed–versus–unexposed comparisons and avoids reliance on comparisons across positive exposure levels. Column 1 compares municipalities experiencing high exposure to never-exposed municipalities, while Column 2 compares low exposure to never-exposed municipalities. The estimates are qualitatively consistent with our baseline results, supporting the interpretation that our findings are not driven by problematic weighting across different exposure intensities.

Table A14: High- and Low-Exposure Effects Relative to Zero Exposure

	(1) High vs 0	(2) Low vs 0
High Exposure	-0.141	
	(0.091)	
Low Exposure		-0.038**
		(0.017)
Coca Controls	Yes	Yes
Climate Controls	Yes	Yes
Municipality FEs	✓	✓
Year FEs	✓	✓
Observations	3682	3689

Note: High and low exposure regimes are defined based on discretized values of the exposure measure. Never-exposed municipalities are defined as municipality–year observations with zero wind-driven exposure. All specifications include plume and year fixed effects, coca-related controls, and climate controls. Standard errors are clustered at the municipality level.