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Abstract

One explanation for the increasing number of hectares with coca cultivation is that eradication strategies displace coca crops but fail to completely clear affected areas. In the drug policy literature, that dynamic shifting is commonly known as the *balloon effect*. This study integrates georeferenced agricultural data through spatially explicit econometric models to test the hypothesis that forced eradication displace coca crops. Using annual data for 1,116 contiguous municipalities in Colombia between 2001 and 2015, we estimate a spatial Durbin model with municipal and time fixed effects. Our results suggest that, on average, aerial fumigation in a municipality diffuses the benefits of this crime control strategy to neighboring municipalities.

JEL Classification: K42, R12, R14.
Keywords: Spatial dependence, Spatial Durbin model; Drug policy; Spillover.

Difusión de los beneficios del control del delito: erradicación forzada y cultivos de coca en Colombia

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Resumen

Una posible razón del crecimiento del número de hectáreas de coca en Colombia es que las estrategias de erradicación desplazan los cultivos de coca, pero no logran despejar por completo las áreas afectadas. En la literatura sobre políticas de drogas, ese cambio dinámico se conoce comúnmente como el efecto globo. Este estudio integra datos agrícolas georreferenciados a través de modelos econométricos espaciales para evaluar la hipótesis de que la erradicación forzada desplaza los cultivos de coca. Utilizando datos anuales de 1.116 municipios contiguos en Colombia, estimamos un modelo espacial Durbin. Nuestros resultados sugieren que, en promedio, la fumigación aérea en un municipio difunde los beneficios de esta estrategia de control del crimen a los municipios vecinos.

JEL Classification: K42, R12, R14.
Keywords: Dependencia espacial, Modelo espacial Durbin; Erradicación; Políticas de drogas.

1. Introduction

Dozens of press headlines have announced that the War on Drugs has failed to curb cocaine consumption, production, and trafficking (Chalabi, 2016; Doward, 2016; Pardo Veiras, 2016). Although the amount of cocaine seized increased more than the potential manufacture, cocaine available for consumption is still large in comparison with more than USD 10 billion spent by the United States in counternarcotic efforts in Colombia since 1999 (GAO, 2018), and annual prevalence of the use of cocaine remained 0.4 percent of the population aged 15-64 worldwide from 2007 to 2017 (UNODC, 2009, 2019). With high costs and weak gains against illegal drug production over decades public figures, and researchers have called for a new public policy approach to control drugs (Bernstein, 2000; LSE & Collins, 2014; Mulholland, 2016; Policy, 2011; Post, 2016).

On the supply side, the strategies to control illicit crops have been blamed for this failure (Bertram, Blachman, Sharp, & Andreas, 1996; Nadelmann, 1989; Stares, 1996; Zepeda Martínez & Rosen, 2015). While forced eradication directly reduces the quantity of coca crops in any one place in the short term, coca crops often shift from one area to another but do not disappear. From the crime prevention perspective, this strategy is mechanical, seeking to reduce opportunities for crime and increasing the risks associated with the criminal activity (Lejins, 1967). Yet, mechanical crime prevention fails to tackle the underlying causes of the criminal activity. Hence, one can expect crime displacement to follow forced eradication (Eck, 1993; Hesseling, 1994).

Crime displacement can take different forms. It can involve relocating crime from one place to another, changing time of occurrence, targeting other victims, switching to another method, or choosing other type of crime (Reppetto, 1976). Many studies have documented the theoretical, methodological, and empirical relevance of crime displacement in criminology (Barr & Pease, 1992; Clarke, 1995; Gabor, 1981). In the drug policy literature, this dynamic shifting is commonly known as the *balloon effect* because cultivation is squeezed in one side; then it emerges in another. While the balloon effect dynamics of coca cultivation are intuitive and popular with both the public and some researchers, empirical testing has been limited (Basov, Miron, & Jacobson, 2001; Reuter, 2014; Reuter et al., 2009; Thoumi, 2003).

Previous studies analyzing coca cultivation in the Andean Region found a negative relationship between coca cultivation in Peru and Bolivia and coca cultivation within Colombia (Raffo Lopez, Castro, & Diaz España, 2016; Rouse & Arce, 2006). Both studies concluded this negative relationship was consistent with the balloon effect hypothesis. However, these studies did not account for the spatial dependence of coca cultivation and forced eradication. An increase in coca cultivation in one country can be caused by within-country reduction in forced eradication or by an increase in forced eradication in neighboring countries. Given the inherently spatial nature of coca cultivation and eradication, neither non-spatial analyses such as pooled cross-sectional time-series analysis (Rouse & Arce, 2006), nor a seemingly unrelated regression models (Raffo Lopez et al., 2016) can capture the spatial dependence of forced eradication effects on cultivation. Estimating the effects of forced eradication on coca crops to inform policy thus requires a spatially explicit approach.

While some studies have attempted to model the dynamic shifts of coca crops, these have not settled the question of the influence of the balloon effect. Using a multivariate Moran's I indicator, Rincón-Ruiz & Kallis (2013) acknowledged the spatial dynamics of coca crops and established a positive relationship between aerial fumigation in a municipality and coca cultivation in neighboring municipalities the following year. This result is a useful initial diagnostic to test for spatial dependence (LeSage, 2008), but Moran's I indicator does not differentiate direct from indirect effects of aerial fumigation on coca cultivation. Direct effects involve the impact of changing a particular explanatory variable on the dependent variable in the same spatial unit, while indirect effects illustrate the impact on the dependent variable in other spatial units (Elhorst, 2014b; LeSage, 2008). Distinguishing these two effects is essential to generate estimates of the benefits, if any, of forced eradication.

To establish whether the main strategy used to control coca crops in the world generated a balloon effect, it is necessary to choose the right spatial model, account for spatial heterogeneity, and distinguish between direct and indirect effects. To address these challenges, this study implements a spatial Durbin model (SDM) with municipal and time fixed effects. This model overcomes previous limitations by: (1) including a spatially lagged dependent variable and spatially lagged independent variables to specify spatial dependence among the observations (Anselin, Gallo, & Jayet, 2008; LeSage & Pace, 2009), (2) incorporating municipal and time fixed effects that allow the intercept to vary over spatial units and account for spatial heterogeneity (Elhorst, 2003), and (3) estimating direct, indirect, and total effects of forced eradication activities on new coca crops. This analysis simultaneously tests the hypotheses of crime displacement (the balloon effect) and diffusion of benefits as a result of implementing forced eradication activities. By testing these two hypotheses we are able to establish if there was a balloon effect or not.

In the illicit crop context, crime displacement implies that coca cultivation increases in municipalities that were not directly targeted by forced eradication, while diffusion of benefits involves coca cultivation reductions as a consequence of forced eradication activities implemented outside the municipality. By estimating direct effects, we tested for the impact of eradication strategies on new coca cultivation in a municipality.[1] By estimating indirect effects, also called spillover effects, we tested for the impact of eradication strategies within a municipality on new coca cultivation in other municipalities. Indirect effects are appropriate estimates to test for crime displacement and diffusion of benefits.

To assess the indirect effects of the strategies used to control coca crops, we use annual data for 1,116 contiguous municipalities in Colombia between 2001 and 2015. The results suggest that one additional hectare of coca manually eradicated a year ago is associated with a reduction of 6 percent of a new hectare under coca cultivation inside the municipality that implemented manual eradication. According to our results, manual eradication does not generate spillover effects. In contrast, aerial fumigation does generate negative spillover effects and has a negative association with new coca crops inside the municipality that implemented aerial eradication. An additional hectare of coca eradicated using aerial fumigation a year ago reduces, on average, the new area under coca cultivation by 9 percent in that municipality and by 7 percent in neighboring municipalities. During the period analyzed, there is no balloon effect at municipal level and aerial fumigation instead generates *diffusion* of crime control benefits.

2. Crime displacement or diffusion of crime control benefits

For decades, scholars have debated how and when crime control strategies reduce the opportunity or increase the risk of committing crime (Clarke & Cornish, 1985; Lejins, 1967; Palmer, 1977; Paternoster, 2010). In other words, whether crime control strategies deter or discourage people from criminal activities. Most of the conclusions are contingent on the type of

[1] The direct effects might include feedbacks effects passing through neighboring municipalities and back to the municipality that initiated the change. This feedback effect could capture the correlation that exists in the coca crops across neighbor spatial units when they have similar geographic and socioeconomic characteristics; these common characteristics might be correlated with the propensity of coca cultivation. We also estimate models in which these type of feedback effects are ignored, and instead spatial effects are modeled through the error term. The latter models are presented and commented as a robustness checks and the results of the estimations does not change importantly.

crime and linked to specific crime control strategies. However, there is agreement that crime displacement is a reasonable response to crime control activities (Gabor, 1981); it is difficult to measure it in all its forms (Hesseling, 1994), and total displacement is uncommon (Barr & Pease, 1990; Eck, 1993; Gabor, 1990). Therefore, crime displacement should be empirically tested in each case.

There are different forms of crime displacement. After a crime control strategy is implemented, criminal activities can move to other places. They can be performed at a different time, target different victims, change its method, or become another type of crime (Reppetto, 1976). Many studies have tested the hypothesis of crime displacement in its different forms, finding that there was some displacement but no total crime displacement (Allatt, 1984; Mehay, 1977; Mukherjee & Wilson, 1987). Other empirical studies have documented no crime displacement (Clarke, 1990; Clarke & Mayhew, 1989; Matthews, 1990; Mayhew, 1991; Miethe, 1991; Poyner, 1991; Schneider, 1986), and many others have found the opposite of crime displacement, diffusion of benefits (Braga, Apel, & Welsh, 2013; Chaiken, Lawless, & Stevenson, 1974; Masuda, 1992; Poyner & Webb, 1992; Weisburd et al., 2006).[2] Thus, although the concept of crime displacement is not new, crime displacement should not be instantaneously assumed without empirical testing.

Crime control strategies could be associated with three different outcomes: crime displacement, no displacement, and the reverse of displacement. The third outcome occurs when the benefits of the crime control strategies go beyond the areas intervened. This means that there is a diffusion of benefits of the crime control strategy, a spread of the benefits beyond the area directly targeted (Clarke & Weisburd, 1994). The diffusion of benefits of a crime control strategy

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[2] For more literature review of empirical studies see Barr & Pease, (1990), Eck, (1993), Hesseling, (1994), and Guerette & Bowers, (2009).

is not a novel concept. It has been extensively discussed before in many studies (Chaiken et al., 1974; Miethe, 1991; Scherdin, 1992; Sherman, 1990), but in the coca cultivation context neither crime displacement nor diffusion of benefits has been tested before. Hence, it is unknown if the strategies used to control coca crops displace coca cultivation from one place to another or discourages cultivation in places not directly targeted by the strategy.

3. Coca crops, forced eradication, and spatial dependence

In Colombia, most illicit crops grow at inaccessible areas of the country isolated by the Andes mountain range and tropical weather regime. More than 50 percent of the area affected by coca crops in Colombia lies in the Amazon region (see Table 1). Municipalities with coca cultivation receive on average 50 percent more annual rainfall and are more than four times larger in comparison to municipalities without coca cultivation. The spatial aggregation of lowland forests is a concern since non-spatial econometric models treat each unit identically.

[Table 1 about here]

Forced eradication follows coca cultivation. Eradication activities took place in municipalities affected by coca crops, 485 municipalities out of 1,116 contiguous municipalities in Colombia as of 2015 (see Table 1). Forced eradication was implemented using manual eradication and aerial fumigation. Manual eradication is a labor-intensive activity to uproot coca bushes. This was the only method of eradication used inside natural parks and indigenous reserves before aerial eradication was permitted inside natural parks in 2005 (Council, 2005) and indigenous reserves in 2007 (Council, 2007). Aerial eradication was accomplished by using airplanes to spray herbicide over coca plantations located in difficult-access areas with active armed conflict (Council, 1994; DNE, 2003). Aerial eradication with glyphosate was carried on in Colombia until September 2015 when it was suspended because of the health and environmental risks associated with the herbicide (ANLA, 2015; Council, 2015).

Although eradication strategies are uniform throughout the country, not all the municipalities affected by coca crops were eradicated every year. Hence, there is variation across municipalities. Analyzing municipalities using a local indicator of spatial association, there is a notable positive spatial clustering of coca crops in the Amazon region of Colombia in 2001 (southeast of the country). Figure 1 illustrates clusters of high-high hectares of coca. Hence, municipalities with much coca cultivation surround municipalities with many coca crops. By 2015, positive spatial clustering also appears in the Pacific (west coast of the country) and Northern region of the country.

[Figure 1 about here]

Eradication activities are concentrated in areas where coca cultivation is high. Figure 2 also shows positive spatial clustering for aerial eradication in the Amazon region of Colombia in 2001. Therefore, there is also a positive spatial clustering for aerial eradication in the Pacific region in 2015. For this descriptive analysis, spatial weights for both Figures were created using a Queen contiguity method, first-order neighbors. Queen criterion of contiguity defines neighbors as municipalities sharing a common edge or a common vertex, and first-order neighbors refers to neighboring municipalities adjacent to the municipality analyzed. The statistical significance of the correlations was calculated using 10,000 permutations. White areas in Figure 1 and 2 showed no statistically significant spatial clustering.

[Figure 2 about here]

4. Data

This paper analyzes annual data for 1,116 contiguous municipalities in Colombia from 2001 to 2015. The outcome variable used in the econometric analysis was calculated using net coca cultivation from the *Annual Coca Survey*. Each year, the Illicit Crops Monitoring Global Program of the United Nations Office of Drugs and Crime (UNODC) collects satellite images of the entire continental territory in Colombia (1,142,000 Km2). The accuracy identifying coca fields from the satellite images ranges between 87 and 90 percent (UNDCP, 2002; UNODC, 2003). Therefore, after the images are captured, the UNODC conducts field verification to calculate the extension of coca crops with gaps or covered by clouds. The area identified in the images is also adjusted for aerial and manual eradication activities performed during the same period. The resulting area after correcting for gaps, clouds, and adjusting for eradication activities is net coca cultivation.[3]

Equation 1 describes the dependent variable used in this analysis. Following Davalos (2016), y_t is the new with coca crops in period t. x_t is net coca cultivation at the cut-off date of the annual coca survey in period t, and x_{t-1} is net area coca cultivation at the cut-off date of the annual coca survey in period $t-1$. This variable was reported in annual hectares.[4] Data on the

[3] For more details about the methodology, see *Ajustes y estimaciones área sembrada* section in UNODC (2016).
[4] 1 hectare = 2.5 acres.

strategies used to control coca crops, manual and aerial eradication, come the Colombian Antinarcotics Police (DIRAN for its Spanish-language acronym). These variables are also reported in annual hectares. To control for policy changes related to the implementation of aerial eradication activities inside natural parks and indigenous reserves, the model includes two dummy variables coded zero before aerial eradication was implemented and one once it was implemented in municipalities with natural parks (after 2005) and indigenous reserves (after 2007).

Equation 1 Outcome variable used in the econometric analysis

$$y_t = x_t - x_{t-1}$$

The analysis also includes other municipal-level characteristics such as public spending and government financing sources. Annually, the Colombian National Planning Department (DNP) reports this information in nominal thousand pesos. To make these data comparable over time and across municipalities, we use per capita measures and adjust for inflation using consumer price index (CPI). To measure armed conflict, we use data from the *Banco de Datos de Derechos Humanos, DIH y Violencia Política*. This data base systematizes and disseminates data on human rights violations and violations of international humanitarian law in Colombia since 2001 (CINEP, 2021). Table 2 provides a summary of the variables included in the spatial econometric analysis.

[Table 2 about here]

5. Methods

To assess the spillover effects of the strategies used to control coca crops, we carried out two sequential steps. First, we ran a spatial autocorrelation test. We calculated Moran's I for the area under coca cultivation and the area fumigated with glyphosate using *GeoDa* (Anselin, Syabri, & Kho, 2006).[5] We tested for spatial autocorrelation for new coca crops and aerial fumigation for each year from 2001 to 2015. The global Moran's I for new coca crops and area fumigated were statistically significant for all years for the national level data (see Appendix 1). Statistically significant results indicate that spatial autocorrelation persists across years, and positive values indicate spatial clustering. Spatial dependence in the dependent and key independent variable implies that previous analyses that did not account for clustering may be statistically biased if the source of spatial dependence relates to the variation in the strategies used to control illicit crops.

After testing for spatial autocorrelation, we ran a spatial econometric analysis using a spatial panel data model (Elhorst, 2014b). The model includes a spatially lagged dependent variable and spatially lagged independent variables to specify spatial dependence among the observations (Anselin et al., 2008; LeSage & Pace, 2009). Following the strategy described in Elhorst, 2010, 2014a, and LeSage and Pace, 2009, we started from a specific-to-general approach to select the model specification. First, we estimated a non-spatial model and tested it against the spatial lag and spatial error model. Table 3 reports results for traditional and robust Lagrange Multiplier (LM) tests (Anselin, 1988; Anselin, Bera, Florax, & Yoon, 1996; Burridge, 1980).

[5] Global Moran's I is defined by Moran, (1950) as:

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} * \frac{\sum_{i=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n} w_{ij}\,(x_i - \bar{x})^2}$$

Where n denotes the number of municipalities, 1,116 for the national level assessment, x and $\bar{x}$ denote the specific region and its mean, and w_{ij} is the spatial weight matrix, representing the spatial relationship between region i and j. The spatial region in this study is contiguous, and the spatial weight matrix was generated using the Queen Contiguity method, first-order neighbors.

The hypothesis of no spatial lagged dependent variable and the hypothesis of no spatial auto-correlated error term were rejected in all model specifications. Then, we estimated a spatial Durbin model (SDM). The spatial lag of the dependent variable included in the SDM models the correlation between the change in coca crops in a specific spatial unit and its neighbors. This feedback effect could capture the correlation that exists in these crops across neighbor spatial units when they have similar geographic and socioeconomic characteristics; these common characteristics might be correlated with the propensity of coca cultivation. As a robustness check, we estimate a set of Spatial Durbin Error Models (SDEM), in which the spatial effects are modeled through correlation of unobserved factors of a spatial unit with unobserved factors across its neighbors, the results are very similar to the ones with the preferred specification (see Appendix 3).

[Table 3 about here]

Equation 2 explains the formal structure of the SDM, where y_{it} is the dependent variable for cross-sectional unit i at period t. The variable $\sum_j w_{ij} y_{jt}$ is the interaction effect of the dependent variable y_{it} with the dependent variables y_{jt} in the neighboring units, w_{ij} is the i, jth element of a prespecified nonnegative $N \times N$ spatial weights matrix W describing the arrangement of the spatial units in the sample, ϕ is the constant term parameter, x_{it} is a $1 \times K$ vector of exogenous variables, and β is a matching $K \times 1$ vector of fixed but unknown parameters. The model also includes municipal fixed effects, c_i, to control for any time invariant unserved or observed heterogeneity across municipalities, and time fixed effects, α_t, to control for any time varying shocks common to all municipalities. Finally, θ is a $K \times 1$ vector of parameters, and v_{it} is the stochastic error term.

Equation 2 Spatial Durbin model that contains a spatially lagged dependent variable and spatially lagged independent variables

$$y_{it} = \lambda \sum_{j=1}^{N} w_{ij}\, y_{jt} + \phi + x_{it}\beta + \sum_{j=1}^{N} w_{ij}\, x_{ijt}\theta + c_i + \alpha_t + v_{it}$$

6. Results

To assess the spillover effects of forced eradication, we regress the size of new coca crops on the area manually eradicated and fumigated with glyphosate. Table 4, columns (1) to (3), reports coefficients on three different spatial panel models. Column (1) presents the results of a spatial autoregressive model (SAR). Column (2) shows estimates of a spatial error model (SEM), and column (3) reports coefficients of a spatial Durbin model (SDM). The three sets of results include spatial and time fixed effects regressors not shown. Numbers without parentheses are spatial panel coefficients; standard errors are in parentheses.

Results are consistent across the three models. The spatial lag of the dependent variable, *rho*, is positive and significant in the SAR and the SDM. As a result, there are spatial effects, clustering of similar municipalities and similar reactions. A significant and positive spatial error term, *lambda*, is equivalent in its interpretation in the SEM. Coefficients on manual eradication and aerial fumigation are also consistent in the three models, negative and statistically significant. Specifically, in the SDM, coefficients on spatially lagged explanatory variables, manual eradication, aerial fumigation, conflict, and indigenous reserves, are significant. We also ran the SDM using different spatial weight matrix definitions. Results are substantively similar to those reported in Table 5 (see Appendix 2). As an additional robustness check, we estimate an SDEM, results are as well very similar to the ones obtained with the preferred specification.

[Table 4 about here]

Table 5 reports direct, indirect, and total effects from the SDM estimation. The direct effect of an additional hectare of coca manually eradicated a year ago in municipality i reduces, on average, new coca crops by 0.06 hectares in municipality i. The direct effect of an additional hectare of coca fumigated a year ago in municipality i reduces, on average, new coca crops by 0.09 hectares in municipality i.[6] Armed conflict also has positive correlation with new coca crops. This result supports previous findings establishing associations between coca cultivation and armed conflict (Angrist & Kugler, 2008; Camacho G. & López R., 2000; Carvajal Contreras & Sánchez Torres, 2002; Diaz & Sanchez, 2004; Holmes, Gutierrez de Pineres, & Curtin, 2006). In this case, coefficients on manual eradication and conflict reported in Table 4 are very close to the direct effect of manual eradication and conflict reported in Table 5. These results imply that there is no feedback effect generated from the impact of passing through neighboring units and back to the unit itself (Elhorst, 2014b, 2014a).

[6] In Annex3, we report the estimation of a SDEM, the direct effect an additional hectare of coca manually eradicated is 0.06 hectares. The direct effect of an additional hectare of coca fumigated is 0.09. These results are very similar of those with the preferred specification. The same is true in the case of indirect effects.

[Table 5 about here]

The indirect effect of aerial eradication is negative and statistically significant. If aerial eradication increases in municipality i during year $t-1$, new coca crops decrease in municipality i and its neighboring municipalities in period t. The change in neighboring municipalities to the change in the municipality itself is in the proportion of 1 to 1.28. The indirect effect of fumigating an additional hectare of coca in municipality i on new coca crops in neighboring municipalities is a reduction of 0.07 hectares. Finally, the total effect of aerial eradication is the sum of its direct and indirect effects. If all municipalities increase aerial eradication by one hectare in period $t-1$, new coca crops will decrease by 16 percent in period t in the typical municipality.[7] This result is consistent with previous findings on the average effects of aerial eradication on coca cultivation (Acevedo, 2015; Davalos, 2016).

Policy changes of implementing aerial eradication inside indigenous reserves also generate spillovers or indirect effects. When aerial eradication was implemented inside indigenous reserves, new coca crops increased in the municipality with indigenous reserves and its neighboring municipalities. A possible explanation for this result is that reserves can spread out through more than one spatial unit. When this control policy is implemented, coca growers might be prone to displace the crops to neighbor spatial unit if they are not fully aware of the change of policy or if there is no other option since spatial units with no reserves have aerial aspersion as well. The ratio of the change in neighboring municipalities to the change in the

[7] 1 hectare = 10,000 square meters. Therefore, a reduction of 0.16 hectares = a reduction of 1,600 square meters or 16 percent of a hectare.

municipality itself is in the proportion of 1.63 to 1; neighboring municipalities bear much of the impact of this policy change. Implementing aerial eradication inside indigenous reserves also reports statistically significant total effects. If all municipalities that have indigenous reserves and coca crops implemented aerial eradication inside them, new coca crops would increase, on average, by 62 hectares. There are 172 in the sample than fall in this category. This is close to 35 percent of all the municipalities affected by coca crops in Colombia during the period of study.

7. Discussion

The balloon effect has been repeatedly invoked to explain both the failures of the War on Drugs and the geographic expansion of coca crops over time. Nevertheless, quantitative evidence for the balloon effect has been scarce; previous literature either involves trends across countries (L. M. Dávalos, Bejarano, & Correa, 2009) or trends in spatial clusters (Rincón-Ruiz, Pascual, & Flantua, 2013). Our analyses reveal that, on average, aerial fumigation in a municipality diffuses the benefits of this crime control strategy to neighboring municipalities. We did find crime displacement, but only in municipalities with indigenous reserves that implement aerial eradication therein, implying negative returns on crime control at these sites. On average, contrary to the balloon effect hypothesis, the crime control benefit of aerial fumigation goes beyond the average municipality targeted. It should be notice that in the literature, different aspects to the ones considered in this study, has been remarked as inconvenient regarding to aerial aspersion; for example, negative environmental and health consequences (Camacho & Mejía, 2017).

Although previous analyses had already identified a negative relationship between aerial eradication and coca cultivation (Acevedo, 2015; Davalos, 2016; Mejía, Restrepo, & Rozo, 2017), our results provide deeper insights for policy design by distinguishing between the change in coca cultivation as a result of eradication activities inside and outside the municipality. This distinction is important because an increase in coca cultivation in a municipality can be caused by the reduction in forced eradication inside that municipality or by the increase in forced eradication in neighboring municipalities. Based on our results, the broad impact of aerial eradication is a reduction of new coca crops *inside* and *outside* the municipality implementing fumigation.

How the negative spillover effect found in our models emerges remains unknown. Possibly, coca growers are aware of eradication activities in neighboring municipalities, and they fear that their coca crops may also be destroyed (Ibanez & Klasen, 2017). A previous study based on interviews reported that coca growers knew that aerial eradication efforts were undergoing because they could see "the planes and helicopters at the airport." (Huezo, 2017, p. 387). Some of these growers then reduce the area under coca cultivation, and others may decide not to grow coca at all. In short, a negative spillover may emerge as coca growers are dissuaded from illegal activities when they acknowledge the negative consequences experienced by others (Braga et al., 2013; Rincke & Traxler, 2011).

Under the conditions of this study, efforts to increase the probability of aerial eradication in a municipality are associated with a reduction of coca cultivation in neighboring municipalities as well. Until 2015, forced eradication was the only credible threat to coca cultivation because too few coca growers were prosecuted.[8] Aerial eradication destroyed most of the coca crops sprayed with glyphosate, with the average survival rate of coca crops sprayed at

[8] The Colombian police reported 855 felonies related with coca cultivation in 2009 (Colombia, 2010), but only 162 people were prosecuted (El Tiempo, 2009). However, for the same period, the UNODC estimated that 56,910 families were involved in coca cultivation (UNODC, 2010).

9.35 percent. However, forced eradication never cleared an entire region of coca even though it had more than 10 years to succeed.

The main reason for this result might be engrained in the nature of the strategy, as opposed to its implementation. Forced eradication focuses on short-term results and fails to tackle underlying causes of coca cultivation, poverty and isolation from legal markets (L. M. Dávalos et al., 2011; Dion & Russler, 2008; Ibañez & Carlsson, 2010; Moreno-Sanchez, Kraybill, & Thompson, 2003; Rincón Ruiz, Pascual, & Romero, 2013). Aerial eradication centered on mechanical crime prevention actions that fail to yield long-term results.

Strategies to control illicit crops should include corrective crime prevention actions aiming to tackle the causes of the criminal activity (Lejins, 1967). In the coca crops case, previous studies have found that expanding rural electrification, providing access to credit, technical support, and contracts on harvest before planting, discourage households from growing coca (E. Dávalos & Dávalos, 2020). Therefore, while discussions on the implementation of eradication in Colombia remain locked between the use or disuse of aerial fumigation, neither alternative has succeeded to control illicit crops in the long-term because they need to be complemented with crime prevention actions aiming to reduce poverty and promote social development.

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Figure 1- Local indicator of spatial association cluster map of coca cultivation per municipality, Colombia 2001 and 2015

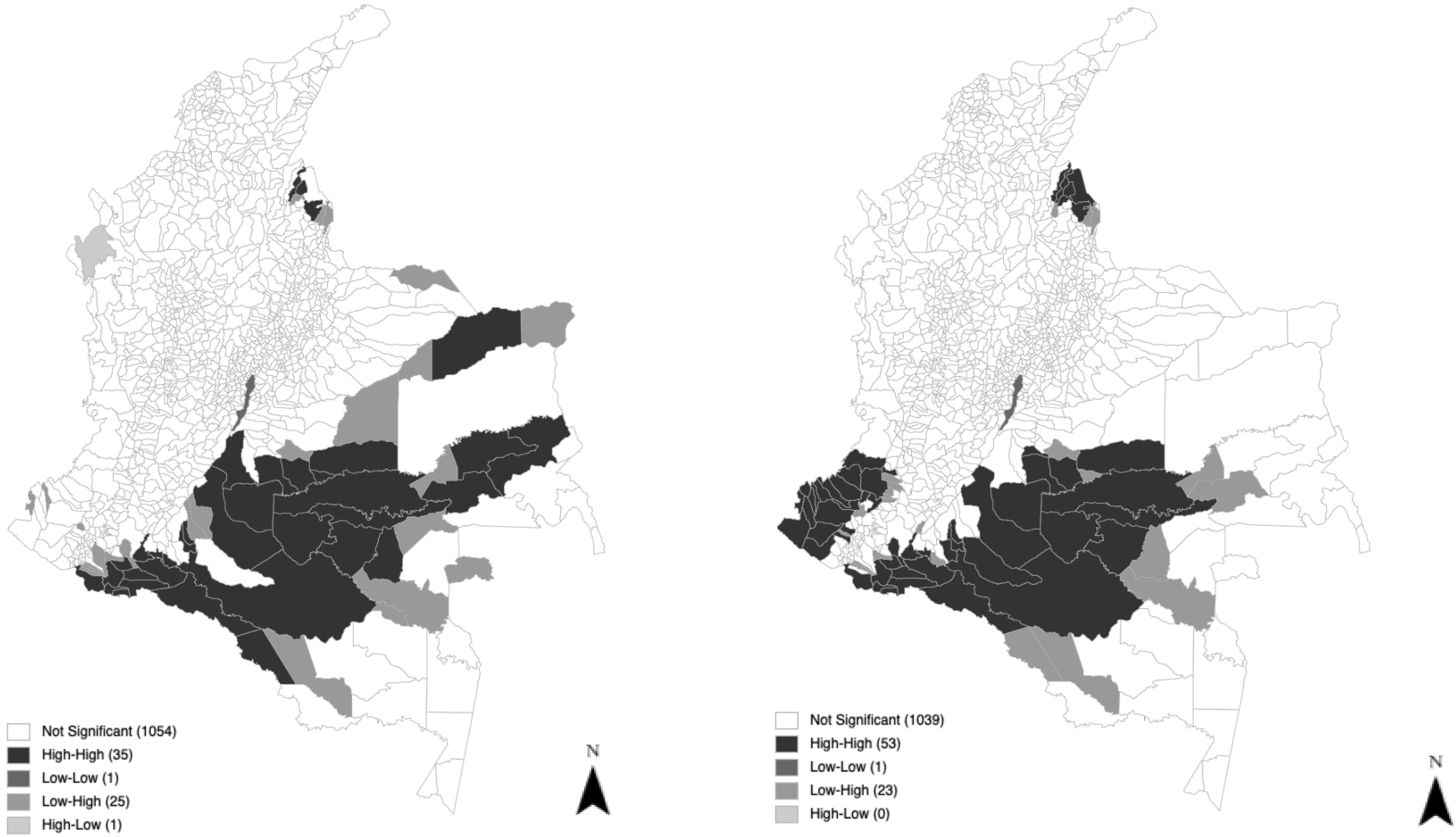

Figure 2- Local indicator of spatial association cluster map of aerial fumigation per municipality, Colombia 2001 and 2015

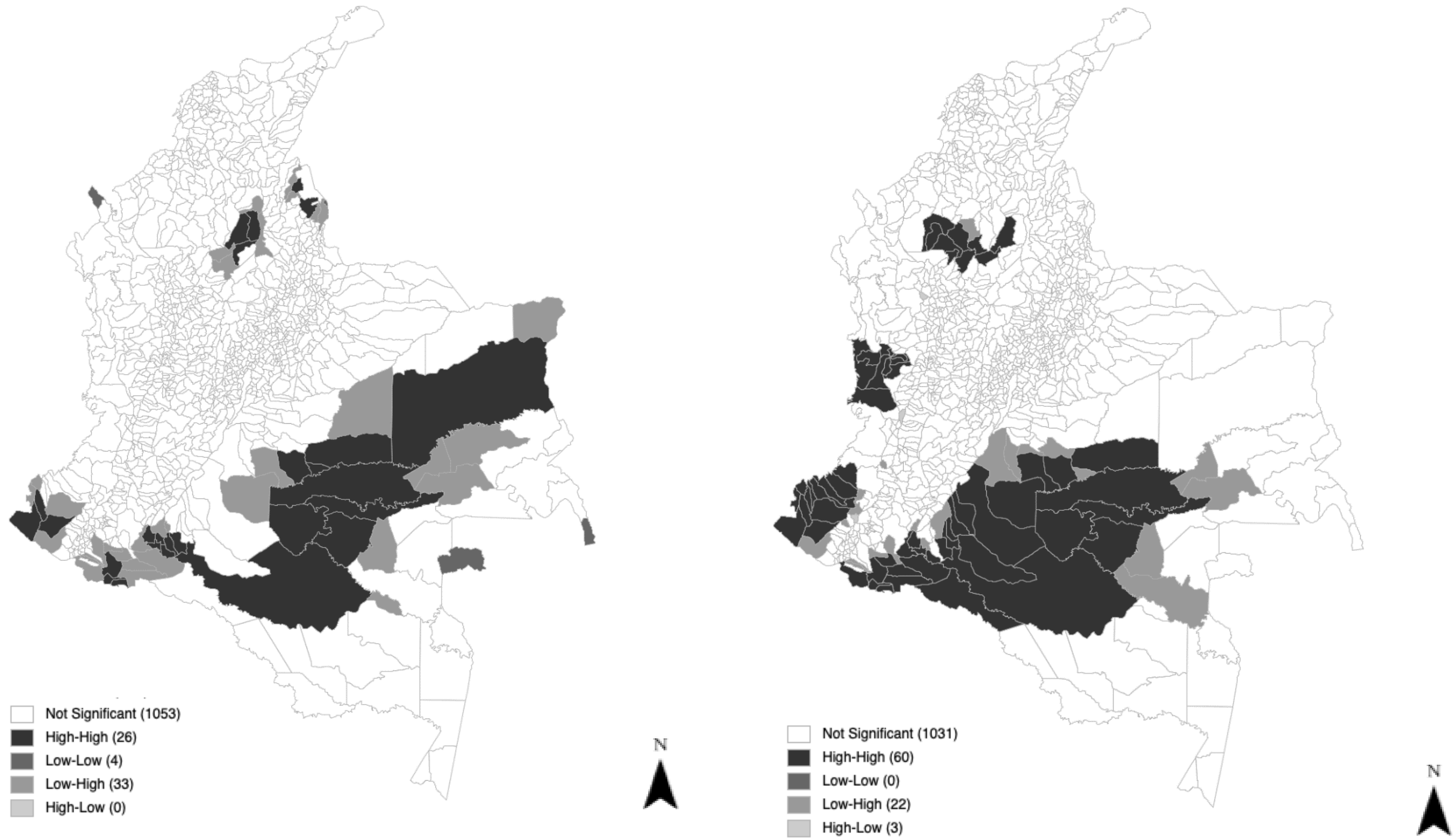

Table 1-Municipalities, area, and precipitation, Colombia 2001-2015

	Municipalities			Area (sq km)			Average precipitation municipalities (mm)	
	Without coca	With coca	Total	Without coca	Affected by coca crops	Total	Without coca	With coca
Amazon region	5	67	72	6,715	526,841	533,556	2,974	3,125
Rest country	626	418	1,044	215,599	391,419	607,018	1,697	2,457
Colombia	631	485	1,116	222,314	918,260	1,140,574	1,709	2,559

Notes: Compiled by the author based on Atlas Amazónico available online at https://siatac.co/la-amazonia-colombiana/. Data on municipalities affected by coca cultivation available online at http://www.odc.gov.co/sidco. Area affected by coca crops is the area that had manual eradication, aerial fumigation, or coca cultivation at some point during the year (UNODC, 2014).

Table 2-Summary of the variables included in the analysis and data sources, Colombia 2002-2015

Type	Short name	Units	Description	Source(s)	Municipalities N=1,116	
					Mean	Std.
Crops	Coca (net of eradication)	Hectare	Area on coca cultivation at the cut-off date of the annual coca survey: December 31	UNODC from ODC	68.27	407.51
	New area coca	Hectare	Annual change area on coca cultivation at the cut-off date of the annual coca survey	UNODC from ODC	-3.13	236.13
Strategies to control illicit crops	Manual eradication	Hectare	Number of hectares manually eradicated throughout the year in each municipality	Ministry of National Defense from ODC	29.14	309.30
	Fumigation	Hectare	Number of hectares fumigated throughout the year in each municipality	DIRAN from ODC	98.99	741.70
Control variables	Conflict	Number	Victims human rights violations and violations of international humanitarian law per 1,000 inhabitants	CINEP	0.68	13.56
	Infrastructure	Constant 2008 COP	Thousands of pesos spent annually, per inhabitant, in each municipality on land, roads, buildings, and equipment	DNP	377.28	507.42
	Human capital	Constant 2008 COP	Thousands of pesos spent annually, per inhabitant, in each municipality on teacher salaries, training, school feeding programs, and education material	DNP	305.59	211.56
	Industry and commerce tax	Constant 2008 COP	Thousands of pesos collected annually, per inhabitant, in each municipality from industry and commerce taxes	DNP	25.09	80.05
	Gasoline tax	Constant 2008 COP	Thousands of pesos collected annually, per inhabitant, in each municipality from gasoline taxes	DNP	14.05	17.31
	Nontax income	Constant 2008 COP	Thousands of pesos received annually, per inhabitant, in each municipality from other sources of income different from taxes	DNP	22.62	58.15
	Natural resources royalties	Constant 2008 COP	Thousands of pesos received annually, per inhabitant, in each municipality from natural resources	DNP	77.57	343.88
	Fiscal performance	Rank from 0 to 100	Municipal fiscal performance, values over 80 mean that the municipality is solvent and values below 40 that has low savings capacity, difficulties to cover its operation expenses, and relies on national transfers	DNP	62.48	9.61

Notes: Descriptive statistics for 1,116 contiguous municipalities in Colombia during the period of study, from 2001 to 2015. Most of these variables were originally defined by Davalos (2016). This analysis uses the same definitions.

Table 3-Specific tests for spatial dependence, Lagrange Multiplier (LM)

Specification	Pooled OLS		Spatial fixed effects		Time-period fixed effects		Spatial and time-period fixed effects	
	Test statistics	*p* value	Test statistics	*p* value	Test statistics	*p* value	Test statistics	*p* value
LM spatial lag	62.33	0.00	58.25	0.00	50.43	0.00	45.41	0.00
LM spatial error	48.99	0.00	44.98	0.00	39.77	0.00	35.31	0.00
Robust LM spatial lag	28.35	0.00	29.09	0.00	24.38	0.00	23.75	0.00
Robust LM spatial error	15.01	0.00	15.82	0.00	13.73	0.00	13.65	0.00

Notes: Lagrange Multiplier test estimated using Matlab, following Elhorst, (2014a).

Table 4-Model comparison of the estimation results explaining new coca crops

	New Area on Coca Crops					
	SAR		SEM		SDM	
Strategies to control illicit crops						
L1. Manual eradication	-0.06***	(0.01)	-0.06***	(0.01)	-0.06***	(0.01)
L1. Aerial fumigation	-0.08***	(0.00)	-0.08***	(0.00)	-0.08***	(0.00)
Control variables						
Conflict	0.84***	(0.13)	0.84***	(0.13)	0.85***	(0.13)
Natural parks	-3.28	(11.14)	-2.73	(12.05)	-0.03	(12.21)
Indigenous reserves	29.92***	(8.45)	32.83***	(10.32)	22.32*	(11.58)
Expenditures infrastructure	-0.01	(0.01)	-0.01*	(0.01)	-0.01	(0.01)
Expenditures human capital	-0.00	(0.01)	-0.00	(0.01)	-0.00	(0.01)
Industry and commerce tax	0.02	(0.04)	0.02	(0.04)	0.03	(0.04)
Gasoline tax	0.26	(0.21)	0.25	(0.21)	0.30	(0.21)
Nontax income	0.01	(0.03)	0.02	(0.03)	0.01	(0.03)
Natural resources royalties	0.00	(0.01)	0.00	(0.01)	0.00	(0.01)
Fiscal performance	-0.38	(0.29)	-0.33	(0.30)	-0.38	(0.30)
W*L1. Manual eradication					0.01	(0.01)
W*L1. Aerial fumigation					-0.01**	(0.01)
W*Conflict					-0.47	(0.30)
W*Natural parks					-13.45	(20.03)
W*Indigenous reserves					12.44	(15.55)
W*Infrastructure					-0.00	(0.02)
W*Human capital					-0.01	(0.03)
W*Industry and commerce tax					-0.03	(0.09)
W*Gasoline tax					-0.09	(0.44)
W*Nontax income					-0.07	(0.08)
W*natural resources royalties					0.01	(0.02)
W*Fiscal performance					0.08	(0.61)
Lambda			0.41***	(0.01)		
Rho	0.41***	(0.01)			0.41***	(0.01)
Observations	15,624		15,614		15,624	
R-squared	0.03		0.03		0.03	
Municipalities	1,116		1,116		1,116	

Notes: Results of Eq. (2) by Spatial Durbin Model. The outcome variable used is new area on coca crops. The sample includes all Colombian contiguous municipalities from 2001 and 2015. The spatial weight matrix was generated using the Queen Contiguity method, first-order neighbors. Municipal and year fixed effects regressors not shown. L1 represents one-year lag. See Table 2 for description, units, and source for all the variables. * p<0.10 ** p<0.05, *** p<0.01.

Table 5-Direct and indirect effects estimates based on the coefficient estimates of the spatial Durbin model reported in Table 4

	Direct effect		Indirect effect		Total effect	
Strategies to control illicit crops						
L1. Manual eradication	-0.06***	(0.01)	-0.02	(0.02)	-0.08***	(0.01)
L1. Aerial fumigation	-0.09***	(0.00)	-0.07***	(0.01)	-0.16***	(0.01)
Control variables						
Conflict	0.85***	(0.12)	-0.04	(0.43)	0.81*	(0.48)
Natural parks	-1.19	(13.30)	-21.25	(30.82)	-22.44	(36.50)
Indigenous reserves	23.60**	(9.83)	38.39*	(22.06)	61.99**	(24.52)
Expenditures infrastructure	-0.01	(0.01)	-0.00	(0.02)	-0.02	(0.03)
Expenditures human capital	-0.00	(0.01)	-0.01	(0.04)	-0.01	(0.05)
Industry and commerce tax	0.03	(0.04)	-0.01	(0.13)	0.02	(0.14)
Gasoline tax	0.31	(0.27)	0.09	(0.52)	0.39	(0.61)
Nontax income	0.00	(0.04)	-0.12	(0.16)	-0.11	(0.18)
Natural resources royalties	0.00	(0.01)	-0.00	(0.03)	0.00	(0.04)
Fiscal performance	-0.38	(0.32)	-0.43	(0.97)	-0.80	(1.12)

Notes: Results of Eq. (2) by Spatial Durbin Model. The outcome variable used is new area on coca crops. The sample includes all Colombian contiguous municipalities from 2001 and 2015. The spatial weight matrix was generated using the Queen Contiguity method, first-order neighbors. Municipal and year fixed effects regressors not shown. L1 represents one-year lag. See Table 2 for description, units, and source for all the variables. *p<0.10, **p<0.05, ***p<0.01.

Appendix 1-Moran's I value of coca crops and forced eradication

Scale	Municipal Level (1,116 municipalities)							
Year	Net area coca		New area coca		Area fumigated		Manual eradication	
2001	0.462	***			0.255	***		
2002	0.313	***	0.519	***	0.332	***		
2003	0.467	***	0.059	***	0.284	***		
2004	0.470	***	0.056	***	0.334	***	0.156	***
2005	0.381	***	0.102	***	0.262	***	0.071	***
2006	0.383	***	0.037	**	0.479	***	0.122	***
2007	0.415	***	0.133	***	0.346	***	0.342	***
2008	0.443	***	0.218	***	0.482	***	0.383	***
2009	0.436	***	0.183	***	0.416	***	0.123	***
2010	0.373	***	0.238	***	0.425	***	0.033	**
2011	0.437	***	0.312	***	0.443	***	0.011	**
2012	0.310	***	0.350	***	0.416	***	0.386	***
2013	0.291	***	0.199	***	0.391	***	0.132	***
2014	0.299	***	0.278	***	0.422	***	0.204	***
2015	0.252	***	0.195	***	0.426	***	0.207	***

Notes: ** $p<0.05$, *** $p<0.01$.

Appendix 2-Model comparison of the estimation results explaining new coca crops

	New Area on Coca Crops					
	SDM (Queen 2nd)		SDM (Rook 1st)		SDM (Rook 2nd)	
Strategies to control illicit crops						
L1. Manual eradication	-0.07***	(0.01)	-0.06***	(0.01)	-0.07***	(0.01)
L1. Aerial fumigation	-0.10***	(0.00)	-0.08***	(0.00)	-0.10***	(0.00)
Control variables						
Conflict	0.82***	(0.13)	0.84***	(0.13)	0.83***	(0.13)
Natural parks	-6.33	(12.25)	-3.95	(12.21)	-7.18	(12.28)
Indigenous reserves	29.24**	(11.38)	23.62**	(11.78)	27.95**	(11.46)
Expenditures infrastructure	-0.01	(0.01)	-0.01	(0.01)	-0.01	(0.01)
Expenditures human capital	-0.00	(0.01)	-0.00	(0.01)	-0.00	(0.01)
Industry and commerce tax	0.04	(0.04)	0.03	(0.04)	0.04	(0.04)
Gasoline tax	0.40*	(0.22)	0.29	(0.21)	0.39*	(0.22)
Nontax income	0.01	(0.03)	0.01	(0.03)	0.01	(0.03)
Natural resources royalties	0.00	(0.01)	0.00	(0.01)	0.00	(0.01)
Fiscal performance	-0.21	(0.31)	-0.36	(0.30)	-0.23	(0.31)
W*L1. Manual eradication	0.00	(0.02)	0.01	(0.01)	0.01	(0.02)
W*L1. Aerial fumigation	0.01	(0.01)	-0.02***	(0.01)	0.01	(0.01)
W*Conflict	1.14**	(0.58)	-0.45	(0.29)	0.97*	(0.56)
W*Natural parks	-7.26	(29.96)	-5.44	(19.87)	-3.66	(29.16)
W*Indigenous reserves	2.92	(18.96)	9.36	(15.64)	4.86	(18.80)
W*Infrastructure	-0.01	(0.02)	-0.00	(0.01)	-0.01	(0.02)
W*Human capital	-0.02	(0.05)	-0.01	(0.03)	-0.02	(0.05)
W*Industry and commerce tax	-0.08	(0.12)	-0.03	(0.08)	-0.09	(0.12)
W*Gasoline tax	-0.86	(0.71)	-0.01	(0.44)	-0.76	(0.69)
W*Nontax income	0.05	(0.12)	-0.07	(0.08)	0.05	(0.12)
W*natural resources royalties	0.01	(0.04)	0.01	(0.02)	0.01	(0.04)
W*Fiscal performance	-0.39	(1.05)	-0.04	(0.60)	-0.15	(1.03)
Rho	0.47***	(0.02)	0.40***	(0.01)	0.46***	(0.02)
Observations	15,624		15,614		15,624	
R-squared	0.02		0.03		0.03	
Municipalities	1,116		1,116		1,116	

Notes: Results of Eq. (2) by Spatial Durbin Model. The outcome variable used is new area on coca crops. The sample includes all Colombian contiguous municipalities from 2001 and 2015. The spatial weight matrix was generated using a Queen second-order neighbors' method (Queen 2nd), Rook first-order neighbors' method (Rook 1st), and Rook second-order neighbors' method (Rook 2nd). Municipal and year fixed effects regressors not shown. L1 represents one-year lag. See Table 2 for description, units, and source for all the variables. * p<0.10 ** p<0.05, *** p<0.01.

Direct and indirect effects estimates based on the coefficients estimates of the spatial Durbin model using a Queen second-order neighbors' method (Queen 2nd)

	Direct effect		Indirect effect		Total effect	
Strategies to control illicit crops						
L1. Manual eradication	-0.07***	(0.01)	-0.05	(0.03)	-0.12***	(0.03)
L1. Aerial fumigation	-0.10***	(0.00)	-0.06***	(0.02)	-0.16***	(0.02)
Control variables						
Conflict	0.88***	(0.12)	3.17***	(0.94)	4.06***	(0.96)
Natural parks	-6.64	(13.20)	-18.61	(56.70)	-25.25	(61.19)
Indigenous reserves	29.17***	(9.65)	36.88	(33.33)	66.05*	(35.23)
Expenditures infrastructure	-0.01	(0.01)	-0.01	(0.04)	-0.02	(0.04)
Expenditures human capital	-0.00	(0.02)	-0.03	(0.09)	-0.03	(0.09)
Industry and commerce tax	0.03	(0.04)	-0.09	(0.21)	-0.06	(0.22)
Gasoline tax	0.38	(0.28)	-1.18	(1.00)	-0.79	(1.02)
Nontax income	0.00	(0.04)	0.09	(0.28)	0.09	(0.30)
Natural resources royalties	0.00	(0.01)	-0.00	(0.07)	0.00	(0.07)
Fiscal performance	-0.22	(0.32)	-1.54	(1.93)	-1.76	(2.02)

Direct and indirect effects estimates based on the coefficients estimates of the spatial Durbin model using a Rook first-order neighbors' method (Rook 1st)

	Direct effect		Indirect effect		Total effect	
Strategies to control illicit crops						
L1. Manual eradication	-0.06***	(0.01)	-0.02	(0.02)	-0.08***	(0.01)
L1. Aerial fumigation	-0.09***	(0.00)	-0.08***	(0.01)	-0.16***	(0.01)
Control variables						
Conflict	0.84***	(0.12)	-0.04	(0.42)	0.81*	(0.46)
Natural parks	-4.58	(13.31)	-10.79	(30.05)	-15.37	(35.78)
Indigenous reserves	24.71**	(9.97)	33.40	(21.48)	58.11**	(23.89)
Expenditures infrastructure	-0.01	(0.01)	-0.00	(0.02)	-0.02	(0.03)
Expenditures human capital	-0.00	(0.01)	-0.00	(0.04)	-0.00	(0.05)
Industry and commerce tax	0.02	(0.04)	-0.01	(0.12)	0.01	(0.14)
Gasoline tax	0.30	(0.27)	0.21	(0.50)	0.51	(0.59)
Nontax income	0.00	(0.04)	-0.11	(0.16)	-0.11	(0.17)
Natural resources royalties	0.00	(0.01)	-0.00	(0.03)	0.00	(0.04)
Fiscal performance	-0.37	(0.32)	-0.59	(0.93)	-0.96	(1.08)

Direct and indirect effects estimates based on the coefficients estimates of the spatial Durbin model using a Rook second-order neighbors' method (Rook 2nd)

	Direct effect		Indirect effect		Total effect	
Strategies to control illicit crops						
L1. Manual eradication	-0.07***	(0.01)	-0.04	(0.03)	-0.11***	(0.03)
L1. Aerial fumigation	-0.10***	(0.00)	-0.06***	(0.01)	-0.16***	(0.02)
Control variables						
Conflict	0.88***	(0.12)	2.75***	(0.89)	3.64***	(0.92)
Natural parks	-7.39	(13.23)	-12.09	(53.61)	-19.48	(58.13)
Indigenous reserves	27.93***	(9.71)	37.65	(32.03)	65.58*	(33.91)
Expenditures infrastructure	-0.01	(0.01)	-0.01	(0.04)	-0.02	(0.04)
Expenditures human capital	-0.00	(0.02)	-0.02	(0.08)	-0.02	(0.08)
Industry and commerce tax	0.03	(0.04)	-0.11	(0.20)	-0.08	(0.21)
Gasoline tax	0.38	(0.28)	-0.99	(0.94)	-0.61	(0.97)
Nontax income	0.00	(0.04)	0.08	(0.27)	0.08	(0.28)
Natural resources royalties	0.00	(0.01)	0.00	(0.06)	0.01	(0.07)
Fiscal performance	-0.23	(0.32)	-1.06	(1.83)	-1.29	(1.92)

Appendix 3: Spatial Durbin Error Model.

$$y_{it} = \phi + x_{it}\beta + \sum_{j=1}^{N} w_{ij}\, x_{jt}\theta + c_i + \alpha_t + v_{it}$$

$$v_{it} = \delta \sum_{j=1}^{N} w_{ij}\, v_{jt} + \varepsilon_{it}$$

	SDEM (Queen 1st)	
Strategies to control illicit crops		
L1. Manual eradication	-0.06***	(0.01)
L1. Aerial fumigation	-0.09***	(0.00)
Control variables		
Conflict	0.81***	(0.13)
Natural parks	-0.63	(12.03)
Indigenous reserves	24.53**	(11.01)
Expenditures infrastructure	-0.01	(0.01)
Expenditures human capital	-0.00	(0.01)
Industry and commerce tax	0.02	(0.04)
Gasoline tax	0.30	(0.22)
Nontax income	0.01	(0.03)
Natural resources royalties	0.00	(0.01)
Fiscal performance	-0.39	(0.31)
W*L1. Manual eradication	-0.01	(0.01)
W*L1. Aerial fumigation	-0.06***	(0.01)
W*Conflict	-0.39	(0.35)
W*Natural parks	-17.74	(23.87)
W*Indigenous reserves	31.06*	(17.93)
W*Infrastructure	-0.00	(0.02)
W*Human capital	-0.02	(0.03)
W*Industry and commerce tax	-0.01	(0.10)
W*Gasoline tax	0.15	(0.54)
W*Nontax income	-0.09	(0.10)
W*natural resources royalties	0.01	(0.03)
W*Fiscal performance	0.03	(0.73)
Rho		
Sigma-squared	42,649.09***	(487.56)
Lambda	0.41***	(0.01)
Observations	15,624	
R-squared	0.03	
Municipalities	1,116	
Log marginal	-103670.6874	
Model probability	0.921	