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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 tests the hypothesis that forced eradication generates spillover effects. Using annual data for 1,116 contiguous municipalities in Colombia between 2001 and 2010, we estimate a spatial Durbin model (SDM) with municipal and time fixed effects. At municipal level, we find no evidence of the *balloon effect*. Our results suggest that aerial eradication activities in a municipality reduce the new area under coca cultivation by 8 percent inside that municipality and by 3 percent in neighboring municipalities. Therefore, and contrary to the balloon effect hypothesis aerial eradication generates negative spillover effects. Our results provide deeper insights for policy design. In our analysis, we are able to distinguish between the change in coca cultivation as a result of eradication activities inside and outside the municipality.

Keywords: Coca crops; Eradication; Spatial dependence; Spatial Durbin model; Spillover

JEL Classification: K42, R12, and R14

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1. Introduction

As dozens of press headlines have announced, the War on Drugs has failed to curb cocaine production, consumption, and trafficking (Chalabi, 2016; Doward, 2016; Pardo Veiras, 2016). Therefore, presidents of the countries involved, public figures, and researchers have called for a new public policy approach to control drugs (LSE, 2014; Mulholland, 2016; Policy, 2011; Post, 2016). On the supply side, the failure has been attributed to the strategies used to control illicit crops, as coca crops shift from one area to another but do not disappear (Bertram, Blachman, Sharp, & Andreas, 1996; Nadelmann, 1989; Stares, 1996; Zepeda Martínez & Rosen, 2015). In the drug policy literature, this dynamic shifting is commonly known as the *balloon effect*. Cultivation is squeezed in one side; then it emerges in another.

Even though balloon effect dynamics of coca cultivation are popular with the public and some researchers, its empirical testing has been limited (Basov, Miron, & Jacobson, 2001; Reuter, 2014; Reuter et al., 2009; Thoumi, 2003). Previous studies evaluating the effectiveness of the strategies used to control illicit crops (Ibañez & Carlsson, 2010; Mejía, Restrepo, & Rozo, 2015; Moreno-Sanchez, Kraybill, & Thompson, 2003; Reyes, 2014), and specifically testing the balloon effect (Raffo Lopez, Castro, & Diaz España, 2016; Rouse & Arce, 2006), did not account for the spatial dependence of coca cultivation and forced eradication. An increase in coca cultivation in one region can be caused by the reduction in forced eradication in its own region or by the increase in forced eradication in neighboring regions. As a result, the broad impacts—including local and spillover effects—on coca crops may lead to biased policy conclusions if the spatial dependence of forced eradication is not factored in the analyses.

A recent study, acknowledging the spatial dynamics of coca crops, established a positive relationship between aerial fumigation in a municipality and coca cultivation in neighboring municipalities the following year (Rincón-Ruiz & Kallis, 2013). However, the analysis used an indicator of spatial correlation (Moran's I) that suggests association but does not imply causation (Anselin, Sridharan, & Gholston, 2007). Hence, the spillover effect of the strategies used to control illicit crops on coca cultivation is still unknown. In contrast to previous research, this study implements a spatial econometric technique to address spatial dependence and estimates the spillover effects of forced eradication activities.

To assess the spillover effects of the strategies used to control illicit crops, we use annual data for 1,116 contiguous municipalities in Colombia between 2001 and 2010. We estimate a spatial Durbin model (SDM) with municipal and time fixed effects. The results suggest that manual eradication does not affect new coca crops. Aerial eradication, in contrast, reduces new coca crops and generates negative spillover effects. Aerial eradication activities in a municipality reduce, on average, the new area under coca cultivation by 8 percent in that municipality and by 3 percent in neighboring municipalities. Thus, there is no balloon effect at municipal level. In addition, implementing aerial eradication inside natural parks generates great spillovers or indirect effects. The change in neighboring municipalities to the change in the municipality itself is in the proportion of 6.25 to 1. Therefore, neighboring municipalities bear much of the impact of this policy change.

The paper is organized as follows. Section two describes the municipalities where coca cultivation takes place, explains the strategies used to control illicit crops in

Colombia, and performs a descriptive analysis to illustrate spatial clustering in the area of study. Section three describes data used in the econometric analysis, and section four explains the econometric methodology used. Section five presents the results of the spatial panel data model, and section six closes with a discussion of the results.

2. Coca crops, forced eradication, and spatial dependence

In Colombia, most coca cultivation takes place in remote areas of the country isolated by the Andes mountain range and the characteristic Amazon inclement weather. 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 are on average six times larger that those without coca crops. These municipalities are covered with thick rainforest and receive on average 50 percent more annual rainfall compared to municipalities without coca crops. 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 take place in municipalities affected by coca crops, 440 municipalities out of 1,116 contiguous municipalities in Colombia as of 2010 (see Table 1). Forced eradication is 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 is 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 conducted in Colombia until September 2015 when it was suspended because of the health and environmental risks associated with the herbicide (ANLA, 2015).

Analyzing the same geographic area 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.[3] Figure 1 illustrates clusters of high-high hectares of coca. Hence, municipalities with high amounts of coca crops surround municipalities with high amounts of coca crops. By 2010, positive spatial clustering also appears in the Pacific and Northern region of the country.

[Figure 1 about here]

Simultaneously, Figure 2 shows positive spatial clustering for aerial eradication in the Amazon region of Colombia in 2001. Eradication activities are concentrated in areas where coca cultivation is high. Therefore, there is also a positive spatial clustering for aerial eradication in the Pacific region in 2010. White areas in Figure 1 and 2 showed no statistically significant spatial clustering.

[Figure 2 about here]

[3] Spatial weights for Figure 1 and 2 were created using a Queen contiguity method, first-order neighbors. The statistical significance of the correlations was calculated using 10,000 permutations.

3. Data

This paper analyzes annual data for 1,116 contiguous municipalities in Colombia from 2001 to 2010. The outcome variable used in the econometric analysis was calculated using the net area under coca cultivation at the cut-off date of the *Annual Coca Survey* (December 31). Annually, the Illicit Crops Monitoring Global Program of the United Nations Office of Drugs and Crime (UNODC) captures satellite images that cover the entire continental Colombian territory (1,142,000 Km^2). 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 the area under coca cultivation 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 resultant area after the corrections for gaps and clouds and the adjustments for eradication activities is the net area under coca cultivation.[4]

Equation 1 describes the dependent variable. y_t is the new area on coca crops in period t. x_t is the net area under coca cultivation at the cut-off date of the annual coca survey in period t, and x_{t-1} is the net area under coca cultivation at the cut-off date of the annual coca survey in period $t-1$. This variable was reported in annual hectares.[5]

Equation 1 Outcome variable used in the econometric analysis

[4] Net area under coca cultivation refers to the area under coca cultivation net of eradication at the cut-off date of the annual coca survey, December 31. For more details about the collection process and methodology, visit: http://www.biesimci.org/SIMCI/metodologia.html

[5] One hectare is equivalent to 2.5 acres.

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

Data on the strategies used to control coca crops, manual and aerial eradication, come the Colombian Antinarcotics Police (DIRAN for its Spanish-language acronym). These variables were also reported in annual hectares. Alternative development is the number of families joining alternative development programs implemented in coca growing areas: *Programa Proyectos Productivos* (productive projects) and *Programa Familias Guardabosques* (forest ranger families). These data were collected by the Colombian Agency for Social Action and International Cooperation, currently known as the *Departamento para la Prosperidad Social*.

In addition to the basic factors related to new coca crops, this analysis controls for policy implementation changes related to eradication activities affecting coca cultivation. The model estimated includes dummy variables capturing the difference between allowing aerial spraying inside natural parks and indigenous reservations. These dummies were coded zero before aerial eradication was implemented and one once it was implemented in municipalities with natural parks (after 2005) and indigenous reservations (after 2007).

This analysis also controls for other municipal-level characteristics. Data on public spending, government financing sources, for instance: property tax, industry and commerce tax, gasoline tax, natural resources royalties, and cofinancing, come from the Colombian National Planning Department (DNP). They are reported annually in nominal thousand pesos. We use the CPI to adjust for inflation and per capita measures to make expenditures comparable over time and across municipalities. The DNP also ranks municipalities based on their fiscal performance. DNP follows the IMF guidelines to generate a rank that ranges from zero to 100, in which values over 80 mean that the municipality is solvent and values below 40 that has low savings capacity, difficulties covering its operation expenses, and relies on national transfers (DNP, 2012). Finally to measure armed conflict, we use the number of victims of all kind of human rights violations perpetrated by different armed groups present in the area: guerrilla, paramilitary, or national army. Human rights violations occurred daily in each municipality, and the data were collected and reported by the Centre for Research and Popular Education/Peace Program. Table 2 provides a summary of the variables included in the spatial econometric analysis.

[Table 2 about here]

4. Methods

The estimation is carried out using two sequential steps:

4.1 Spatial autocorrelation test

To measure spatial autocorrelation, we calculated Moran's I for the area under coca cultivation and the area fumigated with glyphosate using *GeoDa* (Anselin, Syabri, & Kho, 2006). The global Moran's I is defined in Equation 2 (Moran, 1950):

Equation 2 Global Moran's I

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

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.

We tested for spatial autocorrelation for new coca crops and aerial fumigation for each year from 2001 to 2010. Table 3 reports the results by year and scale of analysis. The global Moran's I for new coca crops and area fumigated are significant for all years for the national level data. This result indicates that spatial autocorrelation persists across years, and positive values indicate spatial clustering. The 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.

[Table 3 about here]

4.2 Spatial econometric analysis

To assess the spillover effects of forced eradication, we use 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, Gallo, & Jayet, 2008; LeSage & Pace, 2009). Following the strategy described in LeSage and Pace (2009), Elhorst (2010), and Elhorst (2014a), we start from a specific-to-general approach to select the model specification. First, we estimate a non-spatial model and test it against the spatial lag and spatial error model. Table 4 reports results for traditional and robust Lagrange Multiplier (LM) tests (Anselin, 1988; Anselin, Bera, Florax, & Yoon, 1996; Burridge, 1980). The hypothesis of no spatial lagged dependent variable and the hypothesis of no spatial auto-correlated error term are rejected in all model specifications.

[Table 4 about here]

Then, we estimate a spatial Durbin model (SDM) as a general specification and test for alternative models. Equation 3 explains the formal structure of the SDM.

Equation 3 Spatial Durbin model that contains a spatially lagged dependent variable and spatially lagged independent variables

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

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. To capture time-invariant municipal-specific characteristics that may confound the estimate of interest, the model also includes municipal fixed effects, c_i, and to control for variables that are constant across municipalities but change over time, it has time-period specific effects, α_t. Finally, θ is a $K \times 1$ vector of parameters, and v_{it} is the stochastic error term.

Using a general-to-specific approach, we estimate a spatial Durbin model to test whether it can be simplified to the spatial lag (SAR) or the spatial error model (SEM) (Burridge, 1981). Table 5 summarizes the results of the Hausman test to determine if the spatial panel model should include fix or random effects, and the Wald test for spatial model selection. The Hausman test favors fixed-effects estimations over random-effects estimations. The Wald test indicates that the hypothesis whether the spatial Durbin model can be simplified to the spatial lag model, $H_0: \theta = 0$, must be rejected (243.52, p=0.000). In contrast to the previous result, the hypothesis that the spatial Durbin model can be simplified to the spatial error model, $H_0: \theta + \lambda\beta = 0$, cannot be rejected (17.37, p=0.183). These results imply that the SAR must be rejected in favor of the SDM, but the SEM is preferred over SDM. However, the SEM is a special case of a SDM for which $\theta + \lambda\beta = 0$ (Appendix A), and a SEM is not suitable for a spillover effects analysis as the indirect effects are zero by construction (Elhorst, 2014b). Therefore, the SDM is the model specification that best describes the data.

[Table 5 about here]

5. 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 6, columns

(1) to (3), reports coefficients on three different spatial panel models. Column (1) presents 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 shown without parentheses are spatial panel coefficients. Numbers in parentheses are standard errors.

Results are consistent throughout 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*, has an equivalent interpretation for a SEM. Coefficients on aerial fumigation are also pretty consistent in the three models, negative and statistically significant. Specifically in the SDM, coefficients on spatially lagged explanatory variables, aerial fumigation, conflict, indigenous reserves, and gasoline tax, are significant.

[Table 6 about here]

Table 7 reports direct, indirect, and total effects from the SDM estimation. The direct effect of an additional hectare of coca fumigated a year ago in municipality i reduces, on average, new coca crops by 0.08 hectares in municipality i. The direct effect of expenditures in human capital is also negative and significant. Increasing expenditures in human capital by one thousand pesos per inhabitant in municipality i is associated with a reduction of 0.04 hectare of new coca crops in the same municipality. This result is consistent with previous findings on the effects of social investment on new coca crops (Davalos, 2016). Armed conflict also has a direct effect on new coca crops. One additional victim of a human right violation per thousand inhabitants in municipality i is associated with an increase of 0.84 hectares of new coca crops in municipality i, on average. 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). There is no feedback effect. Coefficients on aerial eradication, conflict, and expenditures in human capital (SDM results in table 5) are very close to the direct effect of aerial eradication, conflict, and expenditures in human capital (Table 7).

[Table 7 about here]

The indirect effect of aerial eradication is negative and statistically significant. Therefore, if aerial eradication increases in municipality i during year t, new coca crops decrease in municipality i and its neighboring municipalities in year $t + 1$. The change in neighboring municipalities to the change in the municipality itself is in the proportion of 1 to -2.7. The indirect effect of spraying an additional hectare of coca in municipality i on the new coca crops in neighboring municipalities is a reduction of 0.03 hectares. There are no indirect effects for expenditures on infrastructure or human capital. However, policy changes of implementing aerial eradication inside natural parks generate great spillovers or indirect effects. When aerial eradication was implemented inside natural parks, new coca crops increase in the municipality with natural parks and its neighboring municipalities. The ratio of the change in neighboring municipalities to the change in the municipality itself is in the proportion of 6.25 to 1. Therefore, neighboring municipalities bear much of the impact of this policy change.

Finally, the total effect of aerial eradication is the sum of its direct and indirect effect. If all municipalities increase aerial eradication by one hectare in period t, new coca crops will decrease by 12 percent in period $t + 1$ in the typical municipality.[6] This result is consistent with previous findings on the average effects of aerial eradication on coca cultivation (Acevedo, 2015; Davalos, 2016). Implementing aerial eradication inside natural parks also reports total effects. If all municipalities had natural parks and implemented aerial eradication inside them, new coca crops would increase, on average, by 49.8 hectares. There are no statistically significant total effects for expenditures on infrastructure or human capital.

6. Conclusions

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, and either involves trends across countries (Dávalos, Bejarano, & Correa, 2009), or trends in spatial clusters (Rincón-Ruiz, Pascual, & Flantua, 2013). Our analyses reveal that aerial eradication activities in a municipality reduce the new area under coca cultivation by 8 percent inside that

[6] One hectare is equivalent to 10,000 squared meters; thus, a reduction of 0.12 hectares equals a reduction of 1,200 squared meters or 12 percent of a hectare.

municipality and by 3 percent in neighboring municipalities. Therefore, and contrary to the balloon effect hypothesis, aerial eradication generates negative spillover effects. Thus, the balloon effect is not responsible for the failures of the 40-year-old War on Drugs.

Although previous analyses had already identified a negative relationship between aerial eradication and coca cultivation (Acevedo, 2015; Davalos, 2016; Mejía et al., 2015), our results provide deeper insights for policy design. In our analysis, we are able to distinguish 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 that strategy.

Previous literature hypothesized that forced eradication activities in some areas may increase coca cultivation in other areas (Raffo Lopez et al., 2016; Rouse & Arce, 2006; Thoumi, 2003). Our spatial model tests that hypothesis at municipal level and provides evidence for the opposite relationship. A plausible explanation for negative spillover effects is that coca growers are aware of eradication activities in neighboring municipalities, and they fear that their coca crops may also be destroyed. Therefore, some of these growers reduce the area under coca cultivation, and others may decide not to grow coca at all. In summary, coca growers (offenders) are dissuaded from illegal activities when they acknowledge the negative consequences experienced by their neighbors (others) (Braga, Apel, & Welsh, 2013; Rincke & Traxler, 2011).

Until 2015, aerial eradication was the only credible threat to coca cultivation because out of many coca growers only few were prosecuted.[7] Aerial eradication destroyed most of the coca crops sprayed with glyphosate; the average survival rate of coca crops sprayed during the period of study was 10.5 percent. Based on our results, aerial eradication discourages coca growers from increasing their area under coca cultivation inside the municipality and in neighboring municipalities as well. However, as September 2015, aerial eradication was suspended in Colombia and coca crops increased by 77,000 hectares from 2014 to 2016 (UNODC, 2017).

As of 2018, manual eradication emerged as one of the main strategies to control illicit crops in Colombia (Semana, 2016). However, manual eradication is a labor-intensive strategy that requires the work of 20 people during one day to eradicate just one hectare of coca (Mansfield, 2011). Manual eradication is an arduous and dangerous activity for those performing the task.[8] In addition, based on our results, manual eradication has no impact on coca cultivation. Therefore, spending time and resources implementing a strategy that does not generate an impact on the area under coca cultivation is uncertain.

[7] The Colombian police reported 855 felonies related with coca cultivation in 2009 (Colombia, 2010). Out of that total only 162 people were prosecuted for this crime. For the same period, it was estimated that about 300,000 people were involved in coca cultivation.

[8] According to Mansfield (2011): "In Peru, thirty eradication staff were killed in the Upper Huallaga Valley between 1986 and 1988. In the Macarena National Park in Colombia there were twenty-nine fatalities during a single day of eradication in December 2005 and a total of one hundred and eighteen were killed between 2005 and 2008. A further forty soldiers and police were killed during manual eradication efforts in Colombia in 2009."

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Figure 1- Local indicator of spatial association cluster map of coca cultivation per municipality, Colombia 2001 and 2010

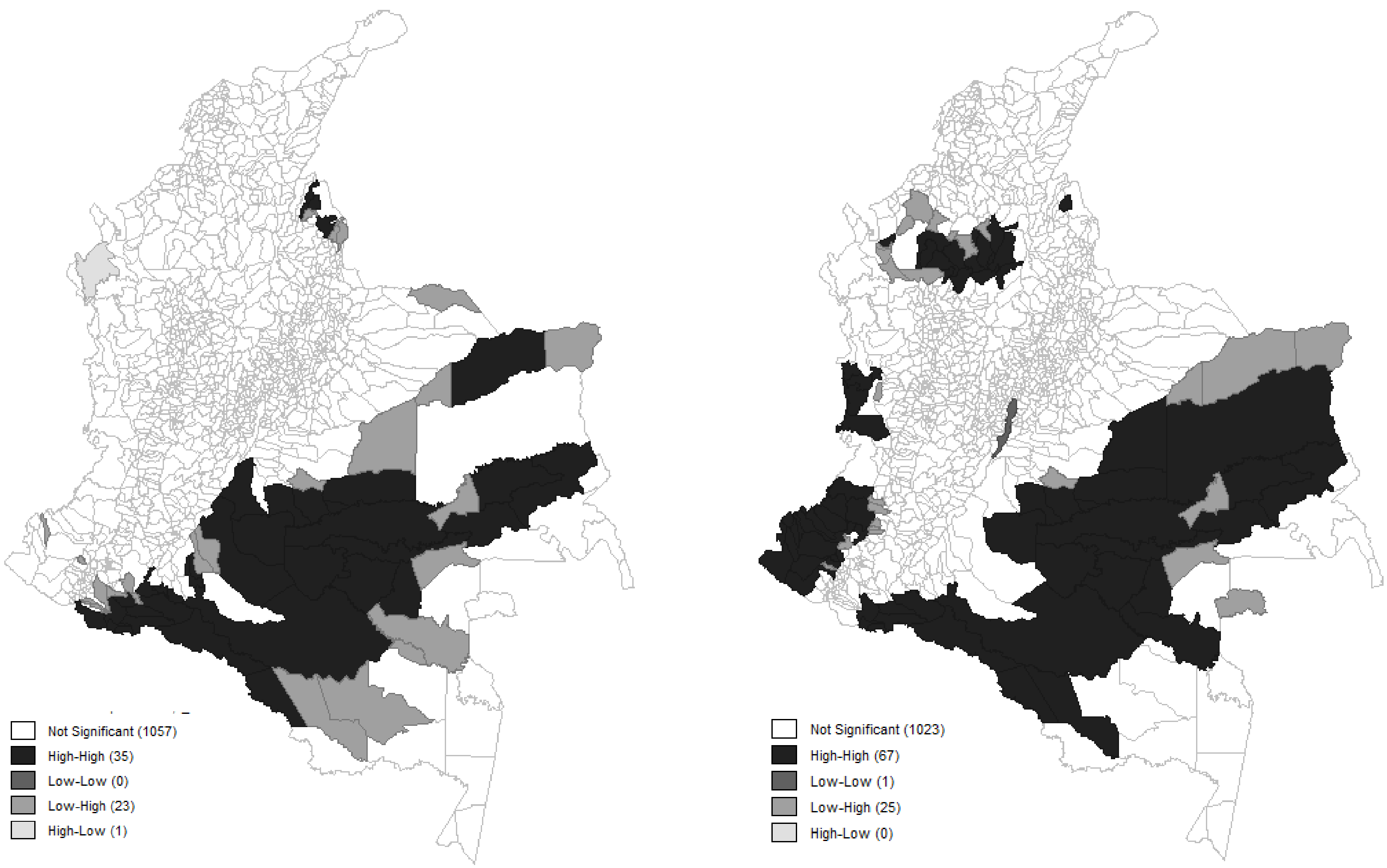

Figure 2- Local indicator of spatial association cluster map of aerial eradication per municipality, Colombia 2001 and 2010

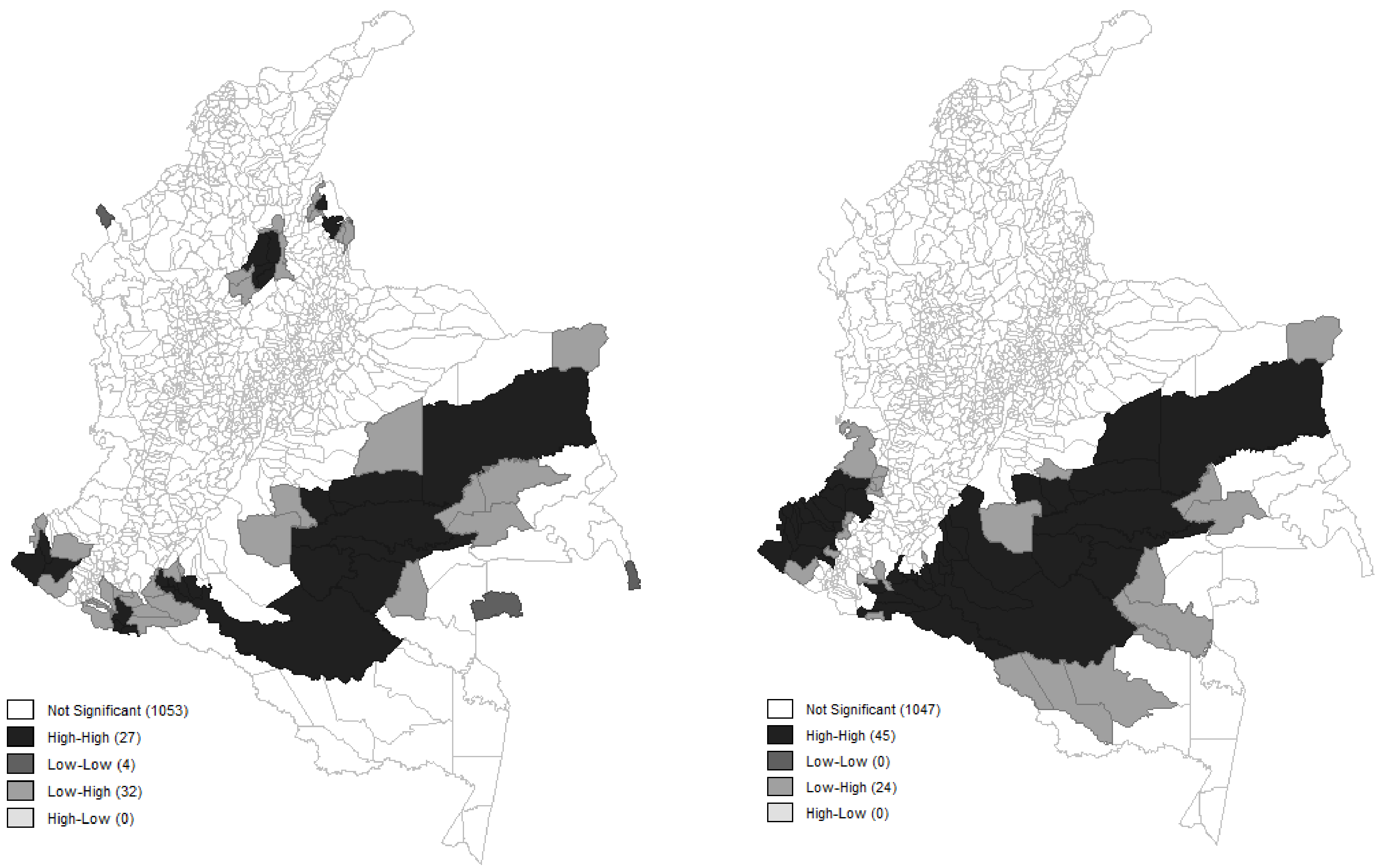

Table 1-Municipalities, area, and precipitation, Colombia 2001-2010

	Municipalities			Area (sq km)			Average annual precipitation (mm)	
	Without coca	With coca	Total	Without coca	Affected by coca crops	Total	Without coca	With coca
Amazon region	7	65	72	11,696	521,860	533,556	2,968	3,130
Rest country	669	375	1,044	241,089	365,929	607,018	1,718	2,504
Colombia	676	440	1,116	252,785	887,789	1,140,574	1,733	2,606

Source: Compiled by the author based on the CEPAL (2013) report for the Amazon region classification, precipitation data from Worldclim 2005 from Armenteras, Cabrera, Rodríguez, and Retana (2013), and UNODC annual surveys for municipalities affected by coca cultivation from 2001 to 2010. The area affected by coca crops is the total area of the municipality that had coca cultivation, manual eradication, or aerial eradication at some point during the year.

Table 2- Summary of the variables considered in the analysis and data sources, Colombia

Type	Short name	Units	Description	Source(s)	Municipalities N=1,116 Mean	Std.
Crops	Coca (net of eradication)	Hectare	Area under coca cultivation at the cut-off date of the annual coca survey: December 31	UNODC annual coca survey	73.88	418.60
	New area coca	Hectare	Annual change on the area under coca cultivation at the cut-off date of the annual coca survey	Calculated from UNODC annual coca survey	-8.26	269.05
Estrategies to control illicit crops	Manual eradication	Hectare	Number of hectares manually eradicated throughout the year in each municipality	UNODC	34.18	347.74
	Fumigation	Hectare	Number of hectares fumigated throughout the year in each municipality	DIRAN from UNODC	119.85	871.42
	Voluntary eradication	Families	Number of families that joined alternative development program implemented in coca growing areas	Acción Social	12.03	118.05
Control variables	Conflict	Number	Victims of all kind of human rights violations per 1,000 inhabitants	CINEP	0.53	14.39
	Infrastructure	Constant 2008 COP	Thousands pesos spent annually, per inhabitant, in each municipality on land, roads, buildings, and equipment	DNP	245.84	344.47
	Human capital	Constant 2008 COP	Thousands pesos spent annually, per inhabitant, in each municipality on teacher salaries, training, school feeding programs, and education material	DNP	291.44	173.02
	Industry and commerce tax	Constant 2008 COP	Thousands pesos collected annually, per inhabitant, in each municipality from industry and commerce taxes	DNP	17.47	46.76
	Gasoline tax	Constant 2008 COP	Thousands pesos collected annually, per inhabitant, in each municipality from gasoline taxes	DNP	14.56	18.24

Non tax income	Constant 2008 COP	Thousands pesos received annually, per inhabitant, in each municipality from other sources of income different from taxes	DNP	21.78	38.40
Natural resources royalties	Constant 2008 COP	Thousands pesos received annually, per inhabitant, in each municipality from natural resources	DNP	50.35	265.17
Fiscal performance	Rank from 0 to 100	Municipal fiscal performance, where 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	59.52	8.96

Notes: This table presents descriptive statistics for 1,116 contiguous municipalities in Colombia during the period of study, from 2001 to 2010.

Table 3- Moran's I value of new area coca and area fumigated

Scale	Municipal Level (1,116 municipalities)			
Year	New area coca		Area fumigated	
2001			0.255	***
2002	0.519	***	0.332	***
2003	0.059	***	0.284	***
2004	0.056	***	0.334	***
2005	0.102	***	0.262	***
2006	0.037	**	0.479	***
2007	0.133	***	0.346	***
2008	0.218	***	0.482	***
2009	0.183	***	0.416	***
2010	0.238	***	0.425	***

Note: ** p<0.05, *** p<0.01.

Table 4-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

Table 5-Specific tests for spatial dependence, Haussman and Wald

Tests	Test statistics	Prob>chi2
Hausman test Ho: difference in coefficients not systematic	267.72	0
Wald test Ho: SDM can be simplified to SAR	243.52	0
Wald test Ho: SDM can be simplified to SEM	17.37	0.183

Table 6-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	0.00	(0.01)	0.02*	(0.01)	0.01	(0.01)
L1. Aerial fumigation	-0.07***	(0.01)	-0.08***	(0.00)	-0.08***	(0.01)
L1. Alternative development	0.02	(0.03)	0.02	(0.02)	0.02	(0.03)
Control variables						
Conflict	0.83***	(0.22)	1.00***	(0.18)	0.84***	(0.21)
Natural parks	0.00	(0.00)	0.00	(0.00)	0.00	(0.00)
Indigenous reservations	28.22*	(15.61)	12.04	(13.41)	34.22**	(15.81)
Expenditures infrastructure	-0.01	(0.02)	-0.01	(0.02)	-0.01	(0.02)
Expenditures human capital	-0.04	(0.03)	-0.02	(0.02)	-0.04	(0.03)
Industry and commerce tax	-0.04	(0.16)	-0.02	(0.13)	-0.07	(0.16)
Gasoline tax	1.10***	(0.40)	0.95***	(0.33)	1.11***	(0.39)
Non tax income	0.07	(0.10)	0.06	(0.08)	0.06	(0.10)
Natural resources royalties	0.03	(0.03)	0.02	(0.02)	0.03	(0.03)
Fiscal performance	-0.09	(0.53)	-0.50	(0.45)	-0.28	(0.53)
W*L1. Manual eradication					-0.00	(0.00)
W*L1. Aerial fumigation					0.03***	(0.00)
W*L1. Alternative development					-0.01	(0.01)
W*Conflict					-0.28***	(0.10)
W*Natural parks					-5.66*	(3.25)
W*Indigenous reservations					-6.09	(5.22)
W*Infrastructure					0.00	(0.01)
W*Human capital					0.01	(0.01)
W*Industry and commerce tax					-0.01	(0.06)
W*Gasoline tax					-0.10	(0.15)
W*Non tax income					0.01	(0.04)
W*natural resources royalties					0.01	(0.01)
W*Fiscal performance					0.32	(0.20)
Rho	0.30***	(0.00)			0.30***	(0.00)
Lambda			0.03***	(0.00)		
Observations	10,044		10,044		10,044	
Municipalities	1,116		1,116		1,116	

Notes: This table presents the results of the specification established in Eq. (3) by Spatial Durbin Model. The outcome variable used in this analysis is new area on coca crops. The estimates correspond to micro data set by municipality. The sample includes all Colombian contiguous municipalities from 2001 and 2010. 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 7-Direct and indirect effects estimates based on the coefficients estimates of the spatial Durbin model reported in Table 6

	Direct effect		Indirect effect		Total effect	
Strategies to control illicit crops						
L1. Manual eradication	0.01	(0.01)	0.00	(0.04)	0.02	(0.04)
L1. Aerial fumigation	-0.08***	(0.01)	-0.03***	(0.01)	-0.12***	(0.01)
L1. Alternative development	0.03	(0.02)	0.02	(0.09)	0.05	(0.09)
Control variables						
Conflict	0.84***	(0.21)	0.10	(0.98)	0.94	(1.03)
Natural parks	6.80	(6.81)	42.98***	(16.27)	49.78**	(21.29)
Indigenous reservations	32.61*	(17.95)	-26.12	(42.13)	6.50	(41.66)
Expenditures infrastructure	-0.01	(0.02)	0.02	(0.05)	0.01	(0.05)
Expenditures human capital	-0.04*	(0.02)	-0.00	(0.08)	-0.04	(0.08)
Industry and commerce tax	-0.07	(0.15)	0.22	-0.54	0.15	(0.53)
Gasoline tax	0.80**	(0.32)	-1.17	(0.97)	-0.37	(0.91)
Non tax income	0.04	(0.09)	-0.22	(0.29)	-0.18	(0.32)
Natural resources royalties	0.01	(0.03)	-0.15	(0.10)	-0.14	(0.10)
Fiscal performance	-0.36	(0.53)	-1.53	(1.30)	-1.89	(1.24)

Notes: This table presents the results of the specification established in Eq. (3) by Spatial Durbin Model. The outcome variable used in this analysis is new area on coca crops. The estimates correspond to micro data set by municipality. The sample includes all Colombian contiguous municipalities from 2001 and 2010. 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 A. Spatial error model (SEM) is a special case of a Spatial Durbin Model (SDM)

Starting from a SDM:

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

If $\theta + \lambda\beta = 0 \Rightarrow \theta = -\lambda\beta$

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

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

$$y_{it} = \lambda \left[\sum_{j=1}^{N} w_{ij} \left(y_{jt} - \beta x_{ijt} \right) \right] + \phi + x_{it}\beta + c_i + \alpha_t + v_{it}$$

$$y_{it} = \lambda \sum_{j=1}^{N} w_{ij} \left(u_{jt} \right) + \phi + x_{it}\beta + c_i + \alpha_t + v_{it}$$

$\Rightarrow$ SEM $y_{it} = \phi + x_{it}\beta + c_i + \alpha_t + u_{it}$

where $u_{it} = \lambda \sum_{j=1}^{N} w_{ij}\, u_{jt} + v_{it}$