Investigaciones Regionales – Journal of Regional Research
https://doi.org/10.38191/iirr-jorr.25.001

Accepted Article

Spatial patterns of crime in Ecuador: analyzing the impact of judicial systems and geographic elements

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Received: 14 July 2024
Accepted: 18 November 2024

Abstract:

This study investigates the spatial patterns of crime in Ecuador and their driving factors, paying special attention to the judicial system's impact. Drawing on data from 218 cantons between 2015 and 2021, we applied exploratory spatial data analysis and spatial econometric models for cross section data and panel data. Our analysis revealed discernible clusters of both high and low crime rates, as well as isolated areas of crime (islands of crime) and safety (islands of non-crime). The findings offer a detailed overview of the crime situation in Ecuador and emphasize the significance of geographic elements in formulating effective crime prevention measures. The analysis also identifies the shift in crime dynamics over time, indicating that cantons typically experiencing low crime rates can evolve into higher crime areas, hinting at a contagion effect within spatial clusters. The study further underscores the critical influence of the judicial system on crime prevalence, where systemic inefficiencies such as case backlogs and a high proportion of unsentenced inmates are associated with rising crime. For policymakers, these insights underscore the necessity of tailoring interventions to the specific contexts and dynamics of each region, considering both the local conditions and the broader surrounding crime environment.

Keywords: Crime; spatial; cluster; Latin America; judicial.
JEL Classification: P25; H50; O17.

Patrones espaciales de la criminalidad en Ecuador: analizando el impacto de los sistemas judiciales y elementos geográficos

Resumen:

Este estudio investiga los patrones espaciales del crimen en Ecuador y sus factores asociados, enfatizando el rol del sistema judicial. Utilizando datos de 218 cantones entre 2015 y 2021, se realiza un análisis exploratorio de datos espaciales y consecuentemente se estiman modelos econométricos espaciales con datos de sección transversal y panel de datos. Nuestro análisis reveló clústeres espaciales tanto de altas tasas de criminalidad como de bajas tasas de criminalidad, así como áreas aisladas (islas de crimen) de criminalidad y áreas aisladas de seguridad (islas de no crimen). Los hallazgos ofrecen una visión detallada de la situación del crimen en Ecuador y enfatizan en la importancia de los elementos geográficos en la formulación de medidas efectivas de prevención del crimen. La investigación también identificó cambios en la dinámica del crimen a lo largo del tiempo, e indica que los cantones que experimentan típicamente

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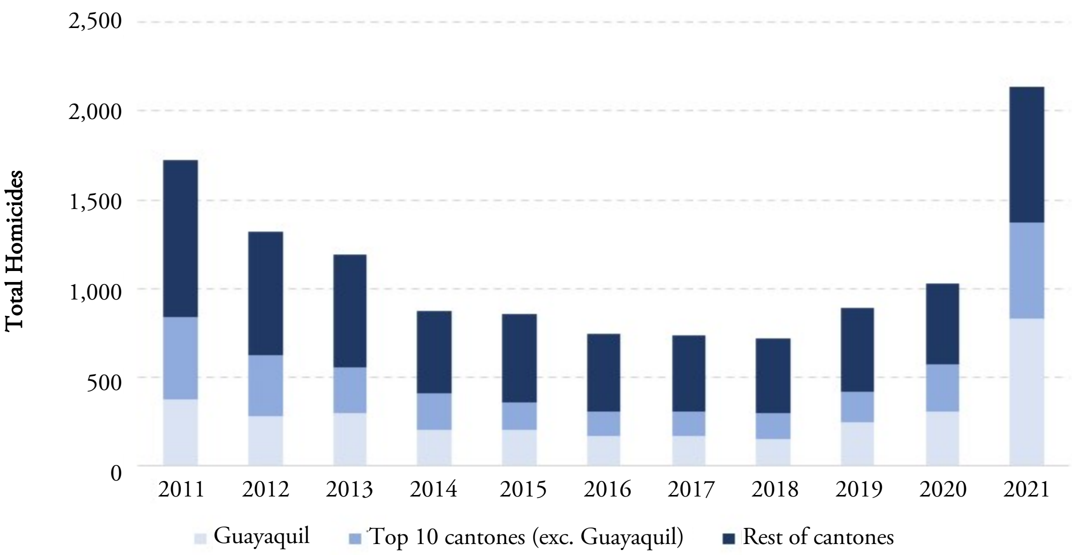
tasas bajas de criminalidad pueden pasar a ser áreas de mayor criminalidad, lo que sugiere un efecto de contagio dentro de los clústeres espaciales. El estudio subraya, además, la influencia del sistema judicial en la prevalencia del crimen, donde las ineficiencias sistémicas como el atraso en los casos y una alta proporción de reclusos sin sentencia se asocian con el aumento del crimen. Para los hacedores de políticas públicas, estos resultados subrayan la necesidad de adaptar las intervenciones a los contextos y dinámicas específicas de cada región, considerando tanto las condiciones locales como el entorno delictivo que lo rodea.

Palabras clave: Crimen; espacial; cluster; América Latina; judicial.
Clasificación JEL: P25; H50; O17.

1. Introduction

According to the United Nations Development Programme-UNDP (2021), the Latin American and the Caribbean region has become the most violent region in the world. Within this context, Ecuador has experienced an increase in violence due to the presence of street gangs, additional to the presence of criminal groups from Colombia, Mexico and Europe for being a strategic point for cocaine trafficking. The increase in homicides in Ecuador has intensified notably since 2018, showing a sustained growth pattern throughout the country. While Guayaquil was initially the epicenter of this violence, the trend has become widespread. As shown in Figure 1, Guayaquil accounted for nearly 39% of all homicides in Ecuador in 2021. The next 10 cantons, excluding Guayaquil, made up 26%, while the remaining cantons across the country accounted for 35%. An increase in violence has been evident in each of these groups of cantons since 2018.

Figure 1.
Homicides Trend in Ecuador by Group of Cantones 2011-2021



By 2021, Ecuador's national homicide rate reached 12.05 per 100,000 inhabitants, making it one of the most dangerous countries in Latin America. This violence is not evenly distributed. Some cantons, primarily along the coast in provinces like Los Ríos, Guayas, Cañar, Esmeraldas, El Oro, and Zamora, recorded over 30 homicides per 100,000 inhabitants. This concentration of violence in specific areas indicates a clear spatial pattern of crime. This may be due to the struggle for territories by important criminal gangs (OECO, 2023). In this context, understanding and addressing crime requires a spatial approach, since crime is not randomly distributed across space (Aguayo & Medellín, 2014; Carrión, 2007; Glaeser et al. 1996) and it diffuses over space (Anselin et al. 2000). Using spatial econometric models, some studies, considering different types of crime, show that crime is a spatially correlated phenomena, in Colombia (Álvarez and González, 2012; Garza, Nieto and Gutiérrez, 2009), in Mexico (Flores & Villareal, 2015; Nedvedovich, Cervera and Botello, 2017; Flores and Gasca, 2016), in Ecuador (Mena, 2023), in Brazil (Puech, 2004), in El Salvador (Alvarado, 2011), among other countries. Most of them identified clusters of crime but less attention is paid to clusters of non-crime or other types of regions considering their crime dynamics. To address crime, apart from identifying clusters of crime, it is also important to identify regions where crime is not high but are surrounded by regions with high crime levels, and vice versa. In addition, crime has been analyzed considering the intricate interplay of factors like socioeconomic conditions, urban planning, and law enforcement strategies, contributing to specific crime patterns (Graif et al 2014). In developing countries countries, apart from aforementioned factors, the low quality of institutions, encompassing law enforcement, the judiciary and penal system, can make that crime deterrence policies be not effective (Paternoster, 2010).

The goal of this study is to assess the spatial dependence of crime in Ecuador, specifically focusing on violent homicides, and to explore the factors associated with it, with a particular emphasis on the role of the judicial system. The paper conducts a detailed spatial analysis of homicide rates at the canton level, identifying various crime clusters and tracking their evolution over time. This analysis enhances the understanding of violence patterns and helps inform the development of mitigation strategies. Additionally, the study evaluates the impact of the judiciary on violence at the subnational level, providing valuable insights for policymakers. To carry out the study, different data sources are used: the Ministry of the Interior, the Ministry of Education, the National Employment and Unemployment Survey (ENEMDU), the State Attorney General's Office, the Ombudsman's Office, the National Service for Attention to Adults Deprived of Liberty and Adolescent Offenders (SNAI) and the Ecuadorian Observatory of Organized Crime (OECE). Our database accounts for information of 218 cantons from 2015 to 2021. An Exploratory Spatial Data Analysis and spatial econometric models are used.

The rest of the paper is structured as follows: Section 2 reviews existing research on crime theory and the judicial system's role in crime control. Section 3 outlines the data and methodology used in the study. Section 4 presents the results of the analysis, and Section 5 offers concluding remarks.

2. Literature review

According to Becker's seminal model (1968), the decision to engage in criminal behavior is primarily guided by assessments of potential benefits and losses. Within this framework, losses are related legal consequences including imprisonment. The likelihood of facing legal consequences depends on two main factors: police action and the legal capacity of a nation. These factors are complementary. Police actions without the effectiveness of the judicial system will not lead to less crime.

Improvements in legal capacity can act as a deterrent against violent conduct, primarily by altering the perceived risk of imprisonment, heightening the likelihood of punishment or intensifying penalties. The literature emphasizes the vital role of strong judicial systems, judicial independence, reforms, and interventions in reducing crime and creating safer societies (Paternoster 2010). The criminal justice system is crucial for maintaining law and order in society, with the judiciary being a key component responsible for fair dispute resolution, justice administration, and deterring criminal activity (UNODC, 2006). Paternoster (2010) argues that the efficacy of deterrence policies hinges on the quality of institutions, encompassing law enforcement, the judiciary, and the penal system. Therefore, deterrence policies are more effective in nations with superior institutions. Addressing criminality and delinquency requires an effective and efficient justice administration system that enjoys the population's trust in terms of its legitimacy to resolve both coexistence and violence-related issues (Benavides et al. 2016). In a review on the link between judicial corruption and crime rates, Powell et al (2010) indicated that judicial corruption is positively associated with an increase in crime rates, emphasizing the corrosive impact of corruption on the effectiveness of the judicial system.

Kuckertz (2022) takes a unique approach by employing a difference-in-differences analysis to estimate the effects of judicial reform on crime rates in Mexico. The study reveals that judicial reform is associated with a reduction in crime rates, shedding light on the potential of legal reforms in curbing criminal activity. Apart from judicial capacity and reforms, some studies have explored the impact of various criminal justice interventions on crime rates. Tonry (2010) conducts a comprehensive review of empirical evidence on the effect of pretrial detention on crime. His analysis suggests that pretrial detention may paradoxically lead to an increase in crime rates, highlighting the need for careful consideration of detention policies. Petersilia (2003) reviews empirical evidence on the impact of sentencing reform on crime. Her findings reveal that sentencing reform can have a substantial impact on crime rates, emphasizing the potential of policy changes in shaping criminal behavior. MacKenzie (2006) explores the impact of rehabilitation programs on crime, demonstrating that such programs can effectively reduce recidivism and prevent future crimes. Similarly, Umbreit et al. (2007) finds that restorative justice approaches can be effective in reducing recidivism and fostering community healing.

If the judicial system works, the probability of incarceration increases influencing on criminal behavior. There is substantial evidence indicating that detention serves to reduce criminal offenses, primarily due to an incapacitation effect (Rose and Shem-Tov, 2021). Additionally, Bhuller et al. (2020) demonstrated that incarceration might also contribute to crime reduction after release, as it provides access to social and rehabilitation programs for those who have been convicted.

Regarding the effect of police actions, many studies focus on the impact of policing strategies, such as increasing the number of police officers or implementing hot spot policing interventions. They consistently find that these strategies reduce crime, often without notable spatial displacement effects (Di Tella and Schargrodsky, 2004; Draca et al., 2015; Cheng and Long, 2018; Mello, 2019; Braga et al., 2019).

However, there are exceptions to this trend. For instance, Blattman et al. (2021) discovered that doubling police patrols and enhancing municipal services in Bogotá had a limited impact on crime reduction in targeted areas, while property crimes increased in surrounding neighborhoods. Notably, they found no evidence of violent crimes being displaced. Strategies aimed at reducing police response times can enhance the likelihood of solving crimes and apprehending offenders, which, in turn, contributes to lower crime rates (Blanes, Vidal and Kirchmaier, 2018; Weisburd, 2021). Doleac (2017) examined the expansion of DNA databases of criminal offenders in U.S. states and demonstrated their effectiveness in deterring crime. The use of information technology by police to predict crimes has also been shown to improve crime clearance rates (Mastrobuoni, 2020).

Nevertheless, it's important to recognize that efforts to combat and penalize crime effectively can have unintended consequences contingent on the specific context. Dell (2015) discussed how crackdowns initiated by mayors in Mexico led to a significant increase in homicides as they weakened existing drug traffickers and fueled conflicts between rival traffickers. In alignment with this finding, Acemoglu et al. (2020) revealed that the introduction of high-powered incentives for the Colombian military resulted in a higher number of civilian casualties, particularly in areas with weaker judicial institutions.

In the context of crime, it is important to consider a theoretical aspect called ecological fallacy, which occurs when researchers make incorrect inferences about individual behavior of offenders or victims based on data collected at a group level (Sampson, 2013; Lawton, 2018) such as geographic units like neighborhoods, cities, states, or countries. In the realm of crime studies, the ecological fallacy has been linked to the social disorganization theory, which are complementary to get a better understanding of the relationship between neighborhood characteristics and criminal behavior (Bellair et al. 2019). Social disorganization theory asserts that high crime rates are a consequence of the breakdown of social cohesion within neighborhoods and the inability to regulate behavior effectively. It attributes the disparity across neighborhoods in crime to specific community characteristics or ecological factors such as poverty, unemployment, frequent residential turnover, and racial composition, which can lead to social breakdown, termed as social disorganization. This weakens social order and control mechanisms, contributing to elevated crime levels (Sampson and Groves 1989; Kubrin et al. 2015). Thus, social disorganization theory underscores the significance of neighborhood-level factors in shaping crime patterns. The ecological fallacy serves as a reminder of the complexities in extrapolating individual actions from neighborhood-level data, reinforcing the need for nuanced analyses when applying social disorganization theory to understand and address crime within communities.

Crime is influenced by various economic and sociocultural factors, including population density, unemployment, income, poverty, and education (Mokline, 2018). Numerous studies have shown that unemployment and poverty have a notable and positive impact on crime rates (Imran et al. 2018; Buonanno et al., 2015; Fadaei-Tehrani & Green, 2002). Based on Becker's economic theory of crime, individuals living in poverty are more likely to engage in property crimes, such as burglary, theft, motor vehicle theft, and arson, because they perceive a greater potential gain from each unlawful act compared to the general population. In poverty conditions, property crimes become a more attractive option for some individuals seeking financial gain (Becker 1968). According to Jawadi et al. (2021), maintaining a stable economy is vital for controlling non-violent crime, as economic downturns lead to increased criminal activity, while economic prosperity reduces it. In addition, crime is a spatial phenomenon with geographical patterns. Glaser et al. (2022) proposed spatial panel models for counts to predict crime counts over space.

Education plays a significant role in reducing crime rates (Huang, Maassen van den Brink, & Groot, 2009), particularly in the case of violent and property crimes (Bradley & Green. 2020). The impact of education on crime can be explained through three main channels in socio-economic literature: income effects, time availability, and differences in patience or risk aversion (Lochner and Moretti 2004). Education tends to decrease criminal participation by increasing the rewards of legitimate work, raising the opportunity costs of illegal activities, and limiting the available time for criminal behavior among teenagers. Additionally, education can influence crime rates by affecting individuals' patience and risk aversion, as those with more patience tend to place higher value on future earnings (Groot et al. 2010; Machin et al. 2011). However, it is important to note that education alone does not guarantee lawful behavior.

3. Data and methodology

3.1. Data

To analyze the factors influencing crime rates in Ecuador, our research utilizes information from the Ministry of the Interior, the Ministry of Education, the National Survey of Employment and Unemployment (ENEMDU), the State Attorney General's Office, the Ombudsman's Office, the National Service for Comprehensive Attention to Adult Persons Deprived of Liberty and Adolescent Offenders (SNAI, acronym in Spanish), and the Ecuadorian Organized Crime Observatory (OECO, acronym in Spanish). Our compiled database encompasses information about 218 cantons from the period of 2011 to 2021. Cantons (3) from the Galápagos province are not considered due to the unavailability of data for them.

The dependent variable in our study is the murder rate, which is quantified as the number of murders per 100,000 inhabitants. Murder is defined as an intentional crime against human life under specific conditions such as premeditation, cruelty, financial incentive, or promise of reward. It is classified as intentional homicide and is subject to penalties as outlined in Article 140 of the Comprehensive Organic Penal Code of Ecuador (Ministry of Justice, 2017). Murder accounts for homicides but is distinguished by its greater criminal intensity. Consequently, for the purposes of this study, the murder rate includes also the crime of contract killing. This indicator serves as a reasonable proxy variable for measuring levels of violence, as endorsed by the United Nations Office on Drugs and Crime (UNODC, 2019). Their accurate recording and comparability across contexts make them valuable for tracking violence trends (Pinker, 2011). Studies demonstrate a strong correlation between homicide rates and other violent crimes, supporting their use as a proxy for overall violence (Eisner, 2003; Zimring & Hawkins, 1997). Furthermore, homicide rates reflect underlying social and economic factors influencing violence, such as inequality and institutional weakness (Fajnzylber et al., 2002; Lederman et al., 2002). Analyzing murder trends provides critical insights for understanding and addressing the complex dynamics of violence. The following Table 1 presents the description of variables and their information sources, while Table A1 in the Appendix shows the descriptive statistics for these variables.

Table 1.
Variable description and information sources

Variable name	Description	Information source	Expected result according to the literature
Congestion rate	The congestion rate (CR) is calculated using the formula: CR=(Cn+Cn−1CRn*CR =(Cn+Cn−1CRn*) where: Cn = Cases filed in the current period n in each province Cn-1= Cases filed in the prior period in each province CRn = Cases resolved in the current period in each province	Judiciary Council	(+) Kuckertz (2022); (Paternoster 2010)
Population Density	It is the number of inhabitants per squared kilometer in each canton	National Institute of Statistic and Census (INEC)	(+) (Mokline, 2018)
Employment rate	It is the percentage of employed people over the economically active population in each province.	National Employment, Unemployment and Underemployment Survey – INEC.	(-) Jawadi et al. (2021)
Rate of young people who do not study	Number of young people between 15 and 19 years old who do not study (not enrolled in educational institutions) divided by the total number of young people between 15 and 19 years old	Ministry of Education of Ecuador (MINEDUC)	(+)(Huang, Maassen van den Brink, & Groot, 2009); (Mokline, 2018)
Income Poverty	It is the ratio between the number of people with monthly income lower than 88.72 over the total population in each province.	National Survey of Employment, Unemployment and Underemployment – INEC.	(+) (Imran et al. 2018; Buonanno et al., 2015; Fadaei-Tehrani & Green, 2002)
Unsentenced prison population index	It is the ratio between the number of people deprived of liberty who have not been sentenced (processed) and the total number of people deprived of liberty.	The National Service for Comprehensive Attention to Adult Persons Deprived of Liberty and Adolescent Offenders (SNAI)	(+) Tonry (2010)

 ISSN: 1695-7253 e-ISSN: 2340-2717

Table 1. cont.
Variable description and information sources

Variable name	Description	Information source	Expected result according to the literature
Seized Weapons per inhabitant	It is the number of weapons seized by the National Police per 100 thousand inhabitants in each province.	Ecuadorian Observatory of Organized Crime (OECO)	(-)
Serious Complaints	It is the ratio of serious complaints—such as illegal money collection, smuggling, organized crime, extortion, money laundering, illegal production of controlled substances, kidnappings for ransom, planting or cultivation of substances, illegal possession and carrying of weapons, illicit trafficking of firearms and substances, and human trafficking—relative to the population of each canton.	Ecuadorian Observatory of Organized Crime (OECO)	(-)
Drug seizure	It is the quantity of illegal controlled substances (in kilograms) seized by the National Police intended for domestic consumption per 1000 inhabitants in each province.	Ecuadorian Observatory of Organized Crime (OECO)	(+)

3.2. Method

For the analysis of crime in Ecuador, two models were estimated. The first model (Model A) is estimated using a spatial panel data model, incorporating the following independent variables: congestion rate, rate of young people who do not study, employment rate, poverty rate, index of unsentenced prison population and population density. The time frame covered for this model is from 2015 to 2021. The second model (Model B) is estimated using a cross-sectional spatial model, with the independent variables from the first model, plus additional provincial-level variables: seized weapons reported, reports of serious crime complaints, and drug seizure. Population density is excluded in the cross-section model due to multicollinearity. This model specifically analyzes the year 2021 due to data availability.

a) Spatial panel model

Spatial panel data consists of observations that are included in two dimensions: cross-sectional and temporal. This model allows addressing the unobserved heterogeneity. For this study, the panel data used for Model A consists of i spatial observations (218 cantons) and time period t (6 years), resulting in a balanced panel. Furthermore, in a spatial panel framework, either a fixed-effects model or a random-effects model can be applied. To determine which model to use, the Hausman test is conducted. Among the diversity of spatial models, the spatial lag model (SLM) is used in the present study. This is a model where the spatial parameter is determined using the lagged spatial dependent variable, Wy, as an additional explanatory variable, and is specified as follows:

$$y_{it} = \rho \sum_{j=1}^{N} W_{ij} y_{jt} + x_{it}\beta + \mu_i + \varepsilon_{it} \tag{1}$$

where i is an index for the cross-sectional dimension (cantons), with =1;...;218; t is an index for the temporal dimension (years), with t=1;...;6; $\boldsymbol{y_{it}}$ represents the murder rate for each canton i in year t; $\boldsymbol{W_{ij}}$ is an element of the spatial weights matrix of dimension N x N; $\boldsymbol{x_{it}}$ is the matrix of dimension NT x k of observations of the independent variables, where k is the number of independent variables (see Table 1); ρ is the spatial parameter associated with the dependent variable; β is the vector of unknown parameters corresponding to the independent variables. The term $\boldsymbol{\mu_i}$ is the fixed spatial effect that captures the unobserved heterogeneity produced by variables that vary across cantons but remain constant over time; $\boldsymbol{\varepsilon_{it}}$ is a vector of independently and identically distributed error terms, capturing the unobserved heterogeneity produced by variables that change both over time and across cantons. For the model estimations, two weight matrices are used: i. the inverse distance weight matrix and ii. the 4 nearest neighbor matrix[1]. The latter was chosen based on the R squared of the estimations between the dependent variable and the spatial lag dependent variable, using different number of neighbors. In panel data analysis, the Hausman test allows for choosing between a fixed-effects model or a random-effects model. According to the results of the Hausman test (Chi-squared=35.773, p-value=0.000008001), the preferred model is the fixed-effects model.

b) Cross-sectional spatial model

Spatial regression models in a cross-section setting allow for examining spatial dependence (spatial correlation) and spatial heterogeneity among observations.

$$y = \rho W y + X\beta + \mu \tag{2}$$

Where y represents the murder rate for each canton i in the year 2021; W is the spatial weight matrix; ρ is the spatial autoregressive parameter; X is an $n \times K$ matrix of observations of the independent variables (see Table 1); β is the vector of unknown parameters corresponding to the observations of the independent variables.

To select between the spatial lag model and the spatial error model, two metrics are used: the Lagrange multiplier test for spatial dependence in linear model test (Anselin, Bera, & Florax, 1996; Borrego Sánchez, 2018) and the Akaike's Information Criterion and the Bayesian Information Criterion (Agiakloglou, C., & Tsimpanos, A. 2023). Table 2 shows that according to the LM test, the spatial lag model is the preferred model in comparison to the spatial error model. Table 3 indicates that the preferred models are the spatial lag models since the AIC and BIC criteria are lower for these models than for the spatial error models.

[1] The rationale behind using these two matrices was to ensure that our analysis captured the spatial relationships between cantons in different ways, reflecting both proximity-based and neighbor-based spatial dependencies. Despite the differences in how these matrices define spatial relationships, the results from both approaches were remarkably consistent, which strengthens the robustness of our findings. By obtaining similar results across both matrices, we can confidently assert that the observed spatial patterns of crime and its determinants are not dependent on the specific choice of the spatial weight matrix. This robustness supports the validity of our spatial econometric models and ensures that the spatial correlations and the effects of the judicial system, socioeconomic variables, and other factors on crime rates are reliable and not an artifact of any particular spatial structure.

TABLE 2.
LM test for spatial models

Test	LM for the panel data model (inverse distance)	LM- for the panel data model (Kn4)	LM- for the cross section model (inverse distance)	LM for the cross section model (Kn4)
LM_{LAG} (p-valor)	9.1419 (0.002498)	19.069 (0.00001261)	1.215 (0.2703)	3.0592 (0.08028)
LM_{ERROR} (p-valor)	5.8185 (0.01586)	17.392 (0.00003042)	0.12802 (0.7205)	1.814 (0.178)

TABLE 3.
AIC and BIC statistics for spatial models

Test	AIC for the panel data model (inverse distance)	BIC- for the panel data model (inverse distance)	AIC for the panel data model (Kn4)	BIC- for the panel data model (Kn4)	AIC for the cross section model (inverse distance)	BIC for the cross section model (inverse distance)	AIC for the cross section model (Kn4)	BIC for the cross section model (Kn4)
$Model_{LAG}$	1572.985	1606.83	1571.365	1605.21	1575.345	1615.958	1573.747	1614.361
$Model_{ERROR}$	1573.636	1607.481	1572.241	1606.086	1576.42	1617.034	1574.786	1615.4

4. RESULTS

Our results stem from the spatial analysis of crime, as showed in Figure 1 and Table 4 and from the econometric models showed in Table 5. For the spatial analysis of crime, the LISA indicator of local spatial correlation is applied using two weight matrices: i. the inverse distance weight matrix (Figure 1a) and ii. the 4 nearest neighbor-based matrix (Figure 1b). The results indicate that there exist clusters of crime and non-crime, islands of crime and islands of non-crime. Overall, they are not constant over time, which reflects that the phenomenon of crime is dynamic, changing according to the time and geographical context. Table 4 details the number and names of cantons in each cluster, based on the two weight matrices, in three specific years: 2011, 2016 and 2021.

a) Clusters of crime

In 2011, Cluster 1, as depicted in Figures 1a and 1b, consisted of 9 cantons using the inverse distance matrix and 7 cantons using the 4kn weight matrix. Over time, this cluster has shown a tendency to shrink. By 2016 and 2021, Cluster 1 included fewer cantons. An interesting observation is that Atacames and Río Verde remained part of this cluster throughout the years, suggesting their significance as potential hubs for organized crime.

In 2021, Cluster 2 comprised 19 cantons when using the inverse distance matrix and 7 cantons when using the 4kn weight matrix. This cluster significantly reduced in size by 2016. Notably, 8 out of the 24 cantons in the 2021 cluster (using the inverse distance matrix) were consistent with the 2011 cluster. These cantons are El Empalme, Balzar, Palestina, Daule, Samborondón, Mocache, Pueblo Viejo, and Babahoyo, indicating the presence of well-established criminal networks. In 2021, Cluster 2 reappeared in a more southern location, consisting of 8 cantons using the 4kn weight matrix.

A third crime cluster was identified in 2011. Using the inverse distance matrix, this cluster was composed of Cuyabeno (Sucumbíos), and using the 4kn weight matrix, it was composed of Putumayo (Sucumbíos). Although different cantons were identified, they are neighboring regions near the Colombian border. In 2016, the size of this cluster grew, but it completely disappeared by 2021 according to both matrices.

b) Non-crime clusters

In 2011, Cluster 4 of non-crime, using the inverse distance matrix, included 73 cantons primarily from the Azuay and Loja provinces. Analyzing with the 4kn weight matrix, this cluster consisted of 22 cantons, mainly from Azuay. By 2016, the cluster's size, using the inverse distance matrix, reduced to 20 cantons, retaining 18 of the original ones. However, with the 4kn weight matrix, the cluster expanded to 36 cantons in 2016, keeping 7 original cantons.

For 2021, the size of the non-crime cluster increased to 52 cantons using the inverse distance matrix, incorporating 18 new cantons. Conversely, with the 4kn weight matrix, the cluster size decreased to 32 cantons in 2021, also including 18 new cantons. Notably, 19 cantons remained consistent within this non-crime cluster, regardless of the matrix used. It is worth mentioning that Quito was part of this non-crime cluster in both 2011 and 2021.

a) Islands of crime

These spatial clusters refer to cantons with high rates of violent deaths per inhabitant surrounded by cantons with low rates. In 2011, using both weight matrices, Celica (Loja) consistently stands out as an island of crime. Other islands of crime are identified depending on the matrix used. By 2016, using both matrices, Pablo VI (Morona Santiago), Paquisha, Palanda (Zamora Chinchipe), Macará, and Paltas (Loja) emerged as consistent islands of crime. In 2021, Nangaritza (Zamora Chinchipe) consistently stands out as an island of crime using both matrices. These islands require attention because interventions to reduce crime in these areas might be effective due to the apparent lack of a strong territorial presence of criminal bands around them.

b) Islands of non-crime

These clusters refer to cantons with low rates of violent deaths per inhabitant surrounded by cantons with high rates. In 2011, using the inverse distance matrix, there were 12 islands of no crime. When using the 4kn weight matrix, this cluster consisted of 2 cantons. The cantons that appeared in both analyses were Puerto Quito and Pedro Vicente Maldonado (Pichincha). By 2016, using the inverse distance matrix, there was 1 island of no crime, while the 4kn weight matrix showed 4 cantons in this cluster. The canton repeated in both analyses was Muisne (Esmeraldas). In 2021, the inverse distance matrix identified 16 islands of no crime, whereas the 4kn weight matrix showed a cluster of 8 cantons. Special attention should be given to these islands of non-crime to prevent the diffusion of crime from neighboring cantons.

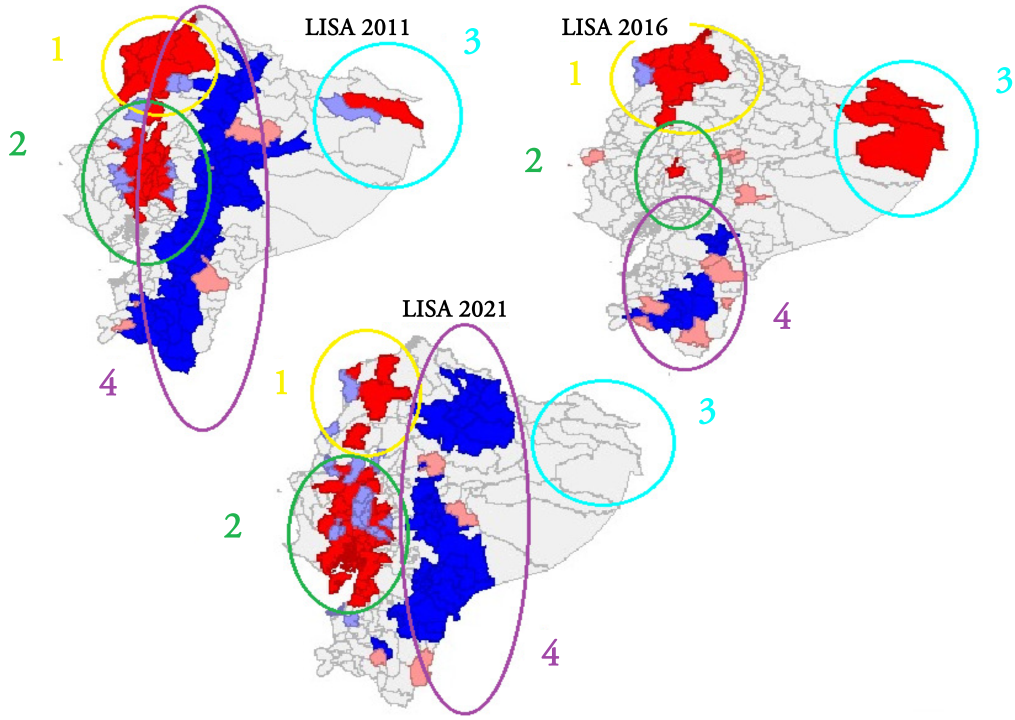
c) Changing cantons

According to the changing status of cantons, four types of cantons can be identified: i. Black sheep becoming white sheep among black sheep: These are cantons with high values of violent deaths that are surrounded by other cantons with high values, which eventually change to low values of violent deaths. ii. Black sheep becoming white sheep among white sheep: These are cantons with high values of violent deaths that are surrounded by cantons with low values, which eventually change to low values of violent deaths. iii. White sheep becoming black sheep among white sheep: These are cantons with low values of violent deaths that are surrounded by cantons with low values, which eventually change to high values of violent deaths. iv. White sheep becoming black sheep among black sheep: These are cantons with low values of violent deaths that are surrounded by cantons with high values, which eventually change to high values of violent deaths.

A detailed description of each type of canton is provided in Appendix C.

FIGURE 2.
Clusters of crime according to the LISA indicator

a) LISA indicator using inverse distance weight matrix



b) LISA indicator using the 4 nearest neighbor weight matrix

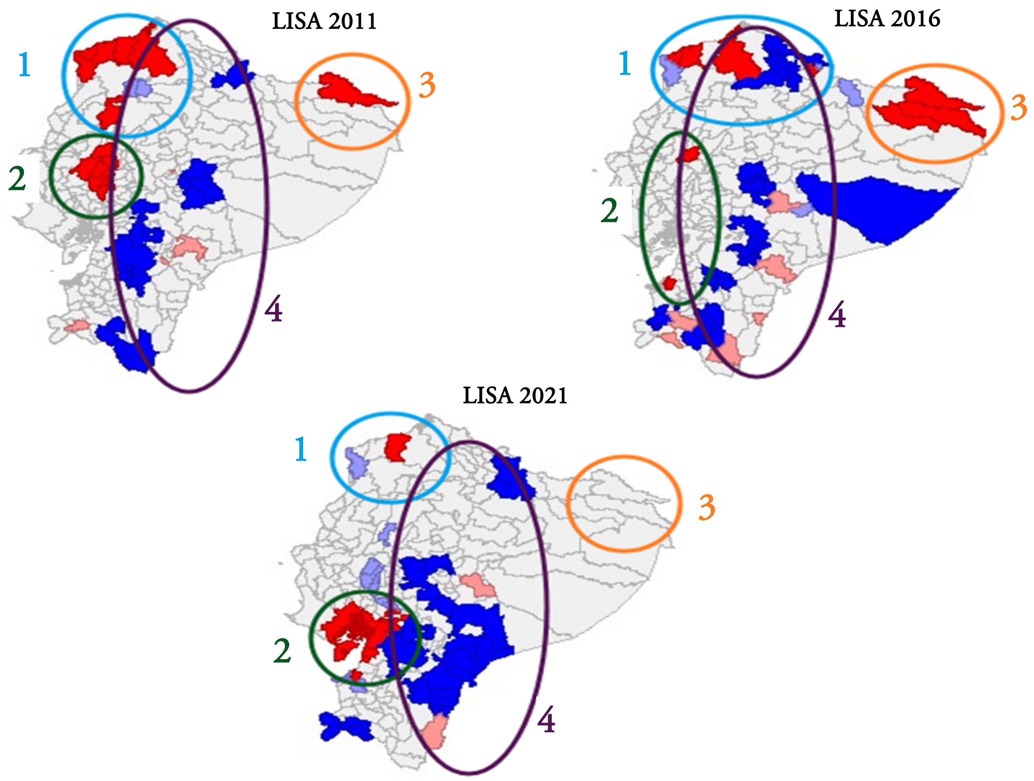


Table 4.
Composition of clusters of crime, non-crime, islands of crime and non-crime

<table>
<tr><th>Cluster type</th><th colspan="2">Year 2011</th><th colspan="2">Year 2016</th><th colspan="2">Year 2021</th></tr>
<tr><th></th><th>4kn</th><th>Inverse distance</th><th>4kn</th><th>Inverse distance</th><th>4kn</th><th>Inverse distance</th></tr>
<tr><td rowspan="3">High-High 1</td><td colspan="2">Muisne, Atacames, Esmeraldas, Río Verde, Eloy Alfaro (Esmeraldas), La Concordia (Santo Domingo de los Tsáchilas), El Carmen (Manabí).</td><td colspan="2">Eloy Alfaro, Esmeraldas, Atacames, (Esmeraldas)</td><td colspan="2">Río Verde (Esmeraldas)</td></tr>
<tr><td>7 cantons:</td><td>9 cantons:</td><td>4 cantons:</td><td>8 cantons:</td><td>1 canton:</td><td>4 cantons:</td></tr>
<tr><td></td><td>Quinindé (Esmeraldas), Pedernales (Manabí).</td><td>Montúfar (Carchi)</td><td>Río Verde, Quinindé (Esmeraldas), La Concordia (Santo Domingo de los Tsáchilas), Puerto Quito (Pichincha), El Carmen (Manabí).</td><td></td><td>Quinindé, Atacames (Esmeraldas), Flavio Alfaro (Manabí).</td></tr>
<tr><td rowspan="3">High-High 2</td><td colspan="2">El Empalme, Balzar (Guayas), Mocache, Palenque, Vinces, Baba, Pueblo Viejo (Los Ríos)</td><td colspan="2"></td><td colspan="2">Guayaquil, Naranjito, Naranjal, Balao (Guayas), La Troncal (Cañar)</td></tr>
<tr><td>7 cantons:</td><td>19 cantons:</td><td>2 cantons:</td><td>1 canton:</td><td>8 cantons:</td><td>24 cantons:</td></tr>
<tr><td></td><td>Daule, Durán, Palestina, Salitre, Samborondón (Guayas), Pichincha (Manabí), San Jacinto de Buena Fe, Quevedo, Quinsaloma, Ventanas, Babahoyo, Urdaneta (Los Ríos).</td><td>El Empalme (Guayas), Machala (El Oro)</td><td>Ventanas (Los Ríos)</td><td>Durán, El Triunfo (Guayas), Machala (El Oro)</td><td>Santa Ana, Bolívar (Manabí), Colimes, Balzar, El Empalme, Palestina, Santa Lucía, Pedro Carbo, Daule, Samborondón, Yaguachi, Milagro, Lomas de Sargentillo (Guayas), Mocache, Pueblo Viejo, Urdaneta, Babahoyo (Los Ríos), El Guabo (El Oro), Camilo Ponce Enríquez (Azuay).</td></tr>
</table>

TABLE 4. CONT.
Composition of clusters of crime, non-crime, islands of crime and non-crime

<table>
<tr><th>Cluster type</th><th colspan="2">Year 2011</th><th colspan="2">Year 2016</th><th colspan="2">Year 2021</th></tr>
<tr><th></th><th>4kn</th><th>Inverse distance</th><th>4kn</th><th>Inverse distance</th><th>4kn</th><th>Inverse distance</th></tr>
<tr><td rowspan="3">High-High 3</td><td colspan="2"></td><td colspan="2">Putumayo, Shushufindi, Cuyabeno (Sucumbíos)</td><td colspan="2"></td></tr>
<tr><td>1 canton:</td><td>1 canton:</td><td>3 cantons:</td><td>4 cantons:</td><td></td><td></td></tr>
<tr><td>Putumayo (Sucumbíos).</td><td>Cuyabeno (Sucumbíos).</td><td></td><td>Aguarico (Orellana).</td><td></td><td></td></tr>
<tr><td rowspan="3">Low-Low 4</td><td colspan="2">Pimampiro (Imbabura), Baños, Tisaleo (Tungurahua), Penipe, Pallatanga (Chimborazo), Palora, Pablo VI (Morona Santiago), Cañar, Suscal (Cañar), Cuenca, San Fernando, Girón, Nabón, Oña (Azuay), Calvas, Espíndola, Gonzanamá (Loja)</td><td colspan="2">Azogues, Biblián (Cañar), Gualaceo, El Pan, Guachapala, Paute, Sevilla de Oro (Azuay), Calvas, Quilanga, Gonzanamá, Loja, Catamayo (Loja)</td><td colspan="2">Sucumbíos, Gonzalo Pizarro (Sucumbíos), San Pedro de Huaca (Carchi), Ambato, Pelileo (Tungurahua), Colta, Guamote (Chimborazo), Morona, Logroño, Tiwintza, Santiago de Méndez, Limón Indanza, San Juan Bosco, Gualaquiza (Morona Santiago), Chordeleg, Oña (Azuay), El Pangui, Yacuambi, Yantzaza (Zamora Chichipe)</td></tr>
<tr><td>22 cantons:</td><td>73 cantons:</td><td>36 cantons:</td><td>20 cantons:</td><td>32 cantons:</td><td>52 cantons:</td></tr>
<tr><td>Sucumbíos (Sucumbíos), Chillanes (Bolívar), Cumandá (Chimborazo), Santa Isabel (Azuay), Palanda, Chinchipe (Zamora Chinchipe)</td><td>Montúfar, Bolívar (Carchi), Otavalo, Ibarra, Antonio Ante (Imbabura), Quito, Cayambe, Mejía, Pedro Moncayo, Rumiñahui (Pichincha), Latacunga, Salcedo, Saquisilí (Cotopaxi), Píllaro, Ambato, Mocha, Quero, Pelileo, Patate (Tungurahua), Mera, Santa Clara, (Pastaza), Carlos Julio Arosemena, Tena</td><td>Tulcán, Mira (Carchi), Cotacachi, Ibarra, San Miguel de Urcuquí (Imbabura), Pastaza (Pastaza), Ambato, Mocha, Tisaleo, Cevallos, Quero, Pelileo (Tungurahua), Guano, Penipe, Riobamba, Alausí (Chimborazo),</td><td>Déleg (Cañar), Chordeleg, Oña (Azuay), Celica, Sozoranga, Olmedo (Loja), Yacuambi, Zamora (Zamora Chinchipe).</td><td>Montúfar (Carchi), Guaranda, Chimbo (Bolívar), Cuenca, Santa Isabel (Azuay), Centinela del Cóndor, Paquisha (Zamora Chinchipe), Zapotillo, Celica, Macará, Sozoranga (Loja), Cañar, Suscal (Cañar)</td><td>El Ángel, Bolívar, San Gabriel (Carchi), Ibarra, Antonio Ante, Otavalo, Pimampiro (Imbabura), El Chaco, Quijos (Napo), Cayambe, Quito, Pedro Moncayo (Pichincha) Saquisilí, San Miguel de Salcedo (Cotopaxi), Tisaleo, Cevallos, Mocha, Quero (Tungurahua), Riobamba, Penipe, Guano, Chambo (Chimborazo), Pablo Sexto, Sucúa (Morona</td></tr>
</table>

TABLE 4. CONT.
Composition of clusters of crime, non-crime, islands of crime and non-crime

Cluster type	Year 2011		Year 2016		Year 2021	
	4kn	Inverse distance	4kn	Inverse distance	4kn	Inverse distance
		(Napo), Huamboya (Morona Santiago), Guano, Riobamba, Chambo, Colta, Alausí, Chunchi (Chimborazo), Biblián, El Tambo, Azogues, Déleg (Cañar), Paute, Sevilla de Oro, Guachapala, El Pan, Gualaceo, Sigsig (Azuay), Saraguro, Loja, Chaguarpamba, Catamayo, Paltas, Sozoranga, Macará, Olmedo, Quilanga (Loja), Yacuambi, Zamora, Palanda, Chinchipe (Zamora Chinchipe), Portovelo, Piñas (El Oro).				Santiago), Azogues (Cañar), Nabón, Sevilla de Oro, Gualaceo, El Pan, Paute, Sigsig, Guachapala (Azuay), Catamayo (Loja).
Low-High Islands of non-crime	Puerto Quito, Pedro Vicente Maldonado (Pichincha)		Muisne (Esmeraldas)		Muisne (Esmeraldas), Buena Fe, Palenque, Vinces, Baba (Los Ríos), Alfredo Baquerizo Moreno, Simón Bolívar (Guayas), Santa Rosa (El Oro)	
	2 cantons:	12 cantons:	4 cantons:	1 canton:	8 cantons:	16 cantons:
		Flavio Alfaro, Bolívar, Olmedo (Manabí), Shushufindi (Sucumbíos), Colimes,	San Pedro de Huaca (Carchi), Cascales (Sucumbíos),			Jama, Pichincha, Tosagua, Junín (Manabí), Salitre, Isidro Ayora, Nobol, General Antonio Elizalde (Guayas)

 ISSN: 1695-7253 e-ISSN: 2340-2717

Table 4. cont.
Composition of clusters of crime, non-crime, islands of crime and non-crime

Cluster type	Year 2011		Year 2016		Year 2021	
	4kn	Inverse distance	4kn	Inverse distance	4kn	Inverse distance
		Santa Lucía, Lomas de Sargentillo (Guayas), Las Naves, Echeandía (Bolívar), Montalvo (Los Ríos).	Huamboya (Morona Santiago)			
High-Low Islands of crime	Celica (Loja)		Pablo VI (Morona Santiago), Paquisha, Palanda (Zamora Chinchipe), Macará, Paltas (Loja)		Nangaritza (Zamora Chinchipe)	
	4 cantons:	4 cantons:	6 cantons:	10 cantons:	2 cantons:	4 cantons:
	Cevallos (Tungurahua), Santiago de Méndez (Morona Santiago), Chordeleg (Azuay)	Balsas (El Oro), Gualaquiza (Morona Santiago), Cevallos (Tungurahua).	Limón Indanza (Morona Santiago)	Montecristi (Manabí), Gualaquiza (Morona Santiago), Sigsig (Azuay), Píllaro (Tungurahua), San Miguel de Salcedo (Cotopaxi).	Palora (Morona Santiago)	Latacunga (Cotopaxi), Gonzanamá (Loja), Pastaza (Pastaza).

Table 5 presents the results of our models: the panel data spatial model in column (1) considering data for cantons from 2011 to 2021, and the cross-section spatial model in column (2) considering data for cantons for 2021. The spatial panel model accounts for the unobservable heterogeneity of cantons. However, due to limited availability of temporal information for some variables, this model includes fewer variables than the cross-section spatial model. Additional variables such as seized weapons per inhabitant, serious complaints, and drug seizures were included in the cross-section spatial model, thereby reducing the omitted variable bias.

Overall, the parameter of spatial correlation is highly significant, indicating that an increase in the murder rate in neighboring cantons leads to an increase in the murder rate in a given canton. The dimension of the spatial correlation is higher when using the inverse distance matrix compared to the 4kn weight matrix. This demonstrates that crime is a spatial phenomenon, concentrating in specific regions and then diffusing to neighboring areas. The analysis of local spatial correlation indicated that there are clusters of crime in the northern and southern parts of the coastal region and along the border with Colombia.

Our variables of interest related to the judicial system include the cause congestion rate, the unsentenced prison population, and the efficiency of the judicial system. The first two variables are significant and positive, indicating a positive association with the level of crime. According to the social disorganization theory (Bellair, 2017) and considerations of ecological fallacy, these factors can be seen as contextual-level factors that shape the spatial crime pattern. A 1% increase in the cause congestion rate leads to a 2.84% increase in the murder rate. This indicates that when the judicial system does not resolve cases timely, the level of crime increases. The inefficiency of the judicial system can be perceived by criminals and associated with a lower probability of being punished, thereby inducing more crime. According to a jurisprudence study by Enríquez Burbano (2017), Ecuador's traditional judicial system does not allow for the use of alternative means for justice, which augments the cause congestion rate. Furthermore, the system has insufficient economic resources to resolve all judicial cases.

Similarly, an increase in the non-sentenced prison population correlates with higher crime levels. A 1% increase in this population leads to an approximate 0.08% increase in the murder rate. This suggests that despite police actions to capture criminals, the collapse of the judicial system leads to more crime for two reasons: first, not all arrested criminals are sentenced, allowing complaints to lapse and criminals to be released to continue their activities; second, a high rate of unsentenced arrested criminals signals judicial inefficiency, further augmenting crime rates. Contrary to findings by Rose and Shem-Tov (2021) for North Carolina, detention itself does not reduce criminal offenses in Ecuador, despite the incapacitation effect. In Ecuador, criminal gang operations primarily occur in prisons, allowing gang members to maintain contact with their leaders and reinforce criminal activities. This undermines the expected inverse relationship between imprisonment and crime as noted by Withers (1984). While Bhuller et al. (2020) argued that incarceration might reduce crime post-release due to social and rehabilitation programs, this is not the case in Ecuador where prison conditions are inadequate for social rehabilitation. The efficiency of the judicial system, measured as the ratio between the prison population and the number of complaints, has no effect on the murder rate, possibly due to the presence of other variables that better proxy judicial system efficiency.

In the judicial system context, the number of serious complaints (per 100,000 inhabitants) related to illegal activities such as smuggling, organized crime, extortion, and money laundering is associated with a reduction in the violent murder rate. This result indicates that reporting crimes can reduce crime levels, as authorities can intervene and legal processes can begin to determine punishments or sanctions. Londoño & Guerrero (1999) also found that the propensity to report reduces the violence rate. However, this propensity could decrease due to judicial system inefficiency (Carrión, 2022). There is a positive association between drug seizures and the murder rate. A 1% increase in seized drugs per inhabitant is associated with 0.88 more violent murders per inhabitant. This can be explained by the fact that police drug seizure operations occur in significant distribution and operational centers for drug dealers (Bulla et al., 2016) where violent acts are more common. Additionally, drug seizure operations often lead to confrontations between the police and cartel members, causing deaths.

TABLE 5.
Results of the model estimations of violent deaths rate

Variables	Panel data model (inverse distance matrix)	Cross-section model (inverse distance matrix)	Panel data model (4kn matrix)	Cross-section mode (4kn matrix)
Congestion rate	3.823*** (0.794)	7.134* (2.321)	3.788*** (0.795)	6.957** (2.326)
Rate of young people who do not study	0.080* (0.039)	0.008 (0.087)	0.078* (0.039)	0.008 (0.086)
Employment rate	-0.339** (0.118)	-0.264 (0.409)	-0.322** (0.118)	-0.234 (0.407)
Income poverty	0.267*** (0.077)	0.027 (0.296)	0.262*** (0.076)	0.027 (0.295)
Income poverty 2	-0.003*** (0.001)	-0.001 (0.003)	-0.003** (0.001)	-0.001 (0.003)
Unsentenced prison population index	0.049*** (0.012)	0.139** (0.047)	0.049*** (0.012)	0.135** (0.047)
Population Density	0.0006 (0.0005)		0.0007 (0.0005)	
Seized Weapons per inhabitant		0.069 (0.068)		0.070 (0.068)
Serious Complaints		-0.236** (0.113)		-0.236* (0.112)
Drug seizure		1.062* (0.582)		1.054* (0.579)
ρ (Rho)	0.504*** (0.119)	0.459 (0.304)	0.160*** (0.038)	0.152 (0.089)

Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1, standard errors in parentheses.

Regarding the socioeconomic situation of regions, poverty, employment, and the rate of young people not in education are important factors influencing crime levels. In Ecuador, the non-monotonic relationship between poverty and violent deaths holds true, as Sánchez and Nuñez (2001) found for Colombia. Crime increases with poverty up to a certain point, where it then starts to decrease. In Ecuador, the average violent death rate per 100,000 inhabitants is 4.98 for the poorest cantons (first quartile), 9.11 for the second quartile, 8.24 for the third quartile, and 5.45 for the wealthiest cantons (fourth quartile). Crime increases up to 36% poverty, beyond which it starts to decrease. In the poorest cantons, crime levels are lower than in moderately poor cantons. This non-linear relationship might be explained by the theory of relative poverty (Braithwaite, 1979). In highly impoverished areas, inequality is evident, potentially leading poor individuals to commit crimes against wealthier individuals to compensate for perceived disparities (Fajnzylber, Lederman, & Loayza, 2002). In the most impoverished areas, where everyone is equally poor, this inequality—and consequently crime—decreases. People in poverty can be more vulnerable, influenceable, and prone to entering the crime environment. According to Becker's (1968) theory, individuals turn to crime when potential benefits outweigh the costs, making those living in poverty more likely to engage in criminal activities. Additionally, in the context of poverty, social bonds may be weak, impeding informal social controls and lowering the likelihood of reporting general deviance to authorities (Sampson, 2013).

Regarding the employment rate, a 1% increase is associated with a 0.52% decrease in violent deaths per 100,000 inhabitants. When a region offers job opportunities, people have a stable economy, which discourages participation in criminal activities. Therefore, as noted by Sani et al. (2018), Jawadi et al. (2021), and Fadaei-Tehrani & Green (2002), a stable economy with job opportunities and economic prosperity is vital for reducing crime and violence. This is exemplified by Esmeraldas, which registers a low level of employment (89.98%) with respect to the national average (95.88%).

Lack of education, measured by the rate of young people who are not studying, is positively associated with the crime rate. It has been observed that criminal gangs involved in drug trafficking engage young people in their activities. These young individuals are more likely not to be in school, giving them free time and a low opportunity cost for engaging in crime. The school dropout rate was also tested in the models, but it was not significant in any of them. This result indicates that what drives crime is the high number of young people who do not engage in education at all, rather than those who initially participate in the education system and later drop out. Contrary to expectations, population density and judicial system efficiency were fund not statistical significant factors in explaining crime rates in the present analysis. This could be related to the presence of criminal gangs in smaller cities in Ecuador. Not all cities with high murder rates have high population densities. For instance, Pueblo Viejo, Naranjal, and Nagaritza have population densities of 134.96, 56.23, and 4.11, respectively, which are lower than the national average of 137.61 inhabitants per square kilometer.

5. Conclusions

This study examined recent crime trends in Ecuador from 2015 to 2021, focusing on the spatial dependence of violent murders at the cantonal level. Utilizing exploratory spatial data analysis and spatial econometric models, the research identified clusters of high and low crime rates as well as isolated clusters of crime and non-crime. These findings offer a comprehensive view of the crime landscape in Ecuador, emphasizing the importance of geographic factors in developing more effective crime prevention policies and strategies.

Additionally, the study explored the evolution of these spatial clusters over time, revealing that the crime status of cantons—whether low-crime "white sheep" or high-crime "black sheep"—can change, indicating a contagion effect. This is particularly notable in cases where a low-crime canton surrounded by high-crime areas shifts towards higher crime rates. For policymakers, these insights underscore the necessity of tailoring interventions to the specific contexts and dynamics of each region, considering both local conditions and the broader surrounding crime environment. This targeted approach could be crucial in effectively addressing and mitigating crime in Ecuador.

Our findings further establish the crucial role of the judicial system in influencing crime rates in Ecuador. Inefficiencies within this system, indicated by high cause congestion rates and a substantial unsentenced prison population, correlate with an increase in crime. The slow processing of cases might signal to potential offenders that the likelihood of punishment is low, thereby reducing the deterrent effect of the law. Additionally, the high unsentenced prison population highlights a disconnection between the police and the judicial system, where the courts fail to promptly sentence individuals apprehended by law enforcement. Moreover, with gang leaders operating within prisons, incarceration may inadvertently serve as a reward rather than a deterrent, providing criminals with opportunities to network and strengthen gang ties rather than being rehabilitated.

Contrary to expectations, our analysis shows that population density does not significantly impact crime rates across Ecuadorian regions. This phenomenon may be attributed to the presence of gangs in smaller, economically disadvantaged areas characterized by low employment and moderately high poverty rates. Given these insights, several policy implications emerge. First, it is vital to address the geographic patterns of crime and consider the specific background and surrounding environment of each region. The evident judicial congestion necessitates innovative reforms to enhance efficiency in the judicial sector.

However, merely improving judicial processes is insufficient. A comprehensive reform must also include restructuring and eliminating corruption from prisons to transform them into facilities that truly aim for social rehabilitation.

Furthermore, eradicating poverty is imperative. Investing in education and economic opportunities can decrease the allure of criminal activities, particularly among the youth. These multi-faceted approaches are essential for developing effective strategies to reduce crime in Ecuador, highlighting the need for targeted interventions that address both the symptoms and root causes of criminal behavior.

Regarding limitations, our study faced challenges due to the limited availability of temporal data for all variables. To address this, we estimated two models: a cross-sectional spatial econometric model and a panel spatial model. While our analysis primarily related crime to the murder rate, focusing solely on intentional homicide, it is important to acknowledge that crime, particularly organized crime, encompasses a broader spectrum of criminal activities. These include property robberies, terrorist acts, and extortion targeting residents and businesses. This complexity suggests that our findings, while insightful, might not fully capture the multifaceted nature of crime.

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Appendixes

Appendix A

Table A1.
Descriptive statistics of the independent variables of year 2021

Variable	Mean	Standard deviation	Min	Max
Congestion rate	1.806	0.3470599	1.402	2.524
Rate of young people who do not study	47.843	8.14523864	16.45	69.06
Employment rate	95.88	2.276573	89.23	98.93
Income poverty	34.013	13.6021633	17.616	70.508
Unsentenced prison population index	29.166	16.760	0	65.854
Population Density	137.606	371.656	0.311	4786.789
Serious Complaints	12.776	15.5151	0.442	73.208
Weapons seized/provincial population per 1000 inhabitants	10.3902	10.3845	0.333	36.673
Drug seizures (kg)/provincial population per 1000 inhabitants	1.2466	2.7491	0.047	16.34

Appendix A2

From the temporal analysis, 4 kinds of cantons could be identified: i. black sheep becoming white sheep among black sheep; that is cantons with high values of violent deaths surrounded by other cantons with high values that change to low values of violent deaths; ii. black sheep becoming white sheep among white sheep, that is cantons with high values of violent deaths surrounded by cantons with low values that change to low values of violent deaths; iii. white sheep becoming black sheep among white sheep, that is cantons with low values of violent deaths surrounded by cantons with low values that change to high values of violent deaths; and iv. white sheep becoming black sheep among black sheep, that is cantons with low values of violent deaths surrounded by cantons with high values that change to high values of violent deaths.

Using both matrices, Muisne canton is identified as black sheep in 2011 (recorded 16.80 violent deaths per 100000 inhab.) becoming white sheep among black sheep in 2016 (recorded 3.26 violent deaths per 100000 inhab.) and 2021 (recorded 6.42 violent deaths per 100000 inhab.).

Regarding the second kind of changing cantons, using both matrices, Célica (Loja) stands as black sheep in 2011 (recorded 13.14 violent deaths per 100000 inhab.), becoming a white sheep in 2016 among white sheep (recorded 0 violent deaths per 100000 inhab.). Using the inverse distance weight matrix, Gualaquiza (Morona Santiago) was a black sheep in 2011 (22.08 violent deaths per 100000 inhab.) and

2016 (5.25 violent deaths per 100000 inhab.) and became a white sheep in 2021 (0 violent deaths per 100000 inhab.), influenced by an environment of white sheep. Canton Cevallos (Tungurahua) recorded a high level of crime in 2011 (11.62 violent deaths per 100000 inhab.), became a White sheep in 2021 (0 violent deaths per 100000 inhab.).

Using the 4kn weight matrix, Chordeleg (Azuay) was a black sheep in 2011 (15.05 violent deaths per 100000 inhab.) and became a white sheep in 2021 ((0 violent deaths per 100000 inhab.), influenced by a white sheep environment. Pillaro (Tungurahua) was also a black sheep in 2016 (4.76 violent deaths per 100000 inhab.) and became a white sheep in 2021 (2.29 violent deaths per 100000 inhab.), influenced by a white sheep environment.

As for the third kind of changing cantons, using the inverse distance matrix, Píllaro (Tungurahua), Salcedo (Cotopaxi), Palanda (Zamora Chinchipe), Sigsig (Azuay), Macará, Paltas (Loja), Gonzanamá (Loja) and Pablo Sexto (Morona Santiago) registered low levels of crime in 2011 and in 2016 and became black sheep in 2021 despite of being surrounded by an environment of white sheep. Using 4kn weight matrix, Nangaritza (Zamora Chinchipe) was a white sheep in 2016 and became a black sheep in 2021. Sucumbíos was a white sheep in 2011 and became black sheep in 2016, surrounded by a white sheep environment.

Using the inverse distance weight matrix, group 4 of changing cantons include Puerto Quito (Pichincha) and Shushufinfi (Sucumbíos), which registered low levels of crime in 2011 (0 and 8.56 violent deaths per 100000 inhab., respectively) and became black sheep in 2016 (12.79 and 11.33 violent deaths per 100000 inhab.), influenced by an environment of black sheep. Using the 4kn weight matrix, Milagro (Guayas) was a white sheep in 2011 and 2016 (6.84 and 3.17 violent deaths per 100000 inhab., respectively) and became a black sheep in 2021 (23.22 violent deaths per 100000 inhab.), influenced by an environment of black sheep.

Table A3.

Variables	Panel data model (inverse distance matrix)	Cross-section model (inverse distance matrix)	Panel data model (4kn matrix)	Cross-section mode (4kn matrix)
Congestion rate	3.833*** (0.795)	7.317 (2.200)	3.798*** (0.796)	7.123 (2.212)
Rate of young people who do not study	0.081* (0.039)	0.025 (0.077)	0.079* (0.039)	0.023 (0.076)
Employment rate	-0.337** (0.118)	-0.245 (0.403)	-0.320** (0.118)	-0.214 (0.401)
Income poverty	0.266*** (0.077)	-0.020 (0.284)	0.263*** (0.076)	-0.021 (0.282)
Income poverty 2	-0.003** (0.001)	-0.001 (0.003)	-0.003** (0.001)	-0.001 (0.003)
Unsentenced prison population index	0.050*** (0.012)	0.139 (0.045)	0.049*** (0.012)	0.135 (0.045)
Population Density	0.001 (0.001)		0.001 (0.001)	
Seized Weapons per inhabitant		0.075 (0.070)		0.076 (0.070)
Serious Complaints		-0.248 (0.108)		-0.249 (0.108)

TABLE A3. CONT.

Variables	Panel data model (inverse distance matrix)	Cross-section model (inverse distance matrix)	Panel data model (4kn matrix)	Cross-section mode (4kn matrix)
Drug seizure		1.115 (0.525)		1.110 (0.523)
Capital	0.173 (0.642)	4.220 (1.863)	0.194 (0.640)	4.317 (1.853)
ρ (Rho)	0.508*** (0.119)	0.493 (0.291)	0.161*** (0.038)	0.164 (0.088)
AIC	1571.435	1572.28	1569.595	1570.403
BIC	1608.665	1616.279	1606.825	1614.402

Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1, standard errors in parentheses.