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Spatial Regression Analysis of Crime Occurrence in DKI Jakarta: Analysis of 2021 *Potensi Desa* Microdata

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Abstract

Urban crime is a critical issue that demands attention to support the realization of urban resilience. Urban areas with complex social conditions face an elevated risk of criminal activity. Besides economic factors, other determinants such as education and urbanization significantly contribute to urban crime. In 2021, the Special Capital Region of Jakarta recorded 20,370 criminal incidents. To gain a more comprehensive understanding of urban crime, conducting spatial analysis is essential. This study aims to perform a spatial regression analysis of crime occurrences in the province in 2021 and examine the influence of contributing factors using the 2021 Potensi Desa microdata as the primary source. The analysis encompassed 261 urban villages and employed a nomothetic explanatory quantitative approach, incorporating descriptive and inferential methods through classical and spatial regression modeling. This study finds that variables such as the urban index, education, and sports activities significantly affect the occurrence of criminal acts, although no spatial influence was observed. This study provides implications for urban planning nad development by emphasizing the importance of optimizing spatial planning and human development in formulating effective strategies to address urban crime challenges.

Keywords: *potensi desa 2021; spatial regression; urban crime; urban resilience*

1. Introduction

Urban resilience refers to the ability of any urban system to maintain its continuity (UN Habitat, 2017). It has become a crucial factor in addressing the increasingly diverse global challenges. The complexity of issues such as climate change, social challenges, and economic concerns compels cities to develop strategies to ensure a high quality of life for their residents. Urban resilience has become a primary paradigm to define urban policy for making cities resilient (Datola, 2023). One of the dimensions of urban resilience is social resilience, which encompasses aspects of social security (Chen et al., 2019). Similarly, the City Resilient Goals developed by Rockefeller-Arup include social stability and security as a sub-indicator that determines the resilience of a city (McGill, 2020).

Regarding security, urban areas generally experience higher crime rates compared to non-urban areas (Knox and Pinch, 2009 in Sukartini et al., 2021), due to distinct social, economic, and spatial characteristics (Malathi and Baboo, 2011 in Cueva and Cabrera-Barona, 2024). Understanding crime is often closely tied to understanding the city itself. Cities serve as primary sites of crime and deviant behavior, acting as focal points for disorder and social unrest while also hosting or generating a wide range of complex harms (Atkinson and Millington, 2019).

Crime significantly affects the quality of life in urban areas (Cueva and Cabrera-Barona, 2024). An in-depth understanding of crime is essential due to its profound effects on society, influencing not only economic outcomes but also generating psychological consequences (Glasson & Cozens, 2011 in

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Kamalipour et al., 2014). Therefore, effective urban planning is essential to reduce opportunities for crime (Chiodi, 2016).

Many factors contribute to the occurrence of urban crime, such as economic conditions (Cueva and Cabrera-Barona, 2024), education (Ahmed et al., 2019), and rapid urbanization without adequate infrastructure provision (Munajat and Yusuf, 2024). In Indonesia, specifically, population size and poverty significantly impact crime rates (Putra et al., 2020). However, several studies highlight factors that contribute to reducing urban crime, including the provision of green spaces (Sukartini et al., 2021) and the implementation of social activities, such as youth sports programs (Cameron and MacDougall, 2000; Jugl et al., 2023).

The Special Capital Region of Jakarta (DKI Jakarta), as the national economic hub, continues to serve as a magnet, attracting people from outside the region to come and work, and even reside, in the city. This has significantly contributed to the influx of migrants into the province. Based on the population census data from 1971 to 2020, released by Badan Pusat Statistik (Central Bureau of Statistics), the inward migration figures for this province have generally shown an upward trend, with an average of around three million people. However, the most recent census shows a slight decrease in migration compared to previous years, as illustrated in Figure 1.

The increase in inward migration undoubtedly has affected the socio-economic dynamics of Jakarta. As Qu et al. (2023) pointed out, migration has often been portrayed as the primary cause to the increase in urban crime. From 1961 to 2020, DKI Jakarta consistently experienced population growth, with an average annual growth rate of 2.22%. The 2020 census recorded the population of DKI Jakarta at 10.56 million. Meanwhile, the latest data from *Dinas Kependudukan dan Pencatatan Sipil* (Population and Civil Registry Office) shows that by the second half of 2023, the population had reached 11.3 million.

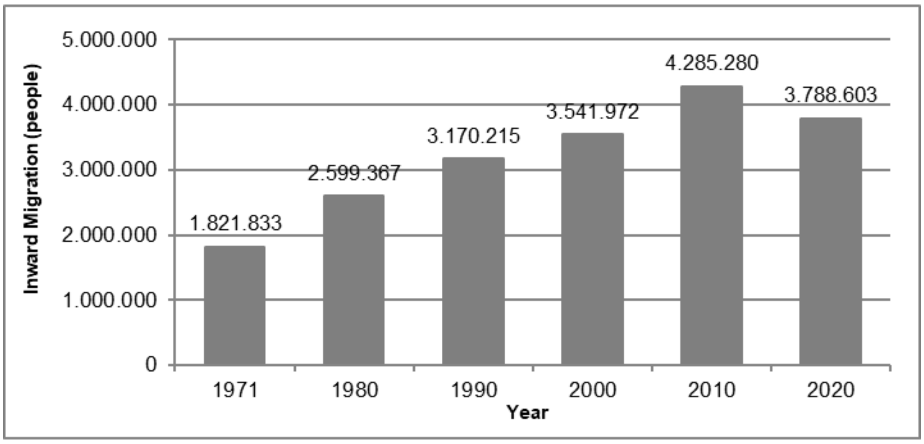

Figure 1. Total Lifetime Inward Migration of DKI Jakarta (Population Census 1971-2020)

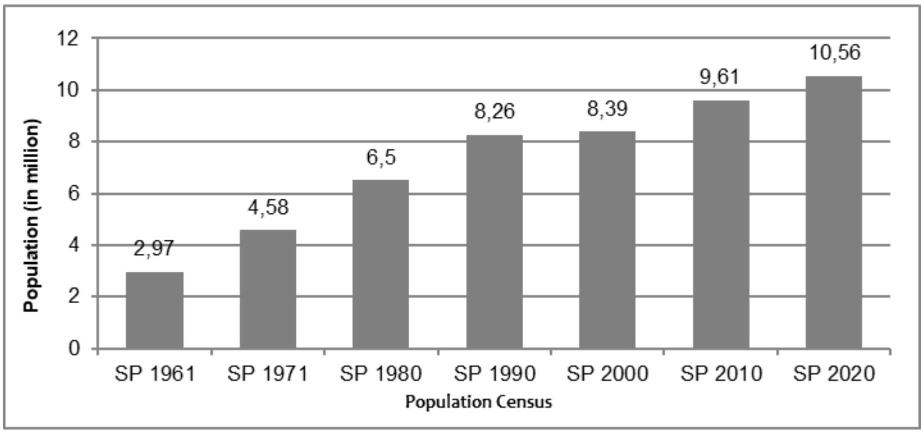

Figure 2. Total Population of DKI Jakarta (Population Census 1961-2020)

The growing population in urban areas is one of the key indications of urbanization. Ha et al. (2019) in Yu et al. (2024) argued that the rapid pace of urbanization can lead to an unequal distribution of resources, uneven job opportunities, and insufficient infrastructure and public services, which ultimately exacerbate social inequality. In relation to inequality, the 2021 Badan Pusat Statistik data shows that Jakarta has a relatively high Gini ratio of 0.411, making it the region with the second-highest social disparity in Indonesia. This condition may contribute to the increase in urban crime rates.

DKI Jakarta records a relatively high crime rate compared to other provinces in Indonesia. This situation reflects the complex challenges of criminality within the region. In 2021, there were 20,370 recorded criminal occurrences in the province (Statistik Kriminalitas DKI Jakarta, 2021), with East Jakarta being the region with the highest number of cases (5,084 incidents). According to crime classification, narcotics-related crimes were the most frequent, totaling 3,633 incidents. Jakarta also recorded the highest number of child crime victims in Indonesia, accounting for 11.7%. Based on the Social Vulnerability Potential Index (BPS DKI Jakarta, 2020), the security and public order risk score increased compared to the previous year. Several urban areas in Jakarta still have security and public order risk scores above the provincial average (15.92). The high crime risk in Jakarta necessitates a detailed spatial analysis of crime patterns. Additionally, it is crucial to examine the variables that may influence the occurrence of these crimes. This effort aims to provide strategic recommendations for crime prevention and management, considering Jakarta's role as the national economic hub and a global city.

A spatial approach is important in addressing urban crime issues. Mapping the urban morphology, spatial patterns, and the spatial structure of a city in relation to the socio-economic conditions of its population is essential for comprehensively understanding urban crime (Kamalipour et al., 2014). Glaser et al. (2022) emphasize that spatial models can serve as adequate predictive tools in analyzing crime rates. Examining crime through a spatial approach can assist cities in developing more effective prevention strategies.

In recent years, numerous studies related to urban crime have been conducted. Cueva and Cabrera-Barona (2024) found that urban crime exhibits specific spatial patterns. Furthermore, Jeong et al. (2009) suggested that urban crime often occurs in particular locations and times. In the context of Jakarta, a study conducted by Ismail (2008) mentioned that educational factors, including the high number of high school dropouts, significantly contribute to the rise of crime in DKI Jakarta. Additionally, Ariyanto et al. (2023) found that the increasing poverty rate in Jakarta has driven the rise in criminal incidents during the period of 1999-2021. Nevertheless, few studies have integrated spatial regression analysis to identify inter-regional influences on crime occurrences.

This study was conducted to address an existing gap in knowledge. The objective was to perform a spatial regression analysis of crime occurrences in DKI Jakarta in 2021 – with a focus on examining the spatial inter-regional influences on crime – and to analyze the factors that contribute to crime occurrences. The findings of this study aim to serve as a reference for urban development policymaking, particularly in shaping strategies to mitigate crime risks in urban areas.

2. Methods

The primary data source of this study is the 2021 microdata from the Potensi Desa (Podes/Village Potential) survey, published by Badan Pusat Statistik. Podes data reflects the potential of an area at the village/urban village, district, and regency or city levels, making it suitable for regional development purposes (BPS, 2024). The survey's specific objectives include providing data for classifying village typologies and calculating indicators of village development. Based on its questionnaire, the Podes dataset comprises over 120 questions covering various aspects such as demographics, environment, education, health, economy, and security. This comprehensive nature allows for the inclusion of multiple variables, one of which pertains to the types of criminal incidents occurring in a given area. The data on criminal occurrences fall under the security category, which also includes information on mass brawls, security personnel, and security facilities.

However, since the data does not represent the number of criminal cases, this study is unable to provide detailed information regarding the severity of crimes. Moreover, as the Podes data is filled out by respective village/urban village officials, there is a risk of incomplete data. These aspects present certain limitations of the Podes data. However, the dataset allows for the inclusion of various independent variables. Additionally, population statistics were obtained from Dinas Kependudukan dan Pencatatan Sipil of DKI Jakarta.

This study's observation units comprise 261 urban villages in DKI Jakarta, excluding the Administrative Regency of Kepulauan Seribu. This exclusion ensures that the spatial analysis provides a contiguous spatial representation without the separation caused by the sea. Kepulauan Seribu region consists of geographically dispersed islands, which could potentially affect the results of the spatial dependency tests.

This study employs a quantitative explanatory nomothetic approach. Explanatory research typically aims to provide reasons for phenomena in the form of causal relationships, while the nomothetic approach seeks to identify several causal factors that generally impact a class of conditions or events (Babbie, 2016). Specifically, this study conducts hypothesis testing to determine the factors influencing crime occurrences in DKI Jakarta, while also analyzing the spatial effects of crime occurrences across the observation units. A similar approach was employed by Rosantiningsih and Chotib (2023) in their analysis of spatial dependency concerning fire occurrences in Jakarta and the role of influencing variables.

The analytical techniques employed in this study comprise two types: descriptive statistical analysis and inferential analysis. Descriptive statistical analysis utilizes cross-tabulation between each independent variable and the dependent variable. Inferential analysis involves classical regression modeling and spatial regression. Regression analysis is a method to investigate the functional relationships among variables (Chatterjee and Hadi, 2012) and is also used to predict the extent of change in the value of one variable resulting from manipulation or alteration of another variable (Kurniawan and Yuniarto, 2016).

The classical regression model, commonly referred to as Classic Ordinary Least Squares (OLS), is formulated as follows:

$$y\_crime = \beta_0 + \beta_1 x_1\_UI + \beta_2 x_2\_up + \beta_3 x_3\_pdkn + \beta_4 x_4\_sktm + \beta_5 x_5\_pospol + \beta_6 x_6\_or + \varepsilon$$

where:

y_crime : number of crime types
x_1_UI : urban index
x_2_up : proportion of the productive age population
x_3_pdkn : proportion of the population with low education level
x_4_sktm : number of applications for the certificate of indigency (SKTM)
x_5_pospol : number of police post
x_6_or : number of sport activity types
β_0 : intercept
$\beta_1 - \beta_6$: regression coefficients of each independent variable

The operational definition of each variable is presented in Table 1 as follows:

Table 1: Explanation of Variables and Operational Definitions

Variable	Operational Definition	Notation
Number of crime types	Data on the number of crime types in each urban village. The types of crimes include: theft, robbery, fraud/embezzlement, assault, arson, rape/sexual offenses, drug abuse/distribution, gambling, murder, human trafficking, and corruption.	y_crime
Urban index	The value indicating the urban status of a village/urban village based on population density per square kilometer, the percentage of agricultural households, and the presence of urban facilities.	x1_UI
Proportion of the productive age population	A comparison of the number of individuals in the productive age group (15-64 years) to the total population.	x2_up
Proportion of the population with low education level	A comparison of the number of individuals with education below the Junior High School level to the population aged 6-8 years and above (school age).	x3_pdkn
Number of applications for the certificate of indigency (SKTM)	Data on the number of certificates of indigency/SKTM issued by villages/urban villages government during 2020, representing the number of poor families.	x4_sktm
Number of police post	Data on the number of police posts (including police stations), representing security facilities.	x5_pospol
Number of sport activity types	Data on the number of sports activity types, including: football, volleyball, badminton, basketball, tennis, table tennis, futsal, swimming, martial arts, billiards, fitness/aerobics, and others.	x6_or

In addition to classical regression modeling, spatial regression analysis was also conducted. As an extension of regression analysis methods, spatial regression addresses the challenges posed by spatial or geographical data (Tarigan, 2021). Key concepts and issues in spatial regression models include spatial autocorrelation, spatial heterogeneity, and neighborhood structure, as well as the spatial weight matrix (Chi and Zhu, 2008). To assess the presence of interdependencies related to criminal occurrences in DKI Jakarta, several spatial autocorrelation methods are employed, such as Moran's I and LISA (Local Indicator Spatial Association). LISA is commonly used to determine local spatial autocorrelation and to identify local clusters along with their significance levels (Anselin, 1995 in Hamdan, 2019).

Two models were applied in the spatial regression analysis in this study: the spatial lag model and the spatial error model. The spatial lag model, also known as spatial autoregressive, interprets an event occurring in one area being influenced by neighboring areas due to interactions between them. In contrast, the spatial error or spatial moving average model accounts for error correlation interactions between areas and reflects instability or shocks (Hamdan, 2019). The spatial lag coefficient (rho/ρ) represents the extent of influence one area has on another, while the spatial error coefficient (lambda/λ) accommodates the error effects from neighboring areas that interact spatially. The spatial regression with the spatial error model is formulated as follows:

$$y\_crime = \lambda + \beta_0 + \beta_1 x_1\_UI + \beta_2 x_2\_up + \beta_3 x_3\_pdkn + \beta_4 x_4\_sktm + \beta_5 x_5\_pospol + \beta_6 x_6\_or + \varepsilon$$

In the spatial lag model, the following formula is applied:

$$y\_crime = \rho + \beta_0 + \beta_1 x_1\_UI + \beta_2 x_2\_up + \beta_3 x_3\_pdkn + \beta_4 x_4\_sktm + \beta_5 x_5\_pospol + \beta_6 x_6\_or + \varepsilon$$

where:

λ : spatial error coefficient
ρ : spatial lag coefficient

The analysis was conducted using GeoDa software version 1.22.0.4. The hypothesis of this study posits that crime occurrences in DKI Jakarta in 2021 are influenced by spatial factors, and that the independent variables also affect these crime occurrences. The relationships between these variables are outlined in the following table.

Table 2: Research Hypotheses

No.	Variable	Effect
1.	Urban Index	+
2.	Proportion of the productive age population	+
3.	Proportion of the population with low education level	+
4.	Number of application for certificate of indigency (SKTM)	+
5.	Number of police post	-
6.	Number of sport activity types	-
No.	**Coefficient**	**Effect**
1.	Lambda (Spatial Error Model)	+
2.	Rho (Spatial Lag Model)	+

3. Results and Discussions

In 2021, on average, each urban village in DKI Jakarta experienced between one and two types of criminal acts, with theft and drug-related offenses being the most common. Lagoa, an urban village in North Jakarta, recorded the highest incidence of various criminal activities, encompassing all crime categories. Following this, the urban villages of Ancol, Bidara Cina, Bintaro, and Sungai Bambu each reported seven distinct categories with varying specifics. According to the Podes (Village Potential) data, no crime was recorded in 96 urban villages. However, due to the data's limitations – reported by urban village officials – an absence of recorded incidents does not necessarily mean no crime occurred. It may, instead, indicate a lack of thorough documentation. It is also plausible that certain urban villages are genuinely safe and free from criminal activity. Meanwhile, 152 urban villages reported between one to four types of criminal incidents during 2021.

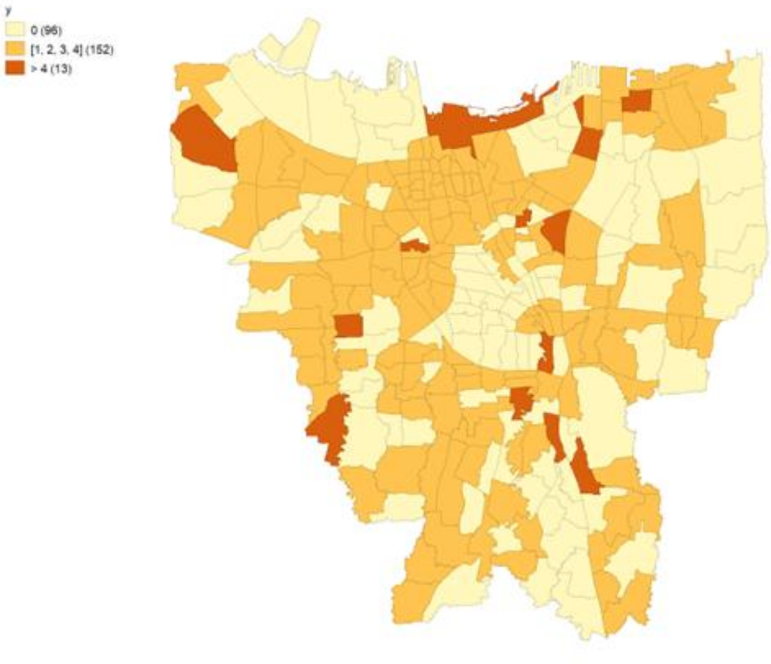

Figure 3. Distribution of The Number of Crime Types in DKI Jakarta in 2021

Overall, the distribution of the number of crime types in Jakarta in 2021 is relatively uniform, with crimes reported in all regions: northern, eastern, western, southern, and central Jakarta. Most areas fall into the moderate category (1–4 types of crime) and are dispersed across various locations without forming specific clusters. Areas with a high number of crime types (>4 types) are also spread across several regions, some located on the outskirts of Jakarta and others in the city center. The phenomenon in the peripheral areas suggests an influence from the surrounding cities on criminal activities, possibly due to urbanization or diverse socio-economic conditions in those areas. Meanwhile, the concentration of crime in the city center strengthens the assumption that areas with high population density and economic activity are more vulnerable to criminal behavior.

In this study, the spatial autocorrelation was analyzed through Moran's I. The Univariate Local Moran's I method allows for assessing spatial autocorrelation of the dependent variable, in this case, the number of crime types in each urban village. The maps and scatter plots below illustrate the analysis.

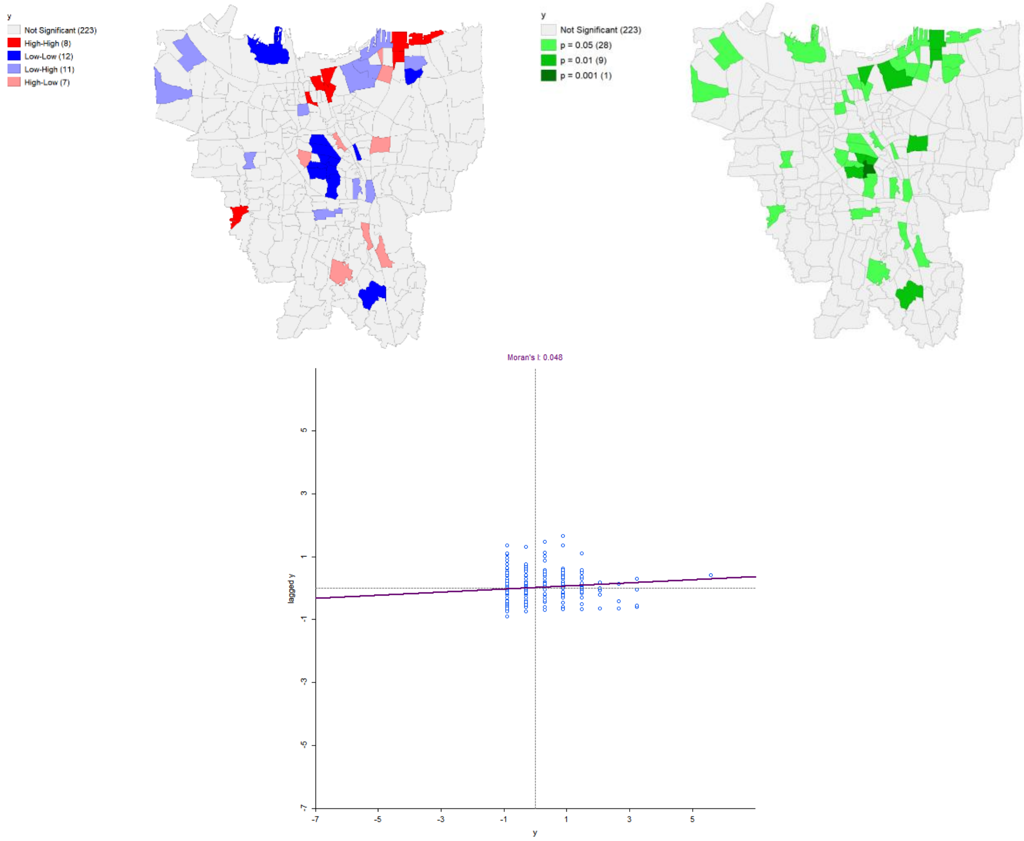

Figure 4. Results of Univariate Local Moran's I Analysis on Dependent Variable

According to the result of cluster map analysis, eight urban villages fall into the High-High category: Gunung Sahari Utara, Kalibaru, Koja, Mangga Dua Selatan, Maphar, Pademangan Barat, Pesanggrahan, and Rawa Badak Utara. These areas have a high number of crime types, and they are surrounded by neighboring urban villages with similarly high number of crime type. This category can be described as a positive cluster. In contrast, the Low-Low category represents a negative cluster, where urban villages with a fewer crime types are surrounded by areas with similarly low crime types. This category includes twelve urban villages: Ciracas, Gondangdia, Guntur, Karet, Karet Kuningan, Kayu Manis, Menteng, Menteng Atas, Menteng Dalam, Pasar Manggis, Pluit, and Tugu Selatan.

Meanwhile, the High-Low and Low-High categories indicate deviations or differences in characteristics between neighboring areas. On the one hand, the High-Low cluster represents areas with a high number of crime types but surrounded by neighboring areas with a low number of crime types. Seven urban villages are included in the High-Low cluster: Karet Tengsin, Kenari, Kramat Jati, Pinang Ranti, Rawamangun, Sungai Bambu, and Tanjung Barat. On the other hand, the Low-High cluster signifies areas with a low number of crime types yet surrounded by areas with a high number of crime types. Additionally, eleven urban villages are part of the Low-High cluster, including Cipinang Cempedak, Duren Tiga, Kalideres, Kebon Baru, Kelapa Dua, Papanggo, Petojo Utara, Sunter Agung, Tanjung Priok, Tegal Alur, and Tugu Utara.

According to the significance map, Menteng Atas emerges as the area with the most significant spatial pattern, boasting a significance value of 0.001, or 0.1%. This indicates that the distribution of crime incidents in this urban village demonstrates a very strong spatial correlation. Furthermore, there are 37 additional urban villages exhibiting spatial patterns with significance values ranging from 0.01 to 0.05, or 1% to 5%. Although these values are not as robust as those for Menteng Atas, they still indicate a moderately significant spatial relationship among crime occurrences in these regions. Overall, the identification of areas with high significance values offers valuable insights for determining priority zones in security management and implementing spatially based crime mitigation strategies.

The majority of urban villages, totaling 223 locations, do not demonstrate any notable clustering tendency and also lack significant spatial patterns. This situation suggests that the distribution of crime occurrences in these areas is more random and not influenced by spatial relationships with surrounding regions. In other words, crime occurrences in these 223 locations appear to be unaffected by neighboring areas.

The scatter plot shows a Moran's I value of 0.048, indicating that urban villages with a high number of crime types tend to have neighboring areas with similarly high numbers of crime types. However, this value indicates weak spatial autocorrelation, implying that spatial relationships are not consistently observed throughout Jakarta. This weak correlation may reflect the influence of various factors contributing to crime occurrences in a more intricate manner. Therefore, a more detailed analysis is necessary to uncover the determinants of crime occurrence.

From the regression test results using the Classic Ordinary Least Squares (OLS) model, which examines the influence of independent variables on the dependent variable, as well as the spatial regression test, the following results were drawn:

Table 3: Results of Classic and Spatial Regression Test

Variable	**Classic Regression** R-squared: 0. 078484 Prob (F-statistic): 0.00189431		**Spatial Error Model** R-squared: 0.078854		**Spatial Lag Model** R-squared: 0.078841	
	Coefficient	***Std. Error***	***Coefficient***	***Std. Error***	***Coefficient***	***Std. Error***
W_y_crime					0.025978	0.0996602
Constant	-0.351418	8.74179	-0.245793	8.56877	-0.386805	8.6221
x1_UI**	0.266669	0.135235	0.273579	0.132849	0.262238	0.133393
x2_up	-6.26004	11.3579	-6.62722	11.1174	-6.10792	11.2026
x3_pdkn**	7.41771	2.93511	7.52027	2.86523	7.28958	2.9094
x4_sktm	0.00001692	0.00004966	0.00001820	0.00004897	0.00001662	0.00004898
x5_pospol	-0.0482464	0.133393	-0.045439	0.131172	-0.0501708	0.131572
x6_or***	-0.105575	0. 03418	-0.106456	0.0334941	-0.104782	0.0337555
Lambda			-0.0282178	0.104004		

Description:
** : significant at α = 5%
***: significant at α = 1%

The R-squared value indicates that, in general, the six independent variables account for approximately 7% of the variance in the dependent variable, which is the number of crime types. This percentage is relatively low, indicating the likelihood of other unmeasured or excluded factors influencing the dependent variable. However, despite the low R-squared value, the results of the classical regression test reveal that the Prob (F-statistic) or Significance F value is below 0.05. This indicates that the model can make statistically significant predictions based on these six independent variables, demonstrating that they contribute meaningfully to predicting the dependent variable.

In terms of coefficient values, three variables exhibit a positive correlation with the increase in the number of crime types: the urban index, the proportion of the population with low education levels, and the number of SKTM (certificate of indigency) applications. The urban index reflects the characteristics of an area that has undergone urbanization, as seen from the population density, the economic activity, and the completeness of urban facilities. The more urbanized a region becomes, the higher the likelihood of crime. Similarly, a higher proportion of poorly educated residents and impoverished families increases the likelihood of crime. In contrast, three other variables exhibit a negative correlation: a higher proportion of the productive age population, the presence of security facilities such as police posts, and the number of sports activities. These factors contribute to a reduction in crime occurrences.

Furthermore, only urban index, low education levels, and sports activities show a significant influence on crime rates, while the other three independent variables show no significant effect. Urbanized areas tend to foster more complex social and economic dynamics, which may contribute to higher criminal activity. Similarly, on the one hand, a higher proportion of residents with low education levels correlate with increased crime. It is possibly because education is linked to welfare, and a lack of education regarding societal norms may drive individuals to crime as a shortcut to meeting their needs. On the other hand, frequent community-level sports activities help reduce crime by serving as an outlet for energy and fostering social interactions that discourage criminal behavior.

Table 4: Research Hypotheses and Regression Test Results

No.	Variable	Effect	Regression Test Result
1.	Urban Index	+	+
2.	Proportion of the productive age population	+	-
3.	Proportion of the population with low education level	+	+
4.	Number of application for certificate of indigency (SKTM)	+	+
5.	Number of police post	-	-
6.	Number of sport activity types	-	-
No.	**Coefficient**	**Effect**	**Regression Test Result**
1.	Lambda (Spatial Error Model)	+	-
2.	Rho (Spatial Lag Model)	+	+

To obtain the results of the spatial regression test, a regression was first conducted incorporating weights. In this study, the Queen Weight was chosen to observe the dependence of one unit on its surrounding areas, not limited to adjacent sides. From this weighting, the largest coefficients values were identified. The Lagrange Multiplier (lag) value was larger than the Lagrange Multiplier (error) value, which led to the application of a spatial lag model in the spatial regression test. The result, a Lag coefficient (Rho) value of 0.025978, indicates a weak and insignificant negative spatial autocorrelation. To better capture the spatial pattern, a spatial regression test with the spatial error model was also applied, which yielded a Lambda of -0.0282178, demonstrating a weak and similarly insignificant spatial effect.

The results suggest that the number of crime types in a specific area is not significantly affected by the conditions of neighboring areas. This finding implies that, in 2021, there was no spatial influence driving criminal activities in DKI Jakarta. It also reinforces the notion that crime occurrences are likely influenced by factors beyond just spatial considerations, underscoring the need for further identification and more in-depth analysis.

4. Conclusions

In terms of its spatial distribution, the number of crime types in DKI Jakarta in 2021 were distributed relatively evenly across the region. However, certain urban villages in northern, western, and southern parts of Jakarta exhibited a higher number of crime types. These areas could be identified as potential hotspots that may require more intensive intervention efforts to reduce crime rates. Despite these findings, the spatial analysis did not reveal a strong inter-regional influence in crime occurrences, with most areas showing no clustering patterns. This suggests that criminal activity in DKI Jakarta was largely spatially random, with no spatial effect between one area and another.

The factors influencing criminal activity also warrant closer examination. In 2021, urban crime in Jakarta was significantly affected by factors such as the urban index, the proportion of the population with low education levels, and the availability of various sports activities. The urban index and low education levels contributed to higher criminal occurrences, while the presence of diverse sports activities in certain areas was associated with a potential reduction in crime rates.

The results presented in this study have considerable implications for urban planning and development, particularly in developing strategies for crime prevention. Policy interventions should prioritize enhancing security aspects within spatial planning. Implementing approaches such as Crime Prevention Through Environmental Design (CPTED) can help reduce opportunities for crime by creating safer environments. Policy interventions should also focus on providing educational facilities and promoting inclusive social activities, especially in areas characterized by elevated crime rates. Equitable access to education and skill development programs can function as a sustainable approach to mitigating crime levels over the long term. Bolstering social infrastructure—by providing sports facilities and community interaction spaces—has the potential to prevent criminality by fostering social cohesion within urban communities. The integration of physical development and human development is anticipated to significantly reduce urban crime rates amidst urbanization challenges, as evidenced in Jakarta.

The findings emphasize that urban crime remains a challenge requiring comprehensive strategies. Policymakers should consider regional characteristics and the types of crime prevalent in each area when formulating interventions. A spatial data-driven approach can be further employed to support decision-making processes in urban security planning, for instance in identifying priority intervention areas and evaluating the efficacy of implemented policies. Through this approach, urban management strategies can be developed more effectively to foster a safer urban environment.

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