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MODELING CRIME IN EAST JAVA USING SPATIAL DURBIN MODEL REGRESSION

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ABSTRACT

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The high crime rate will create unrest and losses for the community. One of the provinces with high crime rates is East Java. This study aims to analyze the factors that influence criminality in East Java to ensure appropriate crime prevention and control measures can be taken. The factors that potentially influence crime in East Java studied include population density, the number of poor people, unemployment, Human Development Index (HDI), Gross Regional Domestic Product (GRDP), and per Capita Expenditure, which are associated with geographical conditions in each region (regency/city) collected from BPS East Java in 2022. Meanwhile, the number of crimes is collected from the East Java Regional Police. This research uses a statistical method, namely the Spatial Durbin Model (SDM), which is a particular form of the Spatial Autoregressive Model (SAR) method with Queen Contiguity weighting by analyzing geographically (spatial processes). Based on the results of the analysis, it was found that the influential factors were unemployment, HDI, GRDP, and per Capita Expenditure, and the R-square result was obtained at 85.18%. This shows a relationship between spatial accessibility and crime, where unemployment, HDI, GRDP, and per Capita Expenditure in an area can affect regional vulnerability to crime.

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1. INTRODUCTION

Crime is a problem that often occurs in many areas worldwide and disturbs society. This phenomenon can affect a region's quality of life, social stability, and economic development. Crime can be in the form of acts of physical violence, theft, robbery, narcotics, vandalism, and various other types of illegal actions [1]. The crime rate in Indonesia in 2022 ranks 4th in ASEAN. While at the global level, it ranks 70th out of 142 countries, with a crime rate that increases by 46.1% [2].

Crime can be caused by development inequality between regions [3]. Excessive inequality between regions can cause regional growth imbalances and encourage differences in development processes, creating underdeveloped and developed areas. If the rate of development inequality between regions is getting higher, it will impact the gap in the level of welfare of the people. For areas with high economic level communities, this is not a problem. Still, for areas with low economic level communities, it will increase poverty and unemployment, which can encourage crime [4].

East Java Province is a province in Indonesia located on the eastern tip of Java Island. It has 29 regencies and nine cities with an area of about 47,800 km^2. East Java is the province with the second largest population in Indonesia after West Java. In 2022, the number of crimes reported as many as 23160 cases occurred in East Java, making East Java the province with the third highest number of crimes in Indonesia after North Sumatra and DKI Jakarta Provinces, with 36534 and 29103 cases respectively [5]. In addition, East Java is a province with a rapidly growing industrial sector, including manufacturing, agriculture, and tourism industries [6]. The existence of these sectors can attract the attention of criminals, including organized crime, such as drug trafficking, theft, and economic crime [7]. Therefore, it is crucial to analyze the factors affecting criminality so that appropriate prevention and countermeasures can be taken.

Previous research on factors that influence crime was conducted by [1], which examines crime in Punjab (Pakistan) with a significant variable population density. Analyzed crime in East Java, obtaining that poverty rates and economic growth (illustrated by the Gross Regional Domestic Product, GRDP) significantly affect crime [8]. Research by [9] analyzed crime (especially violence) in the United States, resulting in the Human Development Index (HDI) and liveability in a region influencing crime. Research by [10], who researched crime in Addis Ababa, Ethiopia, stated that high unemployment rates would trigger corruption. Research by [11] investigated crime in Indonesia and found that Per Capita Expenditure significantly affects crime.

The factors influencing crime often have spatial effects, meaning that crime rates and types tend to converge in certain areas. Areas with high unemployment, poverty, and lack of access to public services tend to have higher crime rates. In addition, the concentration of illegal activities in a particular area can also trigger a domino effect, where the criminal act of one will stimulate similar actions in the surrounding area [12]. The diversity of characteristics in an area has different ways of coping and handling, so spatial linkage factors have become very influential [13]. Policymaking that does not consider spatial factors or regional characteristics can lead to unbalanced and poorly targeted policymaking. The importance of spatial analysis is that everything is interconnected, but the closest one has a more decisive influence than the distant one [14].

Several methods can be used to analyze factors with spatial cases considering spatial influences in regression analysis, where dependent and independent variables are influenced by their spatial location, namely the Spatial Autoregressive Regression (SAR), Spatial Error Model (SEM), Spatial Durbin Model (SDM), Geographically Weighted Regression (GWR), and Multiscale Geographically Weighted Regression (MGWR). SAR, SEM, and SDM are models that accommodate spatial autocorrelation, whereas GWR focuses on accommodating spatial heterogeneity. Several studies have been conducted using spatial regression, including research by [15] modeling criminality in Nigerian territory using GWR. The study results show that the high percentage of crime in a region of Nigeria will influence the high crime in the surrounding area with an R^2 value of 42.7% [16] modeling spatial data on alcohol-related crime rates in the UK using GWR. The results show the importance of using spatial models to understand the relationship between alcohol availability and violence, with R^2 at 43%, where the type of alcohol outlets outside the trade poses problems in a region that can affect the risk of violence. [17] used the MGWR (Multiscale Geographically Weighted Regression) method to find the relationship between economic indicators and traffic accidents in Texas, United States. The modeling results with MGWR obtained R^2 of 44.5% and GWR (Geographically Weighted Regression) with R^2 of 61.8%. [18] modeled crime in Taiwan by comparing three spatial regression methods, namely the Spatial Autoregressive Regression (SAR), Spatial Error Model (SEM), and Spatial Durbin Model (SDM). The best modeling results were obtained using the Spatial Durbin Model (SDM) method with an R^2 value of 89.9%. [19] apply the Spatial Durbin Model (SDM) to analyze the influence of regional characteristics on the incidence of crime and violence in Korea. The results stated that there is a significant relationship between spatial accessibility and crime, where the dominant type of business in an area and the level of road accessibility can affect the vulnerability of the region to crime, especially violence in Korea. [20] used the Durbin Spatial Model (SDM) Method to analyze the incidence of fires in urban Portugal. Considering space dependence and several socioeconomic explanatory variables, it has been shown to strengthen the model's validity corresponding to the R^2 value by 97%. The results of this modeling can be used to map estimates of the likelihood of fires across Portugal with clusters of spatial patterns centered in two central urban districts in Portugal (Lisbon and Porto). The study also shows that SDM methods can be used to recommend to the government the number and location of firefighting facilities that should be established. Apart from being based on several studies, the data in this research indicates the hypothesis of interaction or spatial dependence between locations, which is reflected in the number of crimes in adjacent locations, which are not much different.

Significant innovations in this research differentiate it from other studies that have been mentioned. This research will implement a Durbin Spatial model with Queen Contiguity weighting to model crime cases in East Java based on factors that influence it. Based on the previous study, the SDM method performs well in modeling cases containing spatial autocorrelation effects. This research's contribution lies in an in-depth understanding of crime factors in East Java and in successfully applying the Durbin Spatial model.

2. RESEARCH METHODS

The stages of the research process to achieve the objectives carried out in this study are described in the flow of research methodology in Figure 1.

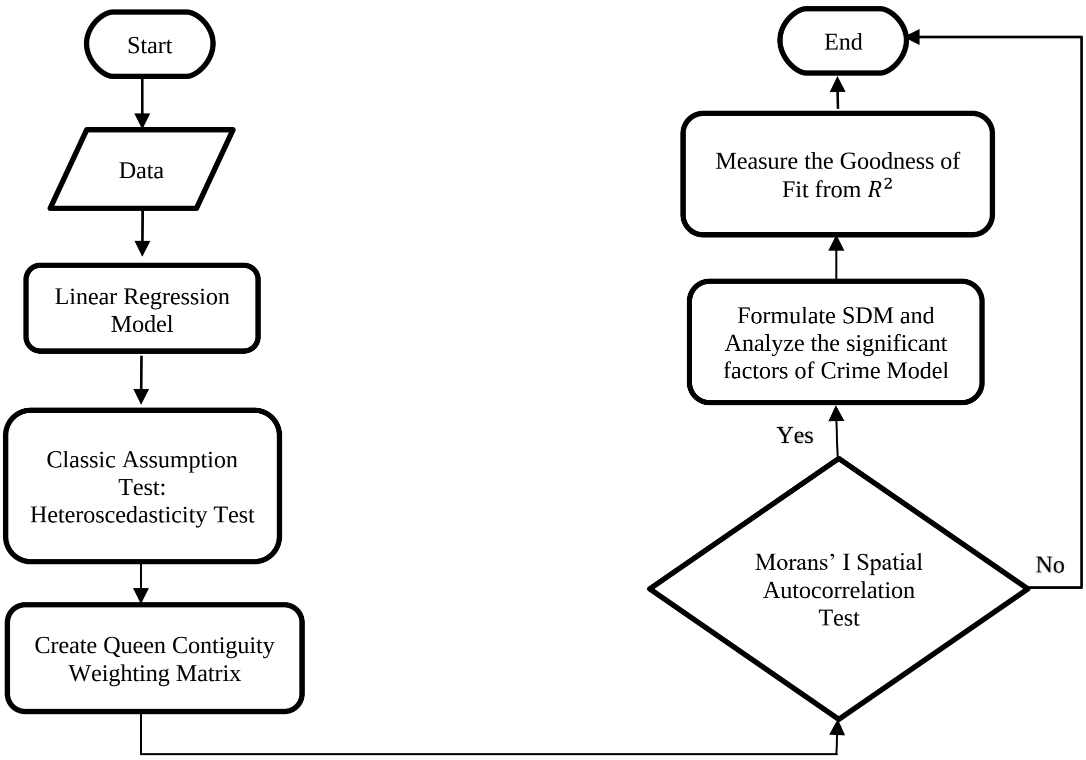

Figure 1. Research flowchart

2.1 Data

The data source used in this study involves secondary data provided by the Central Statistics Agency (BPS) in 2022, which includes population density (X_1) [21], number of poor people (X_2), number of unemployed (X_3), Human Development Index (HDI) (X_4), Gross Regional Domestic Product (GRDP) (X_5)

[22], and per Capita Expenditure (X_6) [23]. Meanwhile, the number of crimes (Y) is obtained from the East Java Regional Police. Sample data are shown in Table 1.

Table 1. Sample Data

No.	District/City	Y	X_1	X_2	X_3	X_4	X_5	X_6
1.	Pacitan Regency	75	414	76930	13923	69.37	17986.47	9184
2	Ponorogo Regency	233	680	81800	29065	71.87	23028.25	10199
3.	Trenggalek Regency	124	592	76750	22109	71	20882.31	10042
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
36.	Madiun City	263	5514	8490	6188	82.01	15825.61	16503
37.	Surabaya City	4764	8595	138210	125276	82.74	6556161.22	18345
38.	Batu City	191	1116	8050	10175	77.22	18587.6	13094

2.2 Linear Regression

The first stage in this study is modeling the data using the linear regression method. Linear regression is a statistical method determining the relationship between response and predictor variables. The linear regression model using Equation (1). [24]

$$y_i = \beta_0 + \beta_1 x_{i1} + \cdots + \beta_p x_{ip} + \varepsilon_i \tag{1}$$

where y is the response variable, and the value of $i = 1,2, \dots, n$ with $x_1, x_2, \dots, x_p$ is the independent variable of the number p variable. Meanwhile, to estimate the parameters of a linear regression model using Ordinary Least Square (OLS) using Equation (2).

$$\hat{\beta} = (X^T X)^{-1} X^T y \tag{2}$$

2.3 Heteroscedasticity Test

In regression analysis, classical assumption tests are required, which must be met. The Glejser test is used to determine whether the variance between the residuals of an observation in a regression model significantly differs from the residuals of other observations, which is the purpose of the heteroscedasticity test [25]. The test statistics for the Glejser test are using Equation (3).

$$\boldsymbol{F} = \frac{\left[\sum_{i=1}^{n} \frac{(|\hat{e}_i| - |\bar{e}|)^2}{p}\right]}{\frac{\left[\sum_{i=1}^{n} (|e_i| - |\hat{e}_i|)^2\right]}{n} - p - 1} \tag{3}$$

where $\hat{e}_i$ is the i^{th} error from the OLS regression, and the decision is made if $F > F_{\alpha;p,n-p-1}$ or the *p-value* < α.

2.4 Queen Contiguity Weighting

If heteroscedasticity is found in the classical assumption test, then to overcome this, we can try to check whether there is a possibility of spatial effects. This study uses the Spatial Durbin Model (SDM) to accommodate spatial effects in the model. To obtain the SDM, initially create the Contiguity Weighting Matrix. The Queen Contiguity Weighting Matrix is a matrix that describes the relationship between regions based on the intersection of regional boundaries. This weighting matrix has the following rules:

$$w_{ij} = \begin{cases} 1, \text{if region } i \text{ and } j \text{ share borders} \\ 0, \text{other} \end{cases}$$

The w_{ij} is the value of the weighting matrix of the i-th row and j-th column. The value 1 is given if the columns in the i-th row and the j-th column are adjacent and vice versa if the i-th row and j-th column are not adjacent, then the value is 0. The Queen Contiguity matrix using **Equation (4)**.

$$W = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1j} \\ w_{21} & \ddots & \cdots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ w_{i1} & w_{i2} & \cdots & w_{ij} \end{bmatrix} \tag{4}$$

After obtaining the Queen Contiguity weighting matrix, standardization is carried out on each entry to get the number of rows equal to one. The formula for standardizing the Queen Contiguity weighting matrix using **Equation (5)**.

$$w_{ij} = \frac{c_{ij}}{c_i} \tag{5}$$

with $c_i = \sum c_{ij}$ represents the total value of the i-th row and c_{ij} represents the value in the i-th row of the j-th column **[26]**.

2.5 Moran's I Spatial Autocorrelation Test

In modeling using SDM methods, analyzing the presence of spatial dependencies or autocorrelation is necessary. The measurement of spatial dependencies can be done using the Moran's I test. Moran's I test aims to identify a location from spatial grouping or spatial dependence on data. The test statistics used are using **Equation (6)** and **Equation (7)**. **[27]**

$$Z(I) = \frac{I - E(I)}{\sqrt{var(I)}} \tag{6}$$

$$\boldsymbol{I} = \frac{\boldsymbol{n}\sum_{i=1}^{n}\sum_{j=1}^{n}\boldsymbol{W_{ij}}(\boldsymbol{x_i}-\overline{\boldsymbol{x}})(\boldsymbol{x_j}-\overline{\boldsymbol{x}})}{\sum_{i=1}^{n}\sum_{j=1}^{n}\boldsymbol{W_{ij}}\left(\sum_{i=1}^{n}(\boldsymbol{x_i}-\overline{\boldsymbol{x}})^2\right)} \tag{7}$$

Where $E(I)$ is Moran's expectation I, $\boldsymbol{var(I)}$ is a variant of Moran's I, and $\boldsymbol{w_{ij}}$ is the Queen Contiguity weighting matrix. When $\boldsymbol{Z(I)} > \boldsymbol{Z_{\alpha/2}}$ or $\boldsymbol{p}$-value is less than $\boldsymbol{\alpha}$, spatial autocorrelation occurs.

2.6 Spatial Durbin Model

The spatial Durbin Model (SDM) is a regression method developed by Anselin **[28]**. This method has a form such as the Spatial Autoregressive Model (SAR), which has spatial lag on the response variable (y). In contrast, the Spatial Durbin Model has spatial lag not only on the response variable but also on the predictor variable. After testing the Moran Index, SDM modeling can be continued, expressed in **Equation (8)**. **[27]**

$$y_i = \rho\sum_{j=1}^{n} w_{ij}y_j + \alpha + \sum_{k=1}^{p}\beta_k x_{ki} + \sum_{k=1}^{p}\sum_{j=1}^{n}\theta_k\left(w_{ij}x_{kj}\right) + \epsilon_i \tag{8}$$

where y_i is the observed value of the i-th independent variable, w_{ij} is the spatial weighting value that determines the relationship between the i-th region and the j-th region, x_{ki} is the value of the k-th independent variable in the i-th region, ρ is the value of the spatial lag coefficient, α is a constant parameter, β is a parameter vector, and θ is the vector of the spatial lag parameter of the independent variable, and ε_i is the error value at the i-th observation value.

2.7 The Goodness of Fit

The best model selection uses the coefficient of determination (R-square). R-square indicates the accuracy of a model (Goodness of fit) using **Equation (9)**.

$$R^2 = 1 - \frac{\mathrm{SSE}}{\mathrm{SST}} \tag{9}$$

where SSE is the sum of the squares of the error, and SST is the sum of the total squares. A large R^2 test shows that the model is good because it explains the changes in bound variables well. We need to know that the coefficient of determination (R^2) ranges from 0 to 1, and a value close to 1 means that the model is more precise in describing the phenomenon of the response variable so that the model is more trusted **[29]**.

3. RESULTS AND DISCUSSION

3.1 Results

The data for this study were obtained from 38 cities/regencies in East Java. Before the analysis, descriptive analysis and mapping were carried out first to find out more details about the explanation of each variable and see the initial picture of crime in East Java Province. A general descriptive analysis is shown in **Table 2**.

Table 2. Descriptive Statistics

Variable	Mean	Max	Min
y	609.4737	4764	75
x_1	2071.105	8595	414
x_2	110033.4	252880	7880
x_3	33045.24	125276	3657
x_4	72.96921	82.74	63.39
x_5	71858.74	655616.2	7637.02
x_6	11837.97	18345	8944

Based on **Table 2**, it can be seen that the average crime in East Java in 2022 reached 609 cases. The highest crime rate occurred in the Surabaya City area, with 4764 cases, while the Pacitan Regency area recorded the lowest number of crimes at 75 cases.

After conducting a descriptive analysis to determine the initial picture of crime in East Java Province, the next stage is selecting the multiple linear regression model. The results of linear regression modeling between bound and independent variables showed that partial testing showed significant variables with a α of 0.05, namely HDI, GRDP, and per capita expenditure. The multiple linear regression model of crime cases in East Java is stated as follows:

$$\hat{y} = \begin{matrix} 4.147 \times 10^{3} + 1.810 \times 10^{-2}x_1 - 9.572 \times 10^{-4}x_2 + 2.786 \times 10^{-3}x_3 \\ -8.140 \times 10^{1}x_4 + 5.301 \times 10^{-3}x_5 + 1.687 \times 10^{-1}x_6 \end{matrix} \tag{10}$$

Based on the results of linear regression modeling, the goodness of the R^2 model was 79.75%. From the classical assumption test, it is obtained that not all assumptions are met. Based on **Equation (3)**, the result of the Glejser test is a p-value of 0.0374, so the $p-$value $< \alpha$. It indicates the heteroscedasticity problem (residual variety is detected). Thus, linear regression is not good at modeling crime cases in East Java. This is likely due to the influence of location factors, so it is necessary to use other methods that consider spatial effects. This study uses the Spatial Durbin Model, which can accommodate spatial heterogeneity using Maximum Likelihood Estimation for parameter estimation **[30]**.

The step before testing spatial effects and modeling criminal cases using SDM is to create a Queen Contiguity weighting matrix according to **Equation (4)**. The key is to be mindful of the borders and neighborliness of each location, as seen in **Figure 2**.

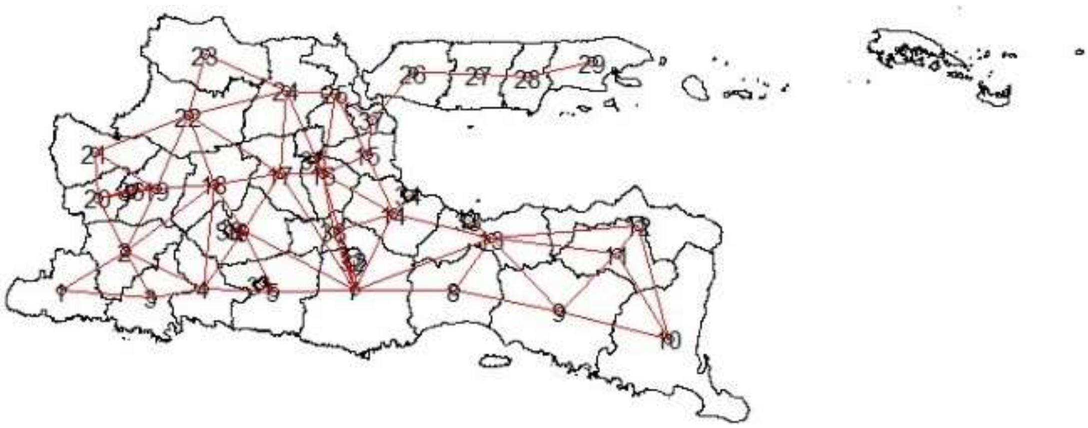

Figure 2. Neighborliness Map Using Queen Contiguity Weighting Matrix

The results of the neighborliness of the East Java region are shown in **Figure 2,** with examples in the Sumenep Regency area bordering Pamekasan Regency. From the neighborliness, a weight of 1 is given, while if there is no intersection, it is given a weight of 0. For other regions, the same method is also used. Here is the result of an unstandardized spatial weighting matrix with 38 rows and columns.

$$W^* = \begin{bmatrix} 0 & 1 & 1 & 0 & \cdots & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 1 & \cdots & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 1 & \cdots & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & \cdots & 0 & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 \end{bmatrix}$$

Consequently, neighboring areas are considered or assumed to have the same significant influence. Therefore, standardization is carried out proportionally or provides the same proportion for neighboring regions to one particular area. To standardize, divide each matrix element by the total number of results per row that are neighboring according to **Equation (5)** with the following results.

$$W = \begin{bmatrix} 0 & 0.5 & 0.5 & 0 & \cdots & 0 & 0 & 0 & 0 \\ 0.167 & 0 & 0.167 & 0.167 & \cdots & 0 & 0 & 0 & 0 \\ 0.333 & 0.333 & 0 & 0.333 & \cdots & 0 & 0 & 0 & 0 \\ 0 & 0.2 & 0.2 & 0 & \cdots & 0 & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \cdots & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 \end{bmatrix}$$

After forming a weighting matrix, the next step is to analyze the results of the spatial autocorrelation test on the linear regression residuals using Moran's I test to determine whether there is a spatial indication or location/region relationship in the data, shown in **Table 3**.

Table 3. Moran's I Value

Variable	I	p-value	z-value
y	0.3513	0.0015	2.964
x_1	0.0064	0.3968	0.2618
x_2	0.0064	0.3969	0.2614
x_3	0.3026	0.0049	2.5826
x_4	0.3204	0.0032	2.7219
x_5	0.2178	0.02754	1.9836
x_6	0.2065	0.0336	1.9882

Based on Moran's I test in Table 3 using significance $\alpha = 5\%$, significant variables are crime, unemployment, HDI, GDP, and per Capita Expenditure where the value of $Z(I)$ is greater than the value in Table $Z_{0.025}$ or $Z(I) > 1.96$ means that the spatial autocorrelation is significant. So, the identification results with Moran's I values for each variable show that dependencies between adjacent locations occur in response variables and predictor variables. Therefore, analysis is carried out using SDM methods. Parameter estimation by the SDM method is presented in Table 4.

Table 4. SDM Model Paremeter Estimation

Parameter	Estimation
β_0	5.6299×10^3
β_3	3.1197×10^{-3}
β_4	-4.0153×10^1
β_5	5.2779×10^{-3}
β_6	1.3024×10^{-1}
θ_3	1.5133×10^{-3}
θ_4	-5.8333×10^1
θ_5	1.1548×10^{-3}
θ_6	3.1224×10^{-3}
ρ	0.18134

After obtaining the estimator values ρ and β from Table 4, it can be written as follows:

$$\hat{y}_i = \left(\begin{array}{l} 0.18134 \sum_{j=1}^{38} w_{ij} Y_j + 5.6299 \times 10^3 + 3.1197 \times 10^{-3} X_{3i} - 4.0153 \times 10^1 X_{4i} \\ +1.3024 \times 10^{-1} X_{6i} + 1.6133 \times 10^{-3} \sum_{j=1}^{38} w_{ij} X_{3j} \\ -58333 \times 10^1 \sum_{j=1}^{38} w_{ij} X_{4j} + 1.1548 \times 10^{-3} \sum_{j=1}^{38} w_{ij} X_{5j} + 3.1224 \times 10^{-3} \sum_{j=1}^{38} w_{ij} X_{6j} \end{array} \right) \quad (11)$$

Based on these equations, it is necessary to test the suitability of the model and the significance of the HR model parameters to obtain variables that significantly affect crime in East Java by testing the model's shuffling and the parameters' importance. The Model Fit Test uses the F test with the decision of this test being rejected H_0 if $\mathrm{F_{count}} > \mathrm{F}_{\alpha,p,n-p-1}$. It is known that the value $\mathrm{F_{count}} = 33.56323 > \mathrm{F}_{\alpha,p,n-p-1} = 2.41$ means that H_0 is rejected. Therefore, it can be concluded that the model is appropriate.

A partial test will be conducted after conducting a model fit test using the Wald test to determine the variables that partially affect the crime model formed. The results of the Wald test are presented in Table 5.

Table 5. Wald Test Results

Parameter	Wald
β_0	3.098
β_3	1.0353
β_4	-1.3605
β_5	6.4839
β_6	1.9667
θ_3	0.3317
θ_4	-1.4455
θ_5	0.6608
θ_6	0.0292
ρ	2.75394

Based on Table 5. Using the significance level $\alpha = 5\%$, the wald value in parameters β_5, β_6, and ρ has a value greater than the value of $Z_{\alpha/2}$. It shows the significant influence of GDP and per capita expenditure variables on the number of crimes. Based on these two tests, the appropriate model is produced, then the model on the Durbin Spatial equation can be sampled in Pacitan Regency. Pacitan Regency ($K1$) has 2 neighbors, namely Ponorogo Regency ($K2$) and Trenggalek Regency ($K3$), so the model equation is as follows:

$$\widehat{y_{K1}} = \begin{array}{l} 0.18134\left(0.5(y_{K2} + y_{K3})\right) + 5.6299 \times 10^3 + 3.1197 \times 10^{-3} X_{3(K1)} - 4.0153 \times 10^1 X_{4(K1)} \\ + \cdots + 1.1548 \times 10^{-3}\left(0.5\left(X_{5_{K2}} + X_{5_{K3}}\right)\right) + 3.1224 \times 10^{-3}\left(0.5\left(X_{6_{K2}} + X_{6_{K3}}\right)\right) \end{array} \quad (12)$$

$$\widehat{y_{K1}} = \begin{array}{l} 0.09067(y_{K2} + y_{K3}) + 5.6299 \times 10^3 + 3.1197 \times 10^{-3} X_{3(K1)} - 4.0153 \times 10^1 X_{4(K1)} \\ + \cdots + 0.5774 \times 10^{-3}\left(X_{5_{K2}} + X_{5_{K3}}\right) + 1.5612 \times 10^{-3}\left(X_{6_{K2}} + X_{6_{K3}}\right) \end{array} \quad (13)$$

Based on the above Equation, it can be interpreted that the crime value in Pacitan Regency is influenced by the number of cases in neighboring areas, namely Ponorogo Regency and Trenggalek Regency, with a positive influence value, which means that if there is an increase in cases in the two districts, it will also increase the number of crime cases in Pacitan Regency. The estimated value for HDI is negative. If HDI increases, crime will decrease [31].

The variables unemployment, GRDP, and per capita expenditure have positive coefficients. Crime will increase if unemployment, GRDP, and per capita expenditure increase [32]. Based on the model results, the influence of crime rates is within the same district/city and neighboring districts/cities, meaning neighboring areas show an essential effect. The estimated spatial lag values for unemployment, GRDP, and per Capita Expenditure are positive. In comparison, the HDI variable has a negative value. It means that the independent variables of each neighboring district/city will influence the independent variables of each district/city. Therefore, it is crucial to incorporate spatial effects into the analysis of increased criminality.

After analyzing crime cases in East Java using Multiple Linear Regression and the Spatial Durbin Model, the R^2 value of both models was obtained, as shown in Table 6.

Table 6. R-Square Each Model

Model	R^2
Multiple Linear Regression	0.7975
Durbin Spatial Regression Model	0.8518

Table 6 shows the R-square values of each method. This result shows that the R^2 value of SDM is greater than the regression method. Thus, 85.18% of crime in the first location is influenced by unemployment, HDI, GRDP, and per capita expenditure in the first location and spatial in the j-th location. These variables can be considered factors that can influence the occurrence of crime. However, there is about 14.82% variation in crime rates that the variables in this study cannot explain. Other factors not included in the study may also play a role in influencing crime rates in each location.

3.2 Discussion

The results of the analysis that have been presented reveal several significant findings related to factors that influence the crime rate in East Java. The following discussion will explain the implications and significance of these findings in the context of crime issues and comparisons with previous research. The study observed that unemployment, GRDP, and per Capita Expenditure variables significantly influenced the region's crime rates. When an area has a high GRDP, it indicates a significant level of wealth. This wealth can attract the attention of bad actors who see an opportunity to take advantage of existing resources and prosperity **[33]**.

The unemployment variable also has a positive influence on the crime rate. High unemployment rates can create economic pressure on society, encouraging individuals to engage in criminal activity to earn an income. These results align with the literature stating that economic instability can be a risk factor for higher crime rates **[34]**. Therefore, increased efforts in creating job opportunities and skills training for unemployed individuals may contribute to reducing crime rates.

The Human Development Index (HDI) variable negatively influences the crime rate. These results suggest that areas with low HDI, which may face greater social and economic challenges, tend to have higher crime rates. It indicates the importance of access to education, health, and employment opportunities in preventing crime. Increased investment in human development can play a role in reducing crime rates in areas with low HDI **[35]**. Based on the model, GRDP and per Capita Expenditure have more influence than other variables. This study's results are the same as research by Yigzaw et al. **[10]**, who analyzed the physical and socioeconomic factors for property crime incidents in Addis Ababa, Ethiopia, which stated that unemployment and HDI determine the occurrence of property crime events. Another study by Anser et al. **[36]** analyzed the dynamic linkages between poverty, inequality, crime, and social spending in 16 countries, yielding several factors that can influence crime. Among them are GDP and per Capita Expenditure.

The variable per capita expenditure has a significant favorable influence. If per Capita Expenditure rises, crime will increase. It happens because there is a possibility of social and economic inequality among the population. Such disparities can create economic inequality, limited access to job opportunities, and feelings of dissatisfaction and injustice that can trigger criminal acts **[37]**.

The results of this model analysis show a significant spatial influence on the crime rate. This means that the crime rate in one region is influenced not only by factors within the region but also by factors in neighboring areas. This spatial relationship can illustrate how crime events can spread from one region to another and underscore the importance of coordination between areas in efforts to deal with crime. The results of the *R-Square* are around 85.18%, which shows that variations in crime rates are not only explained by variables in this study. Other factors not included in the study, such as social, cultural, and environmental factors, may also have a role in influencing crime rates in each location. These factors that are not listed are also supported by the existence of sectors that attract the attention of criminals, including organized crime, such as drug trafficking, theft, and economic crime. Organized criminals often target these sectors, supported by various factors that attract them to potential profits. High potential financial returns, strong market demand for illegal goods or services, and vulnerabilities in economic systems or information technology are the main drivers of criminal activity. In addition, social instability, corruption, and weaknesses in supervision and law enforcement also support these sectors. To address problems in these sectors, measures are needed to reduce contributing factors and improve preventive measures and more effective law enforcement **[38]**. The results of this study can be one of the considerations for policymakers in designing more effective crime prevention and control strategies in the region. In addition, this study's results support previous studies' findings and provide valuable contributions to the literature on factors that influence crime rates.

4. CONCLUSIONS

Based on the results of modeling and analysis, it was obtained that the Durbin Spatial model with Queen Contiguity weighting showed advantages compared to the linear regression model. It can be seen from the value of the most significant coefficient of determination obtained from this model, which is 85.18%, and the form of the Spatial Durbin Model (SDM) regression model formed between variables Y with X_3, X_4, X_5, and X_6. Then unemployment, HDI, Gross Regional Domestic Product (GRDP), and Per Capita Expenditure influence crime cases in East Java, with Surabaya City having many crimes, amounting to 4406 cases.

Meanwhile, for areas with low crime, namely in Pacitan Regency, there are 90 cases. However, about 14.82% variation in crime rates remains unexplained by the variables in the study. Other factors, such as social, cultural, and environmental aspects, may also affect the more complex crime rates in each location. Therefore, the next opportunity can consider additional variables to understand the problems and factors of crime in East Java more deeply.

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