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Spatio-Temporal Modeling of Crime Rates Using Geographically and Temporally Weighted Regression

Robiansyah Putra [a,1,*], Fidelis Nofertinus Zai [a,2]

[a] Department of Mathematics, Faculty of Mathematics and Natural Sciences, Universitas Sumatera Utara, Jln. Bioteknologi 1, Medan, 20155, Indonesia
[1] robiansyah@usu.ac.id*; [2] fidelis@usu.ac.id
* Corresponding author

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ABSTRACT

This study analyzes the spatio-temporal modeling of crime rates in 35 regencies and cities in Central Java using the geographically and temporally weighted regression (GTWR) method. The objective is to investigate how socio-economic factors, including the open unemployment rate, percentage of the poor population, population density, average years of schooling, job vacancies, labor force participation rate, and labor wage, influence crime rates across different regions and periods. The goodness-of-fit test results indicateed that the GTWR model had an R-squared value of 93.51%, higher than the 88.64% of the geographically weighted regression (GWR) model, demonstrating GTWR's ability to explain crime data variations that were heterogeneous both spatially and temporally. Partial significance tests and mapping results showed that the influence of variables differed across years and regions, with population density and labor-related factors consistently being the main predictors. These findings highlight the importance of designing crime prevention policies that are locally tailored and based on spatio-temporal evidence.

1. Introduction

Crime is often regarded as a social phenomenon that becomes a central concern in the security framework of a nation. In criminological studies, criminal acts are defined as behaviors that violate the law and are rejected by societal norms [1]. The complexity of crime lies not only in its material consequences but also in the erosion of public security and its potential to disrupt regional development. In Indonesia, there are clear spatial and temporal variations in crime rates across provinces, influenced by factors such as education and economic inequality [2]. In general, criminal acts can be defined as any form of behavior or action that violates the law and is rejected by both society and the state. This issue is inherently complex, as it not only results in material losses but also diminishes public safety and may hinder regional development [3]. The determinants of crime are highly diverse, ranging from individual psychological factors and social environment to broader

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economic conditions [4], [5]. Therefore, crime is often used as an important indicator for assessing the quality of life in a society as well as the effectiveness of law enforcement and security policies.

In Indonesia, crime rates vary across provinces. Central Java, which consists of 35 regencies and cities, demonstrates considerable diversity in both the number and types of crimes. Based on data from Statistics Indonesia (Badan Pusat Statistik, BPS) and police reports, crime rates in this region fluctuate annually. Major cities such as Semarang, Surakarta, and Magelang tend to exhibit higher crime levels compared to rural areas. Meanwhile, some other regencies show relatively stable trends, although certain types of crimes still predominate. This indicates that the distribution of crime in Central Java is uneven and forms a spatial pattern. In addition to spatial disparities, temporal dynamics also influence crime in this region. For instance, during periods leading up to religious holidays or long vacations, cases of motor vehicle theft are reported to increase [6]. Fluctuations in crime are also influenced by economic dynamics, migration flows, and law enforcement policies [7]. Thus, the analysis of crime phenomena requires an approach that simultaneously takes into account both spatial and temporal dimensions.

Crime rate modeling in Indonesia has been extensively conducted using various nonspatial and nontemporal approaches. One example is the application of the truncated spline estimator, which has been shown to effectively analyze crime rates and outperform classical linear regression [8]. In addition, a panel data regression approach with a fixed effect model has also been employed to analyze property crimes in five provinces on the island of Sumatra [9]. On the other hand, multiple linear regression has been utilized to predict the number of crime cases based on police data, demonstrating the continued relevance of classical regression in crime studies [10]. These various research findings affirm that socio-economic factors make a significant contribution in explaining the variation of crime rates in Indonesia. However, most of these studies still rely on global models that assume the effects of such factors are constant across all regions and time periods.

To address these limitations, this study employed the geographically and temporally weighted regression (GTWR) method. GTWR is an extension of the geographically weighted regression (GWR) approach that incorporates the temporal dimension, thereby capturing nonstationarity across both spatial and temporal domains [11], [12]. With this approach, the regression coefficients not only vary across regions but also change over different observation periods.

The application of GTWR to crime cases in 35 regencies and cities in Central Java is expected to provide a more detailed understanding of: (1) how socio-economic variables influence crime with varying intensities across regions, (2) how these effects change over time, and (3) which areas require more serious policy interventions. Thus, this study aims to deliver a more comprehensive spatiotemporal analysis of crime while also producing evidence-based policy recommendations for local governments and law enforcement agencies.

2. Methods

2.1. Data Source

This study involved several variables consisting of a dependent variable (Y), which represents the crime rate in 35 regencies and cities in Central Java from 2020 to 2024, and independent variables (X), which are presented in Table 1. The selected period of 2020–2024 was chosen to capture the most recent trend in regional crime dynamics following the post-pandemic economic transition. The data were obtained from the BPS of Central Java Province and relevant official publications, accessible through the BPS official website (https://jateng.bps.go.id). The use of BPS data ensures data credibility, consistency, and comparability across years, as all variables were compiled using standardized national statistical methodologies. The dataset covers socio-economic indicators such as unemployment rate, population density, poverty rate, average years of schooling, job vacancies, labor force participation rate, and labor wage, which are assumed to have spatially and temporally varying effects on crime rates.

All data were processed, analyzed, and spatially visualized using RStudio, employing several supporting packages such as tidyverse, sf, and ggplot2 to ensure reproducibility and accuracy in

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spatial–temporal modeling. The analytical workflow included data cleaning, variable transformation, and the construction of spatial weight matrices to support the implementation of the GTWR model. The visualization process was performed to map spatial patterns of crime rates and identify local variations in predictor effects, providing a comprehensive understanding of the spatial and temporal heterogeneity of crime across Central Java.

Table 1. Description of the Data

Variable	Description	Theoretical and Empirical Rationale	Measurement Unit
y	Crime rate	Crime rate reflects spatial and temporal disparities in social stability. Regions with higher or increasing crime levels tend to experience reduced economic activity and weaker employment absorption due to spatial clustering and time-varying security conditions.	Number of cases per 100,000 population
x_1	Open unemployment rate [13]	Open unemployment rate is expected to have a positive influence on the crime rate, as higher unemployment can increase economic stress and social tension, leading to an increase in criminal activities.	Percentage (%)
x_2	Percentage of the poor population [14]	Percentage of the poor population is expected to have a positive relationship with the crime rate, as higher poverty levels may drive individuals toward criminal behavior due to economic hardship and limited access to basic needs.	Percentage (%)
x_3	Population density [15]	Population density is expected to positively influence the crime rate, as densely populated areas tend to experience higher social interaction, anonymity, and competition for resources, which can increase opportunities for criminal activities.	people per square kilometer (people/km²)
x_4	Average years of schooling [16]	Average years of schooling is expected to have a negative influence on the crime rate, since higher education levels generally improve awareness, employment opportunities, and social behavior, thereby reducing the likelihood of engaging in criminal activities.	Years
x_5	Job vacancies [17]	Job vacancies are expected to have a negative relationship with the crime rate, as greater employment opportunities can reduce economic hardship and discourage individuals from engaging in criminal behavior.	Number of vacancies (cases/year)
x_6	Labor force participation rate [18]	Labor force participation rate is expected to have a negative relationship with the crime rate, since higher participation indicates more people are engaged in productive activities, reducing the likelihood of involvement in criminal acts.	Percentage (%)
x_7	Labor wage [19]	Labor wage is expected to have a negative influence on the crime rate, as higher wages improve economic well-being and reduce financial pressure, thereby lowering the motivation to commit crimes.	Rupiah (IDR) per month

2.2. Geographically Weighted Regression (GWR)

The concept of GWR was originally introduced by Fotheringham in 1967 as a refinement of multiple linear regression. In contrast to the classical model, which assumes constant parameters across all locations, GWR performs local estimation, allowing each observation to have its own set of regression coefficients. As a result, the dependent variable Y is affected by the explanatory variables with coefficient values that vary according to the geographic location of the data.

By assumption, the GWR model considers the errors to be normally distributed with a mean of zero and variance σ^2. The fundamental difference between the linear regression model and GWR is that regression coefficients are constant across locations in the former, whereas they are estimated locally in the latter. The GWR modeling can be expressed in (1) [20].

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i)x_{ik} + \varepsilon_i \tag{1}$$

where y_i denotes the value of the response variable at the ith observation location, x_{ik} denotes the kth independent variable at the ith observation location, (u_i, v_i) denotes the geographic coordinates (longitude and latitude) of the ith observation location, $\beta_0(u_i, v_i)$ denotes the local intercept at the ith observation location, $\beta_k(u_i, v_i)$ denotes The kth parameter at the ith location associated with the independent variable x_{ik}. Meanwhile, ε_i denotes the residual at the ith observation location, assumed to be independent and identically distributed, following a normal distribution with a mean of zero and variance σ^2.

Using weighted least squares (WLS), the parameter $\boldsymbol{\beta}$ of the GWR model is estimated as in (2).

$$\widehat{\boldsymbol{\beta}} = (\mathbf{X}^{\mathbf{T}}\mathbf{W}(u_i, v_i)\mathbf{X})^{-1}\mathbf{X}^{\mathbf{T}}\mathbf{W}(u_i, v_i)\mathbf{Y} \tag{2}$$

Equation (2) in matrix form is

$$\mathbf{Y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_1 \end{bmatrix}, \mathbf{X} = \begin{bmatrix} 1 & x_{11} & x_{12} & \cdots & x_{1k} \\ 1 & x_{21} & x_{22} & \cdots & x_{2k} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_{n1} & x_{n2} & \cdots & x_{nk} \end{bmatrix}, (u_i, v_i) = \begin{bmatrix} u_1 & v_1 \\ u_2 & v_2 \\ \vdots & \vdots \\ u_n & v_n \end{bmatrix},$$

$$\mathbf{W}(u_i, v_i) = diag(w_{i1}, w_{i2}, \dots, w_{in})$$

where w_{ij} represents the weighting determined using Gaussian, exponential, bisquare, or tricube kernel functions, and $d_{ij}^S = \sqrt{(u_i - u_j)^2 + (v_i - v_j)^2}$.

2.3. Geographically and Temporally Weighted Regression (GTWR)

GTWR is an extension of GWR that accommodates heterogeneity both spatially (location) and temporally (time) [11]. The general equation for the GTWR model is as in (3).

$$y_i = \beta_0(u_i, v_i, t_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i, t_i)x_{ik} + \varepsilon_i \tag{3}$$

Using WLS, the parameter $\boldsymbol{\beta}$ of the GTWR model is estimated as in (4).

$$\widehat{\boldsymbol{\beta}} = (\mathbf{X}^{\mathbf{T}}\mathbf{W}(u_i, v_i, t_i)\mathbf{X})^{-1}\mathbf{X}^{\mathbf{T}}\mathbf{W}(u_i, v_i, t_i)\mathbf{Y} \tag{4}$$

Equation (4) in matrix form is

$$\mathbf{Y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_1 \end{bmatrix}, \mathbf{X} = \begin{bmatrix} 1 & x_{11} & x_{12} & \cdots & x_{1k} \\ 1 & x_{21} & x_{22} & \cdots & x_{2k} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_{n1} & x_{n2} & \cdots & x_{nk} \end{bmatrix}, (u_i, v_i, t_i) = \begin{bmatrix} u_1 & v_i & t_1 \\ u_1 & v_2 & t_2 \\ \vdots & \vdots & \vdots \\ u_n & v_n & t_n \end{bmatrix},$$

$$\mathbf{W}(u_i, v_i, t_i) = diag(w_{i1}, w_{i2}, \dots, w_{in})$$

where w_{ij} represents the weighting determined using Gaussian, exponential, bisquare, or tricube kernel functions. In $d_{ij}^{ST} = \sqrt{\lambda\left[(u_i - u_j)^2 + (v_i - v_j)^2\right] + \mu\left[(t_i - t_j)^2\right]}$, λ is a spatial scaling parameter that controls the influence of spatial distance, and μ is a temporal scaling parameter that adjusts the contribution of temporal distance in the spatio-temporal weighting process.

2.4. Spatio-Temporal Weighting

In the GWR model, weighting is performed using the Euclidean distance through a kernel function. This kernel function determines the magnitude of the weight assigned to each location based on its proximity to the observation point. The closer a location is to the point (u_i, v_i), the higher its weight, whereas more distant locations receive lower weights. Consequently, the estimation of regression parameters becomes more adaptive to local conditions around the observation point. The determination of weights in GWR can be performed using a kernel function [21].

a. Gaussian

$$w_{ij} = \exp\left(-\frac{1}{2}\left(\frac{d_{ij}}{h}\right)^2\right) \tag{5}$$

b. Exponential

$$w_{ij} = \exp\left(-\frac{d_{ij}}{h}\right) \tag{6}$$

c. Bisquare

$$w_{ij} = \begin{cases} \left(1-\left(\frac{d_{ij}}{h}\right)^2\right)^2 & , d_{ij} \le h \\ 0 & , d_{ij} > h \end{cases} \tag{7}$$

d. Tricube

$$w_{ij} = \begin{cases} \left(1-\left(\frac{d_{ij}}{h}\right)^3\right)^3 & , d_{ij} \le h \\ 0 & , d_{ij} > h \end{cases} \tag{8}$$

where h is the bandwidth in the GWR model and

$$d_{ij} = \sqrt{\left(u_i - u_j\right)^2 + \left(v_i - v_j\right)^2} \tag{9}$$

In spatio-temporal weighting, the distance used is not only the spatial distance between locations but also takes the temporal dimension into account. Consequently, the weight of an observation is determined based on the proximity of the geographic location (u_i, v_i) as well as the closeness of the time period t_i to the observation point. Due to differences in spatial and temporal scales, an ellipsoidal coordinate system is used.

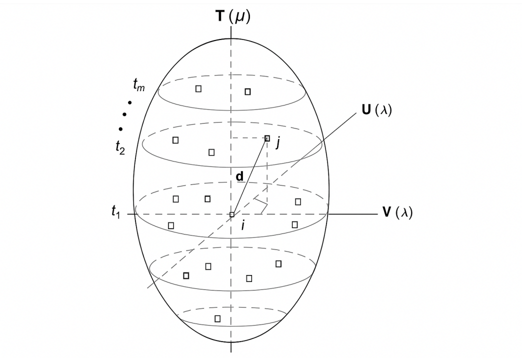

Fig. 1 Illustration of spatio-temporal distance [11].

As illustrated in Fig. 1, the spatio-temporal distance function is constructed by combining the spatial distance function d^S and the temporal distance function d^T. Therefore, the spatio-temporal distance function can be expressed as follows.

$$(d^{ST})^2 = \lambda(d^S)^2 + \mu(d^T)^2 \tag{10}$$

where λ and μ represent scaling factors to balance the differences in effects used to measure spatial and temporal distances. Thus, the spatio-temporal distance is obtained as follows [11].

$$(d^{ST})^2 = \lambda\left[\left(u_i - u_j\right)^2 + \left(v_i - v_j\right)^2\right] + \mu\left[\left(t_i - t_j\right)^2\right]. \tag{11}$$

Let τ be the ratio parameter defined as $\tau = \frac{\mu}{\lambda}$ with $\lambda \neq 0$. Then, the resulting equation is as in (12):

$$\frac{(d^{ST})^2}{\lambda} = \left[\left(u_i - u_j\right)^2 + \left(v_i - v_j\right)^2\right] + \tau\left[\left(t_i - t_j\right)^2\right]. \tag{12}$$

Let $\lambda = 1$, aiming to reduce the number of unknown parameters. There is one unknown parameter, namely τ. The parameter τ serves to amplify or reduce the effect of temporal distance relative to spatial distance. The parameter τ is obtained from the minimum cross-validation criterion by initializing the initial value of τ as in (13):

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$$CV(\tau) = \sum_{i=1}^{n}[y_i - \hat{y}_{\neq i}(\tau)]^2. \quad (13)$$

3. Results and Discussion

3.1. Characteristics of Crime Rates in Central Java, Indonesia

Crime is one of the social issues that has received serious attention from both the government and the wider community. Crime rates are often used as an indicator to assess the security, order, and overall welfare of a region. Central Java, as one of the most populous provinces in Indonesia, has also experienced dynamic changes in crime rates from year to year. Data from the 2020–2024 period showed considerable fluctuations. In 2020, 887 cases were recorded, rising to a peak of 1,356 cases in 2022, before declining again to 1,153 cases in 2024. These variations indicate an interesting trend that warrants further investigation, both in terms of contributing factors, types of crimes, and strategies for addressing them. A statistical summary of the variables analyzed in this study is presented in Table 2.

Table 2. Descriptive Statistics of Study Variables

Variables	Year	Min	Max	Mean	Std. Deviation
y	2020	77	887	271	177.4912
	2021	85	873	237.9429	156.8114
	2022	89	1356	229.6286	211.8389
	2023	80	1293	217.3143	201.2069
	2024	63	1153	192.6	179.9335
x_1	2020	-0.8127	2.320433	0.524234	0.903818
	2021	-1.55669	2.393784	0.247746	1.093244
	2022	-1.90772	2.220886	-0.02919	1.030079
	2023	-1.82389	1.875089	-0.28098	0.8852
	2024	-1.5986	1.545009	-0.46181	0.783045
x_2	2020	-1.89684	2.056788	0.094512	1.051647
	2021	-1.83119	2.128401	0.199032	1.049558
	2022	-1.92369	1.704692	-0.03439	0.976662
	2023	-1.92966	1.683805	-0.08955	0.97415
	2024	-1.98934	1.495821	-0.1696	0.958238
x_3	2020	-0.65299	3.903872	0.019239	1.014254
	2021	-0.65257	3.907228	0.023122	1.015907
	2022	-0.65089	4.124102	0.042706	1.051524
	2023	-0.66516	3.871991	0.008033	1.002804
	2024	-0.82037	3.882479	-0.0931	0.966308
x_4	2020	-1.49595	2.008054	-0.18307	0.934671
	2021	-1.48813	2.172304	-0.112	0.974153
	2022	-1.38645	2.211411	0.014481	0.992451
	2023	-1.34734	2.438233	0.103198	1.024639
	2024	-1.33952	2.625947	0.17739	1.081312
x_5	2020	-0.74743	0.016863	-0.51045	0.200575
	2021	-0.69128	1.676621	-0.13106	0.578791
	2022	-0.71385	6.804281	0.443334	1.390731
	2023	-0.74291	5.347166	0.10636	1.145864
	2024	-0.73966	3.659704	0.091819	0.99334
x_6	2020	-3.21968	1.365691	-0.49668	0.928944
	2021	-2.14711	1.157849	-0.30812	0.878232
	2022	-1.67497	2.127781	-0.03943	0.895049
	2023	-1.71346	2.866778	0.213063	1.060231
	2024	-0.98986	2.055934	0.631167	0.864937
x_7	2020	-1.46149	3.026922	-0.4373	0.821719
	2021	-1.50691	2.402845	-0.37714	0.816039
	2022	-1.80381	2.776281	-0.10992	0.951699
	2023	-0.98608	3.542286	0.289216	0.880332
	2024	-0.92758	4.012301	0.635152	1.112962

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The average pattern of crime rates during the 2020–2024 period in Central Java Province is presented to illustrate both the temporal dynamics and the spatial distribution across districts and cities. Fig. 2 provides a comprehensive overview of crime trends as well as their variations between regions.

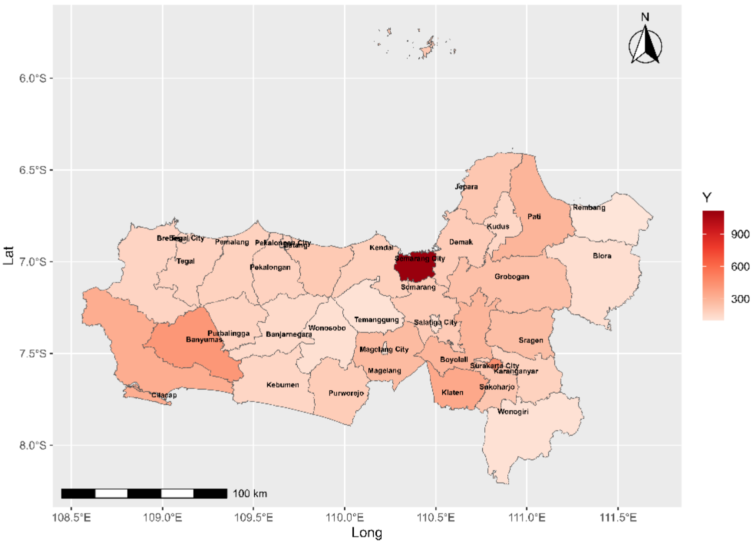

Fig. 2 Spatial distribution pattern of average crime rates in Central Java, 2020–2024

Based on the average crime rate data from 2020 to 2024, there is a noticeable disparity in crime levels among regencies and cities in Central Java. In general, urban areas tend to record higher crime rates compared to rural regions. This is evident in Semarang City, which reported the highest crime rate of 1,112.4 cases, followed by Surakarta City with 445.8 cases, and Banyumas Regency with 418.4 cases. These figures are significantly higher than those in other areas such as Rembang Regency (98.8 cases), Blora Regency (125.6 cases), or Magelang City (103.4 cases).

In addition, there are several regions with medium crime levels, such as Klaten Regency (348.6 cases), Cilacap Regency (327 cases), Pati Regency (293.8 cases), and Boyolali Regency (293 cases). These areas typically have larger populations and more intense economic activities, which increase the likelihood of criminal incidents. Meanwhile, regions with lower crime rates tend to be smaller or located farther from major economic centers. Examples include Rembang Regency (98.8 cases), Magelang City (103.4 cases), and Wonogiri Regency (114.8 cases).

This pattern indicates a strong relationship between crime rates and regional characteristics, such as population density, urbanization level, and economic activity. Therefore, crime prevention strategies in Central Java should take into account the specific conditions of each area to ensure more effective policy implementation.

3.2. Multicollinearity Test

A multicollinearity test was conducted to evaluate the potential correlations among independent variables that could affect the stability of model estimates. The results of the multicollinearity test for the data under study are presented in Table 3.

Table 3. Multicollinearity Test

Variables	VIF
x_1	1.64785
x_2	2.0431
x_3	2.806959
x_4	4.468093
x_5	1.031515
x_6	1.547852
x_7	1.734355

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Based on the calculations, all variables have VIF values ranging from 1.03 to 4.47. These results indicate that there is no significant multicollinearity in the model, as all values are well below the threshold of 10. Therefore, all independent variables are suitable for use in the subsequent regression analysis.

3.3. Spatial Heterogeneity Test

The spatial heterogeneity test was employed to determine whether data across regions were homogeneous. If the data were homogeneous, all regions had the same variance; if they were not, the variance differed between regions. Spatial heterogeneity can be assessed using the Breusch-Pagan statistical test. In this study, the test was conducted simultaneously across 35 regencies and cities in Central Java for the period 2020–2024 at a 5% significance level. The results of the spatial heterogeneity test are presented in Table 4.

Table 4. Spatial Heterogeneity Test

Year	Breusch-Pagan	p-Value	Decision
Full	296.44	2.20E-16	Significant
2020	20.459	0.004659	Significant
2021	12.775	0.07778	Not Significant
2022	112.65	2.20E-16	Significant
2023	72.912	3.80E-13	Significant
2024	68.06	3.64E-12	Significant

The results of the Breusch-Pagan test indicated that for the full period, as well as for the years 2020, 2022, 2023, and 2024, there was significant spatial heterogeneity, as the p-values were smaller than the 0.05 significance level. This suggests that the variances across regions during these periods differed, implying that the model must be accounted for spatial factors in the analysis. In contrast, in 2021, the p-value of 0.07778 (> 0.05) indicated that spatial heterogeneity was not significant, meaning that regional variances for that year were relatively homogeneous. Overall, only 2021 exhibited no indication of differences in spatial variance, while the other years confirmed the presence of spatial heterogeneity in the data.

3.4. Temporal Heterogeneity Test

The temporal heterogeneity test aims to determine whether the data exhibit temporal variation or changes in values over time. In addition to the spatial heterogeneity test, assessing temporal variation is necessary for the application of the GTWR method. In this study, temporal heterogeneity was examined using boxplot visualizations, with the results presented as in Fig. 3.

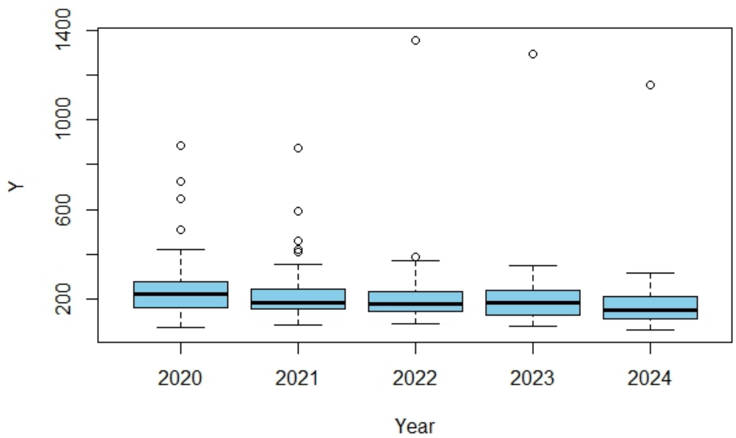

Fig. 3 Boxplot of crime rate distribution in Central Java from 2020 to 2024**.**

The distribution of crime rates over the period 2020–2024 in Fig. 3 indicates that the median values of criminality remained relatively stable each year. This suggests that, in general, crime levels in most regions did not experience substantial year-to-year changes. In other words, the temporal aspect contributes only marginally to the variation in crime rates, with the primary patterns largely determined by inter-regional differences.

Although the median remained relatively constant, the presence of outliers in certain years highlights notable temporal dynamics that warrant attention. From 2022 to 2024, extreme outliers with crime rates significantly higher than those of the majority of regions were observed. This indicates that, while overall crime levels appear stable in aggregate, specific areas experienced significant spikes in cases during this period. Hence, temporal variation is more evident through shifts in the distribution and the occurrence of extreme cases, rather than through changes in the overall mean.

Overall, these findings suggest that over the five-year period, provincial-level crime rates did not exhibit a clear upward or downward trend but rather showed fluctuations in certain regions during particular years. Therefore, spatio-temporal analyses like GTWR, remain relevant, as temporal changes, while not dominant, still provide additional insight into the dynamics of crime distribution across years.

3.5. Geographically and Temporally Weighted Regression (GTWR)

In the GTWR method, there are two main assumptions that must be satisfied: spatial heterogeneity (differences in variable relationships across locations) and temporal heterogeneity (changes in variable relationships over time). During the prior data exploration stage, it was confirmed that the research data contain both elements, making the application of GTWR relevant.

The initial step in GTWR modeling was to determine the spatio-temporal distance parameters, namely τ, μ, and λ in (12). These parameter values were obtained through an optimization process to balance the contributions of spatial and temporal dimensions. The estimation of these parameters was performed using a cross validation (CV) procedure in (13), which identified the optimal parameter set minimizing the prediction error of the model. The results of the temporal parameter in modeling crime rates are presented in Table 5.

Table 5. Temporal Parameter in GTWR

Temporal Parameter	Value	CV
τ	0.002831828	1643524
μ	0.0040413	1600776
λ	1.440332	1600776

In this study, the obtained values were τ = 0.002832, μ = 1.440332, and λ = 0.004041. These results indicate that spatial and temporal factors contribute differently to the weighting, with the relatively larger μ suggesting that spatial distance plays a more dominant role than temporal variation. Once the values of τ, μ, and λ were established, the next step was to calculate the optimal bandwidth. This bandwidth is crucial as it is used to construct the weighting matrix for each observation. The weighting matrix enables GTWR to provide regression coefficient estimates that vary across both regions and time, allowing the model to capture spatio-temporal dynamics more accurately than either GWR or classical regression models. The selection of the kernel function was performed by comparing the CV values generated from several kernel functions. The results of this comparison are presented in Table 6.

Table 6. Spatio-Temporal Weighting

Kernel Function	h_{ST}	CV
Gaussian	0.192331	1,725,178
Exponential	0.13822	1,600,445
Bisquare	1.959008	4,550,102
Tricube	0.000718	7,418,035

Based on the calculations, the exponential kernel produced the smallest CV value of 1,600,445 with a bandwidth of 0.13822. This indicates that the exponential weighting function is more capable of capturing spatio-temporal variations in crime data compared to other kernels. In contrast, the tricube and bisquare kernels yielded relatively large CV values, making them less suitable for this dataset.

Therefore, the exponential kernel was selected as the optimal weighting function in the GTWR modeling. This choice is critical because an appropriate kernel ensures that the regression parameter estimates accurately reflect spatial and temporal heterogeneity patterns, thereby enhancing the model's validity in explaining variations in crime rates across regions and over time.

The results from this kernel selection were subsequently used in the spatio-temporal weighting process, producing parameter estimates for each location and time period. Through this process, the resulting GTWR model could represent the relationships between predictor variables and crime rates in greater detail, both in terms of geographic differences and temporal dynamics. The final GTWR model was then used to interpret the factors influencing crime levels across different regions and periods.

From the estimation results, a total of 35 GTWR models were obtained, each representing a district/city within the study period. Each model has different regression parameters according to the spatial and temporal characteristics of the corresponding area. This demonstrates the variation in the influence of socio-economic factors on crime rates, showing that the GTWR analysis provides a more comprehensive view than a global regression approach. With these 35 local models, it is possible to identify regions with higher crime vulnerability and the dominant factors affecting them during the study period. An example of GTWR modeling for crime rates in three districts/cities in 2024 is presented as follows.

$$\hat{y}_7 = 195.28 + 67.53x_1 - 34.15x_2 - 96.80x_3 + 51.33x_4 + 24.86x_5 - 7.53x_6 + 1.59x_7 \quad (14)$$

$$\hat{y}_{16} = 233.19 + 24.45x_1 - 42.19x_2 + 40.33x_3 + 21x_4 + 34.74x_5 - 9.27x_6 + 6.07x_7 \quad (15)$$

$$\hat{y}_{35} = 218.34 - 8.30x_1 + 10.59x_2 - 51.3x_3 + 58.29x_4 - 0.55x_5 - 23.33x_6 + 5.43x_7 \quad (16)$$

Based on the GTWR model estimation, the local regression equations obtained differed across districts and cities. This confirms that socio-economic factors exert heterogeneous influences on crime rates, both spatially and temporally. For instance, in Wonosobo Regency in 2024, variable x_1 had a substantial positive effect on crime rates with a coefficient of 67.53, whereas variable x_3 showed a strong negative effect with a coefficient of −96.80. In contrast, in Blora Regency, variable x_3 exhibited a positive influence of 40.33, while variable x_1 had only a moderate effect of 24.45. Furthermore, in Magelang City, variable x_1 even had a negative impact of −8.30, whereas variable x_4 demonstrated a dominant positive effect with a coefficient of 58.29.

The variation in both the direction and magnitude of these effects across the three regions indicates that crime prevention policies should be tailored specifically to the characteristics of each area. Thus, the GTWR model not only facilitates the understanding of general factors influencing criminality but also provides detailed information regarding the variable effects in each district or city over a given period.

3.6. Partial Parameter Testing in GTWR

The significance of individual parameters was tested to identify which variables exerted a significant influence on crime rates in each district/city and during each observation period. This test is important because it highlights the differential contribution of each variable across both space and time. The mapped distribution of significant variables in the GTWR model is presented in Fig. 4. These visualizations highlight the spatial–temporal heterogeneity in predictor effects, demonstrating that the impact of socio-economic factors on crime rates is not uniform across regions and time.

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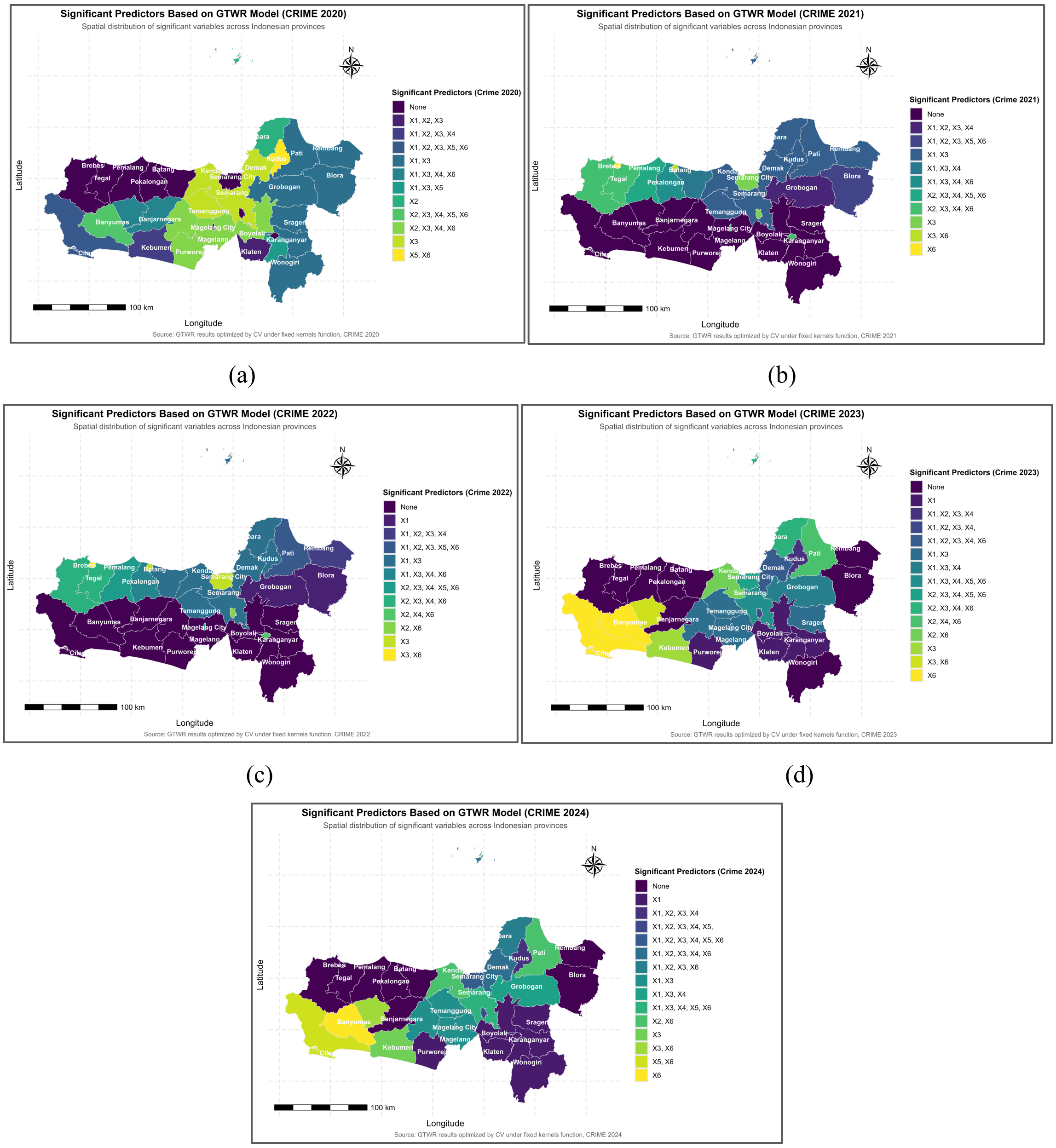

(a) (b) (c) (d) (e)

Fig. 4 Mapping Districts/Cities Based on Significant GTWR Predictors in (a) 2020, (b) 2021, (c) 2022, (d) 2023, and (e) 2024.

The partial parameter significance tests indicated that the influence of variables on crime rates was spatially heterogeneous and changes from year to year. The mapping results for 2020 showed that most districts/cities were simultaneously affected by multiple factors, such as the open unemployment rate (x_1), population density (x_3), and average years of schooling (x_4). This suggests that, in the initial year of observation, crime cannot be explained by a single dominant variable but rather by a combination of several socio-economic factors.

In 2021, notable changes were observed. Some regions were categorized as “none,” indicating no significant variables at the applied significance level. This can be interpreted as a weakening influence of the modeled variables or the presence of other factors outside the model that played a more substantial role that year. Nevertheless, several districts still exhibited significant effects, particularly from population density (x_3).

In 2022, the spatial distribution of significant predictors revealed clear regional contrasts, with the northwestern areas predominantly influenced by percentage of the poor population (x_2), average years of schooling (x_4), and labor force participation rate (x_6), reflecting the socioeconomic nature of crime in these regions. Central and urban zones displayed more complex patterns involving open unemployment rate (x_1), population density (x_3), and average years of schooling (x_4), indicating dynamic labor and demographic effects. Meanwhile, the southern and southeastern regions showed limited or no significant variables, suggesting more stable or unobserved influences. Overall, population density (x_3) and labor force participation rate (x_6) consistently emerged as key determinants shaping local crime variations in 2022.

In 2023, new patterns emerged, with a concentration of regions in the southwest significantly influenced by population density (x_3), labor force participation (x_6), and graduation duration (x_5). This phenomenon represents local spikes that warrant attention, suggesting that these factors became increasingly important in specific areas. These changes align with the temporal dynamics previously detected through spatio-temporal modeling.

In 2024, the distribution of variable influences appeared more stable. Some regions that previously did not show significant variables began to be affected by open unemployment (x_1) and population density (x_3), while the southwestern regions maintained their unique characteristics, influenced by x_3, x_5, and x_6. Overall, these results indicate that population density and labor-related factors are consistently important predictors of crime rate variations in several regions.

These findings imply that crime prevention policies should not be uniformly applied across all regions. High-density areas require urban control strategies and environmental management, whereas regions facing labor issues need interventions such as job creation and workforce development. Regions without significant variables in the model warrant further analysis, taking into account other factors such as security infrastructure or the quality of crime reporting.

3.7. Model Fit Test

The model goodness-of-fit results indicate that the R-squared value for the GWR model is 88.64%, whereas it increases to 93.51% for the GTWR model. The higher R-squared in GTWR suggests that this model can explain a greater proportion of the variation in crime data compared to GWR. In other words, GTWR is more suitable for data that exhibit not only spatial differences across regions but also temporal changes over time.

The increase in R-squared highlights the importance of incorporating the temporal component in GTWR to capture crime dynamics across different periods. Consequently, the GTWR model accounts not only for variations among districts/cities but also for fluctuations in crime rates between years. This improves the accuracy of parameter estimates and enhances the reliability of the model in explaining crime phenomena comprehensively. Practically, these results confirm that GTWR outperforms GWR in the context of this study, as it effectively represents the spatio-temporal heterogeneity that is observed in the real-world data.

4. Conclusion

The application of GTWR to crime cases in 35 regencies and cities in Central Java demonstrates that this model can provide a more comprehensive spatio-temporal analysis compared to GWR. The R-squared value of GTWR was 93.51%, higher than GWR's 88.64%, indicating that GTWR could explain variations in crime data that not only differed across regions but also changed over time. These results confirm that the influence of socio-economic variables on crime is spatially and temporally heterogeneous, suggesting that policy interventions need to be tailored to the characteristics of each region and period. Mapping results showed that the impact of variables on crime differed each year and across regions. Some areas were influenced by a combination of factors such as the open unemployment rate, population density, and average years of schooling, while other

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areas showed different significant variables or even no significant variables at all. Overall, population density and labor-related factors remain the main predictors, indicating that crime prevention policies should be applied locally and adapted to regional conditions.

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