

Geographically Weighted Poisson Regression Modeling Using Adaptive Gaussian Kernel Weighting For Mapping Maternal Mortality Rates In East Java

Inayati Ngoro, Henny Pramodyo, and Ani Budi Astuti



Volume 6, Issue 4, Pages 285–292, December 2025













Received 31 January 2025, Revised 30 August 2025, Accepted 15 October 2025, Published Online 29 November 2025

To Cite this Article : I. Ngoro, H. Pramodyo, and A. B. Astuti, "Geographically Weighted Poisson Regression Modeling Using Adaptive Gaussian Kernel Weighting For Mapping Maternal Mortality Rates In East Java", *Jambura J. Biomath*, vol. 6, no. 4, pp. 285–292, 2025, <https://doi.org/10.37905/jjbm.v6i4.30411>

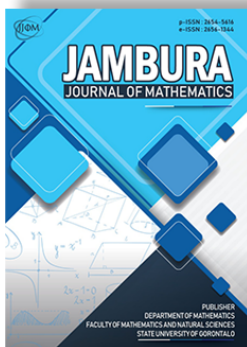
© 2025 by author(s)

JOURNAL INFO • JAMBURA JOURNAL OF BIOMATHEMATICS



	Homepage	:	http://ejurnal.ung.ac.id/index.php/JJBm/index
	Journal Abbreviation	:	Jambura J. Biomath.
	Frequency	:	Quarterly (March, June, September and December)
	Publication Language	:	English
	DOI	:	https://doi.org/10.37905/jjbm
	Online ISSN	:	2723-0317
	Editor-in-Chief	:	Hasan S. Panigoro
	Publisher	:	Department of Mathematics, Universitas Negeri Gorontalo
	Country	:	Indonesia
	OAI Address	:	http://ejurnal.ung.ac.id/index.php/jjbm/oai
	Google Scholar ID	:	XzYgeKQAAAAJ
	Email	:	editorial.jjbm@ung.ac.id

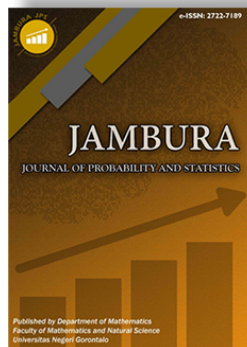
JAMBURA JOURNAL • FIND OUR OTHER JOURNALS



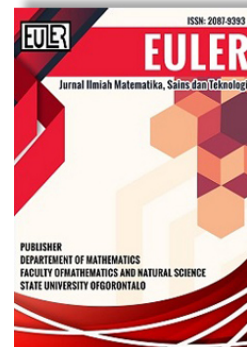
Jambura Journal of Mathematics



Jambura Journal of Mathematics Education



Jambura Journal of Probability and Statistics



EULER : Jurnal Ilmiah Matematika, Sains, dan Teknologi



Geographically Weighted Poisson Regression Modeling Using Adaptive Gaussian Kernel Weighting For Mapping Maternal Mortality Rates In East Java

Inayati Ngoro^{1,*}, Henny Pramodyo¹, and Ani Budi Astuti¹

¹Department of Statistics, Faculty of Mathematics and Natural Sciences, Brawijaya University

ARTICLE HISTORY

Received 31 January 2025
Revised 30 August 2025
Accepted 15 October 2025
Published 29 November 2025

KEYWORDS

Maternal mortality rate
Geographically weighted Poisson regression
Adaptive Gaussian kernel

ABSTRACT. Maternal Mortality Rate (MMR) is a key public health indicator that reflects spatial variation across districts in East Java. This study aims to model the spatial distribution of MMR using Geographically Weighted Poisson Regression (GWPR) with an Adaptive Gaussian Kernel weighting function. Secondary data were obtained from the 2022 East Java Provincial Health Profile, covering 38 districts and municipalities. The results indicate that GWPR outperforms the classical Poisson regression. The intercept $\beta=2.889$ ($\exp=17.95$) suggests an average of 18 maternal deaths in the absence of predictor effects. The coverage of the fourth antenatal care visit (K4) has a significant negative effect ($\beta=-0.027$; $\exp=0.973$), indicating that a 1% increase in K4 coverage reduces MMR by approximately 2.7%. Conversely, obstetric complications managed by midwives show a significant positive effect ($\beta=0.0173$; $\exp=1.017$), meaning that a 1% increase in complications raises MMR by 1.7%. Other predictors—first antenatal care visit (K1), iron-folic acid (IFA) supplementation, and number of health workers—are not statistically significant. This study underscores the importance of expanding K4 coverage and strengthening complication management as priority strategies to reduce maternal mortality. Furthermore, GWPR-based mapping enables more targeted maternal health interventions tailored to local characteristics.



This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution-NonCommercial 4.0 International License. *Editorial of JJBM:* Department of Mathematics, Universitas Negeri Gorontalo, Jln. Prof. Dr. Ing. B. J. Habibie, Bone Bolango 96554, Indonesia.

1. Introduction

Regression analysis is a statistical approach used to examine the effect of predictor variables on a response variable. When the response variable Y follows a Poisson distribution, the appropriate model is Poisson regression. This model is widely applied to count data, particularly when the events of interest are relatively rare within a large sample space.

A key extension of Poisson regression is Geographically Weighted Poisson Regression (GWPR), a local modeling technique designed to capture spatial heterogeneity in count data. GWPR has been extensively applied in epidemiology, ecology, and social sciences to address cases where relationships between predictors and outcomes vary across space. Unlike the classical Poisson regression model, which assumes global and spatially invariant associations between predictors and the outcome, GWPR estimates location-specific parameters by incorporating spatial weighting functions. These weights depend on the geographic distance between observations, allowing the model to capture localized variations in the underlying processes.

The selection of an appropriate weighting function is critical in GWPR. One widely used approach is the Adaptive Gaussian Kernel, where the bandwidth is adjusted according to the density of nearby observations. The optimal bandwidth is typically determined using cross-validation [1]. Adaptive kernels em-

phasize data points closer to the target location while assigning smaller weights to more distant observations, thereby improving the model's sensitivity in detecting local spatial variations.

GWPR has gained increasing application in health research, particularly for mapping disease risk, identifying risk factors, and informing evidence-based interventions. Previous studies, for example, applied GWPR to map the distribution of dengue fever in Bojonegoro Regency [2], comparing several kernel functions including Fixed Gaussian, Fixed Bi-square, Adaptive Bi-square, and Adaptive Gaussian. However, this study was limited to a single regency and primarily focused on evaluating kernel performance [3].

In contrast, the present study focuses on maternal mortality, one of the most critical indicators of population health. According to [4], East Java is among the provinces with the highest maternal mortality cases in Indonesia. Data from the 2020 Population Census long form recorded 184 maternal deaths, which increased to 499 cases in 2022 [5]. Maternal mortality is strongly associated with antenatal care (ANC) practices. Women with fewer than four ANC visits are estimated to have a 2.786 times higher risk of maternal death compared to those with adequate ANC [6]. ANC coverage—particularly the first antenatal visit and the fourth antenatal visit—serves as a crucial indicator for monitoring maternal health [6]. Physiological and pathological changes during pregnancy require timely medical attention, making both health worker supervision and maternal awareness crit-

*Corresponding Author.

ical for safe pregnancies [7].

The factors influencing maternal mortality differ across regencies/cities. For example, coverage of the first antenatal visit is generally high, but the fourth antenatal visit remains challenging to monitor due to limited outreach and health education efforts [8]. In 2022, 13 regencies/cities achieved full coverage for the first antenatal visit, whereas several areas reported coverage below 100%. Such uneven distribution highlights the need for spatial modeling to better capture geographic disparities in maternal mortality determinants.

This study applies GWPR with an Adaptive Gaussian Kernel to model the spatial distribution of maternal mortality across 38 regencies/cities in East Java. The novelty of this research lies in its province-wide application of GWPR for maternal mortality, which has not been previously conducted at this scale. Beyond methodological contributions to spatial modeling, the findings are expected to provide practical insights for maternal health policy, enabling local governments to design more geographically tailored interventions.

2. Methods and Materials

2.1. Data and data sources

This study draws on secondary data from the 2022 East Java Province Health Profile. The dataset includes geographical coordinates—latitude and longitude—for each regency and city in East Java. The analysis covers 29 regencies and 9 cities, totaling 38 regions across the province. The variables used in this study consist of one response variable and five predictors, as follows:

1. response variable (Y)

The number of maternal death cases in 38 regencies/cities in East Java Province. Maternal deaths are defined as deaths occurring during pregnancy, childbirth, or within 42 days of pregnancy termination, irrespective of the pregnancy duration or outcome, due to causes directly or indirectly related to pregnancy. The data reflect annual counts recorded at the regency/city level.

2. predictor variables (X)

2.2. Analytical methods

1. exploratory spatial data analysis (ESDA)

ESDA is employed to explore patterns, relationships, or structures within spatial data. It aims to reveal spatial heterogeneity and spatial autocorrelation that may exist in the data prior to conducting quantitative modeling [9]. Visualization techniques such as maps, diagrams, and plots are used to identify spatial trends.

2. Poisson regression

Poisson regression is used to model the number of events occurring in a given time or spatial interval [10]. The Poisson distribution describes the probability of observing a given number of events within an interval, under the assumption of independence and a constant average rate (λ). The probability mass function of the Poisson distribution is given in eq. (1) [2]:

$$P(Y = y) = \frac{e^{-\lambda} \lambda^y}{y!}; \quad y = 0, 1, 2, \dots \tag{1}$$

$$\lambda_i = \exp(X_i \beta)$$

X_1 : The percentage of pregnant women attending their first antenatal care visit (K1) – the proportion of pregnant women who attended their first visit to a health facility for antenatal care provided by qualified health personnel.

X_2 : The percentage of pregnant women attending their fourth antenatal care visit (K4) – the proportion of pregnant women who attended at least four antenatal visits to a health facility, in accordance with ANC service standards.

X_3 : Percentage of women receiving iron–folic acid (IFA) supplementation – the proportion of pregnant women who consumed at least 90 IFA tablets during pregnancy as part of anemia prevention and management efforts.

X_4 : Percentage of maternal complications managed by midwives – the proportion of pregnant, delivering, or postpartum women who experienced complications and received care from midwives in line with professional standards.

X_5 : The percentage of available medical personnel – the proportion of medical personnel (physicians, midwives, nurses, and other health professionals) relative to the population or healthcare needs within a regency/city.

u_i : Latitude for each regency/city.

v_i : Longitude for each regency/city.

3. geographically weighted Poisson regression

GWPR extends classical Poisson regression by estimating parameters locally for each observation. In this framework, the response variable depends on predictor variables whose coefficients vary geographically [11]. Each observation is associated with spatial coordinates (u_i, v_i) , and parameter estimation incorporates spatial weights based on the distance between locations. The GWPR model is expressed in eq. (2) [12]:

$$y_i \sim \text{Poisson}(\mu_i)$$

$$\mu_i = \exp \left[\beta_0(u_i, v_i) + \sum_{j=1}^p \beta_j(u_i, v_i) x_{ij} \right] \tag{2}$$

Notes:

μ_i : expected value of the response variable at observation i

x_{ij} : observed value of predictor variable j at observation

u_i : spatial coordinate (latitude) of observation i

v_i : spatial coordinate (longitude) of observation i

$\beta_j(u_i, v_i)$: regression coefficient of predictor variable j at location (u_i, v_i)

(u_i, v_i) : geographic coordinates (latitude and longitude) of location i

Model parameters are estimated using Maximum Likelihood Estimation (MLE) with spatial weighting [13]. Parameter

testing is conducted to identify significant predictors at each location [14].

Parameter testing in the GWPR model aims to identify which parameters significantly influence the response variable at each location. The hypotheses used for parameter testing in the GWPR model are formulated as follows:

$$H_0 : \beta_j(u_i, v_i) = 0$$

$$H_1 : \beta_j(u_i, v_i) \neq 0$$

The test statistic is expressed in eq. (3):

$$t_i = \frac{\hat{\beta}_j(u_i, v_i)}{se(\hat{\beta}_j(u_i, v_i))}$$

$$se(\hat{\beta}_j(u_i, v_i)) = \sqrt{var(\hat{\beta}_j(u_i, v_i))} \tag{3}$$

$$= \sqrt{\hat{\sigma}^2 (X^T W(u_i, v_i) X)^{-1}}$$

4. bandwidth Bandwidth represents the spatial boundary around a location, within which neighboring points are considered to contribute to parameter estimation at that location [15]. The value of the bandwidth determines the extent to which distance influences weighting: observations closer to the target location receive larger weights, while those farther away receive smaller weights [16]. If the bandwidth is too large, the assigned weights become very small, approaching global estimation [17]. Conversely, if the bandwidth is too small, the resulting weights tend to be excessively large. Adaptive Gaussian Kernel In the local bandwidth approach, the bandwidth at each observation *i* may vary depending on the number of nearest neighbors. When *k* nearest neighbors are used, the bandwidth at location *i*, denoted as *b_i* is determined by the distance from location *i* to its *k* nearest neighbor, as expressed in eq. (4) [18]:

$$b_i = d_{(k)}^{(i)} \tag{4}$$

Notes:

- d_(k)⁽ⁱ⁾* : distance from location *i* to its *k*-th nearest neighbor, ordered by proximity
- k* : number of nearest neighbors specified
- i* : target location

Therefore, the cross-validation (CV) method is applied to determine the optimal bandwidth, as expressed in eq. (5) [19]:

$$CV(h) = \sum_{i=1}^n (y_i - \hat{y}_{\neq i}(h))^2 \tag{5}$$

y_{≠i}(h) the predicted value of *y_i* obtained by excluding observation at location (u_i, v_i) .

5. adaptive kernel Gaussian

The weighting function produces parameter estimates that vary across locations [20]. The weight matrix at location *i* with coordinates (u_i, v_i) is denoted as $w(u_i, v_i)$. If location *j* is situated at coordinates (u_j, v_j) , the Euclidean distance (*d_{ij}*) between locations *i* and *j* is calculated as shown in eq. (6):

$$d_{ij} = \sqrt{((u_i - u_j)^2 + (v_i - v_j)^2)} \tag{6}$$

The adaptive kernel approach allows each observation point to have a bandwidth value that varies according to its local characteristics [21]. This flexibility arises because the adaptive kernel method adjusts to the distribution of the observation points [22]. The Adaptive Gaussian Kernel weighting function is formulated in eq. (7):

$$W_{ij} = exp(-(\frac{d_{ij}}{b_i})^2) \tag{7}$$

Notes:

- W_{ij}* : Spatial weight between location *i* and location *j*
- d_{ij}* : Distance between location *i* and location *j*
- b_i* : Local bandwidth at location *i*, defined as the distance to the *k*-th nearest neighbor, where *k* is the number of neighbors specified

6. model validation

After estimating the GWPR model, it is necessary to examine whether spatial autocorrelation remains in the residuals [4]. The purpose of this validation is to ensure that the residuals do not exhibit significant spatial patterns [23]. If no spatial autocorrelation is detected, the model can be considered adequate in explaining the spatial variation in the data [24].

2.3. Research Steps

The analysis was conducted using R software, following a structured approach:

- i. Testing whether the response variable Y follows a Poisson distribution using the Kolmogorov-Smirnov test
- ii. Conducting an overdispersion test
- iii. Detecting multicollinearity among predictor variables using the Variance Inflation Factor (VIF) criterion
- iv. Performing simultaneous and partial tests
- v. Constructing a Poisson regression model, including parameter estimation and significance testing
- vi. Testing for spatial heterogeneity and spatial dependence
- vii. Developing the GWPR model through the following steps:
 - a. Calculating Euclidean distances between observation points based on geographic coordinates
 - b. Determining the optimal bandwidth using the cross-validation (CV) method
 - c. Computing the weighting matrix using the Adaptive Gaussian Kernel function
 - d. Testing the equivalence of the GWPR model with the Poisson regression model

- e. Conducting spatial and simultaneous parameter test
 - f. Obtaining the final model
1. Drawing conclusions based on the analysis results.

3. Results and Discussion

3.1. Exploratory spatial data analysis (ESDA)

East Java Province is located in the eastern part of Java Island, covering a land area of 47,803.39 km² and consisting of 29 regencies and 9 cities.

As shown in Figure 1, lighter colors on the map represent lower maternal mortality, while darker red indicates higher maternal mortality across regencies/cities in East Java. The spatial distribution map reveals that Jember Regency recorded the highest maternal mortality, with 19 cases, marked in dark red. In contrast, regencies with relatively low maternal mortality, such as Mojokerto and Kediri, are shown in light pink.

3.2. Testing the assumption of no multicollinearity

Multicollinearity occurs when there is a significant correlation between predictor variables [25]. One of the assumptions of Poisson regression is the absence of multicollinearity among predictor variables. This assumption was tested using the Variance Inflation Factor (VIF) criterion. If the VIF value exceeds 10, multicollinearity is present, indicating a strong relationship between predictor variables.

Table 1. VIF Values of Predictor Variables

Variable	VIF Value
X ₁	1.374
X ₂	1.299
X ₃	1.101
X ₄	1.297
X ₅	1.134

Based on Table 1, all predictor variables have VIF values below 10, indicating no multicollinearity. Therefore, all variables can be used in the Poisson regression and Geographically Weighted Poisson Regression (GWPR) modeling.

3.3. Poisson regression modeling

Poisson regression is used to model the relationship between predictor and response variables under the assumption that the response variable Y follows a Poisson distribution, typically applied to count data.

1. parameter estimation in Poisson regression

Parameter estimation for the Poisson regression model was performed using the Maximum Likelihood Estimation (MLE) method, which maximizes the likelihood function to obtain the estimated parameters.

Table 2. Parameter Testing in Poisson Regression Model

Parameter	Estimate	Standard Error	Significance
β ₀	2.699	1.492	
β ₁	0.005	0.016	Not Significant
β ₂	-0.029	0.007	Significant
β ₃	-0.008	0.002	Significant
β ₄	0.012	0.005	Significant
β ₅	<0.001	<0.001	Not Significant

Based on Table 2, the predictor variables X₂, X₃ and X₄ are

significant, while X₁ and X₅ are not significant. Thus, the Poisson regression model is as follows:

$$\hat{\mu} = exp(2.699 - 0.029X_2 - 0.008X_3 + 0.12X_4) \quad (8)$$

This model provides insights into the factors influencing maternal mortality rates in East Java. The findings indicate that an increase in the percentage of pregnant women who complete K4 antenatal care is associated with a reduction in maternal mortality, with the rate decreasing by 0.02990 for each 1% increase in K4 coverage. Similarly, the consumption of iron supplementation tablets by pregnant women also contributes to a decline in maternal mortality, with a decrease of 0.007792 for every 1% increase in adherence to this supplementation. Conversely, the presence of midwifery complications has the opposite effect, as a 1% increase in complications is associated with a rise in maternal mortality by 0.011532.

2. testing the parameters of the Poisson regression model
- Testing the parameters of the Poisson regression model is essential to determine the influence of each parameter on the model at a given level of significance. This process involves both simultaneous and partial tests.

Table 3. Parameter Testing in Poisson Regression Model

Deviance	Db	AIC
25.928	6	196.36

Table 4. Parameter Estimates for the Poisson Regression Model

Parameter	Z _{Calculate}	Decision
β ₀	1.809	Fail to reject H ₀
β ₁	0.317	Fail to reject H ₀
β ₂	-4.161	Reject H ₀
β ₃	-2.465	Reject H ₀
β ₄	2.129	Reject H ₀
β ₅	1.423	Fail reject H ₀

- (a) simultaneous testing

Simultaneous testing was conducted using the deviance value, χ², which approximates a chi-square distribution with degrees of freedom (n - k - 1). The decision rule states that the null hypothesis H₀ should be rejected if D(β̂) > χ²_{α;n-k-1} at a significance level of α = 0.05.

Based on Table 3, the deviance value of 25,928 > χ²_(0.05;6) exceeds the chi-square critical value χ²_(0.05;6) = 12.592. Consequently, H₀ is rejected, indicating that the Poisson regression model is appropriate for modeling the relationship between the response variable and predictor variables.

- (b) partial testing

Partial testing assesses the significance of each estimated parameter individually. The decision criterion states that H₀ should be rejected if |Z_{calculated}| > Z_{α/2}.

According to Table 4, Z_{calculated} values for parameters β₂, β₃ and β₄ exceed the critical value > Z_{0,025}, indi-

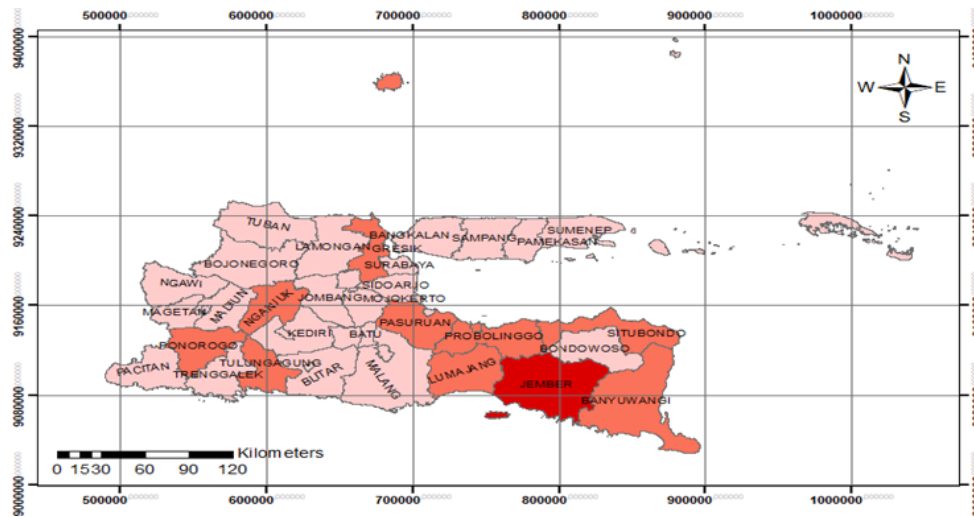


Figure 1. Map of East Java Province

cating that these parameters significantly influence the model. In contrast, parameters β_1 and β_5 are not statistically significant.

3.4. Geographically weighted Poisson regression (GWPR) model

GWPR is an extension of the Poisson regression model that estimates parameters locally for each geographic location where the data follow a Poisson distribution. Given the variations in maternal mortality cases across different districts and cities, the factors influencing maternal mortality rates in East Java differ by region. Therefore, GWPR analysis is necessary to account for spatial heterogeneity in the relationship between maternal mortality and its determinants.

1. adaptive Gaussian kernel weighting function

The weighting function in GWPR provides distinct parameter estimates for different locations. In spatial analysis, the estimated parameter for a given location i is more influenced by nearby points than by distant ones. The adaptive kernel method allows for varying bandwidths for each observation, enabling the model to adjust to the specific conditions of each observation point. This adaptability ensures a more accurate representation of spatial variations in maternal mortality rates.

The optimal bandwidth was determined using the Cross-Validation (CV) method. The optimal bandwidth values for each district/city were obtained using the Adaptive Gaussian Kernel function. The optimal bandwidth value was found to be 0.368438. This bandwidth value was used to generate the weighting matrix for each district/city using the Adaptive Gaussian Kernel function.

2. Gaussian adaptive parameter testing of the GWPR model with adaptive Gaussian kernel weighting

Parameter testing of the GWPR model was conducted to determine which parameters significantly influenced the response variable at each location.

To illustrate these differences more clearly, two regions were selected as representative models with contrasting characteristics. Jember City was identified as the area with the highest maternal mortality, thus its model reflects conditions that require the greatest policy attention and inter-

vention. In contrast, Probolinggo Regency was chosen as a benchmark region because it shows relatively large absolute coefficient values for the fourth antenatal visit (X_2) and complications handled by midwives (X_4). These findings indicate that both predictors significantly affect maternal mortality in the local model, with consistently high beta values that demonstrate parameter stability. The following presents the GWPR model for Jember City.

$$\mu_{JemberReg} = \exp(2.889 - 0.0004X_1 - 0.027X_2 - 0.009X_3 + 0.017X_4 + 0.00001X_5) \quad (9)$$

Based on the model, two variables were found to be significant: the fourth antenatal visit and complications handled by midwives. The intercept $\beta_0 = 2,889$ ($exp = 17,95$) indicates an average of approximately 18 maternal deaths, consistent with secondary data showing 19 deaths in Jember City, the highest in East Java.

The coefficient for the fourth antenatal $-0,027$ ($exp = 0,973$) suggests that a 1% increase in coverage reduces maternal mortality by 2.7%. Conversely, the coefficient for complications handled by 0,017 ($exp = 1,017$) implies that a 1% increase in complications is associated with a 1.7% rise in maternal mortality. These findings emphasize the importance of expanding the coverage of the fourth antenatal visit for early risk detection, as well as strengthening the management of pregnancy complications by healthcare providers. Thus, improving the quality of antenatal care services remains a key strategy for reducing maternal mortality in East Java.

Probolinggo Regency, on the other hand, represents a region with a more stable model.

$$\mu_{ProbReg} = \exp(3.046 - 0.0005X_1 - 0.028X_2 - 0.028X_3 + 0.018X_4 + 0.00001X_5) \quad (10)$$

Based on the GWPR model in Probolinggo Regency, two predictors were identified as significant: the fourth antenatal visit and complications handled by midwives. A 1% increase

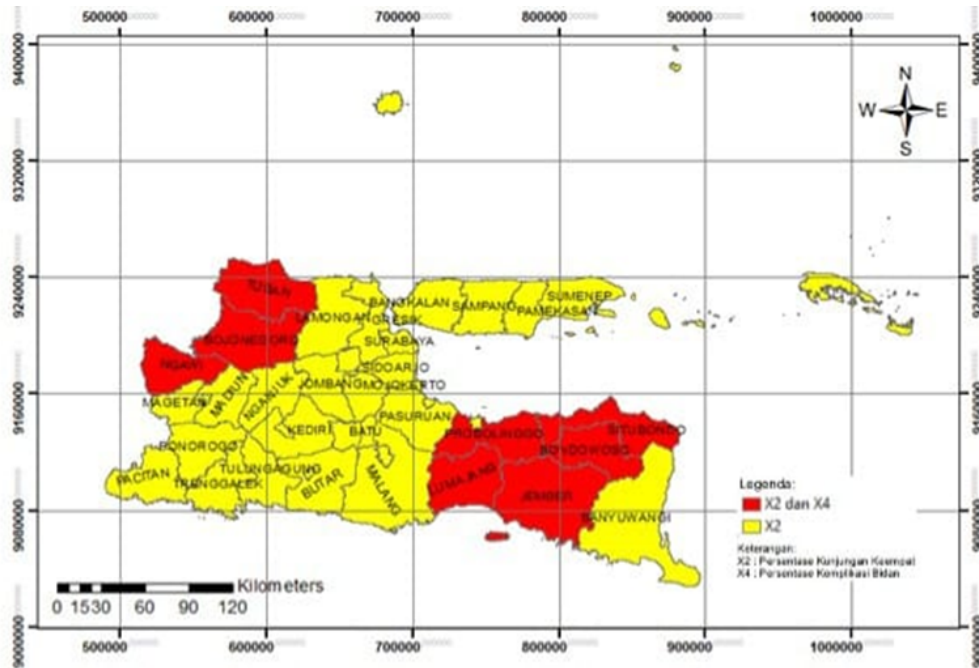


Figure 2. Classified GWPR Models

Table 5. Parameter Estimates for the GWPR Model

Regency/City	$\hat{\beta}_0(u_i, v_i)$	$\hat{\beta}_1(u_i, v_i)$	$\hat{\beta}_2(u_i, v_i)$	$\hat{\beta}_3(u_i, v_i)$	$\hat{\beta}_4(u_i, v_i)$	$\hat{\beta}_5(u_i, v_i)$
Pacitan Regency	2.448539	0.014437	-0.031697	-0.006073	0.005141	0.00008949
Ponorogo Regency	2.568613	0.015989	-0.032432	-0.004727	0.001894	0.00008448
Trenggalek Regency	2.582818	0.155587	-0.032398	-0.004856	0.002254	0.00008947
Tulungagung Regency	2.646887	0.0149013	-0.032534	-0.004749	0.001934	0.00009294
Blitar Regency	2.794564	0.004057	-0.029801	-0.008207	0.011831	0.00009664
Kediri Regency	2.916258	0.014934	-0.030916	0.002932	-0.001528	0.00008916
Malang Regency	2.744697	0.005915	-0.030916	-0.007311	0.001545	0.00001633
Lumajang Regency	2.833358	-0.002153	-0.028119	-0.009218	0.017028	0.00010853
Jember Regency	2.798434	-0.002383	-0.027274	-0.009515	0.016009	0.00010680
Banyuwangi Regency	2.708937	-0.000361	-0.027411	-0.009384	0.016973	0.00010144
Bondowoso Regency	2.831868	-0.002506	-0.027626	-0.009463	0.0169731	0.00010497
Situbondo Regency	2.854968	-0.002831	-0.027690	-0.009482	0.017088	0.00010400
Probolinggo Regency	2.957923	-0.004349	-0.028375	-0.009380	0.017777	0.00010479
Pasuruan Regency	2.599403	0.016231	-0.032569	-0.004428	0.001211	0.00008381
Sidoarjo Regency	2.744820	0.015159	-0.029969	-0.004125	0.001777	0.00008136
Mojokerto Regency	3.234859	0.012727	-0.034222	-0.002595	-0.002509	0.00008809
Jombang Regency	3.269505	0.008530	-0.034426	-0.004192	0.004983	0.00008459
Nganjuk Regency	3.494882	0.005311	-0.034578	-0.004720	0.004893	0.00009488
Madiun Regency	3.377204	0.002578	-0.034020	-0.005577	0.010702	0.00009185
Magetan Regency	3.352079	0.001004	-0.033479	-0.005211	0.010309	0.00009886
Ngawi Regency	3.190621	-0.003465	-0.030909	-0.008524	0.017103	0.00001158
Bojonegoro Regency	3.097855	-0.003569	-0.030496	-0.009150	0.016423	0.00010119
Taban Regency	2.693928	-0.002239	-0.029303	-0.009300	0.015046	0.00010650
Lamongan Regency	2.890064	0.014970	-0.033307	-0.003126	-0.001176	0.00008686
Gresik Regency	2.716102	0.012526	-0.032460	-0.005168	0.002921	0.00009972
Bangkalan Regency	2.913900	0.004942	-0.031337	-0.006395	0.004195	0.00010127
Sampang Regency	3.039950	-0.008009	-0.031148	-0.007428	0.009161	0.00010951
Pamekasan Regency	3.240028	0.001474	-0.033811	-0.005426	0.009617	0.00009096
Sumenep Regency	3.293668	0.012018	-0.034541	-0.004687	0.009274	0.00008971
Kediri City	3.340878	0.013001	-0.034819	-0.008361	-0.004097	0.00008921
Blitar City	3.016679	0.014301	-0.033149	-0.009833	0.010488	0.00009871
Malang City	2.788452	0.016283	-0.029475	-0.003313	-0.001438	0.00007856
Probolinggo City	3.021354	0.003344	-0.034079	-0.009112	0.012064	0.00008874
Pasuruan City	3.020543	0.000804	-0.031549	-0.004986	0.001725	0.00008739
Mojokerto City	2.962847	0.017112	-0.032663	-0.004516	-0.001602	0.00008711
Madiun City	2.690377	0.016712	-0.032764	-0.003641	0.008034	0.00008767
Surabaya City	3.385441	0.003070	-0.033460	-0.005880	0.009821	0.00009877
Batu City	2.886440	0.006897	-0.032328	-0.005586	0.007767	0.00010611

Table 6. Parameter Estimates for the Poisson Regression Model

Groups	Significant Variables	Regency/City
1	X_2 and X_4	Lumajang, Jember, Bondowoso, Situbondo, Probolinggo, Ngawi, Bojonegoro, Tuban, Kota Probolinggo
2	X_2	Pacitan, Ponorogo, Trenggalek, Tulungagung, Blitar, Kediri, Malang, Banyuwangi, Pasuruan, Sidoarjo, Mojokerto, Nganjuk, Madiun, Magetan, Lamongan, Gresik, Bangkalan, Sampang, Pamekasan, Sumenep, Kediri City, Blitar City, Malang City, Pasuruan City, Madiun City, Surabaya City, Batu City.

in fourth antenatal visit coverage reduces maternal mortality by 2.8% ($\exp = 0.972$), while a 1% increase in complications raises maternal mortality by 1.8% ($\exp = 1.018$). This highlights the critical role of the fourth antenatal visit in providing comprehensive pregnancy monitoring, while also confirming that the high incidence of complications managed by midwives substantially increases the risk of maternal death. Meanwhile, the first antenatal visit, IFA supplementation, and number of health workers were not statistically significant in the model, yet they remain relevant in practical contexts. The first antenatal visit is essential for early risk detection, IFA supplementation helps prevent anemia that may trigger complications, and health workers serve as the main providers of maternal health services. The GWPR models were classified into two groups based on the predictor variables that significantly influenced the average maternal mortality rate, as illustrated in Figure 2.

4. Conclusion

GWPR) model with Adaptive Gaussian Kernel weighting effectively captures the spatial variation of maternal mortality across regencies/cities in East Java. The results show that the effects of predictor variables differ geographically, indicating that the relationship between predictors and maternal mortality is not global but location-specific.

Overall, two predictors consistently exhibited significant effects: coverage of the fourth antenatal visit, which reduces maternal mortality, and complications handled by midwives, which increase the risk of maternal death. Other predictors—namely the first antenatal visit, iron–folic acid (IFA) supplementation, and number of health workers—were not statistically significant but remain practically relevant in maternal health programs.

This study has several limitations, including reliance on secondary data from a single year, which does not capture temporal dynamics of maternal mortality, and a limited set of predictors that may not fully reflect broader social, economic, and cultural determinants. Future studies are recommended to employ panel data with a wider range of predictors to develop more comprehensive spatial models.

The findings reinforce the importance of improving the quality of antenatal care services, particularly by expanding coverage of the fourth antenatal visit and strengthening the management of obstetric complications in primary healthcare facilities. By applying GWPR-based mapping, local governments can design geographically targeted interventions that are more responsive to regional characteristics, thereby contributing to more effective reductions in maternal mortality.

Author Contributions. Ngoro, I.: Conceptualization, methodology, data curation, formal analysis, writing, original draft preparation, visualiza-

tion. Pramoedyo, H.: Supervision, validation, writing, review and editing. Astuti, A. B.: Supervision, methodology, writing, review and editing.

Acknowledgement. The authors are thankful to the Department of Statistics, Faculty of Mathematics and Natural Sciences, Universitas Brawijaya, for providing academic and technical support during this research. The authors also express gratitude to the editors and reviewers who have contributed to improving the quality of this manuscript.

Funding. This research was no external funding.

Conflict of interest. The authors declare no conflict of interest.

Data availability. Not applicable.

Abbreviations.

MMR	: Maternal Mortality Rate
GWPR	: Geographically Weighted Poisson Regression
ANC	: Antenatal Care
K1	: First Antenatal Care Visit
K4	: Fourth Antenatal Care Visit
IFA	: Iron–Folic Acid Supplementation

References

- [1] A. S. Fotheringham, C. Brunsdon, and M. Charlton, “Geographically Weighted Regression: The Analysis of Spatially Varying Relationships.” Chichester: Wiley, 2002.
- [2] K. Nisa, “Application of geographically weighted poisson regression (gwpr) to dengue fever cases in bojonegoro,” *Journal of Statistics and Computing*, vol. 1, no. 1, pp. 12–22, 2022. DOI:10.32665/statkom.v1i1.444
- [3] Y. A. N. Qomari and H. B. Notobroto, “Visits of k1 and k4 pregnant women on maternal mortality rate in east java province,” *Preventive: Public Health Journal*, vol. 13, no. 4, pp. 586–595, 2022. DOI:10.22487/preventif.v13i4.309
- [4] E. M. P. Hermanto, “Grouping of Provinces in Indonesia Based on Maternal Health Indicators Using Variable Weighting K-Means and Fuzzy C-Means,” *Jurnal Biometrika dan Kependudukan*, vol. 9, no. 1, pp. 44–52, 2020. DOI:10.20473/jbk.v9i1.2020.44–52
- [5] BPS JATIM, “Human Development Index East Java Province 2022.” BPS of East Java Province, 2022.
- [6] Rohmi and R. A. Rahmat, “The Relationship Between the Frequency of Antenatal Care Visits and Early Detection of Preeclampsia Risk in Pregnant Women in the Third Trimester,” *International Journal of Health Sciences (IJHS)*, vol. 3, no. 3, 2025. DOI:10.59585/ijhs.v3i3.791
- [7] M. Maryuni, M. Y. R. Anandita, and L. Anggraeni, “Hubungan pengetahuan tanda-tanda bahaya kehamilan dan praktik ibu hamil saat mengalami komplikasi kehamilan,” *JOMIS (Journal of Midwifery Science)*, vol. 5, no. 1, pp. 21–27, 2021. DOI:10.36341/jomis.v5i1.1554.
- [8] A. N. Sari, “Analisis jalur faktor-faktor yang mempengaruhi angka kematian ibu di Jawa Timur (Path analysis the factors affecting maternal mortality in East Java),” *JMPM: Jurnal Matematika dan Pendidikan Matematika*, vol. 1, no. 2, pp. 119–132, 2016. DOI:10.26594/jmpm.v1i2.581.
- [9] T. Munikah, H. Pramoedyo, and R. Fitriani, “Geographically Weighted Regression modeling with fixed Gaussian kernel weighted on spatial data (case study of food security in Tanah Laut District of South Kalimantan),” *Natural B: Journal of Health and Environmental Sciences*, vol. 2, no. 3, pp. 296–302, 2014. DOI:10.21776/ub.natural-b.2014.002.03.15.

- [10] S. M. Meliyana, A. S. Ahmar, and S. N. Auliah, "Geographically Weighted Poisson Regression (GWPR) Model with Fixed Gaussian Kernel and Fixed Biquadratic Kernel Weights," *ARRUS Journal of Social Sciences and Humanities*, vol. 5, no. 2, 2025. DOI:10.35877/soshum3812
- [11] B. Lu et al., "Geographically weighted regression with a non-euclidean distance metric: A case study using hedonic house price data," *International Journal of Geographical Information Science*, vol. 28, no. 4, pp. 660–681, 2014. DOI:10.1080/13658816.2013.865739
- [12] E. R. Caraka and H. Yasin, "Geographically Weighted Regression (GWR): A Geographical Regression Approach, 1st ed.," Yogyakarta, Indonesia: Mobius, 2017. DOI:10.5281/zenodo.1168741
- [13] Y. Musdar, Aswi, and Z. Mar'ah, "Pemodelan geographically weighted poisson regression untuk kasus dbd di provinsi sulawesi selatan tahun 2022," *Jurnal Matematika dan Statistika Serta Aplikasinya*, vol. 12, no. 2, 2024. DOI:10.24252/msa.v12i2.51242
- [14] R. R. Hocking, "Methods and Applications of Linear Models: Regression and the Analysis of Variance (2nd ed.)." John Wiley & Sons, 1996. DOI:10.1002/0471434159
- [15] P. McCullagh and J. A. Nelder, "Generalized Linear Models (2nd ed.)." London: Chapman and Hall, 1980. DOI:10.1201/9780203753736
- [16] Y. Leung, C. L. Mei, and W. X. Zhang, "Statistical tests for spatial nonstationarity based on the geographically weighted regression model," *Environment and Planning A: Economy and Space*, vol. 32, no. 1, pp. 9–32, 2000. DOI:10.1068/a3162
- [17] T. Hastie et al., "The elements of statistical learning." Springer series in statistics New-York, 2009. DOI:10.1007/978-0-387-84858-7
- [18] E. M. Bannidi et al., "Estimation of reproduction number of mathematical model of malaria spread in central sumba, Indonesia," *Jambura Journal of Biomathematics (JJBM)*, vol. 2, no. 1, pp. 13–19, 2021. DOI:10.34312/jjbm.v2i1.9971
- [19] R. E. Walpole, "Probability and Statistics for Engineers and Scientists." Pearson, 2012.
- [20] L. D. Marites, "Descriptive statistics as a collection of information," *Fhirts: Journal of Library and Information Science*, vol. 16, no. 1, pp. 40–59, 2021. DOI:10.14421/fhrs.2021.161.40-59
- [21] S. W. Purnami, N. Qomariyah, and S. Pramono, "Pemodelan faktor yang mempengaruhi jumlah kematian ibu di jatim dengan pendekatan gwpr (geographically weighted Poisson regression) ditinjau dari segi fasilitas kesehatan," *Jurnal Sains dan Seni ITS*, vol. 2, no. 2, pp. 2337–3520, 2013. DOI:10.12962/j23373520.v2i2.4864
- [22] J. A. Nursiyono and M. Apriyani, "Determinants of maternal mortality in East Java in 2020: A geographically weighted regression analysis," *Poltekita: Jurnal Ilmu Kesehatan*, vol. 16, no. 1, pp. 89–97, 2022. DOI:10.33860/jik.v16i1.844.
- [23] N. P. Yuriantari, M. N. Hayati, and S. Wahyuningsih, "Analisis autokorelasi spasial titik panas di kalimantan timur menggunakan indeks moran dan local indicator of spatial autocorrelation (lisa): Analisis spatial autocorrelation hotspot in east kalimantan using index moran and local indicator of spatial autocorrelation (lisa)," *Jurnal Eksponensial*, vol. 8, no. 1, 2017.
- [24] E. M. P. Hermanto, "Pengujian autokorelasi spasial pada residual model gwpr: Studi kasus pemodelan balita gizi buruk di kabupaten bojonegoro." Thesis, Institut Teknologi Sepuluh Nopember, 2014.
- [25] N. Aeni, "Risk factors for maternal death," *Kesmas: National Public Health Journal*, vol. 7, no. 10, pp. 453–459, 2013. DOI:10.21109/kesmas.v7i10.4