BAREKENG: Journal of Mathematics and Its Applications
March 2025 Volume 19 Issue 1 Page 0557–0570
P-ISSN: 1978-7227 E-ISSN: 2615-3017
https://doi.org/10.30598/barekengvol19iss1pp0557-0570

SPATIAL MODELING OF MATERNAL HEALTH: GEOGRAPHICALLY WEIGHTED POISSON REGRESSION ON MATERNAL MORTALITY FACTORS

Alfa Yuliana[1], Achmad Fauzan[2*]

[1,2] Department of Statistics, Faculty of Mathematics and Natural Sciences, Universitas Islam Indonesia
Jln. Kaliurang KM. 14.5 Sleman, Yogyakarta, 55584, Indonesia

*Corresponding author's e-mail: ** ***achmadfauzan@uii.ac.id***

ABSTRACT

Data from the 2021 West Java Provincial Health Profile Report, accessed from the official website of the West Java Provincial Health Office, reveals a significant surge in maternal mortality cases, rising from 165 in 2020 to 460 in 2021. In support of efforts to reduce maternal mortality rates, this study investigates the contributing factors to this phenomenon across various districts in West Java Province. The data used is from the year 2021. This study aims to evaluate the effectiveness of Poisson regression, negative binomial regression, and Geographically Weighted Poisson Regression (GWPR) models in capturing the variability of maternal deaths in the study area for that year. A comprehensive analysis revealed that the distribution of maternal mortality fits the Poisson model, displaying significant spatial heterogeneity. Acknowledging this variability, the GWPR approach using an Adaptive Kernel Bisquare weighting was selected due to its capability to produce localized parameter estimates, which more accurately reflect the specific conditions of each location. The analyzed independent variables include the number of community health centers, coverage of antenatal services at the first (K1) and fourth (K4) visits, management of obstetric complications, and coverage of iron supplementation for pregnant women. Of the five variables, only three showed statistically significant effects; therefore, the study proceeded using these three variables. The results indicate that GWPR provides the best explanation for the variability in maternal mortality rates, with an adjusted R^2 value of 63.17% and a MAPE of 37.70%.

Article History:

Received: 3rd August 2024
Revised: 22nd November 2024
Accepted: 22nd November 2024
Published: 12th January 2025

Keywords:

Geographically Weighted Poisson Regression;
Maternal Mortality;
Spatial Heterogeneity;
West Java.

How to cite this article:

A. Yuliana and A. Fauzan., "SPATIAL MODELING OF MATERNAL HEALTH: GEOGRAPHICALLY WEIGHTED POISSON REGRESSION ON MATERNAL MORTALITY FACTORS", *BAREKENG: J. Math. & App.*, vol. 19, iss. 1, pp. 0557-0570, March, 2025.

Journal homepage: *https://ojs3.unpatti.ac.id/index.php/barekeng/*
Journal e-mail: *barekeng.math@yahoo.com; barekeng.journal@mail.unpatti.ac.id*

Research Article · Open Access

1. INTRODUCTION

Maternal mortality, reflected through the Maternal Mortality Rate (MMR), is a vital indicator that illustrates the level of health welfare in a region. MMR measures the risk of death faced by mothers during pregnancy, childbirth, and the postpartum period, calculated per 100,000 live births [1]. Reducing the MMR is one of the 17 Sustainable Development Goals (SDGs), which aim to reduce the MMR to below 70 per 100,000 live births by 2030. In West Java, the MMR is recorded at 147.43 per 100,000 live births, significantly above the SDGs target [2]. This situation underscores the need for a more strategic and comprehensive approach to meet the global target, given the urgent need to improve maternal health and significantly reduce the risk of maternal mortality.

West Java Province was recorded as having one of the highest maternal mortality rates in Indonesia in 2021, according to collected data [3]. An analysis of trends from 2019 to 2021 indicates a consistent increase in maternal deaths across its 27 districts/cities, with a significant rise from 165 cases in 2020 to 460 cases in 2021, as reported in the District Health Profile [1]. The factors contributing to this increase are multifaceted and complex. Key aspects include the availability of health infrastructure, such as the number of community health centers, which play a crucial role in providing essential services. Additionally, the coverage of antenatal services and effectiveness in managing obstetric complications are other critical factors. Further factors such as the provision of iron supplementation tablets to pregnant women also significantly influence the high maternal mortality rates in this region. Further research is needed to identify effective interventions to reduce risks and improve maternal health outcomes in West Java.

Maternal mortality is a serious global health issue that requires thorough investigation to support government policies aimed at reducing its prevalence [4]. One effective method is through the modeling and mapping of maternal mortality rates, taking into account the causative factors. As maternal mortality is often a relatively rare event in a specific period or region, this approach is well-suited to be modeled using the Poisson distribution, which is ideal for counting data of rare events [5]. Poisson regression, frequently utilized in epidemiological studies, allows for the exploration of relationships between the dependent variable (number of maternal deaths) and influential independent variables. This method not only provides a deeper understanding of the dynamics affecting maternal mortality but also aids in formulating appropriate intervention strategies. Implementing Poisson regression analysis can significantly contribute to efforts to reduce maternal mortality rates by providing accurate and relevant data-driven insights. Indonesia remains one of the Southeast Asian countries with the highest maternal mortality rates, characterized by substantial disparities across regions [6], [7]. Contributing factors extend beyond medical issues to include economic challenges, environmental conditions, and disorganized healthcare service management systems, which collectively exacerbate maternal mortality [8].

In Poisson regression analysis, one crucial assumption is equidispersion, where the variance and mean of the data are expected to be equal. However, data often exhibit overdispersion, where the variance exceeds the mean, which can affect the efficiency of the estimators by causing high standard errors, though the estimators remain consistent [9]. This overdispersion reduces the efficiency of parameter estimation in the Poisson model, thus diminishing the reliability of research outcomes [10]. In response to this condition, the negative binomial regression model is often used as an alternative because it includes an additional dispersion parameter that allows for more effective handling of overdispersion. The negative binomial regression model not only addresses the limitations of Poisson regression in overdispersed conditions but also produces more accurate and efficient parameter estimates. The implementation of this negative binomial model is crucial, especially in epidemiological and public health research, where precision and reliability of parameter estimates are key to developing appropriate and evidence-based interventions.

Conventional Poisson regression models often fall short in modeling data with a strong spatial component, such as the geographic variations in maternal mortality, which can be influenced by geographic, social, cultural, and local conditions in West Java Province. These conditions lead to spatial heterogeneity, meaning that regression parameters may not be uniform across the study area [11]. Geographically Weighted Poisson Regression (GWPR) is a method designed to address this issue by allowing regression parameters to adapt locally, acknowledging and integrating spatial variations in the data. GWPR effectively captures and models the dynamics of the relationship between dependent and independent variables that may vary across regions, thus providing a deeper and localized understanding of the factors influencing maternal mortality in West Java. Implementing GWPR can yield more accurate and relevant insights, which are crucial in the formulation of more effective policy and intervention strategies to reduce maternal mortality.

Several studies on the use of GWPR encompass a wide range of critical topics, such as the examination of the relationship between socioeconomic factors and hysterectomy in Belgium [12], the analysis of the spatial patterns of pulmonary tuberculosis and related key factors in Bandar Lampung, Indonesia [13], and the modeling of maternal mortality rates in Indonesia through the geographically weighted Poisson regression approach [14]. Additionally, comparisons have been made between Geographically Weighted Artificial Neural Networks and Geographically Weighted Generalized Poisson Regression in the context of crime cases in East Java, Indonesia [15], as well as the application of geographically weighted Poisson regression for modeling maternal mortality rates in Papua Province [16].

GWPR represents an evolution from traditional Poisson regression that incorporates spatial weights based on the latitude and longitude coordinates of each observation point. In the GWPR model, the dependent variable—for instance, maternal mortality—is influenced by independent variables with regression coefficients that explicitly depend on geographical location. The primary objective of GWPR is to explore and identify the local influence of independent variables on the dependent variable, adjusting for significant spatial variation in the Poisson-distributed data. As a result, this model produces varying parameter estimations at each location, known as local estimators, which allow for the identification of geographical clusters with similar characteristics related to significant independent variables. In the context of researching maternal mortality in West Java Province in 2021, choosing between Poisson regression, negative binomial regression, and GWPR is critical for developing a more accurate understanding of the regional dynamics influencing mortality rates. By implementing GWPR, it is expected to gain deep insights into local factors affecting maternal mortality, fully leveraging spatial information to inform more effective intervention strategies based on distinct geographical characteristics.

2. RESEARCH METHODS

2.1 Research Data and Variables

In this study, we use secondary data sourced from the West Java Health Profile Book 2021, obtained through the official website of the West Java Provincial Health Office at https://diskes.jabarprov.go.id/, accessed in 2022. The data collected covers 27 districts/cities in West Java Province. The dependent variable in this analysis is the number of maternal deaths (Y), which is a primary indicator in assessing the effectiveness of maternal health services in the region. The chosen independent variables include: the number of community health centers (X_1) which represents access to health facilities, coverage of antenatal care at first (X_2) and fourth (X_3) visits of pregnant women which reflects the intensity and quality of prenatal care, coverage of obstetric complication management (X_4) which indicates the capacity to handle pregnancy risks, and coverage of Iron Supplementation Tablets (IST) provision to pregnant women (X_5) which is important for the prevention of anemia. These variables were selected based on their potential influence on maternal mortality and are expected to provide significant insights into the factors affecting the maternal death rate in the region.

2.2 Poisson Regression Model

Poisson regression is a nonlinear regression model that assumes the response variable ($\boldsymbol{y}$) follows a Poisson distribution, which is a common approach for modeling count data, such as the number of events occurring within a specific period or region, often denoted by $\boldsymbol{y}$. The Poisson distribution is specifically utilized because of its ability to describe rare events where the mean value (μ) must always be positive [17]. Therefore, this model requires a link function, such as the logarithm, to connect the mean value to the independent variables, ensuring that the estimation of μ remains positive. As part of the Generalized Linear Models (GLM) category, Poisson regression facilitates analysis where the response variable is Poisson-distributed, and the use of this link function allows the model to accommodate nonlinear relationships between the independent and dependent variables [18].

GLM consists of three components: the random component, the systematic component, and the link function [4]. The random component comprises the variable $\boldsymbol{y}$, with independent observed values denoted as $(y_1, \dots, y_n)^T$. The systematic component of Generalized Linear Models (GLM) connects the vector

$\boldsymbol{\eta} = [\boldsymbol{\eta_1}, \boldsymbol{\eta_2}, \dots, \boldsymbol{\eta_n}]^{\boldsymbol{T}}$ with a set of predictor (p) variables through a linear model, $\boldsymbol{\eta}$ also referred to as a linear estimator, $\boldsymbol{\eta}$ can be written as **Equation (1)**.

$$\boldsymbol{\eta} = \boldsymbol{X\beta} \tag{1}$$

where $\boldsymbol{X}$ is the design matrix containing the values of the explanatory variables for n observations, and $\boldsymbol{\beta}$ is the vector of parameters within the model. Suppose μ_i is the mean of Y_i where $\mu_i = E(Y_i)$, for $i = 1,2,\dots,p$. The model connects μ_i with η_i through the relation $g(\mu_i) = \eta_i$, where g is a differentiable function. Thus, g links the expected value $E(Y_i)$ with the explanatory variables using the formula referred to as **Equation (2)**.

$$g(\mu_i) = \beta_0 + \beta_1 x_{11} + \dots + \beta_k x_{ik} = \beta_0 + \sum_{j=1}^{k} \beta_j x_{ij} \ , i = 1,2,\dots,n \tag{2}$$

In the Poisson regression model, the commonly used link function is the logarithm, hence $log(\mu_i) = \eta_i$. Consequently, the Poisson regression model can be written as **Equation (3)**.

$$ln(\mu_i) = \beta_0 + \sum_{j=1}^{k} \beta_j x_{ij} \, , i = 1,2,\dots,n \tag{3}$$

$$\mu_i = exp\left(\beta_0 + \sum_{j=1}^{k} \beta_j x_{ij}\right)$$

Parameter estimation for the Poisson regression model is conducted using the Maximum Likelihood Estimation (MLE) method and subsequently solved using the numerical iterative method of Newton-Raphson. The testing of parameters in the Poisson regression model employs the Maximum Likelihood Ratio Test (MLRT) **[10]**. A characteristic of the Poisson distribution is equidispersion, where the mean and variance of the response variable are equal. However, in practice, conditions are sometimes found where the variance of the data is greater than the mean. Such conditions are referred to as overdispersion **[9]**. Suppose overdispersion occurs in discrete data but the Poisson regression model is still used. In that case, the parameter estimates of the regression coefficients remain consistent but are not efficient due to the impact on high standard error values.

2.3 Negative Binomial Regression Model

The Negative Binomial Regression Model provides an analytical framework similar to Poisson regression for analyzing relationships between count data dependent variables and one or more predictor variables **[19]**. However, the negative binomial regression offers greater flexibility than the Poisson model because it does not constrain the data's variance to be equal to its mean. This becomes crucial, particularly in situations where the data exhibit overdispersion (the variance of the data exceeds the model's assumption). In negative binomial regression, the presence of an additional dispersion parameter allows the model to more accurately adjust to the real variability in the data, providing more reliable estimates for the regression coefficients. This dispersion parameter is essential in capturing and depicting variation in count data, which often occurs in biological phenomena or social processes **[20]**.

The Negative Binomial Regression Model is designed to address overdispersion in data that are Poisson-distributed by combining the Poisson and Gamma distributions. The negative binomial distribution is an extension of both, incorporating a dispersion parameter, θ, which is crucial for accommodating the extra variation unexplained by the standard Poisson model. The probability mass function of the negative binomial model, which integrates the Poisson-Gamma distribution, can be described using the negative binomial probability mass function. The dispersion parameter in this model, θ, allows for greater flexibility in modeling data with overdispersion, effectively overcoming the limitations of the Poisson. The negative binomial probability mass function illustrates the probability of the number of occurrences in a sample, accounting for a higher frequency of variability than typically expected under a simple Poisson model **[21].**

$$f(y, \mu, \theta) = \frac{\Gamma\left(y + \frac{1}{\theta}\right)}{\Gamma\left(\frac{1}{\theta}\right) y!} \left(\frac{1}{1 + \theta\mu}\right)^{\frac{1}{\theta}} \left(\frac{\theta\mu}{1 + \theta\mu}\right)^{y} , y = 0,1,2,\dots n \tag{4}$$

The Negative Binomial Regression Model is presented in **Equation (5)**.

$$\mu_i = \exp(\beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_k X_{ik}) \tag{5}$$

2.4 Geographically Weighted Poisson Regression Model

Spatial heterogeneity is caused by differences in characteristics among observation location points, and a necessary assumption for GWPR analysis is the presence of spatial heterogeneity **[22]**. Testing for spatial heterogeneity can be performed using the Breusch-Pagan Test statistics **[23]**. GWPR is a local form of Poisson regression that produces local parameter estimates for each location, considering the assumption that the data follows a Poisson distribution. In the GWPR model, the dependent variable y is predicted by independent variables, each of whose regression coefficients depend on the location where the data is observed. The GWPR model, noting the latitude and longitude coordinate vectors (u_i, v_i), is presented in **Equation (6) [24].**

$$E(Y_i) = \mu\big(x_i, \beta(u_i, v_i)\big) = \exp\left(x_i^T \beta(u_i, v_i)\right);\ i\ = 1,2, \dots, n \tag{6}$$

where Y_i is the observed value of the response variable for the i-th observation (i = 1,2,3,…,n), $\mu(x_i, \beta(u_i, v_i))$ is a function of x_i as the predictor variable, β are the regression parameters to be estimated, with $x_i^T = [x_{1i}, x_{2i}, \dots, x_{ki}]$, $\beta = [\beta_0, \beta_1, \beta_2, \dots, \beta_k]$, and (u_i, v_i) are the longitude and latitude coordinates of the i-th point at a geographic location (in Universal Transverse Mercator (UTM) units).

2.5 Kernel Weighting Function

The spatial weight matrix indicates proximity among observations. In the family of Geographically Weighted analyses, the weight matrix is derived using various types of kernel weighting functions. A kernel function, or $K(u)$, is a continuous, symmetric, bounded function, $\int_{\infty}^{\infty} K(u)du = 1$. Continuity implies that the sample point values are infinite, symmetry means the values are balanced, and boundedness means that the weighting function has limits from negative infinity to positive infinity **[25]**. The form of spatial weighting is a diagonal matrix, where its elements are a weighting function of each observation **[9]**. The basic concept of the kernel function weighting is based on a distance function presented in **Equation (7)**.

$$w_{ij} = \begin{cases} 1 & ,\text{if } d_{ij} < h \\ 0 & ,\text{if } d_{ij} \geq h \end{cases} \tag{7}$$

d_{ij} is the Euclidean distance between the i^{th} observation location and the j^{th} observation location, while h is the bandwidth **[26]**. The calculation of d_{ij} can be performed using **Equation (8)**.

$$d_{ij} = \sqrt{\left(u_i - u_j\right)^2 + \left(v_i - v_j\right)^2} \tag{8}$$

u_i represents easting in UTM units, and v_i represents northing in UTM units. Each type of kernel function will provide a different optimum bandwidth, the value of the bandwidth is obtained from iteration results. The optimum bandwidth is determined by comparing Cross-Validation (CV) values, using the formula presented in **Equation (9)**.

$$CV = \sum_{i=1}^{n} [y_i - \hat{y}_{\neq 1}(h)]^2 \tag{9}$$

$\hat{y}_{\neq 1}(h)$ is the estimated value of y_i with observations at the location (u_i, v_i) assigned a value of 0 in the estimation process, and n is the number of research samples. The optimum bandwidth is obtained from the minimum CV value. There are two types of kernel functions: Fixed and Adaptive. The Fixed kernel function obtains a single bandwidth value for all observation locations. In contrast, the Adaptive kernel function obtains different bandwidth values at each observation location by adjusting to the location. Each type of kernel function is further divided into several types, and the following are types of kernel function weighting formulas that can be used, presented in **Equations (10)** to **Equation (12) [26]**, **[27]**.

a. Gaussian Kernel

$$w_j(u_i, v_i) = exp\left(-\frac{1}{2}\left(\frac{d_{ij}}{h}\right)^2\right) \tag{10}$$

b. Bisquare Kernel

$$w_j(u_i, v_i) = \begin{cases} \left(1 - \left(\frac{d_{ij}}{h}\right)^2\right)^2 & , d_{ij} \leq h \\ 0 & , d_{ij} > h \end{cases} \tag{11}$$

c. Tricube Kernel

$$w_j(u_i, v_i) = \begin{cases} \left(1 - \left(\frac{d_{ij}}{h}\right)^3\right)^3 & , d_{ij} \leq h \\ 0 & , d_{ij} > h \end{cases} \tag{12}$$

d_{ij} the Euclidean distance between location i and location j, h_i the bandwidth for location i. Subsequently, w_{ij} will be used as weights to estimate parameters that exhibit spatial heterogeneity.

3. RESULTS AND DISCUSSION

3.1 Descriptive Statistical Analysis

The results of the descriptive statistical analysis to illustrate the number of maternal mortality in the districts/cities of West Java Province can be presented in **Figure 1** and **Table 1** below.

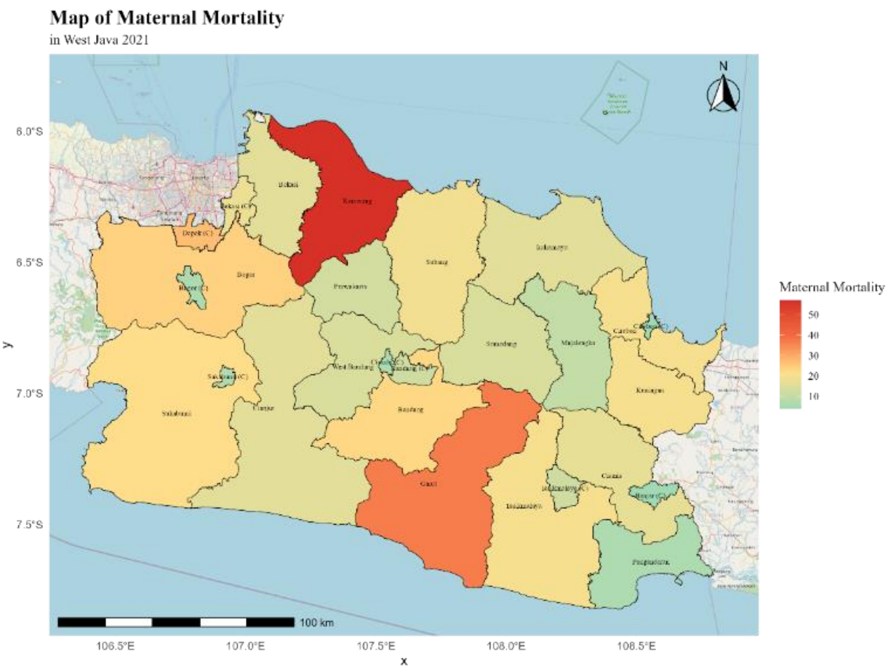

Figure 1. Map of Maternal Mortality in West Java, 2021.

In **Figure 1**, the presence of a "(C)" mark next to each name denotes that the area is classified as a city, whereas the absence of "(C)" indicates that the area is classified as a district.

Table 1. Descriptive Analysis of Each Variable

	Y	X_1	X_2	X_3	X_4	X_5
min	4.00	10.00	90.20	86.10	47.25	67.36
1stQu	11.00	23.50	100.40	96.35	84.84	95.45
median	16.00	38.00	103.70	98.60	100.00	97.55

	$\mathbf{Y}$	$\mathbf{X_1}$	$\mathbf{X_2}$	$\mathbf{X_3}$	$\mathbf{X_4}$	$\mathbf{X_5}$
mean	17.04	40.22	109.74	100.61	104.25	98.51
3stQu	20.00	49.50	109.45	101.00	129.67	100.65
Std.dev	11.06	20.87	20.57	11.72	27.95	12.33
max	57.00	101.00	189.90	144.20	150.04	144.19

Based on the data presented in **Figure 1** and **Table 1**, the average number of maternal deaths in the districts/cities of West Java Province is recorded at 17.04 cases. The distribution of data shows that the lowest number of maternal deaths is 4 cases, while the highest reaches 57 cases, with a median value of 16 cases. Further analysis indicates that the first quartile (Q1) of this data is 11 cases, while the third quartile (Q3) is 20 cases. When associated with independent variables, findings suggest that maternal deaths (Y) tend to be higher in districts/cities that have characteristics such as a larger number of community health center facilities and higher levels of first-visit and fourth-visit antenatal care, obstetric complication management, and coverage of IST provision. This is evident in districts like Karawang, Bogor, and Garut. This phenomenon indicates that despite the provision of adequate health facilities and services, the rate of maternal deaths remains high, suggesting the potential for other factors affecting maternal health outcomes that are not covered in the analyzed variables. This conclusion triggers the need for further investigation into other factors that may contribute to the high rate of maternal deaths in areas with relatively more health facilities and better health services, to understand the complex dynamics affecting maternal health outcomes in West Java.

3.2 Testing the Poisson Distribution on the Maternal Mortality Variable

In the context of this analysis, the Kolmogorov-Smirnov test is used to determine whether the dependent variable, the number of maternal deaths (Y) - follows a Poisson distribution, which is suitable for data about rare occurrences. The hypotheses for the Kolmogorov-Smirnov test are formulated as follows: H_0: the data on maternal deaths follow a Poisson distribution, and H_1: the data on maternal deaths do not follow a Poisson distribution. The Kolmogorov-Smirnov test is a non-parametric test that measures the fit between the empirical cumulative distribution of sample data and the expected cumulative distribution of the Poisson model. This test produces a D statistic, which is the maximum absolute difference between the two cumulative distribution functions. If the D value is statistically significant, it indicates that there is a significant difference between the observed distribution and the theoretical Poisson distribution, leading to the rejection of the null hypothesis.

Based on the results of the Kolmogorov-Smirnov test, a p-value of 0.177 was obtained, which is larger than the significance level of 5%. The resulting test statistic D is 0.250, which is smaller than the critical value $D_{0.05;27}$ for a sample size of 27 at a 5% significance level. According to these criteria, the null hypothesis stating that the data on maternal deaths follow a Poisson distribution cannot be rejected. This conclusion indicates that the Poisson distribution is a suitable model for describing the variability in the data of maternal deaths observed in West Java Province. Therefore, the Poisson regression model approach can be applied to analyze the relationship between the number of maternal deaths and the factors affecting it, allowing further analysis of the determinants of maternal mortality using an appropriate model according to the data distribution.

3.3 Poisson Regression Modeling

In the context of Poisson regression analysis, parameter testing can be conducted either simultaneously or partially. Simultaneous testing aims to assess the collective influence of all independent variables on the dependent variable. The hypotheses tested in the MLRT are as follows: $H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$ (Independent variables do not affect the dependent variable) while $H_1: \exists \beta_k \neq 0, k = 1, 2, 3, 4, 5$ (There exists $\beta_k \neq 0$ which means the independent variables have a simultaneous effect on the dependent variable). If the results of the MLRT indicate that we can reject the null hypothesis, it shows that at least one of the independent variables contributes significantly to the model, and therefore, affects the dependent variable. This testing is crucial to validate the presence of a combined effect of independent variables in the model and to ensure that the applied Poisson regression model is appropriate for the observed data.

Testing in Poisson regression consists of simultaneous and partial. Based on the simultaneous parameter testing of the Poisson regression model with $\alpha =$ 5% (0.05), a value of $D(\hat{\beta}) = 69.22$ was obtained, which is greater than $\chi^2_{(0.05;3)} = 7.81$. Therefore, the decision is made to reject the null hypothesis, concluding that all five independent variables X_1, X_2, X_3, X_4, and X_5 significantly affect the number of maternal deaths in West Java in 2021. Next, partial parameter testing aims to determine whether individual (partial) independent variables have an effect on the dependent variable. The hypothesis for partial testing for a specific k, where $k =$ 1, 2, 3, 4, 5, is H_0: $\beta_k = 0$ (the k-th variable has no significant effect) and H_1: $\beta_k \neq 0$ (the k-th variable has a significant effect) **[28]**. The results of partial testing after eliminating variables that were not significant are presented in **Equation (13)**.

$$\hat{\mu} = \exp(1.12 + 0.026X_1 - 0.043X_3 + 0.05X_5) \tag{13}$$

In the considered Poisson regression model, the effect of percentage changes in the independent variables on the likelihood of maternal mortality is explained through the estimated coefficients and interpreted as follows: (1) Every 1 percent increase in the number of Community Health Centers (X_1) is associated with an increase in the risk of maternal mortality by approximately $e^{0.026}$ ≈1.026, assuming other variables are constant. This indicates that more Puskesmas slightly increase the risk of maternal mortality, possibly due to hidden variables such as population density or the severity of health conditions not explicitly accounted for in the model. (2) A 1 percent increase in the coverage of K_4 services for pregnant women is associated with a decrease in the risk of maternal mortality to approximately $e^{-0.047} \approx 0.954$ times, assuming other variables are constant. This suggests that improving advanced antenatal care services can effectively reduce the risk of maternal mortality. (3) Every 1 percent increase in the coverage of iron tablet supplementation (ITS) is associated with an increase in the risk of maternal mortality by approximately $e^{0.054} \approx$ 1.05 times, assuming other variables are constant. This might indicate that in areas with high anemia rates, increased ITS coverage reflects greater health needs that are not yet fully addressed.

3.4 Examining Overdispersion in the Poisson Regression Model

To properly use the Poisson regression model, it is crucial to ensure that the assumption of equidispersion is met, meaning the mean and variance of the response variable should be equal under the Poisson distribution. To test this assumption, the ratio of the Pearson Chi-Square statistic to its degrees of freedom is utilized **[10]**. The hypotheses tested are: Null Hypothesis: There is no overdispersion in the Poisson regression model, and Alternative Hypothesis: There is overdispersion in the Poisson regression model. In this analysis, the dispersion parameter value resulting from the ratio of the Pearson Chi-Square statistic to its degrees of freedom is 3.050. Because this value is greater than 1, the null hypothesis is rejected, indicating the presence of overdispersion. Overdispersion suggests that the variance of the data is greater than that expected by the Poisson model, potentially due to additional variability in the data not accounted for by the current model.

In response to the findings of overdispersion, the step taken was to adopt the negative binomial regression model, which is more flexible in handling excessive variability by including a dispersion parameter. The initial step in negative binomial regression modeling involves determining initial values for the dispersion parameter θ, which is done through a trial-and-error process. The goal of this approach is to achieve a deviance-to-degrees-of-freedom ratio close to 1, indicating that the model is well-calibrated to the variability in the data **[29]**. The trial-and-error process for determining the initial θ value has resulted in several iterations crucial for determining the optimal parameter, presented in **Table 2.** In this context, the next step is to fit the negative binomial model with the determined θ value and retest for model fit to the data. This will be done through further evaluation of model fit and residual analysis to ensure that the new model accurately reflects the data distribution.

Table 2. Initial Value of θ

Initial θ	Deviance	DF	Deviance/DF
10.96	26.35	23	1.15
9.96	24.89	23	1.08
8.96	23.32	23	1.01
8.77	23.00	23	1

Based on **Table 2**, the initial θ that has a deviance-to-degrees-of-freedom ratio of 1 is 8.77. Therefore, the negative binomial regression modeling is conducted with an initial θ of 8.77.

3.5 Negative Binomial Regression Modeling

Testing in the negative binomial regression consists of testing the fit of the negative binomial regression model and partial parameter testing. The deviance test is used to test the fit of the negative binomial regression model. The hypotheses used are as follows: $H_0: \beta_1 = \beta_2 = \beta_3 = 0$ (The negative binomial regression model cannot be used as a model) and $H_1: \exists \beta_k \neq 0,\ k = 1, 2, 3$ (There exists $\beta_k \neq 0$ which means the negative binomial regression model can be used as a model). Using = 5% and the test statistic obtained $(\hat{\beta}) =$ 23 is greater than $\chi^2_{(0.05;3)} = 7.82$, the decision is to reject H_0, which means that the negative binomial regression model can be used as a model. The next step is partial testing to investigate which independent variable parameters significantly influence the dependent variable. The partial testing hypothesis for certain $k,\ k =$1, 2, 3 is $H_0: \beta_k = 0$ (the k-th variable has no significant effect) and $H_1: \beta_k \neq 0$ (the k-th variable has a significant effect). Based on the analysis results, the variables that have a significant effect on the dependent variable are X_1, X_3, X_5. The negative binomial regression model formed is in **Equation (14)**.

$$\hat{\mu} = \exp(1.08 + 0.03X_1 - 0.04X_3 + 0.05X_5) \tag{14}$$

The model above means that if X_1 increases by 1 percent, then the risk of maternal mortality will increase $exp(0.03)$ =1.027 times, assuming other variables are constant if Coverage of Fourth-visit Antenatal Care for Pregnant Women (X_3) increases by 1 percent, then the risk of maternal mortality will decrease to exp(-0.04) = 0.96 times compared, assuming other variables are constant. If the coverage of iron tablet supplementation (ITS) for pregnant women (X_5) increases by 1 percent, then the probability of death of pregnant women will increase to $exp(0.05) = 1.05$ times, assuming other variables are constant.

3.6 Geographically Weighted Poisson Regression (GWPR) Modeling

Before conducting GWPR modeling analysis, spatial testing is performed, specifically testing for spatial heterogeneity. The spatial heterogeneity test is used to determine whether spatial heterogeneity is present in the case study data. The method used in this test is the Breusch Pagan test **[13]**. This is because the Geographically Weighted Poisson Regression method is used to analyze spatial heterogeneity. The hypotheses used are H_0: $\sigma_1^2 = \sigma_2^2 = \sigma_3^2 = 0$ (no spatial heterogeneity) and $H_1: \exists_i,\ \sigma_i^2 \neq \sigma^2$ (spatial heterogeneity). Based on the test results, it was found that $p - value = 0.04$ and $BP_{score} = 8.2456$ so it was decided to reject H_0 because the $p - value = 0.04 < \alpha = 5\%$ and the $BP_{score} = 8.24 > \chi_{((0.05;3))^2} = 7.82$ which means spatial heterogeneity is present in the data.

The first step in performing the GWPR modeling is to form a weighting matrix (W_{ij}) by substituting the optimal bandwidth value and the Euclidean distance (d_{ij}) between locations (u_i, v_i). Calculating the Euclidean distance requires the easting (u_i) and northing (v_i) values of each Regency/City in West Java Province using the formula found in **Equation (8)**. After obtaining the Euclidean distance, the next step is to select the optimal bandwidth by looking at the minimum CV value. In this study, the researcher uses weighting functions from fixed and adaptive functions. Then, these six kernel functions will be compared based on the best Akaike information criterion (AIC), R^2, and Mean Absolute Percentage Error (MAPE) values **[30]**.

Table 3. Kernel Functions Comparison

Criteria		AIC	R^2	MAPE
Fixed Kernel	Gaussian	77.96	57.22%	41.31
	Bisquare	73.94	61.42%	40.15
	Tricube	77.13	59.01%	41.14
Adaptive Kernel	Gaussian	76.07	58.70%	40.79
	Bisquare	66.15	68.15%	37.70
	Tricube	69.41	65.64%	38.69

Based on the optimum AIC, R^2 and MAPE values, i.e. the minimum AIC value and the maximum R^2 value found in **Table 3**, the most suitable weighting for modeling is the adaptive kernel bisquare weighting, with a minimum CV value of 6866.201. The optimum weighting will obtain different bandwidth values as in **Table 4**.

Table 4. Optimum Bandwidth Value for Each Location

Location	***Bandwidth* (*h*)**	Location	***Bandwidth* (*h*)**	Location	***Bandwidth* (*h*)**
Bandung	116,888.6	Karawang	183,069.5	Tasikmalaya (C)	183,183.9
West Bandung	138,342.8	Bandung (C)	114,730.3	Kuningan	204,224.3
Bekasi	204,910.7	Banjar (C)	218,488.2	Majalengka	167,103.2
Bogor	218,488.2	Bekasi (C)	213,856.9	Pangandaran	227,197.8
Ciamis	200,617.5	Bogor (C)	213,880.4	Purwakarta	152,622.0
Cianjur	160,092.9	Cimahi (C)	125,642.2	Subang	135,296.9
Cirebon	198,348.8	Cirebon (C)	198,526.4	Sukabumi	207,980.0
Garut	149,386.8	Depok (C)	221,968.4	Sumedang	137,318.9
Indramayu	155,487.4	Sukabumi (C)	187,968.3	Tasikmalaya	186,368.3

After deriving the Euclidean distance value and optimum bandwidth value, the next step is to calculate the weighting function. The calculated weighting function forms a diagonal matrix showing different weightings at each location. The calculation of the weighting function uses the Euclidean distance and bandwidth values obtained previously, which are substituted into the adaptive bisquare kernel function formula in **Equation (15)**. The weight values differ for each location of observation, forming 27 different weighting matrices. Based on the calculations, the weighting matrix formed with the bisquare kernel function at the location (u_1, v_1) is as follows.

$$W(u_1,v_1) = diag[W_1(u_1,v_1),\ W_2(u_2,v_2),\dots,W_{27}(u_{27},v_{27})] = diag\left[\left(1-\left(\frac{0}{116888.6}\right)^2\right)^2\left(1-\left(\frac{31374.17}{138342.8}\right)^2\right)^2\cdots\left(1-\left(\frac{73601.71}{186368.3}\right)^2\right)^2\right] \quad (15)$$

The weighting matrix above is only used to estimate the parameters at the location (u_1, v_1), while to estimate the parameters at the location (u_2, v_2) it is necessary to first find the weighting matrix $W(u_2, v_2)$ following the same steps, until the last observation weighting matrix $W(u_{27}, v_{27})$. Next, we derived the summary of the GWPR model parameter estimates with the adaptive bisquare weighting function carried out using the Maximum Likelihood Estimation (MLE) method as follows.

Table 5. GWPR Model Estimates Summary

Variable	**Min**	**1st Qu**	**Median**	**3st Qu**	**Max**
Intercept	0.81	0.89	1.46	1.70	1.73
X_1	0.02	0.02	0.02	0.02	0.03
X_3	-0.06	-0.06	-0.04	-0.02	-0.01
X_5	0.02	0.03	0.05	0.06	0.07

Of the five variables, only three showed statistically significant effects; therefore, the study proceeded using these three variables. In the GWPR model, parameter estimation is done locally, implying that each location has unique parameter values. This allows the model to accurately reflect geographic and demographic inequalities in the analysis. **Table 5** presents summary statistics of the parameter estimates for each measured variable, providing insight into variations in their effects across locations. For example, for the variable (X_1), the estimated parameter values range from a minimum of 0.017 to a maximum of 0.025. This range shows variations in the influence of the number of community health centers on the maternal mortality rate in various districts/cities in West Java Province, with this value representing the expected change in the maternal mortality rate per unit change in the number of community health centers. Furthermore, the parameter distribution for variable X_1 is also explained through quartile statistics, where the value of the first quartile (Q1) is 0.021, the median is 0.0235, and the third quartile (Q3) is 0.024. This shows that most parameter estimates concentrate around the median of 0.023484, but still show significant variation between the lowest and highest locations. Similar interpretations are given for the other variables in the model, where each variable shows a different distribution pattern and range of values, according to the data presented in **Table 5**. This emphasizes the importance of local approaches in understanding the dynamics of maternal mortality, due to factors such as access to health services and the level of medical services that can vary significantly across provinces. Thus, the GWPR model provides a powerful framework for understanding and explaining regional differences in factors influencing maternal mortality, accommodating local heterogeneity in statistical models for more accurate and meaningful results in the context of health policies and interventions.

There are three steps in carrying out GWPR testing, consisting of testing the similarity of the negative binomial regression model and GWPR, testing the fit of the GWPR model, and partial testing of the GWPR model [5]. Firstly, the GWPR model similarity test was carried out to investigate whether there is a significant difference between the negative binomial regression model and GWPR with $H_0: (\beta_k(u_i, v_i)) = \beta_k$; $i = 1, 2, \dots, 27$; $k = 0,1,2,3$ (There is no significant difference between the negative binomial regression model and the GWPR model) and $H_1: \exists(\beta_k(u_i, v_i)) \neq \beta_k$; $i = 1, 2, \dots, 27$; $k = 0,1,2,3$ (There is a significant difference between the negative binomial regression model and the GWPR model) which is presented in **Table 6**.

Table 6. Similarity Test of the Negative Binomial Regression and GWPR models

Variable	Deviance	df	Deviance/df	F_{score}
Negative Binomial Regression Model	23	23	1	0.38
GWPR model	51.60	19.66	2.62	

Using $\alpha = 5\%$, the test statistic obtained, $F_{score} = 0.38 < F_{(0.05;23;20)} = 2.09$, thus the decision is made to fail to reject H_0, inferring that there is no significant difference between the negative binomial regression model and the GWPR model. Next, a fit test for the GWPR model is conducted to determine if the parameters have significant effects, with the hypothesis presented in Equation (16).

$$H_0: (\beta_1(u_i, v_i)) = \beta_2(u_i, v_i) = \cdots = \beta_{27}\,(u_i, v_i) = 0 \; and \; H_1: \exists\left(\beta_j(u_i, v_i)\right) \neq 0 \tag{16}$$

The null hypothesis (H_0) explains that all parameters of the model have no effect, while the alternative hypothesis (H_1) states that there exists j such that $\beta_j(u_i, v_i) \neq 0$ (at least one model parameter has a significant effect) with $i = 1, 2, \dots, 27$ and $j = 0,1,2,3$. Using $\alpha = 5\%$ (0.05) and the test statistic obtained, $D(\hat{\beta}) = 51.\,60 > \chi^2_{(0.05;20)} = 31.41$, the decision is made to reject H_0, inferring that at least one parameter significantly affects the model.

Further, the parameters of the GWPR model will be tested partially to determine which independent variables significantly affect the dependent variable at each observation location i.e. district/city in the West Java Province. This testing is done using the hypothesis $H_0: \beta_k(u_i, v_i) = 0$; $i = 1,2, \dots, 27$; $j = 1,2,3$ (independent variables have no effect on the dependent variable) and $H_1: (\beta_k(u_i, v_i) \neq 0$; $i = 1,2, \dots, 27$; $j = 1,2,3$ (Independent variables have an effect on the dependent variable). Partial testing of the GWPR model parameters using the adaptive bisquare weighting function with α = 5% (0.05) involves examining the t-value at each observation location and comparing them with $t_{(0.025;23)} = 2.07$. If the calculated $t_{value} > t_{(0.025;23)}$ then the decision is made to reject H_0, indicating an effect of independent variables on the dependent variable. Based on the parameters of significant partial effect of independent variables in each district/city, the GWPR modeling results using the adaptive bisquare weighting function form 3 groups presented in **Table 7**.

Table 7. Location Groups Based on Variable Significance from the GWPR Model

Groups	Significant Variables	Regency/City
1	X_1	Bandung, Ciamis, Garut, Banjar City, Tasikmalaya City, Pengandaran, Tasikmalaya
2	X_1, X_3, and, X_5	West Bandung, Bekasi, Bogor, Cianjur, Cirebon, Indramayu, Karawang, Bandung City, Bekasi City, Bogor City, Cimahi City, Cirebon City, Depok City, Sukabumi City, Majalengka, Purwakarta, Subang, Sukabumi, Sumedang
3	X_1 dan X_5	Kuningan

The thematic map of location groups based on variables significant to maternal mortality using GWPR adaptive kernel bisquare is displayed in **Figure 2**.

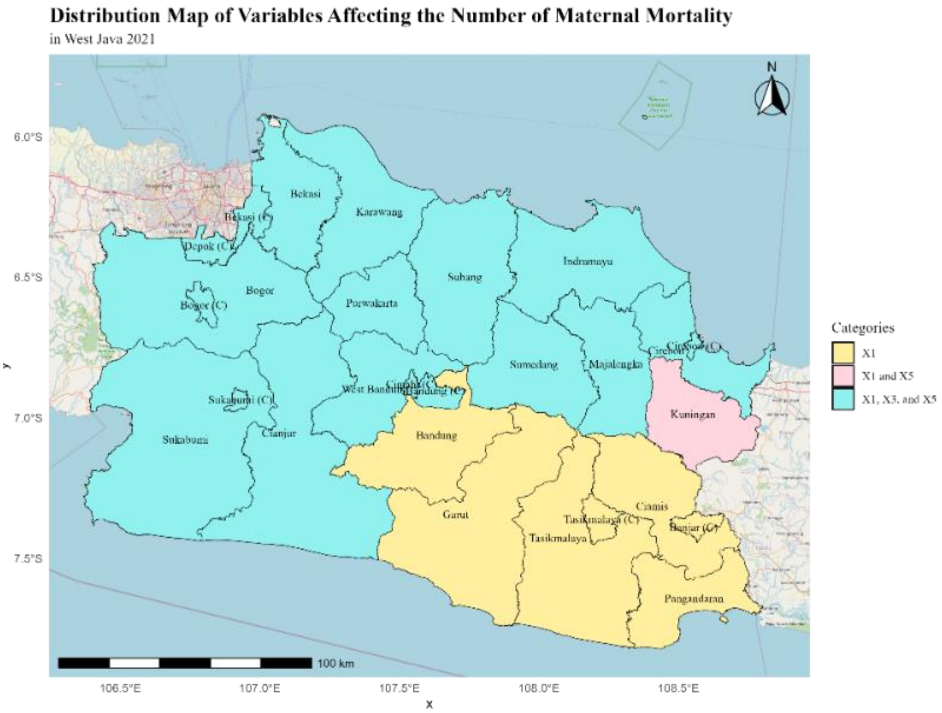

Figure 2. **Map of Regency/City Groups Based on Variables Affecting Maternal Mortality**

The GWPR model with the formed bisquare adaptive kernel weighting function can be seen as follows. For example, the GWPR model was obtained for the Bandung Regency.

$$\hat{\mu}_{(Bandung\ Regency)} = \exp(1.02 + 0.02X_1 - 0.01X_3 + 0.02X_5) \tag{17}$$

The model above means that if the number of Community Health Centers (X_1) increases by 1 percent, then the probability of death of pregnant women will increase by $exp(0.02) = 1.02$ times. This means there is an increase of around 1.8% in the risk of maternal mortality, assuming other variables are constant. If Coverage of the Fourth visit Antenatal Care for Pregnant Women (X_3) increases by 1 percent, the probability of death of pregnant women will decrease to $exp(-0.01) = 0.10$ times. This means there is a decrease of around 0.8% in the probability of maternal death compared to before assuming other variables are constant. Finally, if the coverage of giving ITS pregnant women increases by 1 percent, then the risk of maternal mortality will increase to $exp(0.02) = 1.02$ times. This means there is an increase of around 1.9% in the probability of maternal death, assuming other variables are constant. Next, the best model is determined.

Determining the best model aims to find the right model for the data on the number of maternal deaths in West Java Province in 2021 by comparing the Poisson regression model, negative binomial regression, and GWPR. The best model is determined by the criteria of optimum MAPE, AIC, and adjusted-R^2 values. The results obtained are as **Table 8**.

Table 8. Values of the MAPE, AIC, and R^2 Criteria.

Model	**MAPE**	**MSE**	**RMSE**	**AIC**	***Adjusted-R^2***
Poisson Regression	41.65	59.60	7.72	200.98	42.78%
Negative Binomial Regression	40.18	62.89	7.93	180.04	39.62%
GWPR	37.70	38.36	6.19	66.15	63.17%

After considering all metrics based on **Table 8**, the GWPR model was identified as the most appropriate model for modeling maternal mortality data in West Java Province in 2021. This model shows the optimal combination of prediction accuracy, efficiency, and ability to explain variations in the data, therefore, it can be used for further analysis and policy-making purposes.

4. CONCLUSIONS

This study investigates the factors influencing maternal mortality rates in West Java Province in 2022 using the Geographically Weighted Poisson Regression (GWPR). Three variables were found to significantly impact maternal mortality: 1) the number of community health centers, 2) coverage of antenatal care at fourth visits of pregnant women, and 3) the coverage of Iron Supplementation Tablets (IST) provision to pregnant women. The GWPR model with an adaptive bisquare kernel weighting function was shown to be the most effective model, based on the evaluation metrics, with a Mean Absolute Percentage Error (MAPE) of 37.7%, Mean Square Error of 38.36, and the lowest AIC value compared to other regression models. The GWPR model generates localized parameter estimates for each observation point or location. By examining the significant partial effects of independent variables across districts/cities, the results reveal three distinct groups based on influential variables when using an adaptive bi-square weighting function. Specifically, Group 1 is influenced solely by X_1; Group 2 by by X_1, X_3, and X_5; and Group 3 by Group 3 by X_1 and X_5.

REFERENCES

[1] Dinas kesehatan Jawa Barat, "Profil kesehatan Jawa Barat tahun 2021," Jawa Barat, 2022.

[2] Direktorat Jenderal Kesehatan Masyarakat Kementerian Kesehatan Direktorat Jenderal Kesehatan Masyarakat Kementerian Kesehatan, *Rencana aksi program kesehatan masyarakat tahun 2020-2025*. 2020.

[3] Kementerian kesehatan republik Indonesia, "Profil kesehatan Indonesia," Jakarta, 2022.

[4] M. T. Ruiz-Cantero, M. Guijarro-Garvi, D. R. Bean, J. R. Martínez-Riera, and J. Fernández-Sáez, "Governance commitment to reduce maternal mortality. A political determinant beyond the wealth of the countries," *Health Place*, vol. 57, pp. 313–320, May 2019, doi: 10.1016/j.healthplace.2019.05.012.

[5] P. R. Chaniago, D. Devianto, and I. R. HG, "Analisis faktor risiko angka kematian angka kematian ibu dengan pendekatan regresi poisson," *Jurnal Matematika UNAND*, vol. VII, no. 2, pp. 126–131, 2018.

[6] S. Martafiyah, C. Supriadi, and T. Saifudin, "Modeling the maternal mortality rate in Indonesia using geographically weighted Poisson Regression approach," 2023, p. 080011. doi: 10.1063/5.0181066.

[7] M. Syairaji, D. S. Nurdiati, B. S. Wiratama, Z. D. Prüst, K. W. M. Bloemenkamp, and K. J. C. Verschueren, "Trends and causes of maternal mortality in Indonesia: a systematic review," *BMC Pregnancy Childbirth*, vol. 24, no. 1, p. 515, Jul. 2024, doi: 10.1186/s12884-024-06687-6.

[8] R. Dewi Puspita Sari, D. Wulan Sumekar Rengganis Wardani, S. Bakri, and H. Busman, "Kurdish Studies Indonesian Maternal Mortality: A Systematic Review of Three-Level Determinants 1992-2024," no. 2, pp. 2051–4883, 2024, doi: 10.58262/ks.v12i2.154.

[9] L. Paulo Fávero, H. Luiz Corrêa, and M. F. C Haddad, "Count Data Regression Analysis: Concepts, Overdispersion Detection, Zero-inflation Identification, and Applications with R," vol. 26, 2021, doi: https://doi.org/10.7275/44nn-cj68.

[10] R. E. Caraka and H. Yasin, *Geographically weighted regression (GWR) sebuah pendekatan regresi geografis*. MOBIUS, 2017.

[11] D. C. Wheeler, "Geographically weighted regression," in *Handbook of regional science*, Springer, 2021, pp. 1895–1921.

[12] A. Poliart, F. Kirakoya-Samadoulougou, M. Ouédraogo, P. Collart, D. Dubourg, and S. Samadoulougou, "Using geographically weighted Poisson regression to examine the association between socioeconomic factors and hysterectomy incidence in Wallonia, Belgium," *BMC Womens Health*, vol. 21, no. 1, p. 373, Dec. 2021, doi: 10.1186/s12905-021-01514-y.

[13] H. Helmy, M. T. Kamaluddin, I. Iskandar, and Suheryanto, "Investigating spatial patterns of pulmonary tuberculosis and main related factors in Bandar Lampung, Indonesia using geographically weighted poisson regression," *Trop Med Infect Dis*, vol. 7, no. 9, p. 212, Aug. 2022, doi: 10.3390/tropicalmed7090212.

[14] S. Martafiyah, C. Supriadi, and T. Saifudin, "Modeling the maternal mortality rate in Indonesia using geographically weighted Poisson Regression approach," 2023, p. 080011. doi: 10.1063/5.0181066.

[15] D. S. Nur Fajarini, Y. S. Dewi, and M. Fatekurohman, "Comparison of geographically weighted artificial neural network and geographically weighted generalized poisson regression on crime cases in East Java Indonesia," *SAR Journal - Science and Research*, pp. 19–23, Mar. 2024, doi: 10.18421/SAR71-03.

[16] T. Saifudin, Nur Rahmah Miftakhul Jannah, Risky Wahyuningsih, and Gaos Tipki Alpandi, "Geographically weighted poisson regression for modeling the number of maternal deaths in Papua province," *Jurnal Aplikasi Statistika & Komputasi Statistik*, vol. 16, no. 1, pp. 32–42, Jun. 2024, doi: 10.34123/jurnalasks.v16i1.598.

[17] R. A. J. Taylor, "Spatial pattern," in *Taylor's Power Law*, Elsevier, 2019, pp. 13–25. doi: 10.1016/B978-0-12-810987-8.00002-1.

[18] A. Agresti, *An Introduction to Categorical Data Analysis: Third Edition*. Wiley, 2019. [Online]. Available: http://www.wiley.com/go/wsps

[19] P. Schober and T. R. Vetter, "Count data in medical research: poisson regression and negative binomial regression," *Anesth Analg*, vol. 132, no. 5, pp. 1378–1379, May 2021, doi: 10.1213/ANE.0000000000005398.

[20] R. Muntafiah, R. Wasono, and M. Y. Darsyah, "Pemodelan regresi binomial negatif untuk mengatasi overdispersion pada regresi poisson," *Statistika*, vol. 2, no. 1, pp. 40–45, May 2014.

[21] X. Zhang, M. Kano, M. Tani, J. Mori, and K. Harada, "Defect Data Modeling and Analysis for Improving Product Quality and Productivity in Steel Industry," 2018, pp. 2233–2238. doi: 10.1016/B978-0-444-64241-7.50367-0.

[22] Y. Li and K. Zhu, "Spatial dependence and heterogeneity in the location processes of new high-tech firms in Nanjing, China," *Papers in Regional Science*, vol. 96, no. 3, pp. 519–536, Aug. 2017, doi: 10.1111/pirs.12202.

[23] P. Purhadi and H. Yasin, "Mixed geographically weighted regression model (case study: The percentage of poor households in Mojokerto 2008)," *European Journal of Scientific Research*, vol. 69, no. 2, pp. 188–196, 2012, [Online]. Available: http://www.europeanjournalofscientificresearch.com

[24] K. Kopczewska, *Applied Spatial Statistics and Econometrics*. Routledge, 2020. doi: 10.4324/9781003033219.

[25] R. E. Walpole, R. H. Myers, S. L. Myers, and K. Ye, *Probability & statistics for engineers & scientists*, Ninth Edition. London: Pearson Education, 2016.

[26] A. Djuraidah, *Monograph penerapan dan pengembangan regresi spasial dengan studi kasus pada kesehatan, sosial, dan ekonomi*. Bogor: IPB Press, 2020.

[27] A. Djuraidah and R. Anisa, *Analisis statistika untuk data geospasial: dengan ilustrasi penerapan menggunakan R*. Bogor: IPB Press, 2023.

[28] E. H. Briliant, M. Hasan, and S. Kurniawan, *Perbandingan regresi linier berganda dan regresi buckley-james pada analisis survival data tersensor kanan*, vol. 1, no. 1. 2019.

[29] F. Mudia Sari, H. Frananda Nasution, and P. Robinson Sihombing, "Pemodelan jumlah kematian bayi dengan geographically weighted negative binomial regression," *Lombok Journal of Science (LJS)*, vol. 3, no. 2, 2021.

[30] D. Chicco, M. J. Warrens, and G. Jurman, "The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation," *PeerJ Comput Sci*, vol. 7, p. e623, 2021.