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Geographically Weighted Poisson Regression for Modeling The Number of Maternal Deaths in Papua Province

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Abstract

Introduction/Main Objectives: Maternal Mortality Rate (MMR) in Indonesia is one of the main focuses in achieving the third Sustainable Development Goals (SDGs) in 2030. **Background Problems:** The Central Statistics Agency states that the MMR in Papua Province is the highest, reaching 565. **Novelty:** Given the diverse geographical conditions of each district/city in Papua Province, an analysis was carried out. **Research Methods:** Using the Geographically Weighted Poisson Regression (GWPR) method with the response variable being maternal mortality rates and variables predictors of health, social, and environmental factors. **Finding/Results:** Fixed Gaussian kernel GWPR is the best model with an AIC value of 27.6. Variable significantly influencing MMR include the percentage of households with access to adequate sanitation, the number of recipients of food assistance programs, and the number of doctors.

1. Introduction

One of the indicators of societal welfare in a country is a low maternal mortality rate (MMR). However, so far, maternal mortality cases in Indonesia remain relatively high compared to neighboring countries. According to data from the Indonesian Health Commission in 2022, the maternal mortality rate was around 183 per 100,000 live births, which is significantly higher compared to Malaysia, with an MMR of 20 per 100,000 live births. The data shows that the number of maternal deaths in 2023 increased to 4,129 compared to 4,005 in 2022. The Indonesian Ministry of Health recorded that the Maternal Mortality Rate (MMR) is still around 305 per 100,000 live births, not yet reaching the target of 183 per 100,000 live births by 2024. This certainly poses a barrier to achieving the third SDG, which is good health and well-being.

Papua is one of the provinces in Indonesia that faces complex health issues. According to a publication by the Ministry Health in 2022, Papua has the highest maternal mortality rate in Indonesia [1]. The 2021 report from the Indonesian Ministry of Health indicated that Papua's maternal mortality ratio was 305 per 100,000 live births, significantly higher than the national average of 102 per 100,000 live births. On the other hand, Papua also has heterogeneous geographical and socio-economic conditions, meaning not all areas in Papua face the same health problems. Therefore, a statistical modeling approach that accounts for spatial variability in factors affecting maternal mortality in Papua is needed.

Previous research on maternal mortality risk factors was conducted by Rachmah et al. in 2014 using Poisson regression [2]. The results of this study indicated that the Poisson regression analysis encountered overdispersion, and no measures were taken to address the overdispersion issue. Additionally, the significant influence of predictor variables obtained was not relevant to the existing facts because the predictor variables used lacked variability.

The novelty of this research lies in the use of Geographically Weighted Regression (GWR) in modeling the number of maternal deaths. GWR is used in modeling maternal mortality rates to allow for spatially varying regression parameter estimates [3] . However, the assumption of a Gaussian distribution for the response variable in GWR does not always hold in practice, leading to the development of research aims to contribute to achieving the third SDG, which is to improve health and well-being by reducing maternal mortality rates and increasing access to quality healthcare services in Papua Province.

2. Material and Methods

2.1 Maternal Mortality

The Maternal Mortality Ratio (MMR) is the number of women who die from causes related to pregnancy or its management (excluding accidents, suicide, or incidental cases) during pregnancy, childbirth, and the postpartum period (42 days after childbirth) per 100,000 live births.

Maternal mortality, as defined by the International Classification of Diseases 11th (ICD-11), is the death of a woman while pregnant or within 42 days of termination of pregnancy, regardless of the duration and location of the pregnancy, from any cause related to or aggravated by the pregnancy or its management but not from accidental or incidental causes [4].

2.1.1 Factors Influencing Maternal Mortality

Factors contributing to maternal mortality can broadly be categorized into direct and indirect causes. Direct causes of maternal mortality are factors related to complications of pregnancy, childbirth, and the postpartum period, such as hemorrhage, preeclampsia/eclampsia, infection, obstructed labor, and abortion. Indirect causes of maternal mortality include factors that exacerbate the condition of pregnant women, such as the four "too's" (too young, too old, too frequent childbirth, and too close spacing between births).

Additionally, maternal mortality is influenced by pregnant women suffering from infectious diseases such as malaria, HIV/AIDS, tuberculosis, and syphilis; non-communicable diseases such as hypertension, diabetes mellitus, heart disease, mental disorders, and malnutrition [5].

Medical factors such as Hemoglobin (Hb) levels are significant in increasing the risk of maternal mortality. Anemia in pregnant women increases the relative risk of maternal mortality by 15.3 times compared to non-anemic pregnant women. A delay in decision-making also increases the risk of maternal mortality by 50.8 times compared to women who do not experience referral delays [6].

Health service factors, such as delays in medical treatment, can increase the risk of maternal mortality. Referral hospitals may face shortages of blood supplies and medical procedures may be delayed due to the absence of specialists.

2.2 Data and Data Source

The data used is secondary data, specifically the Health Profile Data of Papua Province. This data was obtained from publications by the Papua Provincial Health Office in 2021, with the unit of observation being the regencies/cities in Papua Province.

2.3 Research Variables

The research variables used are defined as follows:

1. The number of maternal deaths by age group in Papua Province in 2021 (Y)
2. The number of families actively participating in the Family Planning (Keluarga Berencana/KB) program in Papua Province in 2021 (X_1)
3. The percentage of households with access to adequate sanitation in Papua Province in 2021 (X_2)
4. The realization of the number of recipients of food Social Assistance (Bantuan Sosial/Bansos) in Papua Province in 2021 (X_3)
5. The number of health workers (doctors) in Papua Province in 2021 (X_4).

2.4 Multicollinearity

Multicollinearity in a regression model can be determined using the Variance Inflation Factor (VIF), which is expressed in the following equation:

$$VIF_j = \frac{1}{1-R_j^2} \tag{1}$$

Where $R_j^2 = \frac{SSR}{SST} = \frac{\sum_{i=1}^{n}(\hat{X}_{ij}-\underline{X}_{ij})^2}{\sum_{i=1}^{n}(X_{ij}-\underline{X}_{ij})^2}$. SSR (Sum SSR (Sum of Squares Regression) represents the variation caused by the relationship between predictor variables. SST (Sum of Squares Total) is a measure of the variation in the values of *X* from their mean. X_{ij} is the value of X_j in the ith observation, $\underline{X}_j$ is the mean value of X_j and $\hat{X}_j$ is the predicted value of X_j in the ith observations [7].

2.5 Poisson Regression Model

Poisson regression is used to analyze discrete data, where the response in the data follows a Poisson distribution with parameter μ. The Poisson distribution is then used to model an event that is relatively rare or uncommon to occur within a certain unit of observation.

The Poisson regression model can be expressed as follows:

$$E(y_i) = \mu(x_i, \beta) = exp\ exp\ (x_i^T \beta) \tag{2}$$

With $x_i^T = (x_{1i}, x_{2i}, \ldots, x_{ki})$ and $\beta = (\beta_1, \beta_2, \ldots, \beta_k)^T$. Function $\mu(x_i, \beta)$ In the Poisson regression model, it is a function of x_i as the predictor variable and β as the regression parameter to be estimated [8].

One of the methods for estimating Poisson regression parameters is Maximum Likelihood Estimation (MLE). Finding the likelihood equation from the probability mass function of the Poisson distribution is:

$$lnL(\beta) = ln\ ln\ \frac{exp\left(-\sum_{i=1}^{n} exp\ exp\ (x_i^T\beta)\right)\left(exp\left(\sum_{i=1}^{n} y_i x_i^T \beta\right)\right)}{\prod_{i=1}^{n} y_i!}$$
$$= -\sum_{i=1}^{n} exp\ exp\ (x_i^T\beta) + \sum_{i=1}^{n} y_i x_i^T \beta - \sum_{i=1}^{n} ln(y_i) \tag{3}$$

The equation is derived concerning β^T, which is in vector form, as it involves multiple parameters in this case.

$$\frac{\partial ln ln\ L(\beta)}{\partial \beta^T} = -\sum_{i=1}^{n}(x_i^T\beta) + \sum_{i=1}^{n} y_i x_i \tag{4}$$

The equation is equated to zero and then solved using the Newton-Raphson iteration. The iteration stops when the parameter estimates converge [9].

2.6 Geographically Weighted Poisson Regression Model (GWPR)

Geographically Weighted Poisson Regression (GWPR) is a local form of Poisson regression that produces locally parameterized model estimates for each point or observation location assuming Poisson-distributed data [10][11]. The GWPR model can be written as:

$$E(y_i) = \mu\left(x_i, \beta(u_i, v_i)\right) = exp\ exp\ \left(x_j^T \beta\left(u_j, v_j\right)\right)\ , for\ i = 1,2, \dots, n \quad (5)$$

With $x_i^T = (x_{1i}, x_{2i}, \dots, x_{ki})$ and $\beta = (\beta_1, \beta_2, \dots, \beta_k)^T$. The function $\mu\left(x_i, \beta(u_i, v_i)\right)$ in the Poisson regression model is a function of x_i as the predictor variable and β as the regression parameter to be estimated.

The GWPR model parameters can be estimated using the MLE method, resulting in the equation:

$$lnL(\beta) = -\sum_{i=1}^{n} exp\ exp\ \left(x_i^T \beta\right) + \sum_{i=1}^{n} y_i x_i^T \beta - \sum_{i=1}^{n} ln(y_i)! \quad (6)$$

Spatial factors, such as geographic location, act as weighting factors in the GWPR model. These factors have different values for each region, indicating the local nature of the model. Therefore, the weighting is incorporated into the log-likelihood form of the GWPR model, thus obtained:

$$ln\ L^*(\beta(u_i, v_i)) = \sum_{j=1}^{n} \left(y_j x_j^T \beta(u_i, v_i) - exp\ exp\ \left(x_j^T \beta(u_i, v_i)\right) - ln\ ln\ y\ _j!\right) w_{ij}(u_i, v_i) \ (2.8)(7)$$

Then, the estimation of the parameter $\beta(u_i, v_i)$ is obtained by differentiating the equation, leading to:

$$\frac{\partial lnL^*(\beta(u_i, v_i))}{\partial \beta^T(u_j, v_j)} = \sum_{j=1}^{n} \left(y_j x_j - x_j exp\left(x_j^T \beta\left(u_j, v_j\right)\right)\right) w_{ij}(u_i, v_i) \quad (8)$$

The equation is equated to zero and then solved using the Newton-Raphson iteration. The iteration stops when the parameter estimates converge [12].

2.7 Partial Parameter Significance Testing

Model parameter testing is conducted by testing parameters individually. This test aims to determine which parameters significantly affect the response variable with the hypothesis:

$H_0 :\ \beta_k(u_i, v_i) = 0\ ; i = 1,2, \dots, n\ ; k = 1,2, \dots, p$

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

In the hypothesis test above, the following test statistics can be used:

$$t = \frac{\beta_k(u_i, v_i)}{se(\beta_k(u_i, v_i))} \quad (9)$$

The value of $se\left(\beta_k(u_i, v_i)\right)$ or the standard error of $\beta_k(u_i, v_i)$ is obtained by taking the square root of $var\left(\beta_k(u_i, v_i)\right)$

$$se\left(\beta_k(u_i, v_i)\right) = \sqrt{var\left(\beta_k(u_i, v_i)\right)} \quad (10)$$

The testing criterion is to reject H_0 if $|t_{count}| > t_{\frac{\alpha}{2};n-(p+1)}$

2.8 Model Goodness-of-Fit Test

Model goodness-of-fit is performed to compare the global goodness-of-fit with the model considering spatial elements. One method used to select the model is Akaike's Information Criterion (AIC), which can be defined as follows:

$$AIC(h) = D(h) + 2K(h) \quad (11)$$

Where $D(h)$ is the deviance value of the model with bandwidth h, and $K(h)$ is the number of parameters in the bandwidth model.

2.9 Analysis Procedures

The steps of data analysis conducted are as follows:

1. Describing the Maternal Mortality Rate (MMR) in Papua Province and the various influencing variables.
2. To understand the description of regencies/cities in Papua Province based on the research variables, thematic maps of Papua Province are used to describe the dependent variable (Y) and the predictor variables from a regional perspective.
3. Analyzing the Poisson distribution assumption on the dependent variable.
4. Conducting a Multicollinearity test with the criterion that if the Variance Inflation Factor (VIF) value exceeds 10, multicollinearity is indicated.
5. Conducting Poisson regression modeling.
   a. Estimating the parameters of the Poisson regression model.
   b. Conducting a simultaneous test of Poisson regression parameters using the Maximum Likelihood Ratio Test (MLRT).
   c. Conducting a partial test of Poisson regression parameters with the criterion $|Z_{count}| > Z_{\alpha/2}$.
6. Analyzing the GWPR model as follows:
   a. Calculating the Euclidean distance between observation locations based on geographic positions. The Euclidean distance between location i at coordinates (u_i, v_i) toward location j at coordinates (uj, vj).
   b. Sorting the Euclidean distances of all locations relative to location i to obtain the nearest neighbor order of location i.
   c. Determining the optimal bandwidth.
   d. Calculating the weighting matrix using the kernel weighting function.
   e. Estimating the parameters of the GWPR model.
   f. Testing the significance of the GWPR regression model parameters partially.
   g. Calculating the AIC value of the GWPR model.
   h. Testing the model fit between the Poisson regression model and the GWPR model using the deviance values of each model and calculating the $F_{count.}$
7. Determining the best model between Poisson Regression, GWPR-Fixed Bisquare, and GWPR-Fixed Gaussian based on the smallest AIC value. AIC is chosen as the criterion for the best model selection as it measures the quality of the model by balancing model fit and data complexity [13].
8. Concluding to achieve the research objectives

3. Result and Discussion

3.1 Data Description

Before conducting further analysis, a simple analysis with descriptive statistics was performed. Descriptive statistics methods are used to get a general overview of the data. used. The following are the results of the descriptive statistics as shown in Table 1.

Table 1. Descriptive Statistics Results

Variable	Mean	Std.Dev	Min	Max
$\boldsymbol{Y}$	5.4	3.089	1	10
$\boldsymbol{X_1}$	9264	12280	76	50876
$\boldsymbol{X_2}$	53.39	28.34	2.67	85.8
$\boldsymbol{X_3}$	13011	10036	2327	42948
$\boldsymbol{X_4}$	76.3	98.4	5	393

In Table 1, it can be seen that the average number of maternal deaths *(Y)* in 15 regencies/cities in Papua Province is 5.4. This figure means that there are at least 5 maternal deaths per 100,000 live births in each regency/city in Papua Province. However, this result only represents a portion of the regions in Papua Province, as other regions did not report these cases to the local authorities. In Figure 1, it is shown that the highest number of maternal deaths reaches 10 in Merauke City and Biak Numfor Regency. Meanwhile, the lowest number of maternal deaths is 1, found in Puncak Jaya Regency and Supiori Regency. Furthermore, the number of families actively participating in the Family Planning (Keluarga Berencana/ KB) program (X_1), the number of food Social Assistance (Bantuan Sosial/Bansos) recipients (X_3), and the number of health workers (doctors) (X_4) are 138,959, 195,161, and 1,145, respectively. The average percentage of households with access to adequate sanitation (X_2) is 53.39%. The descriptive statistics results above generally show that the health, environmental, and social sectors in Papua Province are relatively low.

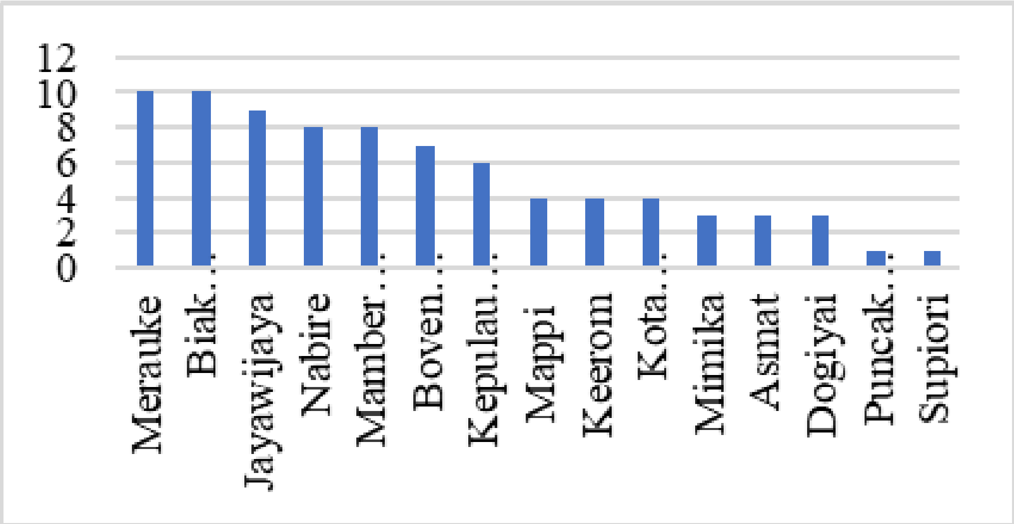

Figure 1. The Distribution of Maternal Mortality Rates in Papua Province 2021

3.2 Poisson Distribution Assumption of the Dependent Variable

The GWPR (Geographically Weighted Poisson Regression) modeling assumes that the dependent variable (Y_i) must follow a Poisson distribution. Therefore, a test was conducted on the variable Y, which represents the number of maternal deaths in Papua Province for each district/city. The following are the results of the Poisson distribution test.

Table 2. Results of the Poisson Distribution Test

DF	*Chi-Square*	*P-Value*
2	4.92993	0.085

Based on Table 2, a *p-value* of 0.085 was obtained, leading to the decision to accept H_0. It can be concluded that the maternal mortality data per district/city in Papua Province follows a Poisson distribution. Therefore, the variable Y_i meets the assumption and can proceed to the multicollinearity assumption test.

3.3 Multicollinearity Test

One of the criteria that must be met in conducting Poisson regression analysis is the detection of multicollinearity. The presence of multicollinearity can be determined based on the Variance Inflation Factor (VIF) values. A VIF value for any predictor variable exceeding 10 indicates the presence of multicollinearity. The following are the results of the multicollinearity test.

Table 3. VIF Values of Predictor Variables

Variables	VIF
X_1	3.329252
X_2	1.610570
X_3	4.312278
X_4	1.158255

Based on Table 3, it is concluded that none of the predictor variables indicate the presence of multicollinearity, as all VIF values are less than 10. Therefore, the analysis can proceed with Poisson regression and GWPR modeling.

3.4 Poisson Regression Modeling

The following are the estimated parameter values for the Poisson regression model.

Table 4. Parameter Estimates for the Poisson Regression Model

Parameter	Estimate	Z-count
β_0	0.833145	2.246126
β_1	0.000028	1.556444
β_2	0.010092	1.861479
β_3	0.000027	2.607824
β_4	-0.004527	-1.745916
Deviance	18.834	
AIC	28.833900	

Table 4 shows that the AIC and deviance values for the Poisson regression model are 28.83 and 18.834, respectively. After obtaining the estimated parameters of the Poisson regression model, simultaneous and partial tests were conducted as follows:

1. Simultaneous Test of Poisson Regression Parameters

   In the simultaneous test, the deviance value of the model is 18.834, with a critical region of $D > \chi^2(10; 0.1)$ or $D > 15.987$. Therefore, we reject H_0 and conclude that there is at least one $\beta_j \neq 0$, indicating that at least one parameter significantly affects the Poisson regression model.
2. Partial Test of Poisson Regression Parameters

   The partial test uses the criterion $|Z_{count}| > Z_{\alpha/2}$. With $\alpha = 10\%$, the critical region is $|Z_{count}| > 1.645$. It can be concluded that the parameters significantly affecting the Poisson regression model are β_2, β_3, and β_4 as they have $|Z_{count}| = 1.645$ or *p-value* < 0.1. Generally, the Poisson regression model for maternal mortality in Papua Province can be written as follows:

$$\hat{\mu} = exp(0.833145 + 0.000028X_1 + 0.010092X_2 + 0.000027X_3 - 0.004527X_4)$$

3.5 GWPR Modelling

Parameter testing for the GWPR (Geographically Weighted Poisson Regression) model is conducted to determine the significance of parameter β with the following hypotheses:

$H_0: \beta_1(u_i, v_i) = \beta_2(u_i, v_i) = \beta_3(u_i, v_i) = \beta_4(u_i, v_i) = 0$

H_1: At least one parameter $\beta_p(u_i, v_i) \neq 0, p = 1,2,3,4$

Based on Table 5, the deviance value of the GWPR model is 15.512. With a significance level of 10%, the critical region for rejecting H_0 is $D > \chi^2(8.407; 0.1)$ or $D > 13.902$. Therefore, we reject H_0 indicating that at least one predictor variable significantly affects the GWPR model. The significance of the GWPR model parameters is then tested partially to identify predictors that significantly affect each district/city with the following hypotheses:

$H_0: \beta_p(u_i, v_i) = 0, i = 1,2, \ldots, 15, p = 1,2,3,4$

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

Table 5. Parameter Test of GWPR Model in Merauke City with Fixed Bisquare Kernel

Parameter	*Estimate*	*Z-count*
$\boldsymbol{\beta_0}$	0.979567	2.521377
$\boldsymbol{\beta_1}$	0.000016	0.909077
$\boldsymbol{\beta_2}$	0.011295	0.006098
$\boldsymbol{\beta_3}$	0.000022	1.992033
$\boldsymbol{\beta_4}$	-0.003585	-1.396888
Deviance 15.512		
AIC 27.583728		

A predictor variable is considered to significantly affect the model if it has $|Z| > Z_{\alpha/2}$ or $|Z| > 1.645$. Based on the results, the percentage of households with access to proper sanitation (X_2), the number of food aid recipients (X_3), and the number of healthcare workers (X_4) significantly affect maternal mortality in Papua Province. In contrast, the number of families actively participating in the family planning program (X_1) does not significantly affect the model. The significant variables in the GWPR model with the Fixed Bisquare kernel for each district/city in Papua Province are grouped as follows:

1. The variables $X_1, X_2, X_3,$ and X_4 are significant for the following districts/cities: Jayawijaya, Yapen Island, Biak Numfor, Puncak Jaya, Mimika, Supiori, Mamberamo Tengah, and Dogiyai.
2. The variables X_2, X_3, and X_4 are significant only for Asmat District.
3. The variables X_2 and X_3 are significant for the following districts/cities: Merauke, Boven Digoel, and Mappi.
4. The variables X_3 and X_4 are significant for the following districts/cities: Nabire, Keerom, and Jayapura City.

Below is a visualization of the grouping of significant variables for each district/city in Papua Province in the GWPR model with the Fixed Bisquare kernel.

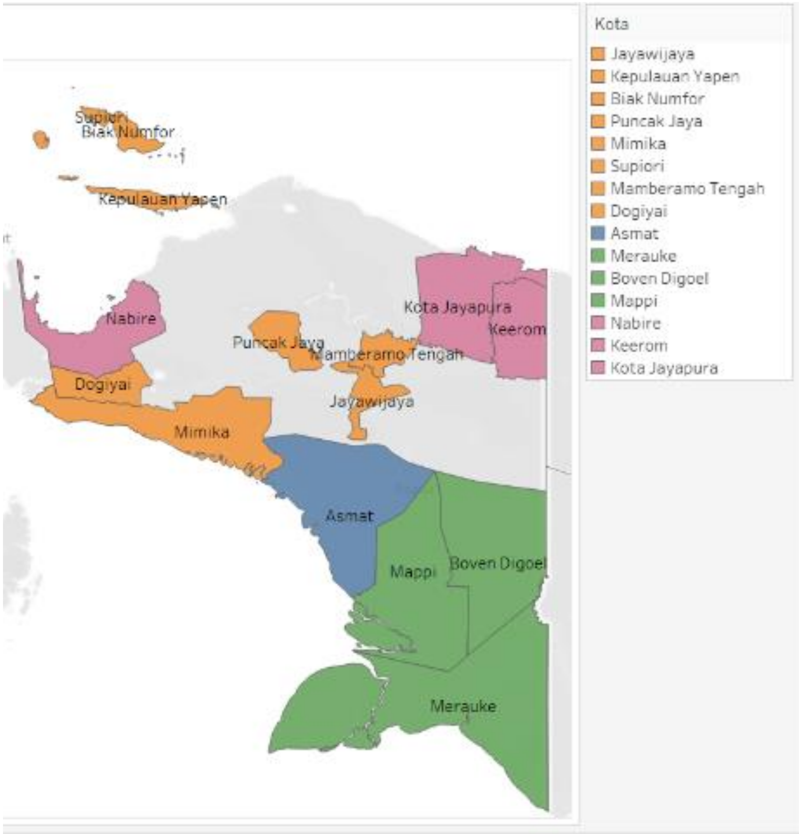

Figure 2. Mapping of Significant Variables in the GWPR Model with Fixed Bisquare Kernel

Partial parameter testing was conducted using the first research location (u_1, v_1), which is Merauke City, as shown in Table 5. In this table, it is evident that the only significant variable is parameter β_3 with $|Z| > Z_{\alpha/2}$. The GWPR model for maternal mortality in Merauke City can be formulated as follows:

$$\hat{\mu} = exp(0.979567 + 0.000016X_1 + 0.011295X_2 + 0.000022X_3 - 0.003585X_4)$$

Based on the GWPR model for Merauke City, it can be interpreted that each increase in the number of food aid recipients (X_3) will increase maternal mortality (Y) in Merauke City by a factor of $exp\, exp\,(0.000022) = 1.000022$, assuming other variables remain constant. Additionally, each increase in the number of healthcare workers (X_4) will decrease maternal mortality in Merauke City by a factor of $exp\, exp\,(0.003585) = 1.00359$ assuming other variables remain constant. The same interpretation method applies to the percentage of households with access to proper sanitation and the number of families actively participating in the family planning program.

3.6 Determining the Best Model

The criterion for determining the best model is the AIC value. The smaller the AIC value, the better the model is considered to be. The following are the AIC values for the Poisson regression model, GWPR with Fixed Bisquare kernel, and GWPR with Fixed Gaussian kernel.

Table 6. AIC Values

Regression Model	AIC
Poisson Regression	28.8
GWPR – Fixed Bisquare	27.6
GWPR – Fixed Gaussian	30.6

The AIC value for the Poisson regression model is 28.83, the AIC value for the GWPR model with Fixed Bisquare kernel is 27.58, and the AIC value for the GWPR model with Fixed Gaussian kernel is 30.64. From these results, it can be concluded that the GWPR model with a Fixed Bisquare kernel is the best model based on the smallest AIC value among the three models.

The GWPR model with Fixed Bisquare kernel for maternal mortality in 14 districts/cities in Papua Province can be seen in Table 7.

Table 7. GWPR Model for Maternal Mortality in Papua Province

District/City	GWPR Model
Merauke	$\hat{\mu} = exp(0.979567 + 0.000016X_1 + 0.011295X_2 + 0.000022X_3 + -0.003585X_4)$
Jayawijaya	$\hat{\mu} = exp(0.903864 + 0.000031X_1 + 0.009243X_2 + 0.000024X_3 + -0.00492X_4)$
Nabire	$\hat{\mu} = exp(0.97635 + 0.00003X_1 + 0.008222X_2 + 0.000024X_3 + -0.004838X_4)$
Yapen Island	$\hat{\mu} = exp(0.695837 + 0.000047X_1 + 0.010478X_2 + 0.000028X_3 + -0.006554X_4)$
Biak Numfor	$\hat{\mu} = exp(0.636394 + 0.00005X_1 + 0.010973X_2 + 0.000029X_3 + -0.006929X_4)$
Puncak Jaya	$\hat{\mu} = exp(0.849427 + 0.000035X_1 + 0.009494X_2 + 0.000025X_3 + -0.005358X_4)$
Mimika	$\hat{\mu} = exp(0.8062 + 0.000037X_1 + 0.010116X_2 + 0.000026X_3 + -0.00545X_4)$
Boven Digoel	$\hat{\mu} = exp(1.011314 + 0.000021X_1 + 0.009252X_2 + 0.000022X_3 + -0.003898X_4)$
Mappi	$\hat{\mu} = exp(0.965983 + 0.000023X_1 + 0.009879X_2 + 0.000023X_3 + -0.004121X_4)$
Asmat	$\hat{\mu} = exp(0.907459 + 0.000029X_1 + 0.009657X_2 + 0.000024X_3 + -0.004691X_4)$
Keerom	$\hat{\mu} = exp(0.988211 + 0.000028X_1 + 0.00838X_2 + 0.000023X_3 + -0.004572X_4)$
Supiori	$\hat{\mu} = exp(0.590476 + 0.000052X_1 + 0.011448X_2 + 0.00003X_3 + -0.007097X_4)$
Mamberamo Tengah	$\hat{\mu} = exp(0.906912 + 0.000032X_1 + 0.00909X_2 + 0.000024X_3 + -0.004984X_4)$
Dogiyai	$\hat{\mu} = exp(0.736044 + 0.000042X_1 + 0.010528X_2 + 0.000027X_3 + -0.005965X_4)$

The high maternal mortality rate in Papua Province in 2021 indicates that the achievement of sustainable development in the region is still not optimal. One of Indonesia's development targets by 2030 is to reduce the maternal mortality ratio to less than 70 per 100,000 live births. BPS also mentioned that the high maternal mortality rate in Papua is influenced by various factors including health status, education, economy, socio-cultural aspects, and healthcare services in the region [14]. Therefore, this issue should be a concern for the government to further enhance equity in various aspects, especially in Eastern Indonesia such as Papua, so that maternal mortality issues and others can be reduced.

4. Conclusion

The average maternal mortality rate in each district/city in Papua Province was 5.4 in 2021, with the highest mortality of 10 cases occurring in Merauke City and Biak Numfor District, and the lowest mortality of 1 case in Puncak Jaya District and Supiori District. The best kernel function chosen was Fixed Bisquare with an AIC value of 27.58. Based on the analysis results, it was found that the percentage of access to proper sanitation, the number of food aid recipients, and the number of healthcare workers significantly affected the maternal mortality rate with an error rate of 10%.

Ethics approval

Not required.

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Competing interests

All the authors declare that there are no conflicts of interest.

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Underlying data

The data used was obtained from publications by the Papua Provincial Health Office in 2021, with the unit of observation being the regencies/cities in Papua Provinces. Data can be accessed via the following link: https://dinkes.papua.go.id/informasi-publik/informasi-berkala/.

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