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Bayesian Geographically Weighted Generalized Poisson Regression Modeling on Maternal Mortality in NTT in 2022

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Abstract

Maternal mortality remains a complex public health issue with significant spatial variability across regions. This study aims to model maternal mortality data in East Nusa Tenggara (NTT) Province using the Bayesian Geographically Weighted Generalized Poisson Regression (BGWGPR) approach, which accounts for both overdispersion and spatial heterogeneity. Initially, modeling was conducted using Generalized Poisson Regression (GPR) with two estimation methods: Maximum Likelihood Estimation (MLE) and Bayesian inference. Based on the Deviance Information Criterion (DIC), the BGPR model demonstrated superior performance, with the lowest DIC value of 26.241, indicating better model fit compared to GPR-MLE. This result served as the basis for advancing to spatial analysis using the BGWGPR model. Parameter estimation was carried out via Gibbs Sampling, utilizing a conjugate Gamma prior for the Poisson distribution. The results revealed significant spatial variation, with 19 regions showing significance across all predictors, while 3 regions demonstrated only partial significance. The BGWGPR model effectively captures local spatial differences, offering more accurate and region-specific estimates. This approach supports the formulation of data-driven and geographically tailored maternal health policies, especially in areas with diverse geographical and service access conditions like NTT.

Keywords: Bayesian, GWGPR, Maternal Mortality, Overdispersion, Poisson.

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1 Introduction

Maternal Mortality Rate (MMR) is one of the key indicators used to assess the quality of a region's healthcare system. Despite various interventions, Indonesia continues to face high MMR, especially in the eastern regions such as East Nusa Tenggara (NTT) Province. According to data from the Ministry of Health, NTT recorded an MMR of 153 deaths per 100,000 live births in 2021 [1]. This figure underscores persistent disparities in access to and quality of maternal healthcare services. The primary medical causes of maternal deaths include postpartum hemorrhage, eclampsia, and infections. However, non-medical factors such as low educational attainment, delayed referrals, difficult geographical terrain, and a shortage of healthcare professionals also significantly contribute to the problem [2]. Geographical factors pose a significant challenge for provinces with an archipelagic landscape like NTT, leading to disparities in health indicator achievements across districts and cities [3].

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In the context of spatial health data analysis, the statistical approach used must be able to capture spatial heterogeneity or variation across regions. Conventional regression models, such as global Poisson regression, tend to assume that the relationship between predictor variables and the respvonse variable is homogeneous across all regions. Therefore, a model that can accommodate the varying influences of factors determining maternal mortality rates (MMR) across different areas is needed. One such approach is the Geographically Weighted Generalized Poisson Regression (GWGPR) method. Geographically Weighted Regression (GWR) is a local modeling technique that extends linear regression by estimating location-specific coefficients, effectively incorporating spatial variation based on geographical coordinates [4]. GWGPR adapts this concept for count data, using a generalized Poisson framework to address overdispersion—where the variance exceeds the mean—which is common in health-related count data [5]. A key component of GWGPR is the use of a kernel function, which determines the spatial weighting scheme. Observations closer to the target location are given more weight than those farther away [6]. Common kernel functions include Gaussian, bisquare, and exponential kernels. The bandwidth parameter controls the spatial extent of the local neighborhood: a smaller bandwidth focuses on more localized patterns but may introduce noise, while a larger bandwidth smooths the results but may overlook local variability. Bandwidth selection can be fixed or adaptive—fixed uses the same spatial distance across the study area, while adaptive adjusts the bandwidth to include a consistent number of neighboring observations, which is particularly useful in areas with varying population densities [7].

Furthermore, the Bayesian approach is employed to obtain more informative and stable parameter estimates, particularly when dealing with limited or complex data [8]. In recent years, Bayesian spatial modeling has gained increasing attention due to its flexibility in capturing spatial heterogeneity and its robustness in handling overdispersed and sparse data [9]. By combining prior information with observed data through the likelihood function, Bayesian inference produces a posterior distribution that better reflects the uncertainty of the parameters. This estimation process often relies on Markov Chain Monte Carlo (MCMC) techniques such as Gibbs Sampling, which enable efficient approximation of complex posterior distributions [10].

The integration of the Geographically Weighted Generalized Poisson Regression (GWGPR) model with the Bayesian approach in this study represents a novel methodological contribution, particularly in the context of maternal mortality analysis in Indonesia's eastern regions such as Nusa Tenggara Timur (NTT). While GWGPR accommodates spatial heterogeneity and overdispersion, the Bayesian framework adds the ability to incorporate prior knowledge and yield more stable estimates under uncertainty. To date, limited studies have explored this combination for localized maternal health data, making this approach a state-of-the-art advancement in spatial epidemiological modeling. This framework not only enables localized inference for each region but also supports more equitable and evidence-based policy planning for maternal mortality interventions.

2 Methods

This study used secondary data from data from the East Nusa Tenggara Central Bureau of Statistics (www.ntt.bps.go.id). The response variable used is the number of maternal deaths, while the predictor variables include the percentage of pregnant women attending the First Visit (K1) (x_1), Percentage Of Pregnant Women Receiving Iron Tablets (TTD) (x_2), Percentage Of Midwifery Complications (x_3), percentage of women under 19 years old who have been pregnant (x_4) and Percentage Of Active Family Planning (KB) Participants (x_5). The analysis in this study covers all districts/cities in East Nusa Tenggara with a total of 22 districts/cities included in the 2022 data. This research uses the Bayesian Geographically Weighted Generalized Poisson Regression method. The research steps are as follows:

1. Poisson Distribution Test
2. Overdispersion/Underdispersion Test
3. Significance Testing of Generalized Poisson Regression Parameters using MLE and Bayesian
4. Best Model Criteria using Deviance Information Criterion (DIC)
5. Spatial Heterogeneity Test using Breusch-Pagan Test (BP-TEST)
6. Spatial Weight Calculation using Adaptive Gaussian Kernel
7. Bandwidth Selection using Cross Validation (CV) Method
8. Estimating the Geographically Weighted Generalized Poisson Regression using Bayesian
9. Gibbs Sampling Simulation
10. Parameter Testing with Credible Intervals
11. Result Interpretation and Mapping

2.1 Poisson Regression

Poisson regression is a statistical model used for analyzing data where the response variable is a count of events (non-negative integers) and does not follow a normal distribution. Instead, it assumes the data follows a Poisson distribution, which is commonly used to model random events that occur at a certain rate over a fixed period or area. The Poisson distribution has a single parameter, λ which represents the average rate or intensity of the events. The probability of observing y events is calculated using the formula [7][8].

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

The Poisson regression model represents the natural logarithm of the expected value Y_i which is proportional to and dependent on the independent variable x_i. The equation can be written as follows [11] :

$$\begin{aligned} \ln(E(Y_i)) &= x_i^T\beta = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_k x_{ki} \\ \mu_i &= \exp(x_i^T\beta) = \exp(\beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_k x_{ki}) \end{aligned} \tag{2}$$

2.2 Overdispersion

In Poisson regression, one of the assumptions that must be met is the assumption of equality between the mean and variance, also known as equidispersion [12]. In statistical analysis, underdispersion occurs when variance is smaller than the mean, while overdispersion occurs when it is larger. Both can lead to inefficient parameter estimates, affecting model interpretation and potentially causing incorrect conclusions due to underestimated standard errors. Overdispersion can be detected by dividing the deviance by the degrees of freedom [13].

$$\phi = \frac{2\sum_{i=1}^{n}\left[y_i \ln\left(\frac{y_i}{\hat{\mu}_i}\right) - (y_i - \hat{\mu}_i)\right]}{db} \tag{3}$$

If $\phi = 1$ equidispersion occurs. If $\phi < 1$, it indicates underdispersion, while $\phi > 1$ suggests overdispersion.

2.3 Spatial Heterogeneity Analysis

The spatial heterogeneity test is used to see the diversity between locations caused by the different structures in each area [14]. One of the methods used in this test is the Breusch-Pagan Test (BP Test). The hypothesis is as follows:

$$H_0 : \sigma^2_{(u_1,v_1)} = \sigma^2_{(u_2,v_2)} = \cdots = \sigma^2_{(u_n,v_n)} = \sigma^2 \quad \text{(no spatial heterogeneity)}$$
$$H_1 : \text{At least one } \sigma^2_{(u_i,v_i)} \neq \sigma^2 \quad \text{(spatial heterogeneity exists)}$$

Test Statistic :

$$BP = \frac{1}{2}\mathbf{b}^T\mathbf{Z}\left(\mathbf{Z}^T\mathbf{Z}\right)^{-1}\mathbf{Z}^T\mathbf{b} \tag{4}$$

where the error element $\mathbf{b}$ is formulated as $b = \dfrac{e_i^2}{\sigma^2} - 1$, where e_i represents the error term for the i observation, with the assumption that e follows an independent and identically distributed normal distribution, $e \sim \text{IIDN}(0, \sigma^2)$. σ^2 is the variance of the error term e_i and $\mathbf{Z}$ is the standardized matrix of size $n \times (p+1)$, where p denotes the number of predictor variables. This formulation is used in the Breusch-Pagan test to assess spatial heterogeneity in the model.

2.4 Spatial Weights

In spatial analysis, spatial weights represent the relationship between geographic locations based on their proximity. These weights give more influence to nearby locations and reduce the influence of farther locations, thus capturing local variations in spatial data [15]. The weight function used in this study is an adaptive Gaussian kernel function, defined by the following formula [16].

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

where w_{ij} represents the weight between location i and location j. The term d_{ij} refers to the Euclidean distance between these two locations. The adaptive bandwidth, denoted as b_i, is specific to each location i and is calculated using the Cross Validation (CV) method to minimize prediction error. This adaptive bandwidth allows the model to adjust the influence of each location based on its proximity to other locations, ensuring that closer locations have more weight in the model's computations.

2.5 Bayesian Method

In Bayesian methods, suppose there is a parameter θ to be estimated. The parameter θ is treated as a variable whose value lies within the domain. The prior distribution represents initial information that is used to form the posterior distribution. By combining prior information with the data, the posterior calculation becomes more straightforward. According to Bayesian theory, the posterior distribution is proportional to the product of the prior distribution and the likelihood function, as expressed in equation (6) [17]:

$$f(\theta \mid y) \propto f(y \mid \theta)\, f(\theta) \tag{6}$$

where $f(\theta \mid y)$ is the posterior distribution, $f(\theta)$ is the prior distribution, and $f(y \mid \theta)$ is the likelihood function.

2.6 Bayesian Generalized Poisson Regression

In the Generalized Poisson Regression model, the conditional probability function of y_i given the predictors $x_{1i}, x_{2i}, \ldots, x_{pi}$ is defined as follows [18]:

$$P(y, \mu, \theta) = \left(\frac{\mu}{1+\theta\mu}\right)^y (1+\theta\mu)^{y-1}\frac{1}{y!}\exp\left(-\frac{\mu(1+\theta\mu)}{1+\theta\mu}\right) \tag{7}$$

Based on Equation (7), the likelihood function is derived and presented in Equation (8). The prior specification in the Generalized Poisson Regression model assumes that the regression parameters β follow a Gamma distribution, while the dispersion parameter θ is assumed to follow a Normal distribution.

$$L(\beta,\theta)=\prod_{i=1}^{n}\left(\frac{e^{x_i^T\beta}}{1+\theta e^{x_i^T\beta}}\right)(1+\theta y)^{y-1}\frac{1}{y!}\exp\left(\frac{e^{x_i^T\beta}(1+\theta y)}{1+\theta e^{x_i^T\beta}}\right) \tag{8}$$

$$f(\theta\mid y)=\frac{\beta^{\alpha}}{\Gamma(\alpha)}\theta^{\alpha-1}e^{-\beta\theta} \tag{9}$$

$$f(\beta\mid y)=\frac{1}{\sqrt{2\pi\sigma^2}}\exp\left(-\frac{(\beta-\mu_\beta)^2}{2\sigma^2}\right) \tag{10}$$

The resulting posterior distribution is as follows:

$$\begin{aligned}f(\beta,\theta\mid y)\propto{}&\frac{1}{\sqrt{2\pi\sigma^2}}\exp\left(-\frac{(\beta-\mu_\beta)^2}{2\sigma^2}\right)\times\frac{\beta^{\alpha}}{\Gamma(\alpha)}\theta^{\alpha-1}e^{-\beta\theta}\\&\times\prod_{i=1}^{n}\left(\frac{e^{x_i^T\beta}}{1+\theta e^{x_i^T\beta}}\right)(1+\theta y)^{y-1}\frac{1}{y!}\exp\left(\frac{e^{x_i^T\beta}(1+\theta y)}{1+\theta e^{x_i^T\beta}}\right)\end{aligned} \tag{11}$$

Due to the analytical intractability of the posterior distribution in Equation (11), a simulation-based estimation was conducted using the Markov Chain Monte Carlo (MCMC) framework, with Gibbs Sampling employed as the primary technique [19].

2.7 Bayesian Model Convergence Test

Convergence checking in MCMC aims to ensure that the generated samples match the target distribution, which is the posterior distribution. Two commonly used methods are trace plots and MC Error [20]. A trace plot is a graph that shows the relationship between iterations and the values generated; if this plot does not show any specific pattern or strong periodicity, then convergence is achieved. However, if convergence has not been reached, the number of iterations needs to be increased. Meanwhile, MC Error is calculated by dividing the samples into several groups (batches), then computing the average for each batch and the overall average. Convergence is considered met if the MC Error is less than 5% of the standard deviation. Thus, trace plots are used to visually assess stability, while MC Error provides a numerical measure to ensure the accuracy of the results [21].

$$\bar{G}(\theta)_b=\frac{1}{v}\sum_{t=(b-1)v+1}^{bv}G(\theta^{(t)}) \tag{12}$$

$$G(\theta)=\frac{1}{R'}\sum_{r=1}^{R'}G(\theta^{(r)}) \tag{13}$$

The formula to calculate MC Error is as follows **ref14**:

$$\mathrm{MCE}[G(\theta)]=\sqrt{\frac{1}{K(K-1)}\sum_{b=1}^{K}\left(\bar{G}(\theta)_b-G(\theta)\right)^2} \tag{14}$$

Notation:

- K : Number of batches
- v : Number of samples in each batch
- b : Index for the number of batches

- $\bar{G}(\theta)_b$: Average sample in each batch
- $G(\theta)$: Overall sample mean
- R' : Total number of generated samples

Considering the importance of capturing spatial variation and ensuring estimation stability in the analysis of complex maternal health data, this study adopts the Bayesian Geographically Weighted Generalized Poisson Regression (BGWGPR) approach. Prior to applying the spatial model, a comparison is conducted between the Generalized Poisson Regression (GPR) models estimated using Maximum Likelihood Estimation (MLE) and Bayesian methods, with the Deviance Information Criterion (DIC) used to determine the best-fitting model. The selected model will then be applied in spatial analysis to identify local variations across regions, and the results will be further discussed in the *Results and Discussion* section.

3 Results and Discussion

This section presents the results obtained from the application of various Poisson-based regression models and discusses their implications in the context of maternal mortality in East Nusa Tenggara Province. The discussion begins with diagnostic tests to validate the core assumptions of Poisson regression, followed by model estimations, spatial analysis, and convergence diagnostics.

3.1 Poisson Regression Assumption Test

In the distribution test using the Kolmogorov–Smirnov test, the p-value obtained is 0.2262, which is greater than the 5% significance level. This indicates that the response variable follows a Poisson distribution. Next, a non-multicollinearity test is performed by examining the Variance Inflation Factor (VIF) values, which are presented in Table 1.

Table 1: VIF for All Predictor Variables

Variable	VIF Value
Percentage of pregnant women attending the first visit (K1)	3.275
Percentage of pregnant women receiving iron tablets (TTD)	3.855
Percentage of Midwifery Complications	2.499
Percentage of Women Under 19 Years Old Who Have Been Pregnant	2.504
Percentage of Active Family Planning (KB) Participants	1.401

The results of the non-multicollinearity test using VIF show that all five predictor variables have values less than 10, indicating that multicollinearity is not present. Next, an overdispersion test was conducted. In Poisson regression, there is an assumption that the mean should be equal to the variance. If the variance is greater than the mean, the data exhibit overdispersion, whereas if the variance is smaller than the mean, the data exhibit underdispersion. In such cases, Poisson regression may no longer be appropriate, and alternative methods are needed to handle overdispersion or underdispersion.

Overdispersion can be detected by dividing the deviance value by the degrees of freedom. In this analysis, the deviance value is 29.817, with 16 degrees of freedom, resulting in a dispersion value of 1.864. Since $\phi > 1$, it can be concluded that maternal mortality data in the East Nusa Tenggara Province exhibit overdispersion.

3.2 Generalized Poisson Regression with MLE

Based on the MLE estimation, the resulting GPR model is as follows:

$$\hat{\mu}_i = \exp\left(4.177 + 0.0074X_3 - 0.0288X_5\right) \tag{1}$$

The model suggests that midwifery complications (X_3) are positively associated with maternal mortality, whereas active participation in family planning programs (X_5) contributes to its reduction. Specifically, a 1% increase in midwifery complications is estimated to elevate the risk of maternal death by approximately 0.74%, while a 1% increase in active family planning participation is associated with a 2.92% reduction in risk. These findings emphasize the critical role of effectively managing obstetric complications and expanding access to family planning services in efforts to lower maternal mortality rates.

3.3 Bayesian Generalized Poisson Regression

The Bayesian-based GPR model can be formulated as follows:

$$\hat{\mu}_i = \exp\left(30.2897 - 0.8480X_1 + 0.9093X_2 - 0.2082X_3 - 4.2417X_4\right) \tag{2}$$

The model indicates that an increase in first antenatal care visits (K1) is associated with a decrease in maternal mortality ($\exp(-0.8480) \approx 0.43$). Conversely, the provision of Iron Tablets (TTD) is correlated with an increase in maternal deaths ($\exp(0.9093) \approx 2.48$), possibly because regions with higher mortality rates implement more intensive TTD distribution. The management of complications by midwives also contributes to reducing maternal deaths ($\exp(-0.2082) \approx 0.81$), reflecting the effectiveness of such interventions. Interestingly, a higher percentage of pregnancies among women under 19 years old is negatively associated with maternal mortality ($\exp(-4.2417) \approx 0.79$), which may be influenced by regional factors or other health-related interventions.

3.4 Best Model

The best model is determined using the DIC value of each model. The better model to use is the one with the smallest DIC value. Table 2 shows DIC values for every model.

Table 2: DIC Values for Each Model

Model	**DIC**
Generalized Poisson Regression with MLE	76.401
Bayesian Generalized Poisson Regression (BGPR)	26.241

Based on Table 2, the smallest DIC value is obtained from the Bayesian Generalized Poisson Regression model, which is 26.241. Therefore, this model is selected as the best model in this study. Subsequently, a spatial heterogeneity test is conducted to examine whether there are significant differences between regions, which then serves as the basis for continuing the analysis using the Bayesian Geographically Weighted Generalized Poisson Regression (Bayesian GWGPR) model.

3.5 Spatial Heterogeneity Assumption Test

The spatial heterogeneity determines whether the regression model residuals vary spatially, showing that the residual variances vary throughout the observed regions. This test utilizes the Breusch–Pagan Test (BP Test) with the following hypotheses:

$$H_0 : \sigma_1^2 = \sigma_2^2 = \cdots = \sigma_i^2 \quad \text{(no spatial heterogeneity)}$$
$$H_1 : \text{At least one } \sigma_i^2 \neq \sigma_j^2 \quad \text{(spatial heterogeneity exists)}$$

The test results show a p-value of 0.026498, which is less than the significance level $\alpha = 0.05$. Thus, it can be concluded that spatial heterogeneity exists in the data.

3.6 Bayesian Convergence Check

In Bayesian modeling, especially when applying the BGWGPR model with MCMC simulations, it is crucial to validate the accuracy of the simulated results. To achieve this, tools such as the MC Error and trace dynamic plots are employed to assess the convergence of the simulation process. Convergence indicates that the output of the simulation aligns with the expected posterior distribution, confirming that the MCMC chain has stabilized. The trace plot visually monitors this process, showing the progression of parameter values across iterations. Ideally, a well-converged chain should display random fluctuations around a central value, without any discernible patterns, trends, or cycles.

To further assess convergence, the MC Error is calculated by dividing the simulation into batches and comparing the mean of each batch. Convergence is considered satisfactory when the MC Error is less than 5% of the standard deviation across the samples. For this analysis, 10,000 iterations were performed using the Gibbs sampling algorithm to ensure thorough exploration of the parameter space. When both the trace plot and MC Error satisfy their respective criteria, it can be concluded that the simulation has converged, and the results are reliable for subsequent analysis.

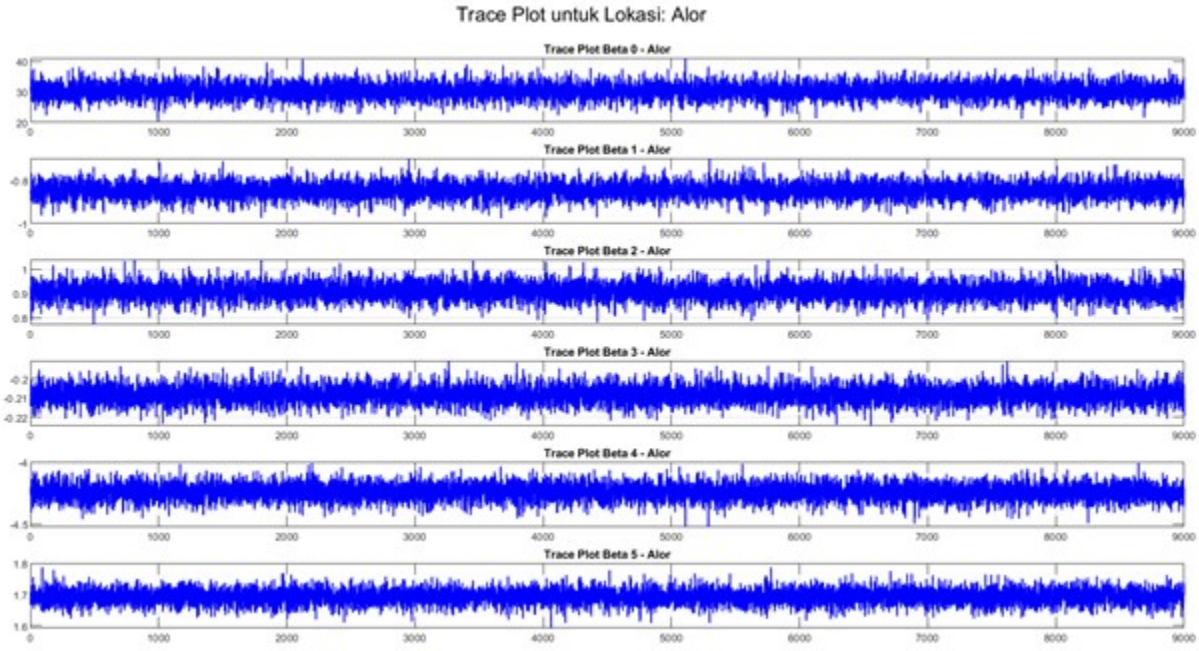

Figure 1: Convergence Trace Plot for Alor Regency

The trace plot displayed above illustrates the progression of parameter values during the iteration process for Alor Regency. This graph provides a visual representation of the fluctuations in parameter values at each iteration of the simulation. In this case, the trace plot shows how the parameter values change throughout the iterations and whether they reach stability, which is an indication of the simulation's convergence.

Meanwhile, the results of the MC Error calculation from the simulation can be found below, providing further numerical information about the accuracy and stability of the simulation results. In other words, the trace plot serves to visually verify the stability of the parameters, while the MC Error provides a numerical measure to assess convergence more objectively.

3.7 Bayesian Parameter Estimation

After confirming convergence for each location, the next step is constructing the BGWGPR model for each location. The model parameters are presented in Table 4.

Table 3: Convergence Test Results with Gibbs Sampling for Alor Regency

Parameter	Std. Dev.	5% of Std. Dev.	MC Error	Description
$\hat{\beta}_0$	1.206421	0.060321	0.003910	Convergent
$\hat{\beta}_1$	0.030538	0.000341	0.001527	Convergent
$\hat{\beta}_2$	0.026332	0.000294	0.001317	Convergent
$\hat{\beta}_3$	0.004054	0.000045	0.000203	Convergent
$\hat{\beta}_4$	0.050274	0.000562	0.002514	Convergent
$\hat{\beta}_5$	0.017327	0.000194	0.000866	Convergent

Table 4: Beta Coefficients of BGWGPR Model

District/City	β_0	β_1	β_2	β_3	β_4	β_5
Alor	2.3451	-0.4887	-1.0050	-0.1681	3.4579	1.2310
Belu	2.0609	-0.8837	-0.1819	-1.5081	0.5771	0.1894
Ende	2.2673	-0.7202	-0.4005	-0.0135	1.1937	0.0909
Flores Timur	2.2650	-0.9374	-0.2342	-0.9893	0.8765	0.4748
Kota Kupang	2.3454	-1.0227	-0.2150	-1.5048	0.7227	0.5368
Kupang	2.2635	-0.9855	-0.2028	-1.5827	0.6576	0.8377
Lembata	2.1634	-0.9175	-0.2021	-1.2457	0.7377	0.6587
Malaka	2.0762	-0.8923	-0.1831	1.5298	0.5766	0.4123
Manggarai	1.8270	-0.2667	-0.5368	0.9659	1.2830	0.9855
Manggarai Barat	1.7383	-0.2132	-0.5334	-1.1158	1.2776	0.5771
Manggarai Timur	1.8762	-0.3093	-0.5283	-0.8704	1.2781	0.2342
Nagekeo	2.0838	-0.5089	-0.4748	0.4835	2.2599	1.2874
Ngada	1.9880	-0.4098	-0.5050	-0.6795	1.2753	0.8874
Rote Ndao	2.4282	-1.0393	-0.2438	1.1730	0.8649	0.9855
Sabu Raijua	2.2905	-0.8165	-0.3414	-0.0909	1.1480	0.1681
Sikka	2.3751	-0.9202	-0.2993	-0.6731	1.0376	0.5771
Sumba Barat	1.6211	-0.1453	-0.5250	-1.3987	1.2973	0.1681
Sumba Barat Daya	1.6389	-0.1738	-0.5114	1.3260	1.2792	1.1730
Sumba Tengah	1.6198	-0.1332	-0.5338	1.4225	1.3081	0.5334
Sumba Timur	1.7500	-0.2586	-0.5022	1.2432	1.3110	0.1453
Timor Tengah Selatan	2.1496	-0.9307	-0.1894	-1.5952	0.7377	0.5923
Timor Tengah Utara	2.0795	-0.8938	-0.1829	1.5675	0.5694	0.5050

Based on Table 4, the Bayesian Geographically Weighted Generalized Poisson Regression (BGWGPR) equation for Alor Regency is as follows:

$$\mu_{\text{Alor}} = \exp(2.3451 - 0.4887X_1 - 1.0051X_2 + 0.1681X_3 + 3.4579X_4 - 1.2310X_5) \quad (3)$$

The model can be interpreted as follows: the number of maternal deaths in Alor Regency is expected to decrease by $\exp(-0.4887) = 0.6134$ times, or approximately by one case, if the percentage of pregnant women attending K1 visits increases, assuming all other variables remain constant. Similarly, maternal deaths will decrease by $\exp(-1.0051) = 0.3660$ times if the percentage of pregnant women receiving iron supplement tablets (TTD) increases by 1%. Conversely, maternal deaths tend to increase by $\exp(0.1681) = 1.183$ times if the percentage of complications handled by midwives rises by 1%. Additionally, maternal mortality is also expected to rise by $\exp(3.4579) = 31.74$ times if the percentage of women under 19 years old who have been pregnant increases by 1%. Meanwhile, the number of maternal deaths is projected to decrease by $\exp(-1.2310) = 0.2917$ times if the percentage of active family planning (KB) participants increases by 1%.

By using Bayesian GWGPR analysis, the significant parameters for each location were identified. The results of the location clustering can be seen in Table 5.

Table 5: Clustering of Regencies/Cities Based on the BGWGPR Model

Group	District/City	Significant Variables
1	Alor, Belu, Ende, Flores Timur, Kota Kupang, Kupang, Lembata, Malaka, Manggarai, Manggarai Barat, Manggarai Timur, Nagekeo, Ngada, Sabu Raijua, Sikka, Sumba Barat Daya, Sumba Timur, Timor Tengah Selatan, Timor Tengah Utara	X_1, X_2, X_3, X_4, X_5
2	Rote Ndao, Sumba Tengah, Sumba Barat	X_3, X_4, X_5

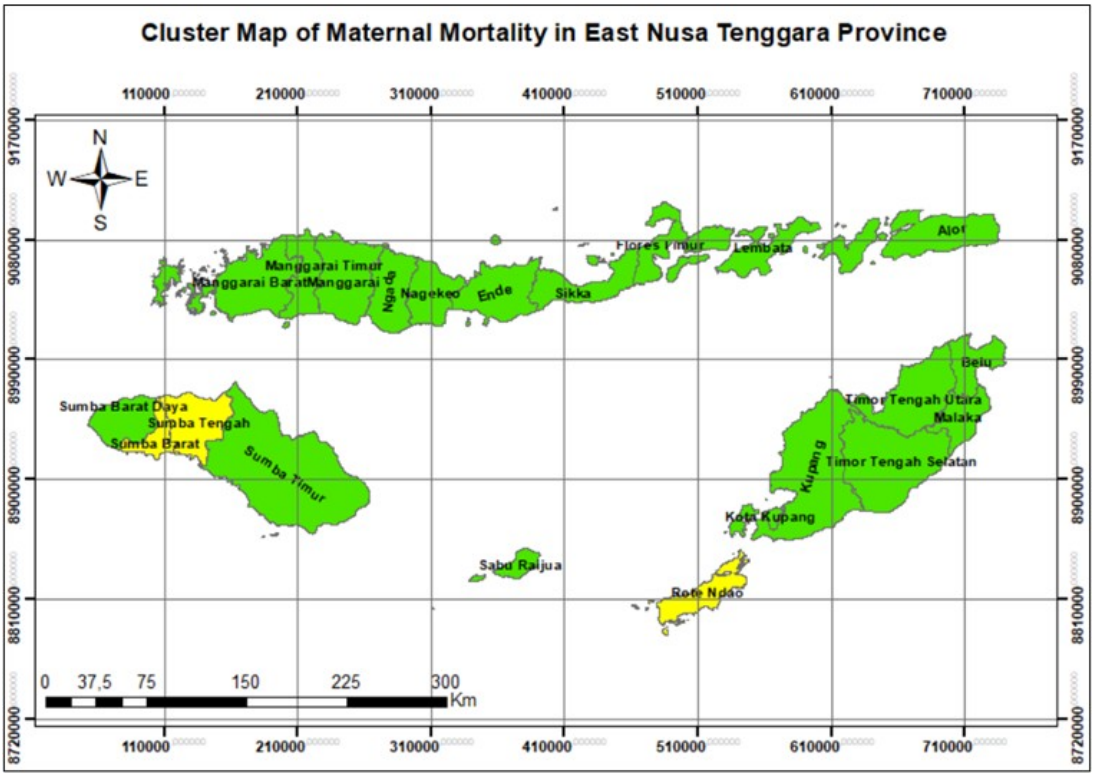

Figure 2: Cluster map of Maternal Mortality in NTT Province

3.8 Discussion

The study results indicate that the Bayesian Geographically Weighted Generalized Poisson Regression (BGWGPR) model effectively accommodates spatial heterogeneity in the relationship between the response and predictor variables. The Bayesian approach in this model allows for more flexible and stable parameter estimation, particularly in cases of overdispersion or underdispersion. Additionally, the model captures complex spatial patterns and variations in relationships across regions, providing a deeper understanding of the factors influencing the studied phenomenon.

The analysis results show that the posterior distribution of model parameters demonstrates good convergence, as evidenced by trace plots and MC Error. This confirms that the Gibbs Sampling method used in Bayesian estimation produces valid and reliable results. The spatial heterogeneity test reveals that the relationship between predictor and response variables differs across regions, emphasizing the importance of a localized approach in spatial regression modeling. Several factors contribute to this variation, including demographic characteristics, access to healthcare services, and economic factors in each region. These findings align with previous studies that highlight the flexibility of nonparametric and Bayesian approaches in capturing complex spatial patterns.

The clustering of districts into two distinct groups based on the model provides important

insights into regional disparities. Districts located further to the north—indicated by the green color—show that all variables in the model significantly influence maternal mortality rates. This finding suggests that these regions require special attention in efforts to reduce maternal mortality. This aligns with the real-world situation, where access to healthcare services in these areas remains very limited. For example, East Manggarai District has a hilly geographical condition with steep slopes, which poses a significant challenge in providing healthcare services to pregnant women. The limited accessibility in this area hinders pregnant women from receiving timely and appropriate medical care, as many areas are difficult to reach by vehicle and require long journeys to reach the nearest healthcare facility.

Malaka District faces similar challenges, particularly related to the uneven distribution of healthcare personnel. Many areas in Malaka are located along the border with East Timor, where infrastructure is limited and the terrain is difficult to access. This situation results in a shortage of medical personnel in healthcare facilities, which presents a significant challenge for the NTT provincial government in improving the quality of maternal healthcare services. In addition to access factors, the issues of early marriage and teenage pregnancy also deserve significant attention. In NTT, the practice of early marriage is still relatively high. The Central Bureau of Statistics (BPS) of NTT Province reported that in 2021, 82,957 women of reproductive age married before the age of 19. In East Manggarai District, around 24% of women married between the ages of 17 and 18. This phenomenon contributes to the high rates of teenage pregnancy, which carry a high risk of complications and maternal mortality during childbirth. This finding is further supported by the coefficient value for East Manggarai regarding the percentage of women under 19 years old who have been pregnant, which shows exp(2.2599), or about 10 maternal deaths. This number indicates that every 1% increase in the percentage of women who marry early could directly impact the increase in maternal deaths in this area.

This suggests that districts in Group 1 should receive more attention from the NTT provincial government in several key areas, including improving access to healthcare services and providing education on the dangers of early marriage. Efforts should focus not only on enhancing healthcare infrastructure but also on raising awareness about the risks associated with early pregnancies, especially in rural and remote areas. Moreover, educational programs aimed at preventing early marriage and supporting women's empowerment are crucial in addressing the root causes of maternal mortality. By prioritizing these areas, the government can significantly reduce maternal mortality rates and improve the overall well-being of women in these regions.

Then, the BGWGPR model has limitations in prior selection. In this study, a Gamma prior was used for the parameter λ due to its conjugacy with the Generalized Poisson distribution. While this prior choice is common in Bayesian regression, further exploration of informative priors could improve estimation accuracy, especially in areas with very few cases.

4 Conclusion

This study demonstrates that the Bayesian Geographically Weighted Generalized Poisson Regression (BGWGPR) model offers a robust and flexible framework for analyzing maternal mortality data characterized by spatial heterogeneity and overdispersion. The Bayesian approach enhances parameter estimation stability, especially in regions with limited data or extreme values, while the geographically weighted mechanism enables the capture of localized variations in relationships between predictors and the response variable.

The model reveals that different regions exhibit distinct influences of health-related factors—such as midwifery complications, family planning participation, antenatal visits, and teenage pregnancies—on maternal mortality. Such localized insights underscore the importance of region-specific policies and interventions rather than uniform national strategies. Moreover, the lower DIC value obtained in the Bayesian model compared to classical methods confirms its superior model fit and suitability for complex epidemiological data. This finding supports the

use of Bayesian spatial models in public health decision-making, especially in underserved and high-risk areas like East Nusa Tenggara (NTT).

For future studies, integrating Bayesian spatial models with machine learning algorithms could improve predictive accuracy and offer automated detection of spatial patterns. Additionally, exploring various prior distributions may enhance model performance, particularly in handling zero-inflated data often found in health and socio-economic datasets.

Declaration of Generative AI and AI-assisted technologies

Generative AI or AI-assisted technologies, specifically Grammarly and ChatGPT (version 4), were used during the preparation of this manuscript to assist in translating the content from Indonesian to English.

Declaration of Competing Interest

The authors declare no competing interests

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References

[1] K. K. RI, *Profil Kesehatan Indonesia Tahun 2021*. Jakarta: Kemenkes RI, 2022. Available online.

[2] I. Arkandi and W. S. Winahju, "Analisis faktor risiko kematian ibu dan kematian bayi dengan pendekatan regresi poisson bivariat di provinsi jawa timur tahun 2013," *Jurnal Teknik ITS*, vol. 4, no. 2, 2016. DOI: 10.12962/j23373520.v4i2.9936.

[3] I. D. Wittiarika, A. G. Ningrum, E. E. Frety, N. I. 'Izza, and K. P. Gamelly, "Penurunan angka kematian ibu (aki) melalui pelatihan deteksi dini preeklampsia pada bidan puskesmas di kabupaten manggarai timur ntt," *Jurnal Pengabdian Masyarakat Bangsa*, vol. 2, no. 9, pp. 4029–4035, Nov. 2024. DOI: 10.59837/jpmba.v2i9.1607.

[4] A. S. Fotheringham, C. Brunsdon, and M. Charlton, *Geographically Weighted Regression: The Analysis of Spatially Varying Relationships*. West Sussex: John Wiley & Sons Ltd, 2002. Available online.

[5] T. Neyens, C. Faes, and G. Molenberghs, "A generalized poisson-gamma model for spatially overdispersed data," *Spatial and Spatio-temporal Epidemiology*, vol. 3, no. 3, pp. 185–194, 2012. DOI: 10.1016/j.sste.2011.10.004.

[6] Y. Sarikhani, S. M. Najibi, and Z. Razavi, "Key barriers to the provision and utilization of maternal health services in low-and lower-middle-income countries; a scoping review," *BMC Women's Health*, vol. 24, no. 1, p. 325, Jun. 2024. DOI: 10.1186/s12905-024-03177-x.

[7] M. A. Aliu, F. Zubedi, L. Yahya, and F. A. Oroh, "The comparison of kernel weighting functions in geographically weighted logistic regression in modeling poverty in indonesia," *J*, vol. 18, no. 3, pp. 362–384, May 2022. DOI: 10.20956/j.v18i3.19567.

[8] H. J. Park, N. H. Kim, and J. H. Choi, "A robust health prediction using bayesian approach guided by physical constraints," *Reliability Engineering & System Safety*, vol. 224, 2024. DOI: 10.1016/j.ress.2024.109954.

[9] M. Bezener, J. Hughes, and G. Jones, "Bayesian spatiotemporal modeling using hierarchical spatial priors, with applications to functional magnetic resonance imaging (with discussion)," *Bayesian Analysis*, vol. 13, no. 4, Dec. 2018. DOI: 10.1214/18-BA1108.

[10] S. Astutik, A. B. Astuti, A. Efendi, Darmanto, D. Irsandy, and F. Y. D. A. Saniawati, *Analisis Bayesian: Teori dan Aplikasi dengan R*. Malang: UB Press, 2023. Available online.

[11] S. N. Aulele, "Pemodelan jumlah kematian bayi di provinsi maluku tahun 2010 dengan menggunakan regresi poisson," *BAREKENG: J. Mat. & Terapan*, vol. 6, no. 2, pp. 23–27, Dec. 2012. DOI: 10.30598/barekengvol6iss2pp23-27.

[12] A. C. Cameron and P. K. Trivedi, *Regression Analysis of Count Data*, 2nd ed. New York: Cambridge University Press, 2013. DOI: 10.1017/CBO9781139013567.

[13] A. Agresti, *Categorical Data Analysis*, 2nd ed. New York: Wiley-Interscience, 2002. DOI: 10.1002/0471249688.

[14] K. C. Land, P. L. McCall, and D. S. Nagin, "A comparison of poisson, negative binomial, and semiparametric mixed poisson regression models: With empirical applications to criminal careers data," *Sociological Methods & Research*, vol. 24, no. 4, pp. 387–442, 1996. DOI: 10.1177/0049124196024004001.

[15] P. E. Bidanset and J. R. Lombard, "The effect of kernel and bandwidth specification in geographically weighted regression models on the accuracy and uniformity of mass real estate appraisal," *Journal of Property Tax Assessment & Administration*, vol. 11, no. 3, pp. 5–14, Sep. 2014. DOI: 10.63642/1357-1419.1165.

[16] R. Putra, S. W. Tyas, and M. G. Fadhlurrahman, "Geographically weighted regression with the best kernel function on open unemployment rate data in east java province," *ENTHUSIASTIC*, pp. 26–36, Apr. 2022. DOI: 10.20885/enthusiastic.vol2.iss1.art4.

[17] Y. P. Putra, A. Aradea, and R. Rianto, "Pemodelan bayesian network untuk menentukan probabilitas penyebab pelanggaran dalam pertandingan karate kumite," *iiroi*, vol. 3, no. 2, Sep. 2021. DOI: 10.37058/innovatics.v3i2.4341.

[18] F. Famoye, J. T. Wulu, and K. P. Singh, "On the generalized poisson regression model with an application to accident data," *Journal of Data Science*, vol. 2, no. 3, pp. 287–295, 2004. DOI: 10.6339/JDS.2004.02(3).167.

[19] A. Anifa, M. A. Mukid, and A. Rusgiyono, "Simulasi stokastik menggunakan algoritma gibbs sampling," *Jurnal Gaussian*, vol. 1, no. 1, pp. 21–30, 2012. DOI: 10.14710/j.gauss.1.1.21-30.

[20] N. Rejki, "Bayesian reversible jump markov chain monte carlo (rjmcmc) untuk pemodelan mixture survival (studi kasus: Lama pernikahan para pihak yang mendaftarkan gugatan perceraian di pengadilan agama kabupaten malang tahun 2014)= bayesian reversible jump markov chain monte carlo (rjmcmc) for modelling mixture survival (case studies: Long marriage of the parties that registers a lawsuit divorces in the religious court kabupaten malang year 2014)," Ph.D. dissertation, Institut Teknologi Sepuluh Nopember, 2015. Available online.

[21] F. A. Farisa, S. N. H. Salby, A. A. Rahman, and P. Purhadi, "Modeling the number of pneumonia in toddlers in east java province in 2021 with generalized poisson regression," *Inferensi*, vol. 6, no. 2, p. 91, Sep. 2023. DOI: 10.12962/j27213862.v6i2.15339.