

# The Disparity of Maternal and Neonatal Death Modeling in Sumatra Region Using Geographically Weighted Bivariate Negative Binomial Regression

Muhammad Gabdika Bayubuana<sup>1\*</sup>, Sigit Nugroho<sup>2</sup>, Dyah Setyo Rini<sup>3</sup>, Muhammad Arib Alwansyah<sup>4</sup>

<sup>1234</sup> S1 Statistics Study Program, Bengkulu University, Bengkulu

\* Corresponding Author: [gabdikabayubuana@gmail.com](mailto:gabdikabayubuana@gmail.com)

---

## Article Info

### Article History:

Received: 23 04 2025

Revised: 24 04 2025

Accepted: 24 04 2025

Available Online: 24 04 2025

### Key Words:

MMR

NMR

BNBR

GWBNBR

DIC

---

## Abstract

The Sumatra region occupies the second highest rank in terms of Maternal Mortality Rate (MMR) and Neonatal Mortality Rate (NMR) in Indonesia in 2020. Many factors are thought to have influenced these two cases, both directly and indirectly. So it is necessary to do an analysis to find out what factors influence MMR and NMR. The methods that can be used to determine these factors are Bivariate Negative Binomial Regression (BNBR) and Geographically Weighted Bivariate Negative Binomial Regression (GWBNBR). The results of the analysis show that the Deviance Information Criterion (DIC) in GWBNBR is smaller than BNBR, so GWBNBR is better than BNBR in modeling MMR and NMR in the Sumatra Region in 2020.

---

## 1. INTRODUCTION

Spatial effects include spatial dependence and heterogeneity [1]. Spatial dependence is a condition in which location observations depend on other nearby locations [2]. Meanwhile, spatial heterogeneity is a regional condition that has differences between one location and another, in terms of geography, socio-culture and other things that can lead to spatial diversity [3]. One of the impacts arising from the existence of spatial heterogeneity is that the regression parameters vary spatially [4].

Geographically Weighted Regression (GWR) is a method used to overcome spatial heterogeneity. The GWR model uses a weighting matrix whose magnitude depends on the proximity between locations and produces estimates of model parameters that are local for each location [5]. The response variable in the GWR model is estimated by predictor variables where each regression coefficient depends on the location where the data is observed [6].

If the response variable in the GWR model contains overdispersion, which is a condition where the mean value is smaller than the variance value, so that it follows a negative binomial distribution, then the development becomes Geographically Weighted Negative Binomial Regression (GWNBR) [7]. Research on GWNBR has been widely applied, for example in the health sector. [8] modeled the number of cases of Dengue Hemorrhagic Fever (DHF) in Bengkulu Province using GWNBR with Adaptive Bisquare Kernel. [9] uses GWNBR to model Corona Virus Disease 2019 (COVID-19) cases in Ciamis Regency with a Fixed Bisquare Kernel.

However, in practice GWNBR can only be applied to a single case or one response variable (univariate), so that in some cases there are two related response variables (bivariate) GWNBR cannot be applied. To deal with this problem, [10] developed the GWNBR method so that it can be applied to bivariate cases so that it becomes Geographically Weighted Bivariate Negative Binomial Regression (GWBNBR) which is applied to data on the number of PB and MB leprosy patients in East Java with an Adaptive Bisquare Kernel. [11] conducted research on GWBNBR on the number of school dropouts of compulsory education age and the number of women who married early in East Java using the Adaptive Bisquare Kernel. The GWBNBR method can be applied to other bivariate data, such as cases of maternal and neonatal deaths.

The World Health Organization (WHO) defines maternal and neonatal deaths not resulting from accidents or injuries. Efforts to improve maternal and neonatal health status including reducing the Maternal Mortality

Rate (MMR) and Neonatal Mortality Rate (NMR) are one of the priorities of the 2020-2024 National Medium-Term Development Plan (RPJMN) [12].

According to the Indonesian Ministry of Health (2021), the 2020 Indonesia Health Profile shows that MMR in Indonesia reaches 98 per 100,000 live births (KH) and NMR reaches 22 per 1000 KH, with 22% of maternal deaths and 21% of neonatal deaths occurring in the Sumatra Region. This figure illustrates that the Sumatra Region is in the second highest position after Java Island with 48% of the total maternal and neonatal deaths in Indonesia. As well as exceeding the RPJMN target which targets MMR 70 per 100,000 KH and NMR 12 per 1000 KH. Therefore, the Sumatra Region requires intervention to reduce MMR and NMR as early as possible.

The issue of disparity in maternal and infant mortality is two things that are interrelated because during this period the nutrients obtained by the fetus are channeled from the mother's body through the placenta so that the condition of the mother during pregnancy will affect the fetus and the baby that will be born. This study aims to examine and determine the factors that influence these two cases for each research unit, namely districts and cities using the GWBNBR method. The GWBNBR method will be compared with the BNBR method to obtain the best method for modeling MMR and NMR in the Sumatra Region in 2020.

### 1.1 Maternal Mortality Rate and Neonatal Mortality Rate

The Maternal Mortality Rate (MMR) is the ratio of women who die during pregnancy or within 42 days after pregnancy, both during pregnancy, childbirth and childbirt in every 100,000 KH. While the Neonatal Mortality Rate (NMR) is the ratio of deaths of newborns to 28 days after birth, that is, from 0-28 days or 4 weeks in every 1,000 KH.

### 1.2 Multicollinearity

Multicollinearity occurs when there is a perfect linear relationship between some or all of the predictors of the multiple regression model [13]. The detection of multicollinearity according to [14] is by looking at the Variance Inflation Factor (VIF) value. The  $VIF_j$  formula is generally written as follows:

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

where  $R_j^2$  is the coefficient of determination of the  $j$ -th predictor on the other predictors. When the value of  $VIF > 10$ , it indicates that there is a multicollinierity among the predictors.

### 1.3 Overdispersion

Overdispersion occurs when the value of the variety of response variables is greater than the average value [15]. The hypothesis of over-dispersion testing on two response variables with the Index of Dispersion Test ( $I_B$ ) approach is as follows [16]:

$$H_0 : V(Y_k) = (\mu + \psi\mu^2)_k \text{ (there are significant overdispersion on both response variables)}$$

$$H_1 : V(Y_k) \neq (\mu + \psi\mu^2)_k \text{ (there are no significant overdispersion on either response variables)}$$

Test statistic:

$$I_B = \frac{n(\bar{y}_2 S_{y_1}^2 - 2Cov_{y_1 y_2}^2 + \bar{y}_1 S_{y_2}^2)}{(\bar{y}_1 \bar{y}_2 Cov_{y_1 y_2}^2)} \tag{1}$$

where

$$S_y^2 = \frac{\sum_{i=1}^n (y_i - \bar{y})^2}{n} \text{ and } Cov_{y_1 y_2} = \frac{\sum_{i=1}^n (y_{1i} - \bar{y}_1)(y_{2i} - \bar{y}_2)}{n}$$

Rejection criteria:

$$H_0 \text{ is rejected if } |I_B| > \chi_{(\alpha; 2n-3)}^2.$$

## 1.4 Correlation

The bivariate regression model is used when a pair of data is correlated [17]. The hypothesis of testing the correlation between  $Y_1$  and  $Y_2$  was carried out using the Pearson's Product Moment Correlation ( $\rho$ ) approach as follows [18]:

$$H_0 : \hat{\rho} = 0 \text{ (there is no significant correlation between } Y_1 \text{ and } Y_2)$$

$$H_1 : \hat{\rho} \neq 0 \text{ (there is a significant correlation between } Y_1 \text{ and } Y_2)$$

Test statistic:

$$t_{cal} = \frac{\hat{\rho}_{y_1 y_2} \sqrt{n-2}}{\sqrt{1-(\hat{\rho}_{y_1 y_2})^2}}$$

$$\text{where } \hat{\rho}_{y_1 y_2} = \frac{\sum_{i=1}^n (y_{1i} - \bar{y}_1)(y_{2i} - \bar{y}_2)}{\sqrt{\sum_{i=1}^n (y_{1i} - \bar{y}_1)^2 \sum_{i=1}^n (y_{2i} - \bar{y}_2)^2}}$$

Rejection criteria:

$$H_0 \text{ is rejected if } |t_{cal}| > t_{\alpha/2; n-2}.$$

## 1.5 Bivariate Negative Binomial Regression

### 1.5.1 Bivariate Negative Binomial Regression Model

Bivariate Negative Binomial Regression (BNBR) is based on the Bivariate Negative Binomial (BNB) distribution. If a pair of response variables  $Y_1$  and  $Y_2$  each have a Negative Binomial distribution which is regressed against the predictor variables  $X_1, X_2, \dots, X_p$  then the form of the BNBR model equation can be expressed as [19]:

$$(y_1, y_2) \sim BNB(\mu_1, \mu_2, \psi_1, \psi_2, \lambda)$$

$$\mu_{ki} = \exp(\mathbf{x}_i^T \boldsymbol{\beta}_k), i = 1, 2, \dots, n; k = 1, 2$$

where

$$\mathbf{x}_i^T = [1 \ x_{i1} \ x_{i2} \ \dots \ x_{ip}]^T$$

$$\boldsymbol{\beta}_k = [\beta_{k0} \ \beta_{k1} \ \beta_{k2} \ \dots \ \beta_{kp}]^T$$

The parameter estimation of the BNBR model was carried out using the Maximum Likelihood Estimation (MLE) method with the Newton-Raphson iteration procedure.

### 1.5.2 BNBR Model Parameter Testing

BNBR model testing is divided into two, namely simultaneous and partial testing.

Simultaneous testing of the BNBR model parameter uses the Maximum Likelihood Ratio Test (MLRT). The hypothesis used is as follows [19]:

$$H_0: \beta_{k1} = \dots = \beta_{kj} = 0; j = 1, 2, \dots, p; k = 1, 2$$

$$H_1: \text{at least one } \beta_{kj} \neq 0$$

Test statistic:

$$D_0 = -2 \ln \left[ \frac{L(\hat{\omega})}{L(\hat{\Omega})} \right]$$

where

$$L(\hat{\omega}) : \text{maximum likelihood value under } H_0$$

$$L(\hat{\Omega}) : \text{maximum likelihood value under } H_1$$

Rejection criteria:

$$H_0 \text{ is rejected if } |D_0| > \chi^2_{(\alpha; (b-a))}.$$

Partial testing of the BNBR model parameter uses the Wald test with the following hypothesis [20]:

$$H_0: \beta_{kj} = 0; j = 1, 2, \dots, p; k = 1, 2$$

$$H_1: \beta_{kj} \neq 0$$

Test statistic:

$$Z_{hit} = \frac{\hat{\beta}_{kj}}{se(\hat{\beta}_{kj})}$$

Rejection criteria:

$H_0$  is rejected if  $|Z_{hit}| > Z_{\alpha}$ .

### 1.6 Spatial Heterogeneity

Spatial heterogeneity indicates regional diversity caused by the fact that the spatial units within an observation area are basically not homogeneous [2]. Hypothesis testing of spatial heterogeneity if there are two or more response variables is carried out using the Glejser'G approach as follows [21]:

$$H_0: \Sigma_1 = \dots = \Sigma_n = \begin{bmatrix} \sigma_1^2 & \sigma_{21} \\ \sigma_{12} & \sigma_2^2 \end{bmatrix} \text{ (there is spatial homogeneity)}$$

$$H_1: \text{at least one } \Sigma_i \neq \begin{bmatrix} \sigma_1^2 & \sigma_{21} \\ \sigma_{12} & \sigma_2^2 \end{bmatrix} \text{ (there is spatial heterogeneity)}$$

Test statistic:

$$G = - \left[ n - p - 1 - \frac{1}{2}(k - p + 1) \right] \ln \left[ \frac{|\Sigma_{\Omega}|}{|\Sigma_{\omega}|} \right] \#$$

where

$\Sigma_{\Omega}$ : variance covariance matrix under  $H_1$

$\Sigma_{\omega}$ : variance covariance matrix under  $H_0$

Rejection criteria:

$H_0$  is rejected if  $|G| > \chi^2_{(\alpha; 2p)}$ .

### 1.7 Geographically Weighted Matrix (GWM)

#### 1.7.1 Geographically Weighted Matrix

A geographically weighted matrix is needed because of spatial diversity. Using the wrong weights will cause the parameter estimates to be biased. While using the right weight will minimize the standard error [22].

The weighting matrix at the  $i$ -th location can be written in the following equation:

$$W(u_i, v_i) = \text{diag}[w_1(u_i, v_i), \dots, w_n(u_i, v_i)]$$

where

$u_i$  : latitude of the  $i$ -th location

$v_i$  : longitude of the  $i$ -th location

Calculation of matrix elements is determined by a weighting function which contains the distance between locations and the smoothing parameter (bandwidth).

#### 1.7.2 Haversine Distance

The Haversine formula is an equation used in navigation, which gives a circle distance between two points on the earth's surface based on longitude and latitude coordinates taking into account that the earth is not a flat plane but a plane that has degrees of curvature. [23]. Here is the Haversine formula [24]:

$$d_{ij} = 2R \arcsin \left[ \sin^2 \left( \frac{u_i - u_j}{2} \right) + \cos(u_i) \cos(u_j) \sin^2 \left( \frac{v_i - v_j}{2} \right) \right]^{1/2}$$

where  $R$  is the unit length of the average radius of the Earth (6.371 km).

#### 1.7.3 Bandwidth Parameters

Bandwidth is a smoothing parameter with a radius  $h$  from the center point of the location, which is used as a basis for determining the weight of each observation, so that a point that is within a circular radius is considered to still have influence. The method used to determine the optimal bandwidth is Cross Validation (CV) as follows:

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

where  $\hat{y}_{\neq i}(h)$  is the estimator of  $y_i$ , with the observation at the  $i$ -th location point is omitted from the assessment process. The optimal bandwidth value is obtained when the CV is minimum [5].

#### 1.7.4 Kernel Function

The kernel function has the advantage that it is flexible, has an easy mathematical form and can reach a level of convergence relatively quickly and functions to control the smoothness of the estimation curve [25]. One of the kernel functions that can be used in geographic weighting is the Adaptive Gaussian Kernel with the following equation [26]:

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

where

$w_{ij}$ : weight of the  $i$ -th location to the  $j$ -th location

$d_{ij}$ : the distance of the  $i$ -th location to the  $j$ -th location

$h_i$ : smoothing parameter at the  $i$ -th location

### 1.8 Geographically Weighted Bivariate Negative Binomial Regression

#### 1.8.1 Geographically Weighted Bivariate Negative Binomial Regression Model

The Geographically Weighted Bivariate Negative Binomial Regression Model (GWBNBR) is an extension of the BNBR model with geographic weights for parameter estimation. The form of the GWBNBR equation is as follows [10]:

$$(y_1, y_2) \sim BNB(\mu_1(u_i, v_i), \mu_2(u_i, v_i), \psi_1(u_i, v_i), \psi_2(u_i, v_i), \lambda(u_i, v_i))$$

$$\mu_{ki}(u_i, v_i) = \exp(\mathbf{x}_i^T \boldsymbol{\beta}_k^*)$$

where

$$\boldsymbol{\beta}_k^* = \boldsymbol{\beta}_k(u_i, v_i) = [\beta_{k0}(u_i, v_i) \beta_{k1}(u_i, v_i) \dots \beta_{kp}(u_i, v_i)]^T$$

GWBNBR model parameter estimation was carried out using the Maximum Likelihood Estimation (MLE) method with the Newton-Raphson iteration procedure.

#### 1.8.2 GWBNBR Model Parameter Testing

GWBNBR model testing is divided into three, namely testing the similarity of the GWBNBR model with the BNBR model, simultaneous testing and partial testing.

Testing the similarity of the GWBNBR model with the BNBR model was carried out to test the significance of geographical factors in the resulting local parameters, with the following hypothesis [27]:

$$H_0: \beta_{kj}^* = \beta_{kj}; j = 1, 2, \dots, p; k = 1, 2 \text{ (there is no geographical influence on the model)}$$

$$H_1: \text{at least one } \beta_{kj}^* \neq \beta_{kj} \text{ (there is a geographical influence on the model)}$$

Test statistic:

$$F_{hit} = \frac{D_0/df_0}{D_1/df_1}$$

where

$D_0$ : test statistic for the simultaneous test of the BNBR model

$D_1$ : test statistic for the simultaneous test of the GWBNBR model

- $df_0$ : degrees of freedom  $D_0$  ( $b - a$ )
- $df_1$ : degrees of freedom  $D_1$  ( $2(b - a)$ )
- $a$  : the number of parameter under  $H_0$
- $b$  : the number of parameter under  $H_1$

Rejection Criteria:

$H_0$  is rejected if  $|F_{hit}| > F_{\alpha;(df_0,df_1)}$ .

Simultaneous testing of the GWBNBR model parameter uses the Maximum Likelihood Ratio Test (MLRT). The hypothesis used is as follows [19]:

$$H_0: \beta_{k1}^* = \dots = \beta_{kj}^* = 0; j = 1, 2, \dots, p; k = 1, 2$$

$$H_1: \text{at least one } \beta_{kj}^* \neq 0$$

Test statistic:

$$D_1 = -2 \ln \left[ \frac{L(\hat{\omega}^*)}{L(\hat{\Omega}^*)} \right]$$

Rejection criteria:

$H_0$  is rejected if  $|D_1| > \chi^2_{(\alpha; 2(b-a))}$ .

Partial testing of the GWBNBR model parameter uses the Wald test with the following hypothesis [20]:

$$H_0: \beta_{kj}^* = 0; j = 1, 2, \dots, p; k = 1, 2$$

$$H_1: \beta_{kj}^* \neq 0$$

Test statistic:

$$Z_{hit} = \frac{\hat{\beta}_{kj}^*}{se(\hat{\beta}_{kj}^*)}$$

Rejection criteria

$H_0$  is rejected if  $|Z_{hit}| > Z_{\alpha}$ .

### 1.9 Goodness-of-fit Criteria

Deviance Information Criterion (DIC) is used to measure the goodness of the Generalized Linear Model (GLM) which is equivalent to AIC and BIC. As with AIC and BIC, the best model is the model that has the smallest DIC value [28].

The formula for the DIC value of the BNBR model is as follows [29]:

$$DIC = -2 \ln \left[ \frac{L(\hat{\Omega})}{L(\hat{\Theta})} \right]$$

where  $L(\hat{\Theta})$  is the maximum likelihood value below  $H_1$  where the  $\mu$  value in the function is replaced by the observed  $y$  value.

## 2. METHOD

This study uses secondary data sourced from the publication of the Health Profiles of 9 Provinces in 2020, the West Sumatra Health Office Performance Report in 2021, 10 Provincial publications in Figures and Statistics on Provincial People's Welfare in 2020 by the Indonesian Central Bureau of Statistics (BPS Indonesia). There are 154 districts/cities in the Sumatra Region as observation units with 2 response variables ( $Y$ ) and 20 predictor variables ( $X$ ). The methods used are Bivariate Negative Binomial Regression (BNBR) and Geographically Weighted Bivariate Negative Binomial Regression (GWBNBR).

The first step in this research is to collect and describe the data. The second step examines the presence of predictor variable multicollinearity. The third step detects the overdispersion of the two response variables. The fourth step measures the correlation between the two response variables. The fifth step is doing BNBR

modeling. The sixth step tested the spatial heterogeneity in the BNBR model. The seventh step forms a geographic weighting matrix. The eighth step is doing GWBNBR modeling. Then the final step is choosing the best model between the BNBR model and the GWBNBR model.

**Table 1.** Research Variables

Variable	Information
$X_1$	Percentage of Pregnant Women Implementing K1 Program
$X_2$	Percentage of Pregnant Women Implementing K4 Program
$X_3$	Percentage of Pregnant Women Receiving Blood Supplement Tablets
$X_4$	Percentage of Birth Receiving Health Services
$X_5$	Percentage of Birth Assisted by Health Workers
$X_6$	Percentage of Birth Assisted by Witch Doctor
$X_7$	Percentage of Babies Receiving Complete Basic Immunization
$X_8$	Percentage of Babies Receiving Exclusive Mother's Milk
$X_9$	Percentage of Infants Suffering from Malnutrition
$X_{10}$	Percentage of Early Married Young Women
$X_{11}$	Percentage of Out of School Teenagers
$X_{12}$	Percentage of Population Following Active Family Planning Program
$X_{13}$	Percentage of Population Having Health Insurance
$X_{14}$	Percentage of Active Smoking Population
$X_{15}$	Percentage of Poor Population
$X_{16}$	Percentage of Households Having Access to Proper Sanitation
$X_{17}$	Percentage of Households Having Access to Clean Water
$X_{18}$	Population Density Ratio Per km <sup>2</sup>
$X_{19}$	Ratio of Health Workers Per 100,000 Population
$X_{20}$	Ratio of Health Facilities Per 100,000 Population
$Y_1$	Maternal Mortality Rate Per 100,000 Live Births
$Y_2$	Neonatal Mortality Rate Per 1000 Live Births
$u$	District/City Latitude Coordinates
$v$	Regency/City Longitude Coordinates

### 3. RESULTS AND DISCUSSION

#### 3.1 Descriptive Analysis

Descriptive analysis was performed to determine the characteristics of a data. Descriptive analysis consists of measures of concentration and distribution of data. The measure of the concentration of the data can use the average value, while the measure of the spread of the data can use the value of the variance. Descriptive analysis shows that the variable percentage of pregnant women implementing the K1 program is a predictor that has the highest average compared to other predictors. Rokan Hulu District is the region with the lowest percentage of pregnant women implementing the K1 program, while the regions with the highest percentage of pregnant women implementing the K1 program are found in 22 districts/cities. Meanwhile, the predictor with the most diverse spread was the percentage of infants who received complete basic immunization because it had the highest variance value. the average value of MMR was 114 cases, while NMR was 5 cases.

The minimum value of MMR and NMR is 0, meaning that there are areas in the Sumatra Region where according to the report there are no MMR or NMR cases recorded at all. However, judging from the maximum value, there are areas that have a fairly large number of cases. The highest MMR values were found in Padang Panjang City with 402 cases, while the highest NMR values were found in Kerinci Regency and Mentawai Islands Regency with 15 cases. In general, the provinces of Aceh, West Sumatra and the Riau Archipelago have relatively high MMR and NMR compared to other regions. Meanwhile, relatively low MMR and NMR were found in the Southern Sumatra region.

Data visualization is presented in the form of thematic maps to better describe the distribution conditions of each variable in each region. Presentation of thematic maps using GeoDa 1.20 software based on Geographic Information System (GIS) and Open Source. The following is a thematic map for the deployment of MMR and NMR:

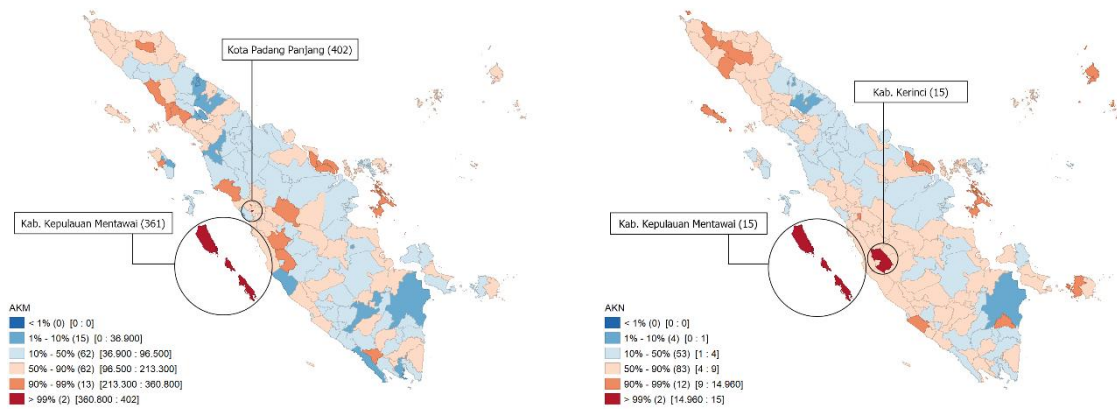


Figure 1. Thematic Map of the Distribution of MMR and NMR in the Sumatra Region

### 3.2 Multicollinearity Check

Multicollinearity checks are carried out by looking at the Variance Inflation Factor (VIF) value. The following is the result of calculating the VIF value for each predictor variable:

Table 2. Predictor variable VIF values

Variable	VIF	Variable	VIF
$X_1$	3,833	$X_{11}$	2,427
$X_2$	7,610	$X_{12}$	2,073
$X_3$	4,291	$X_{13}$	1,127
$X_4$	4,950	$X_{14}$	1,749
$X_5$	3,680	$X_{15}$	1,829
$X_6$	2,127	$X_{16}$	2,209
$X_7$	1,849	$X_{17}$	1,808
$X_8$	1,489	$X_{18}$	1,669
$X_9$	1,268	$X_{19}$	1,525
$X_{10}$	1,641	$X_{20}$	2,090

Based on Table 2, it is found that all predictor variables have a VIF value of less than 10, which means that there is no predictor variable as a source of multicollinearity.

### 3.3 Overdispersion Detection

The overdispersion detection of the two response variables was carried out by the Index of Dispersion Test ( $I_B$ ). Based on the results of the analysis obtained value  $I_B = 321,629 < \chi^2_{(0,05;305)} = 346,729$  and  $p_{value} = 0,246 > \alpha = 0,05$ . Thus  $H_0$  is accepted, which means that the response variables  $Y_1$  and  $Y_2$  have a Bivariate Negative Binomial distribution or the two response variables are overdispersion by the property of Negative Binomial.

### 3.4 Correlation Measurement

Measurement of the correlation of the two response variables was carried out with Pearson's Product Moment ( $\rho$ ). Based on the results of the analysis, a correlation value of 0.502 was obtained which showed that the correlation between the response variables  $Y_1$  and  $Y_2$  was quite strong. Furthermore, testing the



hypothesis produces a value of  $t_{cal} = 7,164 > t_{(0,025;152)} = 1,976$  and  $p_{value} = 0,000 < \alpha = 0,05$ . Thus the decision is to reject  $H_0$ , which means that there is a significant relationship between  $Y_1$  and  $Y_2$ .

### 3.5 Modeling with BNBR

Simultaneous testing of the parameters of the BNBR model was carried out to test whether the predictor variables simultaneously affect the response variable. Based on the results of the analysis, the value of  $D_0 = 64098,3 > \chi^2_{(0,05;40)} = 55,758$  and  $p_{value} = 0,00 < \alpha = 0,05$ , with the decision to reject  $H_0$ , which means that there is at least one predictor variable that has a significant effect on MMR and NMR in the Sumatra Region in 2020.

Furthermore, partial testing of the BNBR model parameters. Partially testing the significance of the parameters of the BNBR model was carried out to test whether each of the  $j$ -th predictor variables affected the  $k$ -th response variable. The results of the analysis for testing the parameters of the BNBR model partially are presented in Table 3. Based on Table 3 it was found that with a significant level of 5% there were 9 predictor variables for  $Y_1$  and 5 predictor variables for  $Y_2$  which have  $Z_{cal} > Z_{0,05} = 1,645$  and  $p_{value} < \alpha = 0,05$ . So it was decided to reject  $H_0$ , meaning that there are 9 predictor variables that affect MMR and 5 predictor variables that affect NMR in the Sumatra Region in 2020.

Predictor variables that have a significant effect on MMR are the percentage of pregnant women carrying out K1 ( $X_1$ ), the percentage of pregnant women carrying out K4 ( $X_2$ ), the percentage of deliveries assisted by health workers ( $X_5$ ), the percentage of poor people ( $X_{15}$ ), the percentage of households having proper sanitation ( $X_{16}$ ) and clean water ( $X_{17}$ ), ratio of population density per km2 ( $X_{18}$ ), ratio of health workers ( $X_{19}$ ) and health facilities per 100,000 inhabitants ( $X_{20}$ ).

Table 3. Estimated Value of BNBR Model Parameters

$\beta$	Maternal Mortality Rate ( $Y_1$ )				Neonatal Mortality Rate ( $Y_2$ )			
	Estimate	Std. Error	$Z_{cal}$	$p_{value}$	Estimate	Std. Error	$Z_{cal}$	$p_{value}$
$\beta_0$	-0,9779	0,9185	-1,0647	0,1435	-1,0704	1,1634	-0,9201	0,1788
$\beta_1$	0,0221*	0,0089	2,4783	<b>0,0066</b>	-0,0242*	0,0128	-1,8868	<b>0,0296</b>
$\beta_2$	-0,0279*	0,0124	-2,2390	<b>0,0126</b>	0,0049	0,0155	0,3157	0,3761
$\beta_3$	0,0055	0,0085	0,6454	0,2593	-0,0005	0,0107	-0,0445	0,4823
$\beta_4$	-0,0063	0,0106	-0,5884	0,2781	0,0007	0,0125	0,0581	0,4768
$\beta_5$	0,0251*	0,0089	2,8106	<b>0,0025</b>	0,0212*	0,0120	1,7675	<b>0,0386</b>
$\beta_6$	0,0048	0,0144	0,3327	0,3697	0,0096	0,0166	0,5783	0,2815
$\beta_7$	0,0035	0,0032	1,0831	0,1394	0,0039	0,0039	0,9914	0,1607
$\beta_8$	0,0009	0,0035	0,2711	0,3931	0,0029	0,0043	0,6799	0,2483
$\beta_9$	0,0012	0,0056	0,2101	0,4168	0,0017	0,0068	0,2476	0,4022
$\beta_{10}$	0,0043	0,0039	1,1264	0,1300	0,0013	0,0046	0,2924	0,3850
$\beta_{11}$	0,0024	0,0138	0,1714	0,4320	-0,0120	0,0172	-0,6974	0,2428
$\beta_{12}$	0,0199	0,0165	1,2067	0,1138	-0,0016	0,0189	-0,0838	0,4666
$\beta_{13}$	-0,0005	0,0028	-0,1853	0,4265	0,0027	0,0038	0,7108	0,2386
$\beta_{14}$	-0,0045	0,0152	-0,2933	0,3846	0,0088	0,0170	0,5173	0,3025
$\beta_{15}$	0,0274*	0,0162	1,6957	<b>0,0450</b>	0,0159	0,0190	0,8372	0,2012
$\beta_{16}$	0,0099*	0,0047	2,1157	<b>0,0172</b>	0,0121*	0,0057	2,1210	<b>0,0170</b>
$\beta_{17}$	0,0086*	0,0045	1,8930	<b>0,0292</b>	0,0007	0,0056	0,1334	0,4469
$\beta_{18}$	-0,0001*	0,0000	-3,0964	<b>0,0010</b>	-0,0003*	0,0001	-3,6070	<b>0,0002</b>
$\beta_{19}$	0,0010*	0,0003	3,2468	<b>0,0006</b>	0,0013*	0,0004	2,9339	<b>0,0017</b>
$\beta_{20}$	0,0061*	0,0019	3,2226	<b>0,0006</b>	0,0029	0,0022	1,3071	0,0956

Meanwhile, predictor variables that have a significant effect on NMR are the percentage of pregnant women carrying out K1 ( $X_1$ ), the percentage of births assisted by health workers ( $X_5$ ), the percentage of households having proper sanitation ( $X_{16}$ ), the ratio of population density per km<sup>2</sup> ( $X_{18}$ ) and the ratio of health workers per 100,000 resident ( $X_{19}$ ).

Based on Table 3, the BNBR model for MMR and NMR in the Sumatra Region in 2020 is as follows:

$$\begin{aligned} \hat{\mu}_1 &= \exp(-0,98 + 0,0221X_1 - 0,0279X_2 + 0,0055X_3 - 0,0063X_4 + 0,0251X_5 + & 0,0048X_6 \\ &+ 0,0035X_7 + 0,0009X_8 + 0,0012X_9 + 0,0043X_{10} + 0,0024X_{11} + & 0,0199X_{12} \\ &- 0,0005X_{13} - 0,004X_{14} + 0,0274X_{15} + 0,0099X_{16} + 0,009X_{17} - & 0,0001X_{18} \\ &+ 0,0010X_{19} + 0,006X_{20}) \\ \hat{\mu}_2 &= \exp(-1,07 - 0,0242X_1 + 0,0049X_2 - 0,0005X_3 + 0,0007X_4 + 0,0212X_5 + & 0,0096X_6 \\ &+ 0,0039X_7 + 0,0029X_8 + 0,0017X_9 + 0,0013X_{10} - 0,0120X_{11} - & 0,0016X_{12} \\ &+ 0,0027X_{13} + 0,009X_{14} + 0,0159X_{15} + 0,0121X_{16} + 0,001X_{17} - & 0,0003X_{18} \\ &+ 0,0013X_{19} + 0,003X_{20}) \end{aligned}$$

The first model estimates the average maternal mortality ( $\hat{\mu}_1$ ) based on 20 explanatory variables ( $X_1$  to  $X_{20}$ ), and is expressed in the form of an exponential function. The estimation results show that several variables such as  $X_1$ ,  $X_5$ ,  $X_6$ , and  $X_{12}$  have positive coefficients, which means that every one unit increase in these variables will increase the exponential value of the average maternal mortality, thus potentially increasing the maternal mortality rate. Conversely, variables such as  $X_2$ ,  $X_4$ , and  $X_{14}$  have negative coefficients, which indicate that an increase in these variables can reduce the maternal mortality rate.

Meanwhile, the second model estimates the mean neonatal mortality ( $\hat{\mu}_2$ ) with a similar structure. The slightly lower intercept value (-1.07) indicates that the baseline log-mean value of neonatal mortality is slightly smaller than maternal mortality. In this model, variables such as  $X_5$ ,  $X_6$ ,  $X_{14}$ , and  $X_{15}$  show a positive relationship to the increase in neonatal mortality, while variables such as  $X_1$  and  $X_{11}$  show a negative relationship. This indicates that each variable has a different impact on the two types of deaths.

### 3.6 Spatial Heterogeneity Testing

Spatial diversity testing in the BNBR model was carried out using the Glejser'G approach. Based on the results of the analysis, the value of  $G = 70,806 > \chi^2_{(0,05;40)} = 55,758$  and  $p_{value} = 0,003 < \alpha = 0,05$ , with the conclusion of rejecting  $H_0$  which means that there is a spatial homogeneity in the model of BNBR.

### 3.7 Modeling with GWNBR

The GWNBR model is an extension of the BNBR model, using a geographic weighting matrix, parameter estimation for each location is carried out by finding the maximum point of the likelihood function that has been multiplied by the weighting matrix.

Testing the similarity of the GWNBR and BNBR models was carried out to test the significance of geographical factors in the resulting local parameters. Based on the results of the analysis obtained the value of  $F_{cal} = 1,978 > F_{(0,05;40,80)} = 1,545$  and  $p_{value} = 0,005 < \alpha = 0,05$ , with the decision of accepting  $H_0$  which means that there is a significant difference between GWNBR and BNBR models and also there is a geographical effect on the model.

Then the simultaneous testing of GWNBR model parameters. Simultaneous testing of the significance of the parameters of the GWNBR model was carried out to test whether the predictor variables simultaneously affect the response variable. Based on the results of the analysis obtained value of  $D_1 = 64799,6 > \chi^2_{(0,05;80)} = 101,879$  and  $p_{value} = 0,000 < \alpha = 0,05$ , resulting a conclusion of rejecting  $H_0$  which is at least one predictor variable having a significant effect on MMR and NMR in the Sumatra Region in 2020.

Partially testing the significance of the parameters of the GWNBR model was carried out to test whether each of the  $j$ -th predictor variables affects the  $k$ -th response variable. The results of the analysis for testing the parameters of the GWNBR model partially in Bengkulu City ( $u_{31}, v_{31}$ ) are presented in Table 4. Based on this table, it is found that with a significant level of 5% there are 3 predictor variables for  $\mu_1$  and 1

predictor variable for  $\mu_2$  which has a value  $Z_{cal} > Z_{0.05} = 1.645$  and  $p_{value} < 0.05$ . So, it is concluded to reject  $H_0$ , meaning that there are 3 predictor variables that have a significant effect on MMR and 1 predictor variable that has a significant effect on NMR in Bengkulu City in 2020.

The predictor variables that significantly influence MMR are the percentage of births assisted by a health worker ( $X_5$ ), the percentage of households with access to clean water ( $X_{17}$ ) and the ratio of health facilities per 100,000 population ( $X_{20}$ ). Meanwhile, the predictor variable that has a significant effect on NMR is the percentage of youth dropping out of school ( $X_{11}$ ).

Table 4. Estimated Value of GWBNBR Model Parameters in Bengkulu City

$\beta$	Maternal Mortality Rate ( $Y_1$ )				Neonatal Mortality Rate ( $Y_2$ )			
	Estimate	Std. Error	$Z_{hitung}$	$P_{value}$	Estimate	Std. Error	$Z_{hitung}$	$P_{value}$
$\beta_0$	-1,0109	1,8562	-0,5446	0,2930	-1,0294	2,0807	-0,4947	0,3104
$\beta_1$	0,0102	0,0188	0,5425	0,2937	0,0020	0,0210	0,0934	0,4628
$\beta_2$	-0,0140	0,0234	-0,5996	0,2744	0,0056	0,0257	0,2170	0,4141
$\beta_3$	-0,0036	0,0156	-0,2335	0,4077	-0,0097	0,0183	-0,5322	0,2973
$\beta_4$	-0,0085	0,0184	-0,4641	0,3213	-0,0011	0,0211	-0,0544	0,4783
$\beta_5$	0,0400*	0,0156	2,5740	<b>0,0050</b>	0,0131	0,0199	0,6602	0,2546
$\beta_6$	-0,0152	0,0252	-0,6037	0,2730	-0,0192	0,0285	-0,6733	0,2504
$\beta_7$	0,0071	0,0063	1,1377	0,1276	-0,0009	0,0077	-0,1194	0,4525
$\beta_8$	-0,0017	0,0065	-0,2595	0,3976	0,0029	0,0077	0,3815	0,3514
$\beta_9$	-0,0048	0,0150	-0,3158	0,3761	0,0095	0,0203	0,4697	0,3193
$\beta_{10}$	-0,0038	0,0080	-0,4750	0,3174	-0,0020	0,0092	-0,2167	0,4142
$\beta_{11}$	0,0216	0,0236	0,9162	0,1798	0,0509*	0,0268	1,8997	<b>0,0287</b>
$\beta_{12}$	0,0259	0,0286	0,9076	0,1821	-0,0302	0,0318	-0,9488	0,1714
$\beta_{13}$	-0,0003	0,0050	-0,0544	0,4783	-0,0005	0,0060	-0,0905	0,4639
$\beta_{14}$	-0,0134	0,0286	-0,4693	0,3194	0,0068	0,0303	0,2246	0,4111
$\beta_{15}$	0,0214	0,0265	0,8076	0,2096	0,0184	0,0306	0,6009	0,2740
$\beta_{16}$	0,0056	0,0082	0,6803	0,2482	0,0058	0,0099	0,5875	0,2784
$\beta_{17}$	0,0129*	0,0074	1,7533	<b>0,0398</b>	0,0045	0,0086	0,5261	0,2994
$\beta_{18}$	0,0000	0,0000	-0,6486	0,2583	-0,0002	0,0001	-1,0920	0,1374
$\beta_{19}$	0,0003	0,0006	0,5103	0,3049	0,0007	0,0008	0,9030	0,1833
$\beta_{20}$	0,0084*	0,0035	2,3984	<b>0,0082</b>	0,0047	0,0037	1,2880	0,0989

Using the information available in Table 4, the GWBNBR model for MMR and NMR in Bengkulu City in 2020 is as follows:

$$\hat{\mu}_1 = \exp(-1,0109 + 0,0102X_1 - 0,0140X_2 - 0,0036X_3 - 0,0085X_4 + 0,0400X_5 - 0,0152X_6 + 0,0071X_7 - 0,0017X_8 - 0,0048X_9 - 0,0038X_{10} + 0,0216X_{11} + 0,0259X_{12} - 0,0003X_{13} - 0,0134X_{14} + 0,0214X_{15} + 0,0056X_{16} + 0,0129X_{17} - 0,0000X_{18} + 0,0003X_{19} + 0,0084X_{20})$$

$$\hat{\mu}_2 = \exp(-1,0294 + 0,0020X_1 + 0,0056X_2 - 0,0097X_3 - 0,0011X_4 + 0,0131X_5 - 0,0192X_6 - 0,0009X_7 + 0,0029X_8 + 0,0095X_9 - 0,0020X_{10} + 0,0509X_{11} - 0,0302X_{12} - 0,0005X_{13} + 0,007X_{14} + 0,0184X_{15} + 0,0058X_{16} + 0,004X_{17} - 0,0002X_{18} + 0,0007X_{19} + 0,005X_{20})$$

After partial testing of the parameters of the GWBNBR model, then grouping areas (locations) based on significant parameter similarities.

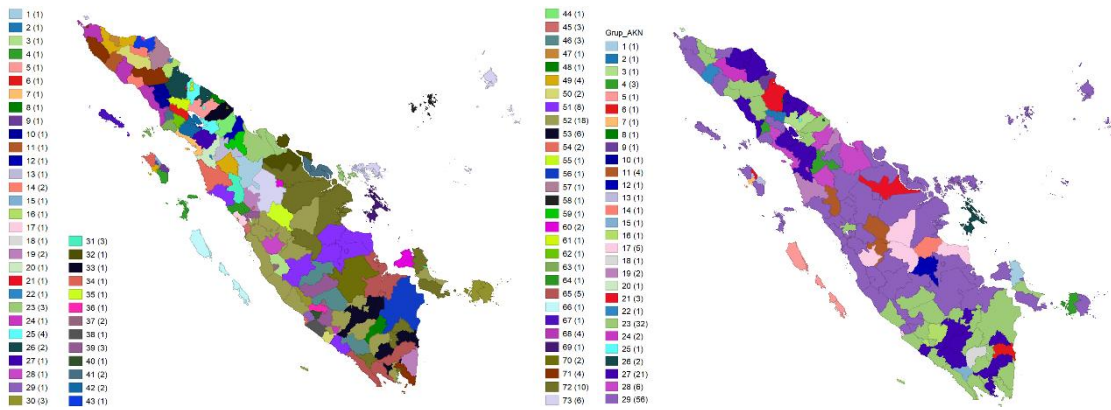


Figure 2. Thematic Map of Regional Group Distribution Based on the Significance of MMR and NMR Parameters

Table 5. Grouping of Regions Based on Significance of MMR Parameters

Group	Variables	Districts/Cities
1	$X_1, X_2, X_5, X_{15}$	Rokan Hulu
2	$X_1, X_2, X_5, X_{15}, X_{16}, X_{19}$	Padang Sidempuan
3	$X_1, X_2, X_5, X_{17}, X_{20}$	Kerinci
4	$X_1, X_2, X_5, X_{20}$	Nias Selatan
5	$X_1, X_4, X_5, X_{12}, X_{20}$	Simalungun
6	$X_1, X_4, X_5, X_{15}, X_{18}$	Dairi
7	$X_1, X_5, X_{15}, X_{18}, X_{19}$	Tapanuli Tengah
8	$X_1, X_5, X_{16}, X_{19}$	Batu Bara
9	$X_1, X_5, X_{18}, X_{19}$	Nias
10	$X_1, X_5, X_{18}, X_{19}, X_{20}$	Aceh Tenggara
11	$X_1, X_5, X_{18}, X_{20}$	Aceh Barat
12	$X_1, X_5, X_{19}, X_{20}$	Labuhanbatu
13	$X_1, X_{16}, X_{20}$	Padang Lawas Utara
14	$X_1, X_{18}, X_{19}$	Aceh Barat Daya, Bener Meriah
15	$X_1, X_{18}, X_{19}, X_{20}$	Gunungsitoli
16	$X_1, X_{20}$	Aceh Tamiang
17	$X_2, X_5$	Padang Pariaman
18	$X_2, X_5, X_{15}$	Padang Panjang
19	$X_2, X_5, X_{17}, X_{20}$	Lampung Timur, Lima Puluh Kota
20	$X_2, X_5, X_{19}, X_{20}$	Tapanuli Selatan
21	$X_4, X_5, X_6, X_8, X_{10}, X_{15}, X_{18}$	Binjai
22	$X_4, X_{18}, X_{19}, X_{20}$	Langsa
23	$X_5$	Karimun, Dumai, Rokan Hilir
24	$X_5, X_7, X_{20}$	Pagar Alam
25	$X_5, X_{10}, X_{15}, X_{16}$	Deli Serdang, Pematang Siantar, Tebing Tinggi, Toba Samosir
26	$X_5, X_{10}, X_{15}, X_{16}, X_{18}, X_{19}$	Langkat, Serdang Bedagai
27	$X_5, X_{10}, X_{15}, X_{16}, X_{19}$	Tapanuli Utara
28	$X_5, X_{11}, X_{15}, X_{16}, X_{20}$	Solok Selatan
29	$X_5, X_{12}, X_{20}$	Bengkulu Tengah
30	$X_5, X_{15}$	Belitung, Belitung Timur, Lebong
31	$X_5, X_{15}, X_{16}$	Pangkalpinang, Bukittinggi, Pasaman
32	$X_5, X_{15}, X_{16}, X_{18}$	Bengkalis
33	$X_5, X_{15}, X_{16}, X_{18}, X_{19}$	Asahan
34	$X_5, X_{15}, X_{16}, X_{19}, X_{20}$	Nias Utara
35	$X_5, X_{15}, X_{16}, X_{20}$	Kuantan Singingi

Group	Variables	Districts/Cities
36	$X_5, X_{15}, X_{17}, X_{18}, X_{20}$	Rejang Lebong
37	$X_5, X_{15}, X_{17}, X_{20}$	Sungai Penuh, Lubuklinggau
38	$X_5, X_{15}, X_{18}$	Seluma
39	$X_5, X_{15}, X_{18}, X_{20}$	Tanah Datar, Empat Lawang, Musi Rawas Utara
40	$X_5, X_{15}, X_{20}$	Kepahiang
41	$X_5, X_{16}$	Subulussalam, Kepulauan Meranti
42	$X_5, X_{16}, X_{18}, X_{19}$	Humbang Hasundutan, Samosir
43	$X_5, X_{16}, X_{18}, X_{19}, X_{20}$	Aceh Utara
44	$X_5, X_{16}, X_{19}$	Labuhanbatu Utara
45	$X_5, X_{16}, X_{20}$	Kota Solok, Padang, Payakumbuh
46	$X_5, X_{17}, X_{18}, X_{20}$	Sarolangun, Musi Rawas, Ogan Komering Ulu Selatan
47	$X_5, X_{17}, X_{19}$	Pidie Jaya
48	$X_5, X_{17}, X_{19}, X_{20}$	Ogan Komering Ulu Timur
49	$X_5, X_{18}, X_{19}$	Bireuen, Pidie, Nias Barat, Padang Lawas
50	$X_5, X_{18}, X_{19}, X_{20}$	Aceh Tengah, Bengkulu Selatan
51	$X_5, X_{18}, X_{20}$	Kaur, Batanghari, Jambi, Merangin, Muaro Jambi, Tanjung Jabung Barat, Tanjung Jabung Timur, Pasaman Barat
52	$X_5, X_{20}$	Bangka Tengah, Bengkulu Utara, Mukomuko, Bungo, Pesawaran, Way Kanan, Indragiri Hulu, Dharmasraya, Pariaman, Pesisir Selatan, Sawahlunto, Sijunjung, Solok, Lahat, Ogan Ilir, Ogan Komering Ulu, Penulak Abab Lematang Ilir, Prabumulih, Sibolga
53	$X_5, X_{17}, X_{20}$	Bengkulu, Lampung Utara, Metro, Pringsewu, Tulang Bawang, Muara Enim
54	$X_5, X_{19}, X_{20}$	Mandailing Natal
55	$X_{10}, X_{15}, X_{19}$	Medan
56	$X_{12}, X_{17}, X_{20}$	Ogan Komering Ilir
57	$X_{14}, X_{18}, X_{19}, X_{20}$	Aceh Timur
58	$X_{15}$	Kepulauan Anambas
59	$X_{15}, X_{18}, X_{19}$	Labuhanbatu Selatan
60	$X_{15}, X_{20}$	Bangka Barat, Pekanbaru
61	$X_{16}, X_{18}, X_{19}$	Karo
62	$X_{16}, X_{19}$	Pakpak Bharat
63	$X_{16}, X_{20}$	Aceh Singkil
64	$X_{17}, X_{19}, X_{20}$	Agam
65	$X_{17}, X_{20}$	Lampung Barat, Lampung Tengah, Tanggamus, Banyuasin, Palembang
66	$X_{18}$	Kepulauan Mentawai
67	$X_{18}, X_{19}$	Simeulue
68	$X_{18}, X_{19}, X_{20}$	Aceh Besar, Aceh Selatan, Lhokseumawe, Nagan Raya
69	$X_{18}, X_{20}$	Lingga
70	$X_{19}$	Musi Banyuasin, Tanjungbalai
71	$X_{19}, X_{20}$	Aceh Jaya, Banda Aceh, Gayo Lues, Lampung Selatan
72	$X_{20}$	Bangka, Bangka Selatan, Tebo, Bandar Lampung, Mesuji, Pesisir Barat, Tulang Bawang Barat, Indragiri Hilir, Pelalawan, Siak
73	-	Sabang, Batam, Bintan, Natuna, Tanjungpinang, Kampar

Based on the information obtained from Table 5, there are 73 regional groups according to parameter significance, with the largest significant number being 18 districts/cities in the 52nd group. The most dominating variable in cases of maternal death is the percentage of deliveries assisted by health personnel ( $X_5$ ), which is significant in 103 regions. While the areas where there are no significant variables are 6 districts/cities in the 73rd group.

Based on Table 6, 29 regional groups were obtained according to the significance of the parameters, with the largest significant number being 32 districts/cities in the 23rd group. The most dominating variable

in neonatal mortality cases is the ratio of population density per km<sup>2</sup> ( $X_{18}$ ) which is significant in 65 regions. While the areas where there are no significant variables are 56 districts/cities in the 29th group.

**Table 6.** Grouping of Regions Based on Significance of PTNMR Parameters

Group	Variables	Districts/Cities
1	$X_1$	Bangka
2	$X_1, X_2, X_{19}$	Karo
3	$X_1, X_{19}$	Simalungun
4	$X_2$	Subulussalam, Belitung, Padang Lawas Utara
5	$X_2, X_{11}$	Kepulauan Mentawai
6	$X_2, X_{11}, X_{18}$	Tulang Bawang
7	$X_2, X_{15}$	Nias Barat
8	$X_2, X_{18}, X_{19}$	Binjai
9	$X_4, X_5, X_{19}$	Aceh Tamiang
10	$X_4, X_5, X_{18}, X_{19}$	Tebing Tinggi
11	$X_5$	Kuantan Singingi, Dharmasraya, Kota Solok, Pasaman
12	$X_5, X_6$	Batanghari
13	$X_5, X_{18}, X_{19}$	Nias
14	$X_6$	Tanjung Jabung Barat
15	$X_9, X_{18}$	Pesisir Barat
16	$X_9, X_{18}, X_{19}$	Lahat
17	$X_{11}$	Bengkulu, Tanjung Jabung Timur, Tebo, Indragiri Hulu, Solok Selatan
18	$X_{11}, X_{18}$	Way Kanan
19	$X_{14}$	Labuhanbatu, Mandailing Natal
20	$X_{14}, X_{18}$	Sabang
21	$X_{14}, X_{19}$	Siak, Gunungsitoli, Langkat
22	$X_{15}, X_{18}$	Aceh Barat
23	$X_{18}$	Aceh Barat Daya, Aceh Tenggara, Banda Aceh, Gayo Lues, Pidie, Pidie Jaya, Bangka Tengah, Bengkulu Utara, Kaur, Seluma, Bandar Lampung, Lampung Barat, Lampung Selatan, Lampung Timur, Lampung Utara, Pringsewu, Tanggamus, Tulang Bawang Barat, Tanah Datar, Empat Lawang, Musi Rawas, Musi Rawas Utara, Ogan Ilir, OKI, OKU Timur, Pagar Alam, Palembang, PALI, Prabumulih, Asahan, Sibolga, Toba
24	$X_{18}, X_{19}, X_{20}$	Aceh Tengah, Batu Bara
25	$X_{19}, X_{20}$	Pematang Siantar
26	$X_{20}$	Lingga
27	$X_{18}, X_{19}$	Aceh Selatan, Aceh Timur, Aceh Utara, Bener Meriah, Langsa, Lhokseumawe, Bengkulu Selatan, Lampung Tengah, Mesuji, Metro, Pesawaran, Muara Enim, OKU, OKU Selatan, Deli Serdang, Humbang Hasundutan, Medan, Samosir, Serdang Bedagai, Tanjungbalai, Tapanuli Selatan, Tapanuli Utara
28	$X_{19}$	Rokan Hilir, Labuhanbatu Utara, Padang Lawas, Padang Sidempuan, Pakpak Bharat, Tapanuli Tengah
29	-	Aceh Besar, Aceh Jaya, Aceh Singkil, Bireuen, Nagan Raya, Simeulue, Bangka Barat, Bangka Selatan, Belitung Timur, Pangkalpinang, Bengkulu Tengah, Kepahiang, Lebong, Mukomuko, Rejang Lebong, Bungo, Jambi, Kerinci, Merangin, Muaro Jambi, Sarolangun, Sungai Penuh, Batam, Bintan, Karimun, Kep. Anambas, Natuna, Tanjung-pinang, Bengkulu, Dumai, Indragiri Hilir, Kampar, Kep. Meranti, Pekanbaru, Pelalawan, Rokan Hulu, Agam, Bukittinggi, Lima Puluh Kota, Padang, Padang Panjang, Padang Pariaman, Pariaman, Pasaman Barat, Payakumbuh, Pesisir Selatan, Sawahlunto, Sijunjung, Solok, Banyuasin, Lubuklinggau, Musi Banyuasin, Dairi, Labuhanbatu Selatan, Nias Selatan, Nias Utara

### 3.8 Best Model Selection

Selection of the best model between the BNBR model and the GWNBR model can take into account the DIC value. Based on the results of the analysis, the DIC values for each model are presented in the following table:

**Table 7.** DIC values

Model	DIC
BNBR	274,855
GWNBR	225,048

Based on Table 7, the DIC value for the GWNBR model produces a smaller value than the BNBR model. It can be concluded that the GWNBR model is better at modeling MMR and NMR in the Sumatra Region in 2020.

## 4. CONCLUSION

Based on the results of the analysis and discussion that have been carried out, the following conclusions can be drawn modeling the maternal and neonatal mortality rates in the Sumatra Region for 2020 using the Ordinary Least Square (OLS) approach has experienced overdispersion problems. This is evidenced by the mean value of the two responses which is smaller than the value of the variance and the significant Index of Dispersion Test, so that a model based on the Bivariate Negative Binomial distribution is suitable for use in this case. However, the results of the homogeneity test show that there is a problem of spatial heterogeneity in the BNBR model, so it is believed that the local model is better used for modeling maternal and neonatal deaths in the Sumatra Region in 2020.

GWNBR parameter estimation is carried out by maximizing the n-function likelihood of the BNBR model for each weighted location. The solution to get the parameter estimator is done by Newton-Raphson iteration. The results of the model similarity test show that the GWNBR model is significantly different from the BNBR model, which means that there is an influence of geographical factors on the BNBR model, so that the GWNBR model is good enough to be used in this study.

The DIC value obtained for the GWNBR model is smaller than the BNBR model, so it can be concluded that the GWNBR model is better than the BNBR model in modeling MMR and NMR in the Sumatra Region in 2020.

## REFERENCES

- [1] Anselin, L., & Getis, A. 1992. Spatial Statistical Analysis and Geographic Information Systems. *The Annals of Regional Science*, Vol. 26 (1), 19-33.
- [2] Anselin, L. 1988. *Spatial Econometrics: Methods and Models*. Jerman: Springer Science & Business Media.
- [3] Munikah, T., Pramoedyo, H., & Fitriani, R. 2014. Pemodelan Geographically Weighted Regression dengan Pembobot Fixed Gaussian Kernel pada Data Spasial (Studi Kasus Ketahanan Pangan di Kabupaten Tanah Laut Kalimantan Selatan). *Jurnal Natural B*, Vol. 2 (3), 296-302.
- [4] Astutik, S., Wayan, N. N., & Kurniawan, D. 2007. *Penggunaan Geographically Weighted Regression pada Data yang Mengandung Heteroskedastisitas Spasial*. Malang: Universitas Brawijaya.
- [5] Fotheringham, A. S., Brunson, C., & Charlton, M. 2002. *Geographically Weighted Regression: The Analysis of Spatially Varying Relationships*. New York: John Wiley & Sons Inc.
- [6] Maggri, I., & Ispriyanti, D. 2013. Pemodelan Data Kemiskinan di Provinsi Sumatera Barat dengan Metode Geographically Weighted Regression (GWR). *Media Statistika*, Vol. 6 (1), 37-49.
- [7] da Silva, A. R., & Rodrigues, T. C. V. 2014. Geographically Weighted Negative Binomial Regression-Incorporating Overdispersion. *Statistics and Computing*, Vol. 24 (5), 769-783.
- [8] Rini, D. S. 2018. Geographically Weighted Negative Binomial Regression untuk Jumlah Kasus Demam Berdarah Dengue Kabupaten/Kota Provinsi Bengkulu. *Prosiding Seminar Nasional Matematika*, Vol. 1 (1), 736-744.
- [9] Rachelia, R. S. S., Jaya, I. G. N. M., & Hendrawati, T. 2022. Pemodelan Kasus COVID-19 di Kabupaten Ciamis Menggunakan Metode Geographically Weighted Negative Binomial Regression (GWNBR). *E-Journal Biostatistics*, Vol. 16 (1), 17-30.

- [10] Ulum, A. F. B. 2016. Penaksiran Parameter dan Pengujian Hipotesis Model Geographically Weighted Bivariate Negative Binomial Regression (Studi Kasus: Jumlah Penderita Penyakit Kusta Tipe PB dan MB di Jawa Timur Tahun 2012). *Tesis*. Surabaya: Institut Teknologi Sepuluh Nopember.
- [11] Alfariz, F. N., & Purhadi. 2019. Pemodelan Jumlah Anak Putus Sekolah Usia Wajib Belajar dan Jumlah Wanita Menikah Dini di Jawa Timur dengan Pendekatan Geographically Weighted Bivariate Negative Binomial Regression (GWBNBR). *Jurnal Sains dan Seni ITS*, Vol. 8 (2), 193-199.
- [12] Permatasari, E., Baroya, N. M., Ramani, A., Wicaksono, D. B. C., Luthfiyana, N. U., Kusumawardani, D. A., & Wati, D. M. 2021. Tantangan Proses Impelementasi Program Penurunan Angka Kematian Ibu di Wilayah Kerja Puskesmas Panti Kabupaten Jember. *Jurnal Penelitian Kesehatan Suara Forikes*, Vol. 12 (1), 21-25.
- [13] Gunst, R. F. 1983. Regression Analysis with Multicollinear Predictor Variables: Definition, Direction, and Effects. *Communications in Statistics-Theory and Methods*, Vol. 12 (19), 2217-2260.
- [14] Hocking, R. R. 1996. *Methods and Applications of Linear Models*. New York: Wiley Inc.
- [15] Darnah, 2011. Mengatasi Overdispersi pada Model Regresi Poisson dengan Generalized Poisson Regression. *Jurnal Ekspansional*, Vol. 2 (2), 5-10.
- [16] Loukas, S., & Kemp, C. D. 1986. The Index of Dispersion Test for The Bivariate Poisson Distribution. *Biometrics*, Vol. 42 (4), 941-948.
- [17] Gurmu, S., & Elder, J. 2007. A Simple Bivariate Count Data Regression Model. *Economics Bulletin*, Vol. 3 (11), 1-10.
- [18] Pearson, K. 1895. Notes on Regression and Inheritance in the Case of Two Parents. *Proceedings of the Royal Society of London*, Vol. 350 (58), 240-242.
- [19] Famoye, F. 2010. On the Bivariate Negative Binomial Regression Model. *Journal of Applied Statistics*, Vol. 37 (6), 969-981.
- [20] Gregory, A. W., & Veall, M. R. 1985. Formulating Wald Tests of Nonlinear Restrictions. *Econometrica: Journal of the Econometric Society*, Vol. 53 (6), 1465-1468.
- [21] Glejser, H. 1969. A New Test for Heteroskedasticity. *Journal of The American Statistical Association*, Vol. 64 (325), 316-323.
- [22] Li, C. H. 2016. Confirmatory Factor Analysis with Ordinal Data: Comparing Robust Maximum Likelihood and Diagonally Weighted Least Squares. *Behavior Research Methods*, Vol. 48 (3), 936-949.
- [23] Yulianto, Ramadiani, & Kridalaksana, A. H. 2018. Penerapan Formula Haversine Pada Sistem Informasi Geografis Pencarian Jarak Terdekat Lokasi Lapangan Futsal. *Informatika Mulawarman : Jurnal Ilmiah Ilmu Komputer*, Vol. 13 (1), 14-21.
- [24] Inman, J. 1835. *Navigation and Nautical Astronomy: For the Use of British Seamen*. London: W. Woodward, C. & J. Rivington.
- [25] Hadijati, M. 2004. Estimasi Kernel dalam Regresi Nonparametrik dengan Error Berkorelasi. *Tesis*. Surabaya: Institut Teknologi Sepuluh Nopember.
- [26] Silverman, B. W. 1986. *Density Estimation for Statistics and Data Analysis (Vol. 26)*. London: CRC press.
- [27] McCullagh, P. & Nelder, J.A. 1989, *Generalized Linear Models Second Edition*. London: Chapman and Hall.
- [28] Hilbe, J. M. 2011. *Negative Binomial Regression*. Cambridge: Cambridge University Press.
- [29] Spiegelhalter, D. J., Best, N. G., Carlin, B. P., & Van der Linde, A. 2014. The Deviance Information Criterion: 12 Years On. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, Vol. 76 (3), 485-493.