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Modeling of the Stunting Cases Using GWPR Incorporating Exposure in Central Java Province

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ABSTRACT

Geographically Weighted Poisson Regression (GWPR) is a local form of Poisson regression that accounts for cases of spatial heterogeneity. Many studies have been conducted on GWPR models; however, these models do not account for the population size in each region. In this study, GWPR incorporating exposure was applied for the modeling of stunting cases in Central Java Province, Indonesia. The exposure in this model is the number of toddlers in each regency/city. The results of the empirical study showed that the percentage of low birth weight has a significant effect on the stunting cases in all regencies/cities, with the exception of Purworejo and Wonosobo. Meanwhile, other independent variables that have a significant effect on stunting cases vary across regencies/cities. The GWPR model incorporating exposure yields lower MSE values than the GWPR model without exposure, which were 4871 and 5730, respectively. The lower MSE indicates that the GWPR incorporating exposure has better accuracy in modeling the number of stunting cases.

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1. INTRODUCTION

Poisson regression is a powerful statistical technique used to analyze count data. This model assumes that the response variable follows a Poisson distribution, which describes the probability of the number of events occurring in a fixed interval of time or space [1][2]. For example, the number of stunting cases, school bullying, traffic accidents, and infant deaths during a given time period, etc.

One of the assumptions underlying the Poisson regression model is that there is no heteroscedasticity [3]. However, this condition will be difficult to fulfill when analyzing spatial data, because the data structure might vary across space. This case is referred to as spatial heterogeneity [4]. Studies on Poisson regression with spatial heterogeneity have been done by Researchers. [5] introduced geographically weighted Poisson regression (GWPR) and its semi-parametric form as a new statistical method for examining disease maps arising from spatially non-stationary processes. For the practical implementation of data analysis on S-GWR and GWPR models, the GWR 4.0 software has been developed [6]. [7] In their article, they compare the use of a GWPR and generalized linear modeling (GLM) to capture these spatially varying relationships in crash data. Meanwhile, GWPR with various modifications has been widely used for modeling response variables, including: the number of stunting toddlers in Indonesia, hysterectomy incidence in Belgium, cancer incidence in Iraq [8][9][10][11]. These GWPR studies do not take into account the population size in each region, whereas in reality, the population is heterogeneous. For example, the prevalence of stunting is related to the number of toddlers in the region, which varies for each region. In the GWPR, if the independent variable is the percentage of an event, while the response variable represents the number of events without taking into account the population size in each region, the model may not fit well. To solve that problem, it is necessary to add exposure to the GWPR model, which is the size of the population in each region.

In this study, GWPR incorporating exposure will be applied for modeling the number of stunting cases in Central Java Province, Indonesia. Stunting is a condition where the growth of a toddler is disrupted, so that the child's height is significantly below the average for their age [12]. This condition is measured by a height that is less than two standard deviations below the median of the World Health Organization (WHO) child growth standards [13]. The WHO declared stunting is a global health issue affecting millions of children. According to WHO reports, around 22,3% (149 million) of children under the age of five globally suffer from stunting in 2022 [14]. Indonesia is one of the countries where the prevalence of stunting is quite high, ranked 2nd among ASEAN countries. Based on data from "Indonesia Health Profile 2023", the prevalence of stunting in Indonesia was around 21,5% (4,8 million) [15]. Central Java is one of the provinces that has contributed greatly to the prevalence of stunting in Indonesia, which is around 480 thousand toddlers [16].

The incidence of stunting in toddlers can be reduced if both direct and indirect risk factors are controlled. The direct factors that cause stunting are low birth weight, poor nutrition, inadequate breastfeeding, incomplete immunization, vitamin deficiency, and infectious diseases [17][18][19]. Indirect causes of stunting include poor environmental health, poor health services, parental education, and family economic status [20][21][22]. This study aims to create a spatial model of the factors influencing the number of stunting cases in the Province of Central Java by considering the characteristics of each regency/city area. The results of this spatial modeling can be used as a consideration by the Central Java Provincial Health Office in implementing effective interventions to reduce stunting cases according to the characteristics of each regency/city.

2. RESEARCH METHOD

2.1 Variables and Data Sources

The application of the GWPR incorporating exposure in this study is used for the modeling of the stunting cases in the Province of Central Java. Dynamic data on stunting cases is taken from the Family Health and Nutrition Section of Central Java Provincial Health Office, and support data from "Health Profile of Central Java Province 2023". Central Java Province is geographically positioned between 5°40'–8°30' south latitude and 108°30'–111°30' east longitude, and is administratively composed of 29 regencies and six cities.

In this study, data analysis was carried out by including six independent variables that influence the number of stunting cases, as presented in Table 1.

Table 1. Variables in Research

Variable	Description	Measurement Unit
Y	The number of stunting cases	Number of cases
X1	Percentage of low birth weight	Percent (%)
X2	Percentage of early initiation of breastfeeding	Percent (%)
X3	Percentage of complete basic immunization	Percent (%)
X4	Percentage of children are given vitamin A	Percent (%)
X5	Percentage of healthy homes	Percent (%)
X6	Percentage of child growth and development services	Percent (%)

2.2 Poisson Distribution Incorporating Exposure

A discrete random variable Y follows a Poisson distribution with parameter $\lambda(s)$, where s represents the exposure (defined as the size of the population each sample unit), if and only if the probability function is written as follows.

$$f(y \mid \lambda(s)) = \begin{cases} \dfrac{e^{-\lambda(s)}\lambda(s)^y}{y!} & ; y = 0,1,2,\dots \; ; \lambda(s) \ge 0 \\ 0 & ; y \text{ otherwise} \end{cases} \tag{1}$$

Moment generating functions, mean, and variance of the random variable Y are written as follows:

$$M_Y(t) = e^{\lambda(s)(e^t-1)},\; E[Y] = \lambda(s), \text{ dan } Var[Y] = \lambda(s). \tag{2}$$

The probability function in Equation (1) can be written as the canonical form of the exponential family with natural parameters $\ln \lambda(s)$, as follows:

$$f(y) = \exp[y \ln \lambda(s) - \lambda(s) - \ln y!]. \tag{3}$$

2.3 Poisson Regression Incorporating Exposure

Let random samples $Y_i \sim P(\lambda(s_i))$; i=1,2,...,n where s_i denotes the exposure, defined as the population size of the i-th unit. According to Equation (3), the Poisson distribution belongs to the exponential family, with $\ln \lambda(s_i)$ as its natural parameter. Consequently, Poisson regression incorporating exposure can be formulated as the natural logarithm of the expected value of Y_i, which is proportional to the population size s_i and influenced by the independent variable $\mathbf{x}_i$ [23], as shown in Equation (4).

$$\ln \frac{E[Y_i]}{s_i} = \mathbf{x}_i^T \boldsymbol{\beta}, \tag{4}$$

$$E[Y_i] = s_i e^{\mathbf{x}_i^T \boldsymbol{\beta}}, \tag{5}$$

Based on the mean of Poisson distribution in Equation (2), Equation (5) can be written as follows.

$$\lambda(s_i) = s_i e^{\mathbf{x}_i^T \boldsymbol{\beta}}, \tag{6}$$

where

$\mathbf{x}_i = [1 \quad x_{1i} \quad x_{2i} \quad \dots \quad x_{ki}]^T$,

$\boldsymbol{\beta} = [\beta_0 \quad \beta_1 \quad \beta_2 \quad \dots \quad \beta_k]^T$.

2.4 Spatial Heterogeneity

Spatial heterogeneity is a property of spatial data that shows variations in the patterns of relationships between dependent and independent variables across locations. The Breusch-Pagan test is a statistical test for detecting spatial heterogeneity. The hypothesis testing formula of Breusch-Pagan test is expressed in Equation (7).

$$\begin{aligned} &H_0 : \sigma_1^2 = \sigma_2^2 = \dots = \sigma_n^2 = \sigma^2 \\ &H_1 : \text{at least one } \sigma_i^2 \neq \sigma^2 \end{aligned} \tag{7}$$

The test statistic is given as:

$$BP = \frac{1}{2} \mathbf{f}^T \mathbf{Z} (\mathbf{Z}^T \mathbf{Z})^{-1} \mathbf{Z}^T \mathbf{f} \tag{8}$$

The element vector **f** is $f_i = (\frac{e_i^2}{\sigma^2} - 1)$

where e_i is the error for i-th observation, σ^2 is the variance of e_i, and $\boldsymbol{Z}$ is standardized of **X**.

The test statistic in Equation (8) follows the chi square distribution. So, reject the null hypothesis at the significance level α when $BP > \chi_{(\alpha,k)}$.

2.5 Spatial Dependence

Spatial dependence is a property of spatial data that occurs when values observed at one location depend on values at neighboring locations. The Moran's I is a statistical test for detecting spatial dependence. The hypothesis testing formula of Moran's I test is expressed in Equation (9).

$$\begin{aligned} &H_0 : I = 0 \\ &H_1 : I \neq 0 \end{aligned} \tag{9}$$

The test statistic is given as:

$$Z = \frac{I - E[I]}{\sqrt{Var[I]}} \sim N(0,1) \tag{10}$$

with $I = \dfrac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{(\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij})\sum_{i=1}^{n}(y_i - \bar{y})^2}$

The test statistic in Equation (10) follows the standard normal distribution. So, reject the null hypothesis at the significance level α when $|Z| > Z_{\alpha/2}$.

3. RESULT AND ANALYSIS

3.1 Geographically Weighted Poisson Regression Incorporating Exposure

The GWPR model is a development of the Poisson regression model. In the GWPR model, to predict the response variable y based on the independent variable, where the regression coefficient in each region varies according to the geographical location of the observed data [5].

Let random samples $Y_i \sim P(\lambda(s_i, \mathbf{u}_i))$; i=1, 2, ..., n where s_i is the exposure and $\mathbf{u}_i = (u_{1i} \quad u_{2i})$ is a vector of point single coordinates geographic space (latitude and longitude) at location-i, then the modified GWPR incorporating exposure can be written as follows:

$$\lambda(s_i, \mathbf{u}_i) = s_i e^{\mathbf{x}_i^T \boldsymbol{\beta}(\mathbf{u}_i)}, \tag{11}$$

where

$\mathbf{x}_i = [1 \quad x_{1i} \quad x_{2i} \quad \ldots \quad x_{ki}]^T$,

$\boldsymbol{\beta}(\mathbf{u}_i) = [\beta_0(\mathbf{u}_i) \quad \beta_1(\mathbf{u}_i) \quad \beta_2(\mathbf{u}_i) \quad \ldots \quad \beta_k(\mathbf{u}_i)]^T$.

3.2 Parameter Estimation of GWPR Incorporating Exposure

The parameters of GWPR incorporating exposure are estimated using the maximum likelihood estimation (MLE). This method gets the optimum parameter estimator by maximizing the weighted logarithm likelihood function.

Let random samples $Y_i \sim P(\lambda(s_i, \mathbf{u}_i))$; i=1, 2, ..., n with GWPR model at Equation (11), then the logarithm likelihood function can be expressed as follows.

$$L\left(\lambda(s_1, \mathbf{u}_i), \lambda(s_2, \mathbf{u}_i), \ldots, \lambda(s_n, \mathbf{u}_i)\right) = \prod_{j=1}^{n} \frac{e^{-\lambda(s_j, \mathbf{u}_i)} \lambda^{y_j}(s_j, \mathbf{u}_i)}{y_j!}. \tag{12}$$

By substituting Equation (11) into Equation (12), the log-likelihood function for location-i is obtained as follows:

$$l\left(\boldsymbol{\beta}(\mathbf{u}_i)\right) = \sum_{j=1}^{n}\left(-s_j e^{\mathbf{x}_j^T \boldsymbol{\beta}(\mathbf{u}_i)} + y_j \mathbf{x}_j^T \boldsymbol{\beta}(\mathbf{u}_i) + y_j \ln s_j - \ln(y_j!)\right). \tag{13}$$

The parameter estimation in the GWPR models used a weighting matrix based on the proximity among locations. [24] proposed some types of weighting functions that can be used to describe proximity between the location-i with other locations, one of which is a *Gaussian function,* where the weight of the j^{th} data point at the i^{th} regression point is calculated by:

$$w_{ij} = \exp\left[-\frac{1}{2}\left(\frac{d_{ij}}{r}\right)^2\right] \tag{14}$$

where w_{ij} is the spatial weight of location-j on location-i, d_{ij} is the Euclidean distance, and r is the bandwidth that controls the degree of distance-decay. The weighting value of data will approach one if the distance is close, and will decrease until it approaches zero if the distance is further.

The choice of optimum bandwidth is thus a trade-off between bias and variance. The optimum bandwidth can be determined using generalized cross validation (GCV), which is as shown in Equation (15).

$$GCV = \frac{n\sum_{i=1}^{n}(y_i - \hat{y}_i(r))^2}{(n-v)^2} \tag{15}$$

where $\hat{y}_i(r)$ is a predicted value y_i for bandwidth r, and v is the number of effective parameters in the model.

Considering the weighting function in Equation (14), to obtain an estimator of the parameter at location-*i* is required by information from location-*j* with w_{ij} as weighted value. So, the weighted log-likelihood function in Equation (13) can be written as:

$$l^*\left(\boldsymbol{\beta}(\mathbf{u}_i)\right)=\sum_{j=1}^{n}\left(-s_j e^{\mathbf{x}_j^T\boldsymbol{\beta}(\mathbf{u}_i)}+y_j\mathbf{x}_j^T\boldsymbol{\beta}(\mathbf{u}_i)+y_j\ln s_j-\ln(y_j!)\right)w_{ij}. \quad (16)$$

The parameter estimates of the GWPR model incorporating exposure are obtained by maximizing the weighted likelihood function over the vector parameter $\boldsymbol{\beta}(\mathbf{u}_i)$. The first partial derivatives of Equation (16) with respect to the vector $\boldsymbol{\beta}(\mathbf{u}_i)$ and setting the result to a vector of zero, as follows.

$$\frac{\partial l^*(\boldsymbol{\beta}(\mathbf{u}_i))}{\partial\boldsymbol{\beta}(\mathbf{u}_i)}=-\sum_{j=1}^{n}w_{ij}\mathbf{x}_j s_j e^{\mathbf{x}_j^T\boldsymbol{\beta}(\mathbf{u}_i)}+\sum_{j=1}^{n}w_{ij}y_j\mathbf{x}_j=0. \quad (17)$$

The MLE method does not give an analytical solution when the result of the partial derivative at Equation (17) is not closed-form. The Newton-Raphson algorithm is a numerical optimization method that works well for concave objective functions. The Newton-Raphson algorithm is formulated as follows.

$$\hat{\boldsymbol{\beta}}_{(t+1)}(\mathbf{u}_i)=\hat{\boldsymbol{\beta}}_{(t)}(\mathbf{u}_i)-\mathbf{H}^{-1}(\hat{\boldsymbol{\beta}}_{(t)}(\mathbf{u}_i)\mathbf{g}(\hat{\boldsymbol{\beta}}_{(t)}(\mathbf{u}_i)), \quad (18)$$

where

$\hat{\boldsymbol{\beta}}_{(t)}(\mathbf{u}_i)$ is an estimator of the parameters at t^{th} iteration, $\mathbf{g}(\hat{\boldsymbol{\beta}}_{(t)}(\mathbf{u}_i))$ is a vector of gradients, where the elements of the vector are the first partial derivatives of the weighted log-likelihood function for each parameter, and $\mathbf{H}(\hat{\boldsymbol{\beta}}_{(t)}(\mathbf{u}_i)$ is matrix of Hessian, where the elements of the matrix are the second partial derivatives of the weighted log-likelihood function for each parameter combination.

The iterative procedure in Equation (18) will be ends when a predefined convergence criterion is satisfied. Convergence occurs when $\left\|\boldsymbol{\beta}_{(t+1)}(\mathbf{u}_i)-\boldsymbol{\beta}_{(t)}(\mathbf{u}_i)\right\|\le\varepsilon$ are close to zero.

3.3 Hypothesis Testing of GWPR Incorporating Exposure

The partial hypothesis test is used to determine the significance of each individual parameter in the model. The hypothesis testing formula of GWPR incorporating exposure is expressed in Equation (19).

$$\begin{aligned}&H_0:\beta_l\left(\mathbf{u}_i\right)=0 \quad ; l=1,2,..,k \text{ and } i=1,2,...,n\\&H_1:\beta_l\left(\mathbf{u}_i\right)\neq 0.\end{aligned} \quad (19)$$

The test statistic is given as:

$$Z=\frac{\hat{\beta}_l(\mathbf{u}_i)}{\sqrt{\text{var}[\hat{\beta}_l(\mathbf{u}_i)]}}\sim N(0,1) \quad (20)$$

where

$\text{var}(\hat{\beta}_l(\mathbf{u}_i))$ is the $(l+1)$ diagonal elements of matrix $[-\mathbf{H}(\hat{\boldsymbol{\beta}}(\mathbf{u}_i))]^{-1}$.

The test statistic in Equation (20) follows the standard normal distribution, denoted as N (0,1). So, reject the null hypothesis at the significance level α when $|Z|>Z_{\alpha/2}$.

3.4 Description of the Number of Stunting Cases

Central Java is one of the provinces that has contributed greatly to the prevalence of stunting in Indonesia. According to data from the "Central Java Provincial Health Profile 2023," there were 174,443 cases of stunting (low height-for-age) in Central Java. Figure 1 shows the distribution of stunting cases, with three regencies (Banyumas, Tegal, and Brebes) having over 10,000 cases of stunting in toddlers.

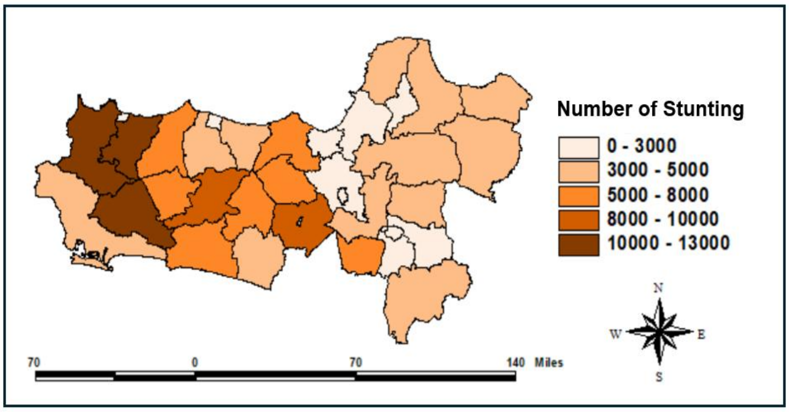

Figure 1. The number of stunting in Central Java Province in 2023

3.5 Spatial Effects Test

Spatial effect tests are conducted to detect spatial heterogeneity and dependency in stunting data. The results of the Breuch Pagan and Moran's index are presented in Table 2.

Table 2. Test of Spatial Heterogeneity and Dependence

Spatial Efects	Test	Statistic Value	p-value
Spatial Heterogeneity	Breuch Pagan	13.0761	0.0418
Spatial Dependence	Moran's I	1.3071	0.1912

Based on the statistical test presented in Table 2, the spatial dependence test yielded a Moran's I of 0.0157 and a p-value of 0.78660, indicating no spatial dependence in the stunting data. Meanwhile, the spatial heterogeneity test yielded a Breusch-Pagan of 13.234 and p-value of 0.4067, indicating spatial heterogeneity in the stunting data. Violating the homogeneity assumption in Poisson regression can lead to biased and inefficient parameter estimates. In these stunting cases, GWPR incorporating exposure is a suitable statistical tool to capture the effects of spatial heterogeneity.

3.6. Spatial Modeling of The Number of Stunting Cases

The results of the GWPR data analysis incorporating exposure show that each region has distinct characteristics. In this paper, we present model examples for two regencies (Magelang and Grobogan). The parameter estimates and Z-statistic values for both regencies are presented in Table 3.

Table 3. Parameter estimators and significance test of GWPR incorporating exposure

Parameter	Magelang Regency			Grobogan Regency		
	Coeff	se	Z	Coeff	se	Z
β_0	-0.2726	0.5830	-0.46758	1.0601	1.0696	0.99112
β_1	0.1056	0.0148	7.13514 *)	0.1478	0.0407	3.63145 *)
β_2	-0.0070	0.0050	-1.40000	-0.0005	0.0065	-0.07692
β_3	-0.0083	0.0040	-2.07500*)	-0.0422	0.0075	-5.62667 *)
β_4	-0.0043	0.0046	-0.93478	-0.0108	0.0035	-3.08571*)
β_5	-0.0083	0.0018	-4.61111 *)	0.0037	0.0058	0.63793
β_6	0.0001	0.0027	0.03704	0.0033	0.0049	0.67347

*) significant for α=5%

Based on the value of the test statistic presented in Table 3, it can be shown that there are differences the independent variables that have a significant effect on the stunting cases for the Magelang and Grobogan Regencies (Z-value>1.96). The percentage of low birth weight and complete basic immunization have a significant effect on the stunting cases in both regencies. Other independent variables with significant effects were the percentage of healthy homes (Magelang Regency) and the percentage of children who were given vitamin A (Grobogan Regency).

The GWPR model incorporating exposure from both regencies is written as follows.

$$\hat{Y}_{\text{Magelang}} = 56973\exp(-0.2726 + 0.1056X_1 - 0.0070X_2 - 0.0083X_3 - 0.0043X_4 - 0.0083X_5 + 0.0001X_6)$$

$$\hat{Y}_{\text{Grobogan}} = 80820\exp(1.0601 + 0.1478X_1 - 0.0005X_2 - 0.0422X_3 - 0.0108X_4 + 0.0037X_5 + 0.0033X_6)$$

The multiplier factor in the GWPR model incorporating exposure is the number of toddlers, which in Magelang and Grobogan Regencies are 56973 and 80820, respectively. The predicted values for the number of stunting cases are $\hat{Y}_{\text{Magelang}} = 8678$ and $\hat{Y}_{\text{Grobogan}} = 4633$, which are close to the actual values of 8676 and 4634, respectively.

For all regions in Central Java province, Figure 2 illustrates that the GWPR model incorporating exposure yields accurate predictions for the number of stunted cases. The predicted values for almost all regencies/cities are close to the actual values, with a mean square error (MSE)=4871. This model is better than the GWPR model without exposure, with MSE=5730.

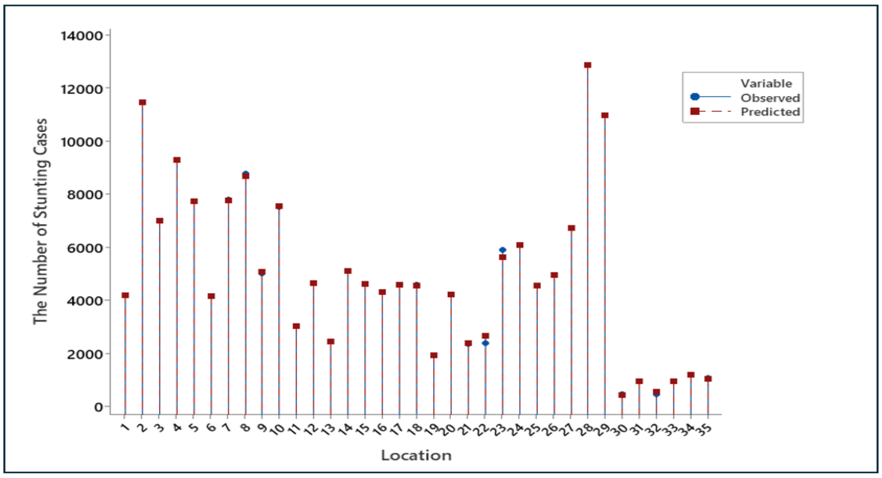

Figure 2. Plotting predicted and observed values for the number of stunting cases

Furthermore, the independent variables that have a significant effect on the stunting cases in each regency/city is presented in Figure 3.

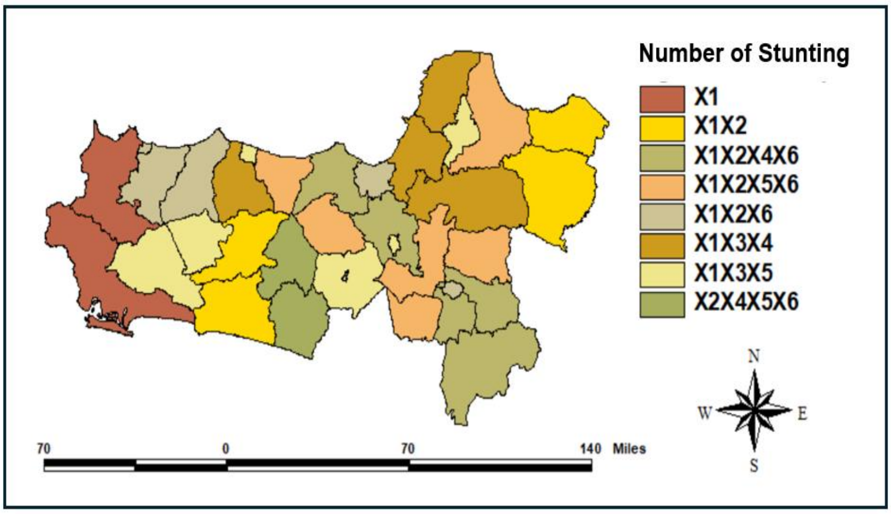

Figure 3. The independent variables that have a significant effect on the stunting cases

Figure 3 shows that the percentage of low-birth-weight significant effects on the stunting cases in all regencies/cities, with the exception of Purworejo and Wonosobo. The percentage of early initiation of breastfeeding is an independent variable that has a significant effect on the stunting cases in 23 regencies/cities. Meanwhile, other independent variables that significant effects the number of stunting cases vary across regencies/cities.

Low birth weight (LBW) babies indicate that the fetus did not receive adequate nutrition during pregnancy. Babies born with LBW often experience digestive problems and difficulty breastfeeding. This condition results in slower physical growth and brain development than babies of normal weight. If LBW is not followed up with adequate nutritional intake, the child is susceptible to stunting [25][26]. Meanwhile, early initiation of breastfeeding helps babies recognize breast milk, stimulates milk production, and increases the success of exclusive breastfeeding. Exclusive breastfeeding ensures optimal nutrition for babies, boosts the immune system, and prevents infections [27].

4. CONCLUSION

GWPR is one of the statistical methods which used to analyze count data with spatial heterogeneity. To solve the problem of heterogeneity in the number of populations in each sample unit, it is necessary to add exposure to the GWPR model, which is defined as the size of the population in each region. The results of the empirical study showed that there are differences in the independent variables that significantly effect on the stunting cases in each regency/city. The percentage of low-birth-weight significant effects the number of stunting cases in all regencies/cities, except in two regencies (Purworejo and Wonosobo). Meanwhile, other independent variables that significant effects the number of stunting cases vary across regencies/cities. The GWPR model incorporating exposure yields accurate predictions for the number of stunted cases. The predicted values for almost all regencies/cities are close to the actual values (MSE=4871), which is better than the GWPR model without exposure (MSE=5730). The lower MSE indicates that the GWPR incorporating exposure has better accuracy in modeling the number of stunting cases.

The results of this spatial modeling can be considered by the Central Java Provincial Health Office in its efforts to reduce stunting cases, based on the characteristics of each district/city. Low birth weight (LBW) is the most dominant variable influencing stunting cases in Central Java Province, so effective management is needed to prevent LBW through interventions before and during pregnancy. Furthermore, the Health Office can provide information and education on stunting and its prevention, for example, by optimizing exclusive breastfeeding programs and promoting healthy lifestyles.

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