Geographically Weighted Negative Binomial Regression (GWNBR) Modeling In Infant Mortality Rate Cases In South Sulawesi

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ABSTRAK

Geographically Weighted Negative Binomial Regression (GWNBR) adalah salah satu metode untuk memodelkan data cacah yang mengalami overdispersi dan mempunyai heterogenitas spasial. Sulawesi Selatan merupakan salah satu provinsi yang mengalami peningkatan pada kasus angka kematian bayi. Oleh karena itu, penelitian ini bertujuan memperoleh model yang lebih baik dalam memetakan faktor-faktor yang mempengaruhi kasus angka kematian bayi di Provinsi Sulawesi Selatan. Metode yang digunakan pada penelitian ini adalah GWNBR dengan menggunakan *Adaptive Tricube Kernel* sebagai pembobot. Hasil penelitian menunjukkan bahwa model GWNBR dengan pembobot *Adaptive Tricube Kernel* menghasilkan nilai AIC terkecil yaitu sebesar 223,4447 sehingga lebih efektif digunakan dalam memodelkan kasus angka kematian bayi di Provinsi Sulawesi Selatan. Variabel-variabel yang berpengaruh signifikan terhadap kasus angka kematian bayi adalah X_1 (Persentase ASI Eksklusif), X_2 (Persentase Inisiasi Menyusu Dini), X_3 (Cakupan Kunjungan Bayi Lengkap), X_4 (Persentase Pemberian Vitamin A), X_5 (Jumlah Puskesmas), X_6 (Persentase Bayi Berat Lahir Rendah), X_7 (Cakupan Persalinan di Fasilitasi Pelayanan Kesehatan), dan X_8 (Pemberian Tablet Tambah Darah pada Ibu Hamil).

Kata kunci: GWNBR, Adaptive Tricube Kernel, Kematian Bayi

ABSTRACT

Geographically Weighted Negative Binomial Regression (GWNBR) is a method used to model count data that exhibit overdispersion and spatial heterogeneity. South Sulawesi is one of the provinces experiencing an increase in infant mortality cases. Therefore, this study aims to obtain a better model for mapping the factors that influence infant mortality cases in South Sulawesi Province. The method used in this study is GWNBR with an Adaptive Tricube Kernel as the weighting function. The results show that the GWNBR model with Adaptive Tricube Kernel weighting produces the smallest AIC value, which is 223.4447, making it more effective for modeling infant mortality cases in South Sulawesi Province. The variables significantly affecting infant mortality cases include X_1 (Percentage of Exclusive Breastfeeding), X_2 (Percentage of Early Initiation of Breastfeeding), X_3 (Complete Baby Visit Coverage), X_4 (Percentage of Vitamin A Supplementation), X_5 (Number of Community Health Centers), X_6 (Percentage of Low Birth Weight Babies), X_7 (Delivery Coverage in Health Service Facilities), and X_8 (Iron Tablet Supplementation to Pregnant Women).

***Keywords**: GWNBR, Adaptive Tricube Kernel, Infant Mortality*

INTRODUCTION

Poisson regression is used to analyze the reliationship between predictor variables and data that follow a Poisson distribution, assuming equidispersion, where the mean is equal to the variance. If the variance exceeds the mean (overdispersion), the Poisson model is no longer appropriate [1], [2]. One solution is to use negative binomial regression, which introduces a dispersion parameter to handle this condition[3]. Additionally, if spatial effects are present in the data, a spatial effect test is required. Spatial effects occur when observations are dependent on neighboring areas. They are divided into spatial dependence, which is handled with an area-based approach, and spatial heterogeneity, which uses a point-based approach. These effects are represented by location coordinates or weighting [4].

One of the analytical tools to handle data cases by considering spatial effects is the Geographically Weighted Regression (GWR) model [5]. The Geographically Weighted Negative Binomial Regression (GWNBR) model is applied when modeling discrete data that exhibit overdispersion and spatial heterogeneity [6].

The infant mortality rate (IMR) is influenced by geographical, socio-cultural, and economic factors that vary by region, leading to spatial heterogeneity. According to Tobler's First Law of Geography, as explained by [7], everything is related, but nearby things are more strongly related than distant ones, which is evident in the clustering of infant mortality in certain areas.

Globally, the IMR has been declining, with a rate of approximately 27 per 1,000 live births in 2020 [8]. In Indonesia, it decreased from 17.6 per 1,000 live births in 2020 to 16.9 in 2022. However, it still does not meet the target standards for mortality reduction[9]. In South Sulawesi, the IMR increased from 5 per 1,000 live births in 2020 to 8 per 1,000 live births in 2022, signaling a need for more effective efforts to reduce infant mortality[10].

Previous studies on the GWNBR method have been conducted by several researchers. Pratiwi, Pramoedyo, Astutik, Astuti and Fauwziyah [11] examined the factors influencing stunting in Malang Regency using Geographically Weighted Negative Binomial Regression (GWNBR). The results showed that five variables significantly affected stunting: Access to durable sanitary latrines, availability of integrated health posts, exclusive breastfeeding, population density, and community empowerment. Based on the smallest AIC criterion, GWNBR was found to be the most suitable method for modeling stunting cases. Another study by Delvia, Mustafid and Yasin [12] addressed overdispersion in poverty rates using GWNBR. The modeling results indicated that the most influential factors were the unemployment rate, economic growth, and the percentage of households occupying non-owned housing. Additionally, Rais and Haris [13] investigated the factors influencing pneumonia in children under five in Central Sulawesi Province. The modeling results showed that the significant factors included exclusive breastfeeding, the proportion of children receiving complete basic immunization, and the percentage of children receiving Vitamin A. and the coverage of early childhood health services. Although the GWNBR method has been used in previous studies, its application in analyzing the factors influencing infant mortality in South Sulawesi has not been conducted before. Therefore, the researcher will use the GWNBR approach to identify the factors affecting infant mortality in South Sulawesi Province.

METHOD

Data Source

The data used in this study is secondary data, specifically infant mortality rate (IMR) records in South Sulawesi, obtained from the South Sulawesi Provincial Health Office in 2023.

Research Variables

This study involves two types of variables: response variables (Y) and predictor variables (X). The response variable used is the infant mortality rate (Y), while the predictor variables include factors that are believed to influence the infant mortality rate in 24 districts/cities in South Sulawesi Province. Below is a further explanation of the predictor variables used in this study.

X_1 = Percentage of Babies Given Exclusive Breastfeeding
X_2 = Percentage Early Initiation of Breastfeeding
X_3 = Coverage of Complete Baby Visits
X_4 = Percentage of Vitamin A Supplementation
X_5 = Number of Community Health Centers
X_6 = Percentage of Low Birth Weight
X_7 = Coverage of Deliveries in Health Care Facilities
X_8 = Percentage of Pregnant Women Consuming Iron Supplement Tablets

Research Produce

The procedures to be followed in this study are as follows:

1. Collecting various data sources and information that will be used in the research.
2. Recapping the infant mortality data in South Sulawesi Province. At this stage, the data will be sourced from the South Sulawesi Provincial Health Office.
3. Processing the data using R-Studio software with the Geographically Weighted Negative Binomial Regression (GWNBR) method.
4. Drawing conclusions.
5. Compiling the research report

Data Analysis Technique

The data analysis techniques commonly used in this study are as follows:

1. Describing the Data
   a. Characteristics of the infant mortality cases in South Sulawesi in 2023 and the factors that are suspected to influence them.
   b. Multicollinearity testing by examining the VIF values[14].

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

   Where:
   R_j^2 : The Coefficient of determination between variable X_j and other predictor variables.
2. Poisson Regression Modeling
   a. Parameter estimation of the Poisson regression model.[15].

$$L(\beta) = \frac{\exp\left(-\sum_{i=1}^{n} \exp\left(x_i^T \beta\right)\right)\left(\exp \sum_{i=1}^{n} y_i x_i^T \beta\right)}{\prod_{i=1}^{n} y_i!}$$

b. Testing the Poisson regression model parameters for significance test on the model [16]
   - Simultaneous test

$$D(\hat{\beta}) = -2 \ln \left(\frac{L(\widehat{\omega})}{L(\widehat{\Omega})}\right)$$

Where:

$\ln(\widehat{\omega})$: The likelihood function for the model excluding predictor variables.

$\ln(\widehat{\Omega})$: Likelihood function for the model without excluding predictor variables.

   - partial tests.

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

Where:

$\hat{\beta}_k$: Coefficient of the k-th predictor variable model

$se(\hat{\beta}_k)$: Standard error of the maximum likelihood estimate

3. Overdispersion Testing [16]
4. Negative Binomial Regression Modeling

a. Parameter estimation of the Negative Binomial regression model.[17].

$$L(\beta, \theta) = \prod_{i=1}^{n} \left[\frac{\Gamma(\mathrm{y_i} + \theta^{-1})}{\Gamma(\theta^{-1})\Gamma(y_i + 1)} \left(\frac{1}{1 + \theta\mu_i}\right)^{\frac{1}{\theta_i}} \left(\frac{\theta\mu_i}{1 + \theta\mu_i}\right)^{y_i} \right]$$

b. Conducting significance testing of the negative binomial regression model parameters both simultaneously and partially [15]

5. Testing spatial effects using spatial heterogeneity with the Breusch-Pagan test [18].

$$BP = \left(\frac{1}{2}\right) f^T Z (Z^T Z)^{-1} Z^T f \sim \chi_p^2$$

where, Vector elements f is $f_i = \frac{\varepsilon_i^2}{\sigma^2} - 1$

6. GWNBR Modeling

a. Calculating The Euclidean distance between observation points based on their geographical coordinates. [19].

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

b. Obtaining the optimal bandwidth for each observation location using Cross Validation (CV)[20].

$$CV = \sum_{i=1}^{n} (y_i - y_{\neq 1}(h))^2$$

c. Calculating the weight matrix using the Adaptive Tricube Kernel[21].

$$w_{ij} = \begin{cases} \left[1 - \left(\frac{d_{ij}}{h}\right)^3\right]^3 & , for\ d_{ij} \leq h \\ 0 & , others \end{cases}$$

Where:

d_{ij} : Euclidean distance between locations(u_i, v_j) to the location (u_i, v_j)

h : Bandwidth

d. Estimating the parameters [15] and structuring them into the model

$$L(\beta_{u_i v_i}, \theta_i | y_i, x_i) = \prod_{i=1}^{n} \left(\prod_{r=0}^{y_i - 1} \left(r + \frac{1}{\theta_i} \right) \right) \frac{1}{(y_i!)} \left(\frac{1}{1 + \theta_i \mu_i} \right)^{\frac{1}{\theta}} \left(\frac{\theta_i \mu_i}{1 + \theta_i \mu_i} \right)^{y_i}$$

e. Testing the GWNBR model parameters for significance test on the model.

$$Z_{hit} = \frac{\hat{\beta}_j(u_i v_i)}{se\left(\hat{\beta}_j(u_i, v_i)\right)}$$

$\hat{\beta}_j$: Coefficient of the j-th predictor variable model

$se(\hat{\beta}_j)$: Standard error of the maximum likelihood estimate

7. Model Interpretation

RESULT AND DISCUSSION

Descriptive Analysis

Descriptive statistics illustrate the distribution of infant mortality cases (IMR) in South Sulawesi in 2023. The total number of IMR cases was 1,431, with an average of 59.62 cases. The minimum number of cases was 15, the maximum was 220, and the standard deviation was 41.68. The descriptive statistics of the predictor variables, including the mean, maximum value, minimum value, and standard deviation, are presented in Table 1.

Table 1. Descriptive Statistics of Predictor Variables

Variable	Mean	Min	Maks	Stdev
X_1	69,55	37,75	85,76	10,77
X_2	86,35	66,63	97,85	9,53
X_3	108,15	68,99	181,64	24,77
X_4	92,64	82,48	98,84	4,17
X_5	19,67	8,00	47,00	8,58
X_6	6,65	3,370	10,150	1,75
X_7	91,80	65,63	121,97	15,09
X_8	56,74	28,09	98,81	22,02

Multicollinearity Test

The VIF values for each predictor variable are presented below.

Table 2. Multicollinearity

Variable	VIF
Percentage of Babies Given Exclusive Breastfeeding (X_1)	1,733
Early Initiation of Breastfeeding (X_2)	1,845
Coverage of Complete Baby Visits (X_3)	1,900
Percentage of Vitamin A Supplementation (X_4)	1,293
Number of Community Health Centers (X_5)	1,458
Percentage of Low Birth Weight (X_6)	1,882
Coverage of Deliveries in Health Care Facilities (X_7)	1,677
Percentage of Pregnant Women Consuming Iron Supplement Tablets (X_8)	1,319

Poisson Regression Modeling

The results obtained can be observed in Table 3.

Table 3. Estimation and Testing of Poisson Regression Model Parameters

	$Estimation$	$Std. Error$	Z_{Score}	$P-Value$	Significant
(Intercept)	4,678	0,788	5,937	$2{,}90 \times 10^{-9}$	Significant
X_1	0,023	0,004	6,425	$1{,}32 \times 10^{-10}$	Significant
X_2	− 0,015	0,004	−4,322	$1{,}55 \times 10^{-5}$	Significant
X_3	0,002	0,002	1,539	0,124	Not Significant
X_4	−0,027	0,008	−3,573	0,0003	Significant
X_5	0,035	0,003	10,966	$< 2 \times 10^{-16}$	Significant
X_6	−0,042	0,021	−2,000	0,045	Significant
X_7	0,008	0,002	3,652	0,0002	Significant
X_8	0,001	0,001	0,534	0,594	Not Significant
Devians:140,60			Df :15		
AIC: 296,769					

Simultaneous testing of Poisson regression parameters with the following hypotheses:

$H_0: \beta_1 = \beta_2 = \cdots = \beta_k = 0$

$H_1 =$ At least one $\beta_k \neq 0; k = 1,2, \dots, p$

Based on the test statistic values in Table 4, the decision is to reject H_0 at a significance level of 0,05. The deviance value $D(\hat{B}) = 140{,}60 > \boldsymbol{x^2_{(0,05,9)}} = 16{,}919$ This indicates that at least one predictor variable significantly influences the response variable. The next step is to conduct individual parameter testing. The hypotheses used in this test are as follows:

$H_0: \beta_k = 0$

$H_1: \beta_k \neq 0$

Based on the results of the partial testing at a 5% significance level, it was found that all variables, except X_3 and X_8 have $P - Value < \alpha = 5\%$. This means that the variables X_1, X_2, X_4, X_5, X_6 dan X_7 significantly influence the model. Therefore, the Poisson regression model formed is as follows:

$$\hat{\mu}_i = \mathbf{exp}\,(4{,}678 + 0{,}023X_1 - 0{,}015X_2 - 0{,}027X_4 + 0{,}035X_5 - 0{,}042X_6 + 0{,}008X_7)$$

Overdispersion

The results of the overdispersion test are presented in the Table 4 below.

Table 4. Dispersion Parameter of Poisson Regression

$\boldsymbol{Devians}$	$\boldsymbol{Df}$	$\boldsymbol{\theta}$
140,60	15	9,373

Based on the overdispersion test, it was found that the deviance divided by its degrees of freedom is greater than 1. Therefore, it can be concluded that the data Fails to satisfy the equidispersion assumption and experiences overdispersion.

Negative Binomial Regression Modeling

The results obtained can be seen in Table 5.

Table 5. Estimasi dan Testing of Negative Binomial Regression

	$\boldsymbol{Estimation}$	$\boldsymbol{Std. Error}$	$\boldsymbol{Z_{Score}}$	$\boldsymbol{P-Value}$	**Significant**
(Intercept)	4,784	1,933	2,475	0,013	Significant
X_1	0,022	0,009	2,527	0,011	Significant
X_2	−0,015	0,009	−1,505	0,132	Not Significant
X_3	0,001	0,004	0,223	0,823	Not Significant
X_4	−0,028	0,019	−1,475	0,140	Not Significant
X_5	0,031	0,009	3,176	0,001	Significant
X_6	−0,024	0,055	−0,435	0,663	Not Significant
X_7	0,011	0,006	1,840	0,066	Not Significant
X_8	0,0002	0,004	0,076	0,939	Not Significant
Devians:24,695				Df:15	
AIC: 225,701					

Simultaneous testing of Negative Binomial regression parameters with the following hypotheses:
$H_0: \beta_1 = \beta_2 = \cdots = \beta_k = 0$
$H_1 =$ At least one $\beta_k \neq 0; k = 1,2, \ldots, p$
Based on Table 5, H_0 is rejected at $\alpha = 5\%$ since $D(\hat{B}) = 24{,}695 > 16{,}919$, indicating that at least one predictor variable significantly influences the response variable, thus partial testing is conducted. The next step is to conduct individual parameter testing. The hypotheses used in this test are as follows:
$H_0: \beta_k = 0$
$H_1: \beta_k \neq 0$
Based on the results of the partial test at a 5% significance level, it was found that only two variables, X_1 dan X_5, have $P - Value < \alpha = 5\%$, meaning that these variables significantly influence the response variable. Hence, the resulting negative binomial regression model is as follows:

$$\hat{\mu}_i = \mathbf{exp}\,(4{,}784 + 0{,}022\mathrm{X}_1 - 0{,}031\mathrm{X}_5)$$

Testing Spatial Heterogeneity

The test statistics for heterogeneity using the Breusch-Pagan test, along with the results, are shown in Table 6.

Table 6. Breusch Pagan Test

Breusch Pagan Test	$x^2_{(0,05,8)}$	*P-Value*	Description
17,77	15,507	0,023	Reject H_0

The hypotheses for this test are as follows:
$H_0: \sigma_1^2 = \sigma_2^2 = \cdots = \sigma_2^n = \sigma^2$
H_1:at least one $\sigma_i^2 \neq \sigma^2$, i = 1,2, ... , n
Based on Table 7, H₀ is rejected at $\alpha = 5\%$ since $BP = 17{,}77 > 15{,}507$ and $P - Value = 0{,}023 < 0{,}05$, indicating spatial heterogeneity across observation points.

GWNBR Modeling

The GWNBR modeling is analyzed, but first, the Euclidean distance between the observed regions is calculated. The obtained Euclidean distances are used to find the bandwidth values and weights using the Adaptive Tricube Kernel. Subsequently, GWNBR modeling is conducted, which includes testing the model parameters for GWNBR.

a. Simultaneous Test

The hypotheses for the simultaneous test are as follows:
$H_0: \beta_1(u_i v_i) = \beta_2(u_i v_i) = \cdots = \beta_p(u_i v_i) = 0$
$H_1 =$ at least one $\beta_j(u_i v_i) \neq 0; j = 1,2, \dots, p$

Table 7. Simultaneous Significance Test of GWNBR Model Parameters

$D(\widehat{B})$	$x^2_{(0,05,9)}$	Description
24,695	16,919	Reject H_0

Based on the simultaneous testing results at a 5% significance level, the value of nilai $D(\hat{B}) = 294770{,}7 > x^2_{(0,05,9)} = 16{,}919$, leading to the rejection of H_0. This indicates that at least one predictor variable significantly influences the model

b. Partial Test

The hypotheses for the partial test are as follows:
$H_0: \beta_j(u_i, v_i) = 0$
$H_1: \beta_j(u_i, v_i) \neq 0$
Partial test results show that at a 5% significance level, a parameter is significant if $Z_{\left(\frac{0.05}{2}\right)} > 1{,}96$. Significant variables vary across regions.

Table 8. Grouping of Parameter Significance Results

Number	District/City	Significant Variable
1	Barru, Bone, Bulukumba, Enrekang, Gowa, Jeneponto, Makassar, Maros, Pangkep, Pare-pare,	$X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8$

	Pinrang, Selayar, Sidrap, Sinjai, Soppeng, Takalar, dan Bantaeng	
2	East Luwu , North Luwu, Luwu, Palopo, North Toraja, dan Toraja	$X_1, X_2, X_3, X_4, X_5, X_7, X_8$
3	Wajo	$X_1, X_3, X_4, X_5, X_6, X_7, X_8$

Table 8 presents the classification of districts/cities based on the significance of predictor variables influencing infant mortality, showing three variations of influencing factor combinations across regions. As seen in Figure 1, the distribution map of the formed clusters exhibits a closely related pattern.

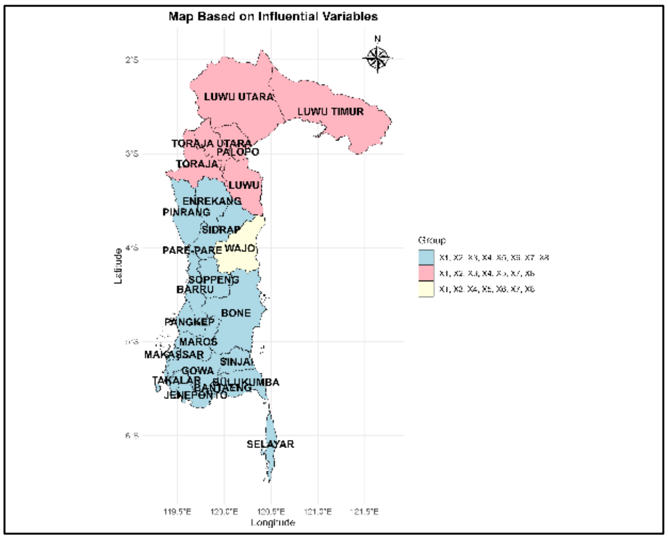

Figure 1. Map of District/City Grouping Distribution in South Sulawesi Province Based on Influential Variables

Model Interpretation

According to Table 8, one of the GWNBR models with Adaptive Tricube Kernel weighting for districts/cities in South Sulawesi Province is as follows :

$$\hat{\boldsymbol{\mu}}_{\boldsymbol{Makassar}} = \textbf{exp}\,(4{,}350 - 0{,}273\mathrm{X}_1 - 0{,}420\mathrm{X}_2 + 0{,}013\mathrm{X}_3 - 1{,}050\mathrm{X}_4 - 0{,}212\mathrm{X}_5 + 1{,}238\mathrm{X}_6 + 0{,}152X_7 - 0{,}160X_8)$$

Based on the GWNBR model in Makassar City, it can be inferred that for each one-unit increase in the percentage of Babies Given Exclusive Breastfeeding (X_1) reduces infant mortality by exp(-0,273) = 0,761 times, this is consistent with research in Susanto and Mustikawati [6]. Similarly, early initiation of breastfeeding (X_2) decreases infant mortality by exp (-0,420) = 0,657 times, aligning with the fingding in Husnah, Sakdiah and Andayani [22]. Conversely, an increase in complete infant visit coverage (X_3) actually increases infant mortality by exp (0,013) = 1,013 times. This result is less realistic, as an increase in complete infant visit coverage should reduce leads to a rise in infant mortality. This occurs due to poor quality of services during visits, incomplete examinations, or inadequate follow-up. Furthermore, each increase in vitamin A supplementation (X_4) reduces leads to a rise in infant mortality by exp(-1,050) = 0,350 times, while the percentage of low birth weight infants (X_6) leads to an increase in infant mortality by exp(1,238) = 3,449 times this finding is consistent with the study in Ismail, Utami, and Haris[23]. The addition of community health centers (X_5) reduces the number of infant deaths by exp(0,212) = 1,236 times this finding aligns with the research in Cabral, Udus, Jamlean, Pramesti and Anuraga [24]. Facility-based delivery coverage (X_7) leads to a rise in infant mortality by exp(0,152) = 1,164 times. This is because not all healthcare facilities have sufficient personnel or equipment, resulting in suboptimal delivery care services. Percentage of Pregnant Women Consuming Iron Supplement Tablets (X_8) reduces infant mortality by exp(-0,160) = 0.852 times by lowering the risk of maternal anemia. This finding is in accordance with study in Maryam and Muslimah [25].

CONCLUSION

The GWNBR model with the Adaptive Tricube Kernel weighting function developed to analyze factors affecting infant mortality rates in South Sulawesi is as follows:

$$\boldsymbol{\hat{\mu}_{Makassar}} = \mathbf{exp}\,(4{,}350 - 0{,}273\mathrm{X}_1 - 0{,}420\mathrm{X}_2 + 0{,}013\mathrm{X}_3 - 1{,}050\mathrm{X}_4 - 0{,}212\mathrm{X}_5 + 1{,}238\mathrm{X}_6 + 0{,}152X_7 - 0{,}160X_8)$$

The factors influencing infant mortality include exclusive breastfeeding, early initiation of breastfeeding, complete baby visit coverage, vitamin A supplementation, number of health centers, low birth weight, facility-based deliveries, and iron tablet consumption by pregnant women. This model can be used for health program planning and it is recommended to compare various weighting functions to obtain the best model.

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