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Non-Linear Regression on the Number of Stunting Cases in Central Java in 2023

Syasya Qonita Azizah[1*], Yohana Herlina Putri[2]

[1,2] Department of Mathematics, The Republic of Indonesia Defense University, West Java, Indonesia
e-mail: syasyaazizah493@gmail.com[1], yohanaherlinaputri@gmail.com[2]

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Abstract
Chronic nutritional problems, namely stunting, have a major impact on physical growth and development of children, especially in Central Java. Central Java Province is one of the regions with the highest number of stunting in Indonesia, reaching 20.7% in 2023. This study used data from the 2023 Central Java Health Profile. This study aims to analyze relationship between factors that cause stunting, including access to proper sanitation, complete basic immunization, underweight, exclusive breastfeeding, maternal health services K4, maternal health services K6, completion of basic education, and Consumption of Blood Supplement Tablets to the number of stunting cases in Central Java. The analysis used the Generalized Linear Model (GLM) and Integrated Nested Laplace Approximation (INLA) approaches with three distributions, namely Poisson, Gaussian, and Negative Binomial distributions. Negative Binomial Model. The Negative Binomial distribution proved to be the best model in analyzing stunting data in Central Java based on the smallest values in AIC, BIC, and DIC. Based on the analysis results obtained, the percentage of underweight in toddlers shows a significant influence on the number of stunting cases in Central Java.

Keywords: Negative Binomial, Poisson, Gaussian, Best-Fit Model Test, Spatial Mapping.

1. Introduction

Overcoming nutrition problems in Indonesia faces complex challenges, especially chronic malnutrition, such as stunting. According to the Indonesian Health Survey 2023, published by the Ministry of Health, the prevalence of stunting in Indonesia reached 21.5%, a decrease of 0.1 percent from the previous year (Caron & Markusen, 2016). Addressing stunting is a key focus of the current government, which aims to improve the quality of nutrition during the first 1000 days of life to tackle one of the country's most significant nutritional problems (Nugraheni et al., 2020). The first 1000 days are a critical period for establishing and improving nutrition for the future. Central Java has one of the highest stunting rates among the provinces in Indonesia. According to the 2023 Indonesian Health Survey (IHS), the prevalence of stunting in toddlers, based on height-for-age measurements in Central Java, reached 20.7% (Tarmizi, 2024). This figure is still far from the stunting reduction target of 14% by 2024.

Stunting is caused by several factors, including poor maternal nutritional status during pregnancy and inadequate parenting practices, particularly in terms of diet and child nutrition (Rita Setyani Hadi Sukirno, 2019). Therefore, a mother should have her pregnancy checked at least once during each trimester. Another contributing factor is inadequate exclusive breastfeeding, which affects toddlers' nutrition (Rambe, 2020). Exclusive breastfeeding is essential for proper nutrition and healthy growth. Additionally, stunting can be affected by economic conditions, maternal education, and low birth weight (Tebi et al., 2022). Complete basic immunization, which helps maintain a child's immune system and prevent infections, can also impact a child's growth and development (Vasera & Kurniawan, 2023).

The relationship between factors contributing to stunting and the number of stunted individuals in Central Java can be studied using a non-linear regression approach, specifically through Generalized Linear Models (GLM) and Integrated Nested Laplace Approximation (INLA). The analysis of stunting and the prevalence of stunted individuals in Central Java can be conducted using a non-linear regression approach with the Generalized Linear Model (GLM) and Integrated Nested Laplace Approximation (INLA) methods. GLM is a method used to analyze stunting data, considering linear or logarithmic relationships between predictor variables. It is used to examine the relationship between response variables and predictor variables (Dobson & Barnett, 2018). INLA, on the other hand, is a method used in Bayesian inference to analyze the relationship between response variables and predictor variables. INLA is designed to overcome the limitations of computational speed and efficiency associated with the Markov Chain Monte Carlo (MCMC) method (Dobson & Barnett, 2018).

The GLM and INLA methods are used to analyze the significant relationships between the percentage of families with access to adequate sanitation, the completion of basic immunization for infants, underweight toddlers, exclusive breastfeeding, K4 health services for pregnant women, K6 health services for pregnant women, completion of basic education, and mothers who consume Blood Supplement Tablets with the number of stunting cases in Central Java. This analysis helps identify areas in Central Java with a high risk of stunting and design targeted intervention strategies based on data and spatial statistics. Therefore, it is hoped that this research will contribute significantly to reducing stunting rates and improving the growth and development of children in Central Java.

2. Methods

2.1 Types and Sources of Research Data

This study used secondary data from the Central Java Provincial Health Office in 2023 in the 2023 Central Java Health Profile Book. Map data in the form of spatial coordinates in the latitude and longitude format of each Regency and City in Central Java was used to support spatial visualization in this study. Other data from the Central Statistics Agency (BPS) were also used to support theoretical understanding and enrich the data.

2.2 Research Variables

This study uses spatial variables (u_i, v_j) as coordinate points for each City/Regency in Central Java and several predictor variables (X) as factors that influence the response variable (Y), namely the number of stunting cases in each City/Regency in Central Java, which are described in Table 1 below.

Table 1 Research Variables

Variables	Description	Factor	Literature
Y	Number of Stunting Cases in Central Java per Regency/City		
X_1	Percentage of families with access to adequate sanitation	Sanitation Factors	(Arring & Winarti, 2024)
X_2	Percentage of complete basic immunization in infants	Baby Health Factors	(Wanda et al., 2021)
X_3	Percentage of underweight body weight in toddlers	Baby Health Factors	(Febria et al., 2022)
X_4	Percentage of babies with exclusive breastfeeding	Infant Nutrition Factors	(Husna Asmaul & Teungku Nih Farisni, 2022)
X_5	Percentage of maternal health services K4	Maternal Health Factors	(Pratiwi, 2023)
X_6	Percentage of maternal health services K6	Maternal Health Factors	(Pratiwi, 2023)
X_7	Percentage of completion of primary education	Parenting Pattern Factors	(Rachman et al., 2021)
X_8	Percentage of mothers who consume Blood Supplement Tablets	Maternal Health Factors	(Asnawi, Arifatul Aini. Maziaturrahman. Handayani, Wulan. Tanjung, 2024)

Multicollinearity can cause errors in factor loadings, resulting in inaccurate estimates in analyzing the relationship between variables and factors (Kyriazos & Poga, 2023). If the predictor variables have a high correlation, the factors are considered unable to capture variance and limit the differences in different dimensions. Therefore, the predictor variables were analyzed using Variance Inflation Factor (VIF) method. The decision to have multicollinearity is when the VIF value is > 10 (Iftitah Mutiara Sudiro & Retno Fuji Oktaviani, 2024).

Table 2 VIF Results on Independent Variables

Variables	Correlation	VIF
X1	-0.373	1.523
X2	0.162	1.185
X3	0.456	1.236
X4	-0.051	1.378
X5	-0.560	2.354
X6	-0.469	2.776

X7	-0.356	2.672
X8	-0.343	1.507

Based on table 2, all variables show VIF values and correlations that tend to be low, indicating no multicollinearity. Variables X5, X6, and X7 have higher VIF values than other variables, but these values are still within the critical threshold, so there is no evidence of multicollinearity between predictor variables.

2.3 Generalized Linear Model (GLM)

Generalized Linear Model (GLM) is a statistical approach introduced by Nelder and Wedderburn in 1972 as an extension of the linear regression model (Kurniati & Budyanra, 2022). GLMs allow the analysis of data with response distributions that are not necessarily normal, thus providing flexibility in modeling more complex data. There are three components of GLM. The first is the random component, which describes how the distribution of Y values is influenced by X values. The second is the systematic component, which establishes a relationship between the parameters η and the predictors X. The third is the link function, which connects the random and systematic components.

2.3.1 Poisson Distribution

The Poisson distribution is a probability distribution that is often used to analyze discrete data. This distribution models the number of occurrences of an event over a period of time or region, assuming that the events occur independently and have a constant mean (Tendriyawati et al., 2023). The probability function for the Poisson distribution is expressed as:

$$f(y;\mu) = \frac{e^{-\mu}\mu^{y}}{y!}$$

where y is the number of events (e.g., stunting) in a given interval.

In the GLM framework, we relate the mean μ to the predictor X through a link function. For the Poisson distribution, the link function commonly used is the logarithmic function, so it can be written:

$$\log(\mu) = \beta_0 + \beta_1 X_{1i} + \cdots + \beta_k X_{ki}$$

Thus, the average μ can be expressed as the exponential of a linear combination of the predictors:

$$\mu = e^{\beta_0 + \beta_1 X_{1i} + \cdots + \beta_k X_{ki}}$$

2.3.2. Negative Binomial Distribution

The negative binomial distribution is a commonly used alternative to the Poisson distribution when the data being analyzed exhibits overdispersion. This model is considered a more flexible version of the Poisson model, with additional parameters to handle data with larger variances. The probability mass function for the negative binomial distribution can be expressed as follows:

$$f(y;r,p) = \binom{y+r-1}{r-1} p^{r}(1-p)^{y}$$

where r represents a dispersion parameter that indicates the number of successes, while p denotes the probability of success in a given trial.

In the context of GLM, the negative binomial distribution allows for capturing more variability in count data (Winata, 2023). The logarithmic link function is still used:

$$\log(\mu) = \beta_0 + \beta_1 X_{1i} + \cdots + \beta_k X_{ki}$$

2.3.3. Gaussian Distribution

The Gaussian distribution or normal distribution is the most commonly used probability distribution in statistics. This distribution is defined by two parameters: the mean (μ) and the variance (σ^2). In the context of GLM, this distribution is used to model continuous response variables and is assumed to follow a normal distribution. The probability density function for the Gaussian distribution is expressed as:

$$f(y;\mu,\sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(y-\mu)^2}{2\sigma^2}}$$

The Gaussian distribution in GLM assumes that the errors of the model are normally distributed with zero mean and constant variance. (Saidi et al., 2021). This makes the Gaussian distribution a good fit for data that meets these assumptions. However, if the data does not meet the normality assumption, researchers may need to consider transforming the data or using other approaches.

2.4. Integrated Nested Laplace Approximations (INLA)

Bayesian estimation, especially when combined with Integrated Nested Laplace Approximation (INLA), is a very powerful and efficient statistical framework for performing inference on complex models, especially those involving latent Gaussian structures (Muharisa et al., 2019). This estimation relies on Bayes' Theorem to update the probability of a hypothesis based on new evidence obtained. In this approach, there are three main components: first, a prior distribution that describes the initial beliefs about the parameters before the data is collected; second, a likelihood function that shows the likelihood of the observed data given a given parameter value; and third, a posterior distribution that reflects the updated beliefs about the parameters after considering the available data.

Integrated Nested Laplace Approximation (INLA) is a Bayesian statistical method developed for modeling Latent Gaussian Models (LGM), which incorporate both fixed and random effects along with latent Gaussian distributions. INLA is used to efficiently compute parameter posteriors in complex models, whether spatial, temporal, or hierarchical, and to model both discrete (Poisson, negative binomial) and continuous (Gaussian) data, accommodating fixed, random, and hierarchical effects structures (Maulina et al., 2019). In general, LGM analyzed through INLA consists of three main components:

1. Likelihood Distribution: The response variable Y follows a certain distribution where η is a linear predictor.
2. Linear Predictor: A linear combination that relates the independent variables and the latent effect, expressed as:

$$\eta = X\beta + Zf$$

where Xβ is a fixed effect and Zf is a random effect.

3. Prior Distribution: The parameters in the model, including β and the random effect f, are given priors according to Bayesian principles.

INLA utilizes a numerical approach to compute the posterior distribution of model parameters. This approach uses a representation of the model as Gaussian Markov Random Fields (GMRF), which allows efficient computation with a matrix space structure. The posterior marginals of the model parameters are computed through an iterative Laplace approximation, yielding accurate estimates in much shorter time than MCMC. (Gómez-Rubio et al., 2020).

2.5. Best-Fit Model

INLA utilizes a numerical approach to compute the posterior distribution of model parameters. This approach uses a representation of the model as Gaussian Markov Random Fields (GMRFs), which allows efficient computation with a matrix space structure. The posterior marginals of the model parameters are computed through an iterative Laplace approximation, yielding accurate estimates in much shorter time than MCMC. (Berg et al., 2001). LogLik and Deviance conclusion is inversely proportional to DIC and AIC. Here are some of the best regression models.

- Defiance Information Critetion (DIC)

$$DIC = \overline{D} + 2PD$$

Where

$PD = E\big(D(\theta)\big) - D\big(E(\theta)\big) = \overline{D} - D(\overline{\theta})$ dan $D(\theta) = -2\log(p(y|\theta))$. The built quality is the inverse proportion of the AIC result. (Fitri et al., 2024).

- Akaike Information Criterion (AIC)

$$AIC = 2\log L\big(\hat{\theta}\big) + 2k$$

Where $L\big(\hat{\theta}\big)$ is the likelihood result of the model based on data when evaluating the maximum likelihood value estimate and k is the number of parameters estimated (Fabozzi et al., 2014).

- Bayesian information criterion (BIC)

$$BIC = -2\log L\big(\hat{\theta}\big) + k\ln n$$

Where n is the number of data, $L\big(\hat{\theta}\big)$ the maximum value of the likelihood function of the model and k is the number of free parameters estimated (Brown et al., 2009).

3. Result and Discussion

3.1. Data Visualization and Description

Stunting cases are spread throughout Central Java. Figure 1 below is a map showing the distribution of stunting cases in Central Java.

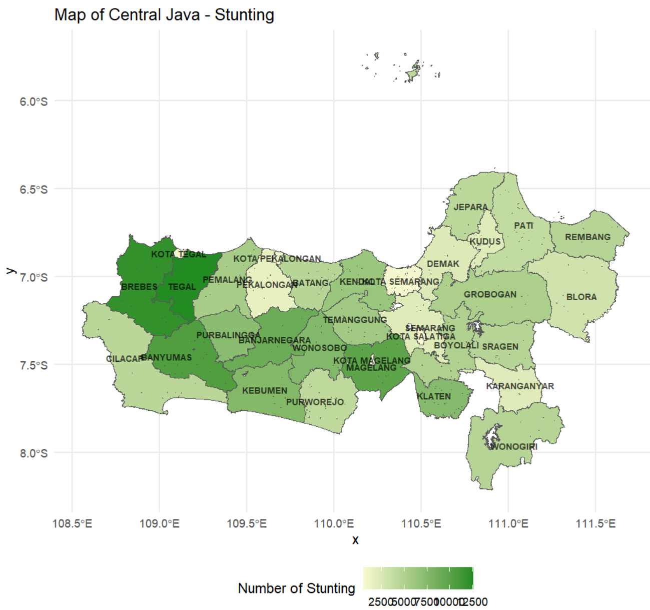
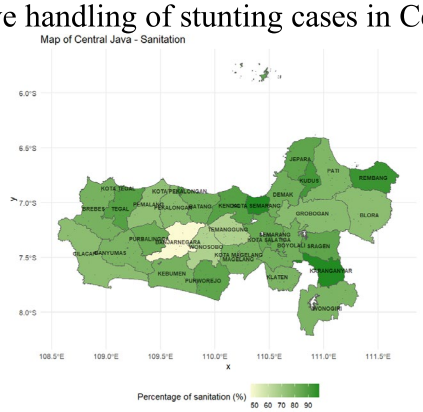
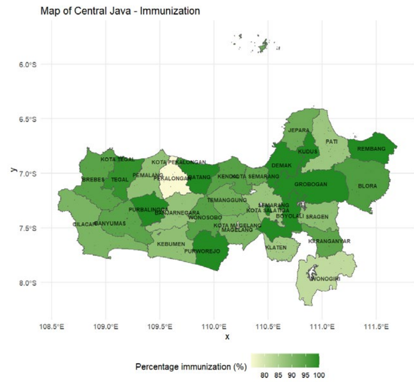


Figure 1 Number of Stunting Cases in Central Java in 2023

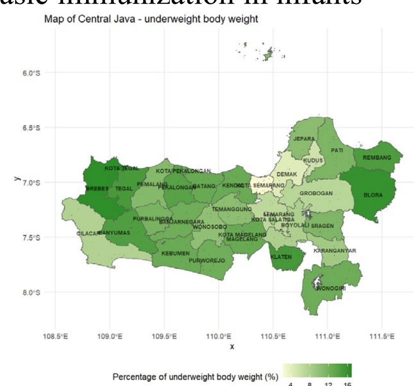
The map shows the distribution of stunting cases in Central Java province in each district and city. Darker colors on the map indicate a higher number of stunting cases, while lighter colors indicate a lower number of stunting cases. Based on the map, the areas with the highest number of stunting cases are Brebes (11,930 cases), Tegal (12,575 cases), and Banyumas (10,495 cases). Meanwhile, the lowest cases of stunting are spread in the central to eastern regions, such as Salatiga City (484 cases) and Magelang City (474 cases). The difference in the number of stunting cases in each region indicates a lack of comprehensive handling of stunting cases in Central Java province.



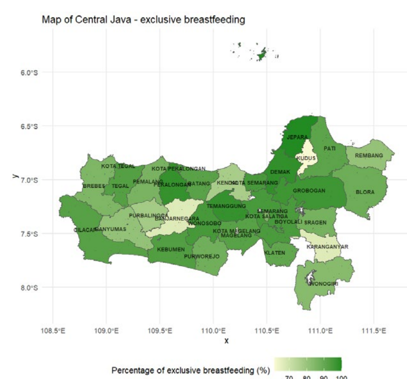
(a) Percentage of families with access to adequate sanitation



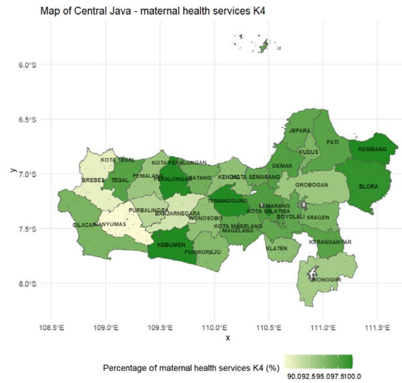
(b) Percentage of complete basic immunization in infants



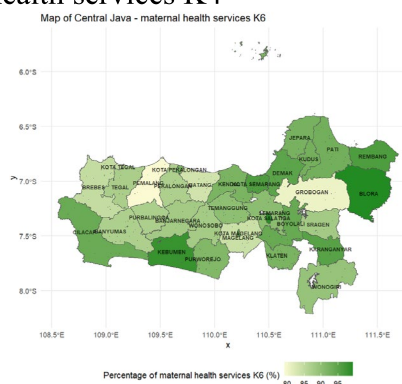
(c) Percentage of underweight body weight in toddlers



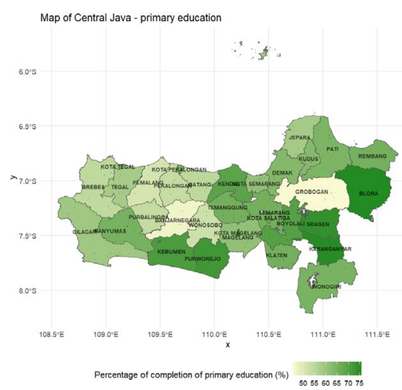
(d) Percentage of babies with exclusive breastfeeding



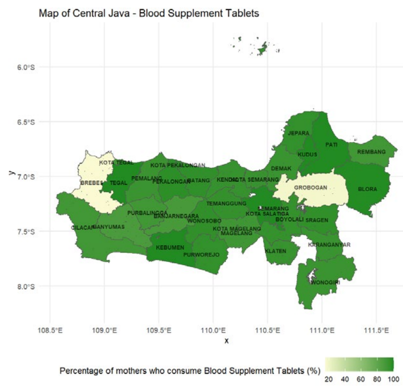
(e) Percentage of maternal health services K4



(f) Percentage of maternal health services K6



(g) Percentage of completion of primary education



(h) Percentage of mothers who consume Blood Supplement Tablets

Figure 2 Percentage of Predictor Variables

Figure 2 shows the distribution location of predictor variables that affect stunting in Central Java. The highest percentage of families with access to proper sanitation is Semarang City (98 percent) and the lowest is Banjarnegara (47 percent). The highest percentage of complete basic immunization in infants is Demak, Kudus, Grobogan, Salatiga City, Boyolali, Batang, Tegal City, Purbalingga, Rembang, and Purworejo at 100 percent and the lowest is Surakarta (73.9 percent). The highest percentage of underweight in toddlers is Tegal City (16.78 percent) and the lowest is Semarang City (2.41 percent). The highest percentage of babies with exclusive breastfeeding is Jepara (100 percent) and the lowest is Kudus (61.53 percent). The highest percentage of K4 maternal health services is Salatiga City, Kebumen, Pekalongan, Rembang, and Temanggung at 100 percent and the lowest is Banyumas (88.2 percent). The highest percentage of maternal health services K6 is Sukoharjo (99.6 percent) and the lowest is Pemalang (79.1 percent). The highest percentage of completion of basic education is Blora (75.7 percent) and the lowest is Grobogan (75.17 percent). The highest percentage of mothers consuming Blood Supplement Tablets is Kudus, Semarang, Kebumen, and Tegal at 100 percent and the lowest is Brebes (15.29 percent).

3.2. Non-Linear Regression Analysis

3.2.1. Negative Binomial

The GLM method can be measured using non-linear regression with Negative Binomial distribution. Table 10 below shows the results of GLM measurements using Poisson.

Table 3 GLM Negative Binomial

Coefficients	GLM		INLA		
	Estimation	P-Value	Estimation	Interval	
				0.025	0.975
(Intercept)	13.326	0.000 ***	13.480	4.630	22.354

X1	-0.018	0.128	-0.018	-0.044	0.007
X2	0.027	0.050*	0.026	-0.009	0.061
X3	0.094	0.003 **	0.093	0.022	0.164
X4	0.016	0.134	0.015	-0.010	0.040
X5	-0.078	0.105	-0.076	-0.184	0.033
X6	-0.018	0.539	-0.018	-0.082	0.045
X7	0.008	0.689	0.007	-0.036	0.050
X8	0.001	0.850	0.000	-0.013	0.014

Significance Codes:
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

With a 99% confidence level, the negative binomial GLM model shows that the Percentage of underweight in toddlers has a significant effect on the number of stunting cases in Central Java. Therefore, every 1% increase in underweight in toddlers will increase the number of stunting cases in Central Java by 0.094 on a logarithmic scale when other variables are held constant. With a 95% confidence level, the percentage of complete basic immunization in infants has a significant effect, indicating an effect on the number of stunting cases in Central Java.

Negative binomial INLA shows that the Percentage of underweight in toddlers has a significant effect on the number of stunting cases in Central Java with a credibility of 95%. A 1% rise in the number of underweight toddlers is projected to result in an increase of 0.0932 stunting cases in Central Java on a logarithmic scale, assuming all other variables remain constant. Other factors do not show any significant relationship to the number of stunting cases in Central Java.

3.2.2. Poisson

The GLM method can be measured using non-linear regression with Poisson distribution. Table 10 below shows the results of GLM measurements using Poisson.

Tabel 4 GLM Poisson

Coefficients	**GLM**		**INLA**		
	Estimation	**P-Value**	**Estimation**	**Interval**	
				0.025	**0.975**
(Intercept)	14.081	0.000	14.081	13.887	14.274
X1	-0.017	0.000	-0.017	-0.018	-0.017
X2	0.016	0.000	0.017	0.016	0.018
X3	0.073	0.000	0.073	0.071	0.074
X4	0.011	0.000	0.011	0.011	0.012
X5	-0.068	0.000	-0.068	-0.071	-0.066
X6	-0.013	0.000	-0.013	-0.015	-0.012
X7	0.002	0.000 ***	0.002	0.001	0.003
X8	0.000	0.369	0.000	-0.000	0.000

Significance Codes:

0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 '.' 0.1 ' ' 1

With a confidence level of 99%, the GLM Poisson model shows that the percentage of families with access to proper sanitation, the percentage of complete basic immunization in infants, the percentage of underweight in toddlers, the percentage of infants with exclusive breastfeeding, the percentage of maternal health services K4, the percentage of maternal health services K6, and the percentage of completion of basic education show a significant influence on the number of stunting cases in Central Java. The percentage of families with access to proper sanitation and the percentage of maternal health services K4 have a negative relationship to the number of stunting in Central Java. Meanwhile, the percentage of mothers who consume Blood Supplement Tablets does not have enough evidence to state a significant influence on stunting cases in Central Java.

INLA Poisson shows the percentage of families with access to proper sanitation, the percentage of complete basic immunization in infants, the percentage of underweight in toddlers, the percentage of infants with exclusive breastfeeding, the percentage of maternal health services K4, the percentage of maternal health services K6, and the percentage of completion of basic education show a significant influence on the number of stunting cases in Central Java with the percentage of underweight in toddlers as the largest positive impact. Meanwhile, the percentage of mothers consuming Blood Supplement Tablets (TTD) did not show any significant influence on stunting cases in Central Java.

3.2.3 Gaussian

The GLM method can be measured regression with Gaussian distribution. Table 10 below shows the results of GLM measurements using Poisson.

Tabel 5 GLM Gaussian

Coefficients	GLM		INLA		
	Estimation	P-Value	Estimation	Interval	
				0.025	0.975
(Intercept)	40271.010	0.044 *	13.480	1479.949	25208.622
X1	-60.166	0.291	-0.019	-82.939	23.993
X2	54.538	0.418	0.026	-45.339	67.199
X3	326.862	0.038*	0.093	-43.152	79.088
X4	42.003	0.428	0.015	-56.461	47.488
X5	-434.075	0.067 .	-0.075	-77.076	45.727
X6	5.507	0.969	-0.018	-79.658	39.731
X7	-12.204	0.896	0.007	-74.004	39.073
X8	-9.354	0.756	0.001	-69.359	12.636

Significance Codes:

0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 '.' 0.1 ' ' 1

With a 95% confidence level, the Gaussian GLM model shows that the Percentage of underweight in toddlers has a significant effect on the number of stunting cases in Central Java. Therefore, every

1% increase in underweight in toddlers will increase the number of stunting cases in Central Java by 326,862 on a logarithmic scale when other variables are held constant. With a 90% confidence level, the Percentage of maternal health services K4 shows an effect on the number of stunting cases in Central Java. Other factors do not have enough evidence to state a strong relationship with the number of stunting cases in Central Java.
INLA Gaussian shows that no predictor variables are proven to have a significant effect on the number of stunting cases in Central Java because the 95% credible interval includes zero. This allows the use of a less good model in analyzing the relationship between factors in the predictor variables and the number of stunting in Central Java.

3.2.1 Best Model Test

The best model is needed to obtain the right distribution for data distribution in analyzing stunting cases in Central Java. The following is a table of the best models based on AIC, BIC, and DIC.

Tabel 6 Best Model Test

Model	GLM		INLA
	AIC	BIC	DIC
GLM Negative Binomial	654.609	670.163	655.540
GLM Poisson	41000.479	41014.478	-40088.410
GLM Gaussian	661.049	676.603	663.380

Based on table 10, negative binomial GLM shows the best model results with the smallest value in AIC of 654.6092 and BIC of 670.1627. Therefore, negative binomial is used as the best model to analyze the distribution of stunting data in Central Java. INLA with a negative binomial model shows the best model results with the smallest value in DIC of 655.54 even though Gaussian gives the smallest value in logLik. Therefore, negative binomial is used as the best model using the INLA approach to analyze stunting in Central Java.

4. Conclusion

According to the research, the Negative Binomial regression model is the most suitable model for analyzing the number of stunting cases in Central Java, outperforming the Poisson and Gaussian models due to its lower AIC, BIC, and DIC values. At a 99% confidence level, the findings from the GLM analysis reveal that the percentage of underweight children under five has a significant impact on the number of stunting cases in Central Java. A 1% increase in the underweight factor in children under five is associated with a potential increase of 0.094 in the number of stunting cases on a logarithmic scale. The results of the INLA analysis, with a 95% confidence interval, show a significant relationship between the percentage of underweight children under five and the number of stunting cases in Central Java. The proportion of infants receiving complete basic immunization also has a significant effect; however, there is insufficient evidence to conclude that INLA significantly impacts the number of stunting cases in Central Java. Meanwhile, other factors such as access to sanitation, exclusive breastfeeding, maternal health services (K4 and K6), completion of primary education, and consumption of Blood Supplement Tablets do not provide sufficient evidence to state that these factors influence the number of stunting cases in Central Java. Hence, reducing the percentage of underweight children should be a primary focus when creating policies to combat stunting in Central Java.

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