BAREKENG: Journal of Mathematics and Its Applications
June 2024 Volume 18 Issue 2 Page 0961–0972
P-ISSN: 1978-7227 E-ISSN: 2615-3017
https://doi.org/10.30598/barekengvol18iss2pp0961-0972

MODELING THE INCIDENCE OF MALNUTRITION IN BOGOR REGENCY USING ZERO-INFLATED NEGATIVE BINOMIAL MIXED EFFECT MODEL

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ABSTRACT

Article History:

Received: 5th December 2023
Revised: 11th January 2024
Accepted: 15st March 2024
Published: 1st June 2024

Keywords:

Malnutrition;
Overdispersion;
ZINB Mixed Model.

Modeling response variables in the form of count data generally uses a model based on the Poisson distribution. However, some conditions, such as the presence of excess zero, can be found in the data that result in overdispersion, which will have an impact on the resulting variance in the model. In this paper, three approaches, namely the Poisson Mixed Model, the Negative Binomial (NB) Mixed Model, and the Zero-Inflated Negative Binomial (ZINB) Mixed Model, are used to model the incidence of malnutrition in Bogor Regency. The data used in this study are secondary data sourced from the West Java open data website. Based on the results of data analysis, it appears that the ZINB Mixed Model method is a method capable of accommodating random effects, overdispersion, and excess zero in modeling malnutrition in Bogor Regency. Variables that significantly affect the occurrence of malnutrition cases in villages in Bogor Regency include the Number of Children Weighed Routinely Every Month, Number of Children Measured for Length and Height Twice a Year, Number of Children under 12 Months Old Who Received Complete Basic Immunization, Number of Posyandu (Integrated Health Post), and Number of Parents/Caregivers Participating in Monthly Parenting (PAUD).

How to cite this article:

D. A. N. Sirodj, K. Sadik, and A. Kurnia., "MODELING THE INCIDENCE OF MALNUTRITION IN BOGOR REGENCY USING ZERO-INFLATED NEGATIVE BINOMIAL MIXED EFFECT MODEL," *BAREKENG: J. Math. & App.*, vol. 18, iss. 2, pp. 0961-0972, June, 2024.

Journal homepage: *https://ojs3.unpatti.ac.id/index.php/barekeng/*
Journal e-mail: *barekeng.math@yahoo.com; barekeng.journal@mail.unpatti.ac.id*

Research Article · Open Access

1. INTRODUCTION

Count data is often found in survey data recapitulations. Count data is often found in survey data recapitulations. Modeling related to response variables in count data will generally be based on the Poisson distribution. The assumption that must be fulfilled when using a model with a Poisson distribution is an equidispersion condition, which is a condition when the variance value of the response variable is equal to its mean value [1] according to the characteristics of the Poisson distribution. In practice, the equidispersion condition is difficult to fulfill as under- or overdispersion often occurs. Thus, it is necessary to adjust the distribution more precisely since the occurrence of under- or overdispersion will have an impact on the resulting variance [2]. For count data with overdispersion, popular distributions include Negative Binomial (NB), Poisson Mixture, and Conway-Maxwell-Poisson [3].

One of the causes of overdispersion is zero inflation, where the amount of observed data is zero (excess zero) and is greater than the expected value [4]. There are several distributions that accommodate the existence of excess zero, including zero-inflated Poisson (ZIP), zero-inflated negative binomial (ZINB) models, zero-altered Poisson (ZAP), and zero-altered negative binomial (ZANB) models [5].

Modeling count data is usually analyzed using the generalized linear model (GLM) method. However, GLM has not considered the presence of random components in the model. If there is a random component, then the model that can be used is the Generalized Linear Mixed Model (GLMM). GLMM is a generalization of a linear model whose independent variables encompass random and fixed factors. Data conditions that contain excess zero, overdispersion, and random effects will certainly affect the model to be created. The ZINB Mixed Model is an alternative model that can be used when these three conditions occur. ZINB Mixed Model has been applied in various fields, including microbiological data [6], genetic data [7] [8], environmental data [9], and social problems such as poverty [10]. For some specific cases, such as binary responses, the zero-inflated binomial (ZIB) model is better for dealing with overdispersed binomial data [11]. In the context of small area estimation (SAE), the SAE ZIB method has a smaller standard error than direct estimation for binary responses [12], and the SAE zero-inflated beta model is better than direct estimation for response types in the form of rate/percentage and containing excess zero [13]. So, when the data has overdispersion and excess zero conditions, the zero-inflated model appears better.

Nutritional status of toddlers is one of the things that needs to be monitored by the government since, currently, toddlers in Indonesia are still facing malnutrition problems. This is in accordance with Indonesia's nutritional status survey results in 2022, which stated that the prevalence of stunting in Indonesia reached 21.6% [14]. Although this figure has decreased from the previous year, it is still above the Ministry of Health's National Medium-Term Development Plan target of 14% by 2024. Therefore, consistent efforts are needed to improve the nutritional status of children under five. Malnutrition can be caused by external and internal factors that, if not addressed early on, will have an impact on health conditions, the growth and development of toddlers, and productivity in adulthood [15]. Modeling related to the incidence of malnutrition has been carried out, including by using GLMM models [16], [17], Spatial Bayes approach [18], [19], Generalized Additive Mixed Models [20], and machine learning [21]. Modeling done in previous studies has not specifically examined cases of overdispersion and excess zero in malnutrition cases, so the modeling still contains bias. This study will model by considering the occurrence of overdispersion and zero excess in malnutrition cases in Bogor Regency.

Poisson regression models, NB regression models, and ZINB regression models have been applied in modeling various health cases, such as the number of measles cases [22], mortality from tuberculosis [23], the frequency of outpatient visits [24], but these models have not involved random factors in the model. The purpose of this study is to model the incidence of malnutrition in Bogor Regency using three approaches: the Poisson Mixed Model, the NB mixed model, and the ZINB mixed model, and to observe the performance of the ZINB Mixed Model in overcoming the problems of overdispersion, excess zero and involving random factors in the model.

2. RESEARCH METHODS

2.1 Poisson Mixed Model, NB Mixed Model, and ZINB Mixed Model

GLMM is a model used to analyze data with fixed and random effects and the shape of the distribution on response variables that do not assume to follow a normal distribution. This research will only discuss three basic distributions: the Poisson distribution, the NB distribution, and the ZINB distribution. The probability mass function for each distribution [10], [25] is as follows:

$$Y \sim Poisson\ (\mu) = P(y|\mu) = \frac{e^{-\mu}\mu^{y}}{y!},\ y = 0,1,2,\ldots \tag{1}$$

$$Y \sim NB\ (y_i|\mu_i,\theta) = P(y|\mu_i,\theta) = \frac{\Gamma(y_i+\theta)}{\Gamma(\theta)y_i!}\left(\frac{\theta}{\mu_i+\theta}\right)^{\theta}\left(\frac{\mu_i}{\mu_i+\theta}\right)^{y_i},\ y = 0,1,2,\ldots \tag{2}$$

$$Y \sim ZINB = P(y|p_i,\mu_i,\tau_i)\begin{cases} p_i + (1-p_i)\left(\frac{1}{1+\tau\mu}\right)^{\frac{1}{\tau}}, where\ y_i = 0 \\ (1-p_i)\frac{\Gamma\left(y_i+\frac{1}{\tau_i}\right)}{\Gamma\left(\frac{1}{\tau_i}\right)y_i!}\left(\frac{1}{1+\tau_i\mu_i}\right)^{\frac{1}{\tau}}\left(\frac{\tau_i\mu_i}{1+\tau_i\mu_i}\right)^{y_i}, where\ y_i > 0 \end{cases} \tag{3}$$

with $0 \le p \le 1$, $\mu \ge 0$, and τ is the dispersion coefficient.

The GLMM model for the three distributions is defined as follows:

- Poisson Mixed Model and NB Mixed Model

$$log(\mu_{ij}) = \boldsymbol{x}_{ij}^{T}\boldsymbol{\beta} + \boldsymbol{v_i} \tag{4}$$

- ZINB Mixed Model

$$ln(\mu_i) = \sum_{j=1}^{k}\beta_j x_{ij} + v_i \tag{5}$$

$$logit(p_i) = ln\left(\frac{p_i}{1-p_i}\right) = \sum_{l=1}^{m}\gamma_l z_{il} + v_i$$

where $\boldsymbol{\beta}$ is the vector of the fixed effects regression coefficients, $\boldsymbol{x}_{ij}^{T}$ is design matrices of predictor variables corresponding for fixed effects, and $\boldsymbol{v_i}$ is the design matrices for random effects.

2.2 Overdispersion and Excess zero

Overdispersion conditions can be identified by looking at the ratio between the deviation value and the degrees of freedom (ϕ_i). If the value of (ϕ_i) is greater than one, it can be identified that there is an overdispersion problem in the data. Overdispersion can occur due to the presence of an excess zero, where the large proportion of zero-valued data will have an impact on the precision of the resulting estimated value.

2.3 The Best Model Selection Criteria

The best model will be based on two measures: the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values. The model is said to be good if it has the smallest AIC and BIC values among other models. The equation of AIC and BIC is as follows:

$$AIC = -2L_p + 2p \tag{6}$$

$$BIC = -2L_p + pln(n) \tag{7}$$

where L_p: the value of the log-likelihood function with $p-1$ predictor variables; p: the number of parameters; n: the number of observations.

The data used in this study are secondary data sourced from https://opendata.jabarprov.go.id/ regarding the incidence of malnourished children under five in Bogor Regency in 2020. The observed data collected is the number of malnourished children under five at the village level in 398 villages spread across 39 sub-districts.

The modeling begins with the use of the basic Poisson Mixed Model when the response data is count data, which will then be corrected using the NB Mixed Model and ZINB Mixed Model. The analysis process is carried out using R software with the following packages: qcc [26], vcdExtra [27], and glmmTMB [28].

This study uses eight predictor variables that are fixed, one response variable, the offset variable, and one random variable, namely the sub-district. All variables used in this study are shown in the following Table 1:

Table 1. List of Variables

Variable	Code	Description
Predictor Variables (Fixed)	W	Travel Time from Village to Nearest Health Facility
	Tr	Number of Children Weighed Routinely Every Month
	Pt	Number of Children Measured for Length and Height Twice a Year
	Jm	Number of Children Aged 0-2 Years Who Have Health Insurance
	Im	Number of Children under 12 Months Old Who Receive Complete Basic Immunization
	Kz	Number of Pregnant Women who Attended Nutrition Counseling/Mother's Class at least 4 Times
	Ps	Number of Posyandu by Village/Urban Village
	pip	Number of Parents/Caregivers Participating in Monthly Parenting (PAUD)
Offset	n	Number of Children Aged 0-23 Months
Random Effects	kec	Sub-Districts in Bogor Regency
Response Variable	y	Number of Malnourished Toddlers

The stages of data analysis are as follows:

1) Data synchronization regarding the variables to be used.
2) Data exploration.
3) Checking excess zero and overdispersion.
4) Modeling the number of malnutrition incidents in Bogor Regency using the Poisson Mixed Model, NB Mixed Model, and ZINB Mixed Model.
5) Selection of the best model based on the AIC and BIC values.
6) Interpretation of the malnutrition incidence model based on the best model selected.

3. RESULTS AND DISCUSSION

The initial stage of this study was to explore the data on response variables and independent variables. The results are as follows:

Table 2. Descriptive Statistics of All Variables

	Y	**n**	**w**	**Tr**	**pt**	**jm**	**im**	**kz**	**ps**	**pip**
min	0.00	2.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Q1	0.00	397.50	5.00	87.50	54.00	35.25	62.00	15.00	8.00	0.00
median	0.00	649.00	5.00	190.00	160.00	100.00	126.00	43.00	10.00	20.00
mean	0.53	809.60	11.06	309.00	279.20	167.53	211.00	71.15	11.32	94.19
Q3	0.00	1020.55	10.00	349.00	319.20	211.75	240.00	85.75	13.00	98.75
max	53.00	5123.00	500.00	7874.00	7874.00	1700.00	3488.00	1274.00	37.00	3336.00

Table 2 shows that related to the response variable (*y*), the number of malnutrition incidences in children under five in 2020 was 53 at most in Gunung Picung Village, Pamijahan Village, where the median value of the y variable was zero, indicating the occurrence of excess zero in the data. The average time taken from the village to the nearest health facility (*w*) in Bogor Regency was 11.06 minutes, with the longest travel time of 500 minutes, or about 8.3 hours for Kuta village, Megamendung sub-district. The average number of children weighed routinely every month (*tr*) in each village was 309, the average number of children measured for length and height twice a year (pt) in each village was 280, the average number of children aged 0-2 years who have health insurance (*jm*) in each village was 168, the average number of children under 12 months old who received complete basic immunization (*im*) was 211, the average number of pregnant women who attended nutrition counseling/mother's classes at least 4 times a year (*kz*) was 72, the average number of posyandu (*ps*) was 12 units, and the average number of parents/caregivers participating in monthly parenting (paud) (*pip*) was 95 people.

Furthermore, checking for the existence of an excess zero on the response variable is carried out descriptively through the histogram as shown in Figure 1.

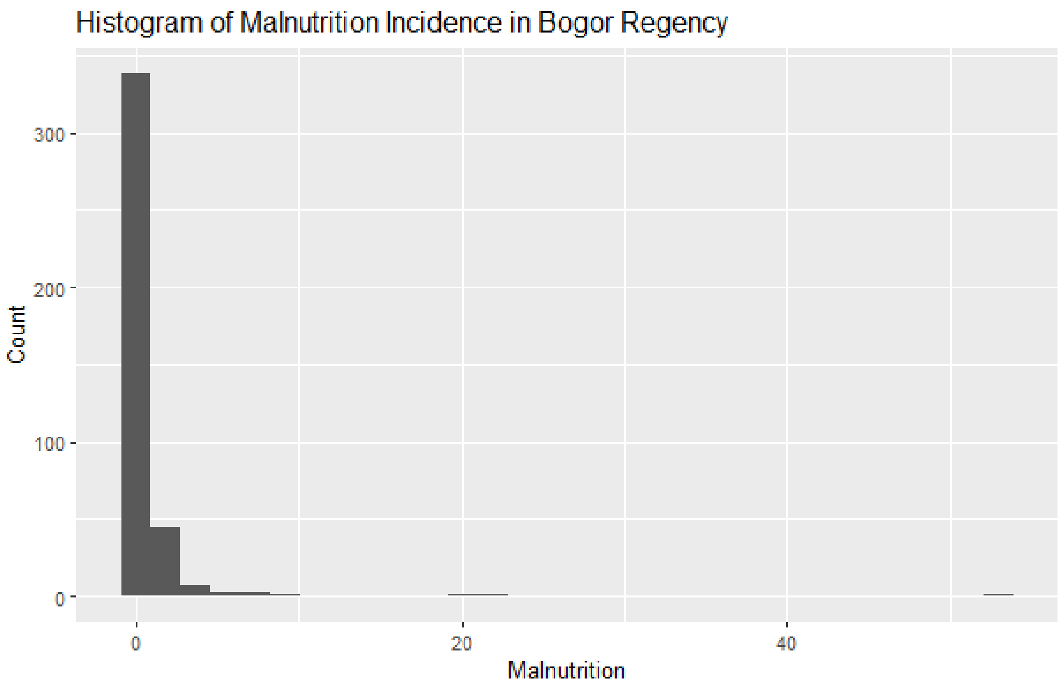


Figure 1. Histogram of Number of Malnourished Toddlers in Bogor Regency

Based on Figure 1, it can be seen that there is quite a lot of excess zero, which occurs in 338 out of 398 villages in Bogor Regency, or 84.9% of all observations to be analyzed. The same thing happens in each sub-district, which is visualized in Figure 2.

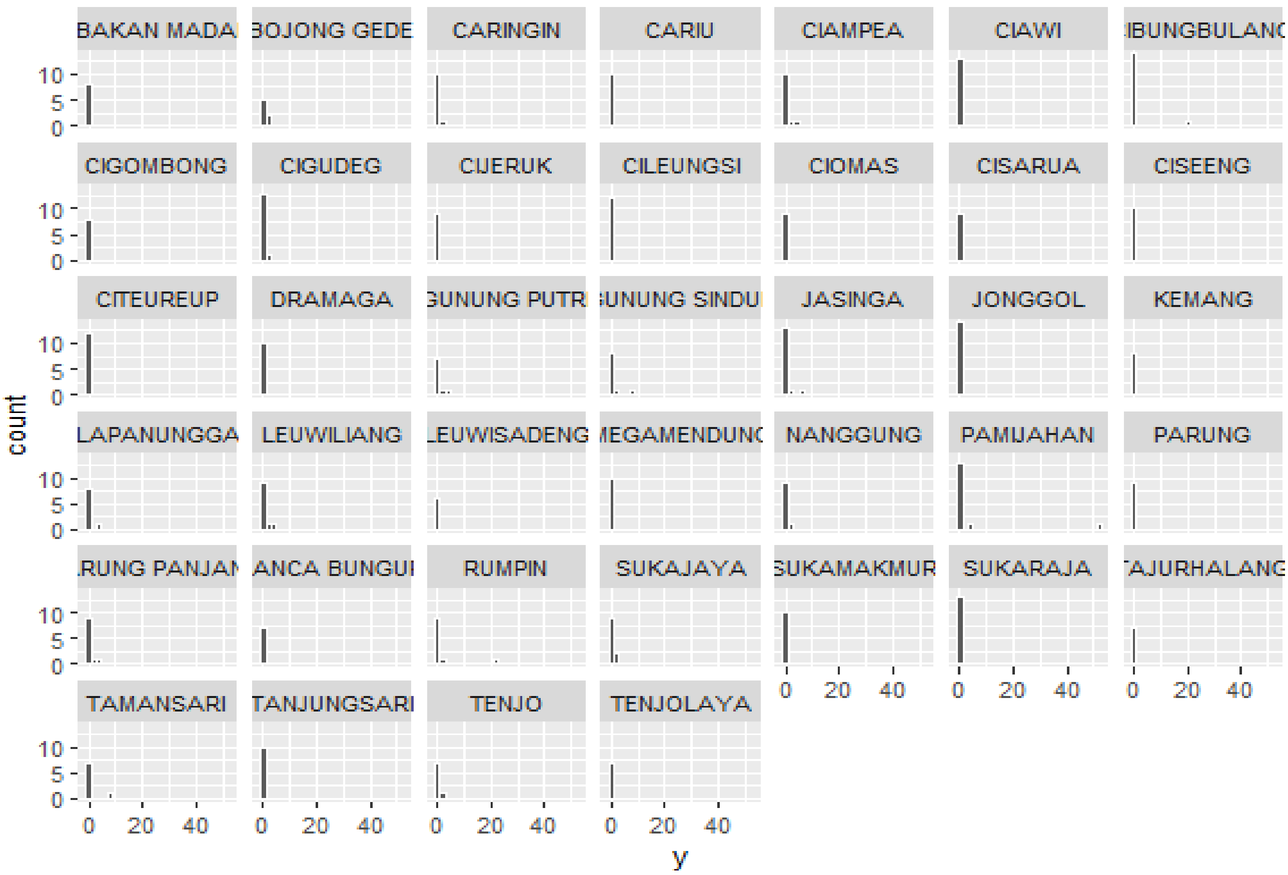
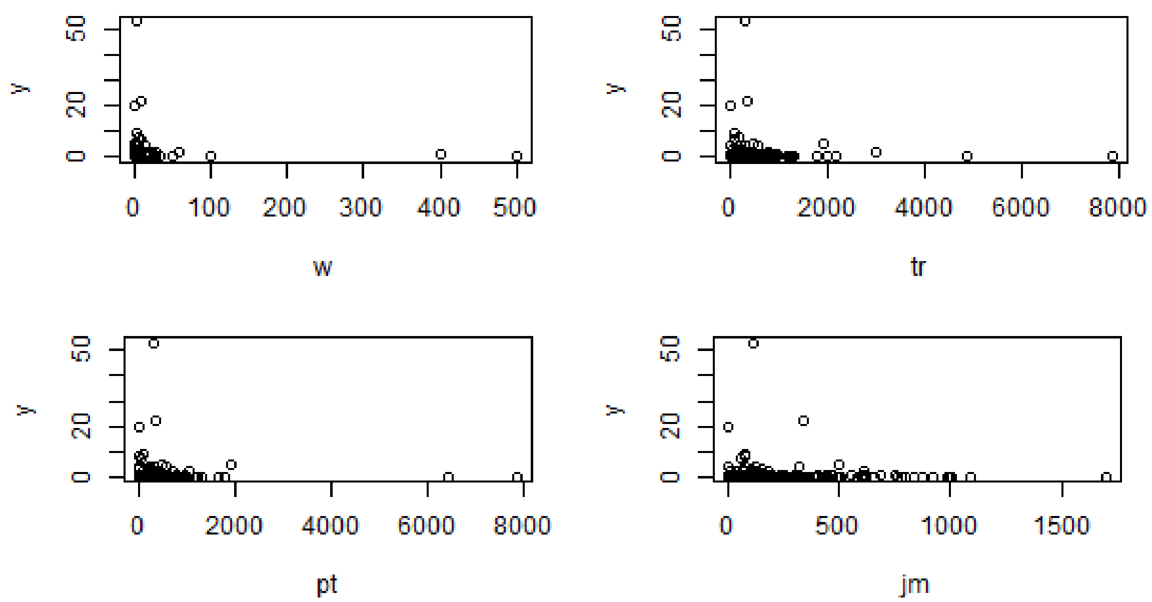


Figure 2. Histogram of Number of Malnourished Toddlers in Each Sub-District in Bogor Regency

The distribution pattern of the number of malnourished children under five in each sub-district (**Figure 2**) shows the same thing as the overall data pattern, namely the occurrence of excess zeros that dominate the observed values. In addition to visual inspection, inference testing is also carried out to check for the presence of excess zeros in the data. The check is done through the zero-inflation test in the vcdExtra package [27] with the following results:

Table 3. Results of Zero Inflation Test

Chi-square	*p-value*
462.13044	< 2.22e-16



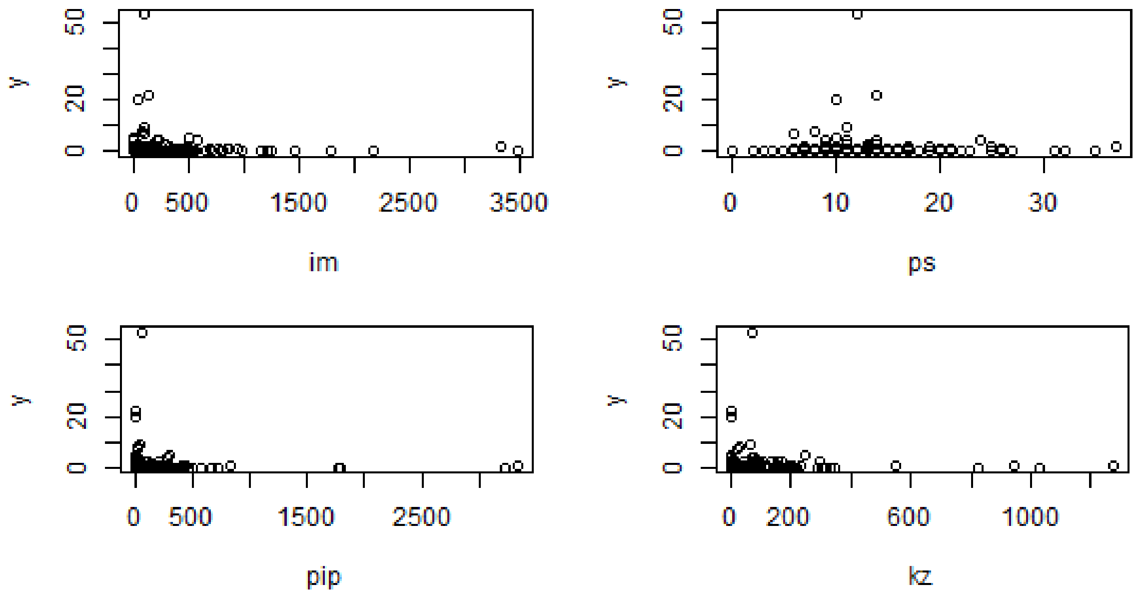


Figure 3. Plot between Response Variables and All Predictor Variables

The test results in **Table 3** show a p-value of <2.22e-16, which is smaller than the 5% significance level. This means that there is an excess zero in the data. The subsequent exploration process is then carried out to see the possible pattern of the relationship between the response variable and each predictor variable. In **Figure 3**, it can be identified that the pattern between the response variable and each predictor variable tends to be non-linear as the distribution of malnutrition cases in Bogor Regency is seen to be skewed to the left. This makes modeling with a normal distribution form inappropriate.

3.1 Poisson Mixed Model

Since the response variable used is the count data and takes into account the random influence of the sub-district, the modeling of malnutrition cases is carried out using the Poisson Mixed Model. The parameter estimates obtained in the Poisson Mixed Model are as follows:

Table 4. Estimated Value of Parameters in Poisson Mixed Model

	Estimate	Std. Error	z value	Pr(>|z|)	
Fixed Components					
(Intercept)	-8.8830	0.5383	-16.5020	< 2e-16	***
W	0.0003	0.0045	0.0780	0.9382	
Tr	-0.0001	0.0002	-0.5930	0.5529	
Pt	-0.0003	0.0002	-1.8410	0.0656	.
Jm	0.0011	0.0006	1.8350	0.0665	.
Im	-0.0005	0.0004	-1.3650	0.1723	
Kz	-0.0009	0.0009	-1.0810	0.2798	
Ps	0.0348	0.0268	1.2950	0.1952	
Pip	-0.0013	0.0003	-4.3200	1.56E-05	***
Random Components					
sub-district (Intercept)	3.458	1.86			

Based on the partial test results in **Table 4** at the 5% significance level, it can be concluded that only the Number of Parents/Caregivers Participating in Monthly Parenting (PAUD) variable has a significant effect on the number of cases of malnutrition in Bogor Regency. Furthermore, overdispersion testing is carried out through the function qcc. overdispersion.test to see whether modeling using the Poisson Mixed Model is appropriate or not.

Table 5. Overdispersion Test Results

Obs.Var/Theor.Var	Statistic	p-value
18.9915	7539.626	0

Based on the test results related to overdispersion in **Table 5** at a significant level of 5%, it can be concluded that there is overdispersion in the data. This will result in biased parameters, and hypothesis testing becomes invalid because the resulting standard errors are small. Furthermore, to overcome the problem of overdispersion, modeling is carried out based on the negative binomial distribution.

3.2 NB Mixed Model

The second modeling is carried out by considering overdispersion. The distribution that can be used to count data that experiences overdispersion is the negative binomial distribution; thus, malnutrition cases are modeled using the NB Mixed Model. The parameter estimates obtained in the NB Mixed Model are as follows:

Table 6. Estimated Value of Parameters in NB Mixed Model

	Estimate	Std. Error	z value	Pr(>|z|)	
Fixed Components					
(Intercept)	-276.400	19.170	-14.416	< 2e-16	***
W	7.518	1.146	6.562	5.32E-11	***
Tr	-0.288	0.060	-4.781	1.75E-06	***
Pt	0.001	0.038	0.035	0.972	
Jm	-0.405	0.088	-4.622	3.81E-06	***
Im	-0.439	0.045	-9.736	< 2e-16	***
Ps	15.980	2.082	7.673	1.68E-14	***
Pip	-0.175	0.012	-14.718	< 2e-16	***
Kz	0.302	0.184	1.643	0.1	
Random Components					
Sub-district (Intercept)	3.719e-120	1.928e-60			

Based on the partial test results in **Table 6** at a significance level of 5%, it can be concluded that the variables of Travel Time from the Village to the Nearest Health Facility, Number of Children Weighed Routinely Every Month, Number of Children 0-2 Years Old Who Have Health Insurance, Number of Children Under 12 Months Old Who Receive Complete Basic Immunization, Number of Posyandu, and Number of Parents/Caregivers Participating in Monthly Parenting (PAUD) have a significant effect on the number of malnutrition cases in Bogor Regency.

3.3 ZINB Mixed Model

The third alternative model is a model that considers overdispersion and excess zero. The distribution that can accommodate the two is the ZINB distribution, so the third model will use the ZINB Mixed Model. The parameter estimates obtained in the ZINB Mixed Model are as follows:

Table 7. Estimated Value of Parameters in ZINB Mixed Model

	Estimate	Std. Error	z value	Pr(>|z|)	
Fixed Components					
(Intercept)	-92.145	39.371	-2.34	0.0193	*
W	-0.208	0.254	-0.819	0.4126	
Tr	0.646	0.143	4.534	5.79E-06	***

	Estimate	Std. Error	z value	Pr(>|z|)	
Pt	-0.916	0.228	-4.013	5.99E-05	***
Jm	0.033	0.245	0.133	0.8939	
Im	-0.478	0.115	-4.147	3.36E-05	***
Ps	5.845	1.082	5.401	6.63E-08	***
Pip	-0.229	0.032	-7.122	1.07E-12	***
Kz	-0.039	0.199	-0.197	0.8437	
Random Components					
Sub-district (Intercept)	5.203e-55	7.213e-28			
Zero-inflation model					
(Intercept)	-0.1971	0.8733	-0.226	0.821	

Based on the partial test results in **Table 7** at the 5% significance level, it can be concluded that the variables Number of Children Weighed Routinely Every Month, Number of Children Measured for Length and Height Twice a Year, Number of Children Under 12 Months Old Who Receive Complete Basic Immunization, Number of Posyandu, and Number of Parents/Caregivers Participating in Monthly Parenting (PAUD) have a significant effect on the number of malnutrition cases in Bogor Regency.

Model comparison between the Poisson Mixed Model, the NB Mixed Model, and the ZINB Mixed Model is carried out using the Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) values. The model is said to be good if it has the smallest AIC and BIC values among the models being compared. In addition, a comparison is also made on the deviance ratio and degrees of freedom as another measure to check for overdispersion, and the comparison results are shown in **Table 8**.

Table 8. **Model Comparison**

	AIC	BIC	Deviance/db
Poisson Mixed Model	973.7	1011.3	3.096
NB Mixed Model	940.3	981.7	2.991
ZINB Mixed Model	934.9	980	2.977

Table 8 shows that the ZINB Mixed Model has an AIC value of 934.9 and a BIC of 980, which is smaller than the Poisson Mixed Model and the NB Mixed Model. In addition, the ratio between the deviance value and the degrees of freedom in the ZINB Mixed Model of 2.977 is smaller than the other models.

This shows that the ZINB Mixed Model is better to use in modeling the factors that influence the number of malnutrition cases in Bogor Regency by considering the random effect of the sub-district and when the count data experience overdispersion and excess zero. Furthermore, the model interpretation will be based on the ZINB Mixed Model by considering the variables that significantly affect the number of malnutrition cases in Bogor Regency.

In the ZINB Mixed Model, the variables that are significant and have a positive sign include the variables Number of Children Weighed Routinely Every Month and Number of Posyandu. These two variables show that the more children under five who are weighed regularly and the more Posyandu, the greater the chance of immediately detecting malnourished children. Puskesmas, as the first-level healthcare facility, is at the forefront of all malnutrition prevention efforts in each region. Other variables that are significant and have a negative sign include the Number of Children Measured for Length and Height Twice a Year, the Number of Children under 12 Months Old Who Received Complete Basic Immunization, and the Number of Parents/Caregivers Participating in Monthly Parenting (PAUD). From these three variables, it can be seen that immunization and parental knowledge related to malnutrition have a major role in preventing or reducing the chance of malnutrition in an area. This is in accordance with the research that states that there is a relationship between maternal knowledge of feeding patterns and the nutritional status of toddlers **[29]** and also in line with the Indonesian government's policy to reduce malnutrition in Indonesia by conducting specific interventions that include; 1) Adequacy of food and nutrient intake; 2) Feeding, care and parenting; and 3) Treatment of infection/disease. The role of Posyandu is also important as a place easily accessed by the lower middle-class community to get health services.

4. CONCLUSIONS

Based on the results of data analysis, the following conclusions are drawn: (1) The ZINB Mixed Model method is a method that is able to accommodate the presence of random effects, overdispersion, and excess zero in modeling malnutrition in Bogor Regency; (2) Variables that significantly affect the occurrence of malnutrition cases in villages in Bogor Regency include the variables of Number of Children Weighed Routinely Every Month, Number of Children Measured for Length and Height Twice a Year, Number of Children Under 12 Months Old Who Received Complete Basic Immunization, Number of Posyandu, and Number of Parents/Caregivers Participating in Monthly Parenting (PAUD). There are limitations related to data availability, so the results of this study only apply to the Bogor Regency and cannot be generalized to other regions. For further research and to get a better interpretation, analysis using tree-based modeling such as GLMM-tree and BiMM Forest can be tried.

ACKNOWLEDGMENT

The authors would like to express their gratitude for the Beasiswa Pendidikan Indonesia (BPI) which has supported the education fund during the doctoral study at the Department of Statistics and Data Science, IPB University

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