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# MODELING OF LEPROSY CASES IN NORTH SULAWESI USING NEGATIVE BINOMIAL REGRESSION

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## ABSTRACT

*Leprosy is a chronic infectious disease that remains a public health concern in Indonesia, particularly in provinces where the disease is still endemic. North Sulawesi Province is among the regions with relatively high leprosy incidence, indicating the need for province-level analysis to better understand the factors associated with the occurrence of the disease. This study aims to identify the factors influencing the number of leprosy cases in North Sulawesi Province. The explanatory variables considered include the percentage of people living in poverty, the number of health workers, the percentage of toddlers immunized with BCG, the percentage of the population covered by health insurance, the percentage of households with access to clean drinking water, and the percentage of households with access to proper sanitation. The study uses secondary data obtained from official publications of the Central Statistics Agency (BPS) of North Sulawesi Province for the year 2023. Since the response variable is count data, Poisson regression was initially applied. However, due to the presence of overdispersion, Negative Binomial Regression was employed as an alternative modeling approach to obtain more reliable parameter estimates. The results indicate that the percentage of the population covered by health insurance has a statistically significant effect on the number of leprosy cases, with higher coverage associated with a reduction in reported cases. Other variables were found to have no significant effect at the chosen significance level. In conclusion, the findings highlight the importance of health insurance coverage in reducing leprosy incidence in North Sulawesi Province. The use of Negative Binomial Regression proves to be appropriate for modeling overdispersed leprosy case data and can support evidence-based policymaking in leprosy control programs.*

**Keywords**: *leprosy, Poisson regression, overdispersion, negative binomial regression.*

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## INTRODUCTION

Leprosy remains a significant public health concern and is classified by the World Health Organization (WHO) as a neglected tropical disease. Despite global control efforts, the disease continues to be reported in more than 120 countries, with annual new case notifications consistently exceeding 200,000 worldwide (Khotimah *et al.*, 2021). Leprosy is caused by Mycobacterium leprae and is transmitted primarily through prolonged close contact, especially via respiratory droplets released from the nose or mouth of an infected individual. The disease mainly affects the skin and peripheral nerves and, in the absence of timely treatment, may lead to irreversible disabilities such as nerve damage, motor impairment, and visual disorders (Ulfa *et al*., 2021; Dhahari & Sofro, 2023).

Indonesia is one of the countries with the highest leprosy burden globally. Although the national prevalence has declined over time, leprosy transmission persists, as reflected in a prevalence rate of 0.63 per 10,000 population and approximately 15,000 newly detected cases reported in 2023 (Dyahlokita, 2025). Importantly, the distribution of leprosy cases across provinces is uneven. North Sulawesi is among the provinces with relatively high incidence, ranking sixth nationally, with a recorded prevalence of 14.04 per 100,000 population in 2021. This indicates that leprosy remains endemic in the province and continues to pose challenges to local health systems.

The selection of North Sulawesi as the study area is motivated by its distinctive regional characteristics. The province consists of both mainland and archipelagic areas, with substantial variation in population density, socioeconomic conditions, sanitation coverage, and access to healthcare services among districts. Such heterogeneity may influence leprosy transmission patterns differently compared to other regions in Indonesia. Nevertheless, empirical studies focusing specifically on leprosy determinants in North Sulawesi are still limited, resulting in a lack of evidence-based insights tailored to the local context. This gap highlights the need for province-level analysis to support more targeted and effective disease control strategies.

From a statistical perspective, leprosy incidence data are inherently count-based and are commonly analyzed using Poisson regression. This method assumes equidispersion, meaning that the variance of the response variable is equal to its mean. In epidemiological studies, this assumption is frequently violated due to unobserved heterogeneity, excess variability, or clustering effects, resulting in overdispersion. (Aipassa *et al.*, 2023; Badriawan & Melaniani, 2023; Maneking *et al*., 2020).

Negative Binomial Regression offers a flexible alternative by incorporating an additional dispersion parameter, allowing it to accommodate overdispersed count data without altering the original data structure (Syafiqoh *et al*., 2024; Sauddin *et al*., 2020; Fadri *et al*., 2025). Previous research on leprosy incidence has demonstrated that Poisson models often exhibit overdispersion, thereby supporting the use of Negative Binomial Regression for more robust estimation (Aipassa *et al*., 2023). Other studies have successfully applied this approach to examine the influence of socioeconomic and environmental factors, such as poverty levels, housing quality, sanitation practices, and population density, on leprosy incidence (Khotimah *et al*., 2021).

Most existing studies rely on national or multi-provincial data and rarely focus on North Sulawesi specifically. In addition, limited attention has been given to recent data, particularly post-pandemic conditions, which may alter disease dynamics. To address these gaps, this study applies Poisson Regression to model the number of leprosy cases in North Sulawesi Province in 2023 and employs Negative Binomial Regression as an alternative model when overdispersion is detected. The results of this study are expected to contribute methodologically by demonstrating appropriate count data modeling techniques for overdispersed epidemiological data and empirically by identifying key factors associated with leprosy incidence in North Sulawesi. These findings may support policymakers and public health authorities in designing region-specific interventions aimed at reducing leprosy transmission and improving disease control outcomes.

## MATERIALS AND METHODS

### Negative Binomial Regression

The Negative Binomial Regression Model is a partial implementation of the General Linear Model that functions to describe the relationship between response variables and predictor variables. This model comes from a combination of Poisson distribution and gamma distribution (Fathurahman, 2022). Because the response variable represents count data, Negative Binomial Regression can be used. This model is applied as an alternative to Poisson regression when overdispersion occurs, which is a condition when the variance of the data exceeds its mean value. This model uses the assumption that bound variables follow a negative binomial distribution, which means that the value of the variance does not have to be equal to the mean (Winata, 2023),(Salaki *et al*., 2021). The general form of the Negative Binomial Regression Model can be expressed as follows:

$$g(\mu_i) = \eta_i = \beta_0 + \beta_1 x_{i1} + \cdots + \beta_k x_{ik} = \beta_0 + \sum_{j=1}^{k} \beta_j x_{ij,}\ i = 1,2,\dots,n$$

The relational function used is a natural logarithmic function, i.e. $g(\mu_i) = \ln(\mu_i)$. The model parameter estimation is carried out through the maximum likelihood approach, with an iterative process using the Newton-Raphson method to obtain the optimal regression parameter value (Halim & Satyahadewi, 2025; Widyaningsih *et al*., 2021).

### Research Data

This study uses secondary data obtained through official publications from the Central Statistics Agency (BPS) of North Sulawesi Province. The data of this study consists of 15 districts/cities in North Sulawesi Province in 2023. Data were analyzed using RStudio software. The variables analyzed in this study are presented in Table 1 below.

Table 1. Research Variables

| Variable | Variable Name |
|---|---|
| $Y$ | Number Of Leprosy Cases |
| $X_1$ | Percentage of poor population |
| $X_2$ | Number of health workers |
| $X_3$ | Percentage of toddlers immunized with BCG |
| $X_4$ | Percentage of the population who have health insurance |
| $X_5$ | The percentage of households that have access to a decent source of drinking water |
| $X_6$ | Percentage of households that have access to proper sanitation |

### Research Procedure

The following are the steps in analyzing the variables that affect the number of leprosy in North Sulawesi:

1. Explain the characteristics for the response variables, namely the number of leprosy in North Sulawesi and the predictor variables used
2. Identify whether multicollinearity exists among the predictor variables.
3. Building modeling using Poisson Regression
4. Run tests for the presence of overdispersion in the Poisson Regression model.
5. Build a Negative Binomial Regression model as an alternative when overdispersion is detected
6. Determine the selection of the best model between Poisson Regression and Negative Binomial Regression by comparing the values *of Akaike's Information Criterion* (AIC) and *Bayesian Informatioasn Criterion* (BIC). Models with lower AIC and BIC numbers are considered best suited for data.

## RESULTS AND DISCUSSION

### Data Description

To provide an overview of the number of leprosy in North Sulawesi Province, analyze 2023 data from 15 districts/cities in the province, with response variables ($Y$) in the form of the number of cases and six independent variables. The following are descriptive statistics of the data displayed in Table 2.

Table 2. Descriptive statistics of data

| Variable | Minimum | Maximum | Median | Average | Standard Deviation |
|---|---|---|---|---|---|
| $Y$ | 4 | 63 | 31 | 30,4 | 21,65 |
| $X_1$ | 5,03 | 12,04 | 7,37 | 7,905 | 2,25 |
| $X_2$ | 465 | 4909 | 806 | 1058 | 1101,93 |
| $X_3$ | 73,24 | 92,2 | 87,63 | 86,2 | 5,17 |
| $X_4$ | 65,32 | 87,83 | 79,79 | 77,40 | 7,70 |
| $X_5$ | 87,09 | 98,19 | 95,2 | 93,87 | 4,14 |
| $X_6$ | 71,05 | 96,92 | 86,05 | 84,22 | 8,73 |

Table 2 shows the statistical value, which shows that the minimum value of $Y$ (number of leprosy) is 4, while the maximum value is 64. The median value for variable $Y$ was 31, while the mean value was 30,4 with a standard deviation of 21,65. The $X_2$ variable has a very wide range of data (from 465 to

4909), and the mean value is greater than the median, indicating a possible outlier. The significantly different median and mean values indicate the possibility of asymmetric (skewed) data distribution. The distribution of leprosy data in North Sulawesi Province is visualized in Figure 1.

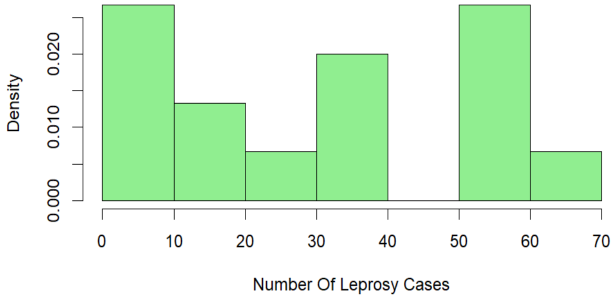

Figure 1. Data distribution

Figure 1 is a histogram plot that shows an asymmetrical shape that looks bimodal (has two peaks) in the range of 0–10, which is an area with a low number of leprosy and a range of 50–60, which is an area with a fairly high number of cases. This asymmetry suggests that the distribution of this data is abnormal, allowing the use of the Poisson distribution method.

**Multicollinearity Test**

The modeled independent variable lacking a significant correlation between variables is a requirement for Poisson regression modeling. Therefore, the multicollinearity test was carried out with two criteria: the size of the correlation between independent variables and *the Variance Inflation Factor* (VIF). Figure 2 shows the correlation values between independent variables.

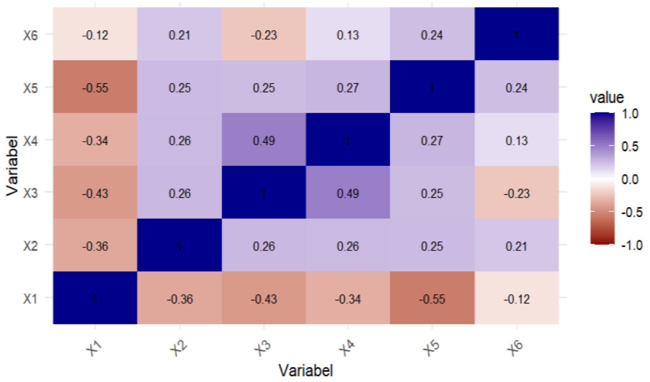

Figure 2. Correlation of independent variables

Based on the large correlation criteria between independent variables used in the analysis, the results of the multicollinearity test are shown in Figure 2. There is no correlation value that is close to or greater than 0,8 (either positive or negative), so there is no strong multicollinearity between the predictor variables. In addition, multicollinearity can be detected based on the value of the Variance Inflation Factor (VIF) shown in Table 3. The results of the VIF value check showed that all variables had a VIF value below ten. The findings indicate that each predictor variable has no correlation relationship so that the assumption of multicollinearity does not occur and all predictor variables can be used in model formation.

Table 3. VIF Value

| Variables | VIF |
|---|---|
| $X_1$ | 1,743487 |
| $X_2$ | 1,245225 |
| $X_3$ | 1,772339 |
| $X_4$ | 1,453857 |
| $X_5$ | 1,524165 |
| $X_6$ | 1,317106 |

## Poisson Regression Model

The use of the Poisson regression model as a modeling technique after ensuring that there were no symptoms of multicollinearity between the predictor variables. Furthermore, the researcher conducted an analysis to evaluate the relationship between predictor variables and the number of leprosy patients that occurred in the North Sulawesi Province area in 2023. The analysis was carried out using Poisson regression. The following is presented parameter estimation in the Poisson regression model obtained using the Maximum Likelihood Estimation (MLE) approach.

Table 4. Estimation of the parameters of the Poisson Regression model

| Parameters | Estimate | Std. Error | Z-value | p-value | Interpretation |
|---|---|---|---|---|---|
| Intercept | $-1{,}968$ | $2{,}350$ | $-0{,}837$ | $< 0{,}402437$ | Insignificant |
| $X_1$ | $-1{,}153 \times 10^{-1}$ | $3{,}568 \times 10^{-2}$ | $-3{,}233$ | $0{,}001224$ | Significant |
| $X_2$ | $1{,}104 \times 10^{-4}$ | $3{,}894 \times 10^{-5}$ | $2{,}835$ | $0{,}004586$ | Significant |
| $X_3$ | $5{,}564 \times 10^{-2}$ | $1{,}656 \times 10^{-2}$ | $3{,}359$ | $0{,}000781$ | Significant |
| $X_4$ | $-6{,}398 \times 10^{-2}$ | $1{,}015 \times 10^{-2}$ | $-6{,}300$ | $2{,}98 \times 10^{-10}$ | Significant |
| $X_5$ | $2{,}470 \times 10^{-2}$ | $1{,}524 \times 10^{-2}$ | $1{,}621$ | $0{,}105125$ | Insignificant |
| $X_6$ | $4{,}595 \times 10^{-2}$ | $9{,}300 \times 10^{-3}$ | $4{,}940$ | $7{,}80 \times 10^{-7}$ | Significant |

Referring to the results of parameter estimation shown in Table 4, the researcher found that the variables $X_1, X_2$, $X_3$, $X_4$, and $X_6$ statistically significantly affected the number of leprosy cases at a significance level of α = 0,05. These findings indicate that the increase in the number of health workers ($X_2$), the percentage of children under five who are BCG immunized ($X_3$), and the percentage of households that have access to proper sanitation ($X_6$) are positively correlated with an increase in the number of leprosy cases. Meanwhile, the increase in the percentage of poor people ($X_1$) and the percentage of the population who have health insurance ($X_4$) is actually negatively correlated, namely reducing the number of leprosy cases. Meanwhile, the $X_5$ variable, did not show a significant influence on the number of leprosy cases. The form of the Poisson Regression model used in modeling the number of leprosy cases per district/city in North Sulawesi Province in 2023 is presented as follows:

$$\begin{aligned}\hat{\mu} = \exp\,(&-1{,}968 - 1{,}153.\,10^{-1}X_1 + 1{,}104.\,10^{-4}X_2 + 5{,}564.\,10^{-2}X_3 - 6{,}398.\,10^{-2}X_4 \\ &+ 4{,}595.\,10^{-2}X_6)\end{aligned}$$

## Overdispersion Detection in Poisson Regression

In Poisson regression, one of the fundamental assumptions is equidispersion, meaning that the mean and variance of the response variable are equal. However, this assumption may be violated in practice, leading to a condition known as overdispersion, where the variance of the data exceeds its mean value. In this study, violations of the equidispersion assumption were first identified through visual analysis using a plot between the mean predicted values and the variance (represented by Pearson squared residuals) of the Poisson regression model, as shown in Figure 3. Under the Poisson assumption, the plotted points are expected to cluster symmetrically around a reference line, indicating a comparable magnitude between the mean and variance. However, the plot shows that the points are widely and randomly dispersed rather than concentrated around a linear pattern. This substantial spread of residuals indicates that the variability in the data increases more rapidly than the mean, providing visual evidence of overdispersion. Consequently, the Poisson regression model does not adequately satisfy its basic assumptions and may not be appropriate for the analyzed data.

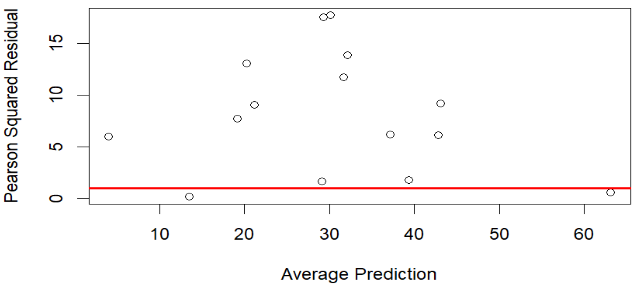

Figure 3. Plot of mean predicted values versus Pearson squared residuals of the Poisson regression model

To further assess the presence of overdispersion, a numerical evaluation was conducted by comparing the deviance and Pearson’s Chi-square statistics with their respective degrees of freedom, as presented in Table 5. In a well-fitted Poisson regression model, the ratios of deviance to degrees of freedom and Pearson’s Chi-square to degrees of freedom are expected to be close to one. However, the results show that both ratios are substantially greater than one, which clearly indicates overdispersion in the Poisson regression model. Overdispersion occurs when the variance of the response variable exceeds its expected value under the Poisson distribution. This condition can lead to serious statistical issues, particularly the underestimation of standard errors, which in turn may result in biased hypothesis testing and unreliable regression parameter estimates. Based on both visual and numerical diagnostics, the Poisson regression model is therefore considered less suitable for modeling the data.

Table 5. Comparison of deviance and Pearson's Chi-square model of Poisson regression

| Criterion | Free Degrees | Value | Free Grades/ Degrees |
|---|---|---|---|
| Deviance | 8 | 135,4001 | 16,92501 |
| Pearson's Chi-square | 8 | 122,4881 | 15,31102 |

## Negative Binomial Regression Model

The presence of overdispersion in the Poisson regression model leads to inaccurate standard error estimation and compromises the validity of statistical inference. To address this issue, the Negative Binomial regression model was employed as an alternative approach. Unlike the Poisson model, the Negative Binomial model incorporates an additional dispersion parameter, allowing the variance to exceed the mean and providing a more flexible framework for overdispersed count data. By accommodating excess variability, the Negative Binomial regression model yields more reliable standard error estimates and more robust parameter inference. The results of parameter estimation from the Negative Binomial regression model are presented in Table 6.

Table 6. Estimation of the parameters of the Negative Binomial Regression model

| Parameters | Estimate | Std. Error | Z-value | p-value | Interpretation |
|---|---|---|---|---|---|
| Intercept | −1,5924735 | 6,4063060 | −0,249 | < 0,8037 | Insignificant |
| $X_1$ | −0,0698191 | 0,099053 | −0,705 | 0,4809 | Insignificant |
| $X_2$ | 0,0001810 | 0,0001649 | 1,098 | 0,2723 | Insignificant |
| $X_3$ | 0,0436832 | 0,0444209 | 0,983 | 0,3254 | Insignificant |
| $X_4$ | −0,054493 | 0,0268647 | −2,028 | 0,0425 | Significant |
| $X_5$ | 0,0326293 | 0,0496984 | 0,657 | 05115 | Insignificant |
| $X_6$ | 0,0312810 | 0,0227753 | 1,373 | 0,1696 | Insignificant |

Based on the estimated results, the researcher concluded that the variables $X_1, X_2, X_3, X_5$, and $X_6$ did not have a significant influence on the number of leprosy cases ($Y$). On the other hand, $X_4$ showed a significant influence on $Y$. These findings indicate that an increase in the percentage of the population with health insurance ($X_4$) can significantly reduce the number of leprosy cases in North Sulawesi Province. The final form of the Negative Binomial regression model obtained from the results of the analysis is written as follows:

$$\mu_i = \exp\,(-\,1{,}5924735 - 0{,}054493X_4)$$

To assess whether overdispersion remains in the fitted model, the ratios of deviance to degrees of freedom and Pearson’s Chi-square to degrees of freedom were examined, as shown in Table 7. Both ratios are close to one, indicating that the Negative Binomial regression model adequately accounts for overdispersion in the data. This result confirms that the Negative Binomial model provides a better fit than the Poisson regression model.

Table 7. Comparison of *deviance* and *Pearson's Chi-square* model of Negative Binomial Regression

| Criterion | Free Degrees | Value | Free Grades/ Degrees |
|---|---|---|---|
| *Deviance* | 8 | 15,85473 | 1,981842 |
| *Pearson's Chi-square* | 8 | 12,47127 | 1,558909 |

## Model Evaluation

The Poisson regression model was deemed unsuitable due to the presence of overdispersion, which violates its fundamental assumptions. As an alternative, the Negative Binomial regression model was selected and evaluated using information criteria. As shown in Table 8, the Negative Binomial model yields substantially lower Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values compared to the Poisson model. Lower AIC and BIC values indicate a better balance between model fit and complexity. Therefore, the Negative Binomial regression model is considered the most appropriate model for explaining the number of leprosy cases in North Sulawesi Province in 2023.

Table 8. AIC and BIC values

| Regression | AIC | BIC |
|---|---|---|
| Poisson | 223,311 | 228,2674 |
| Negative Binomial | 139,1565 | 145,1565 |

## CONCLUSION

The Poisson regression analysis revealed the presence of overdispersion, indicating a violation of the equidispersion assumption and rendering the model unsuitable for the data. Consequently, Negative Binomial regression was applied as a more appropriate alternative. The diagnostic results show that the Negative Binomial model successfully accounts for overdispersion, as indicated by deviance and Pearson's Chi-square ratios close to one, as well as lower AIC and BIC values compared to the Poisson model. Furthermore, the analysis identifies health insurance coverage as the only variable with a significant effect on leprosy cases, where an increase in coverage is associated with a reduction in the number of cases. These findings highlight the importance of using appropriate count data models and support health insurance expansion as a key strategy for reducing leprosy incidence in North Sulawesi Province.

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