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MODELING THE NUMBER OF POOR POPULATION USING *GEOGRAPHICALLY WEIGHTED NEGATIVE BINOMIAL REGRESSION* (GWNBR) IN NORTH SUMATERA PROVINCE

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Abstract. Poverty remains a persistent and unevenly distributed development challenge across North Sumatra Province, so models capable of capturing this regional variation are urgently needed to support more precisely targeted poverty alleviation policies. This study develops a model for the number of poor people in 33 regencies/cities of North Sumatra Province in 2025 using Geographically Weighted Negative Binomial Regression (GWNBR). The response variable is the number of poor people (Y), while the explanatory variables are the Open Unemployment Rate (X1), Human Development Index (X2), Senior High School Education Level (X3), Labor Force Participation Rate (X4), and the percentage of households with access to proper sanitation (X5). The analysis consists of Poisson regression, Negative Binomial regression, Moran's I testing for spatial autocorrelation, the Breusch–Pagan test for spatial heterogeneity, and GWNBR using an Adaptive Bisquare weighting function. The Poisson model shows severe overdispersion, with a deviance-to-degrees-of-freedom ratio of 3,820.53. Moran's I indicates no significant spatial autocorrelation in the residuals ($I = -0.0202$; $p = 0.1180$), whereas the Breusch–Pagan test confirms significant spatial heterogeneity ($BP = 15.7949$; $p = 0.0075$). The GWNBR model produces a deviation of 18.420 and McFadden's R^2 of 0.150000 and captures differences in the effects of explanatory variables across locations. Based on significant local parameters, the study area is divided into two groups. Group 1 consists of Mandailing Natal Regency and South Nias Regency, with X1, X2, and X3 being significant, while Group 2 consists of the other 31 regencies/cities, with X2 and X3 being significant. These findings indicate that GWNBR can describe poverty-related factors locally and provide information relevant to location-specific poverty reduction policies. The results are expected to help local governments design region-specific poverty alleviation programs rather than relying on uniform province-wide policies, and it is recommended that future studies incorporate additional socioeconomic variables and more recent panel data to further improve the model's accuracy and policy relevance.

Keywords: **Poverty, Overdispersion, Spatial Heterogeneity, Geographically Weighted Negative Binomial Regression**

A. Introduction

Poverty is related to unequal abilities, opportunities, and community access to resources. Its impacts are not limited to social and economic aspects, but can also relate to education, health, and political stability. The government continues to make various efforts to reduce the number of people living in poverty through various poverty alleviation programs. The implementation of these programs faces various challenges, including poverty-related behaviors, cultural influences, and societal attitudes that can hinder the process of escaping poverty. These conditions can ultimately affect the accuracy of government assistance provided to groups in need (Sitorus & Elmanani, 2023).

North Sumatra Province has diverse socioeconomic conditions across its districts and cities. Variations in the quality of human resources, employment conditions, labor force participation, education, and access to adequate sanitation can contribute to differences in poverty levels across regions. This diversity of characteristics indicates that the relationship between the number of poor people and its explanatory factors varies across locations.

Therefore, poverty studies need to incorporate a regional dimension to more accurately reflect the conditions in each region.

Because the number of poor people is a count data, Poisson regression can be used as a modeling method. This regression is built on the assumption of equidispersion, meaning the mean and variance of the response variable have the same value. In poor population data, the variance can exceed the mean. This condition is known as overdispersion and can make Poisson regression less accurate. Rahmadeni and RJ (2019) explain that the presence of overdispersion needs to be considered when determining an appropriate model for count data.

Negative Binomial regression can be an option when count data is overdispersed. This model allows for greater response variation than the mean, making it more suitable than Poisson when the equidispersion assumption is not met. Winata (2023) showed that Negative Binomial regression can be an alternative to Poisson regression in overdispersed data. In modeling the number of poor people, this approach is relevant because data characteristics can differ between regions and do not always meet the Poisson assumption.

In addition to overdispersion, differences in poverty conditions between regions can create spatial heterogeneity. This means the relationship between the response variable and the explanatory variables can change depending on geographic location. Sitorus and Elmanani (2023) used Geographically Weighted Panel Regression to examine factors related to poverty in North Sumatra. These findings demonstrate that spatial factors are important to consider in poverty analysis.

Geographically Weighted Negative Binomial Regression (GWNBR) is a development of Negative Binomial regression that incorporates location information into the estimation process. This model estimates parameters locally, allowing the influence of explanatory variables to vary across regions. Priliya, Sulistijowati, and Sugiyanto (2020) demonstrated that GWNBR can be applied to overdispersed census data by considering spatial weighting. Similar applications were also reported by Ayunda and Husein (2025) and Azkia, Dewi, and Raina (2024) on data with spatial characteristics and overdispersal. GWNBR itself extends the geographically weighted regression framework introduced by Brunsdon, Fotheringham, and Charlton (1996), which allows regression coefficients to vary across locations rather than being fixed globally. In the specific context of poverty modeling, Delvia, Mustafid, and Yasin (2021) found that GWNBR produced a better fit than Poisson and global Negative Binomial regression when modeling the number of poor people in Indonesia, while Halim, Satyahadewi, and Preatin (2025) showed that GWNBR could reveal region-specific poverty determinants in Kalimantan that a global model failed to detect.

Based on these conditions, this study applies Geographically Weighted Negative Binomial Regression (GWNBR) to model the number of poor people in 33 districts/cities in North Sumatra Province in 2025. The response variable used is the number of poor people, while the explanatory variables include the Open Unemployment Rate (TPT), Human Development Index (HDI), High School Education Level, Labor Force Participation Rate (TPAK), and the percentage of households with access to proper sanitation. The objectives of the study are to describe the characteristics of the number of poor people, identify overdispersion and spatial effects, build a GWNBR model, and determine variables that have a significant influence on each district/city. With this approach, the study is expected to produce information on local poverty factors that can be considered in formulating policies according to regional conditions.

B. Research method

1. Research Design

This research is a quantitative study using a spatial statistical approach to assess the number of poor people in 33 districts/cities in North Sumatra Province in 2025. The analysis was conducted using Poisson regression, Negative Binomial regression, and Geographically Weighted Negative Binomial Regression (GWNBR). The data used are secondary data, with the number of poor people as the response variable and five explanatory variables.

2. Research Variables

Table 1 Research Variables

Variables	Symbol	Information
Number of poor people	Y	Number of poor people (people)
Open unemployment rate	X1	TPT Percentage
Human development index	X2	HDI Index
High school education level	X3	Number of residents with a high school education level
Labor force participation rate	X4	TPAK Percentage
Access to proper sanitation	X5	Percentage of households with access to proper sanitation

3. Multicollinearity Test

Multicollinearity indicates a strong linear relationship between explanatory variables. This is examined using the Variance Inflation Factor (VIF). A predictor variable is considered not to have severe multicollinearity if the VIF is less than 10.

$$VIF_j = \frac{1}{1-R_j^2} \tag{1}$$

with is the coefficient of determination between$R_j^2 Xj$with other predictor variables

4. Poisson regression

Poisson regression is used to analyze count data. In this model, the response variable Yi is assumed to be distributed Poisson with a mean parameter μi. The general form of the Poisson regression model can be expressed as follows.

$$\hat{\mu}_i = \exp(\boldsymbol{X}_t^T \boldsymbol{\beta})$$

$$\hat{\mu}_i = exp\left(\beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots \beta_p X_{ip}\right) \tag{2}$$

In this equation, μi represents the average value of the number of events in a certain time interval.

5. Negative Binomial Regression

If the equidispersion assumption in Poisson regression is not met, that is, when the variance is greater than the mean, Negative Binomial regression can be used. This model is designed to handle overdispersed count data, making it more appropriate when the variance in the data exceeds the mean.

$$\widehat{\boldsymbol{y}_j} \sim NB[\mu_i, \theta]; \mu_i = \exp(x_i \beta) \tag{3}$$

$$Var(Y_i) = \mu_i + \theta \mu_i 2 \tag{4}$$

Description: Yi indicates the number of poor people in the i-th region, μi states the average value of Yi, while α is the dispersion parameter. Overdispersion conditions are checked through the ratio of deviance to degrees of freedom. A ratio value greater than 1 indicates overdispersion.

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6. Spatial Heterogeneity

Spatial heterogeneity testing is conducted to determine whether the characteristics of the relationship between variables differ according to the observation location, so that the regression parameters can change spatially. In this study, testing was conducted using the Breusch–Pagan (BP) statistic with the following hypothesis:

$$\boldsymbol{BP} = \left(\frac{1}{2}\right)\boldsymbol{f^T Z (Z^T Z)^{-1} Z^T f \sim x^2_{(p)}} \quad (5)$$

Where:
P: number of predictor variables
f : $(f_1, f_2, \dots, f_n)^T dengan\ f_i = \frac{\sigma_i^2}{\sigma^2} - 1$
e_i: error for observation i
σ^2: variance ofe_i
σ_i^2: variance of the i-th predictor variable
Z: a matrix of size n × (p+1) containing constant vectors

H0 is rejected if the BP test statistic is greater than the critical value or the p-value is less than α. This decision indicates that the variances between regions differ.$\boldsymbol{H_0 > X^2(p, \alpha)}$

7. Geographically Weighted Negative Binomial Regression

GWNBR is a Negative Binomial model that estimates parameters locally by incorporating geographic distance between regions, building on the geographically weighted Poisson regression framework developed by Nakaya, Fotheringham, Brunsdon, and Charlton (2005) for spatially varying count models. As a result, each district/city can have different parameters. This study uses the Adaptive Bisquare weighting function, with bandwidth determined based on the number of nearest neighbors.

$$Y_i \sim NB\left(\mu_i(u_i, v_i), \theta(u_i, v_i)\right) \quad (6)$$

$$\mu_i(u_i, v_i) = t_i exp\left(\beta_0(u_i, v_i) + \textstyle\sum_{k=1}^{p}(u_i, v_i)X_{ik}\right) \quad (7)$$

In this equation, the geographic coordinates (longitude and latitude) of the i-th observation are represented in the model, while ti is an offset variable set to 1 if the weighting is not based on the total population. The spatial weights are then calculated using the Adaptive Bisquare Kernel function.$(u_i, v_i)w_{ij}(u_i, v_i)$

$$W_{ij} = \begin{cases} \left[1 - \left(\frac{d_{ij}}{b}\right)^2\right]^2, & if\ d_{ij} \le b_i \\ 0, & if\ d_{ij} > b_i \end{cases} \quad (8)$$

The Euclidean distance between locations i and j is expressed by the distance parameter in the equation, while bi is the adaptive bandwidth determined based on the distance to the Kth nearest neighbor.$d_{ij} = \sqrt{(u_i, u_j)^2 + (v_i, v_j)^2}$

8. Model Selection Criteria

Model performance was assessed by comparing the Akaike Information Criterion (AIC), AICc, deviance, and McFadden's R^2. A model is considered to have a better fit if the AIC, AICc, and deviance are lower and the McFadden's R^2 is higher.

$$AIC = 2p - 2In\hat{L}(\hat{\theta}) \tag{9}$$

$$McFadden'S\ R^2 = 1 - \frac{In\ (L_{model})}{In\ (L_{null})} \tag{10}$$

9. Research Stages

1. Secondary data on the number of poor people and five explanatory variables were collected for 33 districts/cities in 2025.
2. Descriptive statistics are calculated to obtain a general overview of the data characteristics.
3. Multicollinearity between variables was examined using VIF.
4. A Poisson regression model is formed and the significance of its parameters is tested.
5. The presence of overdispersion in the Poisson model is checked.
6. If overdispersion is found, a Negative Binomial regression model is formed.
7. Spatial effects are analyzed through Moran's I and Breusch–Pagan.
8. The geographical distance is calculated and the optimum bandwidth is determined.
9. The weighting matrix is constructed using the Adaptive Bisquare function.
10. The GWNBR model is formed and the significance of local parameters is tested.
11. The Poisson, Negative Binomial, and GWNBR models are compared based on the model fit measure.
12. Local parameters are interpreted and regions are grouped based on significant variables.

C. Research Results and Discussion

1. Descriptive Statistics

Descriptive statistics were used to provide an overview of the characteristics of each variable in the 33 districts/cities. The results are shown in Table 2.

Table 2 Descriptive statistics of research variables

Statistics	Y	X1	X2	X3	X4	X5
Minimum	3,530	0.720	66.650	2,281	64.860	22.630
Q1	16,530	2.080	73.930	5,411	70.310	64.680
Median	23,690	4.210	75.740	8,707	73.730	92.330
Average	34,534	4.135	75.406	11,865	75.173	79.863
Q3	40,490	5.850	78.100	13,084	78.890	94.650
Maximum	171,600	7.990	83.740	71,557	87.280	98.500

The descriptive analysis revealed a significant difference in the number of poor people between regions. The lowest recorded number was 3,530, while the highest reached 171,600. This difference demonstrates that poverty levels across the regencies/cities in North Sumatra Province are not homogeneous. Several regions with relatively high numbers of poor people are Deli Serdang, Langkat, Simalungun, Asahan, Mandailing Natal, and South Nias.

2. Multicollinearity Test

Multicollinearity testing uses VIF values. The null hypothesis states that there is no multicollinearity, while the alternative hypothesis states that there is. The results of the calculations using RStudio are presented in Table 3.

Table 3 Variance Inflation Factor Values

Variables	VIF
X1	3.0005
X2	2.6733
X3	1.4528
X4	2.2630
X5	2.1180

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All five VIF values are below the limit of 10. These results indicate that no severe multicollinearity was found among the explanatory variables, so all variables are still suitable for use in modeling.

3. Poisson Regression

Table 4 Parameter estimation of Poisson parameter estimation

Parameter	Estimate	Std. Error	Z	p-value	Information
(Intercept)	18.788000	1.035002	18.1526	<0.0001	Significant
X1	0.001278	0.000007	182.5714	<0.0001	Significant
X2	−0.001310	0.000004	−327.5000	<0.0001	Significant
X3	0.000037	0.000000	522.5344	<0.0001	Significant
X4	−0.000063	0.000003	−21.0000	<0.0001	Significant
X5	0.000107	0.000001	107.0000	<0.0001	Significant

The Poisson model yielded a null deviance of 658.833 with 32 degrees of freedom, and a residual deviance of 103,154.3 with 27 degrees of freedom. The AIC listed in the document is 103,562.7. All Poisson model parameters are significant at the 5% level.

4. Overdispersion Test

Overdispersion was checked by comparing the deviance and degrees of freedom. The calculation yielded a ratio of 3,820.53.

$$\theta = \frac{nilaidevience}{df}$$

$$\theta = \frac{103.154,3}{27} = 3.820,53$$

This ratio is well above 1, indicating that the Poisson model is overdispersive. This means that the data variation is greater than the mean, and Negative Binomial regression is more appropriate for the next stage of analysis.

5. Negative Binomial Regression Model

Table 5 Negative Binomial Regression Parameter Estimates

Parameter	Estimate	Std. Error	Z	p-value	Information
(Intercept)	18.28800	2.092	8.739	$<2\times10^{-16}$	Significant
X1	0.001202	4.713	2.551	0.0108	Significant
X2	−0.001277	2.589	−4.934	8.07×10^{-7}	Significant
X3	0.0000428	5.957	7.130	1.00×10^{-12}	Significant
X4	−0.00003203	1.515	−0.211	0.8326	Not significant
X5	0.0001044	4.285	2.435	0.0149	Significant

The Negative Binomial Model produced a null deviance of 140.994 with 32 degrees of freedom, a residual deviance of 33.709 with 27 degrees of freedom, and an AIC of 712.89. At a significance level of 5%, variables X1, X2, X3, and X5 showed a significant influence on the number of poor people, while X4 showed no significance.

6. Spatial Effect Testing

To examine the spatial autocorrelation in the residuals of the Negative Binomial model, the Moran's I test was used. The test results are presented in Table 6.

Table 6 Results of Moran's I test

Moran's I	E(I)	Var(I)	Z-Statistic	p-value
−0.020216	−0.056437	0.000934	1,1850	0.1180

Because the p-value of 0.1180 is greater than 0.05, H0 is not rejected. Thus, the residuals of the Negative Binomial model do not exhibit significant spatial autocorrelation. In other words, no significant spatial clustering pattern was found in the residuals between regions.

The next step is to test spatial heterogeneity with the Breusch–Pagan statistic.

Table 7 Breusch–Pagan test results

BP Statistics	Degrees of Freedom	p-value
15,7949	5	0.0075

The Breusch–Pagan statistic obtained was 15.7949 with a p-value of 0.0075. Because the p-value was below 0.05, H0 was rejected and spatial heterogeneity was declared significant. Therefore, the rationale for using GWNBR in this study was the difference in parameters by location, not the residual spatial autocorrelation.

7. GWNBR Modeling

After examining spatial effects, the next step involves calculating geographic distances, determining bandwidth, and generating Adaptive Bisquare weights. For example, the distance between South Tapanuli Regency and North Tapanuli Regency is approximately 0.4687 degrees, or 52.175 km. The optimum bandwidth is used to determine the weight of a region relative to the region being modeled.

At the 5% significance level, testing of the GWNBR local parameters yielded two groups of regions based on the pattern of significant explanatory variables.

Table 8 Grouping of regions based on local GWNBR parameters

Group	Regency/City	Significant variables
1	Mandailing Natal and South Nias	X1, X2, X3
2	31 other districts/cities	X2, X3

The modeling results show spatial diversity in the combination of variables related to the number of poor people. The first group includes Mandailing Natal Regency and South Nias Regency, with X1, X2, and X3 as significant variables. The second group consists of 31 other regencies/cities, with X2 and X3 as significant variables.

In local estimates, the human development index coefficient is consistently reported as negative. This finding suggests a link between improvements in the quality of human development and a reduction in the number of poor people. Meanwhile, high school education has a relatively small positive coefficient in urban areas such as Medan. This indicates that increasing secondary education does not always translate into specific skills or commensurate job opportunities, and therefore its effects may vary depending on regional characteristics.

The map of variables showing significance to the number of poor people in districts/cities in North Sumatra Province is presented in Figure 1.

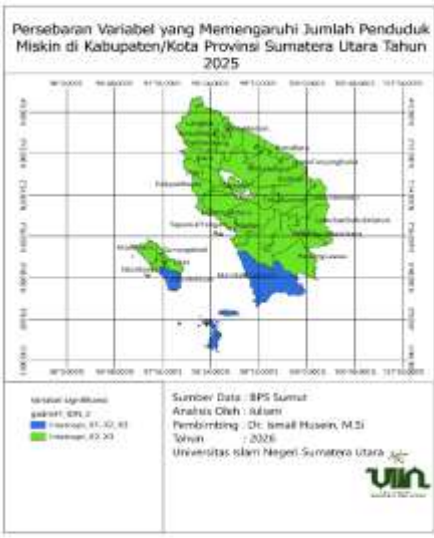

Figure 1. Distribution of Variables Affecting the Number of Poor People

8. Model Comparison

Table 9 Comparison of model fit criteria

Model	Deviance	AIC	AICc	McFadden's R^2	Information
Poisson regression	103,154.3	103,562.7	103,562.93	0.842922	Model with overdispersion
Negative Binomial	33.709	712.89	716.65	0.065986	Global model
GWNBR	18.420	720.82	731.40	0.150000	Local model

Based on the AIC, the global Negative Binomial regression has a lower value than the GWNBR, namely 712.89 compared to 720.82. However, the GWNBR provides a smaller deviance, namely 18.420 compared to 33.709, and a higher McFadden's R^2, namely 0.150000 compared to 0.065986. GWNBR is also able to accommodate spatial heterogeneity which is proven to be significant. Considering the model's fit and ability to capture local variations, the GWNBR was selected as the final model.

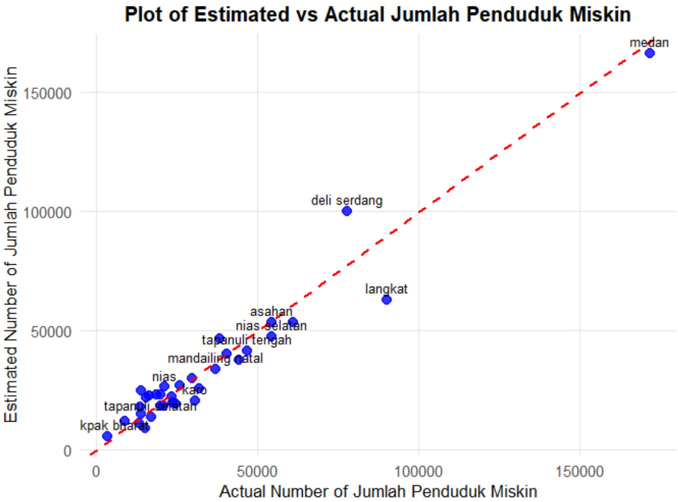

Figure 2 Scatter Plot between Estimated Value and Actual Value

In Figure 2, the distribution of points tends to follow a 45-degree diagonal line. This line represents a condition where the estimated poverty rate is close to the actual value. As an illustration, if the actual poverty rate in a district/city is 4,000, the GWNBR prediction will also be around that value. This pattern indicates that GWNBR can provide predictions close to the actual value in various districts/cities in North Sumatra. This advantage should be considered in conjunction with the AIC value of 720.82, which is slightly higher than the AIC of 712.89 for the global Negative Binomial model. However, GWNBR has the ability to capture spatial heterogeneity. Therefore, GWNBR is more relevant for interpreting poverty factors at the regional level, especially when conditions between regions are quite diverse.

These findings are consistent with previous studies applying GWNBR to overdispersed, spatially heterogeneous count data. Delvia, Mustafid, and Yasin (2021) similarly reported that GWNBR outperformed Poisson and global Negative Binomial regression when modeling the number of poor people in Indonesia, and Halim, Satyahadewi, and Preatin (2025) found that a locally estimated GWNBR model revealed poverty determinants in Kalimantan that a global model could not detect. Comparable improvements from applying GWNBR to overdispersed spatial data have also been reported outside the poverty context, including tuberculosis incidence (Sriningsih et al., 2026; Putri & Fathurahman, 2024), stunting cases (Azkia et al., 2024), malnutrition cases (Priliya et al., 2020), confirmed COVID-19 cases (Fitriani & Jaya, 2020), and poverty case counts in Jambi Province (Jasmadi et al., 2016), indicating that the method performs reliably whenever overdispersion coincides with spatial heterogeneity.

In the specific context of poverty modeling, Suryadi, Jonathan, Jonatan, and Ohyver (2023) likewise found that Negative Binomial regression handled overdispersion in poverty count data more effectively than Poisson regression in West Java, consistent with the overdispersion identified in the Poisson model used in this study. The consistently negative association between the human development index and the number of poor people found here is also in line with Harahap (2022), who reported comparable spatial patterns of human-development-related predictors using Geographically Weighted Regression and Mixed Geographically Weighted Regression for the number of poor people. Meanwhile, the uneven significance of sanitation access across regions parallels the findings of Damayanti and Yanti (2022), who showed that socio-environmental predictors of count outcomes such as pneumonia cases can vary considerably between regions, reinforcing the value of locally estimated models such as GWNBR over a single global coefficient.

D. Conclusion

The number of poor people in 33 districts/cities in North Sumatra Province in 2025 showed significant variation, with a minimum value of 3,530 and a maximum of 171,600. All explanatory variables had VIF values below 10, thus no severe multicollinearity was found.

The deviance-to-degrees-of-freedom ratio in the Poisson regression was 3,820.53, indicating overdispersion. Therefore, Negative Binomial regression was used as an alternative model. In this model, X1, X2, X3, and X5 were globally significant, while X4 was insignificant.

Moran's I yielded a p-value of 0.1180, indicating no significant spatial autocorrelation in the residuals. Conversely, Breusch–Pagan yielded a BP of 15.7949 with a p-value of 0.0075, indicating spatial heterogeneity. These results form the basis for applying GWNBR to obtain parameters that may differ between regions.

Based on significant local parameters, the GWNBR model divides the study area into two groups. The first group consists of Mandailing Natal Regency and South Nias Regency, with X1, X2, and X3 as significant variables. The second group includes 31 other regencies/cities, with X2 and X3 as significant variables.

Model comparison shows that GWNBR has a deviance of 18.420 and McFadden's R^2 of 0.150000. Although the AIC of GWNBR is higher than the AIC of Negative Binomial regression, GWNBR was chosen because it can represent spatial heterogeneity and provide information on poverty factors that are more specific to each region.

These findings carry practical implications for poverty alleviation efforts in North Sumatra Province. Because the significant predictors and their effects differ between Mandailing Natal and South Nias Regency and the remaining 31 districts/cities, poverty reduction programs designed uniformly at the provincial level are unlikely to be equally effective everywhere; policies should instead be tailored to the specific combination of variables identified as significant in each region, for example prioritizing human development index improvement and unemployment reduction where these factors dominate. Based on these results, it is recommended that local governments incorporate the GWNBR-based regional groupings into the targeting of social assistance and infrastructure programs, and that future research extend this study by including additional socioeconomic and infrastructure variables, using panel data across multiple years, and comparing alternative kernel and bandwidth specifications to assess the robustness of the local estimates.

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