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Robust Geographically Weighted Regression Modeling in Cases Of Stunting Toddlers In North Sumatera Utara

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ABSTRACT

Stunting is a problem related to chronic malnutrition that can be caused by inadequate nutritional intake. Stunting is usually found in toddlers aged 12-36 months which is often not realized because usually the difference between normal children and stunted children is not specifically visible. Therefore, researchers want to know the problem of how to model cases of stunted toddlers using Robust Geographically Weighted Regression in North Sumatra. With quantitative research methods, the results obtained were 33 models of the number of cases of stunted toddlers in North Sumatra which were formed using the Robust Geographically Weighted Regression (RGWR) method with a fixed Gaussian kernel weighting function and gave different results for each Regency /City in North Sumatra. Among them is the RGWR mode in Central Tapanuli = 193.2119 + 1.306099 X 1 + 0.013863 X 2 + 0.000913 X 3 – 0.00469 X 4 – 0.051564 X 5 + ε and it is obtained that the level of accuracy of the RGWR model is able to provide better estimation results. This is supported by the MAPE value of the RGWR model of 15%, which is in the range of 10% -20%. So the model used is appropriate and effective in estimating the number of cases of stunting toddlers in North Sumatra.

Keyword : Robust Geographically; Weighted Regression, Stunting, and Modeling

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1. INTRODUCTION

Stunting is one of the most significant factors inhibiting development and globally affects around 162 million children under 5 years of age. Stunting is also defined as less than -2 standard deviations (SD) based on growth standards according to the World Health Organization (WHO) median child growth standards. Stunting is usually found in toddlers aged 12-36 months and is often not realized because usually the differences between normal children and stunted children are not specifically visible (Saralajew et al., 2018). This cannot be corrected, inadequate nutritional stunting and repeated attacks of infection during the 1000 days of a child's life. Stunting has an effect long-term effects on individuals and society, including reduced cognitive and physical development, reduced productivity capabilities and poor health, and increased risk of degenerative diseases such as diabetes. WHO estimates reduced productivity as stunted children earn 20% less income than non-stunted children (de Myttenaere et al., 2016).

Prevalence of *stunting* in 2013 was 37.2%, which means an increase compared to 2010, which was 35.6% and 2007, which was 36.8%. There are 20 national prevalence provinces with order from highest to lowest prevalence (Chang et al., 2007). North Sumatra Province is ranked number 8. In data released by Riskesdas in 2018, cases *stunting* highest in Sumatra North happen in Regency Step up who reaches 23.28% Where Village Secanggang is village with *stunting* cases highest in the district (Partner & Vernitski, 2023) .

The prevalence of very short and stunted toddlers aged 0-59 months in Indonesia in 2018 was 11.5% and 19.3%. Meanwhile, in 2013, very short toddlers were found at 18% and short toddlers at 19.2%. The province with the highest prevalence of very short and stunted toddlers aged 0-59 months in 2018 is East Nusa Tenggara, while the province with the lowest prevalence is DKI Jakarta(Zaki et al., 2024).

One of the important factors that influences the nutritional status of toddlers is a factor in the mother's knowledge about nutrition in toddlers. Mothers' lack of knowledge about the diversity of ingredients and diversity of food types will disrupt the growth and development process of toddlers, especially brain development, therefore it is important for mothers to provide nutritious food intake to their children (Bekti et al., 2014). In general, parents, especially mothers, do not pay attention to the nutritional intake of their toddlers. Even though children under five are vulnerable to disease and infection (Fitrawaty et al., 2020).

The fact that *stunting* is caused by mothers' poor parenting patterns towards their toddlers is because the level of knowledge influences a person's ability to receive information (Chang et al., 2007). Previous research shows that the level of knowledge about nutrition is one of the factors that can influence the occurrence of *stunting* in children under five in both rural and urban area (O'Sullivan, 2003).

So based on the description above, researchers want to know the problem of how to model cases of stunting under five using Robust Geogrphically Weighted Regression in North Sumatra (Bekti et al., 2014).

The development of the population in Indonesia food is increasing in Indonesia is also increasing. Endurance Food in Indonesia is based on food, food utilization, and Food access needed sufficient for all regions in Indonesia.North Sumatra Province has the largest population on the island Sumatra and the fourth largest in Indonesia. From the results of the 2010 population census, the number of residents in North Sumatra is increasing every year. In 2018 there were 14.46 million people. The rate of population growth in 2010-2018 reached 1.30 percent per year higher than in 2000-2010 at 1.22 percent per year, can be seen in Figure 1.

The Geographically Weighted Regression (GWR) model is a model that considers geographical factors as variables that influence the response variable. The assumption used in the GWR model is that the residuals are normally distributed with a mean of zero and a variance of (Fortheringham, Brunsdon, and Charlton, 2022).

The Geographically Weighted Regression (GWR) model is a model that considers geographical factors as variables that influence the response variable. The assumption used in the GWR model is that the residuals are normally distributed with a mean of zero and a variance (Fortheringham, Brunsdon, and Charlton, 2022). The GWR model is not yet robust to data outliers, so a more robust method is needed as an alternative. The RGWR model is a development of the GWR model, so the RGWR model is the same as the model in GWR, the only difference lies in the criteria for selecting the optimum bandwidth. In determining the optimum bandwidth, one method that can be used is Absolute Cross Validation (ACV) (Partner & Vernitski, 2023).

2. RESEARCH METHOD

In this thesis research, the researcher used quantitative methods. Quantitative methods are research methods based on the philosophy of positivism, used to research certain populations or samples, data collection using research instruments, data analysis is quantitative/statistical, with the aim of testing the established hypothesis (Sugiyono, 2019). To support this research, the data source used is secondary data. Secondary data was obtained from the North Sumatra Provincial Health Office.

This type of research is quantitative research. Quantitative research is research that is specific and clear. Related to the title of the research is to describe the Implementation of a Closed System in implementing a policy objectively, then this study uses a type of Quantitative research that describes the empirical reality behind the phenomenon in depth, detail and complete (Sugiyono, 2018).

Known in research This used data secondary Which obtained from North Sumatra Provincial Health Service in 2022. The number of observation data in this study is 33, each from 33 districts/cities in North Sumatra. Table 1 is the result of descriptive statistics for each variable used in this research. Summary results analysis descriptive presented on Table 1.

Table 1. Statistics Descriptive Research Variables

Variable	Mean	Standard Deviation	Minimum	Maximu m
Cases of Stunting Toddlers (Y)	943	938.4486	67	3545
Malnourished Toddlers (X1)	609.7	453.1152	96	1829
Safe Sanitation (X2)	198.97	26624.15	512	126937

Education on Understanding Stunting in Adolescents (X3)	29789	41952.47	562	204949
Providing Exclusive Breastfeeding (X4)	8701	12206.81	0	50376
Babies Get Complete Basic Immunization (X5)	7214	7972.994	778	36944

3. RESULTS AND DISCUSSION

Based on Table 1, it can be seen that variable Y, namely the number of cases of stunted toddlers in North Sumatra, shows that the number of toddlers experiencing stunting is 31,120, of the number of toddlers measured, it is 819.30, where the highest number of stunted toddlers is in Karo Regency (3545 toddlers) with the largest percentage being in West Nias Regency was 31.13% and the least was in Binjai City (67 toddlers) with the lowest percentage being Medan City at 0.31%.

Percentage of malnourished toddlers in North Sumatra has an average of 1.98%. The percentage of malnourished toddlers in North Sumatra was highest at 8.24% in Tebing Tinggi City and the lowest at 0.04% in South Tapanuli Regency.

Percentage of education on understanding stunting among teenagers in North Sumatra has an average of 60.73%. The percentage of education on understanding stunting among teenagers in North Sumatra was the highest at 98.85% in Batubara Regency and the lowest at 3.95% in Serdang Berdagai Regency.

Percentage who have access to safe and adequate sanitation is 74.50% in North Sumatra. The highest percentage of safe and adequate sanitation facilities is Pakpak Bharat Regency (98.29%) and the lowest is South Nias Regency (25.64%).

Percentage of exclusive breastfeeding is 42.73% in North Sumatra. The highest percentage of exclusive breastfeeding is North Tapanuli Regency at 83.03% and the lowest is in Batubara Regency at 11.25%.

Percentage of Babies Receiving Complete Basic Immunization (IDL) in North Sumatra Province in 2022 is known to be 89.14%. The highest percentage of babies receiving complete basic immunization was in Simalungun Regency at 105.20% and the lowest was in Padang Lawas Regency at 55.05%.

3.1 Data Standardization

The data in this study, namely the variables X_1, X_2, X_3 and have different units of measurement, as in the following table.

Table 2. Modeling Data on Stunting Toddler Cases Using RGWR in North Sumatra

Variable	Unit
Cases of Stunting Toddlers (Y)	Case
Malnourished Toddlers (X1)	Soul
Save Sanitation (X2)	Soul
Education on Understanding Stunting in Adolescents (X3)	Soul
Providing Exclusive Breastfeeding (X4)	Family Card
Babies Get Basic Immunizations Complete (X5)	Soul
Latitude	Meters
Longitude	Meters

Because the data in research has different units of measurement, the original data must be standardized first before analyzing using the Robust Geographically Weighted Regression (RGWR) method. The following is a summary of the standardization data.

Table 3. Standardization Results Data

No	Province	Y	X_1	X_2	...	X_5
1	Central Tapanuli	-0.5754	-0.5886	-0.6785	...	-0.0239
2	North Tapanuli	0.8449	-0.1141	-0.8342	...	-0.1943
3	South Tapanuli	-0.6724	-1.0918	-0.6509	...	-0.3460
⋮	⋮	⋮	⋮	⋮	⋮	⋮
33	Mount Sitoli	-0.6148	-1.0697	-0.4617	...	-0.6696

3.2 Normality Test

In this study, the Shapiro-Wilk test was used, where this test is used to see normally distributed data, with the following hypothesis:

H_0 : Data is normally distributed

H_1 : Data is not normally distributed

Normality test results obtained can be seen in table form as follows:

Table 4. Shapiro-Wilk Test Result

Test	W	p-value
Shapiro-Wilk	0.97172	0.529

In Table 4 are the results of the Shapiro-Wilk test using α of 0.05, where the value obtained is W_{hitung} of 0.97172 and $p - value < \alpha$, so it can be concluded that the residuals of the regression model are normally distributed.(Afifah et al., 2017).

3.3 Multicollinearity Test

This test is used to determine whether or not there is a linear relationship between predictor variables in the regression model. This test is carried out by looking at the Variance Influence Factor (VIF) value. If the VIF value is > 10 then multicollinearity occurs. The VIF value results are as follows:

Table 5. VIF value

Variable	VIF
X_1	1.058951
X_2	6.479781
X_3	1.692959
X_4	2.171327
X_5	6.048555

From Table 5, it can be seen that the VIF values of variables (X1), (X3) and (X4) are less than 10. While the VIF values of variables (X2) and (X5) are also less than 10 but quite high, which means that there is a possibility of multicollinearity. So there is a possibility of correlation between predictor variables.

3.5 Autocorrelation Test

In this autocorrelation test, the Durbin-Watson test method is used with the following hypothesis:

$H_0 : \rho = 0$ (There is no autocorrelation)

$H_1 : \rho \neq 0$ (There is autocorrelation)

Autocorrelation test results obtained can be seen in table form as follows:

Table 6. Result test Durbin-Watson

Test	Value d_W	d_L	d_U
Durbin-Watson	2.3293	1.127	1.8128

In Table 6 are the results of the Durbin - Watson test. Where the Durbin - Watson (d_w) value is 2.3293 , the $d_{L\,(5;33)}$ value is 1.1270 and $d_{u\,(5;33)}$ of 1.8128 . Because $d_L \leq d_w \leq d_u$ then a decision can be made to fail to reject H_0 which means there is no autocorrelation.

3.6 Homoscedasticity Test

Homoscedasticity test aims to determine whether the error variance between observations is the same or not. If the errors have the same variance, it is called homoscedasticity and if the variances are not the same it is called heteroscedasticity. This research will use the Breusch-Pagan test with the following hypothesis:

H_0: $\sigma_1^2 = \sigma_2^2 = \cdots = \sigma_n^2 = \sigma^2$ (There is homoscedasticity)

H_1: $\sigma_i^2 \neq \sigma^2$ (There is no homoscedasticity)

The homoscedasticity test results obtained can be seen in table form as follows:

Table7. Results Breusch Test- Pagan

Test	Value BP	p- value
Breusch- Pagan	9.3029	0.04758

From Table 8 can seen that results test *Breusch - Pagan* use α as big as 0.05, so obtained mark $p - value < \alpha$ and $BP_{hitung} = 9.3029 > X^{2}_{(0.05.5)} = 11,070$ So that can taken decision reject H_0 which meaning no there is homoscedasticity.

3.7 Spatial Diversity

The spatial diversity or spatial heterogeneity test can be carried out using the Breusch - Pagan test. The hypothesis used is as follows:

$H_0 : \sigma_1^2 = \sigma_2^2 = \cdots = \sigma_n^2 = \sigma^2$ (No there is diversity spatial)

H_1 : Minimal There is One $\sigma_i^2 \neq \sigma^2$ (There is diversity spatial)

The Breusch - Pagan test results obtained can be seen in table form as follows:

Table 8. Test Diversity Spatial

Breusch - Pagan	Df	P-Value
9.3029	5	0.04758

On Table 8 can seen that mark p - value as big as 0.04758 more small from α of 0.05 and the value $BP = 9.3029 > X^2_{(0.05.9)} = 11 .070$ then reject H_0 Which show there is diversity spatial or there is characteristics different data on the number of cases of stunting under five in each district/city in North Sumatra. It can be concluded that there is spatial variation between the locations of each variable in the data on the number of cases of stunting under five for each district/city in North Sumatra. Therefore, multiple linear regression modeling is not appropriate to use for modeling.

3.8 Outliers

The results obtained using boxplots are as follows:

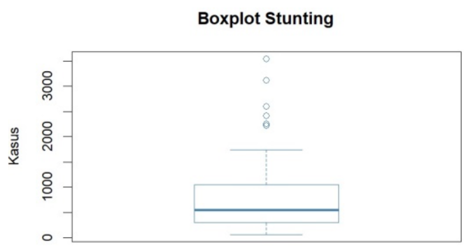

Figure 1. Boxplot Stunting

Based on Figure 1, it can be seen visually that there are six outliers on amount case Stunted Toddlers that is as big as 3545 cases, 3113 cases, 2594 cases, 2252 cases, 2216 cases, and 2412 cases. So it can be concluded that data that has points outside *the* boxplo*t* is an outlier.

3.9 DFFITS (Difference in Standardized Fit)

For determine mark as outlier is use DFFITS with see mark DFFITS, outlier detected if |DFFITS| > 2 that is | DFFITS | > = 1.0. Results detection based outliers mark DFFITS obtained on Table 10.

Table 9. Values DFFITS

No	DFFITS	Note	No	DFFITS	Note
1	0.1746	No	18	-0.1461	No
2	0.2710	No	19	0.4025	No
3	0.0047	No	20	0.4478	No
4	-0,0589	No	21	0.1255	No

5	-1,5425	Outliers	22	-0.0755	No
6	0,8776	Outliers	23	0.1579	No
7	0,6510	No	24	-0.2856	No
8	0,2320	No	25	-0.6884	No
9	-1,2859	Outliers	26	-0.5578	No
10	-1,8284	Outliers	27	-0.1128	No
11	0.7243	No	28	-0.1937	No
12	-0.6693	No	29	0.0790	No
13	-0.0422	No	30	-0.1728	No
14	-0.1283	No	31	-0.2935	No
15	-0.0030	No	32	-0.4115	No
16	0.1587	No	33	-0.1256	No
17	-0.0814	No			

Based on Table 10 Which own mark |DFFITS| > 0.7784 is on data 5,6,9 and 10. So that if seen based on DFFITS value can be determined that the data detected as an outlier is the 4h observation location, 5,6,9 and 10.

3.10 Modeling Robust Geographically Weighted Regression (RGWR)

In the GWR model, one of the weaknesses is that it is sensitive to outliers so it is necessary to detect outliers in errors. By using a boxplot, the research data has outliers. So every district/city must use a robust technique, namely the RGWR model. In the RGWR model, the Euclidean distance used is the same as the GWR model, the only difference being the optimum bandwidth selection criteria.

3.11 Bandwidth optimum RGWR

In this research, the weighting function used is the Gaussian kernel. As for weighter Which used must own mark bandwidth optimal, Where method For determine bandwidth Which The optimum is Absolute Cross Validation (ACV). So it is obtained as in the following table:

Table 10. Values Bandwidth RGWR

Function Weighter	Bandwidth	ACV
Fixed Gaussian	624428	21.416

From Table 10 it can be seen that the weighting used for modeling is the Fixed Gaussian Kernel weighting, where the bandwidth value obtained is the same for each observation location because the kernel function obtained is fixed. The bandwidth value for each location h = 624428 with the smallest ACV score of 21.416. Then the RGWR weighting matrix can be calculated.

3.12 Matrix weighter RGWR

In the RGWR weighting matrix, the function used is *Fixed Gaussian Kernel* because it produces the smallest ACV value, by substituting it into Equation (2.11) to form a matrix ($\boldsymbol{W}_{ij}$) measuring 33 × 33, so that the calculation results for the RGWR weighting matrix are obtained as follows:

Table 11. RGWR Weighting Matrix

Regency/City	Central Tapanuli	North Tapanuli	South Tapanuli	...	Mount Sitoli
Central Tapanuli	1	0.9995	0.9990	...	0.9995
North Tapanuli	0.9995	1	0.9972	...	0.9922
South Tapanuli	0.9990	0.9972	1	...	0.9995
⋮	⋮	⋮	⋮	⋮	⋮
Mount Sitoli	0.9995	0.9957	0.9992	...	1

From Table 11 you can see a summary of the RGWR weighting matrix for each Regency/City in North Sumatra.

3.13 Model Robust Geographically Weighted Regression (RGWR)

In the RGWR model the method used to estimate parameters is Least Absolute Deviation (LAD). Estimation of RGWR model parameters with LAD is estimated based on on every observation location, so that each point has different parameters. By using Equation (2.16), in summary the parameter estimation results obtained are as follows:

Table 12. Mark Coefficient Parameter Model RGWR

Regency/City	β_0	β_1	β_2	...	β_5
Central Tapanuli	193.211	1.3060	0.0138	...	-0.0515
North Tapanuli	193.211	1.3060	0.0138	...	-0.0515
South Tapanuli	193.211	1.3060	0.0138	...	-0.5155
⋮	⋮	⋮	⋮	⋮	⋮
Mount Sitoli	1.93.211	1.3060	0.0138	...	-0.0515

Using Equation (2.16), the following RGWR model is generated from Table 4.16 as an example for Central Tapanuli = 193.2119 + 1.306099 X_1 + 0.013863 X_2 + 0.000913 X_3 – 0.00469 X_4 – 0.051564 $X_5 + \varepsilon$

Based on the RGWR model, it can be seen that in Central Tapanuli, variables $X1$ (number of malnourished toddlers), $X2$ (safe sanitation), $X3$ (education on understanding stunting in adolescents) have positive estimated parameter coefficients on the number of stunting cases which shows a direct relationship between these variables and North Tapanuli. This coefficient shows that every one unit increase in the variable will increase the value of North Tapanuli. Meanwhile, variables $X4$ (exclusive breastfeeding) and $X5$ (number of babies who receive complete basic immunization) have negative estimated parameter coefficients on the number of stunting cases in toddlers in North Tapanuli which shows an inverse relationship..

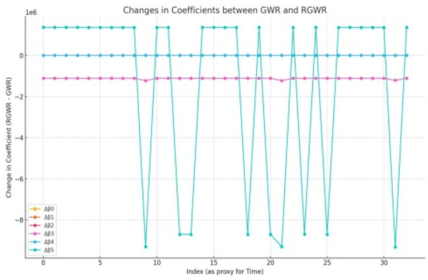

Figure 2. Changes in Coefficients between GWR and RGWR

3.14 Model Accuracy Level

To determine the level of accuracy of the RGWR model, it can be seen using MAPE as follows:

Table 13. MAPE values

Model	MAPE
RGWR	15%

Table 13 shows that the accuracy level of the RGWR model with MAPE is 15%. This means that the model is obtained from parameter estimation using Robust

4. CONCLUSION

1. There are 33 models for the number of cases of stunting under five in North Sumatra which were formed using the Robust Geographically Weighted Regression (RGWR) method with a fixed Gaussian kernel weighting function and provide different results for each Regency/City in North Sumatra. Among them is the RGWR mode in Central Tapanuli = 193.2119 + 1.306099 X_1 + 0.013863 X_2 + 0.000913 X_3 – 0.00469 X_4 – 0.051564 X_5 + .
2. The level of accuracy of the RGWR model is able to provide better estimation results. This is supported by the MAPE value of the RGWR model of 15%, which is in the range of 10%-20%. So the

model used is appropriate and effective in estimating the number of casesof stunting under five in North Sumatra.

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