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MIXED GEOGRAPHICALLY WEIGHTED REGRESSION (MGWR) WITH ADAPTIVE WEIGHTING FUNCTION IN POVERTY MODELING IN NTT PROVINCE

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ABSTRACT

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Poverty modeling is a crucial economic and social development issue in various regions, including in East Nusa Tenggara (NTT) Province. This research proposes using the Mixed Geographically Weighted Regression (MGWR) model with an adaptive Bisquare weighting function to analyze variables influencing poverty levels in NTT Province. The MGWR model is an extension of the Geographically Weighted Regression (GWR), which allows some variables in the model to have local effects while others have global effects. The adaptive weighting function in the MGWR model enhances the analysis by providing different weights at each location according to its local characteristics, thus making the results more accurate and representative for each area. The data includes economic, social, and infrastructure variables from 22 districts/cities in NTT Province for 2023. The MGWR model with an adaptive weighting function is applied to model the relationship between these variables and poverty levels. The analysis integrates statistical software to manage and analyze spatial data. The study findings show that the MGWR model with an adaptive weighting function offers better estimates than the global regression and GWR models. The results revealed the smallest AIC value for the MGWR model at 104.1888, compared to the global regression model at 140.1427 and the GWR model at 117.6174. This model successfully identifies significant local and global variables and shows variations in influence at different locations in NTT Province. These findings provide valuable insights for policymakers and practitioners in designing and implementing more effective poverty alleviation strategies tailored to local conditions in NTT Province.

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1. INTRODUCTION

Poverty is among the most complex and challenging social issues in many countries, including Indonesia[1]. The poverty issue in the East Nusa Tenggara (NTT) province has become critically acute, given the unique geographical conditions and limited natural resources. Conventional approaches in poverty modeling and mapping often need to be revised to depict the actual conditions on the ground, especially in regions with significant geographical and socio-economic variations like NTT.

East Nusa Tenggara is one of the provinces categorized as the poorest in Indonesia. The Central Bureau of Statistics recorded the number of poor people in East Nusa Tenggara in March 2023 at 20.99 percent, an increase compared to 2022, which was 20.90 percent (BPS, 2023). The poverty issue in East Nusa Tenggara is the high number or percentage and the very high disparity between regions. Comparisons between districts/cities show significant disparities. This inequality occurs due to the high poverty rates in certain areas. Given the diverse conditions, there are differences in each region in the East Nusa Tenggara Province, leading to spatial effect issues because geographical factors will influence. East Nusa Tenggara Province is one of the island provinces consisting of 22 districts and is the province with the highest poverty rate category.

In addressing the challenges of poverty alleviation, especially in East Nusa Tenggara (NTT) Province, an innovative and locally sensitive approach is required. With its unique geographical and socio-economic characteristics, this province shows that conventional poverty modeling often needs to be revised. In this context, this research proposes the application of Mixed Geographically Weighted Regression (MGWR) with an adaptive weighting function. This methodology overcomes the limitations of traditional approaches in understanding the complex and diverse dynamics of poverty [2].

The Mixed Geographically Weighted Regression (MGWR) approach introduces the ability to combine regression analysis that considers specific locations, allowing for spatial variability in the data to be more effectively accounted for [3]. It represents a significant advancement, facilitating more accurate poverty modeling in NTT by acknowledging that determinants of poverty may vary significantly from one location to another. Using an adaptive weighting function in MGWR further enhances the model's flexibility, ensuring that local variability can be captured and understood with finer nuance [4].

Through the implementation of this methodology, this study aims to provide deeper insights into the patterns of poverty in NTT. The approach strives to identify regions with high poverty levels and understand the factors contributing to these conditions [5]. Consequently, this research collects and analyzes data from various sources, including population censuses, to build a model that can reveal the complex interactions between economic, social, and geographic factors.

MGWR is a spatial regression approach that allows changes in regression parameters between different locations. In other words, MGWR enables the influence of independent variables on dependent variables to vary across geographic space [6]. It allows for more precise and accurate modeling in situations where location influence is highly variable. However, sustainability in developing geospatial analysis methods requires the introduction of innovations that can enhance the quality and flexibility of models. One of the latest innovations in MGWR is using an adaptive weighting function. The adaptive weighting function allows the model to adjust the weights given to observations based on the surrounding characteristics of each data point [7]. Thus, the model can provide more attention to more relevant and significant data in the analysis.

The novelty that arises is using Mixed Geographically Weighted Regression (MGWR) as the primary analysis tool. MGWR is an approach that allows a better understanding of the relationship between dependent and independent variables in a spatial context [8]. It is achieved by modeling regression parameters locally, meaning that the influence of independent variables on dependent variables can vary across geographic space. It is one of the main advantages of MGWR in modeling phenomena that are highly influenced by spatial factors [9] .

Moreover, the novelty presented in this journal is the use of an adaptive weighting function within MGWR. The adaptive weighting function enables MGWR to dynamically adjust the weights given to observations based on the surrounding characteristics of each data point. It is highly relevant when data exhibit significant spatial heterogeneity, where the surrounding environment's influence can vary from place to place. This adaptive weighting function enhances the model's ability to make more accurate decisions based on existing situations.

The implications of applying Mixed Geographically Weighted Regression (MGWR) with an adaptive weighting function are significant in geospatial analysis. They can positively impact several aspects, including research, decision-making, and policy planning. First, regarding research, using MGWR with an adaptive weighting function opens new opportunities to explore more subtle patterns and relationships within spatial data. It will result in a deeper understanding of local differences in factors affecting dependent variables [10]. Researchers can more accurately identify areas facing specific problems and detail the factors contributing to these issues. More precise research outcomes can lead to more effective and sustainable solutions to various regions' social, economic, and environmental issues.

Secondly, in decision-making and policy planning, using MGWR with an adaptive weighting function provides policymakers with a more powerful tool to design targeted interventions. Policies can be tailored to different local conditions with a better understanding of spatial variability in the data. It reduces the risk of making decisions based on less relevant data or overly broad generalizations. In other words, the implication of using MGWR with an adaptive weighting function is an improvement in the efficiency and effectiveness of efforts to address issues at the regional or local level [11]. This also has the potential to lead to more judicious use of resources and overall improvement in community welfare.

The adaptive weighting function in MGWR becomes a significant innovation in this study, allowing the model to be more flexible in adapting to local differences. It means that the model considers economic and social factors in poverty modeling and how these factors uniquely interact across different locations [12]. This approach is expected to yield a deeper understanding of the patterns and causes of poverty in NTT.

This research aims to provide new insights into more detailed and location-specific mapping and analysis of poverty in NTT. By utilizing data from household surveys, population censuses, and other information-rich sources, this study strives to identify critical factors influencing poverty across different regions of NTT and how they interact within the geographical context.

2. RESEARCH METHODS

2.1 Data

The data used in this study is the poverty data for the year 2022 obtained from the official website of the Central Bureau of Statistics of East Nusa Tenggara Province https://ntt.bps.go.id/, consisting of the response variable (Y), which is the percentage of the population living in poverty, and eight predictor variables, namely literacy rate (X_1), school participation rate (X_2), open unemployment rate (X_3), population consuming safe drinking water (X_4), population using their toilet facilities (X_5), population receiving non-cash food assistance (X_6), population with higher education status (X_7), and expenditure per capita on food (X_8). The reason for using the eight independent variables in this study is that these eight variables demonstrate an influence on the phenomenon being studied and are also expected to show significant spatial variation.

2.2 Regression Analysis

The global regression equation, which is commonly defined using the Ordinary Least Square (OLS) method for estimating parameters, can generally be written in the following mathematical Equation (1) [13]:

$$y_i = \beta_{i0} + \sum_{k=1}^{p-1} \beta_{ik} x_{ik} + \varepsilon_i \tag{1}$$

where β_0 is the constant, β_i are the coefficient values of the explanatory variable x_i , p is the number of explanatory variables used in the model, n is the number of observations (data), and **e** represents the random errors assumed to be normally distributed as N$(0,\sigma^2 I)$, with **e** = $(e_1, e_2, e_3, \dots, e_n)$ and I is the identity matrix. By minimizing the sum of squared errors, the OLS estimator of the parameters in vector form is given as follows:

$$\hat{\boldsymbol{\beta}}_{\boldsymbol{i}} = [\boldsymbol{X}^{\boldsymbol{T}}\boldsymbol{X}]^{-1}\boldsymbol{X}^{\boldsymbol{T}}\boldsymbol{Y} \tag{2}$$

where $\hat{\beta} = \hat{\beta}_0, \hat{\beta}_1, \dots, \hat{\beta}_p$ is a vector of p+1 as regression coefficients, X is the matrix of explanatory variables of size n x(p+1) with the first column being 1 for the constant, and Y is the vector of response variables.

2.3 Mixed Geographically Weighted Regression (MGWR)

Mixed Geographically Weighted Regression (MGWR) is a hybrid model that combines global regression with the Geographically Weighted Regression (GWR) model, considering situations where some predictor variables affecting the response variable are global and other predictor variables are local. The MGWR model, with q predictor variables being local and p predictor variables being global, assumes that the model's intercept value is local. The MGWR model can be written as follows [14]:

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{q} \beta_k(u_i, v_i)x_{ik} + \sum_{k=q+1}^{p} \beta_k x_{ik} + \varepsilon_i, i = 1,2, \dots, n \quad (3)$$

With:

y_i	: response variable at the i observation location
(u_i, v_i)	: geographic coordinates of the observation location
$\beta_0(u_i, v_i)$	: intercept value at the i-th observation location
$\beta_k(u_i, v_i)$	: regression coefficient of local predictor variables
β_k	: regression coefficient of global predictor variables
x_{ik}	: local predictor variable
ε_i	: residual of the i-th observation, assumed to be normally distributed

The Mixed Geographically Weighted Regression (MGWR) model uses the Weighted Least Squares (WLS) method to estimate parameters. Parameter estimation for the Mixed Geographically Weighted Regression model is conducted by first identifying variables that influence all observation locations (global) and variables that have an impact at specific locations based on their geographic position (local) [15]. The MGWR equation is then expressed in matrix form as follows:

$$y_i = \boldsymbol{X_l}\beta_l(u_i, v_i) + \boldsymbol{X_g}\beta_g + \varepsilon$$

with:

$$\boldsymbol{X_l} = \begin{bmatrix} 1 & x_{11} & \dots & x_{1q} \\ 1 & x_{21} & \dots & x_{2q} \\ \vdots & \dots & \ddots & \vdots \\ 1 & x_{n1} & \dots & x_{nq} \end{bmatrix}, \quad \boldsymbol{X_g} = \begin{bmatrix} x_{1(q+1)} & x_{1(q+2)} & \dots & x_{1(q+p)} \\ x_{2(q+1)} & x_{2(q+2)} & \dots & x_{2(q+p)} \\ \vdots & \dots & \ddots & \vdots \\ x_{n(q+1)} & x_{n(q+2)} & \dots & x_{n(q+p)} \end{bmatrix}$$

$$\boldsymbol{y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}, \quad \beta(u_i, v_i) = \begin{bmatrix} \beta_0(u_i, v_i) \\ \beta_1(u_i, v_i) \\ \vdots \\ \beta_q(u_i, v_i) \end{bmatrix}, \beta_g = \begin{bmatrix} \beta_{q+1} \\ \beta_{q+2} \\ \vdots \\ \beta_p \end{bmatrix}, \quad i = 1,2, \dots, n$$

The first step to be taken is to express the MGWR model as a GWR model to find the parameter estimates for the MGWR model [11]:

$$\tilde{y} = y - \boldsymbol{X_g}\beta_g = \boldsymbol{X_l}\beta_l(u_i, v_i) + \varepsilon \quad (4)$$

In the estimation of the GWR model, suppose the weight for each location (u_i, v_i) is $w_j(u_i, v_i)$ where $j = 1,2, \dots, n$, then the parameter estimation by adding weights and then minimizing the sum of squared residuals from **Equation (4)** is as follows:

$$\sum_{j=1}^{n} w_j(u_i, v_i)\, \varepsilon_j^2 = \sum_{j=1}^{n} w_j(u_i, v_i) \left[y_j - \beta_0(u_i, v_i) - \sum_{k=1}^{p} \beta_k(u_i, v_i)x_{jk} \right]^2$$

If expressed in matrix form, the sum of squared residuals is as follows [15]:

$$\begin{aligned} \varepsilon^T \boldsymbol{W} \varepsilon &= (y - \boldsymbol{X}\beta)^T \boldsymbol{W}(y - \boldsymbol{X}\beta) \\ &= y^T \boldsymbol{W} y - (y^T \boldsymbol{W X}\beta)^T - \beta^T \boldsymbol{X^T W} y + \beta^T \boldsymbol{X^T W X}\beta \\ &= y^T \boldsymbol{W} y - 2\beta^T \boldsymbol{X^T W} y + \beta^T \boldsymbol{X^T W X}\beta \end{aligned} \quad (5)$$

then it is written as follows:

$$\boldsymbol{W}(u_i, v_i) = diag[w_1(u_i, v_i), w_2(u_i, v_i), \dots, w_n(u_i, v_i)]$$

2.4 Spatial Weighting

The spatial weighting function becomes crucial in the MGWR model because the weight values represent the spatial relationships between observation data points. The spatial weighting matrix (**W**) can be obtained based on distance information between neighbors or the distance between one region and another. This research uses an adaptive Gaussian weighting function because it involves continuous distance values between observation locations in constructing the weighting matrix. Therefore, each location will receive a weight based on distance from the observation locations [17].

$$w_{ij}(u_i, v_j) = \exp\left(-\frac{1}{2}\left(\frac{d_{ij}}{h_{i(p)}}\right)^2\right) \quad (6)$$

Where d_{ij} is the distance between location i and location j using coordinate points. In the Bisquare weighting function, there is an Optimum bandwidth parameter. The optimum bandwidth is analogously considered as the radius of a circle so that an observation location within the circle's radius is still regarded as influential in determining the parameter at the i observation location. Several methods can be used to select the optimum bandwidth, one of which is Cross Validation (CV). Mathematically, the Cross Validation (CV) method equation can be written as follows:

$$CV = \sum_{i=1}^{n}(y_i - \hat{y}_{\neq i}(h))^2 \quad (7)$$

where:

n : the number of observation locations
y_i : the i-th observation
$\hat{y}_{\neq i}(h)$: the estimated value of the i-th observation obtained without involving the i -th observation location

2.5 Moran's I

Moran's I coefficient is a development of the Pearson correlation for univariate data series. The Moran's I coefficient is used to test for spatial dependency or autocorrelation between observations or locations [18].

The hypothesis used is:

H_0: I = 0 (no autocorrelation between locations)
H_1: I ≠ 0 (there is autocorrelation between locations)
With the test statistic being used [19]

$$I = \frac{n\sum_{i=1}^{n}\sum_{i=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}\sum_{i=1}^{n} w_{ij}(x_i - \bar{x})^2} \quad (8)$$

Information:

x_i : data of the variable at location i ($i = 1, 2, \ldots, n$)
x_j : data of the variable at location j ($j = 1, 2, \ldots, n$)
$\bar{x}$: average of the data
w : weighting matrix

The value of the Moran's I index ranges between -1 and 1. if I > Io, the data exhibits positive autocorrelation. If I < Io, the data exhibits negative autocorrelation.

2.6 Selection of the Best Model

The best model selection is conducted to compare the prediction accuracy levels among several models. The Akaike Information Criterion (AIC) selects the best model. The best model is chosen by determining the model with the smallest AIC value [20]. The formula used is as follows:

$$AIC = e^{\frac{2k}{n}} \frac{\sum_{i=1}^{n} \hat{u}_1^2}{n} \quad (9)$$

where:
k : the number of parameters estimated in the regression model
n : the number of observations
u : residual

3. RESULTS AND DISCUSSION

3.1 Regression Analysis

Multiple linear regression analysis was conducted to determine the influence of predictor variables, namely literacy rates (X_1), school participation rates (X_2), open unemployment rates (X_3), population consuming potable water (X_4), population using private latrines (X_5), recipients of non-cash food assistance (X_6), population with higher education status (X_7), and per capita food expenditure (X_8) on the response variable without considering spatial effects. The analysis can be seen in the following Table 1:

Table 1. Regression parameter values

Parameter	Estimate	P-Value	Decision
Intercept	62.85676	0.1140	
X_1	-0.05710	0.8764	Not significant
X_2	0.02374	0.8862	Not significant
X_3	-3.33167	0.0392	significant
X_4	-0.24588	0.0257	significant
X_5	-0.00245	0.9830	Not significant
X_6	0.03974	0.6455	Not significant
X_7	-0.12308	0.7338	Not significant
X_8	-0.13798	0.7050	Not significant

The results in Table 1 show that the independent variables that significantly affecting the response variable, the poverty rate percentage, are the open unemployment rate (X_3) and the population consuming potable water (X_4). The results above do not incorporate spatial elements, suggesting a need for further investigation by adding spatial components to the analysis.

3.2 Spatial Effect Testing

In the regression analysis, spatial elements were not included. Thus, a study was performed using the mixed geographically weighted Poisson regression method. The spatial dependency test through Moran's I aim to observe the spatial effects on each variable by examining the p-value and comparing it with α. If the p-value < α, then there is a spatial effect on that variable. The Moran's I test values can be seen in Table 2.

Table 2. Spatial dependency test

Variable	Moran I	P-value
Y	0.07999	0.03021
X_1	0.22074	0.00004
X_2	0.14562	0.00110
X_3	0.11142	0.00321
X_4	0.06840	0.04390
X_5	0.23233	0.00002
X_6	0.05995	0.01985
X_7	0.06342	0.02718
X_8	0.05340	0.01846

From Table 2 above, it can be seen that there are all variables with a p-value < α=5%, which are the percentage of the poor population (Y), literacy rates (X_1), school participation rates (X_2), open unemployment rates (X_3), population consuming potable water (X_4), population using private latrines (X_5), recipients of non-cash food assistance (X_6), population with higher education status (X_7), and per capita food expenditure (X_8). Therefore, all eight variables have a spatial effect and can be further analyzed using the MGWR (Mixed Geographically Weighted Regression) model.

3.3 Geographically Weighted Regression Model

Several important steps must be taken to develop a Geographically Weighted Regression (GWR) model. The first is to determine the weights used in this study. The weights employed are Adaptive Bisquare. Adaptive Bisquare weights for poverty research in the province of East Nusa Tenggara involve a Bandwidth that is applied individually for each location. Subsequent analyses using GWR and MGWR are conducted. The analysis results yield a GWR model for each location, presented in **Table 3**.

Table 3. GWR model beta coefficient

Region	β_0	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8
Alor	-32.9104	1.2076	-0.2449	-2.5024	-0.3721	0.1909	0.0969	-0.4533	-0.3068
Belu	-32.1009	1.2557	-0.2650	-2.4282	-0.3915	0.1980	0.0971	-0.5077	-0.3448
Ende	24.0187	0.6738	0.0778	-4.2687	-0.2707	-0.1260	0.0388	-0.1101	-0.1806
East Flores	-39.7903	1.2458	-0.2216	-2.9104	-0.3585	0.1316	0.1175	-0.2878	-0.2351
Kupang City	-30.8568	1.3213	-0.3012	-2.4663	-0.4139	0.1760	0.1208	-0.4950	-0.3602
Kupang	-31.7059	1.3009	-0.2883	-2.4471	-0.4070	0.1802	0.1134	-0.4901	-0.3482
Lembata	35.5122	1.2289	-0.2428	-2.6158	-0.3721	0.1622	0.1101	-0.3786	-0.2706
Malaka	-31.9362	1.2618	-0.2679	-2.4239	-0.3939	0.1979	0.0979	-0.5122	-0.3490
Manggarai	29.7266	0.0497	0.1112	-2.9799	-0.2389	-0.1091	-0.0133	0.1367	0.1879
West Manggarai	31.2192	-0.0600	0.1057	-2.7526	-0.2399	-0.1066	-0.0205	0.1610	0.2431
East Manggarai	28.9702	0.0773	0.1134	-3.0899	-0.2379	-0.1106	-0.0955	0.1244	0.1609
Nagekeo	23.2465	0.2320	0.1098	-3.4559	-0.2518	-0.1130	0.0175	0.0911	0.0624
Ngada	26.3625	0.1481	0.1121	-3.2554	-0.2463	-0.1109	-0.0528	0.1124	0.1169
Rote Ndao	-26.2626	1.3649	-0.3375	-2.6013	-0.4271	0.1642	0.1474	-0.5163	-0.4117
Sabu Raijua	24.1337	0.3465	0.0271	-3.2930	-0.3317	-0.0471	0.0718	0.1690	0.1978
Sikka	-32.5820	1.4703	-0.1839	-3.9248	-0.3640	0.0492	0.1154	-0.1739	-0.2708
West Sumba	33.0113	-0.0886	0.0824	-2.2324	-0.2671	-0.0920	-0.0438	0.2483	0.3663
Southwest Sumba	33.0877	-0.0959	0.0820	-2.2039	-0.2646	-0.0933	-0.0436	0.2502	0.3731
Central Sumba	32.7361	-0.0781	0.0843	-2.2804	-0.2671	-0.0922	-0.0426	0.2423	0.3550
East Sumba	33.0243	-0.0495	0.0829	-2.4004	-0.2784	-0.0852	-0.0437	0.2290	0.3250
South Central Timor	-31.6096	1.2798	-0.2776	-2.4246	-0.4007	0.1920	0.1037	-0.5093	-0.3529
North Central Timor	-32.2096	1.2625	-0.2683	-2.4320	-0.3938	0.1930	0.1004	-0.4980	-0.3409

Based on **Table 3** above, a model for each location was obtained. The model formed for the Kupang City area is as follows:

$$\hat{y}_{Kupang\ City} = -30.8568 + 1.3213_{X1} - 0.3012_{X2} - 2.4663_{X3} - 0.4139_{X4} + 0.1760_{X5} + 0.1208_{X6} - 0.4950_{X7} - 0.3602_{X8}$$

The model explains that the poverty rate in Kupang City will increase by 1.32 percent, 0.18 percent, and 0.12 percent if the variables literacy rate (X1), residents using private toilets (X5), and residents receiving non-cash food assistance (X6) increase by one percent, assuming other variables remain constant. The poverty rate in Kupang City will decrease by 0.30 percent, 2.47 percent, 0.41 percent, 0.50 percent, and 0.36 percent if there is an increase in the school participation rate (X2), open unemployment rate (X3), residents consuming safe drinking water (X4), residents with higher education (X7), and expenditure per capita on food (X8) by one percent, assuming other variables are constant.

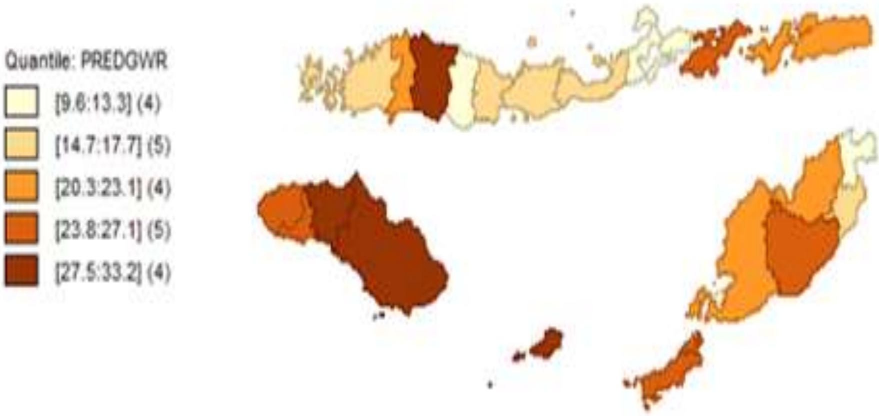

Figure 1. GWR model prediction map using geoda

Based on **Figure 1**, there is a significant variation in poverty levels across the regions shown. For example, Central Sumba and East Sumba are marked in red, indicating higher poverty levels. In contrast, other areas like East Flores are marked in green, indicating lower poverty levels.

3.4 Mixed Geographically Weighted Regression Model

After obtaining the GWR model, the next step is to develop a Mixed Geographically Weighted Regression (MGWR) model. The parameters for each location can be seen in the following **Table 4**:

Table 4. Beta coefficient of MGWR model

Region	β_0	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8
Alor	-32.0214	1.1359	-0.3708	1.7022	-0.5527	-0.0611	0.4286	-0.4564	-0.3485
Belu	-33.3109	1.4877	-0.4061	1.7022	-0.6741	-0.0600	0.4286	-0.7549	-0.6478
Ende	21.5487	0.0827	-0.0618	1.7022	-0.1988	-0.0778	0.4286	0.0362	0.3207
East Flores	-45.1603	0.1516	-0.0787	1.7022	-0.2122	-0.0811	0.4286	0.0063	0.2637
Kupang City	-35.8568	0.2777	-0.0935	1.7022	-0.2552	-0.0835	0.4286	-0.0877	0.1661
Kupang	-36.7059	0.3186	-0.1044	1.7022	-0.2668	-0.0828	0.4286	-0.1090	0.1359
Lembata	29.4122	0.2284	-0.0982	1.7022	-0.2355	-0.0794	0.4286	-0.0359	0.2080
Malaka	-33.1462	1.3680	-0.3774	1.7022	-0.6214	-0.0464	0.4286	-0.7250	-0.5982
Manggarai	22.9366	-0.0578	-0.0428	1.7022	-0.1515	-0.0799	0.4286	0.1270	0.4358
West Manggarai	33.0992	-0.1859	-0.0314	1.7022	-0.0967	-0.0961	0.4286	0.1930	0.5500
East Manggarai	22.1802	-0.0324	-0.0456	1.7022	-0.1603	-0.0791	0.4286	0.1107	0.4137
Nagekeo	21.2065	0.0523	-0.0576	1.7022	-0.1906	-0.0763	0.4286	0.0535	0.3465
Ngada	24.1425	0.0282	-0.0543	1.7022	-0.1828	-0.0763	0.4286	0.0692	0.3662
Rote Ndao	-18.4426	0.2243	-0.0772	1.7022	-0.2409	-0.0848	0.4286	-0.0653	0.2045
Sabu Raijua	29.0337	0.1075	-0.0667	1.7022	-0.2094	-0.0774	0.4286	0.0114	0.3082
Sikka	-33.7720	0.1186	-0.0690	1.7022	-0.2074	-0.0796	0.4286	0.0186	0.2918
West Sumba	34.4513	-0.1745	-0.1539	1.7022	-0.0770	-0.1242	0.4286	-0.1196	0.7528
Southwest Sumba	34.5277	0.1524	-0.6135	1.7022	0.0908	-0.4304	0.4286	-1.9798	1.3078
Central Sumba	34.1761	-0.1608	-0.0709	1.7022	-0.1264	-0.0773	0.4286	0.1474	0.5972
East Sumba	28.8643	-0.0134	-0.0594	1.7022	-0.1790	-0.0687	0.4286	0.0831	0.4238
South Central Timor	-36.6096	0.5642	-0.1523	1.7022	-0.3422	-0.0819	0.4286	-0.2705	-0.0567
North Central Timor	-33.4196	0.6965	-0.1988	1.7022	-0.3865	-0.0755	0.4286	-0.3283	-0.1367

Based on Table 4 above, the MGWR model for Kupang City can be described as follows:

$$\hat{y}_{Kupang\ City} = -35.8568 + 0.2777_{X1} - 0.0935_{X2} + 1.7022_{X3} - 0.2552_{X4} - 0.0835_{X5} + 0.4286_{X6} - 0.0877_{X7} + 0.1661_{X8}$$

The model explains, assuming other variables remain constant, the poverty rate in Kupang City will increase by 0.28 percent, 0.43 percent, and 0.17 percent if the literacy rate (X1), residents receiving non-cash food assistance (X6), and expenditure per capita on food (X8) increase by one percent. The poverty rate in Kupang City will decrease by 0.09 percent, 1.70 percent, 0.26 percent, 0.08 percent, and 0.09 percent if there is an increase in the school participation rate (X2), open unemployment rate (X3), residents consuming safe drinking water (X4), residents using private toilets (X5), and residents with higher education (X7) by one percent.

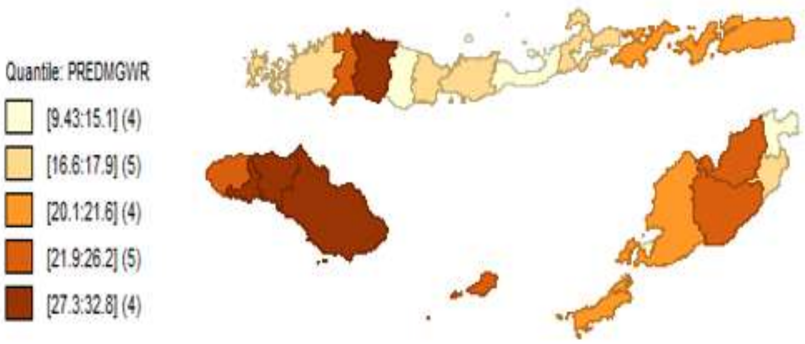

Figure 2. MGWR model prediction map using geoda

Figure 2 above shows a variation in predicted poverty levels in East Nusa Tenggara Province. For example, Central Sumba and East Sumba are marked in red, indicating that these districts have very high poverty levels. Meanwhile, East Flores, Sikka, and Lembata are marked in green, indicating lower poverty levels.

From the analysis of the MGWR model, significant variables were identified for each location on a partial basis. A grouping can be formed of districts/cities that have standard variables that significantly influence the percentage of the poor population, as seen in Table 5 below:

Table 5. Significant variables for each district/city

Significant Variable	Regency/City
X_4	Ende, Lembata, Manggarai, East Manggarai, Nagekeo, Ngada, Sabu Raijua, Central Sumba, East Sumba
X_2, X_4	Timor Tengah Selatan
X_4, X_5	Flores Timur, Kota Kupang, Kupang, Manggarai Barat, Rote Ndao, Sikka
X_2, X_4, X_7	North Central Timor
X_2, X_4, X_5	West Sumba
X_2, X_4, X_7, X_8	Malaka
X_2, X_4, X_5, X_7	Alor, Belu, Southeast Sumba

3.5 Selection of the Best Model

Determining the best model aims to identify the most suitable model for representing the data on the percentage of the poor population in each district/city in East Nusa Tenggara Province by comparing multiple linear regression, GWR, and MGWR models. The best model is determined based on the AIC value criteria, which are displayed in the following Table 6:

Table 6. AIC and R^2 values

Model	AIC	R^2
Global Regression	140.1427	68.45%
GWR Adaptive Bisquare	117.6174	81.94%
MGWR Adaptive Bisquare	104.1888	91.88%

Based on **Table 6**, it is known that the MGWR model with adaptive bisquare weighting function is a better model for representing the percentage of poverty in East Nusa Tenggara Province, with a smaller AIC value of 104.1888 and a larger R-squared value of 91.88%.

4. CONCLUSIONS

The modeling results of the poverty percentage in East Nusa Tenggara Province show that the Mixed Geographically Weighted Regression model with an Adaptive Bisquare weighting function has a smaller AIC value than the GWR and Global Regression models. This result indicates that the MGWR model is better than the GWR and Global Regression models in modeling the percentage of the poor population in East Nusa Tenggara Province. These findings provide valuable insights for policymakers and practitioners in designing and implementing more effective poverty alleviation strategies tailored to local conditions in NTT Province.

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