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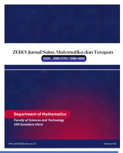

Spatial Modeling of Food Security Index in Central Java Using Mixed Geographically Weighted Regression

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ABSTRACT

Central Java plays an important role in Indonesia's food security, ranking second nationally in the 2023 Food Security Index (FSI). However, nearly 45% of its districts/cities fall below the provincial average, reflecting spatial disparities. This study applies the Mixed Geographically Weighted Regression (MGWR) method to model the factors influencing FSI in Central Java by considering global and local spatial heterogeneity, with the each of the seven variables using 2023 data. Six clusters were formed based on similar characteristics. The MGWR model identifies that the factor of households not having access to clean water has a global negative effect which contributes 0.17 points in decreasing the FSI, while population density is the dominant local factor that has a significant negative effect on the FSI covering approximately 60% of Central Java. MGWR model using a fixed Gaussian kernel outperforms global regression and GWR, with the lowest AIC, highest R^2 (93.11%), and a MAPE of 1.01%.

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1. INTRODUCTION

The Global Food Security Index ranks Indonesia 63rd out of 113 countries, with a food security score below the global average [1]. As one of the national food barns, Central Java plays a vital role in maintaining Indonesia's food stability. In 2023, Central Java ranked second nationally in terms of FSI with a score of 84.8, and in 2024, Central Java produced 8,850,920 tons of rice from 1,554,931 hectares of harvested land, contributing approximately 17% to national food needs [2]. Despite its strong overall FSI performance, significant disparities remain among districts and municipalities in Central Java. Around 46% of them have FSI scores below the provincial average, such as Brebes (77.21), Wonosobo (77.82), and Temanggung (77.84). These disparities stem from factors such as high rates of agricultural land conversion, limited agricultural infrastructure, declining soil fertility, climate change, and low household purchasing power [3]. The disparities in FSI across Central Java indicate that food security is strongly influenced by local characteristics, including geographical, social, and economic conditions [4]. These variations create spatial heterogeneity, meaning that the determinants of FSI are not uniform across regions. The presence of spatial heterogeneity in food security has been illustrated by Safitri et al. [5], who analyzed food security across districts in South Sulawesi using Moran's I in Spatial Error Model (SEM) analysis. The analysis revealed a negative spatial autocorrelation, so this suggests that local factors vary significantly between regions, and that location has limited influence on neighboring food security levels, reinforcing the presence of spatial heterogeneity in the food system. Additionally, a region's food security may be influenced by its neighboring areas, indicating spatial dependency [6]. This spatial dependency has been empirically confirmed by Supriadi et al. [7], who applied the Spatial Autoregressive Combined (SAC) model and found significant spatial spillover effects. These findings indicate that the level of food security in a given region is not isolated but closely linked to conditions in neighboring regions, underscoring the importance of interregional connectivity in shaping food security outcomes. Given the presence of spatial heterogeneity and dependency, choosing the right analytical method becomes critical.

An alternative method that can be applied to the problem is Geographically Weighted Regression (GWR) that can overcome by allowing regression coefficients to vary across locations [9]. GWR improves spatial estimation accuracy, it uses a single bandwidth for all predictor variables, which can be limiting. To address this, the Mixed Geographically Weighted Regression (MGWR) method was developed. MGWR assigns an optimal bandwidth to each predictor, offering more precise spatial influence measurement [10]. MGWR enables variable-specific spatial bandwidths, offering more precise insights into both local and global influences. In this case, empirical studies by Yao et al. [13], who found that MGWR outperformed GWR in modeling rice and wheat yields at the country level during the COVID-19. In their study, MGWR yielded higher R^2 values, lower AICc, and lower residual sums of squares, confirming that MGWR is more effective at capturing the local-scale variability compared to GWR. The statement further supports this research. With the advantages of MGWR, the novelty of this research is in the selection of the best kernel weighting function in determining the local globality of each variable, between Fixed Gaussian and Fixed Bisquare kernels, which are known for their stability and consistency [14]. Furthermore, Cross Validation (CV) and the Akaike Information Criterion (AIC) were employed as criteria to ensure that the model is not only spatially appropriate but also statistically optimal, resulting in more accurate and reliable estimates [15]. The output of this research is expected to supports the achievement of Sustainable Development Goal (SDG) 2: Zero Hunger, which aims to eliminate hunger, achieve food security and improved nutrition, and promote sustainable agriculture by 2030. Through a spatial data-driven approach, this study aims to strengthen food availability and sustainability at the local level.

2. RESEARCH METHOD

2.1 Data and Research Variables

The data used in this study are secondary data, specifically the 2023 Food Security Index of Central Java Province, obtained from the official websites of the Badan Pusat Statistik and the National Food Agency. Seven predictor variables were used in the same year (2023), so that the results could reflect the conditions in that year. The unit of observation consists of 35 districts/cities within Central Java Province. These factors serve as the variables in this study and are presented in Table 1.

Table 1. Research Variables

Variable	Description	Measurement Unit	Data Type
Y	Food security index of Central Java	Index (score)	Ratio
X_1	Population Poverty	Percent (%)	Ratio
X_2	Households without access to clean water	Percent (%)	Ratio
X_3	Rice crop productivity	Quintals per hectare (qu/ha)	Ratio
X_4	Average monthly per capita expenditure on food	Rupiah (IDR)	Ratio
X_5	Households with access to proper sanitation	Percent (%)	Ratio
X_6	Population density	Persons/km2	Ratio
X_7	Protein sufficiency ratio	Percent (%)	Ratio

2.2 Data Analysis Procedures

The data analysis in this study was conducted using a significance level of α = 10%. Data analysis in this study used R Studio and GWR4 Software, with the following steps:

1. Modeling the food security of Central Java Province with global linear regression to obtain residuals, then proceed with the classical assumption.

a. Residual normality was tested using the Kolmogorov-Smirnov test. Residuals are considered normally distributed if p-value > α [16].
b. The absence of multicollinearity among independent variables is assumed. Variance Inflation Factor (VIF) values > 10 indicate significant multicollinearity [17]. VIF value is calculated according to Equation (1).

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

c. Regression assumes no heteroscedasticity. The Glejser test indicates heteroscedasticity if $|t_{stat}| > t_{(n-k\,;\,\alpha)}$ or p-value < α [18].

2. Conducting spatial assumption tests on the GWR model, following the equation and hypothesis as follows.
   a. The test statistics can be used to test for spatial dependence is Moran's I test with the hypothesis [19]:
   $H_0: I = 0$ (There is no spatial dependence between regions)
   $H_1: I \neq 0$ (There is spatial dependence between regions)
   The test statistics used is:

$$Z_I = \frac{I - E(I)}{\sqrt{var(I)}} \tag{2}$$

   where $I = \frac{n\sum_{i=1}^{n}\sum_{i=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}\sum_{i=1}^{n} w_{ij}(x_i - \bar{x})^2}$
   The Moran's I index ranges from -1 to 1. A positive value indicates the presence of positive spatial autocorrelation, while a negative value indicates the presence of negative spatial autocorrelation. The critical region is defined as rejecting H_0 if the $|Z_I| > Z_{\frac{\alpha}{2}}$.
   b. Spatial heterogeneity is a spatial to identify variability in observations. The Breusch-Pagan test is used to assess spatial heterogeneity with the following hypotheses [20]:
   $H_0: \sigma_1^2 = \sigma_2^2 = \cdots = \sigma_n^2 = \sigma^2$ (There is no spatial heterogeneity between regions)
   H_1 : At least one $\sigma_i^2 \neq \sigma^2; i = 1,2,\ldots,n$ (There is spatial heterogeneity between regions)
   The test statistics used is:

$$BP = \left(\frac{1}{2}\right)\boldsymbol{f}'(\boldsymbol{Z}'\boldsymbol{Z})^{-1}\boldsymbol{Z}'\boldsymbol{f} \tag{3}$$

   With a significance level α, the critical region is defined as the rejection of H_0 if the test statistic $BP > \chi^2_{\alpha;p}$ or p-value < α.
3. Perform GWR modeling after standardizing the data, followed by the selection of a kernel function and determination of the optimal bandwidth based on the minimum cross-validation (CV) value. This study applies the following kernel function [21].
   a. Fixed Gaussian Kernel

$$w_{ij}(u_i v_i) = exp\left(-\left(d_{ij}/h\right)^2\right) \tag{4}$$

   b. Fixed Bi-square Kernel

$$w_{ij}(u_i v_i) = \begin{cases} \left(1 - \left(d_{ij}/h\right)^2\right)^2, & if\ d_{ij} \leq h \\ 0 & , if\ d_{ij} > h \end{cases} \tag{5}$$

   Using a fixed weighting function, the minimum CV is determined by Equation (6) [22].

$$CV(b) = \sum_{i=1}^{n}[y_i - \hat{y}_{\neq i}(b)]^2 \tag{6}$$

4. Testing the variability in the selected GWR model to determine global and local variables through the DIFF of criterion (DOF) value. DIFF of Criterion is calculated as the difference between the AIC or AICc values of the global and local model specifications [23]. A positive DIFF value indicates that the global specification yields a better model fit, implying the variable has no spatial variation and should be treated as global. Conversely, a negative value suggests the variable exhibits spatial heterogeneity and should be modeled as local [24].
5. Perform MGWR modeling using the kernel and optimal bandwidth identified during the preceding GWR modeling. Subsequently, the global and local predictor variables determined from the previous variability test are input into the model. The MGWR modeling procedure involves the following steps.
   a. Estimating the parameters of the selected MGWR model, then a goodness-of-fit test is conducted to evaluate the adequacy of the model. This test compares the global linear regression model with the MGWR model, with the hypothesis [25]:
   $H_0: \beta_k(u_i, v_i) = \beta_k$ (there is no difference between the global regression model and the MGWR model)
   H_1 : at least one $\beta_k(u_i, v_i) \neq \beta_k$ (there is a difference between the global regression model and the MGWR model)
   The test statistics used are:

$$F = \frac{\boldsymbol{y}'[(\boldsymbol{I}-\boldsymbol{H})-(\boldsymbol{I}-\boldsymbol{S})'(\boldsymbol{I}-\boldsymbol{S})]\boldsymbol{y}/v_i}{\boldsymbol{y}'(\boldsymbol{I}-\boldsymbol{S})'(\boldsymbol{I}-\boldsymbol{S})\boldsymbol{y}/u_i} \tag{7}$$

Where,
$v_i = tr([(\boldsymbol{I}-\boldsymbol{H})-(\boldsymbol{I}-\boldsymbol{S})'(\boldsymbol{I}-\boldsymbol{S})]^i), i = 1,2$
$u_i = tr([(\boldsymbol{I}-\boldsymbol{S})'(\boldsymbol{I}-\boldsymbol{S})]^i), i = 1,2$
$\boldsymbol{H} = \boldsymbol{X}(\boldsymbol{X}'\boldsymbol{X})^{-1}\boldsymbol{X}'$
where a significance level α and $df_1 = \left(\frac{v_1^2}{v_2}\right)$ and $df_2 = \left(\frac{u_1^2}{u_2}\right)$, the critical region is defined as rejecting H_0 if the $F > F_{\alpha(df_1,df_2)}$. This section also presents the selection of the best regression model by considering the lowest AIC and the highest R^2 value, as defined by the Equation (8) and (9)

$$AIC = e^{\frac{2k}{n}} \frac{\sum_{i=1}^{n} \hat{u}_1^2}{n} \tag{8}$$

where k is number of model parameters estimated, *u* denotes residual, and *n* is the number of observations [26]. The coefficient of determination is the most commonly used measure to assess the goodness of fit of a regression line, calculated using the following formula [27].

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2}{\sum_{i=1}^{n}(Y_i - \bar{Y})^2} \tag{9}$$

With y_{ij} is the actual value of the dependent variable at location *i*, $\hat{Y}_{ij}$ is the predicted value at location *i*, Y is the overall mean of the dependent variable, and *n* is the number of observations.

b. Partially testing global and local parameters to determine which predictor variables have a significant effect in each district/city [25].
For the partial test of global parameters, the hypotheses are formulated as:
$H_0 : \beta_k = 0$ (the global variable β_k has no significant effect)
$H_1 : \beta_k \neq 0$ (the global variable β_k has a significant effect)
The test statistics used are:

$$t_{g_{hit}} = \frac{\hat{\beta}_k}{\hat{\sigma}\sqrt{g_{kk}}} \tag{10}$$

Where g_{kk} is the *k*-th diagonal element of the matrix $\boldsymbol{GG'}$, with:

$$\boldsymbol{G} = \left[\boldsymbol{X}_g(\boldsymbol{I}-\boldsymbol{S}_l)'(\boldsymbol{I}-\boldsymbol{S}_l)\boldsymbol{X}_g\right]^{-1}\boldsymbol{X}_g'(\boldsymbol{I}-\boldsymbol{S}_l)'(\boldsymbol{I}-\boldsymbol{S}_l), \text{ and } \hat{\sigma} = \frac{\boldsymbol{y}'(\boldsymbol{I}-\boldsymbol{S})'(\boldsymbol{I}-\boldsymbol{S})\boldsymbol{y}}{tr((\boldsymbol{I}-\boldsymbol{S})'(\boldsymbol{I}-\boldsymbol{S}))}$$

Given a significance level α and degrees of freedom $df = \left(\frac{u_1^2}{u_2}\right)$, the critical region is defined as the rejection of H_0 if $\left|t_{g_{hit}}\right| > t_{\frac{\alpha}{2};df}$
For the partial test of local parameters, the hypotheses are stated as:
$H_0 : \beta_k(u_i, v_i) = 0$ (the local variable β_k has no significant effect at location *i*)
$H_1 : \beta_k(u_i, v_i) \neq 0$ (the local variable β_k has no significant effect at location *i*)
The test statistics used are:

$$t_{l_{hit}} = \frac{\hat{\beta}_k(u_i, v_i)}{\hat{\sigma}\sqrt{m_{kk}}} \tag{11}$$

Where m_{kk} is the *k*-th diagonal element of the matrix $\boldsymbol{MM'}$, with:

$$\boldsymbol{M} = [\boldsymbol{X}_l'\boldsymbol{W}(u_i, v_i)\boldsymbol{X}_l]^{-1}\boldsymbol{X}_l'\boldsymbol{W}(u_i, v_i)\left(\boldsymbol{I} - \boldsymbol{X}_g\boldsymbol{G}\right)$$

Given a significance level α and degrees of freedom $df = \left(\frac{u_1^2}{u_2}\right)$, the critical region is defined as the rejection of H_0 if $\left|t_{l_{hit}}\right| > t_{\frac{\alpha}{2};df}$

c. Make a plot between the observation data and the MGWR model estimation results and then calculate the MAPE value as a measure of model goodness according to Equation (12) [27].

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{12}$$

6. Interpret the factors that significantly affect the Food Security Index of Central Java Province.

2.3 Mixed Geographically Weighted Regression

In situations where some predictor variables have both global and local effects, Fotheringham [23] developed the MGWR model, which is expressed by the following Equation (13).

$$y_i = \sum_{k=1}^{q} \beta_k x_{ik} + \sum_{k=q+1}^{p} \beta_k(u_i, v_i)x_{ik} + \varepsilon_i, i = 1,2, \dots, n \tag{13}$$

Where y_i is the observed value of the response variable at location i; x_{ik} is the observed value of predictor variable k at location i; (u_i, v_i) is the coordinate point (latitude, longitude) for location i; β_k : the global parameter for predictor variable x_k; $\beta_k(u_i, v_i)$ is the local parameter for predictor variable x_k at location i; ε_i is the error term at observation i.

To estimate the parameters $\hat{\boldsymbol{\beta}}_v(u_i, v_i)$ in the MGWR model, the Weighted Least Squares (WLS) method is used [28]. The parameters at observation location $(u_i v_i)$ are estimated by incorporating the weight element $w_j(u_i v_i)$ into the GWR model equation and then minimizing the function given in Equation (14).

$$Q_i = \sum_{j=1}^{n} w_j(u_i v_i)\left(y_j - \beta_0(u_i v_i) - \beta_1(u_i v_i)x_{j1} - \cdots - \beta_p(u_i v_i)x_{jp}\right)^2 \tag{14}$$

The local parameter estimation, using the WLS approach, is obtained by minimizing the function Q_i as in Equation (14), resulting in the GWR parameter estimate at location (u_i, v_i) as in Equation (15).

$$\hat{\boldsymbol{\beta}}_v(u_i, v_i) = [\boldsymbol{X}_v' \boldsymbol{W}(u_i, v_i)\boldsymbol{X}_v]^{-1}\boldsymbol{X}_v' \boldsymbol{W}(u_i, v_i)\tilde{\boldsymbol{y}} \tag{15}$$

With $\tilde{\boldsymbol{y}}$ is the MGWR model on Equation (13) in the matrix notation is expressed as $\boldsymbol{y} - \boldsymbol{X_c\beta_c} = \boldsymbol{X_v\beta_v}(u_i, v_i) + \boldsymbol{\varepsilon}$. Hence, the predicted value for $\tilde{\boldsymbol{y}}$ at all locations can be expressed in Equation (16).

$$\hat{\tilde{\boldsymbol{y}}} = \left(\hat{\tilde{\boldsymbol{y}}}_1, \hat{\tilde{\boldsymbol{y}}}_2, \dots, \hat{\tilde{\boldsymbol{y}}}_n\right)' = \boldsymbol{S}_v\tilde{\boldsymbol{y}} \tag{16}$$

where,

$$\boldsymbol{S}_v = \begin{pmatrix} \boldsymbol{x}_{v1}'(\boldsymbol{X}_v'\boldsymbol{W}(u_1, v_1)\boldsymbol{X}_v)^{-1}\boldsymbol{X}_v'\boldsymbol{W}(u_1, v_1) \\ \boldsymbol{x}_{v2}'(\boldsymbol{X}_v'\boldsymbol{W}(u_2, v_2)\boldsymbol{X}_v)^{-1}\boldsymbol{X}_v'\boldsymbol{W}(u_2, v_2) \\ \vdots \\ \boldsymbol{x}_{vn}'(\boldsymbol{X}_v'\boldsymbol{W}(u_n, v_n)\boldsymbol{X}_v)^{-1}\boldsymbol{X}_v'\boldsymbol{W}(u_n, v_n) \end{pmatrix}$$

3. RESULT AND ANALYSIS

As one of the national rice production centers, Central Java Province has the second highest average Food Security Index (FSI) nationally, with a score of 84.8. However, it can be seen in Figure 1 that the FSI values tend to be lower (marked in dark green) in the western or left side of the map, covering areas such as Brebes, Pekalongan City, Purbalingga, Banyumas, Wonosobo, Temanggung, and Magelang.

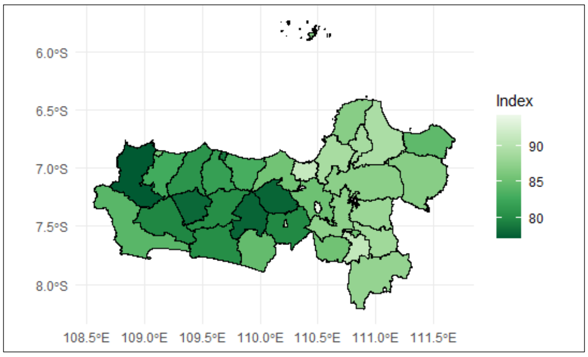

Figure 1. Map of the 2023 Food Security Index in Central Java by District/City

This phenomenon is interesting to investigate further because it indicates a spatial influence that causes the concentration of areas with low FSI in the western part of the province. This suggests the potential for local factors to influence food security unevenly at the district/city level.

3.1 Modeling Food Security Index with Global Regression

The modeling was carried out by regressing the food security index as the response variable on the factors suspected to influence it, without accounting for spatial components. The resulting global model is presented in Equation (17).

$$\hat{Y} = 90.96 - 0.4755X_1 - 0.171X_2 + 0.0243X_3 + 0.00003X_4 + 0.0729X_5 - 0.00098X_6 - 0.1956X_7 \tag{17}$$

The multiple linear regression model in Equation (17) yields an R^2 value of 0.6599. The global regression model explains that every one unit increase the X_3, X_4, and X_5 will increase the FSI. Conversely, the X_1, X_2, X_6, and the X_7 variables show a negative effect, which means that each unit increase in these variables will reduce the FSI. Then, based on the Kolmogorov-Smirnov normality test, the p-value is 0.6924 > 0.1, it can be concluded that the residual data is normally distributed. The next assumption is the absence of multicollinearity. While based on testing the VIF value, all predictor variables show that values of VIF < 10, indicating no high correlation among the predictors, it can be concluded that there is no multicollinearity issue, and this assumption is satisfied. The homoscedasticity test results at a 10% significance level, the p-values for variables X_1 (0.00858) dan X_6 (0.01563) < α (0,1) with the $|t_{stat}| > t_{(28\,;\,0.1)} = 1.7011$, indicating the presence of heteroscedasticity in the linear regression model. In contrast, variables X_2, X_3, X_4, X_5, and X_7 have p-values > 0.10, indicating that their variances are homoscedastic and do not significantly vary across observations. Therefore, the global regression method is less appropriate, and spatial modeling is necessary for this study.

3.2 Spatial Assumptions and Local Variability in Geographically Weighted Regression (GWR) Modeling

Using a Queen contiguity weight matrix, the results of the spatial dependency test shown in Table 4, the p-value is 3.153e-05 < 0.1, and the test statistic $|Z_I| = 4.0011 > Z_{0.05} = 1.645$. Therefore, the null hypothesis is rejected, indicating the presence of spatial dependency in the Food Security Index data across provinces in Central Java. With one assumption having been satisfied, the next step is to test for spatial heterogeneity, which aims to identify spatial variability within the observational data. Using the Breusch–Pagan test, the p-value of heterogeneity test is 0.04883 < 0.1, and the Breusch–Pagan test statistic (14.135) > $\chi^2_{0.1;7}(12.017)$. Therefore, the null hypothesis is rejected, indicating the presence of spatial heterogeneity in the observational data. Both spatial assumptions have been satisfied, allowing the analysis to proceed with the GWR. In GWR analysis, the first step involves determining the best weighting kernel through the selection of an optimal bandwidth that minimizes the Cross-Validation (CV) score. The results of the best kernel and optimal bandwidth selection are presented in Table 6.

Table 2. GWR Model Weighting Results

Kernel	Minimum CV	Bandwidth
Fixed Gaussian	**9.148787**	**0.614**
Fixed Bisquare	9.533374	1.603

As shown in Table 2, the best weighting scheme is the Fixed Gaussian kernel, which yields the lowest CV score of 9.148787. Therefore, the GWR modeling is conducted using the Fixed Gaussian kernel with a bandwidth of 0.614. The resulting GWR model is then used for spatial variability testing.

Table 3. Variability Test Result

Variable	*DIFF of Criterion*	Decision
X_1	-0.136286	Local
X_2	0.277016	Global
X_3	0.766189	Global
X_4	-1.104691	Local
X_5	-0.450390	Local
X_6	-1.742303	Local
X_7	-0.354701	Local

Based on the output of the spatial variability test shown in Table 3, it can be concluded that two predictor variables, X_2 and X_3, have a global effect on the food security index, as indicated by a positive DIFF of Criterion value. Meanwhile, the other five variables such as X_1, X_4, X_5, X_6, and X_7 exhibit a local effect on food security index in Central Java Province, as evidenced by a negative DIFF of Criterion value. Given the presence of both global and local variable effects, the data are appropriate for further analysis using the MGWR analysis.

3.3 Modeling Food Security Index with Mixed Geographically Weighted Regression (MGWR)

Parameter estimation for the MGWR model with a Fixed Gaussian kernel involves the estimation of global parameters followed by the estimation of local parameters. A summary of parameter estimates for 35 regencies/cities in Central Java Province is presented in Table 8.

Table 4. MGWR Model Parameter Estimation Results

No	Location	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	$\hat{\beta}_4$	$\hat{\beta}_5$	$\hat{\beta}_6$	$\hat{\beta}_7$
1	Banjarnegara	83.8756	-0.9056	-0.1710	0.0243	5.6020	0.0158	-4.1941	-2.6092
2	Banyumas	84.1845	-1.2891	-0.1710	0.0243	7.7995	-0.1768	-6.5873	-3.3999
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
35	Wonosobo	84.1646	0.6614	-0.1710	0.0243	4.7631	0.2967	-2.8031	-2.394

In Table 4, each column header shows the MGWR coefficient estimates for predictor variable in each location. The estimated parameters $\hat{\beta}_2$ and $\hat{\beta}_3$ have identical values across all regencies/cities, indicating that variables X_2 and X_3 are global in nature. In contrast, the estimated local parameters vary across different locations. These parameter estimates can then be used to construct individual regression equations for each regency/city in Central Java Province. The best regression model is selected by considering the lowest AIC value and the highest R^2 value, using the optimal kernel, Fixed Gaussian kernel that previously selected. The model comparison results are presented in Table 5.

Table 5. Regression Model Comparison Results

Regression Model	AIC	R^2
Global Regression	182.500180	0.729929
GWR	161.202185	0.881264
MGWR	**149.261203**	**0.931117**

Based on Table 5, the MGWR model demonstrates the best performance compared to Global Regression and GWR. MGWR yields the lowest AIC value of 149.261203 and the highest coefficient of determination of 93.1117%, making the MGWR is the most appropriate model for analyzing the Food Security Index in Central Java. To validate the best model, model fit testing is conducted to determine whether the MGWR model provides a significant improvement over the global linear regression model.

Table 6. MGWR Model Fit Test Results

Source	SS	DF	MS	F
Global Residuals	183.417	27.000		
GWR Improvement	136.636	14.556	9.387	
GWR Residuals	46.781	12.444	3.759	2.497016

Based on the model fit test results shown in Table 6, the F_{stat} (2.497016) > $F_{0,1(15,556\,;\,12,444)} = 2,08614$ by providing a substantial improvement value. Therefore, the null hypothesis is rejected, indicating a significant difference between the MGWR model and the global linear regression model.

A partial test of the global parameters was subsequently conducted to identify which global predictor variables significantly influence the Food Security Index in Central Java Province. The global variables considered in this study are X_2 and X_3. Based on the partial test, using a significance level of 10%, the critical value was determined to be $t_{0.05\,;\,27}$ = 1,703228. So, the test statistic for X_2 with $|T_2| >$ 1.703228, the null hypothesis is rejected. This indicates that the variable representing the percentage of households without access to clean water significantly affects the food security index in Central Java. That means, every 1 percent increase in households without access to clean water will decrease the value of the Food Security Index by 0.1710 points, assuming other variables are constant. Conversely, for variable X_3, the null hypothesis is accepted because $|T_3| <$ 1.703228, suggesting that rice crop productivity does not have a significant impact on the food security index.

The local variables in this study consist of X_1, X_4, X_5, X_6, and X_7. A partial test of local parameters was conducted for these variables to determine which local predictor variables significantly influence the Food Security Index in each district/city in Central Java Province. In this study, the partial test of local parameters is exemplified using the location with the lowest Food Security Index in Central Java, Brebes District. MGWR model estimation form in Brebes District is expressed in Equation (18).

$$\hat{Y}_{Brebes} = 83{,}6342 - 0.4755X_1 - 0.1710X_2 + 0.0243X_3 + 9.4425X_4 - 0.4376X_5 - 7.7506X_6 - 3.8364X_7 \quad (18)$$

Based on Partial test of Equation (18), the critical value was determined to be $t_{0.05\,;\,12.444}$ = 1,777004, so the null hypothesis is rejected for parameters β_4, β_6, and β_7 because $|T_k| >$ 1.777004. This indicates that the variables average monthly per capita food expenditure (X_4), population density (X_6), and protein sufficiency ratio (X_7) significantly affect the Food Security Index in Brebes Regency. Using the same parameter testing, the significance of predictor variables for all 35 districts/cities in Central Java Province was evaluated. As a model evaluation metric, the estimated results of the MGWR model were compared to the observed data through a plot to visually assess how well the model predicts the response variable.

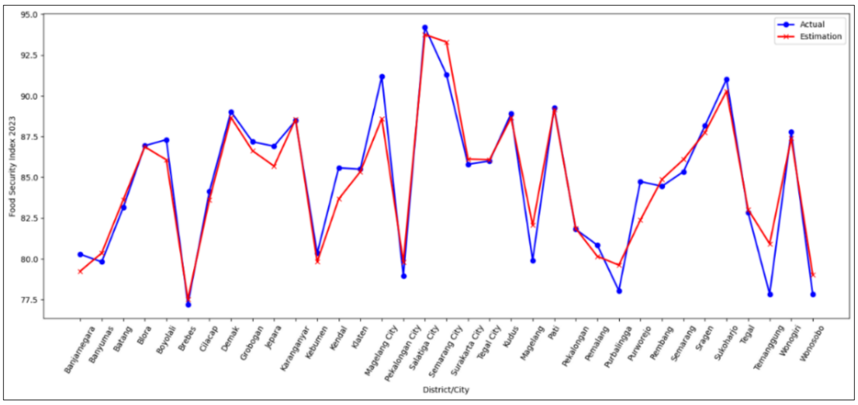

Figure 2. Plot of Estimation Results of MGWR Model

As shown in Figure 2, most of the estimated values are close to the actual values. The alignment between the actual and predicted lines indicates that the MGWR model is capable of accurately predicting the Food Security Index across districts/cities in Central Java Province. Statistically, the model's predictive ability is measured using the Mean Absolute Percentage Error (MAPE) based on calculation as in Equation (12).

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\%$$

$$MAPE = \frac{1}{35} \times 0.35293 \times 100\% = \mathbf{1.00838\%}$$

The resulting MAPE value indicates that the MGWR model yields an average prediction error of only 1.00838% compared to the actual observations. Therefore, it can be concluded that the MGWR model used in this study possesses a very high level of predictive accuracy.

3.4 Clustering Based on Significant Factors Affecting Food Security in Central Java

The clustering of provinces that have a similar significant influence on the FSI. This suggests the presence of spatial influence that affects the condition of surrounding areas. To understand the distribution of FSI clusters in Central Java based on significant variables, a visualization is provided in Figure 3.

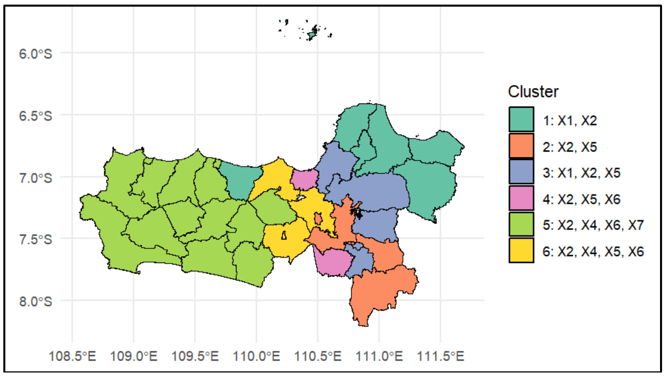

Figure 3. Thematic Map of Significant Variables Affecting Food Security in Central Java

The FSI in the areas included in Cluster 1 is influenced by local factors such as the poverty level of the population (X_1). These areas include Batang, Blora, Jepara, Kudus, Pati, and Rembang. The estimation results of the MGWR model show that as the percentage of poor people decreases, FSI in this cluster region will increase. For cluster 2 show that the regional FSI in Boyolali, Karanganyar, Salatiga City, and Wonogiri will increase when the local factors of percentage of households with access to proper sanitation increases (X_5). In Cluster 3, the FSI tends to increase when the percentage of poor people (X_1) and the percentage of households with access to proper sanitation increases (X_5). Both local factors influence Demak, Grobogan, Surakarta City, Sragen, and Sukoharjo. Meanwhile in cluster 4, the model show suggests that reducing population density (X_6), along with increasing access to proper sanitation (X_5) will increase the region's FSI. Both local factors influence Klaten and Semarang City. The results for Cluster 5 highlight a negative effect from variables X_6 and X_7, and a positive effect from X_4. This means that the food security index is likely to increase when the percentage of households without clean water, population density, and protein suffiency ratio decrease, and when monthly food expenditure per capita increases. Based on the analysis results, a decrease in the protein adequacy ratio is actually associated with an increase in the Food Security Index. Although this may seem contradictory, it can be explained by the findings of Simanjuntak [3], who observed a shift in the food consumption pattern of people in Central Java since 2018, marked by a decline in rice consumption and an increase in protein intake. The study shows a negative relationship that supports this finding. These three local factors affect Banjarnegara, Banyumas, Brebes, Cilacap, Kebumen, Pekalongan City, Tegal City, Pekalongan, Pemalang, Purbalingga, Purworejo, Tegal, Temanggung, and Wonosobo. For cluster 6, the MGWR model imply that FSI in this cluster can be enhanced by reducing population density (X_6), while also increasing household food expenditure (X_4), and access to proper sanitation (X_5). Referring back to Figure 1, it can be observed that the western part of Central Java, which has a lower average FSI, is influenced by similar local factors, and as many as 14 districts/cities in Central Java belong to this cluster.

4. CONCLUSION

The variable representing the percentage of households without access to clean water has a significant global effect on the FSI. Meanwhile, other variables such as the percentage of poor population, average monthly food expenditure per capita, percentage of households with proper sanitation access, population density, and protein sufficiency ratio show significant local effects. The MGWR model outperforms both the global regression and GWR models. The determination of the six clusters was based on the combination of variables identified as significant through partial testing in the MGWR model. These findings conclude that MGWR analysis is effective in identifying key influencing factors, with the population density is the dominant local factor that significantly influences the Food Security Index in 21 districts/cities or about 60% of the area in Central Java, then followed by the factor average monthly per capita expenditure on food which is significant in 18 districts/cities in Central Java. The findings provide evidence that spatially adaptive modeling can support more nuanced and region-specific policy interventions. Policymakers may benefit from these insights to design targeted strategies that enhance food security outcomes across heterogeneous regions.

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