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Modeling The Food Security Index In Indonesia Using The Mixed Geographically Weighted Regression (MGWR) Method

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Abstract: *Food security is a strategic development issue characterized by differences in conditions between regions in Indonesia. These differences are reflected in the Food Security Index (FSI), which shows spatial variations between provinces. This study aims to model the Food Security Index in Indonesia in 2024 and identify the economic, social, and demographic factors that influence it, taking into account spatial heterogeneity. The method used is Mixed Geographically Weighted Regression (MGWR), which is able to distinguish between the influence of global and local variables. The data used is secondary data from the Central Statistics Agency and the National Food Agency with 38 provinces in Indonesia as the unit of analysis. The explanatory variables used include Gross Regional Domestic Product (GRDP) per capita, Human Development Index (HDI), Open Unemployment Rate (OUR), population, and number of poor people. The results of the study show autocorrelation and spatial heterogeneity, making a global regression model less suitable. Based on a comparison of AIC values and determination coefficients, the MGWR model provides the best performance with the lowest AIC value of 225.379 and a determination coefficient of 85.8%. The variables of GRDP per capita and population are global in nature, while HDI, OUR, and the numbers of poor people are local in nature with varying influences between provinces. The MAPE value of 4.27% indicates that the MGWR model has excellent prediction accuracy. The results of this study are expected to form the basis for the formulation of food security policies that are more targeted and based on regional characteristics, in line with efforts to achieve Sustainable Development Goal (SDG) 2: Zero Hunger.*

Keywords: Food Security Index; Regression; MGWR; Fixed Gaussian Kernel

1. INTRODUCTION

Food security is a fundamental development issue because it is directly related to the health and productivity of the population. Based on Law No. 18 of 2012, food security is defined as the condition of sufficient food for the country and individuals, reflected in the availability of food that is sufficient, safe, of high quality, diverse, evenly distributed, and affordable, as well as in accordance with the religion, beliefs, and culture of the community to live healthy, active, and productive lives in a sustainable manner [1]. Food security is not only influenced by agricultural production, but also by socioeconomic conditions, demographics, and the heterogeneous distribution of public services across regions. Therefore, measuring food security requires instruments that are capable of capturing this complexity.

In Indonesia, comprehensive food security measurements are conducted through the Food Security Index (FSI), a composite index constructed from the normalization and aggregation of a number of indicators across three main pillars: food availability, food affordability, and food utilization, with categories ranging from "highly vulnerable" to "highly resilient" [2]. The FSI is used as the basis for formulating policies and regional intervention priorities. The Indonesian government is targeting an increase in the national FSI from 76.20 in 2024 to 80.72 in 2029 as part of its national strategic priorities in the area of food security [3]. However, the 2024 FSI data shows significant disparities between provinces, with some provinces falling into the "highly resilient" category (FSI > 85), while others remain in the "vulnerable" category (FSI < 70) [4]. This condition indicates that there is still disparity in access to and availability of food between regions.

The factors that influence the FSI are diverse, covering economic, social, and demographic aspects, such as gross regional domestic product (GRDP) per capita, human development index (HDI), open unemployment rate, population size, and number of poor people as indicators of vulnerable groups. The diversity of these factors necessitates spatial analysis to understand variations in food security between regions. Farida (2023) used the Geographically Weighted Regression (GWR) method in her research to model the FSI of provinces in Indonesia and obtained an R^2 value of 94.55% with an Adaptive Gaussian kernel, showing that the influence of variables differs spatially [5]. The study recommends the use of additional variables and other spatial methods to gain a more comprehensive understanding.

In addition, Hasanah (2025) shows spatial dependence in food security through spatial regression in East Java Province, with findings of a significant positive spatial lag effect, indicating spillover between regions [6]. Furthermore, Chamidah (2025) used Mixed Geographically Weighted Regression (MGWR) to model the Food Security Index at the district/city level in Central Java and found that some variables had a global influence, while other variables were local in nature with varying influences between regions [7]. These results confirm that MGWR is capable of capturing spatial heterogeneity more realistically than global regression or standard GWR.

Based on these findings, MGWR was chosen in this study because of its ability to distinguish between global and local variables, as well as accommodate spatial heterogeneity and dependencies between regions [8]. To date, there has been no national-scale study using MGWR with the latest 2024 FSI data and covering a wide range of economic, social, and demographic variables. Therefore, this study models the FSI in 38 provinces in Indonesia using MGWR to produce a more accurate understanding of the determinants of food security and support the formulation of more targeted place-based policies. This approach is expected to contribute to the achievement of Sustainable Development Goal (SDG) 2: Zero Hunger through comprehensive spatial analysis based on the latest data [9].

2. RESEARCH METHOD

2.1 DATA AND RESEARCH VARIABLES

This study uses secondary data on the Food Security Index (FSI) for 2024 and the variables that influence it, all of which are sourced from the Indonesian Central Statistics Agency (BPS). The variables analyzed include the FSI, Gross Regional Domestic Product (GRDP) per capita, Human Development Index (HDI), Open Unemployment Rate (OUR), population size, and number of poor people. The analysis unit covers 38 provinces in Indonesia, enabling the use of the Mixed Geographically Weighted Regression (MGWR) method to analyze the influence of economic, social, and demographic factors on the FSI locally and globally.

2.2 DATA ANALYSIS PROCEDURES

Data analysis in this study used R-Studio and GWR4 software with a significance level of 5%.

1. Perform multiple linear regression analysis to obtain residuals, then perform classical assumption testing.
   a. Perform the Shapiro-Wilks normality test and compare the *p-value* with α. If *p-value* $\geq \alpha$ then the normality assumption is satisfied
   b. Perform multicollinearity testing and compare the VIF values. If the VIF value is < 10 then the multicollinearity assumption is satisfied. The VIF value for each location is written in the following equation [10]
   $$VIF_k = \frac{1}{1 - R_K^2}$$
2. Performing spatial assumption testing
   a. Performing spatial dependency tests using *Moran's I* test statistics. If $|Z_I| > Z_{\alpha/2}$ or *p-value* < α, then the spatial dependency assumption is satisfied.
   $$Z_I = \frac{I - E(I)}{\sqrt{var(I)}}$$
   with
   $I = \frac{n\sum_{i=1}^{n}\sum_{i=1}^{n} W_{ij}(y_i - \bar{y})(y_j - \bar{y})}{S_0 \sum_{i=1}^{n}(y_i - \bar{y})^2}$
   The hypotheses used are :
   H_0 : $I = 0$ (no dependence between locations)
   H_1 : $I \neq 0$ (there is dependence between locations)
   The critical region of Moran's I test is to reject H_0 if the value $|Z_I| > Z_{\alpha/2}$ or $p - value < \alpha$ which means that the data meets the assumption of spatial dependency [11]
   b. Perform a spatial heterogeneity test using the Breusch-Pagan test statistic.
   H_0 : $\sigma_1^2 = \sigma_2^2 = \cdots = \sigma_n^2 = \sigma^2$ (no heterogeneity between regions)
   H_1 : Minimal terdapat satu $\sigma_i^2 \neq \sigma^2$ (heterogeneity between regions)
   The Breusch-Pagan test statistic is
   $$BP = \frac{1}{2}\boldsymbol{f}'\boldsymbol{Z}(\boldsymbol{Z}'\boldsymbol{Z})^{-1}\boldsymbol{Z}'\boldsymbol{f} \sim \chi_p^2$$
   The H_0 decision is rejected if $BP > \chi_{\alpha,1}^2$ or $p - value < \alpha$, which means that the data meets the assumption of spatial heterogeneity [12].
3. Performing GWR modeling
   a. Calculating the Euclidean distance is formulated as follows [10].
   $$d_{ij} = \sqrt{\left(u_i - u_j\right)^2 + \left(v_i - v_j\right)^2}$$
   b. Determine the optimal kernel function and bandwidth based on the CV method, then select the model based on the smallest CV criterion.
   - Fixed Gaussian Kernel
   $$w_{ij} = \exp\left[-\left(\frac{d_{ij}}{h}\right)^2\right]$$
   - Fixed Bisquare Kernel
   $$w_{ij} = \begin{cases} \left[-\left(\frac{d_{ij}}{h}\right)^2\right]^2, & if \ d_{ij} \leq h \\ 0 & , if \ d_{ij} > h \end{cases}$$
   Systematically, the CV value is written as follows
   $$CV(h) = \sum_{i=1}^{n}(y_i - \hat{y}_{\neq i}(h))^2$$
   c. Performing variability tests on the selected GWR model to determine global and local variables in the MGWR model.
   H_0 : $\beta_j(u_1, v_1) = \beta_j(u_2, v_2) = \cdots = \beta_j(u_n, v_n)$
   H_1 : not all $\beta_j(u_i, v_i), i = 1,2, \dots, n$ have the same value
   with the following test statistic: $F(j) = \frac{{V_j}^2/\gamma_1}{SSE(H_1)/\delta_1}$
   H_0 will be rejected if the value of $F(j) > F_{\alpha,v_1,v_2}$, which means that the predictor variables are local. Conversely, if H_0 accepted, then the predictor variables are global [13].
4. Performing MGWR modeling
   a. Estimate the parameters of the selected MGWR model

b. Performing MGWR model suitability tests using test statistics

$$F = \frac{y'[(I-H)-(I-S)'(I-S)]y/v_1}{y'(I-S)'(I-S)y/u_1}$$

With the hypothesis

$H_0 : \beta_k(u_i, v_i) = \beta_k$ (there is no difference between the global linear regression model and the MGWR model)

H_1: there is at least one $\beta_k(u_i, v_i) \neq \beta_k$ (there is a difference between the global linear regression model and the MGWR model).

Reject H_0 if the value $F > F_{\alpha(df_1, df_2)}$ [14]

c. Compare the goodness-of-fit of the global linear regression, GWR, and MGWR models using the AIC value, which can be formulated as follows [10]:

$$AIC = -2\ln(L) + 2k$$

In addition, the coefficient of determination is also used, which is formulated as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

d. Conduct partial testing of global and local parameters using test statistics to determine the predictor variables that have a significant effect in each province.

For partial testing of global parameters, hypotheses are used.

$H_0 : \beta_k = 0$ (The global variable X_k is not significant)

$H_1 : \beta_k \neq 0$ (The global variable X_k significant)

Test statistics :

$$T_g = \frac{\hat{\beta}_k}{\hat{\sigma}\sqrt{g_{kk}}}$$

where,

g_{kk} = The - k diagonal element of the $\boldsymbol{GG^T}$ matrix

$\boldsymbol{G} = \left[\boldsymbol{X_g^T}(\boldsymbol{I}-\boldsymbol{S_l})^{\boldsymbol{T}}(\boldsymbol{I}-\boldsymbol{S_l})\boldsymbol{X_g}\right]^{-1}\boldsymbol{X_g^T}(\boldsymbol{I}-\boldsymbol{S_l})^{\boldsymbol{T}}(\boldsymbol{I}-\boldsymbol{S_l})$

$\hat{\sigma}^2 = \frac{\boldsymbol{y^T}(\boldsymbol{I}-\boldsymbol{S})^{\boldsymbol{T}}(\boldsymbol{I}-\boldsymbol{S})\boldsymbol{y}}{tr((\boldsymbol{I}-\boldsymbol{S})^{\boldsymbol{T}}(\boldsymbol{I}-\boldsymbol{S}))}$

Decision criteria :

If $p - value < \alpha$ or $|T_g| > t_{\frac{\alpha}{2};db}$ with $db = \left(\frac{\delta_1^2}{\delta_2}\right)$ then H_0 is rejected.

For partial testing of local parameters, the hypothesis is used.

$H_0 : \beta_k(u_i, v_i) = 0$ (Local variable X_k at location-*i* is not significant)

$H_1 : \beta_k(u_i, v_i) \neq 0$ (Local variable X_k at location-*i* is significant)

Test statistic:

$$T_l = \frac{\hat{\beta}_k(u_i, v_i)}{\hat{\sigma}\sqrt{m_{kk}}}$$

dengan :

m_{kk} = The - k diagonal element of the $\boldsymbol{MM}^T$ matrix

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

$\hat{\sigma}^2 = \frac{\boldsymbol{y^T}(\boldsymbol{I}-\boldsymbol{S})^{\boldsymbol{T}}(\boldsymbol{I}-\boldsymbol{S})\boldsymbol{y}}{tr((\boldsymbol{I}-\boldsymbol{S})^{\boldsymbol{T}}(\boldsymbol{I}-\boldsymbol{S}))}$

Decision criterion: if $p - value < \alpha$ or $|T_l| > t_{\frac{\alpha}{2};db}$ with $db = \left(\frac{\delta_1^2}{\delta_2}\right)$ then H_0 is rejected [15].

e. 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.

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

3. Result and Discussion

3.1 Description of Research Variables Related to the Food Security Index

Fig. 1. *Map of the 2024 Food Security Index in Indonesia*

Figure 1 shows that the average Food Security Index (FSI) value for provinces in Indonesia is 67.46. The FSI values between provinces vary widely, ranging from 34.56 to 77.62, reflecting significant differences in food security levels between provinces in Indonesia. The province with the highest FSI value is South Kalimantan with a value of 77.62, which indicates relatively better food security conditions. Conversely, the lowest FSI value is found in Highland Papua Province, at 34.56, indicating higher food vulnerability. The spatial distribution pattern on the map shows that provinces with high FSI tend to be concentrated in western and central Indonesia, while provinces with low FSI are more commonly found in eastern Indonesia.

3.2 Global Regression Analysis

Estimation of model parameters using the ordinary least square (OLS) method. So that the regression model formed is as follows.

$$\hat{Y} = 67.4565 - 0.3335X_1 + 9.5201X_2 - 1.2214X_3 - 2.1558X_4 + 0.8703X_5$$

Simultaneous testing results show that the regression model formed is statistically significant, with a value of $F_{stat}(17.56) > F_{0.05(5\,;\,32)} = 2.51225$ and a *p-value* sebesar of 2.35×10^{-8}, so the null hypothesis is rejected. This indicates that the independent variables collectively have a significant effect on the Food Security Index. In addition, an Adjusted R^2 value of 0.6911 was obtained, indicating that approximately 69.11% of the variation in the Food Security Index can be explained by the independent variables used in the model, while the remaining 30.89% is influenced by other factors outside the model. After obtaining the linear regression model, classical regression assumptions were tested to ensure that the model met statistical feasibility criteria. The results of the regression assumption testing are presented in the next section.

3.2.1 Normality Test

The normality assumption test used in this study is the Shapiro-Wilk test. Based on the results of the Shapiro-Wilk test on the global regression model residuals, a statistical value of W = 0,96788 with a *p-value* of $0{,}3379 > \alpha = 0.05$. This indicates that the global regression model residuals are normally distributed, thus fulfilling the assumption of normality of residuals in the global regression model.

3.2.2 Multicollinearity Test

The multicollinearity assumption test in this study used the VIF test statistic. The VIF values for each predictor variable are shown in Table 1 below.

Table 1: Independent Variable VIF Value

	X_1	X_2	X_3	X_4	X_5
VIF	2.107	1.486	1.293	1.952	1.146

Based on Table 1, all VIF values are well below the critical limit of 10, so it can be concluded that there is no multicollinearity problem in the global regression model.

3.2.3 Autocorrelation Test

Global Spatial Autocorrelation Test (Moran's I) was conducted on the global regression model residuals using Monte Carlo simulation with 10,000 replications. The test results showed a Moran's I value of 0,27865 with a *p-value* $0{,}005 < \alpha = 0.05$., indicating significant positive spatial autocorrelation. This finding shows that the assumption of independence of observations in the global regression model is not met, so that the relationship between FSI and explanatory variables is spatially interdependent. Therefore, a spatial regression approach is needed to model FSI more accurately.

3.2.4 Heteroscedasticity Test

The heteroscedasticity test was conducted using the studentized Breusch–Pagan test. The test results showed a BP statistical value of 11,337 with a *p-value* of $0{,}0451 < \alpha = 0.05$ so the null hypothesis was rejected, meaning that there was an indication of heteroscedasticity in the global regression model.

This finding indicates that the residual variance is not constant between observations, so that the global regression model has limitations in meeting the assumption of homoscedasticity. This condition indicates that the relationship between the KPI and the explanatory variables may differ between regions, requiring a more flexible modeling approach.

3.3 Geographically Weighted Regression Modelling of FSI

In GWR modeling, the first step is to calculate the Euclidean distance between observation locations. After calculating the Euclidean distance, weighting calculations for each observation are performed using the Fixed Gaussian or Fixed Bisquare kernel function. The selection of the optimal bandwidth is performed using the cross-validation (CV) method for each weighting function in order to minimize CV.

Table 2: GWR Model Weighting Results

Kernel	Minimum CV	Bandwidth	AIC
Fixed Gaussian	22.599	1671.358	230.030
Fixed Bisquare	23.899	4527.960	232.627

Based on Table 2, the best weighting scheme in GWR modeling is the Fixed Gaussian kernel, because it produces the lowest Cross Validation (CV) value, which is 22.599, compared to the Fixed Bisquare kernel. In addition, the Fixed Gaussian kernel also provides a smaller AIC value, which is 230.030, with an optimal bandwidth of 1671.358. Therefore, GWR modeling in this study was performed using a Fixed Gaussian kernel with a bandwidth of 1671.358. The resulting GWR model was then used for spatial variation testing to identify differences in the influence of explanatory variables between regions.

Table 3: Variability Test Results

Variable	F Statistic	F Tabel	Decision
Intercept	21.655638	3.01213	Local
X_1	1.005403	3.16599	Global
X_2	10.886526	3.14415	Local
X_3	9.908262	3.1215	Local
X_4	0.234884	2.3572	Global
X_5	4.806051	2.19942	Local

The parameter variability test was conducted to identify whether the effect of each variable was global or varied locally between regions. The variability test results presented in Table 3 show that Intercept, X_2, X_3, and X_5 have $F_{stat} > F_{table}$ values, so the null hypothesis is rejected. This indicates that the four parameters are local, meaning that their influence on the Food Security Index varies between regions. Conversely, variables X_1 and X_4 have F values smaller than F table, so the null hypothesis is accepted. Thus, these two variables are classified as global variables, indicating that their influence on the Food Security Index is relatively consistent across all research regions. These findings confirm that not all explanatory variables have a uniform spatial influence. Therefore, the use of the Mixed Geographically Weighted Regression (MGWR) approach is appropriate because it can accommodate variables with global influences as well as variables with local influences.

3.4 *Mixed Geographically Weighted Regression*

Parameter estimation in the MGWR model with Fixed Gaussian kernel is performed in two stages, namely global parameter estimation and local parameter estimation. A summary of the parameter estimation results for 38 provinces in Indonesia is presented in Table 4.

Table 4: MGWR Model Parameter Estimation Results

No	Location	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$
1	Aceh	70.37769	-0.281652	4.335696
2	North Sumatera	70.41166	-0.281652	4.521471
⋮	⋮	⋮	⋮	⋮
38	Highland Papua	65.12015	-0.281652	10.17609

No	Location	$\hat{\beta}_3$	$\hat{\beta}_4$	$\hat{\beta}_5$
1	Aceh	0.792035	-1.754473	-0.30824
2	North Sumatera	0.854171	-1.754473	-0.31359
⋮	⋮	⋮	⋮	⋮
38	Highland Papua	-3.28277	-1.754473	1.513386

In Table 4, each column heading displays the MGWR coefficient estimates for each predictor variable at each location. The parameter estimates $\hat{\beta}_1$ and $\hat{\beta}_4$ have the same value across all provinces, indicating that variables $X_1$and X_6 are global in nature. Conversely, the values of the other parameters vary between locations, indicating local effects. Furthermore, these parameter estimates can be used to form regression equations specific to each province in Indonesia. The performance of the Global Regression, GWR, and MGWR models was compared using AIC values and the coefficient of determination (R^2), as shown in Table 5.

Table 5: Regression Model Comparison Results

Regression Model	AIC	R^2
Global Regression	244.914	0.733
GWR	230.030	0.838
MGWR	225.379	0.858

Based on Table 5, the MGWR model is the best performing model compared to global regression and GWR. MGWR produces the lowest AIC value of 225.379 and the highest coefficient of determination of 0.858%, making MGWR the most appropriate model for analyzing the Food Security Index in Indonesia. Furthermore, the MGWR model suitability test was conducted to assess whether the model provided a significant improvement compared to the global linear regression model.

Table 6: MGWR Model Suitability Test Results

Source	SS	DF	MS	F
Global Residuals	969.126	32.000		
GWR Improvement	454.778	3.506	129.728	
GWR Residuals	514.348	28.494	18.051	7.186787

Based on the results of the model suitability test shown in Table 4, $F_{stat}(7.186787) > F_{0.05(3.506\,;\,28.494)} = 2.21253$ These results indicate that the improvement in MGWR model performance compared to global linear regression is statistically significant at a 5 percent significance level. Thus, MGWR is empirically proven to provide a better model fit in explaining the variation in the Food Security Index.

Next, a partial global parameter test was conducted to identify global predictor variables that significantly affect the Food Security Index in Indonesia. The global variables analyzed in this study were X_1 and X_6. Using a significance level of 5%

and a degree of freedom of 28.494, a value was obtained $t_{0.025}(28.49) = 1.70012$. he test results obtained for X_1 were $|T_1| > 1.70012$ so the null hypothesis was accepted. This indicates that X_1 does not have a significant global effect on the Food Security Index.

Conversely, the value $|T_4| > 1.70012$, so the null hypothesis is rejected. Thus, X_4 has a significant global effect on the Food Security Index. The local variables in this study include X_2, X_3, and X_5. A partial test of local parameters was conducted to identify variables that have a significant effect on the Food Security Index in each region. The estimation results show spatial variation in influence between regions. In this analysis, the partial test for local parameters is shown by the province of Highland Papua, which has the lowest Food Security Index value. The MGWR model estimation for the province of Highland Papua is written as follows:

$$\hat{Y}_{Highland\ Papua} = 65.12015 - 0.281652X_1 + 10.17609X_2 - 3.28277X_3 - 1.754473X_4 + 1.513386$$

Based on the partial test estimate in the equation above, the critical value is determined to be $t_{0.025}(28.49) = 1.70012$, so the null hypothesis is rejected for parameters $\hat{\beta}_2$, $\hat{\beta}_3$, and $\hat{\beta}_5$ because $|T_k| > 1.70012$. This indicates that the Human Development Index, Open Unemployment Rate, and Number of Poor People variables have a significant effect on the Food Security Index in the Highland Papua Province. To clarify which variables are significant in each province, the mapping results are presented in Figure 2 below.

Fig. 2. Thematic Map of Local Variables Significantly Affecting the FSI of Various Provinces in Indonesia

The predictive ability of the model is also measured using Mean Absolute Percentage Error (MAPE) based on calculations using the formula

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

The MGWR model produced a MAPE value of 4.27%, indicating a low prediction error rate and demonstrating excellent prediction accuracy.

4. Conclusion

Based on the results of the analysis and discussion, it can be concluded that the Food Security Index (FSI) in Indonesia in 2024 shows significant differences between provinces, indicating spatial heterogeneity. The results of Moran's I and Breusch–Pagan tests show spatial autocorrelation and heteroscedasticity, so that the global linear regression model is less able to explain FSI variations optimally. Modeling using Geographically Weighted Regression (GWR) and Mixed Geographically Weighted Regression (MGWR) shows that the MGWR model is the best model with the lowest AIC value and the highest coefficient of determination. The results of the parameter variability test show that per capita GRDP and population size have a global influence on the FSI, while the Human Development Index, Open Unemployment Rate, and number of poor people have a local influence that varies between regions. In addition, the low MAPE value indicates that the MGWR model has excellent predictive capabilities. Thus, MGWR has proven to be effective in modeling FSI and is capable of providing a more comprehensive picture of the determinants of food security in Indonesia.

Based on the results of the research that has been conducted, several suggestions can be given as follows. The central and regional governments are expected to use the results of this study as a basis for formulating place-based food security policies, given the differences in dominant factors between provinces. Efforts to improve food security should focus on significant local variables in each region, especially in provinces with low FSI values. For further research, it is recommended to add other relevant variables, such as food infrastructure, transportation access, or environmental aspects, and to use more detailed units of analysis, such as districts/cities, in order to obtain more in-depth results. In addition, the use of panel data or a spatial-temporal approach can be considered to observe the dynamics of food security over time.

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