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Prediction of Potential Food Vulnerability and Food Security in Pekanbaru City Using the Geographically Weighted Regression Method

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ABSTRACT

Food vulnerability reflects a region's inability to adequately meet community food needs in terms of availability, accessibility, and utilization. This study aims to analyze the factors influencing food vulnerability and to compare the performance of the global regression model and the Geographically Weighted Regression (GWR) model in modeling food vulnerability in Pekanbaru City, Indonesia. This study employs secondary data obtained from the 2023 Pekanbaru Food Security and Vulnerability Report, covering 83 urban villages as the unit of analysis. The independent variables include the Priority of Infrastructure Ratio, Priority of Poor Population Ratio, Priority of Road Access, Priority of Households without Access to Clean Water, and Priority of Population per Health Worker Ratio, while Composite Priority is used as the dependent variable. The analysis was conducted using multiple linear regression as the global model and GWR as the local model to capture spatial heterogeneity. The results of the ANOVA analysis indicate that the global regression model produces a residual sum of squares of 3,208,363.416, suggesting that a considerable proportion of food vulnerability variation remains unexplained. The GWR model demonstrates superior performance, with an R^2 value of 0.820164 and an adjusted R^2 value of 0.773799, both higher than those of the global regression model. Additionally, the GWR model produces lower Akaike Information Criterion (AIC) and corrected AIC (AICc) values of 556.080285, indicating a better balance between model accuracy and complexity. These findings confirm that spatial heterogeneity significantly influences food vulnerability patterns. Therefore, spatially targeted and location-specific policy interventions are required to effectively reduce food vulnerability across urban villages in Pekanbaru City.

Keywords: *Food Vulnerability, Geographically Weighted Regression, Spatial Analysis, Food Security, Global Regression Model*

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1. INTRODUCTION

Pekanbaru City consists of 15 districts and 83 urban villages, with a total population of 1,016,366 people and 328,162 households in 2023 (bps, 2023). Pekanbaru covers a land area of approximately 632.26 km² or 63,226 hectares (Wilayah Geografis - Pekanbaru, 2021). (Pekanbaru Geographical Region, 2021). In accordance with Law Number 18 of 2012 concerning Food, both national and regional governments are mandated to ensure food security down to the individual level. However, food security conditions in Pekanbaru City still face several challenges. The results of the Food Security and Vulnerability Atlas (FSVA) of Pekanbaru City in 2022 identified 22 urban villages as vulnerable to food insecurity. In addition, data from Statistics Indonesia indicate that 22.21% of households remain classified as food insecure (Dinas Ketahanan Pangan - Pekanbaru, 2024).

From the perspective of food self-sufficiency, Pekanbaru City's food production has not yet met local food demand. Based on food availability analysis, local food production only fulfills approximately 17% of the total food requirement in Pekanbaru City. To monitor and evaluate food security conditions, the Pekanbaru Food Security Agency annually publishes the Food Security and Vulnerability Analysis Report in the form of the Food Security and Vulnerability Atlas (FSVA). The FSVA is a thematic map that provides a geographical visualization of food vulnerability indicators. The information presented in the FSVA identifies vulnerable areas and highlights the key indicators contributing to food insecurity in each region (FSVA, 2023) .

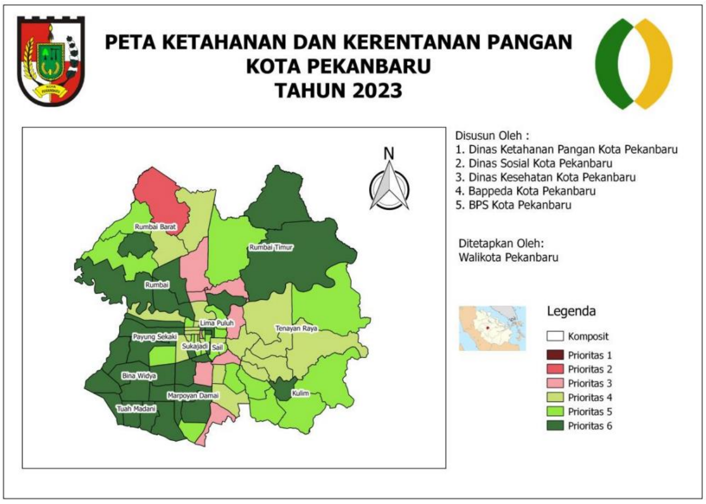

Figure 1. Pekanbaru City Food Security and Vulnerability Map for 2023
Source: Pekanbaru City Food Security Office

Figure 1 illustrates that food-vulnerable urban villages are represented in red (priority levels 1, 2, and 3). The darker the shade of red, the more severe the level of food vulnerability in the urban village. Meanwhile, food-secure urban villages are indicated in green (priority levels 4, 5, and 6). The Food Security and Vulnerability Atlas (FSVA) is an instrument used by government institutions and research organizations to map food vulnerability and food security conditions down to the district level. The main indicators used in FSVA include food availability, economic access, and price stability. However, this information has not been further analyzed to predict food vulnerability and food security conditions in Pekanbaru City. The prediction results can serve as a basis for mapping the levels of food vulnerability and food security across Pekanbaru City (Pangan Nasional, 2019).

Food security is one of the strategic issues in regional development. Based on data from the Food Security and Vulnerability Atlas (FSVA) and spatial data from 83 urban villages, the prediction method applied in this study is Geographically Weighted Regression (GWR). GWR is a statistical method that analyzes data by considering geographical location or spatial heterogeneity in the observed variables. This method allows the regression parameters to vary across locations, enabling a more detailed understanding of spatial variations in food vulnerability patterns. Previous studies have widely applied the Geographically Weighted Regression (GWR) method across various research fields (Abdul Rohman, 2024). A study conducted by Lin and Billa demonstrated that the GWR method has greater potential in flood vulnerability mapping compared to traditional models, such as non-spatial logistic regression and frequency ratio models. The results indicated that incorporating spatial heterogeneity improves the accuracy of flood vulnerability assessment (Lin & Billa, 2021). In another study, GWR was applied to predict winter wheat yield. Accurate prediction of crop yield is essential for marketing, transportation, and storage planning, as well as for managing associated risks (Feng et al., 2021). The study showed that GWR is capable of capturing spatial variations in agricultural productivity, thereby improving prediction accuracy compared to global regression approaches . Furthermore, research conducted by Monjarás-Vega et al aimed to predict spatial patterns of wildfire occurrences at both regional and national levels in Mexico. In this study, GWR was used to model wildfire density and successfully identified location-specific spatial patterns of fire occurrence. The findings confirmed that GWR is effective in analyzing spatially varying phenomena across different geographical regions (Monjarás-Vega et al., 2020).

The problem-solving approach in this study employs the Geographically Weighted Regression (GWR) model to predict the potential food vulnerability and food security conditions in Pekanbaru City by mapping and forecasting their local spatial distribution. This model estimates regression coefficients locally for each geographical observation point, allowing the analysis to capture spatial heterogeneity across regions.

The objective of this study is to generate predictive patterns of food vulnerability and food security in Pekanbaru City using the GWR method. The prediction results are expected to provide valuable information for policymakers at the municipal level in Pekanbaru City to prioritize interventions and programs based on local needs and the potential impact of food insecurity. The variables used in this study include the city-level food security priority status based on five indicators and a Composite Index Score. The indicators consist of: (1) the ratio score of food supply facilities and infrastructure to the number of households, representing food availability; (2) the ratio score of the population with the lowest welfare level to the total population; (3) urban villages with inadequate road accessibility, representing food accessibility; (4) the ratio score of households without access to clean water; and (5) the ratio score of health workers to the population, representing food utilization.

2. METHODS

The data used in this study are secondary data obtained from the 2023 Pekanbaru Food Security and Vulnerability Report, with observation points covering 83 urban villages. The variables employed in this study include the Priority of Infrastructure Ratio, Priority of Poor Population Ratio, Priority of Road Access, Priority of Households without Access to Clean Water, and Priority of Population per Health Worker Density Ratio. In addition, spatial variables such as latitude and longitude coordinates, urban village classification, and Composite Priority (Y) as the dependent variable were also included in the analysis. A detailed description of the variables used in this study is presented in Table 1.

Table 1. Research Data Variables

Variables	Information	Type
Ward	name of the sub-district	Categorical
lon, lat	Geographic coordinates of each sub-district	Numeric
Priority Ratio of Facilities (X1)	Results of the analysis of the ratio of food supply facilities and infrastructure to the number of households in 83 sub-districts of Pekanbaru City	Independent

Priority of the Ratio of the Unprivileged Population (X2)	Results of the analysis of food security and vulnerability in Pekanbaru City based on the ratio of the number of poor people	Independent
Road Access Priority (X3)	Results of analysis of regional food security and vulnerability based on connecting road access	Independent
Priority of Waterless Ratio (X4)	Results of the analysis of the ratio of households without access to clean water to the number of households in 83 sub-districts of Pekanbaru City	Independent
Priority Ratio of Population per Health Worker per Density (X5)	The results of the analysis of the ratio of the number of health workers to the number of residents of sub-districts in Pekanbaru City, from 83 sub-districts	Independent
Composite Priority (Y)	The results of the analysis of vulnerability to composite food insecurity are determined through a weighting analysis of each indicator.	Dependent

After obtaining the data sources and determining the research variables, the next step involves data processing and analysis. The data processing and analysis were conducted using GWR4 software through several analytical stages, as illustrated in Figure 2.

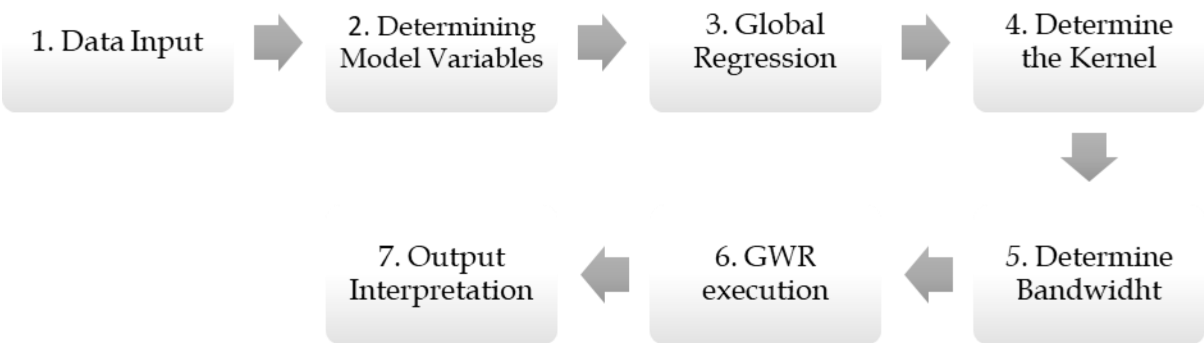

Figure 2. Data Processing and Analysis Flow

Figure 2 is described as follows: (1) Importing data in CSV file format; (2) Specifying the model variables, which include urban villages, location coordinates (longitude and latitude), the dependent variable (Y), and independent variables (X1, X2, X3, X4, and X5); (3) Performing global regression analysis; (4) Determining spatial weighting using a kernel function, where the Adaptive Gaussian kernel type is selected ; (5) Determining the optimal bandwidth, which is used to define the spatial influence of neighboring areas; (6) Running the GWR analysis; and (7) Generating outputs in the form of local parameter tables, model statistics, and residual values (Tizona et al., 2017)(Taek et al., 2023) (Wati et al., 2020).

3. RESULTS AND DISCUSSION

The analytical stages in this study began with importing the research data in CSV file format into the GWR analysis software. The unit of analysis in this study consists of 83 urban villages serving as observation locations. The observation locations were determined based on the geographical coordinates of each urban village. The independent variables used in this study include the Priority of Infrastructure Ratio (X1), Priority of Poor Population Ratio (X2), Priority of Road Access (X3), Priority of Households without Access to Clean Water (X4), and Priority of Population per Health Worker Density Ratio (X5). Spatial coordinate variables, including latitude and longitude, were also incorporated into the analysis. The dependent variable in this study is Composite Priority (Y). The selection of these variables aims to examine the influence of factors suspected to affect the level of food vulnerability.

The next stage involves conducting global regression modeling to examine the overall relationship between the independent variables and the dependent variable without considering spatial variation across regions. The results of the global regression analysis are presented as follows:

Tabel 2. Hasil Regresi Global

Parameters	Value
Residual sum of squares	3208363,415563
Classic AIC	556,632706
AICc	556,632706
R square	0,803102
Adjusted R square	0,764992

Based on the results of the global regression analysis, the Residual Sum of Squares (RSS) value obtained is 3,208,363.42. This value indicates the level of model error in predicting food vulnerability. The coefficient of determination (R^2) reflects the ability of the independent variables to explain the dependent variable. The R^2 value of 0.803 indicates that approximately 80.31% of the variation in food vulnerability can be explained by the independent variables included in the model, while the remaining variation is influenced by other factors outside the model. The adjusted R^2 represents the coefficient of determination that has been adjusted for the number of variables included in the model. The adjusted R^2 value of 0.765 indicates that, after accounting for the number of explanatory variables, the model is still capable of explaining approximately 76.50% of the variation in food vulnerability. This value provides a more realistic measure of model performance compared to the unadjusted R^2. Furthermore, the corrected Akaike Information Criterion (AICc) value is 556.632706. A lower AICc value indicates a better model in terms of the trade-off between model goodness-of-fit and model complexity. The classical Akaike Information Criterion (AIC) value obtained is 552.899372. The Akaike Information Criterion is commonly used to evaluate model quality by considering both the level of model fit and the number of parameters employed.

The following table shows the global regression results showing the regression coefficient (Estimate), standard error, and t value :

Table 3. Regression coefficient values, standard errors, and t-values

Variable	Estimate	Standard Error	t(Est/SE)
Intercept	4992,997963	4043,573344	1,234798
X1	0,487137	0,043612	11,169815
X2	0,002447	0,043612	0,329975

X3	0,000706	0,023830	0,029642
X4	0,100103	0,023211	4,312677
X5	-0,033774	0,411485	-0,082077

The next stage involves performing global regression modeling to examine the overall relationship between the independent variables and the dependent variable without considering spatial variation across regions. The results of the global regression are used as a baseline model for comparison with the GWR model. Subsequently, spatial weighting is determined using a kernel function. In this study, the Adaptive Gaussian kernel type is selected because it can adjust the number of neighboring observations at each observation location, making it more suitable for data with uneven spatial distribution. The following stage is determining the optimal bandwidth, which functions to define the spatial range of influence from neighboring areas on each observation location. The optimal bandwidth is obtained through an optimization process to produce a model with minimal prediction error.

After obtaining the optimal bandwidth, the Geographically Weighted Regression (GWR) modeling is conducted to generate local regression parameters for each urban village. The GWR model allows the relationship between independent and dependent variables to vary across observation locations.

Table 4. GWR Results

Parameters	Value
Residual sum of squares	2930336,638564
Classic AIC	556,080285
AICc	556,080285
R square	0,820164
Adjusted R square	0,773799

Based on the results of the Geographically Weighted Regression (GWR) analysis, the Residual Sum of Squares (RSS) value obtained is 2,930,336.638564. The coefficient of determination (R^2) value of 0.820164 indicates that approximately 82% of the variation in food vulnerability can be explained by the independent variables included in the model, while the remaining variation is influenced by other factors outside the model. The adjusted R^2 value of 0.773799 indicates that, after accounting for the number of explanatory variables, the model is still capable of explaining approximately 77% of the variation in food vulnerability. This demonstrates that the GWR model maintains strong explanatory power even after adjustment for model complexity. Furthermore, the corrected Akaike Information Criterion (AICc) value is 556.080285, and the classical Akaike Information Criterion (AIC) value is also 556.080285. The Akaike Information Criterion is used to evaluate model quality by considering the trade-off between model goodness-of-fit and the number of parameters used. Lower AIC values indicate better model performance.

The following GWR results table shows the regression coefficient (Estimate), standard error, and t value:

Table 5. Regression coefficient values, standard errors, and t values:

Variable	Estimate	Standard Error	t(Est/SE)
Intercept	4992,997963	4043,573344	1,234798
X1	0,487137	0,043612	11,169815
X2	0,002447	0,043612	0,329975
X3	0,000706	0,023830	0,029642

X4	0,100103	0,023211	4,312677
X5	-0,033774	0,411485	-0,082077

A comparison between the Global Regression model and the Geographically Weighted Regression (GWR) model was conducted to determine which model performs better in explaining the variation in food vulnerability in Pekanbaru City. Model performance was evaluated using several indicators, including the Residual Sum of Squares (RSS), coefficient of determination (R Square), Adjusted R Square, Akaike Information Criterion (AIC), and corrected Akaike Information Criterion (AICc). The GWR modeling results produced an RSS value of 2,930,336.64, which is lower than that of the global regression model, indicating that the GWR model has a lower prediction error. The reduction in RSS by approximately 278,027 suggests that incorporating spatial approaches improves model accuracy. These findings indicate the presence of spatial heterogeneity in the influence of independent variables on food vulnerability. Therefore, the GWR model is considered more representative in describing the spatial variation of food vulnerability across urban villages in Pekanbaru City. The R Square value of the GWR model (0.820164) is higher than that of the Global Regression model, indicating that the independent variables are able to explain the variation in food vulnerability more effectively when spatial aspects are considered. The Adjusted R Square value of the GWR model (0.773799) is also higher than that of the Global Regression model, suggesting that the variables included in the GWR model provide stronger explanatory power compared to the global regression model. Furthermore, the GWR model produces lower Akaike Information Criterion (AIC) and corrected Akaike Information Criterion (AICc) values of 556.080285 compared to the global regression model. Lower AIC and AICc values indicate that the GWR model achieves a better balance between model goodness-of-fit and model complexity. Based on the comparison between the two models, the GWR model demonstrates superior performance compared to the Global Regression model. The following is the GWR ANOVA table.

Table 6. GWR ANOVA

ource	SS	DF	MS	F
Global Residuals	3208363,416	32,000		
GWR Improvement	278026,777	1,584	175518,236	
GWR Residuals	2930336,639	30,41	96342,053	1,821824

The Analysis of Variance (ANOVA) results of the Geographically Weighted Regression (GWR) model were used to evaluate the improvement in model performance compared to the global regression model. Based on the analysis, the global regression model produced a Residual Sum of Squares (RSS) value of 3,208,363.416. This value indicates the magnitude of variation in food vulnerability that cannot be explained by the global regression model. After conducting the Geographically Weighted Regression (GWR) modeling, the model improvement value (GWR Improvement) was found to be 278,026.777. This value indicates an additional amount of data variation that can be explained by the GWR model through a spatial approach. This finding suggests that the GWR model is capable of capturing variations in the influence of food vulnerability factors across different regions. Furthermore, the GWR residual value of 2,930,336.639 indicates a reduction in model error compared to the global regression model. The decrease in the residual value demonstrates that the GWR model has better predictive capability in explaining food vulnerability in Pekanbaru City. The F-statistic value of 1.821824 indicates that the GWR model provides an improvement in model performance compared to the global regression model. The GWR ANOVA results confirm that incorporating spatial approaches enhances model accuracy in explaining regional variations in food vulnerability. This finding indicates the presence of spatial heterogeneity in the influence of the research variables, suggesting that the GWR model is more appropriate for analyzing food vulnerability in Pekanbaru City.

4. CONCLUSION

Based on the results of food vulnerability modeling in Pekanbaru City using global regression and Geographically Weighted Regression (GWR), it can be concluded that the infrastructure ratio and the ratio of households without access to clean water have a significant influence on the level of food vulnerability. Meanwhile, the ratio of the poor population, road accessibility, and the population-to-health worker ratio show no significant influence in the global regression model. The model comparison results indicate that the GWR model demonstrates better performance than the global regression model. This is evidenced by the lower Residual Sum of Squares (RSS) value, as well as higher coefficients of determination (R Square) and Adjusted R Square values in the GWR model. In addition, the lower Akaike Information Criterion (AIC) and corrected Akaike Information Criterion (AICc) values obtained from the GWR model indicate that it provides a more optimal explanation of food vulnerability variation. The GWR model is capable of accommodating spatial variations in the influence of research variables across regions, thereby providing a more representative depiction of food vulnerability conditions among urban villages in Pekanbaru City. Therefore, the spatial approach using GWR is considered more appropriate for food vulnerability analysis, as it is able to capture regional characteristic differences in greater detail.

Based on the results of this study on food vulnerability modeling in Pekanbaru City, several recommendations can be proposed. For the Pekanbaru City Government, it is recommended to prioritize the improvement of infrastructure supporting food distribution and the equitable provision of access to clean water, as both factors have been proven to significantly influence the level of food vulnerability. Infrastructure development programs and basic service provision should be focused on areas with high levels of food vulnerability. In terms of food security policy planning, the findings of this study indicate spatial variations in the influence of food vulnerability factors across regions. Therefore, the formulation of food security policies should consider the local characteristics of each urban village to ensure that food vulnerability intervention programs are more targeted and effective. For future research, it is recommended to incorporate additional variables that may influence food vulnerability, such as household economic conditions, education levels, and environmental factors. Furthermore, the application of other spatial analysis methods is suggested to provide comparative results and to develop more comprehensive modeling approaches.

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