BAREKENG: Journal of Mathematics and Its Applications
March 2023 Volume 17 Issue 1 Page 0361–0370
P-ISSN: 1978-7227 E-ISSN: 2615-3017
https://doi.org/10.30598/barekengvol17iss1pp0361-0370

ANALYSIS OF SPATIAL EFFECTS ON FACTORS AFFECTING RICE PRODUCTION IN CENTRAL SULAWESI USING GEOGRAPHICALLY WEIGHTED PANEL REGRESSION

Nurul Fiskia Gamayanti [1*], Junaidi[2], Fadjryani[3], Nur'eni[4]

[1,2,3,4]*Department Statistics, Faculty of Mathematics and Natural Sciences, Tadulako University*
Jl. Soekarno Hatta Km 9, Palu, Sulawesi Tengah, 94118, Indonesia

*Corresponding author's email : * **nurulfiskia@gmail.com***

ABSTRACT

Fulfillment of rice stock in Indonesia to always be distributed based on demand in the community is certainly closely related to the results of rice production. The results of rice production in various regions of Indonesia are very different. This difference can of course, be influenced by geographic location or spatial effects between regions. Central Sulawesi, which is one of the provinces with a large population compared to other provinces on the island of Sulawesi, has a responsibility to meet the needs of its community, so it is necessary to take into account and increase the production of rice by relying on production in the province. Modeling rice production that has spatial effects or heterogeneity between regions is needed as an analytical tool because if the modeling ignores spatial effects and generalizes the model, the modeling predictions will be biased. So, we need an analytical model that can accommodate the problem of spatial effects using Geographically Weighted Panel Regression. The purpose of this study was to determine the factors that can affect rice production in Central Sulawesi. The data used comes from BPS Central Sulawesi Province from 2014-2020. This study focuses on the spatial effect factors that are considered to be able to affect rice production in Central Sulawesi. The results of the study there are eight districts/cities are affected by land area, and four districts/cities are affected by land area and harvested area.

Article History:

Received: 19th October 2022
Revised: 29th December 2022
Accepted: 4th February 2023

Keywords:

Geographically Weighted Panel Regression;
Central Sulawesi;
Rice Production

How to cite this article:

N. F. Gamayanti, Junaidi, Fadjryani and Nur'eni., "ANALYSIS OF SPATIAL EFFECTS ON FACTORS AFFECTING RICE PRODUCTION IN CENTRAL SULAWESI USING GEOGRAPHICALLY WEIGHTED PANEL REGRESSION," *BAREKENG: J. Math. & App.*, vol. 17, iss. 1, pp. 0361-0370, March 2023.

Journal homepage: *https://ojs3.unpatti.ac.id/index.php/barekeng/*
Journal e-mail: *barekeng.math@yahoo.com; barekeng.journal@mail.unpatti.ac.id*
Research Article • Open Access

1. INTRODUCTION

Since 2020, Indonesia has been hit by the Covid-19 pandemic. Where the negative effects of the pandemic can overwhelm all aspects of Indonesia. One of which is the disruption of economic activity, where one of the economic factors that have a large contribution is the agricultural sector. One of the impacts of the Covid-19 pandemic on the agricultural sector is the availability of food for all Indonesians. It is considered that in Indonesia, rice is one of the main types of food. Fulfilling the availability of rice certainly must be kept from the results of rice production, which must remain balanced and can meet all the demands that exist in the community.

The fulfillment of this food security cannot be separated from the results of rice production, which are expected to continue to increase and remain stable during the Covid-19 pandemic. The results of rice production in the territory of Indonesia cannot be generalized where each region has different production results [1] so each region contributes to the other by cross-subsidizing their production. However, the government must still be able to maximize the yield of rice production for each region so that it can rely on the rice production of each region to provide food security for each region [2]. Previous research conducted on modeling rice production in West Java in fact sometimes varies according to conditions from one location to another. Conditions that are influenced by spatial aspects or geographical conditions of an area allows for spatial heterogeneity [3].

Differences in rice production in each region are certainly very likely to occur due to spatial effects or often referred to as heterogeneity effects between regions. Central Sulawesi is one of the second largest provinces with the highest consumption rate compared to other provinces in the province of Sulawesi, so the Central Sulawesi local government needs to take action and pay attention to the availability of food in its area by modeling the results of its rice production.

Modeling of rice production in reality sometimes varies according to conditions from one location to another. Conditions that are influenced by spatial aspects or geographical conditions of an area allow for spatial heterogeneity [4]. We need a method that can accommodate aspects of spatial heterogeneity using the Geographically Weighted Regression (GWR) method approach [5]. The Geographically Weighted Panel Regression (GWPR) model is a development of the GWR model where the GWR model only uses cross-sectional data in the analysis, in contrast to the GWPR which combines cross-sectional data with time series data, which is commonly referred to as panel data [6]. They use panel data as analysis data to provide more information than time series or cross-section data. The GWPR resulting model is not general but will produce a model for each region because the method can accommodate aspects of spatial heterogeneity. Previous studies using GWPR in modeling the human development index in East Java produced a coefficient of determination of 98.74% [6]. So that this research will focus on modeling rice production results in Central Sulawesi using Geographically Weighted Panel Regression (GWPR).

2. RESEARCH METHODS

2.1 Spatial Heterogeneity

Spatial heterogeneity is a condition where the error variance is not uniform that can occur due to differences in the characteristics of one region with other regions [7]. This results in the variance in the regression model are no longer constant but varying according to the location of the observation. To detect the effect of spatial heterogeneity on the data, it is necessary to test with the Breusch-Pagan test.

The hypothesis is as follows:

$H_0 = \sigma_1{}^2 = \sigma_2{}^2 = \cdots = \sigma_n{}^2 = \sigma^2$ (There is no spatial heterogeneity)

$H_1 =$ at least there is one $\sigma_i{}^2 \neq \sigma^2$ (There is spatial heterogeneity)

statistics Test

$$\mathrm{BP} = \frac{1}{2} f'Z(Z'Z)^{-1}Z'f \tag{1}$$

Test criteria: Reject if BP ≥ $\chi^2_{(k)}$ or p-value < α. It means that there is spatial heteroscedasticity.

2.2 Geographically Weighted Panel Regression (GWPR)

Geographically Weighted Regression is a method used to explore spatial nonstationary, which is defined as the nature and significant relationship between different variables from one location to another. The GWR model uses a point approach, resulting in the estimation of local parameters, which for each observation area will have different parameters with weighting based on the position or distance of one observation area from another observation area [8]. The Geographically Weighted Regression model can be written as follows [9]:

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

while the Geographically Weighted Panel Regression (GWPR) is the development of the GWR model using panel data as research data [10].

GWPR has a similarity with the cross-section GWR analysis. In this study, it is assumed that the intercept differs between individuals, so panel regression with the FEM model is used. The general form of the panel regression model with FEM is as follows:

$$y_{it} = \alpha_i + \boldsymbol{x}_{it}^T \beta + \varepsilon_{it} \qquad (3)$$

The general GWPR model is obtained from a combination of the GWR model and the panel regression model. The following is a combination of the GWR equation and the FEM panel regression model equation with the within estimator:

$$\ddot{y}_{it} = \beta_0(u_{it}, v_{it}) + \sum_{k=1}^{p} \beta_k(u_{it}, v_{it}) \ddot{\boldsymbol{x}}_{itk} + \ddot{\varepsilon}_{it} \qquad (4)$$

Where:

$\ddot{y}_{it}$	:	The value of the dependent variable that has been averaged on the observations
$\beta_0(u_{it}, v_{it})$	:	The intercept of the equation formed at the *i* and *t*-time observations.
$\beta_k(u_{it}, v_{it})$	:	Regression coefficient on the *k*-th independent variable
$\ddot{\varepsilon}_{it}$	:	Error

2.3 Weight Model Geographically Weighted Panel Regression with Fixed Effect Model

In the GWPR model, the weights play a very important role because the weighting values represent the location of the observation data with one another. At the time of parameter estimation at the location point (u_i, v_i) it will be more influenced by the points closer to the location (u_i, v_i)) than the more distant points. One way to determine the amount of weight for each different location in the GWPR model is to use a fixed kernel function or Fixed Kernel. The Fixed Kernel function is a kernel function that has the same bandwidth at each observation location [11].

Bandwidth is a smoothing parameter that can adjust the level of smoothness of the curve in the kernel function [10]. In the kernel function, bandwidth selection is very important because bandwidth plays a role in controlling the balance between the suitability of the curve to the data and the smoothness of the data. One type of fixed kernel function that can be used is the exponential kernel function.

There are several methods that can be used to select the optimum bandwidth. One of them is to use Cross Validation (CV). CV in GWPR is the same as GWR, calculated based on the average of the dependent and independent variables for the entire time [6]. CV calculation can be written as follows [12]:

$$CV = \sum_{i=1}^{n} [y_i - \hat{y}_{\neq i}(b)]^2 \qquad (5)$$

Where

$\hat{y}_{\neq i}(b)$: estimated value for y_i by eliminating the observation location at point i from the parameter testing process with bandwidth b.

2.4 Geographically Weighted Panel Regression Parameter Estimation with Fixed Effect Model

Parameter estimation for Geographically Weighted Panel Regression with Fixed Effect Model can use the same approach as estimation of Geographically Weighted Regression in general, namely by using

Weighted Least Square (WLS) [13]. The approach using the Weighted Least Square (WLS) is a method that provides different weighting for each observation location.

The estimated GWPR model parameters for each location will have different weights for each observation location namely $w_{it}(u_{it}, v_{it})$.The weighting element $w_{it}(u_{it}, v_{it})$ different for each observation location. Then the next step is to minimize the number of squared errors, and will be reduced and then equalized to zero

So that the estimator for the local regression coefficient in the GWPR model is

$$\hat{\beta}(u_{it,}v_{it}) = [\ddot{\boldsymbol{X}}^T W(u_{it,}v_{it})\ddot{\boldsymbol{X}}]^{-1}\ddot{\boldsymbol{X}}^T W(u_{it,}v_{it})\ddot{\boldsymbol{y}} \qquad (6)$$

Where $\hat{\beta}(u_{it,}v_{it})$ is as follows:

$$\hat{\beta}(u_{it}, v_{it}) = \begin{bmatrix} \hat{\beta}_1(u_{it}, v_{it}) \\ \hat{\beta}_2(u_{it}, v_{it}) \\ \vdots \\ \hat{\beta}_p(u_{it}, v_{it}) \end{bmatrix} \qquad (7)$$

with:

$$i = 1,2, \ldots, N$$
$$t = 1,2, \ldots, T$$

2.5 Simultan Regression Coefficient Test

The model fit test was used to test the suitability of the parameters simultaneously and to see the differences between the global regression model and the Geographically Weighted Panel Regression.

The hypothesis is as follows:

$H_0: \beta_k(u_{it}, v_{it}) = \beta_k$ (for each k = 1, 2, ..., p) (there is no significant difference between the global regression model and the GWPR model)

$H_1: there\ is\ at\ least\ one\ \ \beta_k(u_{it}, v_{it}) \neq \beta_k$ (for each k = 1, 2, ..., p) (there is a significant difference between the global regression model and the GWPR model)

Test statistics [14]:

$$F = \frac{RSS(H_1)/df1}{RSS(H_0)/df2} \qquad (8)$$

Where:

$$RSS(H_0) = \ddot{\boldsymbol{y}}^T(I - H)\ddot{\boldsymbol{y}}$$
$$\boldsymbol{H} = \ddot{\boldsymbol{X}}(\ddot{\boldsymbol{X}}^{\boldsymbol{T}}\ddot{\boldsymbol{X}})^{-\boldsymbol{1}}\ddot{\boldsymbol{X}}^{\boldsymbol{T}}$$
$$\boldsymbol{RSS}(\boldsymbol{H_1}) = \ddot{\boldsymbol{y}}^{\boldsymbol{T}}(\boldsymbol{I} - \boldsymbol{L})^{\boldsymbol{T}}(\boldsymbol{I} - \boldsymbol{L})\ddot{\boldsymbol{y}}$$

$$df1 = \frac{{\delta_1}^2}{\delta_2}$$
$$\delta_1 = trace((\boldsymbol{I}-\boldsymbol{L})^{\boldsymbol{T}}(\boldsymbol{I} - \boldsymbol{L}))$$
$$\delta_2 = trace((\boldsymbol{I}-\boldsymbol{L})^{\boldsymbol{T}}(\boldsymbol{I} - \boldsymbol{L}))^{\boldsymbol{2}}$$
$$df2 = n * t - k$$

I is an identity matrix having the order $N \times T$. While the matrix L is stated as follows [14]:

$$\boldsymbol{L} = \begin{bmatrix} \ddot{x}_{11}^T(\ddot{\boldsymbol{X}}^T W(11)\ddot{\boldsymbol{X}})^{-1}(\ddot{\boldsymbol{X}}^T W(11)) \\ \ddot{x}_{21}^T(\ddot{\boldsymbol{X}}^T W(21)\ddot{\boldsymbol{X}})^{-1}(\ddot{\boldsymbol{X}}^T W(21)) \\ \vdots \\ \ddot{x}_{N1}^T(\ddot{\boldsymbol{X}}^T W(N1)\ddot{\boldsymbol{X}})^{-1}(\ddot{\boldsymbol{X}}^T (N1)) \\ \vdots \\ \ddot{x}_{1T}^T(\ddot{\boldsymbol{X}}^T W(1T)\ddot{\boldsymbol{X}})^{-1}(\ddot{\boldsymbol{X}}^T W(1T)) \\ \ddot{x}_{2T}^T(\ddot{\boldsymbol{X}}^T W(2T)\ddot{\boldsymbol{X}})^{-1}(\ddot{\boldsymbol{X}}^T W(2T)) \\ \vdots \\ \ddot{x}_{NT}^T(\ddot{\boldsymbol{X}}^T W(NT)\ddot{\boldsymbol{X}})^{-1}(\ddot{\boldsymbol{X}}^T W(NT)) \end{bmatrix} \qquad (9)$$

Test Criteria:

Reject H_0 if F > $F_{1-\alpha,df1,df2}$. This means that there is a difference between the global regression model and the Geographically Weighted Panel Regression.

2.6 Partial Parameter Significance Test

Testing the parameters of the GWPR model is done by testing the parameters partially. This partial test aims to determine which parameters significantly affect the dependent variable at each observation location.

$H_0: \beta_k(u_{it}, v_{it}) = 0 \; (for\ each\ k = 1,2, \dots p)$

$H_1: there\ is\ at\ least\ one\ \beta_k(u_{it}, v_{it}) \neq 0 \;\; (for\ each\ k = 1,2, \dots p)$

Test statistics [14]:

$$T = \frac{\hat{\beta}_k(u_{it}, v_{it})}{\hat{\sigma}\sqrt{C_{kk}}} \tag{10}$$

where C_{kk} is the diagonal element to-*k* from matrix $\boldsymbol{C}_{it}\boldsymbol{C}_{it}^{T}$.

$$C_{it} = (\ddot{\mathbf{X}}^{T}\boldsymbol{W}(u_{it}, v_{it})\ddot{\mathbf{X}})^{-1}\left(\ddot{\mathbf{X}}^{T}\boldsymbol{W}(u_{it}, v_{it})\right)$$

Test Criteria:

Reject H_0 if $|T_{hit}| > t_{\alpha/2,df}$ with $df = \frac{\delta_1^{\,2}}{\delta_2}$. Thats means that there is an effect of the k variable on the GWPR model.

2.8 Variable

The variables used in this study are as follows:

Y = rice production in Central Sulawesi (Tons)
X1 = land area (Ha)
X2 = harvested area (Ha)
X3 = productivity (Ku/Ha)

The number of districts and cities studied were 12 regions, and the year of research was 6 years from year 2014-2020 [15].

3. RESULTS AND DISCUSSION

3.1. Descriptive Statistics

Rice production in Central Sulawesi illustrates the difference in yield between each district/city. This could be due to spatial effects. This difference in rice production results is a concern to continue maximizing all locations as producers of rice production in meeting food needs. In maximizing rice production, effective factors are needed in each region because different factors can influence each region.

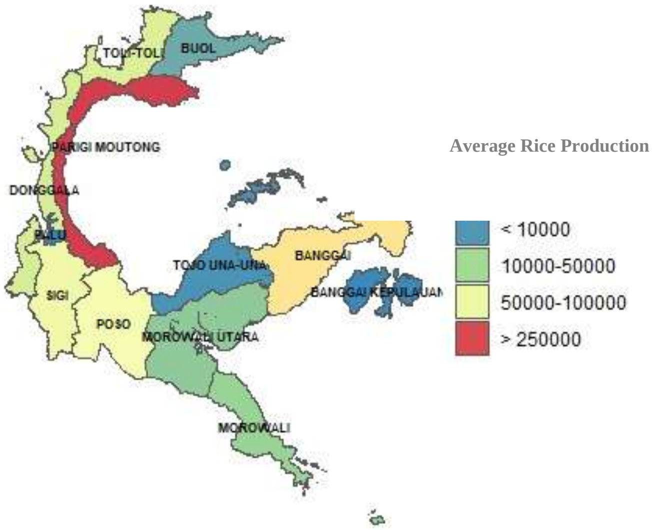

Figure 1. Map of Average Rice Production Yield in Central Sulawesi 2014-2020

Based on **Figure 1**, it can be seen that the location that had the highest average rice production during 2014-2020 is Parigi Moutong Regency, where the average rice production is above 250,000 tons per year. The locations with the lowest average rice production in Central Sulawesi are Banggai Islands Regency, Tojo Una-Una, and Palu City. Where the average production is less than 10,000 tons per year. This difference in rice production between regions underlies the possibility of spatial heterogeneity in rice production in Central Sulawesi.

3.2 Spatial Heterogeneity Effect Test

To detect the presence of spatial heterogeneity, the Breusch-Pagan test can be used with the following results:

Table 1. Result of Breusch-Pagan Test

Breusch-Pagan Test	p-value	Decision
9.8522	0.0199	Reject H_0

Based on **Table 1** above obtained p-value of 0.0199 less than $\alpha = 0{,}05$ then H_0 is rejected, meaning that there is a diversity of variance between observations or spatial heterogeneity. This problem is to be overcome by making local modeling by considering the spatial aspect, namely the diversity between observations, so that a Geographically Weighted Panel Regression analysis was carried out, which took into account the spatial aspect, namely the diversity between observation locations.

3.3 Geographically Weighted Panel Regression for Rice Production in Central Sulawesi

The first thing to do in estimating the GWPR model is to transform the data according to the FEM concept within the estimator. Data transformation with FEM within the estimator is done by subtracting each data from the corresponding average time series data. Then the data will be used in estimating GWPR. The estimation of the GWPR model begins by calculating the optimum bandwidth value. Where the selection of the optimum bandwidth is based on the bandwidth that has the minimum CV value. Based on the calculation results, the bandwidth value with the fixed exponential kernel function is obtained as follows:

Table 2. Optimum CV Value & Bandwidth

Cross Validation (CV)	Bandwidth Optimum
5.9583	3.6574

Based on Table 2 the optimum bandwidth value is 3.6574, then the next step is to form a weighting matrix. The weighting matrix will be formed using the fixed exponential kernel weighting function. The weighted values that have been obtained will be used in estimating the parameters of the GWPR model in each district/city. The following is the result of parameter estimation for Fixed Effect GWPR:

Table 3. Parameter Estimation of GWPR Fixed Effect Model

Location	β_0	β_1	β_2	β_3
Banggai Kepulauan	1.2126	0.0834	0.9425	0.0663
Banggai	1.1701	0.0926	0.9379	0.0718
Morowali	1.1512	0.0793	0.9532	-0.0144
Poso	1.0344	0.1189	0.9267	-0.1360
Donggala	0.9439	0.1552	0.9014	-0.2909
Tolitoli	1.0426	0.1188	0.9261	0.0558
Buol	1.0792	0.1039	0.9365	0.1037
Parigi Moutong	0.9542	0.1487	0.9068	-0.2354
Tojo Una-una	1.0641	0.1169	0.9254	0.0682
Sigi	0.9539	0.1512	0.9042	-0.3068
Morowali Utara	1.0924	0.1024	0.9365	-0.0463
Palu	0.9402	0.1561	0.9009	-0.3262

Based on the parameter estimation results in Table 3 it can be seen that there are 12 regression models for each location, where each location has its own model of rice production.

3.4 Model Fit Test

The regression coefficient test was simultaneously carried out to determine whether there was a difference between the global regression model and the GWPR model. Based on the test results obtained the following results:

Table 4. Model Conformity Test Results

F Test	decision
26.8549	Reject H_0

Based on the rejection test criteria H_0 if $F > F_{table}$. From the test results obtained F = 26.8549 > F_{table} = 4.07 then with a significant level of 5% it can be concluded that H_0 is rejected. This means that there is a significant difference between the global regression model and the GWPR model.

3.5 Parameter Significance Test

The significance test of the GWPR model parameters was carried out to determine the parameters significantly affecting the response variable. The GWPR model produces different model equations for each district/city but is the same between years, so that 12 model equations are obtained. The following is an example of a GWPR model in Palu.

$$\hat{y}_{palu(t)} = 0.9402 + 0.1561X_{1palu(t)} + 0.9009X_{2palu(t)}$$

The GWPR model in Palu can be interpreted if other variables are assumed to be constant. the rice production in Palu increase by 0.9539 tons. Every 1 hectare of paddy field area increases and other variables are held constant. it will increase rice production by 0.1024 tons. Every 1 hectare of harvested area increases and other variables are held constant. it will increase rice production by 0.9042 tons. The GWPR model of Sigi Regency has a coefficient of determination (R^2) of 0.9782 or 97.82%. This means that the land area (X_1) and harvested area (X_2) can explain the diversity of rice production in Sigi Regency by 97.82% while the remaining 2.18% is influenced by other factors outside the model.

The predictor variables that affect rice production in Central Sulawesi Province are generally influenced by factors of land area and harvested area. The following table presents the grouping of districts/cities based on significant predictor variables.

Table 5. Districts/Cities based on predictor variables that significantly affect rice production in Central Sulawesi Province

Significant Variables	Districts/Cities
X_1	Banggai Kepulauan, Banggai, Morowali, Poso, Toli-Toli, Buol, Tojo Una-Una, dan Morowali
X_1 & X_2	Donggala, Parigi Moutong, Sigi dan Palu

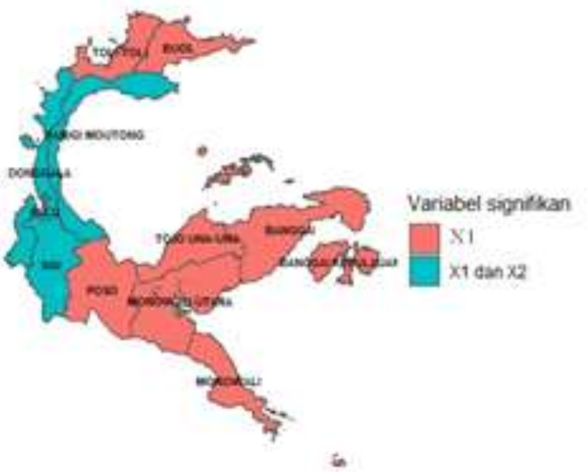

Figure 2. Map of Distribution of Significant Variables

Figure 2 shows a spatial map of the distribution of districts/cities in Central Sulawesi Province based on variables that significantly affect rice production. In this case, two groups were formed, where the predictor variables that had a significant effect on rice production were land area and harvested area. The variable of the land area has a significant impact in all districts/cities in Central Sulawesi. Meanwhile, the harvested area variable has a significant effect on Donggala, Parigi Moutong, Sigi, and Palu districts.

4. CONCLUSIONS

Based on the analysis results that have been carried out using the Geographically Weighted Panel Regression method by looking at all the spatial aspects of the model using the fixed exponential kernel weighting function. Twelve models are obtained that are used to model local rice production for each city district in Central Sulawesi. 8 city districts are only affected by land area, and four urban districts are affected by land area and harvested area.

REFERENCES

[1] D. T. Utari, T. Yuliana, and A. P. Hendradewa, "A Panel Data Analysis of Rice Production in Ngawi Regency, East Java," in *Proceedings of the 2nd International Seminar on Science and Technology (ISSTEC)*, 2020, vol. 474, no. Isstec 2019, pp. 212–217, doi: 10.2991/assehr.k.201010.031.

[2] N. F. Gamayanti and J. Junaidi, "Pemodelan Hasil Produksi Padi Di Provinsi Sulawesi Tengah Menggunakan Fixed Effect Model (Fem)," *BAREKENG J. Ilmu Mat. dan Terap.*, vol. 15, no. 2, pp. 347–354, 2021, doi: 10.30598/barekengvol15iss2pp347-354.

[3] N. S. Rahayu, "Geogrephically Weighted Panel Regression For Modelling The Percentage of Poor People in Jawa Tengah Province," pp. 7–32, 2017.

[4] A. Fitrianto and N. F. K. Musakkal, "Panel Data Analysis for Sabah Construction Industries: Choosing the Best Model," *Procedia Econ. Financ.*, vol. 35, no. October 2015, pp. 241–248, 2016, doi: 10.1016/s2212-5671(16)00030-7.

[5] rizka zulfikar, "Estimation Model And Selection Method Of Panel Data Regression : An Overview Of Common Effect, Fixed Effect, And Random Effect Model," 2018, doi: 10.31227/osf.io/9qe2b.

[6] D. C. Wati, D. A. Azka, and H. Utami, "The Model of Per-Capita Expenditure Figures in Sumatera Selatan uses a Geographically Weighted Panel Regression," *Indones. J. Stat. Its Appl.*, vol. 5, no. 1, pp. 61–74, 2021, doi: 10.29244/ijsa.v5i1p61-74.

[7] O. L. Olvera and B. D. Zumbo, "Heteroskedasticity in Multiple Regression Analysis: What it is, How to Detect it and How to Solve it with Applications in R and SPSS [Heteroscedasticidad en análisis de regresión múltiple: qué es, cómo detectarlo y cómo resolverlo con aplicaciones en R y," *Pract. Assessment, Res. Eval.*, vol. 24, no. 1, 2019.

[8] C. H. Lin and T. H. Wen, "Using geographically weighted regression (GWR) to explorespatial varying relationships of

immature mosquitoes andhuman densities with the incidence of dengue," *Int. J. Environ. Res. Public Health*, vol. 8, no. 7, pp. 2798–2815, 2011, doi: 10.3390/ijerph8072798.

[9] P. Harris, C. Brunsdon, and A. S. Fotheringham, "Links, comparisons and extensions of the geographically weighted regression model when used as a spatial predictor," *Stoch. Environ. Res. Risk Assess.*, vol. 25, no. 2, pp. 123–138, 2011, doi: 10.1007/s00477-010-0444-6.

[10] F. Bruna and D. Yu, "Geographically weighted panel regression," *XI Congr. Galego Estatica e Investig. Oper.*, 2013, [Online]. Available: https://old.reunionesdeestudiosregionales.org/Santiago2016/htdocs/pdf/p1763.pdf.

[11] J. Mummolo, "Improving the Interpretation of Fixed Effects Regression Results*," vol. 6, no. 4, pp. 829–835, 2018, doi: 10.1017/psrm.2017.44.

[12] S. Martha, Y. Yundari, S. W. Rizki, and R. Tamtama, "Penerapan Metode Geographically Weighted Panel Regression (Gwpr) Pada Kasus Kemiskinan Di Indonesia," *BAREKENG J. Ilmu Mat. dan Terap.*, vol. 15, no. 2, pp. 241–248, 2021, doi: 10.30598/barekengvol15iss2pp241-248.

[13] R. Cai, D. Yu, and M. Oppenheimer, "Estimating the spatially varying responses of corn yields to weather variations using geographically weighted panel regression," *J. Agric. Resour. Econ.*, vol. 39, no. 2, pp. 230–252, 2014.

[14] S. M. Meutuah, "Pemodelan Fixed Effect Geographically Weighted Panel Regression Untuk Indeks Pemodelan Fixed Effect Geographically Weighted Panel Regression Untuk Indeks," vol. 6, pp. 241–250, 2017.

[15] S. badan pusat, "BPS Prov Sulawesi Tengah." https://sulteng.bps.go.id/statictable/2017/12/21/664/luas-areal-dan-produksi-tanaman-perkebunan-rakyat-menurut-jenis-komoditi-dan-kabupaten-kota-2016-.html.