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Geographically Weighted Panel Regression Modeling of Rice Production in Indonesia

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Abstract

Rice production plays a strategic role in supporting Indonesia's national food security. However, differences in climatic conditions, pest's and disease infestation (PDI), and harvested area cause rice production to vary across regions. This study aims analyze the effects of PDI, rainfall, air temperature, and harvested area on rice production in Indonesia using the Geographically Weighted Panel Regression (GWPR). Panel data from 34 provinces during 2018-2025 were analyzed, with rice production as the dependent variable and PDI, rainfall, air temperature and harvested area as the independent variables. The best model was selected based on the highest R^2 value and the lowest Akaike Information Criterion (AIC). Results indicate that the GWPR model with the Adaptive Bisquare Kernel weighting function performed best, yielding an R^2 (0,9997) and an AIC (6696,51). The effects of the predictor variables varied across provinces. Harvested area was the most influential factor in several provinces, while PDI, rainfall, and air temperature were significant in major rice-producing regions, particularly on Java Island. These findings suggest that GWPR model is more effective than global panel regression model in capturing spatial variation in rice production across Indonesia.

Keywords: Geographically Weighted Panel Regression; Rice Production; Air Temperature; Harvested Area; Pest and Disease Infestation (PDI)

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1. Introduction

Rice production plays a vital role in maintaining national food security in Indonesia, as rice remains the primary staple food for the majority of the population. Population growth continues to increase the demand for rice, making the sustainability of rice production essential for ensuring food availability and supporting national food self-sufficiency efforts [1]. However, Indonesia's food security faces several challenges, including agricultural land conversion, climate change, and declining production capacity in certain regions [2]. Data from the Central Statistics Agency (BPS) show that Indonesia's rice production has fluctuated over time, decreasing from 59.20 million tons of milled dry paddy (MDP) in 2018 to 54.60 million tons in 2019 and reaching 53.14 million tons in 2025. These figures indicate that national rice production in 2025 remained below the level recorded in 2018 [3, 4].

Changes in rice production over time indicate that rice production is influenced by various dynamic factors. Variations in geographical characteristics, environmental conditions, and

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agricultural practices contribute to differences in rice production patterns across regions. These variations suggest that the relationships between rice production and its determinants are not spatially uniform, as the effects of influencing factors may differ from one region to another. Such spatial heterogeneity highlights the importance of considering local characteristics when modelling rice production [5].

Climate conditions are among the key determinants of rice production. Climate change, characterized by shifts in rainfall patterns, rising temperatures, and the increasing frequency of extreme weather events, can adversely affect agricultural productivity and threaten the stability of food crop production [6]. Rainfall is essential for maintaining water availability throughout the rice growth cycle, and changes in rainfall patterns may consequently influence crop yields. However, the effects of rainfall on rice production are not spatially uniform, as they depend on local environmental conditions and agricultural practices [7]. Temperature is another important climatic factor affecting rice growth and productivity. Temperatures exceeding the optimal range for plant development can reduce yields, although the magnitude of this effect may differ among regions due to variations in local environmental characteristics [8].

In addition to climatic factors, rice production is influenced by several agricultural factors, including Pest and Disease Infestation (PDI) and harvested area. PDI can reduce rice productivity by damaging crops and increasing yield losses, while climatic changes may further promote the development and spread of certain pests and diseases [9]. Harvested area is another important determinant of rice production, as larger harvested areas generally contribute to higher production levels. However, the magnitude of this relationship may vary across regions due to differences in land characteristics, agricultural resources, and farming practices [10].

Variations in geographical, environmental, and agricultural characteristics across regions may lead to spatially heterogeneous relationships between rice production and its influencing factors, including climatic variables, Pest and Disease Infestation (PDI), and harvested area. Previous studies have shown that the effects of these factors are not spatially uniform, indicating that relationships observed in one region may differ from those in another [11]. To capture such spatial variation, local regression approaches such as Geographically Weighted Regression (GWR) have been widely employed. However, GWR is primarily designed for cross-sectional data and does not explicitly account for temporal variation. Consequently, this method may be less suitable for analysing rice production data that vary across both locations and time periods.

Previous studies on rice production have predominantly employed global regression models or examined individual production factors separately. As a result, the spatially varying effects of climatic factors, Pest and Disease Infestation (PDI), and harvested area on rice production have received limited attention, particularly within a panel data framework. To address this issue, the present study applies Geographically Weighted Panel Regression (GWPR) to panel data from 34 provinces in Indonesia during the 2018–2025 period. This approach enables the simultaneous examination of spatial and temporal variations in the relationships between rice production and its determining factors. The findings are expected to provide a more comprehensive understanding of regional differences in the effects of climate factors, PDI, and harvested area on rice production, thereby supporting the development of agricultural management policies that are tailored to local conditions.

2. Methods

This study employed a quantitative approach using the Geographically Weighted Panel Regression (GWPR) method to analyze the effects of climate factors, pest and disease infestation (PDI), and harvested area on rice production in Indonesia. The study utilized secondary panel data from 34 provinces in Indonesia covering the period 2018–2025. Rice production (Y) was used as the dependent variable, while the independent variables consisted of pest and disease infestation (PDI) (X_1), rainfall (X_2), air temperature (X_3), and harvested area (X_4). The data were obtained from Statistics Indonesia (BPS) and the Ministry of Agriculture of the Republic of Indonesia.

The stages of data analysis using the GWPR model are described as follows:

a. Performing descriptive statistical analysis to examine the general characteristics of the research variables and constructing thematic maps to illustrate their spatial distribution across provinces.

b. Panel data regression analysis was performed using the Common Effects Model (CEM), Fixed Effects Model (FEM), and Random Effects Model (REM) [12].
The Common Effects Model (CEM) assumes identical intercepts and slope coefficients across all observations. The model is formulated as follows:

$$Y_{it} = \beta_0 + \sum_{k=1}^{p} \beta_k X_{kit} + \varepsilon_{it} \tag{1}$$

The Fixed Effects Model (FEM) accounts for differences in characteristics among the observed cross-sectional units [13]. The model is formulated as follows:

$$Y_{it} = \alpha_i + \beta_1 X_{1it} + \beta_2 X_{2it} + \cdots + \beta_k X_{kit} + \varepsilon_{it} \tag{2}$$

The Random Effects Model (REM) assumes that unobserved differences across cross-sectional units are random and captured within the model's error component [13]. The model is formulated as follows:

$$Y_{it} = \beta_0 + \beta_1 X_{1it} + \beta_2 X_{2it} + \cdots + \beta_k X_{kit} + u_i + \varepsilon_{it} \tag{3}$$

c. The best panel regression model was selected using the Chow test and the Hausman test. The Chow test was used to compare the Common Effects Model (CEM) and the Fixed Effects Model (FEM), whereas the Hausman test was applied to compare the Fixed Effects Model (FEM) and the Random Effects Model (REM) [12]. The test statistics are given as follows:

$$F = \frac{(RSS_{CEM} - RSS_{FEM})/(N-1)}{RSS_{FEM}/(NT-N-k)} \tag{4}$$

H_0 = The Common Effects Model (CEM) is preferred
H_1 = The Fixed Effects Model (FEM) is preferred
The Hausman test statistic is formulated as follows [14]:

$$H = (\hat{\beta}_{FEM} - \hat{\beta}_{REM})^T \left[Var(\hat{\beta}_{FEM}) - Var(\hat{\beta}_{REM})\right]^{-1} (\hat{\beta}_{FEM} - \hat{\beta}_{REM}) \tag{5}$$

H_0 = The Random Effects Model (REM) is preferred
H_1 = The Fixed Effects Model (FEM) is preferred

d. The multicollinearity test was conducted using the Variance Inflation Factor (VIF). If

$$VIF < 10$$

it indicates the absence of multicollinearity symptoms. The test statistic is formulated as follows:

$$VIF_j = \frac{1}{1 - R_j^2} \tag{6}$$

e. The GWPR model allows regression parameters to vary across regions according to local characteristics [15]. The model is expressed as follows:

$$Y_{it} = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i) X_{kit} + \varepsilon_{it} \tag{7}$$

GWPR employs several kernel weighting functions to construct spatial weights, including the Adaptive Gaussian, Adaptive Bisquare, and Adaptive Tricube kernels [16].

f. Parameter Estimation of Geographically Weighted Panel Regression (GWPR):

$$\hat{\beta}^*(u_i, v_i) = \left(X^{*T} W(u_i, v_i) X^*\right)^{-1} X^{*T} W(u_i, v_i) y^* \tag{8}$$

The parameter estimates are obtained using the Weighted Least Squares (WLS) method. In Equation (8), $\hat{\beta}^*(u_i, v_i)$ denotes the local parameter vector at location (u_i, v_i), $W(u_i, v_i)$ represents the spatial weighting matrix constructed based on regional proximity, X^* is the within-transformed independent variable matrix, and y^* is the within-transformed dependent variable vector [16].

g. Calculate the Euclidean distance between provinces using the latitude and longitude coordinates of each provincial centroid. The distance is computed as follows [17]:

$$d_{ij} = \sqrt{(u_i - u_j)^2 + (v_i - v_j)^2} \tag{9}$$

h. The best GWPR model was selected by comparing the performance of models constructed using the Adaptive Gaussian, Adaptive Bisquare, and Adaptive Tricube kernel functions. The optimal bandwidth for each kernel function was first determined using the Cross-Validation (CV) approach. Subsequently, model performance was evaluated based on the Cross-Validation (CV), Akaike Information Criterion (AIC), corrected Akaike Information Criterion (AICc), coefficient of determination (R^2), and adjusted coefficient of determination (Adjusted R^2) values. The best model was identified as the model with the smallest CV, AIC, and AICc values, and the largest R^2 and Adjusted R^2 values [15]. The CV statistic is formulated as follows:

$$CV = \sum_{i=1}^{n} \left(y_i - \hat{y}_{\neq i}(b)\right)^2 \tag{10}$$

$$AIC = 2n \ln(\hat{\sigma}) + n \ln(2\pi) + n + tr(S) \tag{11}$$

i. Conduct parameter significance tests and group provinces according to the combinations of significant predictor variables affecting rice production.

j. Interpret the local parameter estimates and spatial patterns identified by the GWPR model.

k. Formulate conclusions based on the results of the analysis.

3. Results and Discussion

a. Descriptive Statistics

Descriptive statistical analysis was performed to summarize the characteristics of the research variables before spatial model estimation. The study utilized panel data from 34 provinces in Indonesia during the period 2018–2025. The descriptive statistics of the variables are presented in Table 1.

Table 1: Descriptive Statistics

Variable	Minimum	Maximum	Mean	Standard Deviation
Rice Production (Y)	305	10,537,922	1,626,050.2	2,666,336.798
Pests and Disease Infestation (X_1)	0	75,589	7,977.732	11,845.05
Rainfall (X_2)	490.3	31,363.11	2,929.816277	2,517.51
Air Temperature (X_3)	24.89	30.04	27.72973562	0.90981
Harvested Area (X_4)	113	1,841,346	311,817.81	470,405

Source: Processed Data (2026)

Table 1 shows that the average rice production across 34 provinces in Indonesia during the 2018–2025 period was 1,626,050.18 tons per year. Based on the average value, eight provinces recorded rice production above the national average, while the remaining 26 provinces produced below the average level. The highest rice production was observed in East Java Province in 2018, reaching 10,537,922 tons. In contrast, the lowest rice production was recorded in Riau Islands Province in 2024, amounting to 305 tons

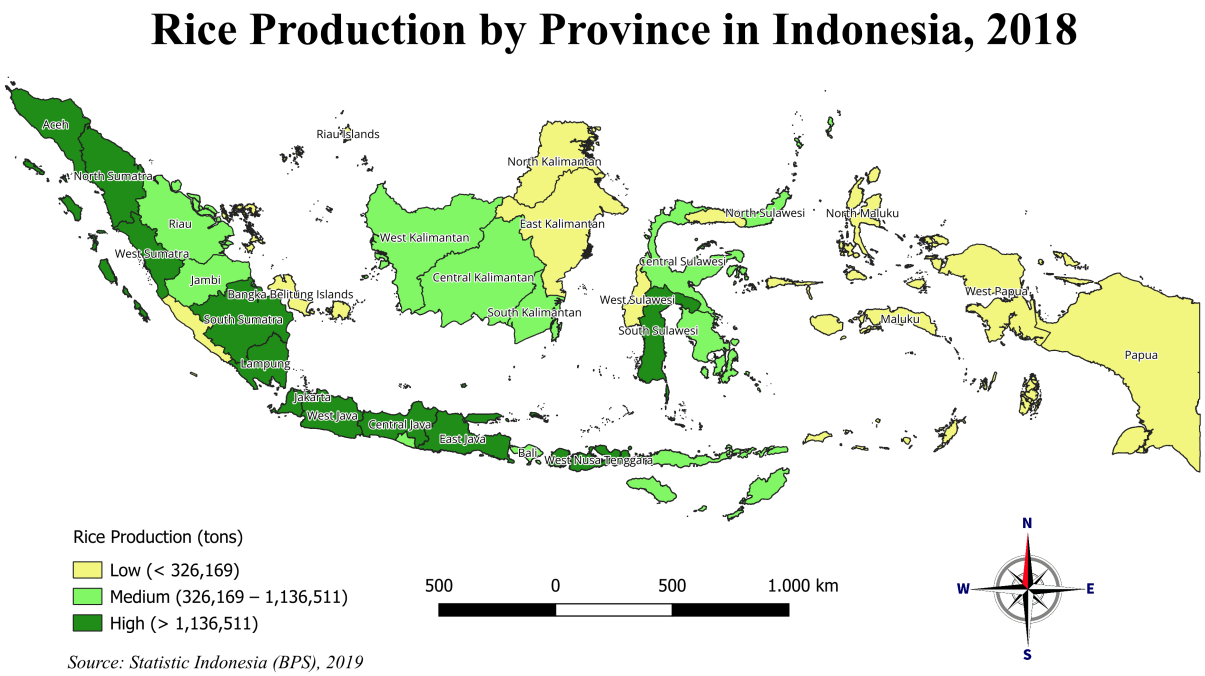


Fig. 1: Distribution of Rice Production in Indonesia in 2018

Figure 1 illustrates the spatial distribution of rice production across Indonesia in 2018, classified into three categories: low ($\leq$ 326,000 tons), medium (326,001–1.14 million tons), and high ($>$ 1.14 million tons).. The distribution was relatively balanced, with 11 provinces in the low category, 12 in the medium category, and 11 in the high category. Provinces with high rice production were predominantly located on the islands of Java and Sumatra, as well as in South Sulawesi.

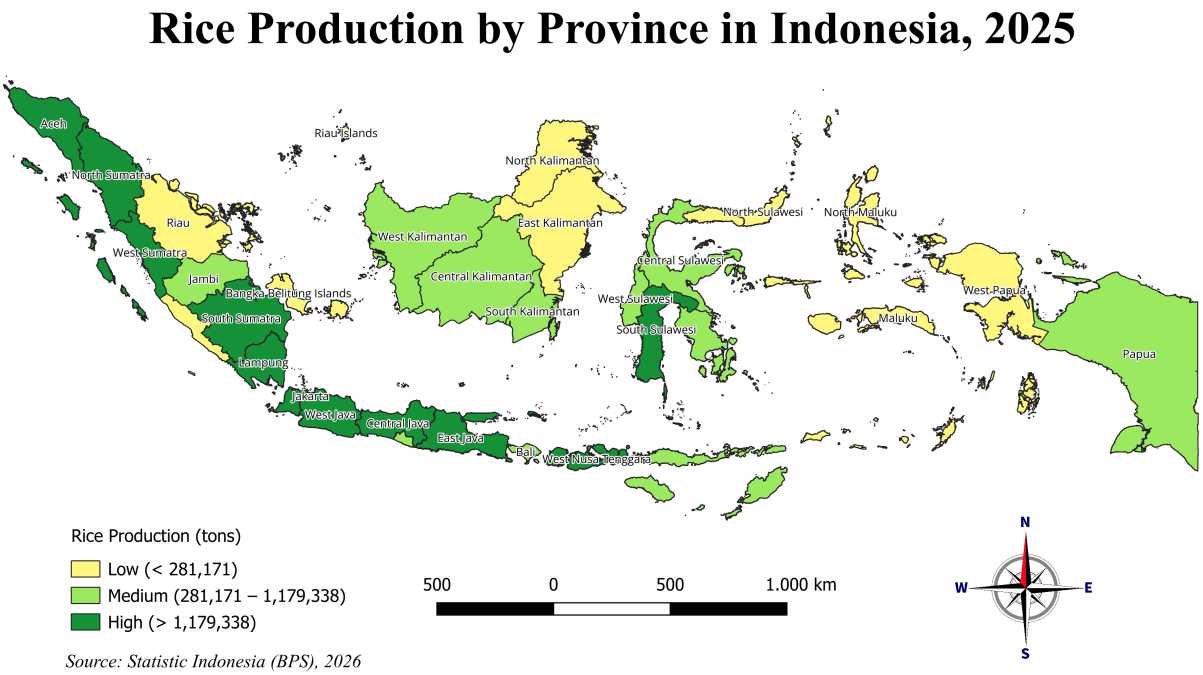


Fig. 2: Distribution of Rice Production in Indonesia in 2025

Figure 2 illustrates the spatial distribution of rice production in Indonesia in 2025, classified into three categories: low ($\leq$ 281,000 tons), medium (281,001–1.18 million tons), and high ($>$ 1.18 million tons). Provinces in the high-production category remained concentrated on the islands of Java and Sumatra, as well as in South Sulawesi, indicating that these regions continued to be the main rice-producing areas in Indonesia.

b. Panel Data Regression Estimation

Parameter estimation for the panel data regression model was carried out using three approaches: the Common Effects Model (CEM), Fixed Effects Model (FEM), and Random Effects Model (REM). The estimated models obtained from each approach are presented as follows.

The estimated Common Effects Model (CEM) is given by:

$$\hat{Y}_{it} = 1,414,600 + 2.936X_{1(it)} - 9.588X_{2(it)} - 54,929X_{3(it)} + 5.578X_{4(it)}$$

The estimated Fixed Effects Model (FEM) is given by:

$$\hat{Y}_{it} = \alpha_i + 3.289X_{1(it)} - 11.560X_{2(it)} - 49.856X_{3(it)} + 5.538X_{4(it)}$$

The estimated Random Effects Model (REM) is given by:

$$\hat{Y}_{it} = 1,380,300 + 3.017X_{1(it)} - 10.118X_{2(it)} - 53.551X_{3(it)} + 5.568X_{4(it)}$$

.

c. Selection of the Panel Data Regression Model

The selection of the panel data regression model was conducted using the Chow test and Hausman test. The results of both tests are presented in Table 2.

Table 2: Results of the Chow Test and Hausman Test

Test	Test Statistic	p-value	Conclusion
Chow Test	F statistic $= 1.9764$	< 0.002019	FEM model is better than CEM
Hausman Test	$\chi^2 = 50.843$	2.407×10^{-10}	FEM model is better than REM

Source: Processed Data (2026)

Table 2 shows that the Chow test produced a p-value (< 0.002019), indicating that the Fixed Effects Model (FEM) is preferred over the Common Effects Model (CEM). Furthermore, the Hausman test yielded a p-value ($2.407 \times 10^{-10} < 0.05$), indicating that the Fixed Effects Model (FEM) is preferred over the Random Effects Model (REM). Therefore, the FEM was selected for subsequent analysis.

d. Multicollinearity Test

Multicollinearity among the predictor variables was assessed using the Variance Inflation Factor (VIF) to determine whether a high correlation exists among the independent variables. The results of the multicollinearity test are presented in Table 3.

Table 3: Multicollinearity Results

Variable	**VIF**
Pests and Disease (X_1)	3.213
Rainfall (X_2)	1.032
Air Temperature (X_3)	1.049
Harvested Area (X_4)	3.225

Source: Processed Data (2026)

Table 3 shows that all predictor variables have VIF values below 10, indicating that there is no serious multicollinearity among the independent variables. Therefore, all variables can be included in the subsequent modeling process.

e. Spatial Heterogeneity Test

The spatial heterogeneity test was conducted using the Spatial Breusch–Pagan (BP) test based on a 34×34 spatial weighting matrix. The results are presented in Table 4.

Table 4: Results of the Spatial Heterogeneity Test

Weighting Matrix	**Test Statistic**	***p*-value**	**Decision**
A1	913.3177	$3.489456 \times 10^{-195}$	Reject H_0
A2	1407.5485	$3.185440 \times 10^{-302}$	Reject H_0
A3	1374.9368	$3.710691 \times 10^{-295}$	Reject H_0

The Spatial Breusch–Pagan (BP) test results using three weighting functions, namely A1 (Adaptive Gaussian), A2 (Adaptive Bisquare), and A3 (Adaptive Tricube), produced p-values less than $\alpha = 0.05$. Therefore, H_0 was rejected, indicating the presence of spatial heterogeneity in rice production across provinces in Indonesia. This result confirms that the GWPR model is suitable for capturing local variations in regression parameters.

e. Geographically Weighted Panel Regression (GWPR) Modelling.

The GWPR model was constructed using spatial weights derived from Euclidean distances between provinces and three adaptive kernel functions: Adaptive Gaussian, Adaptive Bisquare, and Adaptive Tricube. The optimal bandwidth values obtained for the 34 provinces are summarized in Table 5.

Table 5: Optimal Bandwidth of GWPR Kernel Functions

Kernel Function	Optimal Bandwidth	Selection Method
Adaptive Gaussian	20 nearest neighbours	Cross Validation
Adaptive Bisquare	26 nearest neighbours	Cross Validation
Adaptive Tricube	26 nearest neighbours	Cross Validation

Table 5 shows that the optimal bandwidth varies across kernel functions . The Adaptive Gaussian function yields an optimal bandwidth of 20 nearest neighbors, while the Adaptive Bisquare and Adaptive Tricube functions yield an optimal bandwidth of 26 nearest neighbors, respectively. These differences indicate that each kernel function applies a different spatial weighting scheme in capturing local variations across regions.

f. Selection of the Best GWPR Model.

The best GWPR model was selected by comparing the R^2 and AIC values of the three kernel functions. The preferred model was determined based on the lowest AIC value and the highest R^2 value. The comparison results are presented in Table 6.

Table 6: Model Performance of GWPR Kernel Functions

Kernel Function	R^2	AIC
Adaptive Gaussian	0.9984	7101.183
Adaptive Bisquare	0.9997	6696.951
Adaptive Tricube	0.9997	6700.092

Table 6 shows that the Adaptive Bisquare kernel was selected as the best GWPR model because it produced the lowest AIC value (6696.951) and the highest R^2 value (0.9997). Therefore, the estimation and interpretation of local parameters were based on the GWPR model using the Adaptive Bisquare kernel.

g. Parameter Significance Test

The parameter significance test was conducted to identify predictor variables that significantly affect rice production in the GWPR model. A predictor variable is considered significant if its p-value is less than 0.05. Table 7 presents the parameter significance test results for East Java Province as an example.

Table 7: Results of the GWPR Parameter Significance Test for East Java Province

Variable	p-value	Decision
Pest and Disease Infestation (PDI) (X_1)	0.04316	Significant
Rainfall (X_2)	0.00134	Significant
Air Temperature (X_3)	0.55085	Not Significant
Harvested Area (X_4)	1.0381×10^{-305}	Significant

Table 7 shows that Pest and Disease Infestation (PDI) (X_1), rainfall (X_2), and harvested area (X_4) significantly affected rice production in East Java Province, as their p-values were less than 0.05. In contrast, air temperature (X_3) was not statistically significant because its p-value exceeded 0.05. These results indicate that rice production in East Java was more strongly influenced by agricultural and rainfall-related factors than by air temperature during the study period. The differences in variable significance across provinces reflect the spatial heterogeneity captured by the GWPR model.

Based on the parameter significance tests conducted for all provinces, the provinces were subsequently grouped according to the combinations of significant predictor variables affecting rice production. The results are presented in Table 8.

Table 8: Grouping of Provinces Based on Significant Variables

Significant Variables	Number of Provinces	List of Provinces
X_1, X_2, X_3, X_4	3	Bali, DKI Jakarta, West Java
X_1, X_2, X_4	4	East Java, Bangka Belitung Islands, Lampung, South Sumatra
X_1, X_4	1	Bengkulu
X_2, X_3, X_4	1	West Nusa Tenggara
X_2, X_4	4	Special Region of Yogyakarta, West Sulawesi, South Sulawesi, Southeast Sulawesi
X_3, X_4	1	Banten
X_4	18	Aceh, Gorontalo, Jambi, Central Java, West Kalimantan, South Kalimantan, Central Kalimantan, North Kalimantan, Riau Islands, North Maluku, East Nusa Tenggara, Papua, West Papua, Riau, Central Sulawesi, North Sulawesi, West Sumatra, North Sumatra

Source: Processed Data (2026)

Table 8 shows that harvested area (X_4) was the most dominant factor affecting rice production, as it was the only significant variable in 18 provinces. The combination of all predictor variables, namely Pest and Disease Infestation (PDI) (X_1), rainfall (X_2), air temperature (X_3), and harvested area (X_4), was significant in three provinces, namely Bali, DKI Jakarta, and West Java. Other combinations of significant predictors were identified in the remaining provinces, indicating spatial variation in the factors influencing rice production. The provincial grouping based on these significant predictors is further illustrated through the thematic map presented in Figure 3.

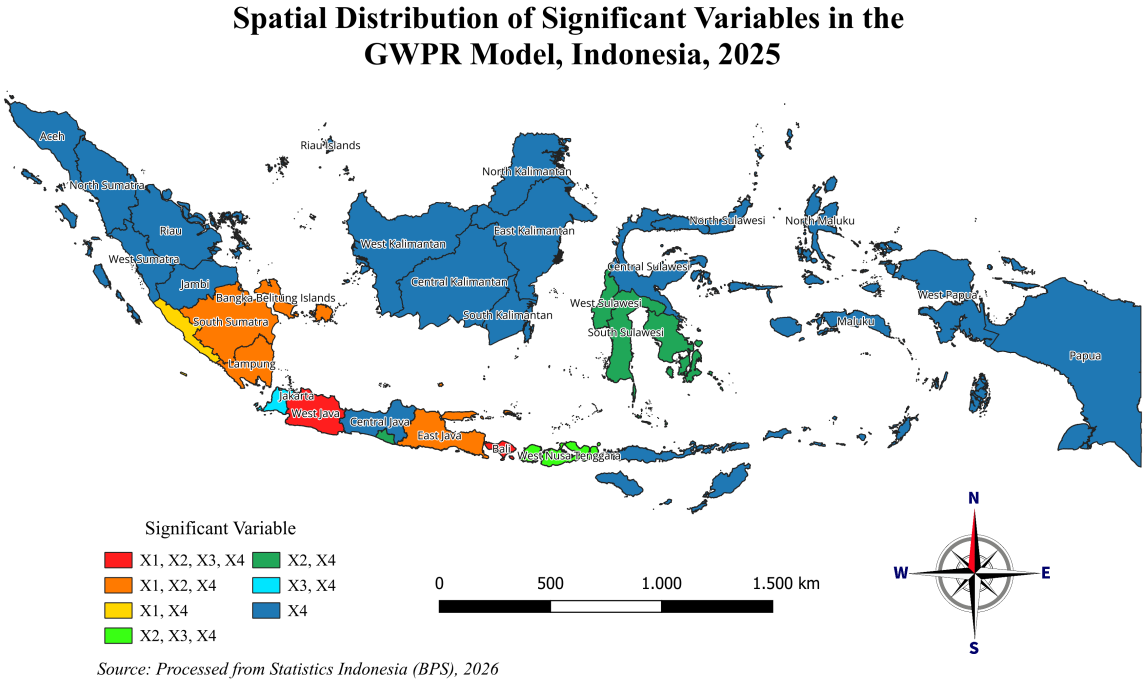


Fig. 3: Map of Provincial Groupings in Indonesia Based on Variables That Significantly Influence Rice Production

Figure 3 illustrates the spatial heterogeneity of variables that significantly affect rice production across provinces in Indonesia in 2025. Harvested area (X_4) was the most dominant factor, showing a significant effect in most provinces, particularly in Sumatra, Kalimantan, and Eastern Indonesia. In contrast, Java and several other provinces exhibited more complex combinations of significant factors, including Pest and Disease Infestation (PDI) (X_1), rainfall (X_2), air temperature (X_3), and harvested area (X_4). These regional differences indicate that the factors determining rice production vary spatially, highlighting the importance of using a local modelling approach such as GWPR to capture location-specific characteristics.

These findings are consistent with previous studies reporting that the influence of harvested area and other determinants of rice production varies across regions. In addition, climatic factors such as rainfall and air temperature have been shown to exhibit spatially varying effects on agricultural production.

4. Conclusion

Based on the analysis results, it can be concluded that the Geographically Weighted Panel Regression (GWPR) model with the Adaptive Bisquare weighting function was the best model for modelling rice production in Indonesia. This local model performed better than the global panel regression model, as indicated by its higher R^2 value and lower AIC value. The results confirmed the presence of spatial heterogeneity, indicating that the effects of predictor variables on rice production varied across provinces according to their local characteristics.

Overall, Pest and Disease Infestation (PDI) (X_1), rainfall (X_2), air temperature (X_3), and harvested area (X_4) significantly influenced rice production, although the combinations of significant variables differed among provinces. Among these variables, harvested area (X_4) was the most dominant factor because it was significant in a greater number of provinces compared with the other variables. Based on the similarity of significant variable patterns, provinces in Indonesia could be classified into several groups with similar rice production determinant characteristics.

CRediT Authorship Contribution Statement

Rahmawati Tri Iriani: Conceptualization, Methodology, Software, Formal Analysis, Data Curation,Writing–Original Draft, Visualization. Danang Ariyanto: Conceptualization, Methodology, Supervision, Validation, Writing Review and Editing.

Declaration of Generative AI and AI-assisted technologies

The authors used ChatGPT, Grammarly, and DeepL solely as language-support tools during the preparation of this manuscript, including translation, grammar checking, and improvement of writing clarity. These tools did not contribute to the study design, data collection, data analysis, interpretation of results, or scientific conclusions. All content was critically evaluated, revised, and approved by the authors, who bear full responsibility for the manuscript.

Declaration of Competing Interest

The authors declare no competing interests

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Data and Code Availability

The data supporting the findings of this study were obtained from the Central Statistics Agency (BPS) and the Center for Agricultural Data and Information Systems (PUSDATIN), Ministry of Agriculture of the Republic of Indonesia. The datasets include rice production, harvested area, rainfall, air temperature, and pest and disease infestation (PDI) data for 34 provinces in Indonesia during the period 2018–2025. Requests for data and code access will be considered for academic and research purposes, subject to confidentiality and data use agreements

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