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A Spatial Error Model Approach to Identifying Determinants of Rice Availability in Mamasa and Polewali Mandar Regencies

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ABSTRACT

Food availability is a crucial aspect in maintaining regional food security. Rice, as the main staple food for Indonesians, plays a crucial role in maintaining social and economic stability. Mamasa Regency and Polewali Mandar Regency in West Sulawesi Province are linked in rice production, which influences rice availability. However, in recent years, rice availability has decreased in both regions. This study aims to analyze the factors that influence rice availability spatially. The approach used is spatial analysis with the Spatial Error Model method. The data used is secondary data from 2023, covering rice availability, rice production, population, cultivated land area, and the number of farming households. The results show a significant spatial influence between regions with a parameter value of 0.023[A1]1, indicating that the conditions of one region influence the surrounding areas. The results show that the spatial error parameter (λ) is statistically significant, as indicated by a p-value of 0.0231, suggesting the presence of spatial dependence in the error component due to unobserved factors shared across neighboring regions. The model has a very high level of accuracy with a coefficient of determination close to one and a relatively small level of prediction error. Rice production has a positive effect, while the number of farming households has a negative effect on rice availability. Thus, these two factors are the main determinants of rice availability in the study area.

1. Introduction

Rice availability is a strategic concern in the national development of Indonesia, as rice constitutes the staple food for the majority of the population. The heavy reliance of Indonesia on a single food commodity renders the rice production and distribution systems critical to ensuring economic, social, and political stability. Variations in rice supply, resulting from production disruptions or distribution bottlenecks, have the potential to cause inflation, food shortages, and social instability. Data from Statistics Indonesia indicate that national rice production has exhibited substantial fluctuations over time, driven by factors including

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climate change, land degradation, inadequate infrastructure, and evolving agricultural policies.

Effective management of rice availability requires accurate information on rice supply, demand, and stock levels to avoid imbalances between surpluses and shortages in the market. Maintaining this balance is crucial for ensuring rice price stability, thereby keeping rice affordable for consumers while providing reasonable economic returns to farmers as primary producers. Consequently, the government has consistently implemented various strategic policies aimed at increasing rice production, including the expansion of cultivated land and the intensification of agricultural activities.

However, issues related to rice availability are not uniformly distributed across regions. For instance, Mamasa Regency in West Sulawesi is a mountainous area characterized by challenging geographical conditions and limited infrastructure, resulting in suboptimal rice distribution. These conditions contribute to high transportation costs and relatively higher rice prices compared with those in other regions. In addition, extreme climate events, such as the El Niño phenomenon and excessive rainfall, have adversely affected paddy production, leading to instability in rice availability. In contrast, Polewali Mandar Regency, which shares a border with Mamasa, has better infrastructure and plays an important role in supporting interregional rice distribution. This interregional linkage suggests the presence of spatial dependence in rice availability, emphasizing the importance of employing analytical approaches that account for locational characteristics and spatial interactions among regions.

Several previous studies have investigated factors influencing various phenomena using regression approaches. Studies on crime rates in Bali and East Java Provinces found that the Spatial Error Model (SEM) provided the best fit for explaining the observed patterns [15]. Another study on diarrhea incidence in Bali Province also demonstrated that the SEM was able to capture spatial effects significantly [17]. These findings highlight the superiority of spatial regression approaches over conventional regression methods in analyzing data characterized by spatial dependence.

Conventional regression methods generally rely on the assumption of independence among observations and are therefore limited in their ability to capture interregional relationships. In the case of rice availability, however, the conditions of a given region are likely to be affected by those of neighboring regions through production, distribution, and accessibility mechanisms. Accordingly, a spatial regression approach, particularly the Spatial Error Model (SEM), is needed to account for spatial dependence through the error structure of the model. By incorporating such spatial effects, the resulting model may yield more accurate and representative estimates of the underlying conditions, particularly when spatial dependence is evidenced by appropriate diagnostic tests such as Moran's I and the Lagrange Multiplier test.

This study aims to identify the factors influencing rice availability in Mamasa Regency and Polewali Mandar Regency by employing the Spatial Error Model (SEM[A2][A3]). The findings are expected to contribute to the development of spatial statistical analysis and to

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provide empirical evidence for more effective and data-driven policymaking aimed at maintaining the stability of rice availability in these regions.

2. Literature Review

2.1 Spatial Regression

Spatial regression is a statistical approach used to analyze the relationship between a dependent variable and multiple independent variables while accounting for spatial effects across observational units. The general form of the spatial regression model is given as follows [10]:

$$\boldsymbol{y} = \rho \boldsymbol{W} y + \boldsymbol{X\beta} + \boldsymbol{u} \tag{1}$$

$$\boldsymbol{u} = \lambda \boldsymbol{W u} + \boldsymbol{\varepsilon} \tag{2}$$

$$\boldsymbol{\varepsilon} \sim N\,(0, \sigma^2 I)$$

2.2 Spatial Error Model (SEM)

SEM is a spatial regression model that accounts for spatial autocorrelation in the disturbance term. It is applied in this study because rice availability is assumed to exhibit spatial dependence, implying that observations in one region are not independent but influenced by neighboring areas. In SEM, spatial dependence is captured through the error structure, where the error terms of adjacent regions are correlated, indicating spatial autocorrelation. The general form of the model is given as follows [1].

$$\boldsymbol{y} = \boldsymbol{X\beta} + \boldsymbol{u} \tag{3}$$

$$\boldsymbol{u} = \lambda \boldsymbol{W u} + \boldsymbol{\varepsilon} \tag{4}$$

$$\boldsymbol{\varepsilon} \sim N\,(0, \sigma^2 I_n)$$

Where:

- **y** : An $(n \times 1)$ vector of the dependent variable
- ρ : Spatial autoregressive coefficient for the dependent variable
- $\boldsymbol{W}$: Spatial weight matrix $(n \times n)$
- $\boldsymbol{\beta}$: Regression coefficient vector of size $(p+1) \times 1$
- $\boldsymbol{X}$: Matrix of independent variables of size $n \times (p+1)$
- λ : Spatial error coefficient
- $\boldsymbol{u}$: Spatially structured error vector of size $n \times 1$
- $\boldsymbol{\varepsilon}$: Error term vector of size $n \times 1$ representing the difference between observed and fitted values for each region

2.3 Residual Analysis

This test is performed to assess whether the residuals of the regression model are normally distributed. A regression model is considered appropriate when its residuals follow a normal distribution. Normality can be evaluated using the Shapiro-Wilk one-sample test.
Hypotheses:

- H_0 : The residuals are normally distributed
- H_1 : The residuals are not normally distributed

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The Shapiro-Wilk test is a widely used method for assessing normality, particularly for small sample sizes ($n < 50$). It evaluates whether a sample distribution follows a normal distribution and is performed based on the Shapiro-Wilk test statistic.

$$W = \frac{\sum_{i=1}^{\frac{n}{2}} a_i(\varepsilon_{n-i-1} - \varepsilon_i)^2}{\sum_{i=1}^{n}(\varepsilon_i - \bar{\varepsilon})^2} \tag{5}$$

Where:

W : Shapiro-Wilk test statistic coefficient
a_i : Weight coefficients derived from the Shapiro-Wilk table
ε_i : Residual value of the i-th observation
$\bar{\varepsilon}$: Mean residual value
n : Sample size (number of observations)

The decision is based on the p-value. The null hypothesis is rejected when the p-value is less than the significance level (α), implying that the data do not follow a normal distribution.

2.4 Multicollinearity Test

The multicollinearity test is conducted to ensure that the independent variables in the regression model are not highly correlated with one another. One commonly used statistical measure to detect multicollinearity is the Variance Inflation Factor (VIF). In general, a VIF value exceeding 10 indicates the presence of multicollinearity among the predictor variables. The VIF can be computed using the following formula [4].

$$VIF_J = \frac{1}{1-R_J^2}, \text{j} = 1, \ldots, p \tag{6}$$

Where:

VIF : *Variance Inflation Factor*
p : Number of independent variables

Decision rule:
Multicollinearity is not indicated when $VIF < 10$, whereas $VIF \geq 10$ indicates the presence of multicollinearity among the predictor variables.

2.5 Homoscedasticity Test

The homoscedasticity assumption states that the variance of the error terms is constant and equal to σ^2, meaning that the error variances are identical and do not exhibit any systematic pattern. In contrast, heteroscedasticity occurs when the variance of the error terms is not constant and shows a certain pattern. The heteroscedasticity test aims to determine whether there is inequality in the error variance across observations in the regression model [2]. One commonly used method to test for heteroscedasticity is the Breusch-Pagan test.
Hypotheses:

$H_0 : \sigma_1{}^2 = \sigma_2{}^2 = \cdots = \sigma_n{}^2 = \sigma^2$ (homoscedasticity)
H_1 : at least one $\sigma_i{}^2 \neq \sigma^2$ untuk $\text{i} = 1_\text{i}, \ldots \sigma$ (heteroscedasticity)

Test statistic:

$$BP = \frac{\mathbf{1}}{\mathbf{2}}\boldsymbol{f}^T\boldsymbol{Z}(\boldsymbol{Z}^T\boldsymbol{Z})^{-1}\boldsymbol{Z}^T\boldsymbol{f} \tag{7}$$

Decision rule is the null hypothesis H_0 is rejected if the Breusch-Pagan (BP) test statistic exceeds the critical value of $x^2_{(\alpha,p-1),}$ or equivalently if the p-value is less than 0.05.

2.6 Spatial Weight Matrix

The spatial weight matrix, denoted as $\boldsymbol{W}$, is an $n \times n$ matrix that represents the spatial relationship or proximity between regions or observational units. For each observational unit i, the element w_{ij} indicates which location j may influence the variable at location i [10]. The smaller the distance between two locations, the larger the value of w_{ij} conversely, the greater the distance between two locations, the smaller the value of w_{ij}. All diagonal elements w_{ij} are equal to zero, as a location is assumed not to influence itself. In general, the spatial weight matrix $\boldsymbol{W}$ can be expressed as follows

$$\boldsymbol{W} = \begin{pmatrix} w_{11} & \cdots & w_{1n} \\ \vdots & w_{ij} & \vdots \\ w_{n1} & \cdots & w_{nm} \end{pmatrix}, w_{ij} = w_{ji} \tag{8}$$

Where:

w_{ij} : Represents the weight between region i and region j

i : 1,2…n

j : 1,2…n

There are various methods for determining spatial weights, one of which is distance-based weighting. In principle, spatial weights between two locations are determined based on the distance between them. The closer two locations are, the larger the assigned weight. In general, the distance between locations i and j is calculated using the Euclidean distance, which can be obtained using the following formula:

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

Where:

u_i : Latitude of location i

u_j : Latitude of location j

v_i : Longitude of location i

v_j : Longitude of location j

Distance-based weight matrices include K-Nearest Neighbors (KNN), radial distance, inverse distance, exponential distance, and double-distance weighting. In this study, a K-Nearest Neighbors (KNN)-based spatial weight matrix is employed. The main principle of the KNN algorithm is to identify the K nearest locations to a given point based on the smallest distance. The distance is calculated using the Euclidean method [20].

The construction of the spatial weight matrix W using the K-Nearest Neighbor (KNN) approach aims to determine the most appropriate number of neighbors. The main objective is to select the value that yields the strongest Moran's I index, while minimizing the Akaike Information Criterion (AIC). The process of constructing the spatial weight matrix W using the K-Nearest Neighbor approach is carried out through the following steps:

1. Calculate the Euclidean distance between locations i and j
2. Sort the resulting distances in ascending order

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3. Select K-nearest locations as the optimal number of neighbors based on the smallest distance values.

The selection of the K value is initially based on the Moran's Index obtained through an iterative procedure. The optimal K value is chosen as the one that yields the highest Moran's Index.

2.7 Model Goodness of Fit

a. Coefficient of Determination (R^2)

The selection of the most appropriate model is based on the coefficient of determination, namely R^2 and Adjusted R^2. The coefficient of determination (R^2) indicates the extent to which the independent variables are able to explain the variation in the dependent variable. A higher R^2 value, or a value closer to 1, indicates better model performance in explaining the relationship among the variables. The formula for calculating R^2 is expressed as follows (Hair et al., 2011).

$$R^2 = \frac{JKR}{JKT} \text{ atau } R^2 = 1 - \frac{JKR}{JKT} \tag{10}$$

Where SSR denotes the regression sum of squares, SSE denotes the error (residual) sum of squares, and SST denotes the total sum of squares (Said and Susanti, 2024). Meanwhile, Adjusted R^2 is used to provide a more accurate assessment of the model's ability to explain the dependent variable by taking into account the number of independent variables included in the model. This measure helps to prevent overfitting, a condition in which adding more independent variables increases R^2 without genuinely improving the model's explanatory power. Thus, Adjusted R^2 reflects how effectively the model explains the variation in the data relative to its complexity. A higher Adjusted R^2 value indicates a better model in representing the relationship among variables in a more accurate and efficient manner. The formula for calculating Adjusted R^2 is given as follows.

$$R^2_{adj} = 1 - \frac{(1-R^2)(n-1)}{n-p-1} \tag{11}$$

Where:

R^2 : Coefficient of determination
p : Number of independent variables
n : Number of observations

b. Root Mean Square Error (RMSE)

According to [19], the Root Mean Square Error (RMSE) is one of the most commonly used measures for comparing two or more models in spatial analysis. A smaller RMSE value indicates that the model has higher accuracy.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y})^2} \tag{12}$$

Where:

n : Number of observations
y_i : Observed value of the i-th observation
$\hat{y}_i$: Predicted value of the i-th observation

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3. Methods

3.1 Data Sources

This study utilizes secondary data obtained from the Agricultural Offices of Mamasa and Polewali Mandar Regencies, as well as from the official website of Statistics Indonesia (BPS) in 2023. The units of analysis in this study consist of 33 sub-districts located in Mamasa and Polewali Mandar Regencies. The variables used in this study include rice availability, rice production, population size, cultivated land area, and the number of farming households.

In analyzing the factors influencing rice availability, this study applies spatial regression methods using location-based data, which include latitude (u) and longitude (v) coordinates for each observational area. The dependent variable in this study is rice availability (Y), while the independent variables used are:

X_1: Rice production
X_2: Population size
X_3: Cultivated land area
X_4: Number of farming households

3.2 Analysis Procedure[A4]

In modeling the Spatial Error Model (SEM) for factors affecting rice availability, several analytical steps are carried out as follows:

1. Conducting model assumption tests, including the residual normality test, multicollinearity test, and homoscedasticity test.
2. Constructing the spatial weight matrix based on K-Nearest Neighbors (KNN), where the optimal value of K is selected based on the highest Moran's I index and the lowest Akaike Information Criterion (AIC)
3. Testing spatial dependence using Moran's I to detect the presence of spatial autocorrelation.
4. Performing model selection using Lagrange Multiplier (LM) tests to detect spatial autocorrelation in the error term, which justifies the use of the Spatial Error Model (SEM)
5. Estimating the SEM parameters using Maximum Likelihood Estimation (MLE)
6. Evaluating model performance using R-Square and Adjusted R-Square
7. Conclusions.

4. Results and Discussion

4.1 Distribution of Rice Availability Data in 2023

This analysis uses data on rice availability levels in 2023 across 33 sub-districts as the basis for examining its distribution pattern.

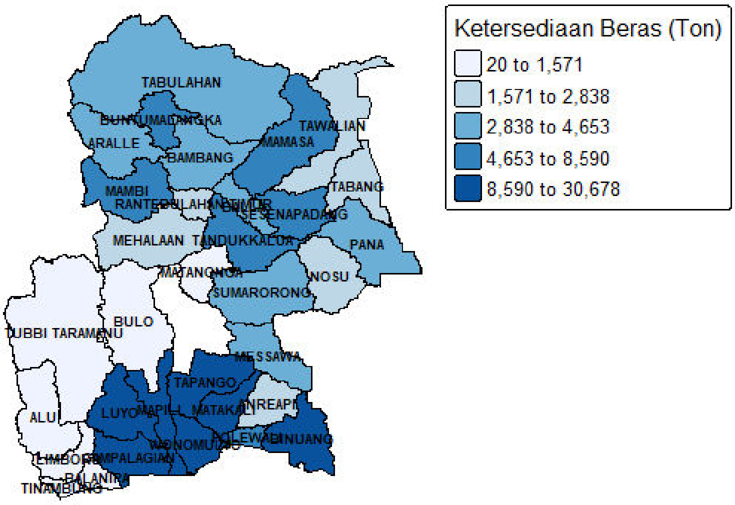

Figure 1. Map of Rice Availability Distribution in Mamasa and Polewali Mandar Regencies

The distribution of rice availability in Mamasa and Polewali Mandar Regencies can be seen in Figure 1. The figure shows that neighboring sub-districts tend to have relatively similar levels of rice availability and form clustering patterns. Differences in color gradients on the map indicate variations in rice availability across sub-districts. Darker colors represent sub-districts with higher levels of rice availability. Based on the spatial distribution pattern in 2023, it can be concluded that spatial autocorrelation exists, indicating that a given region is influenced by its neighboring areas[A5][A6].

4.2 Assumption Tests

a. Residual Normality Test

To examine whether the residuals are normally distributed, the Shapiro-Wilk one-sample test is applied with the following hypotheses:

H_0 : The residuals are normally distributed

H_1 : The residuals are not normally distributed

Table 1. Normality results

W	W_{table}	***p-value***
0.95129	0.931	0.1451

Based on the Shapiro–Wilk test results, the obtained value is W = 0.95129 > W_{table}= 0.931, and the p-value is 0.1451 $> \alpha = 0.05$. Therefore, the decision is to fail to reject H_0, indicating that the residuals of the model are normally distributed.

b. Multicollinearity Test

One commonly used method to detect multicollinearity is the Variance Inflation Factor (VIF). In general, a VIF value greater than 10 indicates the presence of multicollinearity among the independent variables. The results of the multicollinearity test are presented below.

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Table 2. Multicollinearity results

Variable	VIF
X_1	7.407600
X_2	1.226487
X_3	3.826932
X_4	7.691210

Based on Table 2, it can be seen that the VIF values for variables X_1, X_2, X_3, and X_4 are all less than 10. This indicates that the independent variables in the model are not highly correlated with each other. Therefore, it can be concluded that there is no multicollinearity problem, and the multicollinearity assumption is satisfied.

c. Homoscedasticity Test

Homoscedasticity refers to a condition in which the variance of the residuals in a regression model remains constant across all observations. When the variance of the residuals is not constant, the condition is referred to as heteroscedasticity, which may affect the validity of the estimation results. To ensure that the homoscedasticity assumption is satisfied, one commonly used method is the Breusch-Pagan test, which is applied with the following hypotheses:

$H_0 : \sigma_1{}^2 = \sigma_2{}^2 = \cdots = \sigma_n{}^2 = \sigma^2$ (Homoscedasticity)

H_1 : at least one $\sigma_i{}^2 \neq \sigma^2$(heteroscedasticity)

Decision rule: Reject H_0 if the BP statistic is greater than $x^2_{(\alpha,p-1)}$, or if the p-value is less than 0.05.

Table 3. Homoscedasticity results

Breusch-Pagan	***p-value***	$x^2_{(0,05;4)}$
9.0425	0.06005	9.488

From Table 3, the Breusch-Pagan value is 9.042 < $x^2_{(0.05;4)}$ and the p-value is greater than 0.05. Therefore, H_0 is not rejected, indicating that there is no heteroscedasticity and the homoscedasticity assumption is satisfied.

4.3 Spatial Dependence Test

Spatial dependence refers to the existence of relationships among observed spatial units. Testing for spatial autocorrelation is carried out using Moran's Index, a statistical measure used to identify spatial relationships among observational locations and to describe the resulting spatial distribution pattern. To determine whether spatial autocorrelation exists, a significance test of Moran's Index is conducted.

Hypotheses:

H_0 : There is no spatial autocorrelation

H_1 : There is spatial autocorrelation

Test statistic:

$$z(I) = \frac{I - E\,(I)}{\sqrt{Var(I)}} \tag{13}$$

Decision rule:

Reject H_0 if $z(I) > z_{\alpha/2.}$ or if the p-value is less than α (0.05). The results are presented in Table 4.

Table 4. Spatial autocorrelation results

Test Statistic	Value
$z(I)$	4.571
Moran's I	0.5932
E (*I*)	0.000002426

Based on the results, the absolute value of $|\ Z(I)\ |$ is 4.571, which is greater than 1.96. This indicates the presence of positive spatial autocorrelation among sub-districts in Mamasa and Polewali Mandar Regencies. Furthermore, the Moran's Index value is 0.5932, which lies within the range $0 \leq I \leq 1$. This implies the existence of positive spatial autocorrelation. Since $I > E(I)$, it can be concluded that the spatial pattern exhibits spatial dependence[A7].

4.4 Spatial Error Model (SEM)

SEM is one of the approaches in spatial regression used when spatial dependence exists in the error component, meaning that disturbances in one region are influenced by neighboring regions. The selection of the SEM is based on the Lagrange Multiplier test, which aims to detect spatial autocorrelation in the error term. If the lambda (λ) parameter is statistically significant ($p - value < 0.05$), it indicates the presence of spatial effects in the error component, and thus the SEM is appropriate to use. The parameter estimation results of the SEM are presented in the following table 5.

Table 5. SEM Parameter Estimates

Variable	Estimated coefficients	*P-value*
Intercept	24.3474	0.0884
X_1	0.54137339	0.0001
X_2	0.00012370	0.7738
X_3	0.01954042	0.2435
X_4	-0.04891711	0.0001
λ	0.60721	0.0231

Based on Table 5, at a 5% significance level, there are two independent variables that significantly affect rice availability, namely rice production (X_1) and the number of farming households (X_4), as indicated by p-values less than 0.05. In addition, the estimation results show that the lambda (λ) parameter in the SEM has a p-value of 0.0231 and a coefficient value of 0.60721 at the 5% significance level, indicating the presence of spatial dependence among regions in rice availability.

4.5 Goodness of Fit

One of the measures used to evaluate model goodness of fit includes R^2, Adjusted R^2, and RMSE. The results are presented in the following Table 6.

Table 6. Goodness of fit results

Criteria	SEM
R^2	0.9999821
Adjusted R^2	0.9999795
RMSE	26.59936[A8]

Based on the results of the SEM analysis, it can be concluded that the coefficient of determination R^2 is 0.9999821 and the Adjusted R^2 is 0.9999795, indicating that the model explains the data variation very well. In addition, the RMSE value of 26.59936 indicates that the average prediction error between the model outputs and the actual rice availability values is relatively small. This suggests that the SEM has strong predictive performance and is capable of producing estimates that are close to the observed values.

5 Conclusion[A9]

Based on the analysis results, the significant model is the SEM, as indicated by the lambda (λ) coefficient of 0.60721 with a p-value of $0.0231 < 0.05$, suggesting the presence of spatial dependence in rice availability. The model demonstrates excellent performance, with an R^2 value of 0.9999821, an Adjusted R^2 of 0.9999795, and an RMSE of 26.59936, indicating its strong ability to explain variation across regions in Mamasa and Polewali Mandar Regencies. The exceptionally high R^2 and Adjusted R^2 values may be attributed to the strong linear relationship between the explanatory variables rice production, population size, cultivated land area, and the number of farming households and rice availability at the subdistrict level. Furthermore, the incorporation of spatial error dependence through the SEM specification effectively captures unobserved spatial factors shared across neighboring subdistricts, thereby reducing unexplained variation in the model. Post-estimation diagnostics further support the model validity, as the Shapiro-Wilk test confirms normally distributed residuals ($W = 0.95129$, $p > 0.05$). In addition, the estimation results show that rice production and the number of farming households significantly affect rice availability, where rice production has a positive effect, while the number of farming households has a negative effect

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