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Robust Spatial Autoregressive (Robust SAR) Modeling in the Case of Poverty Percentage in West Java

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ABSTRACT
Poverty is a complex problem influenced by various economic and social factors, such as the open unemployment rate, the minimum wage, population density, and the school participation rate. This study aims to model the poverty rate in West Java Province by considering spatial effects and the existence of outliers through the application of Spatial Autoregressive (SAR) and Robust Spatial Autoregressive (Robust SAR) models. Based on the Lagrange Multiplier test, the SAR model is declared suitable for use. However, the presence of outliers in the data necessitated the use of a robust approach to obtain more accurate results. The analysis showed that the Robust SAR model had a coefficient of determination (R^2) of 81.53%, higher than that of the SAR model at 77.48%, making it a better model for explaining variations in poverty levels. Of the four independent variables, only School Participation Rate had a significant effect in both models, where an increase in School Participation Rate contributed to a decrease in the poverty rate. This finding confirms the importance of investment in education as a strategic effort to reduce welfare inequality between regions in West Java.

KEYWORDS
Poverty, West Java, Robust SAR, SAR.

1. INTRODUCTION

Poverty is one of the main problems in Indonesia, including in of BPS-Statistics Jawa Barat Province, in September 2024 the percentage of poor people in West Java reached 7.08%, which means that millions of people still live below the poverty line. Some districts/cities even show higher poverty rates than the provincial average, such as Indramayu District, which reached 12.13%. This indicates that there are still development gaps between regions in West Java.

In the socio-economic context, there are a number of factors related to poverty. The open unemployment rate indicates labor absorption and is closely related to the availability of jobs. The district/city minimum wage reflects wage policies that have the potential to affect people's purchasing power. Population density can put pressure on resources, infrastructure, and job creation. Meanwhile, the School Participation Rate is an indicator of the quality of human resources, as higher education is expected to increase the competitiveness of the workforce. However, in analyzing the relationship between these variables, extreme values (outliers) or abnormal data distributions are often found, which can affect the validity of statistical model estimation results [1].

Conventional estimation methods, such as Ordinary Least Squares (OLS), tend to be vulnerable to the presence of outliers, which can potentially produce biased and inaccurate conclusions [2]. In addition, conventional estimation methods, such as OLS, tend to be vulnerable to the presence of, which can potentially produce biased and inaccurate conclusions [2]. In addition, there is often spatial dependence between regions, where the value of a variable in one location is influenced by the value of variables in surrounding locations.

This spatial dependence cannot be adequately addressed by standard regression models, potentially causing bias in the estimation [3]. Therefore, more sophisticated approaches such as the Spatial Autoregressive (SAR) method are needed to account for spatial dependence [4]. However, SAR models are still vulnerable to the presence of outliers, which can disrupt the resulting estimates. For this reason, the Robust SAR method was developed, which is more resistant to extreme data while still taking spatial effects into account. This approach allows for more stable parameter estimation and more reliable analysis results.

Several previous studies have discussed poverty in West Java using a spatial approach. Research by [5] used the Spatial Autoregressive Fixed Effect Model to identify poverty factors, but did not consider the existence of outliers in the data. In fact, poverty data in West Java shows extreme values, such as Indramayu Regency, which has a poverty rate far above the provincial average, thus potentially affecting the model estimation results [6]. The research by [7] used Spatial Autoregressive Quantile Regression to analyze poverty. Although this approach considers differences in influence between quantiles, the method was not specifically designed to deal with extreme data, so the estimation results may be less stable.

Based on this, it can be concluded that there has been no research specifically discussing outliers in poverty analysis in West Java. Therefore, this study uses the Robust Spatial Autoregressive (Robust SAR) method to produce more stable parameter estimates in data containing outliers, thereby providing a more accurate analysis. Therefore, this study uses the Robust SAR method to analyze the relationship between TPT, UMK, population density, and APS on poverty levels in West Java. The results of the analysis are expected to provide a more comprehensive understanding of socio-economic dynamics at the district/city level, as well as a basis for formulating more targeted poverty reduction policies.

2. LITERATURE REVIEW

2.1 Multiple Linear Regression

Multiple linear regression is a regression model with multiple independent variables. The multiple linear regression equation with k independent variables is as follows [8]:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_k x_{ik} + \varepsilon_i \tag{1}$$

Where y_i is the value of the dependent variable in observation i, $\beta_0,\ \beta_1, \beta_2, \dots,\ \beta_k$ are regression coefficient, $x_{i1}, x_{i2}, \dots,\ x_{ik}$ are the values of the independent variables from observation i, and ε_i is error.

2.2 Ordinary Least Square

The regression technique known as OLS (Ordinary Least Squares) aims to minimize the sum of squared errors. The parameter estimation process uses the OLS approach, which determines the regression coefficient (β) by minimizing the error. The parameter estimator is expressed as follows [9]:

$$\hat{\beta} = (X^T X)^{-1} X^T y \tag{2}$$

Where y is an observation vector of the response variable sized $n \times 1$, X is a predictor variable matrix sized $n \times (p+1)$, and $\hat{\beta}$ is a vector of estimated parameters sized $(p+1) \times 1$.

2.3 Classical Assumption Test

Classical assumption tests are performed to ensure that the data being analyzed has a normal distribution (normality test) and that there is no multicollinearity, no autocorrelation, and homoscedasticity in the model [10]. The normality test aims to assess whether the residuals of the regression model follow a normal distribution. The null hypothesis (H_0) posits that the residuals follow a normal distribution, whereas the alternative hypothesis (H_1) suggests that the residuals deviate from normality. If H_0 is rejected, it implies that residuals are not normally distributed. The multicollinearity test is used to find relationships or correlations between independent variables in the regression model. In addition, the autocorrelation test is used to determine whether the regression model residuals in period t and the residuals from the previous period $(t-1)$ are correlated with each other. The homoscedasticity test is performed to determine whether the residuals for each observation in the regression model have constant variance, where H_0 states that the data is homoscedastic and H_1 states that the data is heteroscedastic. Rejection of H_0 indicates heteroscedasticity in the regression model.

2.4 Spatial Weight Matrix

The weight between the observed locations based on the distance between these locations is determined using a spatial weighting matrix. Contiguity can be defined in several ways, namely [11]:

1. Rook Contiguity: Corners are not considered when determining the observation area; instead, adjacent sides are used.
2. Bishop Contiguity (Angle Contiguity): Intersecting corners are used to determine the observation area, while sides are not considered.
3. Queen Contiguity (Side-Corner Contiguity): Corners are considered when determining the observation area, as are intersecting sides.

2.5 Spatial Regression

The regression method known as spatial regression is applied to data that is spatial in nature or has a spatial influence[12]. Spatial regression is an analysis used to analyze the relationship between one variable and several other variables by providing spatial effects for many locations that function as observation points. The spatial regression model has the following general form.

$$y = \rho W_1 + X\beta + U \tag{3}$$

$$U = \lambda W_2 U + \varepsilon,\ \varepsilon \sim N\left(0, I\sigma^2\right) \tag{4}$$

Where y is an $n \times 1$ dependent variable vector, ρ is the coefficient of spatial lag parameter for dependent variable, W is an $n \times n$ spatial weight matrix, X is an independent variable matrix of size $n \times (k+1)$, β is a regression parameter coefficient vector of size $(k+1) \times 1$, λ is the spatial error parameter coefficient, U is a vector of errors spatial effects measuring $n \times 1$, ε is an $n \times 1$ error vector.

General spatial regression models can be used to form other models as follows:

1. If $\rho = 0$ and $\lambda = 0$, this model referred to be a classical linear regression model with the following equation:

$$y = X\beta + \varepsilon \tag{5}$$

2. If $\rho \neq 0$ and $\lambda = 0$, it is referred to as a spatial autoregressive regression (SAR) with the following equation:

$$y = \rho W y + X\beta + \varepsilon \tag{6}$$

3. If $\rho = 0$ and $\lambda \neq 0$, it is referred to as a spatial error model (SEM) with the following equation:

$$y = X\beta + u \tag{7}$$

$$u = \lambda W u + \varepsilon \tag{8}$$

4. If $\rho \neq 0$ and $\lambda \neq 0$, it is called to as a spatial autoregressive moving average (SARMA) with the following equation:

$$y = \rho W y + X\beta + u \tag{9}$$

$$u = \lambda W u + \varepsilon \tag{10}$$

2.6 Spatial Dependency Test

2.6.1 Moran's Index

The use of Moran's I statistics in spatial correlation testing is one method for detecting spatial dependency between locations. The estimation of correlation between observations that relate to location on the same variable is known as spatial autocorrelation [12]. Moran's index can be defined as follows [13]:

$$I = \frac{n \sum_{i=1}^{n} \sum_{i=1}^{n} w_{ij} \ (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=j}^{n} w_{ij} \ \ (x_i - \bar{x})^2} \tag{11}$$

Where, n is the count of observations, $\bar{x}$ is the average value of x_i from the location n, x_j is the observation value at location j, x_i is the observation value at location i, w_{ij} is the element of spatial weight matrix between location i and location j.

Adjacent regions have similar values if Moran's I > 0, and the data pattern is more likely to be cluster, whereas if the value of $I < 0$, then adjacent regions have significant differences in value, so that the data pattern is randomly distributed. Meanwhile, a value of I close to 0 indicates no spatial dependence between regions.

2.6.2 Lagrange Multiplier

The Lagrange Multiplier is also used in determining the spatial dependence of lag on independent variables with the general form of the Lagrange Multiplier test as follows [14]:

$$LM_{lag} = \frac{\left(U^{‘}Wy\right)^2}{nP} \tag{12}$$

where

$$nP = T + \frac{(WX\beta)^{‘} M\,(WX\beta)}{s^2} \tag{13}$$

$$T = trace\,\left(\left(W + W^{‘}\right)W\right) \tag{14}$$

$$M = I - X\left(X^{‘}X\right)^{-1}X^{‘} \tag{15}$$

$$s^2 = \frac{u^{‘}u}{n} \tag{16}$$

U as the residual. If the value of $LM_{lag} > X^2{}_{(a,1)}$, then there is spatial dependence in the independent variables. If a model contains spatial lag dependence, then spatial regression is performed using a spatial autoregressive (SAR) model.

2.7 Spatial Regression Model

2.7.1 Spatial Autoregressive (SAR)

Spatial Autoregressive, also known as Spatial Lag, is a spatial regression analysis with spatial effects located in the response variable. A response variable at location I depends on a response variable at location j, or in other words, there is spatial dependence in the response variable. The SAR model can be defined as follows [7]:

$$y = \rho Wy + X\beta + \varepsilon\,; \qquad \varepsilon\; N(0, \sigma_\varepsilon^2 l_n) \tag{17}$$

The equation describes the variation in y as a linear combination of neighboring units. In spatial autoregressive models, parameter estimation uses maximum likelihood estimation techniques, which maximize the probability function to determine unknown parameters. Biased and inconsistent parameters are produced when OLS methods are used to estimate SAR model parameters

2.8 Robust Spatial Autoregressive Model (Robust SAR)

Robust regression is a regression method that is necessary when there are outliers that affect the model or when the error distribution is not normal. This robust approach can produce results that are resistant to outliers and evaluate data containing outliers. The basic principle of the robust regression method is to weight the estimation of the regression model parameters to produce a normal error distribution. Robust Spatial Regression (RSAR) is the result of combining robust regression techniques with spatial regression models (SAR). Outliers in spatial regression models can be accommodated using Estimation-M, which is the simplest estimation technique both theoretically and computationally [14].

Robust M-estimation is an estimation that minimizes the objective function ρ, it's $min_\beta \rho(ui)$. The weight function in regression is determined by the objective function ρ. Weight values are generated using the weight function or $w(ui)$. The weighting function used is the Tukey Bisquare function. In robust-M SAR estimation, the objective function ρ is as follows [8]:

$$min_\beta \rho(\frac{U}{S}) = min_\beta \rho(\frac{(I - \lambda W)Y - X\beta)}{s} \tag{18}$$

Where s is the robust estimation scale with the following formula:

$$s = \frac{median\,|u_i - median(u_i)|}{0,6745} \tag{19}$$

The value 0.6745 is used so that s becomes an unbiased estimator of σ when the sample size is large and the errors are normally distributed.

3. METHODOLOGY

The secondary data used in this study came from Open Data Jabar and the BPS-Statistics Jawa Barat Province website. The data consists of 18 districts and 9 cities in West Java province. Variables to be examined in this study are four predictor variables (X) and one response variable (Y). These include The analytical method applied in this study is the spatial autoregressive regression model. The analysis was conducted using R. The steps of the analysis include:

Table 1. Variables of the Study

Variable	Scale	Description
Y	Numeric	Percentage of Poverty Population
X_1	Numeric	District/City Minimum Wage
X_2	Numeric	Open Unemployment Rate
X_3	Numeric	Population Density
X_4	Numeric	School Participation Rate

1. Describe dependent variables to illustrate regional conditions using graphs or visualizations to gain informative insights for analysis.
2. Develop a multiple linear regression model using OLS method.
3. Conduct classical assumption tests to ensure model validity.
4. Define a spatial weight matrix to represent spatial interactions between regions.
5. Conduct a spatial dependency test to identify the presence of spatial autocorrelation.
6. Estimate the Spatial Autoregressive (SAR) model.
7. Detect spatial outliers in SAR model using Moran's scatterplot
8. Estimate the Robust Spatial Autoregressive (Robust SAR) model.
9. Select the best model according to the coefficient of determination (R^2).

4. RESULT & DISCUSSION

4.1 Descriptive Analysis

Figure 1 shows a map of poverty distribution in West Java, indicating that areas in dark purple, such as Indramayu, Kuningan, Majalengka, and Tasikmalaya City, have higher poverty rates than other regions, while areas in yellow, such as Depok City, Bekasi City, and Bandung City, have lower poverty rates. Areas with similar poverty levels tend to cluster together, where dark areas are adjacent to other dark areas and light areas are close to other light areas, indicating a possible spatial influence. This suggests that poverty levels in one area may be related to those in neighboring areas.

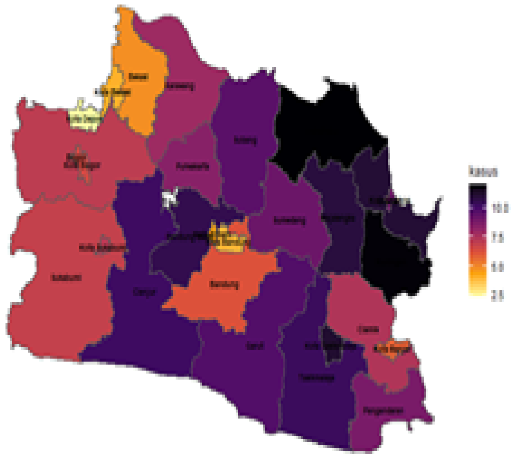

Figure 1. Map of Poverty Percentage Distribution in West Java.

4.2 Multiple Regression Modeling

Multiple linear regression modeling was first performed prior to the application of spatial regression. Parameter estimation in this model employs the Ordinary Least Squares (OLS) method. Based on the results, the following regression equation was obtained:

$$\hat{Y} = 13.32 - 9.457 \times 10^{-7}\, X_1 + \; 0.1886X_2 - 0.0001438X_3 - 0.1139X_4$$

4.3 Classical Assumption Tests

The values of each classical assumption test result are presented in **Table 2**. Based on the results of all classical assumption tests,

Table 2. Classical Assumption Test Results

Assumption Test	Method	Test Statistic	p-value
Normality	Anderson-Darling	0.68968	0.06356
Multicollinearity	Variance Inflation Factor (VIF)	$X_1 = 1.8669$	-
		$X_2 = 1.7908$	
		$X_3 = 2.162$	
		$X_4 = 2.0921$	
Autocorrelation	Durbin-Watson	2.3871	0.7982
Homoscedasticity	Breusch-Pagan	2.1314	0.7116

the p-values for normality, autocorrelation, and homoscedasticity are greater than 0.05, indicating that the null hypothesis is accepted. In addition, all VIF values are below 10, indicating no multicollinearity among the independent variables. Therefore, it can be concluded that all classical assumptions are satisfied, indicating that the regression model meets the requirements for further analysis.

4.4 Spatial Dependency Tests

4.4.1 Moran's I Test

The spatial autocorrelation analysis was conducted using Moran's I test on the poverty percentage variable in West Java in 2024. The analysis result are presented in **Figure 2**.

Figure 2 shows that most regions are in quadrants I and III, indicating a positive spatial correlation. This explains that regions with high poverty rates tend to be located close to other regions with similar poverty rates, and vice versa. These results are reinforced by the test statistics in **Table 3**.

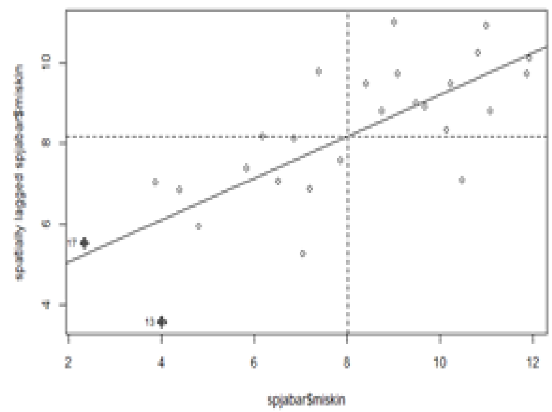

Figure 2. Moran scatterplot of Poverty Percentage in West Java.

Table 3. Table 4.2. Moran's I Test Results

Moran's I	E(I)	Var(I)	p-value
0.5189	-0.0385	0.0224	0.00009731

According to **Table 3**, it is known that Moran's I value is 0.5189 and the p-value is 0.00009731. Because the p-value < 0.05, it means that there is significant positive spatial autocorrelation in the observations. Because there is spatial autocorrelation in the dependent variable (Y), the spatial autoregressive model is considered appropriate to capture the spatial dependence effect in the data.

4.4.2 Lagrange Multiplier Test

The Lagrange Multiplier (LM) test is used to determine the spatial regression model that fits the data. The test results are shown in **Table 4**.

Table 4. Lagrange Multiplier Test Results

Uji Lagrange Multiplier	Value	p-value
Lagrange Multiplier (Error)	0.0006	0.98042
Lagrange Multiplier (Lag)	2.6698	0.10227
Robust Lagrange Multiplier (Error)	3.0618	0.08015
Robust Lagrange Multiplier (Lag)	5.7310	0.01667
Lagrange Multiplier (SARMA)	5.7316	0.05694

According to **Table 4**, it can be known that the p-value of the Robust Lagrange Multiplier (Lag) of 0.01667 is less than 0.05, meaning that there is lag dependency. Thus, the appropriate spatial regression model is the Spatial Autoregressive Model, so this model is selected for further modeling.

4.5 Spatial Model

4.5.1 Spatial Autoregressive (SAR) Model

In accordance with the Lagrange Multiplier tests, the appropriate model to model the factors affecting the poverty rate in West Java is Spatial Autoregressive (SAR). The following are the results of the SAR model parameter estimation.

As shown in **Table 5**, it is known that the spatial coefficient (ρ) is 0.365 and significant at the 5% level, meaning that the poverty rate in a district/city will increase by 0.365 times the average poverty of the districts/cities neighboring that region, assuming that other variables remain constant. In addition, the independent variable that considerably influences poverty rate is the School Participation Rate variable (X_4) because it has a p-value of 0.004083, which is less than 0.05. This means that 1%

Table 5. SAR Model Parameter Estimation Results

Parameter	Coefficient	p-value
ρ	0.3651	0.0138
Intercept	8.7009	0.00002
X_1	-6.218e-07	0.0549
X_2	0.2030	0.2867
X_3	-0.0001	0.0872
X_4	-0.0977	0.0041

increase in school participation rate is estimated to reduce the poverty rate in West Java by 0.0977, assuming other variables remain constant.

4.5.2 Moran's Scatterplot

Before RSAR modeling is performed, outliers are first detected in the SAR model, which can be seen from the following Moran's Scatterplot Model SAR graph.

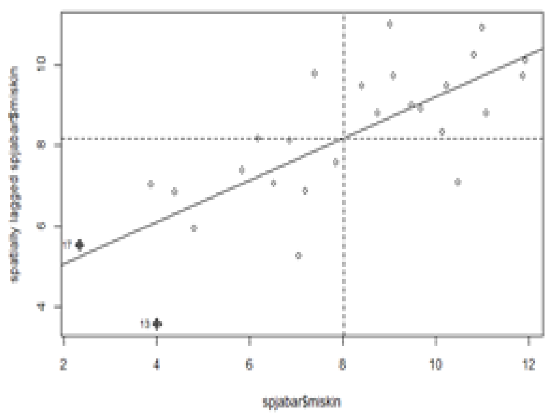

Figure 3. Moran's Scatterplot SAR Model.

Figure 3 shows that there are two outliers in the SAR residuals. Therefore, further analysis was conducted using the Robust Spatial Autoregressive model.

4.5.3 Robust Spatial Autoregressive (RSAR) Model

Model parameter estimates were resulted from an iterative process using the IRLS (Iteratively Reweighted Least Square) approach. The Robust SAR estimation-M results are presented in **Table 6**.

Table 6. Robust SAR Model Parameter Estimation Results

Parameter	Coefficient	p-value
ρ	0.3651	0.3867
Intercept	11.8883	0.0989
X_1	-3.9932e-07	0.5386
X_2	0.25598	0.2567
X_3	-0.00008	0.3541
X_4	-0.09248	0.0190

As **Table 6** shows, the spatial lag coefficient (ρ) is 0.365 and is not significant, so there is no strong spatial dependence between regions. Furthermore, among the independent variables, the School Participation Rate variable (X_4) has a significant effect on the poverty rate because it has a p-value of 0.01903, which is less than 0.05. This means that every 1% increase in school participation rate is estimated to reduce the poverty percentage in West Java by 0.09248, assuming other variables remain constant.

The Robust SAR model based on parameter estimation is as follows.

$$\widehat{y_i} = 0.3651 \sum_{j=1}^{27} w_{ij} y_j + 11.8883 - 3.9932 \times 10^{-7} X_{i1} + 0.25598 X_{i2} - 0.00008 - 0.09248 X_{i4}$$

Based on the estimation results, the Robust SAR model obtained can be used to predict poverty levels in each region by considering internal factors and the influence of surrounding regions. For example is Indramayu Regency, with a minimum wage of Rp 2.623.697, an open unemployment rate of 6.25%, a population density of 922 people/km2, and a school participation rate of 12.8%, so the predicted poverty percentage is around 14.47%. This shows that regional characteristics and educational conditions play an important role in reducing poverty percentage .

4.6 Selection of the Best Model

The model selection process was to choose the best estimation model for examining the variables affecting West Java's poverty rate. One of the evaluation criteria used was the coefficient of determination (R^2). The R^2 values for the two models are as follows. Based on **Table 7**, the R^2 value for the Robust SAR model is 81.53%, which is higher than the SAR model at 77.48%.

Table 7. Selection of the Best Model

Spatial Regression Estimation Model	R^2
SAR	77.48%
Robust SAR	81.53%

Therefore, the Robust SAR model is selected as the best model for analyzing the variables influencing the poverty rate in West Java and is able to overcome spatial outliers because the M-estimation in the Robust SAR model can account for the presence of outliers in the spatial regression model.

4.7 Discussion

In this study, the Robust Spatial Autoregressive (Robust SAR) model was applied to handle spatial data containing outliers. In the initial SAR model, the spatial lag coefficient (ρ) was statistically significant, indicating spatial autocorrelation between regions. However, after the Robust approach was applied and two outliers were controlled, the coefficient ρ became statistically not significant. This finding indicates that the spatial effects detected in the initial SAR model were most likely caused by the influence of extreme data, rather than by actual spatial dependence. Thus, variations in poverty levels in West Java are more influenced by the internal characteristics of each region, such as school participation rates, than by the influence of surrounding regions.

The findings of the research indicate that the School Participation Rate has a negative and significant effect on the poverty percentage in West Java Province in 2024. It means that the higher the school participation rate in a region, the lower the poverty rate. These findings are in line with a study by [15], which states that the SPR has a negative and significant impact on poverty. Education has an important influence on the increase or decrease of poverty in a region. These results also support studies by [16], which claims that poverty levels are impacted by the SPR. Theoretically, it can be concluded that educational factors influence poverty in Indonesia. School Participation Rate shows that the influence of education is significant on poverty, so there needs to be equal distribution of educational facilities, which will help reduce poverty rates.

Meanwhile, the District/City Minimum Wage do not impact poverty rate. This is also finding research by [17], which claims that the regional minimum wage has no statistical effect on the poverty rate in regencies/cities. This is because the minimum wage in most regencies/cities follows the provincial wage and is relatively uniform, so it does not have a significant impact on the poverty rate in those areas.

Poverty is also not affected by the open unemployment rate. This finding is reinforced research by [18], which claims that poverty is not significantly impacted by the unemployment rate. This can occur if individuals who are classified as unemployed are not actually financially poor, due to the presence of family members with high income capable of supporting these individuals' need. In addition, there is no statistically significant relationship between population density and poverty. Research conducted by [19] shows similar findings, where population density does not affect poverty. This is because if there are sufficient job opportunities, high population density does not always lead to an increase in poverty. In some areas, even though there are many residents, people can still find decent jobs so that poverty percentage can be reduced.

5. CONCLUSION

The model selection results indicate that the Robust Spatial Autoregressive (Robust SAR) model is the most appropriate model for analyzing the variables affecting the poverty percentage in West Java. That's because the Robust SAR model has a higher coefficient of determination (R^2) than the SAR model and is able to overcome the existence of spatial outliers. The estimation results show that the School Participation Rate (X_4) is a variable that significantly affects the poverty rate, where an increase in this variable expected to reduce the poverty percentage in West Java.

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