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Spatial Autoregressive Quantile Regression Model of Population in Central Kalimantan

Ajeng Diah Amanda, Netti Herawati*, Tiryono Ruby, Nusyirwan

Department of Mathematics, University of Lampung, Indonesia

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***Corresponding Author:** Netti Herawati

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Abstract **Original Research Article**

Central Kalimantan exhibits regional variation in population size, which is suspected to be influenced by several factors. This study aims to determine the best model and identify the factors that influence the population in Central Kalimantan. The method used is Spatial Autoregressive Quantile Regression because it can overcome spatial dependence and spatial heterogeneity. The data used are population size, population growth rate, number of poor people, and number of midwives in Central Kalimantan in 2024. The results of the best model are at the 0.1 quantile, where the number of poor people and the number of midwives significantly influence the population size in Central Kalimantan.

Keywords: Central Kalimantan, Population Size, Spatial Dependence, Quantile Regression, Number of Poor People, Number of Midwives, Population Growth Rate.

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I. INTRODUCTION

Regression analysis is a statistical method used to analyze the relationship between one dependent variable and one or more independent variables. In regression, several assumptions must be met, namely, normally distributed errors, homoscedasticity, and no multicollinearity [1]. The method is sensitive to violations of these assumptions, such as when the data do not meet the normality assumption, the variance is not homogeneous, there is autocorrelation, and so on. To estimate parameter values, the Ordinary Least Squares method is commonly used. However, if the data exhibits these problems, the Ordinary Least Squares method cannot be applied.

To address these issues, the median regression method emerged. This method replaces the mean approach in Ordinary Least Squares with the median. It is applied particularly when the data distribution is skewed or not bell-shaped. However, in practice, this method is also considered insufficient for deep analysis because it only considers two segments of the data. Since data can be divided into more than two groups, the quantile regression method was developed [2].

Quantile regression is a regression method that involves dividing the data into specific quantiles by minimizing asymmetrically weighted absolute residuals and estimating the conditional quantile function of a data distribution [3]. Quantile regression is used to describe the effects of several independent variables on the dependent variable at a specific point.

If an observed object is influenced by spatial effects, the method should be spatial regression. Spatial regression is a regression method used for spatial-type data or data that has spatial effects [4]. Spatial effects consist of two types, that is, spatial dependence and spatial heterogeneity. Spatial dependence means that the observation at location i depends on observations at other locations j, where j≠i. On the other hand, spatial heterogeneity occurs due to random location effects, which are differences between one location and another [5].

The Spatial Autoregressive Model is a regression model that incorporates spatial effects into its modeling. Spatial Autoregressive, also known as the Spatial Lag Model, is a type of spatial model that applies an area-based approach by considering the influence of spatial lag only on the dependent variable [5]. This model is also referred to as the Mixed Regressive-Autoregressive model because it combines a conventional regression model with a spatial lag regression model on the dependent variable [6]. Spatial Autoregressive Quantile Regression is a model that combines the spatial autoregressive model with the quantile regression model. This model can address issues of dependence and variability in spatial data modeling.

Based on the explanation above, the authors are interested in developing a Spatial Autoregressive Quantile Regression model for the population in the regencies/municipalities of Central Kalimantan Province. This study is expected to produce the best-fitting model and identify the factors that influence the population size in Central Kalimantan.

2. Spatial Autoregressive Quantile Regression Model (SARQR)

A fundamental aspect of a spatial model is the spatial weight matrix. This matrix indicates the relationship between one region and another. It is an $n \times n$ matrix and is denoted by W. The general form of the spatial weight matrix is as follows:

$$\boldsymbol{W} = \begin{bmatrix} W_{11} & W_{12} & \dots & W_{1j} \\ W_{21} & W_{22} & \dots & W_{2j} \\ \vdots & \vdots & \vdots & \vdots \\ W_{i1} & W_{i2} & \dots & W_{ij} \end{bmatrix}$$

There are several types of contiguity, namely rook contiguity, bishop contiguity, and queen contiguity [7]. In this study, the spatial weight matrix was constructed using queen contiguity, in which districts that share either a common side or corner with another district are considered neighboring regions. The spatial weight matrix is obtained from the standardized estimation of the contiguity matrix. The estimated matrix is the sum of each row equals one [8].

$$W_{ij} = \frac{C_{ij}}{\sum_{i=1}^{n} C_{ij}}$$

The test of spatial effects includes the assessment of spatial dependence and spatial heterogeneity. The test for spatial dependence is conducted using the Lagrange Multiplier (LM) test and Moran's Index test, while the test for spatial heterogeneity is conducted using the Breusch-Pagan test [9].

Moran's Index is a widely used method for measuring global spatial autocorrelation. This method can be used to detect the initial presence of spatial randomness. Such spatial randomness may indicate the existence of patterns that are clustered or form trends across space [10]. The formula for Moran's Index is as follows [8]:

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}((x_j - \bar{x})(x_j - \bar{x}))}{\sum_{i=1}^{n} (x_1 - \bar{x})^2}$$

The range of Moran's Index values, when using a standardized spatial weight matrix, is between -1 and 1. A Moran's Index value between -1 and 0 indicates the presence of negative spatial autocorrelation, meaning that neighboring regions tend to have dissimilar values. A value between 0 and 1 suggests positive spatial autocorrelation, where similar values are clustered in space. Meanwhile, a value of zero indicates the absence of spatial clustering, meaning the spatial pattern is random.

In spatial models, the Lagrange Multiplier test is used to detect whether there is a significant spatial effect in the model. The general form of the Lagrange Multiplier test is as follows [6]:

$$LM_{lag} = \frac{\left(\frac{u'Wy}{s^2}\right)}{nP}$$

In decision-making, H_0 is rejected if $LMlag > \chi^2_{\alpha,1}$ or if the p-value < α. If H_0 is rejected, it can be concluded that there is spatial dependence in the dependent variable within the model.

The Breusch-Pagan test statistic can be expressed in the following equation [11]:

$$BP = \frac{1}{2}(f'X)(X'X)^{-1}(X'f)$$

The decision rule is to reject H_0if $BP > X^2_{\alpha,k-1}$ or if the p-value < α, which indicates that at the significance level α, there is spatial heterogeneity among the locations.

SARQR is a model that combines two approaches: quantile regression and the Spatial Autoregressive (SAR) model. This model is capable of addressing both spatial dependence and heterogeneity [12].
The SARQR model can be expressed in the following equation [13]:

$$Y = \rho_\tau Wy + X\beta\tau$$

To estimate the parameters in the SARQR model, the Instrumental Variable Quantile Regression (IVQR) method is used. The IVQR method was introduced as a quantile regression approach capable of addressing endogeneity issues in econometric models [14]. In general, the IVQR model can be expressed in the following form:

$$Q_Y(\tau|D,X) = D\beta_1(\tau) + X'\beta_2(\tau)$$

II. MATERIALS AND METHODS

This study uses secondary data obtained from the Central Bureau of Statistics of Central Kalimantan. The data collected includes population size in Central Kalimantan is used as the dependent variable, while the population growth rate, number of poor people, and number of midwives and healthcare workers are used as independent variables.

To begin the analysis, descriptive data analysis was conducted. Then, multicollinearity analysis and spatial weight matrix were conducted. In this study, contiguity matrix was used, especially queen contiguity, and testing of spatial influence on data was conducted by testing spatial dependence using Moran's I test and Lagrange Multiplier test. Furthermore, spatial heterogeneity was conducted using Breusch-Pagan. Finally, a comparison of the results of the SARQR model parameter estimation and determination of the best model was conducted using Akaike Information Criterion (AIC). The AIC is calculated using the following formula [1]:

$$IC = \exp\left(\frac{2p}{n}\right)\sum\sum\frac{\varepsilon_{ij}^2}{n}$$

III. RESULT AND DISCUSSION

The first step taken in this study is to conduct a descriptive analysis of the data. This step is carried out to obtain a better understanding of the data's characteristics. The descriptive analysis shows in Table 1.

Table 1 Statistic Descriptive

Variable	N	Max	Min	Mean	Median	Std. Deviation	Variance
Population Size (Y)	14	448.10	67.80	200.686	154.05	119.9704	14392.894
Population Growth Rate (X1)	14	1.95	0.96	1.429	1.4	0.3084	0.095
Number of Poor People (X2)	14	26.69	2.79	10.401	8.395	6.5931	43.469
Number of Midwives Healthcare Workers (X3)	14	0.467	0.116	0.302	0.296	0.0986	0.1

As seen in Table 1, the average of the population in Central Kalimantan in 2024 is 200.686 and the standard deviation value is 119.9704, with the largest population in East Kotawaringin regency which is 448.10. While the smallest population is in Sukamara Regency with a total of 67.80.

Next, a multicollinearity test is conducted to detect a strong linear relationship between the independent variables in the regression model. This can be seen from the tolerance and VIF value. The result of the multicollinearity test is shown in Table 2 below.

Table 2 Multicollinearity Test

Variable	Tolerance	VIF
Population Growth Rate (X1)	0.846	1.182
Number of Poor People (X2)	0.457	2.19
Number of Midwives Healthcare Workers (X3)	0.412	2.428

From Table 2, it can be seen that that the tolerance values are greater than 0.1, which indicating the absence of high multicollinearity. Additionally, it also can be seen that the VIF values are less than 10, which is suggests that there is no significant multicollinearity among the independent variables.

In addition, spatial weight matrix needs to be constructed. In this study, the type of spatial weight matrix used is the queen contiguity matrix. The queen contiguity matrix defines two regions as neighbors if they share either a common border or corner point.

Figure 1 Central of Kalimantan Province.

As shown in Figure 1, Central Kalimantan Province is divided into 14 regencies/cities. Since the spatial weight matrix **W** is an $n \times n$ matrix, the matrix used in this study is of size 14×14, corresponding to the number of regencies/cities in the province. The following is the spatial weight matrix **W** used in this study:

$$\mathbf{W} = \begin{bmatrix} 0 & 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 1 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix}$$

The matrix is constructed based on the regional order listed in Table 3. Where the regions are neighbors, the value in the matrix is one.

Table 3. Neighbor List

No.	Regencies/cities	Neighboring Areas
1.	South Barito	East Barito, North Barito, Kapuas
2.	East Barito	South Barito
3.	North Barito	South Barito, Kapuas, Murung Raya
4.	Gunung Mas	Kapuas, Katingan, Palangkaraya Cities, Murung Raya, Pulang Pisau
5.	Kapuas	South Barito, North Barito, Gunung Mas, Murung Raya, Pulang Pisau
6.	Katingan	Gunung Mas, Palangkaraya Cities, East Kotawaringin, Pulang Pisau, Seruyan

7.	Palangkaraya Cities	Gunung Mas, Katingan, Pulang Pisau
8.	West Kotawaringin	Lamandau, Seruyan, Sukamara
9.	East Kotawaringin	Katingan, Seruyan
10	Lamandau	West Kotawaringin, Seruyan, Sukamara
11.	Murung Raya	North Barito, Gunung Mas, Kapuas
12.	Pulang Pisau	Gunung Mas, Kapuas, Katingan, Palangkaraya Cities
13.	Seruyan	Katingan, West Kotawaringin, East Kotawaringin, Lamandau
14.	Sukamara	East Kotawaringin, Murung Raya

The obtained queen contingency matrix will be transformed into a row-standardized matrix. The following is the **W** matrix in which the sum of each row equals one:

$$\mathbf{W}=\begin{bmatrix}
0 & \frac{1}{3} & \frac{1}{3} & 0 & \frac{1}{3} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0\\
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0\\
\frac{1}{3} & 0 & 0 & 0 & \frac{1}{3} & 0 & 0 & 0 & 0 & 0 & \frac{1}{3} & 0 & 0 & 0\\
0 & 0 & 0 & 0 & \frac{1}{5} & \frac{1}{5} & \frac{1}{5} & 0 & 0 & 0 & \frac{1}{5} & \frac{1}{5} & 0 & 0\\
\frac{1}{5} & 0 & \frac{1}{5} & \frac{1}{5} & 0 & 0 & 0 & 0 & 0 & 0 & \frac{1}{5} & \frac{1}{5} & 0 & 0\\
0 & 0 & 0 & \frac{1}{4} & 0 & 0 & \frac{1}{4} & 0 & \frac{1}{4} & 0 & 0 & \frac{1}{4} & \frac{1}{4} & 0\\
0 & 0 & 0 & \frac{1}{3} & 0 & \frac{1}{3} & 0 & 0 & 0 & 0 & 0 & \frac{1}{3} & 0 & 0\\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \frac{1}{3} & 0 & 0 & \frac{1}{3} & \frac{1}{3}\\
0 & 0 & 0 & 0 & 0 & \frac{1}{2} & 0 & 0 & 0 & 0 & 0 & 0 & \frac{1}{2} & 0\\
0 & 0 & 0 & 0 & 0 & 0 & 0 & \frac{1}{3} & 0 & 0 & 0 & 0 & \frac{1}{3} & \frac{1}{3}\\
0 & 0 & \frac{1}{3} & \frac{1}{3} & \frac{1}{3} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0\\
0 & 0 & 0 & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & 0 & 0 & 0 & 0 & 0 & 0 & 0\\
0 & 0 & 0 & 0 & 0 & \frac{1}{4} & 0 & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & 0 & 0 & 0 & 0\\
0 & 0 & 0 & 0 & 0 & 0 & 0 & \frac{1}{2} & 0 & \frac{1}{2} & 0 & 0 & 0 & 0
\end{bmatrix}$$

The standardized spatial weight matrix will be used for testing spatial dependence, spatial heterogeneity, and for model estimation.

Then, spatial effect analysis was performed on the data regarding the population size in Central Kalimantan Province to assess the presence of spatial influence. This analysis consists of two components: spatial dependence testing and spatial heterogeneity testing. In this study, the Lagrange Multiplier (lag) test is applied to assess whether the Spatial Autoregressive Regression (SAR) model is suitable for use.

Table 4 Dependence Spatial Test

Test	MI/DF	Value	p-value
Moran's I	0.1549	1.691	0.04542
Uji Lagrange Mulitiplier (lag)	1	4.0838	0.0433

Based on Table 4, the Moran's I value is 0.1549 with a z-value of 1.691 and a p-value of 0.04542. At a significance level of $\alpha = 0.05$, we reject H_0 if the p-value < α. Therefore, it can be concluded that there is spatial autocorrelation. In addition, the Lagrange Multiplier test statistic value is 4.0838 with a p-value of 0.0433. The null hypothesis states that there is no spatial dependence in the lag of population in Central Kalimantan. With a 5% confidence level, it can be stated that H_0 is rejected. Therefore, it can be concluded that there is spatial dependence in the lag of the population in Central Kalimantan.

Next, the test for spatial heterogeneity is conducted to determine whether there is spatial variation among regions. The test used is the Breusch-Pagan test.

Table 5 Heterogeneity Spatial Test

Test	DF	Value	p-value
Uji Breusch-Pagan	3	3.2035	0.3613

Based on Table 5, the Breusch-Pagan test value is 3.2035 with a p-value of 0.3613. The null hypothesis states that the residual variance is the same across all regencies or cities in Central Kalimantan Province. At a significance level of $\alpha = 0.05$, we fail to reject H_0 because the p-value (0.3613) is greater than α (0.05). It can be concluded that the variance is homogeneous across all regions in Central Kalimantan Province.

To obtain the SARQR model, parameter estimation must be carried out using the Instrumental Variable Quantile Regression (IVQR) method. The parameter estimation results at each quantile are display in Table 6.

Table 6 Parameter Estimates of the SARQR Model

Quantile (τ)	**Model Parameter Estimation**				
	Constanta	ρ	β_1	β_2	β_3
0.1	-194.940	-0.44	49.042	9.403*	925.421*
0.15	-190.132	-0.44	46.077	9.490*	922.279*
0.2	-97.491	-0.54	25.524	9.300*	817.974
0.25	31.150	-0.64*	-8.209	9.100*	667.897*
0.3	27.880	-0.59*	-13.532	8.710*	693.514*
0.35	48.563	-0.64	-3.836	7.747	653.802
0.4	48.888	-0.64	-0.066	7.661	642.260
0.45	29.680	-0.59	0.197	9.005*	634.888*
0.5	141.795	-0.84*	1.888	9.740*	429.742*
0.55	145.685	-0.84*	-2.706	9.388*	454.523*
0.6	154.894	-0.74	-19.992	8.925	468.680*
0.65	156.217	-0.74*	-20.431	8.917*	467.300*
0.7	176.034	-0.84*	-12.773	9.219*	422.876*
0.75	227.183*	-0.84*	-41.929	7.715*	475.934*
0.8	227.183*	-0.84*	-41.929	7.715*	475.934*
0.85	227.205*	-0.84*	-41.978	7.853*	473.039*
0.9	227.205*	-0.84*	-41.978	7.853*	473.039*
0.95	227.205*	-0.84*	-41.978	7.853*	473.039*

*Significant if p-value < 0.05

Based on Table 6, the variables number of poor people (X2) and number of midwife healthcare workers (X3) are significant at several quantile levels at the 5% significance level. The estimation results in Table 7 indicate variation in coefficients across quantiles, particularly in the lower quantiles (0.1–0.7). This suggests that the influence of the independent variables on the population size is not homogeneous and varies across regions. Conversely, in the higher quantiles (0.75–0.95), the coefficients tend to be more stable, indicating that these variables have a relatively consistent effect in regions with a high population.

Next, we will examine whether the SARQR model is able to address spatial dependence and spatial heterogeneity. The following are the results of the Moran's I test and the Breusch-Pagan test for each model:

Table 7. Dependence Spatial Test and Heterogeneity Test

Quantile (τ)	Dependence Spatial		Heterogeneity Spatial	
	Moran's I	*p-value*	*Breusch-Pagan*	*p-value*
0.1	0.1234	0.1513	1.71	0.6347
0.15	0.1304	0.1423	1.5953	0.6604
0.2	0.0596	0.2391	1.4512	0.6936
0.25	0.0675	0.2131	2.4353	0.4871
0.3	0.1465	0.1097	1.977	0.5772
0.35	0.0576	0.2173	2.8358	0.4176
0.4	0.0313	0.2633	3.0216	0.3883
0.45	0.069	0.2077	3.081	0.3793
0.5	0.0137	0.2685	4.6559	0.1988
0.55	0.0189	0.2528	4.3996	0.2214
0.6	0.1355	0.0675	4.1409	0.2466
0.65	0.1386	0.0646	4.144	0.2463
0.7	0.1003	0.1013	4.4433	0.2174
0.75	0.2193	0.0207	3.6384	0.3033
0.8	0.2193	0.0207	3.6384	0.3033
0.85	0.2169	0.0215	3.6696	0.2994
0.9	0.2169	0.0215	3.6696	0.2994
0.95	0.2169	0.0215	3.6696	0.2994

It can be seen that the model successfully addresses spatial dependence at quantiles 0.1 to 0.7, as indicated by the p-values of the Moran's I test being greater than the 5% significance level. However, at quantiles 0.75 to 0.95, the p-values are less than the 5% significance level, suggesting that the model fails to account for spatial dependence in these quantiles. Meanwhile, in the Breusch-Pagan test, all p-values are greater than the significance level, indicating that the model can address spatial heterogeneity.

The last step is to determine the best model based on the AIC value for each qua ntile. The smaller the AIC value, the better the model. The AIC values are shown in Table 8.

Table 8. Akaike Information Criterion (AIC)

Quantile (τ)	AIC
0.1	27.92
0.15	33.58
0.2	37.23
0.25	39.06

0.3	40.15
0.35	40.68
0.4	41.13
0.45	41.54
0.5	40.62
0.55	39.97
0.6	39.19
0.65	38.04
0.7	36.99
0.75	34.81
0.8	31.74
0.85	27.74
0.9	22.07
0.95	12.36

Table 8 shows that the 0,95 quantile has the smallest AIC value. However, Table 7 shows that the Breusch-Pagan test results indicate the model is unable to address spatial dependence. Therefore, the best model is selected at the 0.1 quantile, which has a relatively low AIC value and is also able to address issues of spatial dependence and spatial heterogeneity.

The following is the SARQR model at the 0.1 quantile:

$$Y_{0.1} = -0.44\boldsymbol{W}y - 194.940 + 49.042X_1 + 9.403X_2 + 925.421X_3$$

Based on the SARQR model at the 0.1 quantile, the spatial lag coefficient is -0.44. This indicates a negative spatial influence, where regions or districts with high population tend to border areas with low population, and vice versa. Furthermore, assuming other variables or factors are held constant, a 1% increase in population growth rate will lead to an increase of approximately 49042 people. If the number of poor residents increases by 1000 people, the population in the region will increase by about 9403 people. Additionally, for every additional midwife in the area, the population is associated with an increase of approximately 925 people.

IV. CONCLUSION

Based on the results of the discussion in this study, it can be concluded that SARQR modeling on the population in Central Kalimantan Province produced different models for quantiles 0.1 to 0.7. However, at quantiles 0.75 and 0.8, the models were identical, as were the models at quantiles 0.85 to 0.95. This indicates that the models from quantiles 0.75 to 0.95 are not sufficiently reliable for use. This is further supported by the results of the Moran's I test at quantiles 0.75 to 0.95, which show that the models are unable to address spatial dependence, as the p-values are less than $\alpha = 0,05$. And the best model was obtained at the 0.1 quantile. From the model, the variables number of poor people and number of midwife health workers significantly affect the population in Central Kalimantan Province at the 5% confidence level.

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