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Identifying Factors Affecting Waste Generation in West Java in 2021 Using Spatial Regression

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ABSTRACT

Responsible consumption and production is the 12th of the seventeen SDGs which is difficult for developing countries to achieve due to high waste production. Indonesia is the second largest producer of food waste in the world. Garbage is solid waste generated from community activities. Population density is an indicator to estimate the amount of waste generated in an area. The choice of West Java Province as the research area is based on the fact that this Province has the second highest population density in Indonesia. This study aimed to determine the predictors/factors that influence waste production in the districts/cities of West Java Province. The data used in this study are total waste as a response variable and GRDP (gross domestic product), total spending per capita, average length of schooling, literacy rate, number of MSMEs (micro, small, and medium enterprises), and several recreational and tourism places, the number of people's markets, and the number of restaurants as predictors. The methods used in this research are spatial autoregressive regression/SAR, spatial Lag-X/SLX, and spatial Durbin/SDM. The results of this study show that the SAR is the best model with the lowest BIC (74.442) and pseudo-R-squared (0.7934). Factors that significantly affect total waste production are literacy levels, the number of MSMEs, the number of traditional markets, and the number of recreational and tourist places.

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A. INTRODUCTION

Indonesia is one of the countries facing challenges in achieving 12th of seventeen Sustainable Development Goals (SDGs). This is primarily due to waste issues, particularly in developing nations with high population growth rates (Sarasati et al., 2021). Solid waste is generated from daily activities such as households, traditional markets, recreational sites, tourist destinations, restaurants, and more (Fatimah et al., 2020). According to data from The Economist Intelligence Unit (2021), Indonesia is the world's second-largest producer of food waste. This is further supported by data from the National Waste Management Information System (SIPSN) of the Ministry of Environment and Forestry of the Republic of Indonesia, which indicates that Indonesia generated 29.8 million tons of waste in 2021, with 39.29% of it being food waste. The substantial volume of waste can lead to public health issues. This is emphasized by the study of Karim et al. (2022), which states that household waste management impacts the health status of residents in the Citarum River area.

West Java is Indonesia's second most densely populated province after DKI Jakarta (Badan Pusat Statistik, 2021). The high population density in West Java serves as an indicator that the waste produced from the activities of its residents is also substantial. Activities contributing to a large amount of waste can derive from households, industrial activities, and public spaces. Public activities include markets, malls, recreational sites, tourist destinations, restaurants, and economic centers (Demirbas, 2011). Population density, the number of traditional markets, recreational and tourist sites, restaurants, and micro, small, and medium-sized enterprises (MSMEs) in each area influence the total waste production. This suggests a spatial influence on the total waste production in West Java. Apart from community activities, socio-economic aspects of the community, such as average years of schooling, literacy rates, per capita expenditures, and regional gross domestic product (GDP), can impact waste generation in the region (Prajati & Pesumay, 2019). Previous research on factors influencing total waste in several provinces on Java and Sumatra islands was conducted by Prajati et al. (2015) using multiple linear regression methods.

Spatial regression is an appropriate method for analyzing data with spatial effects (Elhorst, 2014). The choice of the spatial model to be used should be determined through spatial effect tests. Some commonly used spatial models are the spatial autoregressive/SAR, spatial lag-X/ SLX, and spatial Durbin models/SDM (LeSage & Pace, 2009). The spatial autoregressive model considers spatial effects on the response variable. The spatial Durbin model extends this by adding spatial effects to the predictors (Chen et al., 2021; Feng & Chen, 2018). The spatial lag-x model only considers spatial effects on predictors (Adekayanti, 2023; Griffith & Anselin, 1989). West Java's population's activities and socio-economic conditions exhibit spatial effects, making the most suitable model to use a spatial regression. This study aims to determine a model for waste production in West Java Province in 2021 using spatial regression and identify significant influencing factors.

B. METHODS

The data used in this study are secondary data collected from all cities or regencies in West Java. Data was sourced from the Open Data West Java, Indonesia website (https://opendata.jabarprov.go.id/id). The variables to be utilized in the study are listed in detail in Table 1.

Table 1. The variables used in this study

Variable	Description	Reference
Y	Total waste production in tons/person/km^2	
X1	Gross Domestic Product (GDP) in 2021	(Prajati et al., 2015)
X2	Per capita expenditure in thousands of Indonesian Rupiah	(Prajati et al., 2015)
X3	Average years of schooling	(Prajati et al., 2015)
X4	Literacy levels	(Prajati et al., 2015)
X5	The Number of Micro, Small, and Medium-sized Enterprises (MSMEs)	(Demirbas, 2011)
X6	The number of recreational and tourist places	(Karim et al., 2022)
X7	The number of traditional markets	(Fatimah et al., 2020)
X8	The number of restaurants	(Demirbas, 2011)

The data analysis procedure conducted in this study is as follows:

1. Conducting data exploration to understand the characteristics of data distribution using data distribution maps and box plots.
2. Detecting multicollinearity among predictors by examining the *variance inflation factor* (VIF). The formula for calculating VIF is as follows:

$$VIF = \frac{1}{1 - R_i^2} \tag{1}$$

   Where R_i^2 is the coefficient of determination between X_i and other explanatory variables. IF values greater than five identify multicollinearity in the independent variables (Akinwande et al., 2015).
3. Construct a spatial dependence matrix, the spatial weighting matrix ($\boldsymbol{W}$). The spatial weighting matrix is a crucial component in spatial modeling that demonstrates the dependence between observation locations (Djuraidah, 2021). According to Dubin (2009), the weight matrix can be categorized into two, namely, weight matrix based on contiguity and weight matrix based on distance.The matrices used are as follows: (a) Rook contiguity; (b) Queen contiguity; (c) Inverse distance; and (d) Exponential distance.
4. Performing Spatial Effects Tests, including: (a) Spatial Heteroscedasticity using the Breusch-Pagan test (Arbia, 2006); and (b) Spatial Dependence using the Lagrange Multiplier test (Djuraidah, 2020).
5. Estimating the parameters of the spatial regression model using the maximum likelihood method:
   a. SAR: $\boldsymbol{y} = \rho \boldsymbol{W}_1 \boldsymbol{y} + \boldsymbol{X}^* \boldsymbol{\beta}^* + \boldsymbol{\varepsilon}$
   b. SLX: $\boldsymbol{y} = \boldsymbol{X}^* \boldsymbol{\beta}^* + \boldsymbol{u}$, $\boldsymbol{u} = \lambda \boldsymbol{W}_2 \boldsymbol{u} + \boldsymbol{\varepsilon}$
   c. SDM: $\boldsymbol{y} = \boldsymbol{X}^* \boldsymbol{\beta}^* + \boldsymbol{W}_2 \boldsymbol{X} \boldsymbol{\gamma} + \boldsymbol{u}$ dengan $\boldsymbol{u} = \lambda \boldsymbol{W}_3 \boldsymbol{u} + \boldsymbol{\varepsilon}$

   assuming $\boldsymbol{\varepsilon} \sim N(\boldsymbol{0}, \sigma^2 \boldsymbol{I})$, where $\boldsymbol{y}$ is an $n \times 1$ vector of dependent variables, ρ is the lag coefficient of the dependent variable, $\boldsymbol{W}_1$ is an $n \times n$ spatial weighting matrix for dependent variable, $\boldsymbol{X}^* = (\boldsymbol{i}_n, \boldsymbol{x}_1, \cdots, \boldsymbol{x}_p)$ is an $n \times (p+1)$ matrix of constants and predictors, $\boldsymbol{i}_n$ is an $n \times 1$ vector of ones, $\boldsymbol{\beta}^* = (\beta_0, \beta_1, \cdots, \beta_p)'$ is a $(p+1) \times 1$ vector of regression parameter coefficients, $\boldsymbol{W}_2$ is an $n \times n$ spatial weighting matrix for predictors, $\boldsymbol{X} = (\boldsymbol{x}_1, \cdots, \boldsymbol{x}_p)$ is an $n \times p$ matrix of predictors, $\boldsymbol{\gamma}$ is a $p \times 1$ vector of predictor autoregressive coefficients, $\boldsymbol{W}_3$ is an $n \times n$ spatial weighting matrix for errors $\boldsymbol{u}$ is an $n \times 1$ vector of errors assumed to have autocorrelation, λ is the error autoregressive coefficient, and $\boldsymbol{I}$ is an $n \times n$ identity matrix.
6. Evaluate the models based on the smallest Bayesian Information Criterion (BIC) and the largest pseudo R-squared, and perform assumption tests on the model residuals.
7. Interpret the best model results using marginal effects (Djuraidah, 2021). In the SAR model, the direct effect (DE), total effect (TE), and indirect effect (IE) formulas for the kth predictor are as follows:

8. $DE = \frac{1}{n} tr\left(S_k(\boldsymbol{W}_1)\right), TE = \frac{1}{n}\, \boldsymbol{i}_n'\left(S_k(\boldsymbol{W}_1)\right)\boldsymbol{i}_n$, dan $IE = TE - DE$ (2)
9. where $S_k(\boldsymbol{W}_1) = \beta_k(\boldsymbol{I}_n - \rho\boldsymbol{W}_1)^{-1}$.

C. RESULT AND DISCUSSION

1. Data Exploration

West Java Province has the highest population in Indonesia in 2021 (48.22 million people). The large population makes the average waste production per population density in West Java in 2021 equal to 0.324 tons/person/km2 per day. The region with the highest waste production per population density is Sumedang Regency, with a total production of 0.92 tons/person/km2 per day. On the contrary, Cimahi Regency has the lowest waste per population density, with a total production of 0.013 tons/person/km2 per day.

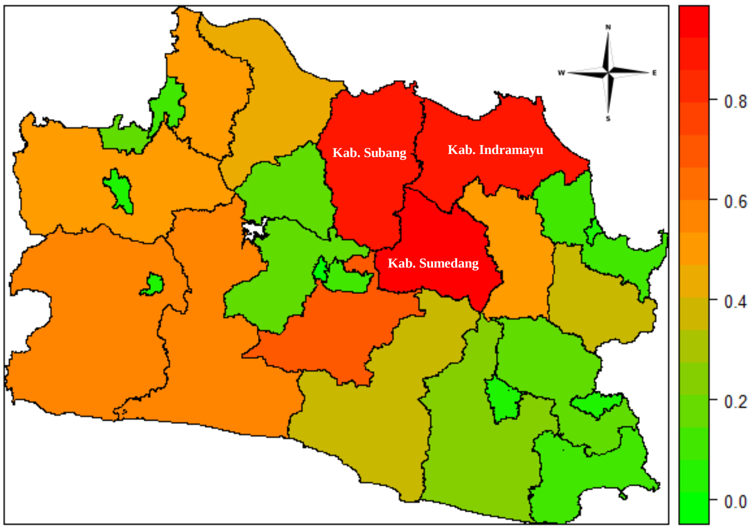


Figure 1. Distribution of average waste production per population density in West Java in 2021(non-scale map)

Figure 1 shows that three districts are colored red, namely Subang, Indramayu, and Sumedang Regency. The red indicates that the region has a waste production per population density of more than 0.8 tons/life/km2.

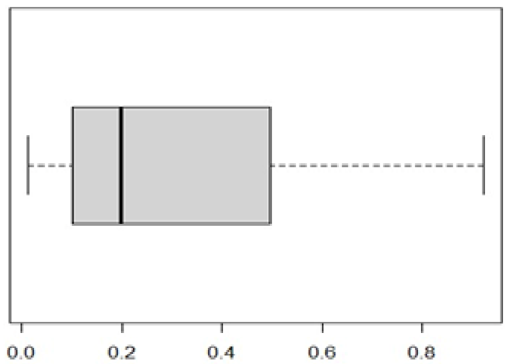


Figure 2. Box plot of waste production per population density tons/person/km2

The box plot in Figure 2 illustrates that there are no outlier data. The variance of waste production per population density is 0.0801 tons/person/km2. The longer line on the right side of the line box diagram in Figure 2 shows that the waste production per population density data tends to stretch to the right.

Table 2. Descriptive statistics of all variables

Descriptive statistics	Variable								
	Y	X1	X2	X3	X4	X5	X6	X7	X8
Minimum	0,01	3364	7829	6,52	93,76	34962	7	4	0
Maximum	0,92	251829	16996	11,46	99,95	506347	300	95	1024
Median	0,20	32898	10368	8,20	99,38	219238	63,00	33,00	47,00
Mean	0,32	56562	10781	8,66	98,70	231755	95,67	36,26	176
Standard Deviation	0,28	63128,75	2278,91	1,47	1,52	133918,7	81,51	24,66	294,79

The descriptive values of all variables used in this study are shown in Table 2. The explanatory variable with the highest average value is variable X5 or the number of MSMEs. While the explanatory variable with the smallest average compared to other variables is X3 or average years of schooling. The explanatory variables with high standard deviation values are variables X1 and X5.

2. Detecting Multicollinearity

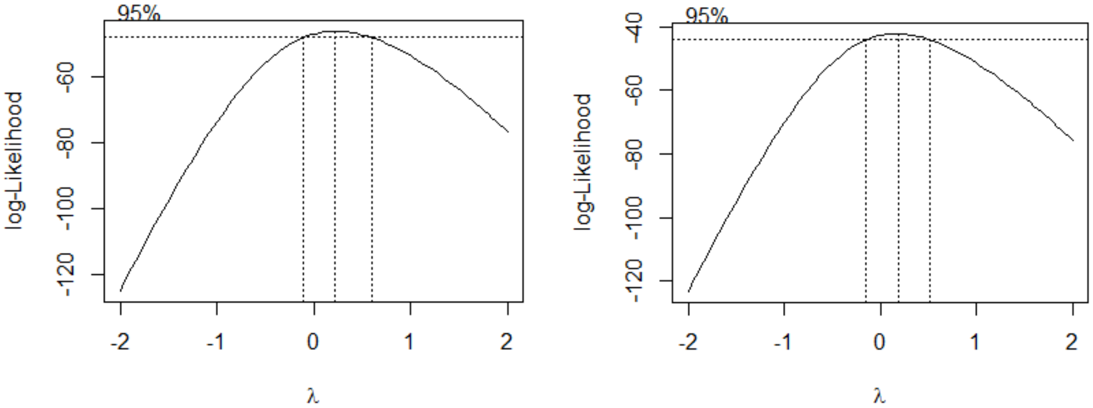
Table 3 illustrates that the average years of schooling, X3, has the highest VIF value of 9,261. In other words, variable X3 has a strong relationship with other explanatory variables due to the VIF value greater than five (Akinwande et al., 2015). Thus, variable X3 will not be included in further data analysis.

Table 3. V*ariance Inflation Factor of All Explanatory Variables*

Explanatory Variable	X1	X2	X3	X4	X5	X6	X7	X8
VIF	2,788	4,750	9,261	2,884	3,640	1,565	4,041	2,754

3. Transformation of Variable

The distribution of response variables that skew to the right indicates it needs to be handled in the form of transformation. Natural logarithm transformation is common for variables that skew to the right (Gujarati & Porter, 2009). Further, Table 2 shows that variables X1 and X5 have high standard deviation values. A high average deviation indicates that the variable has a high diversity of values. The wide variety of explanatory variables can affect the confidence interval of the regression coefficients of the explanatory variables to be wider (Burruss & Bray, 2005). Coefficients with wide confidence intervals indicate that the coefficients obtained lack precision. Therefore, it is necessary to transform variables X1 and X5. Figure 3 presents the results of Box-Cox transformation on variables X1 and X5. The results show zero (0) is the interval value λ of variables X1 and X5. Thus, the transformation to be used is the natural logarithm transformation.



(a) (b)

Figure 3. Lambda value diagram of Box-Cox transformation results on (a) variable X1 and (b) variable X5

4. Spatial Effect Test

Spatial effects testing was conducted to determine the presence of spatial variability and spatial dependency. The results of spatial variability using the Breusch Pagan test obtained a p-value of 0.967, thus there was no spatial diversity at the level of 0.05. Spatial dependence is tested using the Lagrange Multiplier test obtained by LMlag, RLMlag, and SARMA on the inverse distance weight matrix power one (1) has the smallest p-value.

Table 4. The value of the Lagrange Multiplier test statistic

	Queen contiguity	Rook contiguity	Inverse distance weight P=1	Inverse distance weight P=2	Negative exponential distance weight P=1	Negative exponential distance weight P=2
Lmerr	0,746	0,746	1,987	1,844	0,551	0,316
Lmlag	2,730	2,730	6,578*	6,447*	0,171	0,004
RLMerr	0,717	0,717	1,172	0,5444	3,777	3,382
RLMlag	2,701	2,701	5,764*	5,148*	3,396	3,069
SARMA	3,447	3,447	7,751*	6,992*	3,948	3,386

*) significant at $\alpha = 5\%$

To determine spatial dependence on predictors, the Moran Index test is used. The results of the predictor Moran index test for each weighting matrix are in Table 5. The Moran index test on six (6) kinds of weight matrices for predictors X1♦, X2, X4, and X8 is significant at α=0.05. The selection of the weight matrix is based on the largest Moran index value or the smallest p-value from the Moran index test. Based on Table 5, the exponential distance weighting matrix has the smallest p-value. The determination of the spatial regression model is based on the results of the spatial dependency test with LMlag, RLMlag, and SARMA (Table 4) and the results of the Moran Index test (Table 5). Based on the results of the two Tables, the appropriate spatial regression models are the SAR, SLX model, and SDM model. The estimation of these three models uses the maximum likelihood method.

Table 5. Moran index values of explanatory variables on some weight matrices

Explanatory variable	Queen contiguity	Rook contiguity	Inverse distance weight P=1	Inverse distance weight P=2	Negative exponential distance weight P=1	Negative exponential distance weight P=2
X1♦	2,597*	2,597*	2,112*	2,365*	5,477*	5,002*
X2	2,470*	2,470*	1,205	1,556	2,627*	2,489*
X4	3,755*	3,755*	1,567	1,961*	3,201*	3,435*
X5•	-0,496	-0,496	-1,216	-1,155	0,841	0,546
X6	0,323	0,323	0,288	0,001	-0,667	-0,678
X7	-0,446	-0,446	-0,831	−1,488	-0,865	-1,055
X8	5,260*	5,260*	3,376*	4,243*	6,889*	6,797*

*) significant at α = 5% , ♦ natural logarithm transformation

5. Spatial Regression Modeling

The parameter estimation values of the SAR, SLX, and SDM models are presented in Table 6. The spatial lag coefficient (ρ) in the SAR and SDM models is significant. The significant predictors in the SAR model are variables X4, X5, X6, and X7, while in the SDM the predictor X4 is insignificant. In the SLX model, there are no significant predictors. The selection of the best model for modeling waste production per population density in West Java in 2021 is based on the smallest BIC value and the largest pseudo-R-squared value (Table 7). The SAR model is the model that has the smallest BIC value compared to the other two models. The SAR model has a pseudo R-squared value that is not much different from the SDM model, but the BIC value of the SAR model is smaller than the SDM model. In addition, it can be seen that none of the spatial lag coefficients of the predictors in the SDM model are significant. This shows that the addition of spatial lags to the predictors does not effect on the model so the SAR model is the model that will be chosen as the best model for modeling waste production per population density in West Java in 2021.

Table 6. Estimation parameters of spatial regression model

Parameter	Coefficient		
	SAR	SLX	SDM
β_0	14.89	234.6	154.9
β_1	-0.049	0.0743	-0.4946
β_2	-0.000049	-0.00015	0,0001
β_4	-0.2483*	-0.2030	-0,1175
β_5	0.7058*	0.6881	1.103*
β_6	0.0038*	0.00431	0,0033*
β_7	0.0146*	0.01756	0,0159*
β_8	0.0000056	-0,00008	-0,0006
ρ	0.5211*	-	06205*
$lag\ \beta_1$	-	2.456	1.840
$lag\ \beta_2$	-	-0,00086	0.0034
$lag\ \beta_4$	-	-2.443	-1.732
$lag\ \beta_8$	-	-0,00379	-0,0087

*) significant at α = 5%

Table 7. Comparison of BIC and pseudo R-squared values in spatial regression models

Model	**BIC**	**Pseudo R-Squared**
SAR	74.442	0.7934
SLX	86.811	0.6074
SDM	81.739	0.8338

To choose the best model, in addition to using the BIC and pseudo-R-square values, the model must meet the assumptions that the residuals spread normally, are homogeneous in variety, and do not contain autocorrelation. The complete SAR model assumption test results are listed in Table 8 which shows that all model assumptions have been met. Based on these results, the SAR model is the best model for modeling waste cases in West Java Province.

Table 8. Diagnostic model results on the SAR model

Assumption	**Statistics test**	***p-value***
Normality	0.955	0.288
Homogeneity	2.526	0.925
Autocorrelation	0.001	0.973

The predictors (Table 6) of the SAR model that significantly ($\alpha = 0.05$) affect waste production per population density in West Java in 2021 are the literacy rate, the number of MSMEs, the number of recreation and tourism places, and the number of public markets. The literacy rate variable has a negative coefficient, which means that every one percent increase in the literacy rate will reduce waste production per population density in West Java. The coefficients on the variables of the number of MSMEs, the number of recreation and tourism sites, and the number of public markets have positive values, which means that every one percent increase in these variables will increase waste production per population density in West Java Province.

The SAR model has dependencies in the response variable, so the interpretation uses the marginal effect of each predictor. The value of the direct effect, indirect effect, and total effect on the real predictors are listed in Table 9. The value of the indirect effect of each predictor is greater than the value of the direct effect. This is due to the value of the spatial lag coefficient (ρ) in the SAR model, which is 0.5211. The large value of the indirect effect shows that the amount of waste production per population density of a district/city is due to the influence of the surrounding district/city.

Table 9. Direct, Indirect, and Total Effect of the SAR Model

Predictor	**Direct effect**	**Indirect effect**	**Total effect**
X4	-0.3234	-0.5015	-0.8250
X5•	0.5348	0.8293	1.3641
X6	0.0047	0.0074	0.0121
X7	0.0191	0.0296	0.0487

In Table 9, the direct, indirect, and total effect values are the sum of the values in 27 districts/cities in West Java Province. Maps of the direct effect and indirect effect values for each real predictor are presented in Figures 4 and 5. The direct effect (Figure 4) is the change in the average value of the response variable in a district/city caused by changes in certain predictors in the district/city. The direct effect of variable X4 has a negative value, which means that every increase in the literacy rate of a region will decrease the waste production per population density in the region. In contrast to variable X4, variables X5•, X6, and X7 have a positive direct effect which means that an increase in the value of each of these variables in a region can increase waste production per population density in the region.

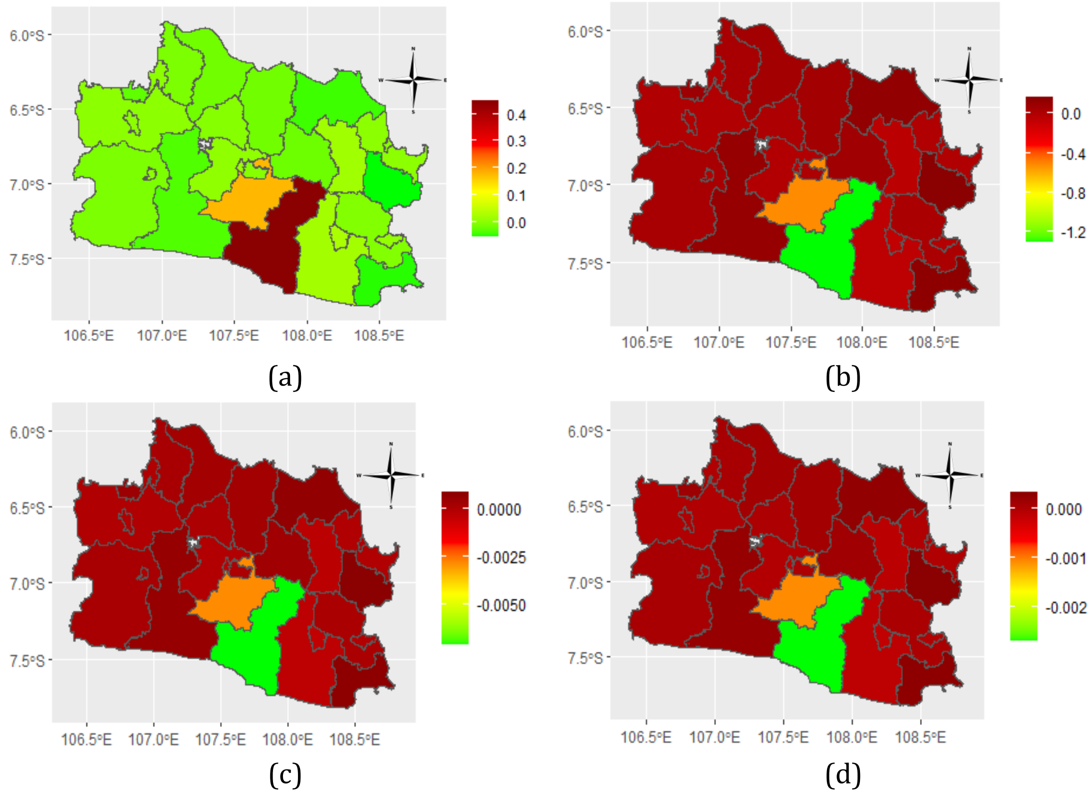
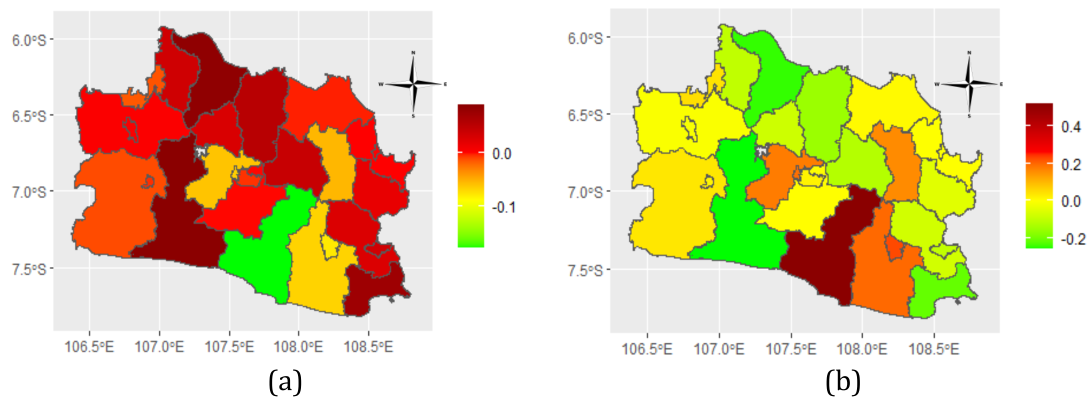
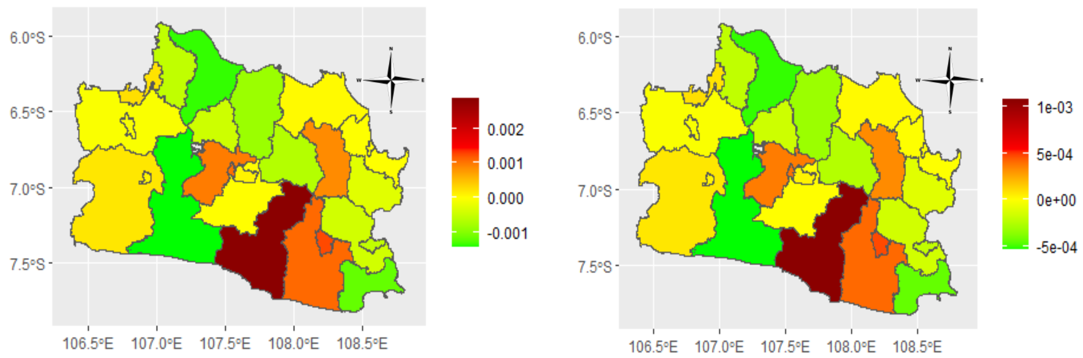


Figure 4. Direct effect maps of variables (a) X4, (b) X5•, (c) X6, and (d) X7 (non-scale map)

An indirect effect (Figure 5) is a change in the average value of the response variable in a region caused by an increase in the predictor in another region (Golgher and Voss, 2015). The indirect effect of variable X4 has a negative value, which means that every increase in the literacy rate of a region will reduce waste production per population density in the surrounding area. In contrast to variable X4, variables X5•, X6, and X7 have a positive indirect effect, which means that an increase in the value of each of these variables in a region can increase waste production per population density in the surrounding area.





(c) (d)

Figure 5. Indirect effect maps of variables (a) X4, (b) X5•, (c) X6, and (d) X7 (non-scale map)

D. CONCLUSION AND SUGGESTIONS

The best model to model waste production per population density in West Java in 2021 is the spatial autoregressive (SAR) model. The variables that have a significant effect on waste production per population density in West Java are literacy rate, number of MSMEs, number of recreation and tourism sites, and number of public markets. The variables of the number of MSMEs, number of recreation and tourism venues, and number of public markets have a positive influence on waste production per population density both directly and indirectly, while the variable of literacy rate has a negative influence on waste production per population density both on the direct and indirect level.

REFERENCES

Adekayanti, B. R. (2023). *Investigating Multidimensional Child Poverty in Indonesia : A Spatial Regression Approach*. IPB University. http://repository.ipb.ac.id/handle/123456789/115956

Akinwande, M. O., Dikko, H. G., & Samson, A. (2015). Variance Inflation Factor: As a Condition for the Inclusion of Suppressor Variable(s) in Regression Analysis. *Open Journal of Statistics*, *05*(07), 754–767. https://doi.org/10.4236/ojs.2015.57075

Arbia, G. (2006). Spatial Econometrics. In *Springer* (1st Editio). Springer. http://link.springer.com/content/pdf/10.1007/978-3-662-04853-5.pdf

Badan Pusat Statistik. (2021). *Kepadatan Penduduk menurut Provinsi (jiwa/km2), 2019-2021*. https://www.bps.go.id/indicator/12/141/1/kepadatan-penduduk-menurut-provinsi.html

Burruss, G. W., & Bray, T. M. (2005). Confidence Intervals. *Encyclopedia of Social Measurement*, 455–462. https://doi.org/https://doi.org/10.1016/B0-12-369398-5/00060-8

Chen, D., Lu, X., Hu, W., Zhang, C., & Lin, Y. (2021). How urban sprawl influences eco-environmental quality: Empirical research in China by using the Spatial Durbin model. *Ecological Indicators*, *131*, 108113. https://doi.org/10.1016/j.ecolind.2021.108113

Demirbas, A. (2011). Waste management, waste resource facilities and waste conversion processes. *Energy Conversion and Management*, *52*(2), 1280–1287. https://doi.org/10.1016/j.enconman.2010.09.025

Djuraidah, A. (2020). *Monograph Penerapan dan Pengembangan Regresi Spasial dengan Studi Kasus pada Kesehatan, Sosial, dan Ekonomi*. PT Penerbit IPB Press.

Dubin, R. (2009). Spatial Weights. In *The SAGE Handbook of Spatial Analysis*. SAGE Publications, Ltd. https://doi.org/10.4135/9780857020130

Elhorst, J. P. (2014). Spatial Panel Models. *Handbook of Regional Science*, 1637–1652. http://link.springer.com/10.1007/978-3-642-23430-9

Fatimah, Y. A., Govindan, K., Murniningsih, R., & Setiawan, A. (2020). Industry 4.0 based sustainable circular economy approach for smart waste management system to achieve sustainable development goals: A case study of Indonesia. *Journal of Cleaner Production*, *269*, 122263. https://doi.org/10.1016/j.jclepro.2020.122263

Feng, Z., & Chen, W. (2018). Environmental regulation, green innovation, and industrial green development: An empirical analysis based on the spatial Durbin model. *Sustainability (Switzerland)*, *10*(1), 223. https://doi.org/10.3390/su10010223

Griffith, D. A., & Anselin, L. (1989). Spatial Econometrics: Methods and Models. In *Economic Geography 65*(2),160. https://doi.org/10.2307/143780

Gujarati, D. N., & Porter, D. C. (2009). *Basic Econometrics* (5th Editio). McGraw-Hill/Irwin.

Karim, U. N., Lubis, E., & Dewi, A. (2022). Hubungan Pengelolaan Sampah Rumah Tangga terhadap Status Kesehatan Penyakit Menular. *NERS Jurnal Keperawatan*, *18*(1), 26. https://doi.org/10.25077/njk.18.1.26-36.2022

LeSage, J., & Pace, R. K. (2009). Introduction to spatial econometrics. In *Introduction to Spatial Econometrics*. https://doi.org/10.1111/j.1467-985x.2010.00681_13.x

Prajati, G., Damanhuri, T. P., & Rahardyan, B. (2015). Pengaruh Faktor-Faktor Ekonomi Dan Kependudukan Terhadap Timbulan Sampah Di Ibu Kota Provinsi Jawa Dan Sumatera. *Jurnal Tehnik Lingkungan*, *21*(1), 39–47. https://doi.org/10.5614/jtl.2015.21.1.5

Prajati, G., & Pesumay, A. J. (2019). Analisis Faktor Sosiodemografi dan Sosioekonomi Terhadap. *Jurnal Rekayasan Sipil Dan Lingkungan*, *3*(1), 8–16. https://jurnal.unej.ac.id/index.php/JRSL/article/view/8721

Sarasati, Y., Azizah, R., Zuhairoh, Z. A., Sulistyorini, L., Prasasti, C. I., & Latif, M. T. (2021). Analysis of Potential Waste-to-Energy Plant in Final Waste Disposal Sites iIn Indonesia Towards SDGs 2030 (A Literature Review). *Jurnal Kesehatan Lingkungan*, *13*(1), 24. https://doi.org/10.20473/jkl.v13i1.2021.24-34

The Economist Intelligence Unit. (2021). Global Food Security Index 2021; The 10-year anniversary. *The Global Food Security Index (GFSI) Is the Preeminent Source of Intelligence on the Drivers of Global Food Security. Developed by Economist Impact and Supported by Corteva Agriscience, It Evaluates Food Security in 113 Countries across Four Key Pillars:*, 47. https://my.corteva.com/GFSI?file=ei21_gfsir