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Robust Spatial Regression Model in City Minimum Wages (CMW) in East Java 2018

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ABSTRACT

The minimum wage determination has always been a moment that is eagerly awaited every year by both workers and employers, even though it always creates polemics. The government seeks to raise the minimum wage every year to guarantee a decent life for workers. The fulfillment of the need for a decent living is different in each region so that it will affect the minimum wage in that area. If the minimum wage applies to city/regency areas, it is called the city minimum wage (CMW). The size of the CMW varies widely and even raises an extensive range so that outliers appear. Many factors influence the minimum wage, including Decent Living Needs (KHL), Consumer Price Index (CPI), Gross Regional Domestic Product (GRDP), labor force participation rate, per capita income, number of job seekers, number of the labor force, expenditure per capita, economic growth, and level of productivity. Modeling with regression analysis can be used to get the best model and the factors that affect CMW. Because the size of the CMW in each region is different, and there are outliers, a robust spatial regression analysis is used. This research will compare the results of the analysis of robust SAR and robust SEM using the method of moment estimation in modeling the variables that affect the city minimum wage (CMW). From the analysis, the best model is obtained from the robust SEM model, which has a smaller AIC value than the AIC value of the robust SAR model.

Keywords: *City Minimum Wage (CMW), Robust Spatial Regression model.*

1. INTRODUCTION

The minimum wage fixing policy is a system of regulating workers' wages that has been implemented in various countries. In Indonesia, the minimum wage is regulated in Law no. 13 of 2013 [1]. The government's objective in establishing wage policies is to ensure a decent standard of living for workers and their families, increase productivity, and increase the community's purchasing power [2].

Meeting the needs for a decent life in each region is not the same, so it is considered in determining the minimum wage in each region. The provincial minimum wage (PMW) must be higher than the national minimum wage. Likewise, the city minimum wage (CMW) must be higher than the provincial minimum wage (PMW). The minimum wage rate in each region represents the level of welfare in each region.

The amount of the CMW is influenced by many factors, including Decent Living Needs (KHL), Consumer Price Index (CPI), Gross Regional Domestic Product (GRDP) [3], labor force participation rate, income per capita [4], the number of job seekers [5], the number of the labor force, per capita expenditure, economic growth [6], and the level of productivity [7].

Based on data from the Central Statistics Agency [8], the PMW in 2018 in Indonesia is in the range of 1.4 million to 3.6 million. Of the 34 provinces in Indonesia, there are four provinces on the island of Java that fall into the lowest PMW category, namely the Special Region of Yogyakarta for IDR 1,454,154, Central Java for IDR 1,486,065, East Java for IDR 1,508,894, and West Java for IDR 1,544,360. The similarity in the PMW size in the four provinces gives a neighborhood effect or spatial effect. So it can be assumed that the minimum wage affects regions where adjacent areas have the same characteristics.

Spatial data defines the relative location of observations that can be used as dimensions in the analysis. In spatial information, it explains the location of each individual data is, and also observations are linked to one another. Outliers often appear in spatial data. Characteristics of spatial outliers are different from spatial in general, so it needs to be explicitly analyzed.

Robust regression is a method that can be used to analyze outliers data. If the spatial data contains outliers, it will be analyzed using robust spatial regression. In many contexts, the Robust Spatial Error Model (RSEM) has been identified and applied to the Human Development Index (HDI) data in East Java [9], robust spatial regression has also been applied to model Life Expectation (LE) with Robust Spatial Autoregressive (RSAR) [10], and compare the SAR and RSAR model to the Original Local Government Revenue OLGR) data [11], looking for the best model between Robust Spatial Cross Regressive (RSCR), RSAR, and Robust Spatial Durbin Model (RSDM) with M-estimator from life expectancy data [12], The purpose of this study is This study aims to compare the RSEM and RSAR models with Method of Moment (MM) estimator the City Minimum Wage (CMW) data in East Java. Robust spatial regression modeling can be formed using the R software.

2. LITERATURE REVIEW

2.1. City Minimum Wage (CMW)

Wages are rights that are given to workers as compensation in the form of money by agreed regulations [13]. Based on the Minister of Manpower Regulation (Permenaker) No. 7 of 2013 Article 1 paragraph 1, the minimum wage is the lowest monthly wage consisting of the basic wage, including a fixed allowance determined by the governor as a safety net. The definition of city minimum wage (CMW), according to the Minister of Manpower Regulation (Permenaker) No. 5 of 1999, is the minimum standard of wages for workers in a district/city in a year. The governor determines the CMW, the amount of which must be higher than the PMW, and announced no later than November 21 after the PMW's stipulation every year. (Permenaker No.7 of 2013).

2.2. Factors Affecting CMW

2.2.1. Gross Regional Domestic Product (GRDP)

Gross Regional Domestic Product (GRDP) is an important indicator to determine economic conditions in an area in a certain period. GRDP value is the added value generated by all business units in an area [14].

2.2.2. Labor Productivity

The level of labor productivity affects the number of labor wages. Companies will provide higher wages if labor productivity increases because the resulting production also increases. With the increase in production, the level of public consumption will increase because the prices of goods are stable.

2.2.3. Number of Workforces

The labor force is a workforce that is more than 15 years old [15], working or not working [16]. The increase in population will further increase the number of the workforce. Changes in the number of the workforce will affect the amount of the minimum wage. The increasing number of the workforce will reduce the minimum wage for workers, on the contrary, if the number of the labour force is reduced, the minimum wage for workers will be increased [17]

2.3. Moran's I

Moran's I (Moran's Index) is a method used to calculate global spatial autocorrelation. Moran's I test statistics are as follows [18]:

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

where:

w_{ij} : element of the spatial weighted location matrix *i* and J

x_i : attribute value to the location of concern (location *i*)

x_j : attribute value to the location of concern (location *j*)

$\bar{x}$: average attribute value at the location *i* (x_i) from n observation locations

n : many observation sites

Moran's I values between -1 and 1, where -1 is negative extreme spatial autocorrelation and 1 is positive extreme spatial autocorrelation.

2.4. Breusch-Pagan Test

The Breusch-Pagan test is a test statistic for testing spatial heterogeneity. The hypothesis of the Breusch-Pagan test is as follows [19]:

$H_0: \sigma_1^2 = \sigma_2^2 = \cdots = \sigma_n^2 = \sigma^2$ (homoscedasticity)

$H_1: at\ least\ there\ are\ \sigma_i^2 \neq \sigma^2$ (heteroscedasticity)

Breusch-Pagan test statistics:

$$BP = \frac{1}{2}[\boldsymbol{f^T Z}(\boldsymbol{Z^T Z})^{-1}\boldsymbol{Z^T f}] \sim \chi_p^2 \quad (1)$$

By element value: $\boldsymbol{f}$

$$f_i = \frac{e_i^2}{\left(\frac{e^T e}{n}\right) - 1} \quad (2)$$

Where:

e_i : the remainder for the second observation i

$\boldsymbol{Z}$: independent variable matrix that has been standardized in size $n \times (k+1)$

If the BP value is more than $\chi^2_{\alpha,k+1}$ value, H_0 rejected or there is spatial heterogeneity.

2.5. Jarque Bera Test

The Jarque-Bera test is a residual normality test on a large sample. The test statistics used are [20]:

$$JB = n\left[\frac{S^2}{6} + \frac{(K-3)^2}{24}\right] \quad (3)$$

Where:

n : sample size

S : *expected* Skewness

K : *expected excess* Kurtosis

$$S = \frac{\hat{\mu}_3}{\hat{\sigma}_3} = \frac{\frac{1}{n}\sum_{i=1}^{n}(e_i - \bar{e})^3}{\left(\frac{1}{n}\sum_{i=1}^{n}(e_i - \bar{e})^2\right)^{3/2}} \quad (4)$$

$$K = \frac{\hat{\mu}_4}{\hat{\sigma}_4} = \frac{\frac{1}{n}\sum_{i=1}^{n}(e_i - \bar{e})^4}{\left(\frac{1}{n}\sum_{i=1}^{n}(e_i - \bar{e})^2\right)^{2}} \quad (5)$$

With the hypothesis:

$H_0 : e_i \sim N(\mu, \sigma^2)$

$H_1 : e_i \nsim N(\mu, \sigma^2)$

The test criteria are to compare the value of JB with the value of $\chi^2_{\alpha,2}$. If the JB result is greater than $\chi^2_{\alpha,2}$ value, H_0 rejected, which means that the error is not normally distributed.

2.6. Spatial Autoregressive (SAR)

Model *Spatial Autoregressive*(SAR) occurs because of the spatial interaction of the dependent variable. The SAR model is defined as follows: [19]

$$\boldsymbol{Y} = \delta\boldsymbol{WY} + \boldsymbol{X\beta} + \boldsymbol{\varepsilon} \quad (6)$$

where:

$\boldsymbol{Y}$: dependent variable matrix, size $n \times 1$

$\boldsymbol{X}$: independent variable matrix, size $n \times k$

δ : lag coefficient of spatial dependent variable

$\boldsymbol{\beta}$: regression parameter vector, size $k \times 1$

$\boldsymbol{W}$: weighting matrix, size $n \times n$

$\boldsymbol{\varepsilon}$: error vector, size $n \times 1$

2.7. Spatial Error Model (SEM)

The Spatial Error Model (SEM) appears when the error value at a location is correlated with the error value in the surrounding location. In other words, there is a spatial correlation between errors. The SEM model is defined as follows: [19]

$$\boldsymbol{Y} = \lambda\boldsymbol{Wu} + \boldsymbol{X\beta} + \boldsymbol{\varepsilon} \quad (7)$$

where:

λ : spatial error coefficient

$\boldsymbol{Wu}$: interaction between errors

2.8. Robust Regression MM-Estimator

Robust regression is a technique used when there are outlier cases. Several estimates can be used in robust regression, one of which is the MM-estimator. The MM estimator is a combination of the S-estimator, which has a high breakdown value (0.5) with the M-estimator, which has high efficiency (95%) [21].

$$\widehat{\beta_{sp}} = \arg\min \sum_{i=1}^{n} T\left(\frac{Y_i - \sum_{p=0}^{k} X_{pi}\widehat{\beta_p}}{\hat{\sigma}}\right) \quad (8)$$

$$\hat{\sigma} = \frac{median\{|e_i - median(e_i)|\}}{0.6745}$$

$\hat{\sigma}$ is a nearly unbiased estimate of σ if n large and error is normally distributed [22].

$$\sum_{i=1}^{n} X_{pi} w_i \left(Y_i - \sum_{p=0}^{k} X_{pi}\widehat{\beta_p}\right) = 0 \quad (9)$$

Then, can be written as matrix

$$\boldsymbol{X'W^qX\hat{\beta}^q} = \boldsymbol{X'W^q\hat{Y}} \quad (10)$$

$$\boldsymbol{\hat{\beta}^q} = (\boldsymbol{X'W^qX})^{-1}\boldsymbol{X'W^q\hat{Y}} \quad (11)$$

2.9. Tukey Bisquare Weighting Functions

The weighting function of Tukey Bisquare uses the following objective functions [23].

$$w_i = w(e_i) = \frac{\psi(e_i)}{e_i} = \begin{cases} \left[1 - \left(\frac{e_i}{c}\right)^2\right]^2 & , |e_i| \le c = 4{,}685 \\ 0 & , |e_i| > c = 4{,}685 \end{cases} \quad (12)$$

3. RESEARCH METHOD

3.1. Types, Data Sources And Research Variables

The data used in this study is secondary data obtained from the Central Statistics Agency (BPS) of East Java Province in 2018. The data used are Regency/City Minimum Wage data as Y variable, GRDP (X_1), Macro Productivity (X_2), and Labor (X_3). The statistical software used in this study is R 4.0.2 software with functions use in this study is read.gal (rgdal package), nb2listw (rgeos package), lagsarlm (spatialreg package), errorsarlm (spatialreg package), and lmrob (robustbase package).

3.2. Data Analysis Steps

As for the data analysis steps carried out are as follows: (a) Get the data to be analysed and multicollinearity testing. (b) Forming a Contiguity (C) matrix with the Queen Contiguity method. (c) Forming a spatial weighting matrix (W). (d) Testing of spatial autocorrelation using Moran's I and perform modelling with SAR and SEM. (e) Estimating model parameters with Maximum Likelihood Estimation (MLE) and testing the significance of model parameters. (f) Testing the model residuals: testing for normality using the Jarque Bera, testing spatial heterogeneity using the Breusch Pagan, testing of spatial autocorrelation using Moran's I. (g) Detecting spatial outliers using Moran's Scatterplot graph. (h) Modelling with Robust SAR and Robust SEM and determine the best model. (i) Mapping and interpretation of the model obtained.

4. RESULTS AND DISCUSSION

4.1. Multicollinearity Detection

Multicollinearity detection can be seen from the Variance Inflation Factor (VIF) value. Based on the results of linear regression analysis, the VIF value was obtained, which is presented in Table 1.

Table 1. VIF Value for each independent variable

Variable	VIF value
X_1 (GRDP)	3.23
X_2 (Macro Productivity)	1.85
X_3 (Labor)	2.41

Based on the results in Table 1, it is known that the VIF value of all independent variables is less than 10, so it can be concluded that there is no multicollinearity.

4.2. Test Spatial Autocorrelation

The autocorrelation test was carried out using the Moran's I test statistic. The results of Moran's I testing are presented in Table 2.

Table 2. Results of Moran's I model test

Variable	I	E (I)	*p-value*
$error$	0.5084	-0.0270	2.446810-5$\times 10^{-5}$
Y	0.7496	-0.0270	1.180110-9$\times 10^{-9}$
X_1	0.3042	-0.0270	9.651810-5$\times 10^{-5}$
X_2	0.0557	-0.0270	0.3312
X_3	0.0726	-0.0270	0.4372

Based on Table 2, it can be seen that the p-value of Moran's I on the remaining is less than the real level of 5%, so H_0 is rejected.

4.3. Spatial Autoregressive (SAR)

Estimation of SAR model parameters are presented in Table 3.

Table 3. Estimation of SAR model parameters

Variable	Coefficient	*p-value*
Intercept	5.0208×10^5	0.0509
X_1 (GRDP)	2.9842×10^4	0.2889
X_2 (Macro Productivity)	6.7690×10^5	0.4141
X_3 (Labour)	5.2967×10^{-1}	0.0471
ρ (Average MSEs in neighboring locations)	0.51826	5.9052×10^{-6}

Based on the results in Table 3, it is known that the p-value on the spatial parameter of the dependent variable (ρ) is significant. It show that there is an effect of the dependent variable and independent variable at the neighboring location (j) on the dependent variable and the independent variable at the observation location (i).ρ The estimation equation for the Spatial Autoregressive (SAR) model that is formed is as follows:

$$\hat{y}_i = 5.0208 \times 10^5 + 0.51826 \sum_{j=1}^{38} w_{ij} y_j + 2.9842 \times 10^4 x_{1i} + 6.7690 \times 10^5 x_{2i} + 5.2967 \times 10^{-1} x_{3i}.$$

4.4. Testing The Rest Of The Spatial Autoregressive Model (SAR)

4.4.1. Spatial Autocorrelation Testing

The spatial autocorrelation test is carried out to determine whether there is a spatial interaction in the SAR model left. The p-value of Moran's I is 0.9198 that is more than the real level of 5%, so H_0 is accepted. These results indicate that there is no autocorrelation in the remainder.

4.4.2. Spatial Heterogeneity Testing

The spatial heterogeneity test is used to determine the spatial variance instability. This test is performed using the Breuch-Pagan test. The p-value in the Breusch-Pagan is 0.02239 that is known to be smaller than the real level of 5%, so H_0 is rejected. These results indicate spatial heterogeneity in the remainder, so it is necessary to handle assumptions. The problem of heteroscedasticity can be handled by transforming data that can be done with inverse logarithmic (ln).

4.4.3. Spatial Autoregressive Remodeling (SAR)

Based on the heteroscedasticity test results on the remainder of the SAR model, it is known that in the remainder, there is spatial heterogeneity, so it is necessary to handle assumptions with inverse logarithmic transformations and carry out SAR modeling again. The

SAR model parameters after data transformation are presented in Table 4.

Table 4. Estimation of SAR model parameters after data transformation

Variable	Coefficient	*p-value*
Intercept	1.4739×10^{-2}	0.0352
X_1 (GRDP)	-5.2440×10^{-6}	0.8385
X_2 (Macro Productivity)	8.8648×10^{-4}	0.0302
X_3 (Labour)	9.0769×10^{-2}	5.9052×10^{-5}
ρ (Average MSEs in neighboring locations)	0.6918	4.364×10^{-10}

Based on the results in Table 4, it is known that the p-value on the spatial parameter of the dependent variable (ρ) is significant. It shows that there is an influence of the dependent variable and independent variable in the neighboring location (j) on the dependent variable and the independent variable at the observation location (i) so that the estimator equation is obtained. the Spatial Autoregressive (SAR) model after the transformation of the data formed is as follows:

$$(\ln \hat{y}_i)^{-1} = 1.4739 \times 10^{-2} + 0.6918 \sum_{j=1}^{38} w_{ij} \left(\ln y_j\right)^{-1} - 5.2440 \times 10^{-6} (\ln x_1)^{-1} + 8.8648 \times 10^{-4} (\ln x_2)^{-1} + 9.0769 \times 10^{-2} (\ln x_3)^{-1}$$

4.4.4. Testing Of Spatial Heterogeneity After Transformation

The spatial heterogeneity test is used to determine the spatial variance instability. The p-value in the Breusch-Pagan test is 0.844 that is known to be higher than the real level of 5%, so H_0 is accepted. These results indicate that there is no spatial heterogeneity in the remainder.

4.4.5. Normality Testing

The normality test was carried out by using the Jarque Bera test statistic. The p-value in the Jarque Bera test is 0.0959 that is known to be higher than the real level of 5%, so H_0 is accepted. These results indicate that the remainder of the SAR model is normally distributed.

4.5. Detection Of Spatial Outlier In The Sar Model

Outlier detection is done by creating a Moran's Scatterplot graph using Geoda software.

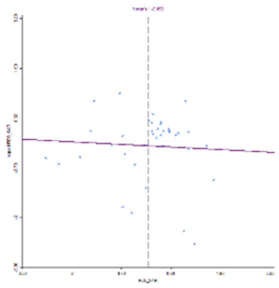

Figure 1 Graph of Moran's scatterplot SAR

Based on Figure 1, it can be concluded that there are spatial outliers, namely plots that are scattered in quadrant II (top left), quadrant III (bottom left), and quadrant IV (bottom right). Besides using Moran's Scatterplot graph, spatial outliers can also be identified using R software. Based on the output of software R, it was found that 14 spatial outliers were detected, namely data 14, 15, 16, 23, 24, 25, 30, 31, 32, 34, 35, 36, 37, and 38.

4.6. Robust Spatial Autoregressive (Robust SAR) MM-Estimator

Robust SAR model parameters are presented in Table 5.

Table 5. Estimation of SAR Robust model parameters

Variable	Coefficient
Intercept	6.980×10^{-2}
X_1 (GRDP)	2.335×10^{-6}
X_2 (Macro Productivity)	1.686×10^{-2}
X_3 (Labour)	6.534×10^{-2}
ρ (Average MSEs in neighboring locations)	0.6918

Based on Table 5, the Robust SAR regression model is obtained as follows:

$$(\ln \hat{y}_i)^{-1} = 6.980 \times 10^{-2} + 0.6918 \sum_{j=1}^{38} w_{ij} \left(\ln y_j\right)^{-1} + 2.335 \times 10^{-6} (\ln x_1)^{-1} + 1.686 \times 10^{-2} (\ln x_2)^{-1} + 6.534 \times 10^{-2} (\ln x_3)^{-1}.$$

4.7. Spatial Error Model (SEM)

SEM model parameters are presented in Table 6.

Table 6. Estimation of SEM model parameters

Variable	Coefficient	*p-value*
Intercept	1.5412×10^{6}	2.22×10^{-16}
X_1 (GRDP)	2.3792×10^{4}	0.4026
X_2 (Macro Productivity)	8.4134×10^{5}	0.3344
X_3 (Labour)	5.1315×10^{-1}	0.0489
λ	0.5833	8.0175×10^{-5}

Based on the results in Table 6, it is known that the p-value on the spatial parameter error (λ) is significant so that the estimator equation for the Spatial Error Model (SEM) model that is formed is as follows:

$$\hat{y}_i = 1.5412 \times 10^{6} + 0.5833 \sum_{j=1}^{38} w_{ij}u_j + 2.3792 \times 10^{4}x_{1i} + 8.4134 \times 10^{5}x_{2i} + 5.1315 \times 10^{-1}x_{3i} + \varepsilon.$$

4.8. *Testing The Rest Of The Spatial Error Model (SEM) MODEL*

4.8.1. Spatial Autocorrelation Testing*)*

The spatial autocorrelation test was carried out to determine whether the remainder in the SEM model had spatial interactions in the error model. The p-value of Moran's I is 0.8139 that is more than the real level of 5%, so H_0 is accepted. These results indicate that there is no autocorrelation in the remainder.

4.8.2. Spatial Heterogeneity Testing

The spatial heterogeneity test is used to determine the spatial variance instability. This test is performed using the Breuch-Pagan test. The p-value in the Breusch-Pagan test is 0.9165 that is known to be higher than the real level of 5%, so H_0 is accepted. These results indicate that there is no spatial heterogeneity in the remainder.

4.8.3. Normality Testing

The normality test was carried out by using the Jarque Bera test statistic. The p-value in the Jarque Bera test is $4{,}189\times 10^{-6}$ that is known to be smaller than the real level of 5%, so H_0 is rejected. These results indicate that the remainder in the SEM model is not normally distributed. This problem can be handled by transforming data that can be done with logarithmic transformation (ln).

4.8.4. Spatial Error Model (SEM) Remodeling

Based on the normality test results on the remainder of the SEM model previously known, the remainder is not normally distributed. Hence, it is necessary to handle assumptions with logarithmic transformations and to do SEM modeling again. SEM model parameters after data transformation are presented in Table 7.

Table 7. Estimation of SEM model parameters after data transformation

Variable	Coefficient	*p-value*
Intercept	5.6529	0.1826
X_1 (GRDP)	0.0514	0.8955
X_2 (Macro Productivity)	0.1010	0.7938
X_3 (Labour)	0.0834	0.8327
λ	0.5523	3.027×10^{-8}

Based on the results in Table 7, it is known that the p-value on the spatial parameters λ is significant, so that the estimator equation for the Spatial Error Model (SEM) model after the transformation of the data is formed is as follows:

$$\ln \hat{y}_i = 5.6529 + 0.5523 \textstyle\sum_{j=1}^{38} w_{ij} \ln u_j + 0.0514 \ln x_1 + 0.1010 \ln x_2 + 0.0834 \ln x_3 + \varepsilon$$

$$\hat{y}_i = exp\left(5.6529 + 0.5523 \textstyle\sum_{j=1}^{38} w_{ij} \ln u_j + 0.0514 \ln x_1 + 0.1010 \ln x_2 + 0.0834 \ln x_3 + \varepsilon\right).$$

4.8.5. Normality Testing

The normality test was carried out by using the Jarque Bera test statistic. The p-value in the Jarque Bera test is 0.2044 that is known to be higher than the real level of 5%, so H_0 is accepted. These results indicate that the remainder of the SEM model is normally distributed.

4.9. Detection of Spatial Outliers in the SEM Model

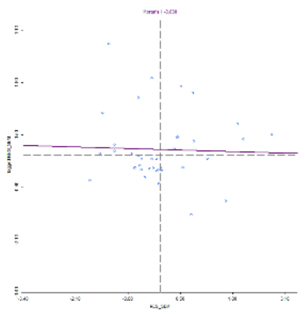

Figure 2 Graph of Moran's scatterplot SEM

Based on Figure 2, it can be concluded that there are spatial outliers, namely plots that are scattered in quadrant I (top right), quadrant II (top left), and quadrant IV (bottom right). Besides using Moran's Scatterplot graph, spatial outliers can also be identified using R software. Based on the output of software R, it was found that ten spatial outliers were detected, namely, data 14, 15, 16, 23, 25, 30, 31, 34, 37, and 38.

4.10. Robust Spatial Error Model (Robust SEM) MM-Estimator

The parameters of the Robust SEM model are presented in Table 8.

Table 8. Estimation of SEM Robust model parameters

Variable	Coefficient
Intercept	30.9411
X_1 (GRDP)	1.6843
X_2 (Macro Productivity)	-1.2583
X_3 (Labour)	-1.5997
λ	0.5523

Based on Table 8, the SEM Robust regression model is obtained as follows:

$$\ln \hat{y}_i = 30{,}9411 + 0{,}5523 \sum_{j=1}^{38} w_{ij} \ln u_j + 1{,}6843 \ln x_1 - 1{,}2583 \ln x_2 - 1{,}5997 \ln x_3 + \varepsilon \text{ or}$$

$$\hat{y}_i = exp\left(30{,}9411 + 0{,}5523 \sum_{j=1}^{38} w_{ij} \ln u_j + 1{,}6843 \ln x_1 - 1{,}2583 \ln x_2 - 1{,}5997 \ln x_3 + \varepsilon\right)$$

4.11. Model Goodness Testing

The goodness of the model is determined based on the AIC value obtained in each model. Table 9 shows the AIC value in the Robust SAR and Robust SEM models.

Table 9. Spatial Model AIC value

Spatial Model	AIC value
Robust SAR	-296.3043
Robust SEM	4.8956

Based on the AIC values of the Robust SAR and Robust SEM models in Table 9. It can be seen that the Robust SEM model has a smaller AIC value than the AIC Robust SAR model, so the model suitable for modeling the City Minimum Wage in East Java in 2018 is the Robust SEM.

Table 10. Classification of mapping class

Classification	Colour	Category
Class 1	Red	Very high
Grade 2	Orange	High
Grade 3	Yellow	Moderate
Grade 4	Green	Low
Grade 5	Blue	Very low

4.12. Discussion

This research discusses the CMW modeling in East Java. In addition to the results of the spatial model obtained, mapping results are also provided to show the visualization of the model. Based on the results of the analysis with the Robust SEM approach, the predictive value of MSEs is divided into five classes where the classification can be seen in Table 10.

The results of the prediction mapping of MSEs in East Java are presented in Figure 3 below.

Figure 3 Mapping of MSE prediction with SEM Robust model

Based on Figure 3, that there is one city that belong to the "very high" category, namely Kediri City. Kediri City has a very high macro productivity value and a relatively high GRDP value compared to other cities. Based on the results of a survey by the Central Statistics Agency (BPS) for the 2014-2018 period, the city of Kediri became the third richest city in Indonesia, beating the city of Surabaya which was ranked sixteenth. In addition to the clove industrial sector, which has contributed a lot to GRDP, the Micro Small and Medium Enterprises (MSME) sector has also begun to increase significantly.

5. CONCLUSION

Based on the AIC value, the Robust SEM model is more suitable for analyzing MSEs in districts/cities in East Java in 2018. The SEM Robust model obtained is

$$\hat{y}_i = exp\left(30{,}9411 + 0{,}5523 \sum_{j=1}^{38} w_{ij} \ln u_j + 1{,}6843 \ln x_1 - 1{,}2583 \ln x_2 - 1{,}5997 \ln x_3\right).$$

Based on the prediction level of MSEs obtained by the Robust SEM model approach, there is one city that belongs to the "very high" category because it has a very high macro productivity value and a relatively high GRDP value compared to other cities. There is one city that belongs to the "high" category because the city has the highest GRDP value and labour force in East Java. There is one regency that belongs to the "medium" category because it has a reasonably high GRDP value among other cities in East Java. There are nine cities in the "low" category because these nine cities have sufficient value for GRDP, macro productivity, and workers. There are 26 cities classified in the "very low" category because these 26 cities have low GRDP, macro productivity and workforce values.

REFERENCES

[1] Pemerintah Indonesia 2013 Undang-Undang No. 13 Tahun 2013 yang mengatur tentang Ketenagakerjaan

[2] Kertiasih L 2017 Pengaruh Tingkat Inflasi dan Tingkat Pertumbuhan Ekonomi terhadap Upah Minimum Regional (UMR) di Provinsi Bali pada Tahun 2008-2015. *E-journal Pendidikan Ekonomi* **9**

[3] Merdekawaty R Analisis Faktor-Faktor yang Mempengaruhi Upah Minimum Kabupaten/Kota di Provinsi Jawa Tengah menggunakan Model *Spatial Autoregressive* (SAR). *Jurnal Gaussian* **5**

[4] Nurtyas F 2016 Analisis Faktor-Faktor yang Mempengaruhi Upah Minimum Provinsi di Pulau Jawa Tahun 2010 – 2014 *Skripsi* (Yogyakarta: Universitas Negeri Yogyakarta)

[5] Nursakinah E 2017 Analisis Faktor-Faktor yang Mempengaruhi Penetapan Upah Minimum di Jabodetabek Tahun 2007-2016 *Skripsi* (Yogyakarta: Universitas Negeri Yogyakarta)

[6] Yunita I 2019 Penerapan SAR pada Upah Minimum Kabupaten/Kota di Pulau Kalimantan Tahun 2017 *Seminar Nasional Official Statistics 2019* (Sekolah Tinggi Ilmu Statistika Jakarta)

[7] Soesilowati E S 2010 *Analisis Tingkat Upah dan Produktivitas* (Jakarta: LIPI Press)

[8] Badan Pusat Statistika 2018 *Upah Minimum Regional/Propinsi (UMR/PMW) dan Rata-rata Nasional per Tahun (dalam Rupiah)*

[9] Wardani Y 2019 Estimasi Parameter Spatial Error Model yang Memuat Pencilan *Skripsi* (Malang: Universitas Islam Negeri Maulana Malik Ibrahim)

[10] Musyarofah H 2020 Robust Spatial Autoregressive untuk Pemodelan Angka Harapan Hidup Provinsi Jawa Timur *Jurnal Gaussian* **9**

[11] Mastuti W C 2020 Robust Spatial Regression Model on Original Local Government Revenue in Java 2017 *Indonesian Journal of Statistics and Its Applications* **4**

[12] Yasin H Hakim A R and Warsito B 2020 Development Life Expectancy Model in Central Java using Robust Spatial Regression with M-estimators *Communications in Mathematical Biology and Neuroscience* 2020

[13] Bachrun S 2012 *Desain Pengupahan untuk Hubungan Industrial dalam Praktek* (Jakarta: PPM)

[14] Bank Indonesia *Metadata Produk Domestik Regional Bruto (PDRB)* (Jakarta: BI)

[15] Sabri M 2014 *Ekonomi Sumber Daya Manusia dalam Perspektif Pembangunan* (Jakarta: PT. Rajagrafindo Persada)

[16] Feriyanto N 2014 *Ekonomi Sumber Daya Manusia dalam Perspektif Indonesia* (Yogyakarta: UU STIM YKPM)

[17] Mankiw G 2006 *Makroekonomi* (Jakarta: Erlangga)

[18] Lee J and Wong D W S 2001 *Statistical Analysis ArcView GIS* (New York: John Wiley & Sons, Inc)

[19] Anselin L 1988 *Spatial Econometrics: Methods and Models* (London: Kluwer Academics Publishers)

[20] Gujarati D 2003 *Basic Econometry* (Jakarta: Erlangga:

[21] Hurint H S, Purnamasari I, and Hayati M N 2016 Metode Regresi Robust Dengan Estimasi Method of Moment (Estimasi-MM) Pada Regresi Linier Berganda (Studi Kasus: Data Indeks Harga Konsumen (IHK) Provinsi Kalimantan Timur) *Jurnal Eksponensial* **7**

[22] Midi H and Mohammed M A 2014 The Performance of Robust Latent Root Regression Based on MM and modified GM estimators *WSEAS TRANSACTIONS on MATHEMATICS* **13**

[23] Setyarini Z and Listyani E 2017 Analisis Regresi Robust Estimasi-S Menggunakan Pembobot Welsch dan Tukey Bisquare *Jurnal Matematika* **6**