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Mixed Geographically Weighted Poisson Regression Model in the Number of Maternal Mortality

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ABSTRACT

This study aims to prove and to use the multiple regression analysis methods can be developed into Poisson regression because the total data follows the assumption of a Poisson distribution. Conditions that occur in poisson regression obtained a global regression coefficient value, which means that each observation point has generalized observation characteristics influenced by the same variables. Based on this problem, a spatial regression is developed where the geographical weighting that called geographically weighted Poisson regression. The results obtained in the geographically weighted poisson regression method allow for variables that have an effect at all observation points. So developed by geographically weighted Poisson regression semiparametric method. This method is implemented in solving the problem of maternal mortality in East Java which is thought to be influenced by the some independent variables. In this study, using East Java data in 2019. The results of mixed geographically weighted poisson regression results, with kernel function used in the analysis is fixed gaussian and the variable number of health facilities was used as a global variable, and obtained 12 groups with local variables that both had a significant effect.

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1. INTRODUCTION

The application of multiple regression analysis needs to be adjusted to the form of the y variable or the response variable used in the analysis. When the y variable data is in the form of total data or count data which collects the number of events that rarely occur within a certain time span, then the development and approach of the method used is Poisson regression (Maneking et al., 2020). So it can be said that it is assumed that the response variable used in the analysis is Poisson distribution where the variance and average value of the y variable are more than zero. Poisson regression is the development of multiple regression in which the variable y uses count data (Sundari, 2012). In the analysis process by applying the Poisson regression method, the first step in the parameter coefficient estimation process is to form the ln-likelihood function on the Poisson distribution which is then derived β^T and an iterative process is carried out using the Newton-Raphson method (Darnah, 2010). Then, after the parameter assessment, the analysis of the significance of the parameters is tested either simultaneously or simultaneously and the coefficient of the model parameter is tested partially.

The results of the Poisson regression analysis show global conditions, which means that each object of research will have the same coefficient value. Predictor variables that affect the response variable will also be the same (Darnah, 2010). However, the problem is that each object of observation has different characteristics so that it cannot be generalized to the same. This will give an error in the direction of the policy provisions that are decided when the characteristics are different but the results of the parameter coefficients are "forced" to be the same. Especially when the object of observation used is a region, it cannot be generalized to the same. Therefore, Poisson regression is also developed so that the results obtained are not global or are called spatial parameter coefficients. With the object of observation involved in the study is an area or area by taking into account the longitude and latitude, the development of Poisson regression is called the geographically weighted Poisson regression (GWPR) method which is weighted based on geographical location (Saefuddin et al., 2013).

The GWPR method is a Poisson regression development where the GWPR method uses geographic location, both latitude and longitude, to calculate the weighting function. The concept of the GWPR method is a spatial regression method that produces a model for each object of observation (Yasin, 2013). So that the model parameter coefficients are not global but local. The GWPR method is a non-parametric method and the coefficient value is influenced by latitude and longitude. The GWPR method also requires the assumption of multicollinearity to determine the initial steps of the Newton-Raphson iteration process. In addition to the multicollinearity test, another thing that needs to be considered in the GWPR method is the determination of bandwidth. Bandwidth is used to see which objects around a certain object have an effect or impact on a certain object (Khaulasari, 2019). Determination of bandwidth is influenced by the latitude and longitude. In addition, the determination of the optimum bandwidth will affect the kernel function used in the analysis process. The kernel function is a weighting function that is used to estimate the parameters. The kernel functions used in the analysis include adaptive gaussian, adaptive bisquare, fixed bisquare, and adaptive bisquare. The use of kernel functions used in the analysis process, is based on the criteria of model goodness (Destyanugraha & Kurniawan, 2017).

Based on the results of the analysis using the GWPR method, it is possible that there are predictor variables that affect all objects of observation. So that the GWPR method can be developed into a mixed method geographically weighted poisson regression (Khoeriyah & Hajarisman, 2021). The MGWPR method is a development method of GWPR that involves 2 predictor variables that are parametric or global or non-parametric which are local so that the MGWPR regression is called semiparametric spatial regression. The determination of parametric variables is global in GWPR which has an influence on all objects of observation. The analysis process in MGWPR is the same as with the GWPR method where the determination of the optimum bandwidth has a significant effect on determining the kernel function or weighting in the parameter coefficient estimation process (Utami et al., 2021). So for taking the best model, that is by using the value of the goodness of the model. Meanwhile, the good values of the model are the Akaike information criterion (AIC), the Akaike information criterion corrected (AICc), and the Bayesian information criterion (BIC).

The use of Poisson regression, GWPR, and MGWPR methods were applied in the formation of spatial models in districts/cities in East Java related to maternal mortality and the influencing factors. Maternal mortality shows the number of maternal deaths both during pregnancy, childbirth, and during the puerperium. Maternal mortality as described in the Health Profile report of East Java Province, it is stated that maternal mortality from internal factors is caused by congenital factors, which is shown in Figure 1 as follows:

Various kinds of government programs to reduce maternal mortality, one of which is the Making Pregnancy Safer (MPS) program and the Maternal Love Movement (GSI), but there are still areas that have relatively high maternal mortality rates. In line with research conducted by Aeni that maternal internal factors indicate the cause of death, namely the direct cause is uterine atony, bleeding, preeclampsia and eclampsia, infection, disturbed ectopic pregnancy, abortion, urinary retention and the indirect cause is heart disease (Aeni, 2013). Another study related to the number of maternal deaths or maternal mortality conducted by Arkandi and Winahju showed that external conditions or conditions outside the patient's condition also had an influence on the mortality rate, namely the percentage of visits by pregnant women with K1 and K4, the percentage of pregnant women receiving Fe3, the percentage of obstetric complications handled, the percentage of active family planning, household participants with PHBS, and deliveries assisted by health workers have a globally significant impact on maternal mortality in districts/cities in East Java (Arkandi & Winahju, 2015).

The thing that needs to be considered is the variety of heterogeneous conditions in the East Java region where districts/cities show different demographic characteristics. In addition , human resources in each region have different capacities and implementation of work programs in reducing maternal mortality . Therefore, it can be explained that each region or region needs a different approach because it has different characteristics. Because if an analytical approach is carried out and global results are obtained, it will be generalized that the conditions that occur tend to be homogeneous or the same. So that the policy steps that have been implemented and the steps taken can be said to be less precise. Therefore, it is necessary to analyze the factors that influence maternal mortality partially in order to determine the condition of the regional character so that the policy direction to be determined is more appropriate and more targeted. Thus, given the importance of the issue of maternal mortality in East Java and the increasing incidence from year to year, the title of this research is "Mixed Geographically Weighted Poisson Regression Model in the number of Maternal Mortality"

2. RESEARCH METHOD

The data used in the analysis for this research is data in East Java in 2019 which is divided into 2 variables, namely the independent variable and the dependent variable. The dependent variable in this study was maternal mortality. Meanwhile, the independent variables are the number of health facilities, the percentage of women giving birth to non-medical helpers, the percentage of households that do not have proper sanitation, the percentage of active family planning participants, the percentage of the poor, K1 coverage, K4 coverage, and the percentage of midwife handling coverage. The data analysis technique used is mixed geographically weighted Poisson regression

The results of the analysis obtained from method geographically weighted poisson regression which has possibility obtained variable significant independent influence across point observation. Variable influential independent globally then made as variable for parametric whereas for variable independent with significance in each point observation so made as non- parametric variables. The MGWPR model is development from the GWPR model where predicting parameters that are local as well as global (Dong et al., 2018). In GWPRS modeling where variable suspected dependent with variable independent where in the variable independent for variable locally affected by location latitude and location longitude symbolized with ($\boldsymbol{\beta}_{\mathbf{j}}(u_i, v_i)$). As for global variables, it is symbolized with γ_{j*}. The GWPRS model is as follows (Khaulasari & Antonius, 2019):

$$\hat{\mu}_i = \exp\left(\boldsymbol{\beta}^{\mathbf{T}}(u_i,v_i)\mathbf{x_i}' + \hat{\boldsymbol{\gamma}}^{\mathbf{T}}\mathbf{x_i}^{*`}\right)$$
$$y_i \sim \text{Poisson}\left[\exp\left(\sum_{j=0}^{k}\beta_j(u_i,v_i)\,x_{ij} + \sum_{j*=1}^{k*}\gamma_{j*}x_{ij*}\right)\right] \quad (1)$$

2.1 Estimate Coefficients of Mixed Geographically Weighted Poisson Regression

Estimation model parameter coefficients for method mixed geographically weighted poisson regression using MLE or maximum likelihood estimation. In method the then the first step to take that is use likelihood functions (Yasin, 2013).

$$L(\boldsymbol{\beta}^*(u_i,v_i),\boldsymbol{\gamma}) = \prod_{i=1}^{n} f(y_i) = \prod_{i=1}^{n}\frac{\exp(-\mu_i)\mu_i^{y_i}}{y_i!} \quad (2)$$

Following this is function ln - likelihood from MGWPR method :

$$\ln L\,(\boldsymbol{\beta}^*(u_i,v_i),\boldsymbol{\gamma}) = \ln\prod_{i=1}^{n} f(y_i) = \sum_{i=1}^{n}\ln\left(\frac{\exp(-\mu_i)\mu_i^{y_i}}{y_i!}\right) \quad (3)$$

$$\ln L\,(\boldsymbol{\beta}^*(u_i,v_i),\boldsymbol{\gamma}) = -\sum_{i=1}^{n}\mu_i + \sum_{i=1}^{n} y_i\ln(\mu_i) - \sum_{i=1}^{n}\ln(y_i!)$$

$$\ln L\,(\boldsymbol{\beta}^*(u_i,v_i),\boldsymbol{\gamma}) = -\sum_{i=1}^{n}\exp\left(\boldsymbol{\beta}^{\mathbf{T}}(u_i,v_i)\mathbf{x_i}' + \hat{\boldsymbol{\gamma}}^{\mathbf{T}}\mathbf{x_i}^{*`}\right) + \sum_{i=1}^{n} y_i\ln\left(\exp\left(\boldsymbol{\beta}^{\mathbf{T}}(u_i,v_i)\mathbf{x_i}' + \hat{\boldsymbol{\gamma}}^{\mathbf{T}}\mathbf{x_i}^{*`}\right)\right) - \sum_{i=1}^{n}\ln(y_i!)$$

$$\ln L\,(\boldsymbol{\beta}^*(u_i,v_i),\boldsymbol{\gamma}) = -\sum_{i=1}^{n}\exp\left(\boldsymbol{\beta}^{\mathbf{T}}(u_i,v_i)\mathbf{x_i}' + \hat{\boldsymbol{\gamma}}^{\mathbf{T}}\mathbf{x_i}^{*`}\right) + \left(\sum_{i=1}^{n} y_i\hat{\boldsymbol{\beta}}^{\mathbf{T}}(u_i,v_i)\mathbf{x_i}' + \sum_{i=1}^{n} y_i\,\hat{\boldsymbol{\gamma}}^{\mathbf{T}}\mathbf{x_i}^{*`}\right) - \sum_{i=1}^{n}\ln(y_i!)$$

The MGWPR method is also influenced by weighting based on location geography from each point observation . So that ln-likehood function changed as following:

$$\ln L\,(\boldsymbol{\beta}^*(u_i,v_i),\boldsymbol{\gamma}) = -\sum_{i=1}^{n}\exp\left(\hat{\boldsymbol{\beta}}^{\mathbf{T}}(u_i,v_i)\mathbf{x_i}' + \hat{\boldsymbol{\gamma}}^{\mathbf{T}}\mathbf{x_i}^{*`}\right)w(u_i,v_i) + \left(\sum_{i=1}^{n} y_i\hat{\boldsymbol{\beta}}^{\mathbf{T}}(u_i,v_i)\mathbf{x_i}' + \sum_{i=1}^{n} y_i\,\hat{\boldsymbol{\gamma}}^{\mathbf{T}}\mathbf{x_i}^{*`}\right)w(u_i,v_i) + -\sum_{i=1}^{n}\ln(y_i!)w(u_i,v_i)$$

Next steps to take differentiation ln-likehood function the to local parameters as well as global parameters and equal with zero value.

$$\frac{\partial\ln L^*(\boldsymbol{\beta}^*(u_i,v_i),\gamma)}{\partial\boldsymbol{\beta}^{\mathbf{T}}(u_i,v_i)} = -\sum_{i=1}^{n}\left[\exp\left(\hat{\boldsymbol{\beta}}^{\mathbf{T}}(u_i,v_i)\mathbf{x_i}' + \hat{\boldsymbol{\gamma}}^{\mathbf{T}}\mathbf{x_i}^{*`}\right)\right]\mathbf{x_i}'w(u_i,v_i) + \sum_{i=1}^{n} y_i\mathbf{x_i}'w(u_i,v_i) \quad (4)$$

$$\frac{\partial\ln L^*(\boldsymbol{\beta}^*(u_i,v_i),\gamma)}{\partial\boldsymbol{\gamma}(u_i,v_i)} = -\sum_{i=1}^{n}\left[\exp\left(\hat{\boldsymbol{\beta}}^{\mathbf{T}}(u_i,v_i)\mathbf{x_i}' + \hat{\boldsymbol{\gamma}}^{\mathbf{T}}\mathbf{x_i}^{*`}\right)\right]\mathbf{x_i}^* + \sum_{i=1}^{n} y_i\mathbf{x_i}^* \quad (5)$$

Based on equation, then obtained implicit results. So for getting results that are not ambiguous, resolved with use Newton-Raphson method.

2.2 Mixed Geographically Weighted Poisson Regression Parameter Test

Following this is testing hypothesis for test the similarity of the model between the MGWPR model and the Poisson model with apply MLRT method or maximum likelihood ratio test (Octavianty et al., 2017):

H_0: $(\beta_j(u_{i,}v_i),\gamma_{j*}) = (\beta_j,\gamma_{j*})$

H_1: at least one of them $\beta_j(u_{i,}v_i),\gamma_{j*}$ has a spatial effect or there is a difference between the GWPRS model and the Poisson model

Statistics Test: $D(\hat{\boldsymbol{\beta}}) = 2(\ln L\,(\hat{\Omega}) - \ln L\,(\hat{\omega}))$

If the Poisson model considered as model A which has degrees free as df.a whereas for the MGWPR model considered as mode B with score degrees free as df.b , so that the test statistic for the model similarity test is as following (Li et al., 2013):

$$F_{hit} = \frac{\text{Devians Model A}/df_a}{\text{Devians Model B}/df_b}$$

Follow distribution F with degrees free $df_A$and df_B.
Decision: Refer to the results analysis the test statistic\, then could decided reject H $_0$ or there is difference between Poisson models with the GWPR model when $F_{hit} > F_{(\alpha,df_a,df_b)}$with a significance level of 5%.
Following this is hypothesis for GWPRS model parameter testing simultaneously with use Maximum Likelihood Ratio Test (MLRT)(Utami et al., 2021)
H_0: $\boldsymbol{\beta} = \mathbf{0}$ and $\boldsymbol{\gamma} = \mathbf{0}$
H_1:there is at least one parameter that has a significant effect on the model, both global and local parameters.
$D(\hat{\beta})$as the deviation value of the GWPRS model. $L(\hat{\Omega})$is a likelihood function with a set Ωconsisting of parameters except the parameters below $H_0$and $L(\hat{\omega})$is a likelihood function for the set of parameters below H_0.
Decision: Reject H $_0$ if $D(\hat{\beta}) > \chi^2_{\alpha;k}$it means that at least one parameter of the GWPRS model has a significant effect.
For the next test is testing by Partial for any influential parameter variable. Following this is testing hypothesis by partial (Khoeriyah & Hajarisman, 2021).
a. H_0: $\beta_j(u_i, v_i) = 0$
H_1: $\beta_j(u_i, v_i) \neq 0$
b. H_0: $\gamma_{j*} = 0$
H_1: $\gamma_{j*} \neq 0$
Test Statistics : (a) $t = \frac{\hat{\beta}_j(u_i,v_i)}{se(\hat{\beta}_j(u_i,v_i))}$
(b) $t = \frac{\hat{\gamma}_{j*}}{se(\hat{\gamma}_{j*})}$
Decision: If the result analysis obtained that $|Z_{hitung}| > Z\alpha_{/2}$then the conclusion is reject H_0 which means that the jth parameter at location i-th $(u_i, v_i)$and the j* variable which is a parameter that shows the global variable has a significant effect against the model. However conclusions reached that is to accept H_0 when results analysis $|Z_{hitung}| \leq Z\alpha_{/2}$ it means that the jth parameter at location i-th (u_i, v_i) and the j* variable which is a parameter that shows the global variable has no significant effect on the model (Lu et al., 2015)

3. RESULTS AND DISCUSSIONS

The following are the results of the analysis using the MGWPR method:

3.1 Goodness of Fit Test MGWPR Model

At the initial analysis stage, a suitability test for the MGWPR model was carried out which was compared with the Poisson model. The following is a test of the suitability of the MGWPR model and its hypothesis:
H_0: $(\beta_j(u_i, v_i), \gamma_p) = (\beta_j, \gamma_p)$
H_1: $(\beta_j(u_i, v_i), \gamma_p) \neq (\beta_j, \gamma_p)$
The following are the results of the model suitability test where the MGWPR model is compared with the Poisson model shown in Table 1

Table 1. Goodness of Fit MGWPR Model

Model	Deviance	df	Deviance/df	F-score
Global	170,684	29	5,886	1,2553
MGWPR	99,123	21,141	4,689	

Referring to the results of the analysis shown in Table 1, it is found that the F-value is 1.2553. Then it's compared with the F-table value where the significance level value is 5% with df1 of 29 and df2 of 21.141 so that the F-table value is 2.01639. Then the decision obtained is to accept H_0. However, with heterogeneity conditions and it was found that there were global and local variables in the previous analysis, the MGWPR model was deemed more appropriate and appropriate compared to the Poisson model.

3.2 Test

The initial stage is conducting simultaneous testing to find out whether there are any local variables and global variables that have a significant effect on maternal mortality. The following is the hypothesis of concurrent testing of the parameters of the MGWPR model:

H_0: $\boldsymbol{\beta} = \mathbf{0}$ dan $\gamma_1 = 0$

H_1: at least one parameter both local and global that is not equal to zero or there is one parameter that has a significant effect for the model.

The results of the analysis for the simultaneous test are showed in the deviation value $D(\hat{\beta})$ is 99,122961. Then the deviance value is compared with the value of the chi-square table where the significance level value is 5% and df value is k (a number of independent variables) involved in the analysis. The value of the chi-square table obtained a value of 15.5073. So the conclusion is t $D(\hat{\beta}) > \chi^2_{(\alpha,k)}$ which means reject H_0. Therefore, the conclusion obtained is that there is at least one parameter, both local and global.

2.1 Partial Test

The following are hypotheses for global variables:

H_0: $\gamma_1 = 0$

H_1: $\gamma_1 \neq 0$

The following are hypotheses for local variables:

H_0: $\beta_j(u_j, v_j) = 0$

H_1: $\beta_j(u_j, v_j) \neq 0$

For example, the results of the parameter testing in Pasuruan Regency can be seen in Table 2 as follows:

Table 2. Partial Test of Pasuruan District of MGWPR Model

Global Variable			
Parameter	Estimate	Error Standard	Z-score
β_1	0,00376	0,000536	6,85346*
Local Variable			
Parameter	Estimate	Error Standard	Z-score
β_0	2.4795	1.7157	1.4451
β_2	0.0324	0.0283	1.1455
β_3	0.0071	0.0029	2.4919*
β_4	0.0339	0.0160	2.1216*
β_5	-0.0966	0.0206	-4.6913*
β_6	0.0445	0.0197	2.2592*
β_7	-0.0697	0.0117	-5.9592*
β_8	-0.0051	0.0042	-1.2008

The following are local predictor variables or non-parameters that are significant in each district/city in East Java and the formation of a spatial model for each district/city as shown in Table 3.

Table 3. Pemodelan GWPR Berdasarkan Variabel Signifikan

District/City	Significant Local Variable	Model
Pacitan	-	$\ln(\hat{y}) = -0{,}1462 + 0{,}00368X_1$
Ponorogo	X_3	$\ln(\hat{y}) = -1{,}423 + 0{,}00368X_1 + 0{,}0109X_3$
Trenggalek	X_3	$\ln(\hat{y}) = -0{,}3682 + 0{,}00368X_1 + 0{,}0131X_3$
Tulungagung	X_3	$\ln(\hat{y}) = -0{,}2631 + 0{,}00368X_1 + 0{,}0137X_3$
Blitar	X_3, X_5, X_7	$\ln(\hat{y}) = 0{,}5791 + 0{,}00368X_1 + 0{,}014X_3 - 0{,}0623X_5 - 0{,}0262X_7$

District/City	Significant Local Variable	Model
Kediri	X_3, X_5, X_6, X_7	$\ln(\hat{y}) = -0{,}9161 + 0{,}00368X_1 + 0{,}00104X_3 - 0{,}0623X_5 + -0{,}0319X_7$
Malang	X_3, X_5, X_6, X_7	$\ln(\hat{y}) = 0{,}3755 + 0{,}00368X_1 + 0{,}0097X_3 - 0{,}071X_5 + 0{,}0406X_6 - 0{,}0461X_7$
Lumajang	X_3, X_4, X_5, X_7	$\ln(\hat{y}) = 4{,}098 + 0{,}00368X_1 + 0{,}0081X_3 + 0{,}0334X_4 - 0{,}1113X_5 - 0{,}0768X_7$
Jember	X_3, X_5, X_7, X_8	$\ln(\hat{y}) = 4{,}9983 + 0{,}00368X_1 + 0{,}007X_3 - 0{,}1179X_5 + -0{,}085X_7 - 0{,}009X_8$
Banyuwangi	X_5, X_7, X_8	$\ln(\hat{y}) = 10{,}9801 + 0{,}00368X_1 - 0{,}1425X_5 - 0{,}106X_7 - 0{,}0221X_8$
Bondowoso	X_5, X_7, X_8	$\ln(\hat{y}) = 5{,}4868 + 0{,}00368X_1 - 0{,}1201X_5 - 0{,}09X_7 - 0{,}0116X_8$
Situbondo	X_5, X_7, X_8	$\ln(\hat{y}) = 5{,}8397 + 0{,}00368X_1 - 0{,}1221X_5 - 0{,}0919X_7 - 0{,}0124X_8$
Probolinggo	X_3, X_4, X_5, X_6, X_7	$\ln(\hat{y}) = 2{,}4795 + 0{,}00368X_1 + 0{,}0071X_3 + 0{,}034X_4 - 0{,}0966X_5 + +0{,}0445X_6 + -0{,}0697X_7$
Pasuruan	X_3, X_4, X_5, X_6, X_7	$\ln(\hat{y}) = 1{,}475 + 0{,}00368X_1 + 0{,}0074X_3 + 0{,}032X_4 - 0{,}0864X_5 + 0{,}0445X_6 + -0{,}0697X_7$
Sidoarjo	X_3, X_5, X_6, X_7	$\ln(\hat{y}) = -0{,}3241 + 0{,}00368X_1 + 0{,}0077X_3 - 0{,}066X_5 + 0{,}056X_6 - 0{,}05X_7$
Mojokerto	X_3, X_5, X_6, X_7	$\ln(\hat{y}) = -0{,}6598 + 0{,}00368X_1 + 0{,}0086X_3 - 0{,}06X_5 + 0{,}0523X_6 - 0{,}0437X_7$
Jombang	X_3, X_5, X_6, X_7	$\ln(\hat{y}) = -1{,}0794 + 0{,}00368X_1 + 0{,}0092X_3 - 0{,}0527X_5 + 0{,}0505X_6 - 0{,}0374X_7$
Nganjuk	X_3	$\ln(\hat{y}) = -1{,}7866 + 0{,}00368X_1 + 0{,}0101X_3$
Madiun	X_3	$\ln(\hat{y}) = -1{,}7579 + 0{,}00368X_1 + 0{,}0085X_3$
Magetan	-	$\ln(\hat{y}) = -1{,}6117 + 0{,}00368X_1$
Ngawi	X_3, X_6	$\ln(\hat{y}) = -1{,}9398 + 0{,}00368X_1 + 0{,}0082X_3 + 0{,}0436X_6$
Bojonegoro	X_3, X_6	$\ln(\hat{y}) = -2{,}337 + 0{,}00368X_1 + 0{,}0092X_3 + 0{,}0542X_6$
Tuban	X_3, X_6, X_7	$\ln(\hat{y}) = -3{,}1227 + 0{,}00368X_1 + 0{,}0067X_3 + 0{,}094X_6 - 0{,}0435X_7$
Lamongan	X_3, X_5, X_6, X_7	$\ln(\hat{y}) = -1{,}4247 + 0{,}00368X_1 + 0{,}008X_3 - 0{,}053X_5 + 0{,}0647X_6 - 0{,}0441X_7$
Gresik	X_3, X_5, X_6, X_7	$\ln(\hat{y}) = -1{,}375 + 0{,}00368X_1 + 0{,}008X_3 - 0{,}0534X_5 + 0{,}0636X_5 - 0{,}0439X_7$
Bangkalan	X_3, X_5, X_6, X_7	$\ln(\hat{y}) = -0{,}8871 + 0{,}00368X_1 + 0{,}0064X_3 - 0{,}0612X_5 + 0{,}0674X_6 - 0{,}0519X_7$
Sampang	X_5, X_6, X_7	$\ln(\hat{y}) = 2{,}8904 + 0{,}00368X_1 - 0{,}098X_5 + 0{,}0517X_6 - 0{,}0764X_7$
Pamekasan	X_5, X_6, X_7	$\ln(\hat{y}) = 3{,}6353 + 0{,}00368X_1 - 0{,}1039X_5 + 0{,}0493X_6 - 0{,}0803X_7$
Sumenep	X_5, X_7, X_8	$\ln(\hat{y}) = 4{,}94 + 0{,}00368X_1 - 0{,}1134X_5 - 0{,}0866X_7 - 0{,}0108X_8$
Kediri City	X_3, X_5, X_6, X_7	$\ln(\hat{y}) = -0{,}9278 + 0{,}00368X_1 + 0{,}0105X_3 - 0{,}0497X_5 + 0{,}0398X_6 - 0{,}0305X_7$
Blitar City	X_3, X_5, X_7	$\ln(\hat{y}) = 0{,}8414 + 0{,}00368X_1 + 0{,}0138X_3 - 0{,}0674X_5 - 0{,}0301X_7$
Malang City	X_3, X_5, X_6, X_7	$\ln(\hat{y}) = 0{,}3807 + 0{,}00368X_1 + 0{,}0096X_3 - 0{,}071X_5 + 0{,}0412X_6 - 0{,}0466X_7$
Probolinggo City	X_4, X_5, X_6, X_7	$\ln(\hat{y}) = 3{,}2527 + 0{,}0036X_1 + 0{,}0334X_4 - 0{,}1031X_5 + 0{,}0462X_6 - 0{,}0769X_7$
Pasuruan City	X_3, X_4, X_5, X_6, X_7	$\ln(\hat{y}) = 0{,}4204 + 0{,}00368X_1 + 0{,}0078X_3 - 0{,}075X_5 + 0{,}0513X_6 - 0{,}0504X_7$
Mojokerto City	X_3, X_5, X_6, X_7	$\ln(\hat{y}) = -0{,}8573 + 0{,}00368X_1 + 0{,}0085X_3 - 0{,}058X_5 + 0{,}054X_6 - 0{,}0428X_7$
Madiun City	X_3	$\ln(\hat{y}) = -1{,}7268 + 0{,}00368X_1 + 0{,}0089X_3$
Surabaya City	X_3, X_5, X_6, X_7	$\ln(\hat{y}) = -0{,}5871 + 0{,}00368X_1 + 0{,}007X_3 - 0{,}064X_5 + 0{,}0618X_6 - 0{,}0514X_8$
Batu City	X_3, X_5, X_6, X_7	$\ln(\hat{y}) = -0{,}0438 + 0{,}00368X_1 + 0{,}0095X_3 - 0{,}066X_5 + 0{,}044X_6 - 0{,}0438X_7$

Referring to the results of the analysis of the formation of the MGWPR model which shows that each model involves the X_1 variable which has a significant effect because the variable is a global variable. But what makes the difference is the local variables that have an effect. The results of the analysis inform that the variables X_3, X_4, and X_6 have a significant effect. In other words, the percentage of households that do not have proper sanitation, the percentage of active family planning participants, and K1 coverage where each variable increase by one unit will also increase maternal mortality by the parameter coefficient of each independent variable. Meanwhile, the variables X_5, X_7, and X_8 also have a significant negative effect, which means that each increase in one unit of the variable will reduce maternal mortality by the parameter coefficient of each independent variable. The X4 variable only affects several areas, namely Lumajang, Probolingo, Pasuruan, and Probolinggo City. While the X_8 variable only has a significant effect in the areas of Jember, Banyuwangi, Situbondo, and Sumenep.

3.3 Clustering MGWPR Model

Based on the results of the analysis, districts/cities can be mapped into groupings based on local variables that have a significant effect on maternal mortality. The following is the result of mapping districts/cities in East Java with the similarity of predictor variables that have a significant influence based on the results of the analysis of the MGWPR analysis method:

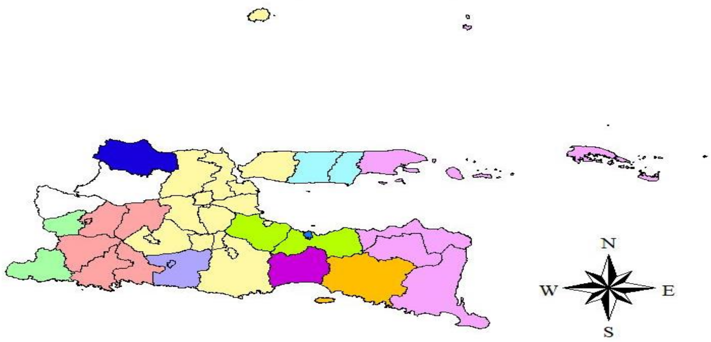

Figure 1. Mapping Model MGWPR Maternal Mortality

Based on the mapping results shown in Figure 2 where the MGWPR method forms 12 clusters or groups that have the same variables even though there are clusters that do not have significant local variables in common. Tuban, Lumajang, Jember, and Ponorogo City have different results with other regions. This means that the districts and cities are classified separately. In Tuban the independent variables that have an effect are the percentage of households that do not have proper sanitation, k1 coverage, and k4 coverage. In Lumajang, the influential predictor variables are the percentage of households that do not have proper sanitation, the percentage of active family planning participants, the percentage of poor people, and K4 coverage. Meanwhile, in Jember, the independent variables that have an effect are the percentage of households that do not have proper sanitation, the percentage of the poor, the K4 coverage, and the percentage of the coverage of the midwife. The results that are quite different are shown in the results of Pacitan and Madiun, there are no local variables that have a significant effect.

The districts of Kediri, Malang, Sidoarjo, Mojokerto, Jombang, Lamongan, Gresik, Bangkalan, Kediri City, Malang City, Pasuruan City, Mojokerto City, Surabaya City, and Batu City are grouped with the same cluster where the local independent variable that influences is the percentage of houses households do not have proper sanitation, percentage of poor population, k1 coverage, and k4 coverage. Meanwhile, Banyuwangi, Bondowoso, Situbondo, Sumenep districts are grouped into 1 cluster which is influenced by the percentage of poor people, K4 coverage, and percentage of midwife handling coverage. Similar to the results of the GWPR analysis, the MGWPR analysis of Blitar Regency and Blitar City grouped into the same 1 group which was influenced by the percentage of households that did not have proper sanitation, the percentage of poor people, and K4 coverage.

4. CONCLUSION

The results of the mixed geographically weighted Poisson regression analysis used the number of health facilities as a global variable, while the other independent variables were used as local variables. Testing the suitability of the model with the Poisson regression comparison showed that the MGWPR model had similarities with the Poisson model. However, the MGWPR model is considered to be much better because it can accommodate spatial heteroscedasticity conditions in maternal mortality data in East Java. The results of the MGWPR analysis also show that districts and cities in East Java can be formed into clusters of 12 based on local variables that have a significant effect. The kernel function applied in the analysis is fixed gaussian with AIC value of 128,326 and BIC value of 152,238. This research can be developed into a bivariate form on the dependent variable so that the model formed will be more specific in problem solving

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