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On Comparisson between Ordinary Linear Regression and Geographically Weighted Regression: With Application to Indonesian Poverty Data

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Abstract

Ordinary linear regression (OLR) is one of popular techniques in analyzing relationship between response variable and its predictors. It is an analysis that produces global models applied to all observations assuming no correlation among responses. In social studies, such as poverty analysis, response variable might be spatial nonstationarity, i.e. depends on the region or neighborhood. Therefore, of course, OLR model will not comply the assumption of independence. In dealing with the problem, an OLR model has to be calibrated by accommodating spatial variation. Alternatively, geographically weighted regression (GWR) involves geographical weights in estimating the parameters. GWR yields models in each region uniquely, i.e. local model, by setting the weights as a function of distance. The weights are greater as the distance is closer, and then continuously decrease to zero as the distance is farther.

This paper shows an application of GWR in poverty analysis in Java, Indonesia. Performance of GWR and OLR model in describing poverty is compared. The results show that GWR has better performance than OLR does based on residuals, R^2, AIC statistics and some formal tests.

Keywords: Global model, geographically weighted regression, local model, spatial analysis

1. Introduction

In describing relationship between response variable and its predictors, it typically uses global models, i.e. ordinary linear regression (OLR) applied to all circumstances. However, in regional based modeling, global model theoretically provides reliable local information if there is no spatial variation over regions. In other word, global models are able to capture relationship when the observations tend to homogenous among regions, i.e. measurement of a relationship do not depend on regions, called spatial stationarity (Fotheringham, Brunsdon, and Charlton 2002). In the case of social studies, such as poverty analysis, the objects usually are non-stationary. Therefore, if global model applied universally to all regions of study, the relationship might be not valid due to ignorance of spatial variations (Fotheringham, Brunsdon, and Charlton 2002). On the other side, OLR relies on the assumption of response independence. However, on poverty study, the percentage of the poor in a region might depend on relative position to the other regions. Therefore, independence assumption is violated (Rahmawati 2010).

To avoid misleading conclusions, model has to be calibrated to accommodate spatial variation over regions using spatial statistics approach. An alternative approach to construct models of spatial nonstationary is to implement geographically weighted regression (GWR) (Brunsdon, Fotheringham, and Charlton 1996, 1999; Fotheringham, Brunsdon, and Charlton 2002; Leung, Mei, and Zhang 2000a). The technique is an extension of weighted regression in which the weights are based on relative position or distance among regions. In GWR model, local parameters are estimated by assigning higher weights to nearby observation than farther ones thus they tend to vary continuously over region (Jetz, Rahbek, and Lichstein 2005). By using GWR each region is allowed to have its own model specifically which referred to as a local model. By holding local models in appropriate region, local variation which is ignored in a global model is accommodated properly by GWR.

GWR procedure has been being developed, for example, by Brunsdon, Fotheringham, and Charlton (1996, 1999), Leung, Mei, and Zhang (2000a, 2000b), Fotheringham, Brunsdon, and Charlton (2002) and Mennis (2006). GWR applied widely in regional development, socio-economic and demographic studies (Propastin, Kappas, and Muratova 2006; Pavlyule 2009; Shariff, Gairola, and Tahib 2010; Rahmawati 2010).

With national symbol Bhinneka Tunggal Ika (means unity in diversity), Indonesia is a very big country (consist of 33 provinces with more than 10.000 islands) with huge diversity. Therefore, the GWR method seems to be suitable in analyzing Indonesian data which normally contain large regional variations. Until now, however, the use of the GWR in Indonesia is very limited although it could be applied in almost all area such as regional development, regional economic, epidemiology, environmental sciences and other issues involving regional aspects. In this paper, we will compare the GWR and the standard Ordinary Least Regression (OLR). The results of this study will enrich the scientific knowledge about comparison of GWR and OLR performance and the possible application of GWR in a region with large diversity such as Indonesia.

The rest of this paper would be organized as follow. On Section 2, authors describe the data and methodology. In this section, basic techniques of GWR are reviewed. Section 3 provides the empirical results and discussion of OLR and GWR modeling and comparison of the two. Summary of results and conclusions are presented on Section 4.

2. Data and Methodology

2.1. Data

The model is on poverty as a linear function of Human Development Index (HDI). The data was provided by The National Team for Accelerating Poverty Reduction, Office of Vice President of Republic of Indonesia (2010) for the year of 2008. Observation units are 116 districts and administrative cities in Java, Indonesia, spread out in six provinces.

Java is inhabited by about 58% of Indonesia's population (BPS 2010) thus it is referred to as the most densely populated island in the country. Java is centered near 7°30′10″ S, 111°15′47″ E and stretches from about 106° E to 114° E, along the northeast edge of the Indian Ocean in southeast Asia.

The island can be considered spatial nonstationary due to several circumstances, like (1) differences of provincial and district governments, (2) distance of regions to central government, (3) regional autonomy, and (4) differences of agro-ecosystem or climate. Due to the existing Java condition, it is very reasonable to implement the GWR to analyze relationship between poverty and HDI rather than the OLR. However, performance of GWR has to be tested.

2.2. Geographically Weighted Regression

In general statistical analysis the geographical analysis, ordinary linear regression (OLR) is one of popular methods in identifying relationship between variables. OLR forms the response variable as linear function of one or several predictors (Fotheringham, Brunsdon, and Charlton 2002; Leung, Mei, and Zhang 2000a). For given n observations (i=1,2,…,n) and p predictors, OLR model is expressed as

$$y_i = \beta_0 + \sum_{k=1}^{p} \beta_k x_{ik} + \varepsilon_i \tag{1}$$

where y_i is the outcome of i-th observation, x_{ik} is i-th observation of k-th predictors, β_0, β_1, …, β_p are regression parameters and ε_i is error term that follows normal distribution with zero mean and known standard deviation. In matrix notations, equation (1) could be written as

$$\boldsymbol{y} = \boldsymbol{X\beta} + \boldsymbol{e} \tag{2}$$

Regression parameter in OLR model $\boldsymbol{\beta}$ is usually estimated by least square method which is expressed as

$$\hat{\boldsymbol{\beta}} = (\boldsymbol{X}^T\boldsymbol{X})^{-1}\boldsymbol{X}^T\boldsymbol{y} \tag{3}$$

where $\boldsymbol{X}$ is $n \times (p+1)$ matrix of predictors, $\boldsymbol{Y}$ is $n \times 1$ column vector of response and $\hat{\boldsymbol{\beta}}$ is $(p+1)\times 1$ column vector of parameter estimates. To obtain estimated value of $\boldsymbol{y}$, $\hat{\boldsymbol{\beta}}$ has to be formerly multiply with $\boldsymbol{X}$, that is

$$\hat{\boldsymbol{y}} = \boldsymbol{X}\hat{\boldsymbol{\beta}} = \boldsymbol{X}(\boldsymbol{X}^T\boldsymbol{X})^{-1}\boldsymbol{X}^T\boldsymbol{y} \tag{4}$$

or

$$\hat{\boldsymbol{y}} = \boldsymbol{S}_0\boldsymbol{y}$$

where

$$\boldsymbol{S}_0 = \boldsymbol{X}(\boldsymbol{X}^T\boldsymbol{X})^{-1}\boldsymbol{X}^T \tag{5}$$

Then $\boldsymbol{S}_0$ is referred to as hat matrix of OLR.

OLR produces global model and therefore the parameter estimates apply to all observation universally. This model is reliable to all regions when there is no spatial nonstationarity over regions, which means that the measurement of variables does not depend on region where there are taken. On the other hand, if there is any spatial nonstationarity, OLR models may not be appropriate since information on spatial variation in neglected. In dealing with nonstationarity, GWR could be adopted to investigate spatial variation occurred in parameter estimates (Fotheringham, Brunsdon, and Charlton 2002).

General form of GWR model is expressed as

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i) x_{ik} + \varepsilon_i \tag{6}$$

where (u_i, v_i) denotes the location of i-th observation in geographical space, $\beta_k(u_i, v_i)$ is k-th parameter of i-th observation. Unlike OLR model, this model allows parameter to vary over region. Therefore, it will be useful to present the local parameter estimates or other related statistics on the map (Mennis 2006).

The parameter estimate of GWR $\beta_k(u_i, v_i)$ is obtained using weighted least square method. Suppose the diagonal elements of matrix $\boldsymbol{W}(u_i, v_i)$ are the weights assigned to any region (u_i, v_i). However, the $\boldsymbol{W}(u_i, v_i)$ would be different as (u_i, v_i) is changed depending its location (Leung, Mei, and Zhang 2000a). Then, in matrix notation parameter estimates takes form

$$\hat{\boldsymbol{\beta}}(u_i, v_i) = (\boldsymbol{X}^T \boldsymbol{W}(u_i, v_i)\boldsymbol{X})^{-1} \boldsymbol{X}^T \boldsymbol{W}(u_i, v_i)\boldsymbol{y}$$

or simply

$$\hat{\boldsymbol{\beta}}(i) = (\boldsymbol{X}^T \boldsymbol{W}(i)\boldsymbol{X})^{-1} \boldsymbol{X}^T \boldsymbol{W}(i)\boldsymbol{y} \tag{7}$$

For given y_i, then

$$y_i = \boldsymbol{X}_i(\boldsymbol{X}^T \boldsymbol{W}(i)\boldsymbol{X})^{-1} \boldsymbol{X}^T \boldsymbol{W}(i)\boldsymbol{y} \tag{8}$$

If $\boldsymbol{X}_i(\boldsymbol{X}^T\boldsymbol{W}(i)\boldsymbol{X})^{-1}\boldsymbol{X}^T\boldsymbol{W}(i)$ is i-th row of matrix $\boldsymbol{S}_1$, then

$$\hat{\boldsymbol{y}} = \boldsymbol{S}_1 \boldsymbol{y} \tag{9}$$

and $\boldsymbol{S}_1$ is referred to as hat matrix of GWR.

2.3. Choices of the Weighting Function

Spatial weighting function is an important aspect in GWR. It depends on the distances among observations. However, in spatial analysis observation close to a region *i* is generally assumed to has greater effect on parameter estimates at region *i* than those farther away (Leung, Mei, and Zhang 2000a). Therefore, corresponding weights in matrix $\boldsymbol{W}(u_i, v_i)$ will be greater as the distance is closer. Note, when all elements of $\boldsymbol{W}(u_i, v_i)$ remains constant in every region, then ordinary weighted regression holds. Suppose d_{ij} denotes the distances between region *i* and *j,* and $w_j(i)$ denotes the element of weighting matrix at region *i* assigned to region *j.* A possible choice of $w_j(i)$ is expressed as function of

$$w_j(i) = \exp\left[-\frac{1}{2}\left(\frac{d_{ij}}{b}\right)^2\right] \tag{10}$$

$$j = 1, 2, \ldots, n$$

where *b* is the bandwidth. If *i* is exactly equal to *j*, the weights at the point will be unity and the weight of the others will decrease follow a Gaussian curve as *dij* increases. An alternative to Gaussian function to determine elements of weighting matrix is bisquare function which sets the weights of data point inside radius of bandwidth to decrease to zero as *dij* increases and discards the others. Bisquare functions is expressed as

$$w_j(i) = \left[1 - \left(\frac{d_{ij}}{b}\right)^2\right]^2 \text{ if } d_{ij} < b \text{ otherwise } w_j(i) = 0 \tag{11}$$

Both Gaussian and bisquare function allow the weights to vary continuously over region (Brunsdon, Fotheringham, and Charlton 1996; Leung, Mei, and Zhang 2000; Fotheringham, Brunsdon, and Charlton 2002).

Related to the process of choosing the weighting matrix, it is very important to predetermine an optimum bandwidth *b.* This could be done by minimizing either cross-validation *(CV)* score or Akaike Information Criteria (*AIC*). *CV* statistic is expressed as

$$CV = \sum_{i=1}^{n} \left[y_i - \hat{y}_{\neq i}(b)\right]^2 \tag{12}$$

where $\hat{y}_{\neq i}(b)$ is the fitted value of y_i when the observation in regional *i* discarded. While *AIC* statistic is given by

$$AIC = 2n\log(\hat{\sigma}) + n\log(2\pi) + n + \mathrm{tr}(\boldsymbol{S}) \tag{13}$$

or corrected *AIC* statistic is

$$AIC_C = 2n\log(\hat{\sigma}) + n\log(2\pi) + n\left\{\frac{n + \mathrm{tr}(\boldsymbol{S})}{n - 2 - \mathrm{tr}(\boldsymbol{S})}\right\} \tag{14}$$

where $\hat{\sigma}$ is estimated standard deviation of error term and $\boldsymbol{S}$ is hat matrix (Forteringham, Brunsdon, and Chartlon 2002).

2.4. Significance Test for GWR Model

Due to flexibility of parameter estimates over region, according to residual sum of squares, GWR almost performs better than OLR does. However, GWR model has to be investigated statistically in order to answer two major questions. The first question is whether the performance improvement provided by GWR is significant or not. In the fact, this refers to a goodness-of-fit test. Then, the second one is whether the set of parameters vary over region or not (Brunsdon, Forteringham, and Chartlon 1999; Leung, Mei, and Zhang 2000).

Suppose the error term, both on OLR or GWR model, is expressed as :

$$\hat{\boldsymbol{\varepsilon}} = (\boldsymbol{I} - \boldsymbol{S}_z)\boldsymbol{y} \tag{15}$$

where $\boldsymbol{I}$ is identity matrix. Then, residual sum of squares is :

$$\hat{\boldsymbol{\varepsilon}}^T\hat{\boldsymbol{\varepsilon}} = \boldsymbol{y}^T(\boldsymbol{I} - \boldsymbol{S}_z)^T(\boldsymbol{I} - \boldsymbol{S}_z)\boldsymbol{y} = \boldsymbol{y}^T\boldsymbol{R}_z\boldsymbol{y} \tag{16}$$

where $R_z = (\boldsymbol{I} - \boldsymbol{S}_z)^T(\boldsymbol{I} - \boldsymbol{S}_z)$ and z is either 0 or 1 corresponds to OLR or GWR model, respectively. Thus, for z=0, that is OLR model, residual sum of squares takes form :

$$RSS_{OLR} = \boldsymbol{y}^T\boldsymbol{R}_0\boldsymbol{y} = \boldsymbol{y}^T(\boldsymbol{I} - \boldsymbol{S}_0)^T(\boldsymbol{I} - \boldsymbol{S}_0)\boldsymbol{y} \tag{17}$$

and for z=1, that is GWR model residual sum of squares is

$$RSS_{GWR} = \boldsymbol{y}^T\boldsymbol{R}_1\boldsymbol{y} = \boldsymbol{y}^T(\boldsymbol{I} - \boldsymbol{S}_1)^T(\boldsymbol{I} - \boldsymbol{S}_1)\boldsymbol{y} \tag{18}$$

Then, the difference between the two, $GWR_{IMP} = RSS_{OLR} - RSS_{GWR}$, denotes GWR improvement.

To investigate goodness-of-fit of GWR model compared to OLR model, that is to test null hypothesis that GWR and OLR model describe data variability equally well against alternative hypothesis that GWR model has better fit than OLR model does, one of the following statistical procedures could be employed :

1. Brunsdon, Forteringham and Chartlon F Test

F test statistic is expressed as

$$F = \frac{(RSS_{OLR} - RSS_{GWR}) / v}{RSS_{GWR} / \delta_1}$$

or

$$F = \frac{GWR_{IMP} / v}{RSS_{GWR} / \delta_1} \tag{19}$$

where $v = \mathrm{Tr}(\boldsymbol{R}_0 - \boldsymbol{R}_1)$ and $\delta_1 = \mathrm{Tr}(\boldsymbol{R}_1)$. *F* statistic approximately follows *F*-distribution with $df_1 = v^2 / v^*$ and $df_2 = \delta_1^2 / \delta_2$ degrees of freedom, where $v^* = \mathrm{Tr}[(\boldsymbol{R}_0 - \boldsymbol{R}_1)^2]$ and $\delta_2 = \mathrm{Tr}(\boldsymbol{R}_1^2)$. A large value of *F* leads to reject null hypothesis (Brunsdon, Fotheringham, and Charlton 1999).

2. Leung, Mei and Zhang F1 Test

F1 test statistic is expressed as

$$F_1 = \frac{RSS_{GWR} / \delta_1}{RSS_{OLR} / (n - p - 1)} \tag{20}$$

which has approximated *F*-distribution $df_1 = \delta_1^2 / \delta_2$ and $df_2 = n - p - 1$ degrees of freedom. A small value of F_1 supports alternative hypothesis (Leung, Mei, and Zhang 2000a).

3. Leung, Mei and Zhang F2 Test

An alternative procedure to F_1 test is F_2 test whose test statistic is expressed as

$$F_2 = \frac{GWR_{IMP} / v_1}{RSS_{OLR} / (n-p-1)} \tag{21}$$

F_2 statistic approximately follows *F*-distribution with $df_1 = v_1^2 / v_2$ and $df_2 = n-p-1$ degrees of freedom, where $v_1 = n-p-1-\delta_1$ and $v_2 = n-p-1-2\delta_1+\delta_2$. A large value of F2 supports in rejecting null hypothesis (Leung, Mei, and Zhang 2000a).

2.5. Test for Parameter Estimates of GWR Model

Since GWR produces parameter estimates for each location, a test of their variability is needed. Leung, Mei and Zhang (2000a) proposed *F3* test which takes place in diagnosing the null hypothesis that the set of parameters tend to be constant over region. Its test statistic is expressed as

$$F_3(k) = \frac{V_k^2 / \gamma_1}{\hat{\sigma}^2} \tag{22}$$

where

$$V_k^2 = \boldsymbol{\varepsilon}^T \left[\frac{1}{n} \boldsymbol{B}^T \left(\boldsymbol{I} - \frac{1}{n}\boldsymbol{J} \right) \boldsymbol{B} \right] \boldsymbol{\varepsilon} \text{ and} \tag{23}$$

$$\gamma_i = \mathrm{Tr}\left[\frac{1}{n} \boldsymbol{B}^T \left(\boldsymbol{I} - \frac{1}{n}\boldsymbol{J} \right) \boldsymbol{B} \right]^i$$

$\boldsymbol{\varepsilon}$ is row vector of error terms, $\boldsymbol{J}$ is $n \times n$ matrix with unity for each of its elements and *i*-th row of $\boldsymbol{B}$ is given by $\boldsymbol{e}_k^T [\boldsymbol{X}^T \boldsymbol{W}(i) \boldsymbol{X}]^{-1} \boldsymbol{X}^T \boldsymbol{W}(i)$ and e_k is a column vector with unity for the $(k+1)$-th element and zero otherwise. For any parameter, F_3 statistic approximately follows *F*-distribution with $df_1 = \gamma_1^2 / \gamma_2$ and $df_2 = \delta_1^2 / \delta_2$ degrees of freedom. A large value of F_3 support alternative hypothesis that given parameter tends to be vary over region.

Beside formal procedures described above, performance of GWR model and OLR model could be compared by according to determination coefficient (R^2) and Akaike Information Criterion *(AIC)* statistic. However, *AIC* which accounts the complexity of model is considered to as a more relevant index (Jetz, Rahbek, and Lichstein 2005).

3. Results and Discussion

3.1. Result of OLR

The model of poverty which is analyzed in the study takes simple linear form of

$$POV = \beta_0 + \beta_1 * HDI \tag{24}$$

which is describing the relationship between the numbers of poverty as a percentage of population numbers (POV) and Human Development Index (HDI).

HDI is a composite index of three major component, namely healthy, education, and income. HDI is a benchmark of development in a region. A region where has higher HDI ideally has better quality of life. In other word, there is a lower percentage of poverty in a region with higher HDI (Lismawatie 2007). Therefore, we argue that β_1 in equation (24) would be non-positive. Fitting an OLR model in the form of equation (24) provides the results in Table 1.

Table 1: Parameter Estimates of OLR Model

Variable	$\hat{\beta}$	$SE(\hat{\beta})$	*t*	*Pr*(>|*t*|)
Intercept	104.99	8.78	11.95	<.0001
HDI	–1.27	0.12	-10.17	<.0001

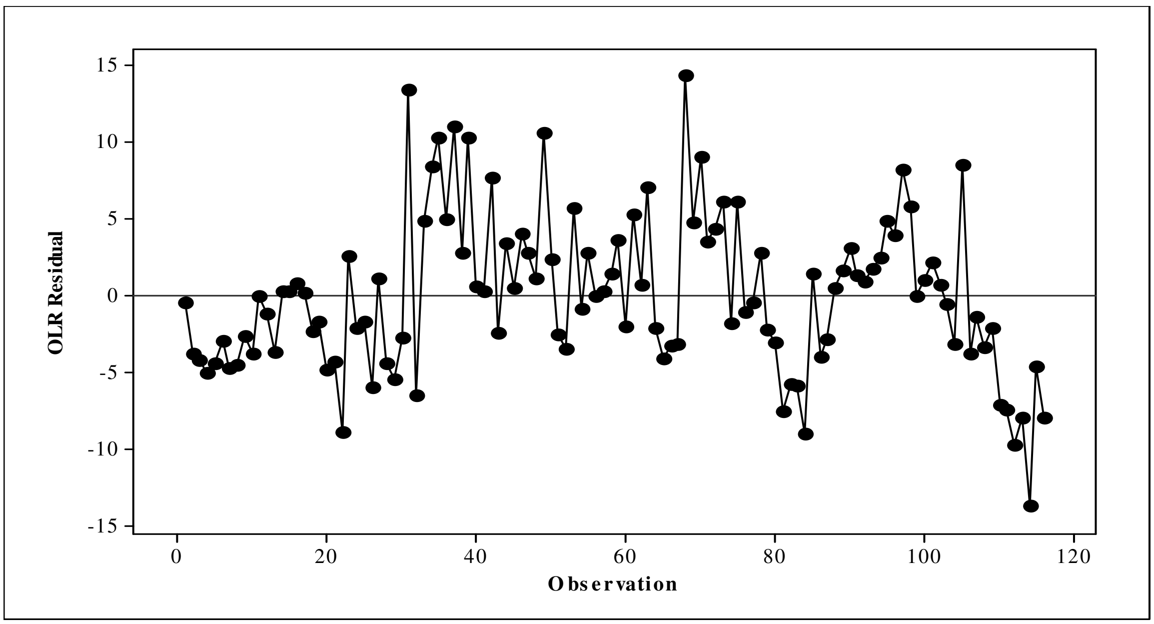
Therefore, based on OLR, a global model is

$$POV = 104.99 - 1.27HDI \qquad (25)$$

which will be hold in all regions. All corresponding *p*-values of regression coefficients in this model are smaller then 0.05, thus intercept and HDI significantly affect the percentage of poverty. This model has *RSS*=3004.52, *AICc*=712.95, *AIC*=708.74 and R^2=47.56%. On the other words, OLR model can only describe less than 50% of poverty variability. Hence, of course, this is not an ideal goodness-of-fit of model.

In addition, scatter plot of residual by observation order shows certain systematic trend, as provided in Figure 1. This indicates that model does not meet assumption of independence and also to be non-stationary over region. Due to the lack-of-fit of model and violation of assumption, it is advisable to use GWR model to describe relationship of poverty and HDI.

Figure 1: Scatter plot of OLR residual by observation order



3.2. Result of GWR

As outlined in the previous sections, the first and critical step in estimating GWR model takes place in obtaining weighting matrix are applied both Gaussian and bisquare kernel function to define weighting. To optimize the bandwidth, both CV score and AIC statistic are implemented. Thus, there are four alternatives of optimum bandwidth correspond to combination of kernel function and optimization method. According to Table 2, combination of Gaussian function and CV score yield optimum bandwidth, according to four indicators (*AICc*, *AIC*, *RSS* and R^2). Since *b*=56.29 km, each element of weighting matrix is expressed as

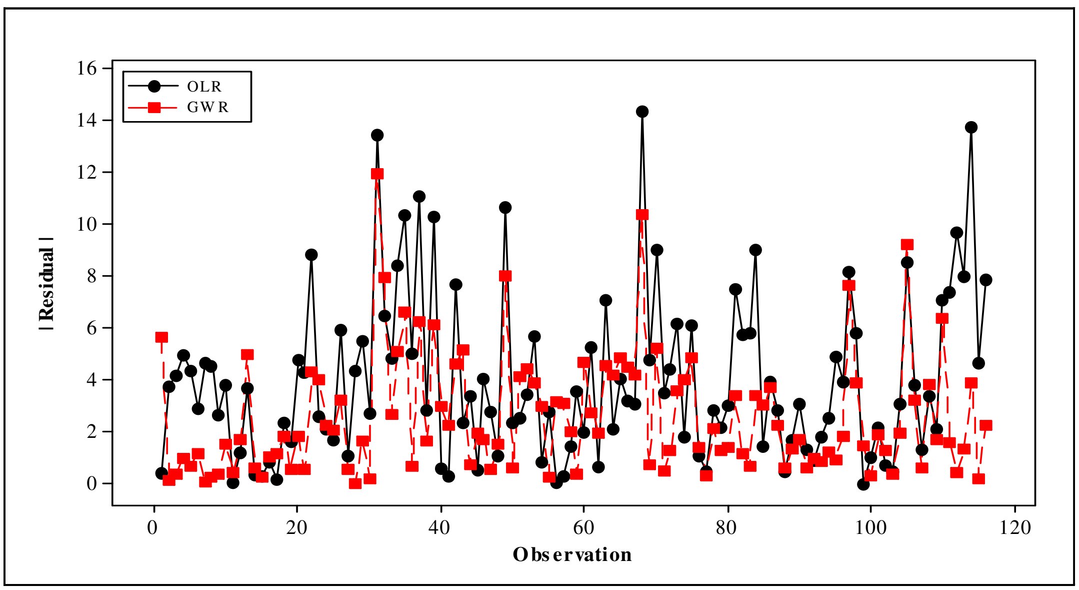
$$w_j(i) = \exp\left[-\frac{1}{2}\left(\frac{d_{ij}}{56.29}\right)^2\right] \qquad (26)$$

Table 2: Alternative of Optimum Bandwidth of GWR Weighting Function

	Gaussian Function		Bisquare Function	
	CV	**AIC**	**CV**	**AIC**
Bandwidth	56.29	68.93	141.10	179.57
AICc	661.38	660.28	663.00	660.29
AIC	633.92	640.34	637.02	642.57
RSS	1376.66	1509.72	1423.79	1557.50
R^2	0.76	0.74	0.75	0.73

Up to this point, once it is applied, GWR model using weighting function of Equation (26) performs better fits than OLR model does according to R^2 and *AIC* (or *AICc*) statistic. In each region, residual of GWR relatively is less than OLR, as displayed in Figure 2. Therefore, *RSS* of GWR is smaller than that of OLR. The difference of the two *RSS*s is about 1627.86. The quantity is referred to as the GWR improvement.

Figure 2: Scatter plot of OLR residual by observation order



However, to ensure that GWR improvement is statistically significant, several goodness-of-fits tests of GWR model have to be performed. In Table 3, we could see that *p*-values of *F*, *F1* and *F2* test, which test null hypothesis that GWR and OLR model fits data equally well, are all smaller than 0.05. Therefore, confidently we reject null hypothesis and conclude that GWR model perform better fits than OLR model does, that means GWR improvement is significant.

Table 3: Summary of Goodness-of-Fits Test of GWR Model

Test	df_1	df_2	***F*-statistic**	***p*-value**
F	114.00	98.24	2.18	<.0001
F1	100.24	114.00	0.57	0.0021
F2	34.31	114.00	2.77	<.0001

Table 4: Summary Statistics of Parameter Estimates on GWR Model

Variable	Min	Q1	Median	Q3	Max	Global
Intercept.	48.90	98.73	114.90	126.20	147.70	104.99
IPM	-1.85	-1.52	-1.38	-1.18	-0.58	-1.27

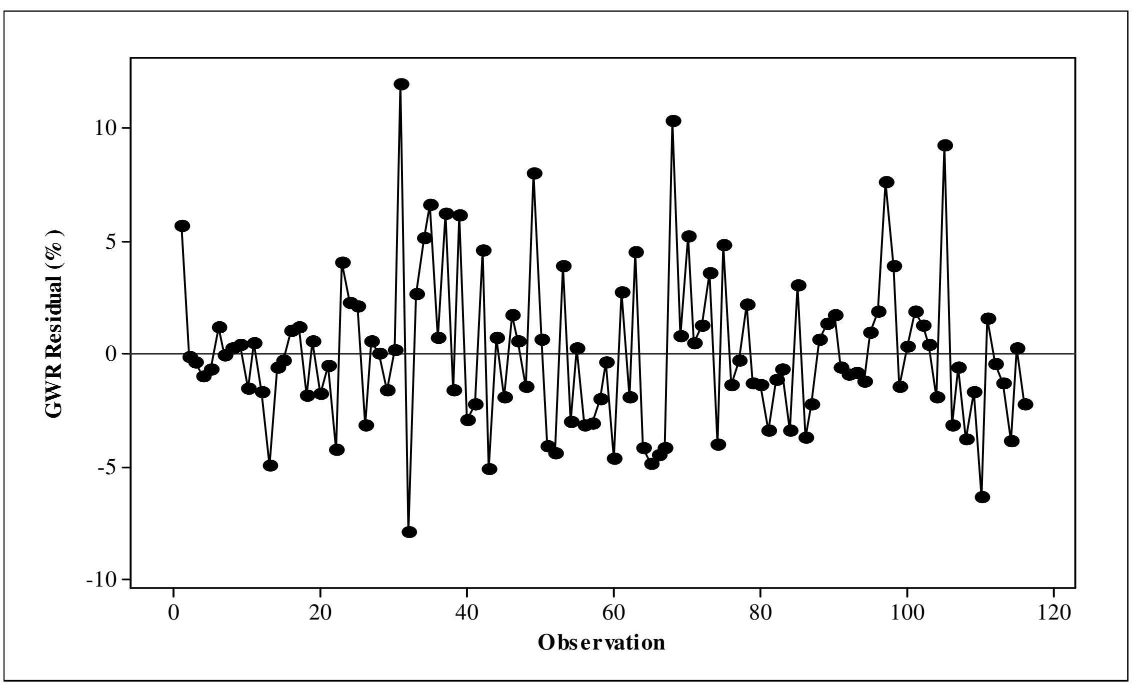
GWR estimates local model of each region. Therefore, the number of local models would be equal to the region number, in this case is 116. Showing all models in mathematical forms might be not interesting and not a statistical issue. Alternatively, presenting summary statistics of the parameter estimates of local models might be more appropriate and useful to explore their variations. The second until fifth column of Table 4 record summaries statistics of parameter estimates in GWR model, while the last column show global parameter estimates of OLR model as provided on Table 2. By the table, there are any variations on all parameters estimates over region. This finding is strengthened by the results of *F*3 test which are presented on Table 5. *P*-values of *F*3 test, which is carried out to test whether the set of parameters are constant or vary over region, are all very small and suggest that variation on parameter estimates are statistically significant.

Table 5: Result of *F*3 Test

	df_1	df_2	***F* statistic**	***Pr*(>*F*)**
Intercept	27.91	100.24	2.99e+06	<.0001
IPM	28.20	100.24	2.41e+06	<.0001

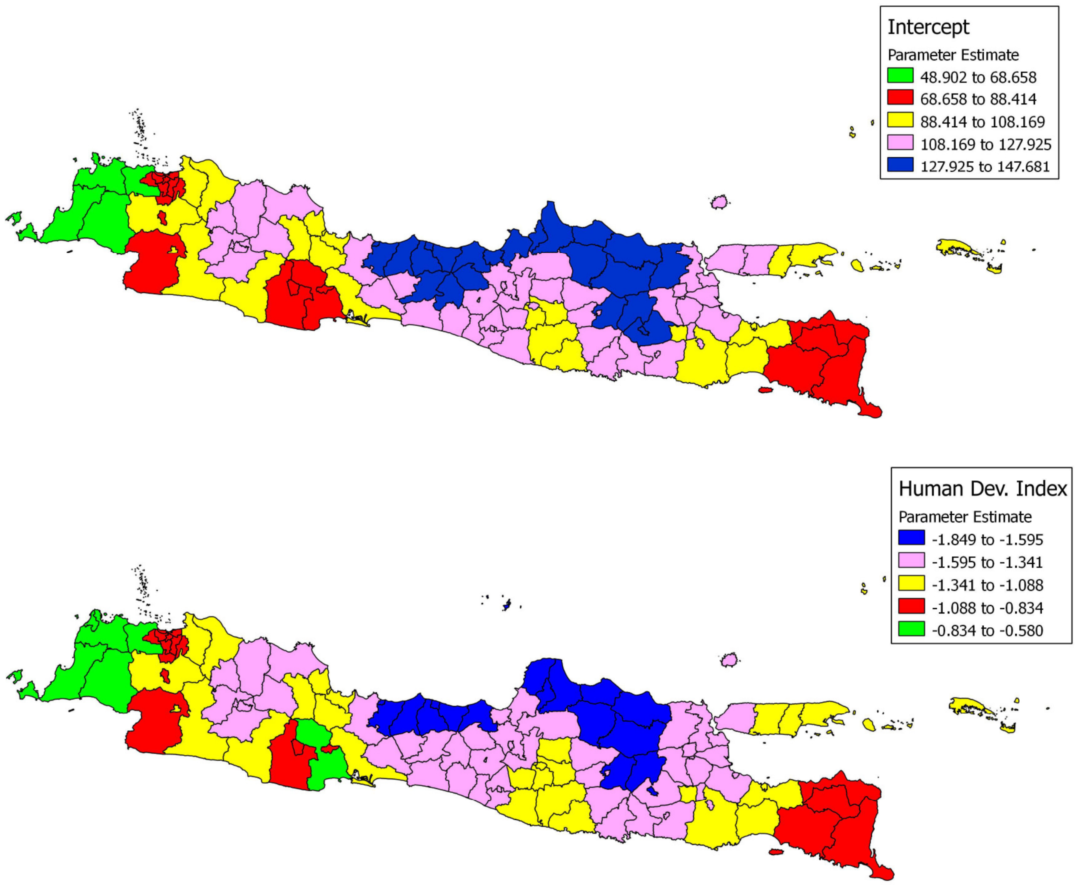
Once GWR model is used to predict percentage of poverty, the residual tend to be stationary. It can be seen on the scatter plot of GWR residual by observation order which is provided by Figure 3. The plot fluctuates at about zero and does not show any systematic pattern.

Figure 3: Scatter plot of GWR residual by observation order



Parameter estimates of local models and others spatial statistics often generate geo-referenced data, so maps and other graphics are typically used to present and interpret them (Mennis 2006). Maps and other graphics might be friendly to explore in which variations exactly are happened. The simple maps presenting present local variation on parameter estimates of GWR model of the poverty analysis are provided on Figure 4. From the maps, it is clear that GWR provides specific information based on its parameter estimates in each location, while OLR only produces same model for all regions. Hence, for regional analysis, the GWR is much more powerful than the OLR. For more advance guidelines, Mennis (2006) described how to mapping the result of GWR comprehensively.

Figure 4: Map of parameter estimates of GWR model



4. Conclusion

Application of simple OLR model in predicting percentage of poverty as a function of Human Development Index (HDI), in the case of poverty study – but not always, yields correlated residual due to spatial non-stationarity of response variable. The residual also very high, thus model cannot describe relationship between variables properly. As one of spatial statistics techniques, GWR that calibrates model by accommodating correlation between regions proposes good solution in dealing with the problem. Once GWR applied, the residuals decrease significantly.

As a conclusion, GWR has better performance than OLR does according to R^2, *AIC* (or *AICc*) statistics, and also *F*, *F1* and *F2* tests. The residuals also tend to be uncorrelated and stationary distributed. These estimates are required to analyze some variables or factors in models affecting to response in each region. Hence, policy recommendation can be proposed specifically in each region.

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