Modelling of GRDP the Construction Sector in Java Island Using Robust Geographically and Temporally Weighted Regression (RGTWR)

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ABSTRACT

Infrastructure development is government focus in 2015-2019. One indicator used to measure economic activities construction sector in one area is GRDP of the construction sector. The Robust Geographically and Temporally Weighted Regression (RGTWR) model is the development of GTWR model to overcome the outliers. This study used GRDP the construction sector as a response variable with population, local revenue, area, and the number of construction establishments as explanatory variables. The RGTWR model is more effective in describing the value of data GRDP the construction sector of the regencies/municipalities in Java Island in 2010-2016. This is indicated by a decrease in the value of RMSE, MAD, and MAPE. The RGTWR model with M-estimator has been able to reduce the measure goodness of fit model, even though the decrease is not too large. Some residuals the RGTWR model still detected as outlier so it is recommended to use another estimator.

Keywords : Construction, GRDP, RGTWR, Spatial, Spatiotemporal

I. INTRODUCTION

Indonesia is administratively divided into several provinces and provinces divided into several regencies and municipalities. Each regency/municipality has different characteristics, both in terms of geography, public facilities, social facilities, and government. Characteristic changes can occur along with changes the time. Differences in characteristics between regions and time require the government to make policies that are in accordance with these characteristics to be on target. So, we need a model that considers the diversity of characteristics between regions and time.

The Geographically and Temporally Weighted Regression (GTWR) method is one of the forms a regression analysis which is local to each location and time. The GTWR model was developed by Huang et al. [1] and Fotheringham et al. [2] from the

Geographically Weighted Regression (GWR) model introduced by Brunsdon et al. [3], Fotheringham et al. [4], and Fotheringham et al. [5] taking into the account the location and time elements. Aisyiah et al. [6], Widiyanti et al. [7], Yasin et al. [8], Ispriyanti et al. [9], Conita and Purwaningsih [10], and Sholihin et al. [11] applied the GTWR model to various fields in Indonesia.

One of the problems that arise in the applicated of the GTWR is some of the residuals of the model was detected as the outlier. Another study from Haryanto et al. [12], GTWR modeling still produces outliers every year. Outliers have a large effect on the value of the parameter estimator from GTWR. Erda et al. [13] conducting a GTWR model development using the Robust method to overcome outliers that occur with exponential weighting functions. The weighting function used for the Robust Geographically and

Temporally Weighted Regression (RGTWR) model in this study is the bisquare weighting function.

Infrastructure development is the focus of government development in 2015-2019. Infrastructure development consists of various types of development projects including the construction of roads, bridges, airports, and so on. Based on the agreement of the ministries/institutions, only 30 projects are prioritized, most of them are located on Java. The Committee for the Acceleration of Provision the Priority Infrastructure (KPPIP) was formed with the aim of overseeing the implementation of the 30 priority projects. To monitor the implementation of development and evaluate the development of the construction sector in Indonesia, actual, accurate and continuous statistical data are needed [14].

Economic activities in the construction sector can be seen the developments using the Gross Regional Domestic Product (GRDP) of the construction sector. One indicator used to measure economic activity in a region is GRDP (BPS, 2016). GRDP is a value added from the output of goods and services produced against input a certain period. The economic structure of a region can be seen using GRDP at current prices or known as nominal GRDP. While economic growth is measured by GRDP based on constant prices or real GRDP.

Research on factors that influence GRDP has been carried out. Rahmatullah [15], Agustiana [16], and Astuti et al. [17] stated that the population has a significant effect on GDP. Research by Novianto and Atmanti [18], Haiyadi & Yasa [19] and Manek & Badruddin [20] showed that local revenue (PAD) has a positive and significant effect on GRDP. Dardak [21] and Putra [22] stated that the area has a significant influence on GRDP with negative direction. Whereas Afandi and Soesatyo [23] and in the draft Construction Services Bill [24] stated that one of the important factors influencing the development of the construction sector was business actors (establishments).

The response variable in this study is the GRDP of the construction sector in 119 regencies/municipalities in Java Island in 2010-2016. Explanatory variables as the factors that will be examined for their influence on the GRDP of the construction sector are population, local revenue, area, and the number of construction establishments. The data used in this study was location and time dimensions, so it is possible to use the RGTWR model. The benefits of this study are addressing regencies/municipalities which as the outlier in the GTWR model and providing information to regencies/municipalities governments in Java on modelling the factors that influence the GRDP of the construction sector. So that it can be used as the material for policy making and its evaluation in accordance with influential factors in each regency/municipality. The aim of this study is to determine the factors that influence each regency/municipality and each year observing the GRDP of the construction sector in Java with the RGTWR model.

II. METHODS AND MATERIAL

The Ordinary Least Square (OLS) method does not always produce a model that follows the normal distribution and/or outliers that affect the model [25]. One method that provides estimation results that are resistant to outliers is robust regression [26]. The most important and most widely used robust regression estimator is the M-estimator introduced by Huber [27]. According to Fox [28], robust regression with M-estimator is done by minimizing the residuals using the equation as follows:

$$\sum_{i=1}^{n}\rho(\varepsilon_i) = 0 \qquad (1)$$

with $\varepsilon_i = y_i - \hat{y}_i$ and ρ are the objective function.

The function used to find weighting functions in robust regression is an objective function. The objective function used in this study is Tukey bisquare with the following formula:

$$\rho(\varepsilon_i)=\begin{cases} \dfrac{c^2}{6}\left\{1-\left[1-\left(\dfrac{\varepsilon_i}{c}\right)^2\right]^2\right\}, & |\varepsilon_i|\le c \\ \dfrac{c^2}{6}, & |\varepsilon_i|> c \end{cases} \qquad (2)$$

with the weighting function as follows:

$$w_i=\begin{cases} \left(1-\left(\dfrac{\varepsilon_i}{c}\right)^2\right)^2, & |\varepsilon_i^*|\le c \\ 0, & |\varepsilon_i^*|> c \end{cases} \qquad (3)$$

The constant c for Tukey weights is 4.685. This value is a constant which results in high efficiency with normal distribution and can provide protection against outliers [28].

The equations for location and time i^{th} that contain outliers [13] are:

$$\rho\,(y_i)=\rho\left[\beta_0(u_i,v_i,t_i)+\sum_{k=1}^{p}\beta_k(u_i,v_i,t_i)x_{ik}+\varepsilon_i\right] \qquad (4)$$

with: $i=1,2,3,\dots,n$; $x_{ik}=x_{i1},\,x_{i2},\,\dots,\,x_{ip}$

The M-estimator is carried out using Iteratively Reweighted Least Square (IRLS). In the iteration method, the value of w_i will change its value in each iteration, so $\hat{\beta}(u_i,v_i,t_i)^m$ with m the number of iterations is:

$$\hat{\beta}(u_i,v_i,t_i)^m=\left(X_i^T W^{m-1} X_i\right)^{-1} X_i^T W^{m-1} y_i \qquad (5)$$

If the weight is W^m, then obtained the estimator is:

$$\hat{\beta}(u_i,v_i,t_i)^{m+1}=\left(X_i^T W^m X_i\right)^{-1} X_i^T W^m y_i \qquad (6)$$

The calculation above will continue to be repeated until obtained the convergent estimator, namely when the difference in value $\hat{\beta}(u_i,v_i,t_i)^{m+1}$ and $\hat{\beta}(u_i,v_i,t_i)^{m}$ close to 0 with m is the number of iterations.

The data used in this study is the GRDP of the construction sector as a response variable. The explanatory variables are 4, namely the number of populations, local revenue (PAD), area, and the number of construction establishments. The scope of research data is 119 regencies/municipalities in Java Island in 2010-2016. The variables used in this study can be seen in Table 1.

Table 1 Details of the variables used in secondary data

Variables	Unit	Sources
GRDP of the construction sector (Y)	Million rupiah	BPS
Populations (X_1)	People	BPS
Local revenue (X_2)	Million rupiah	DJPK
Area (X_3)	Km^2	BPS
Number of Construction Establishments (X_4)	Establishment	BPS

Analysis and modeling are carried out using a statistical software R 3.4.2. The stages of analysis in this study are as follows:

1. Data description to get an overview and information about the response variable and explanatory variables used.

2. Normality test for residuals the model, transformation the response variable if not normal.

Common and widely methods used for converting data in linear models were developed by Box and Cox [29]. The explanatory variables in the linear model used in the Box-Cox approach are usually assumed to have been measured correctly or without significant errors. The formula used in the Box-Cox transaction is:

$$y_i^*=\begin{cases} \dfrac{(y_i^\lambda-1)}{\lambda}, & \text{if } \lambda\ne 0 \\ \ln(y_i), & \text{if } \lambda=0 \end{cases} \qquad (7)$$

with y is response variable, i=1,2,…, n, and λ is the coefficient used as a benchmark to determine what type of transformation is appropriate to be applied. Osborne [30] research presented an overview of traditional normalization transformations and how Box-Cox combined, expanded, and enhanced traditional approaches

to data normalization using software applications.

3. Identify patterns of relationship between response variables and explanatory variables using correlation analysis and multicollinearity tests of explanatory variables.

4. Identify spatial and time diversity by:

   a. Breusch-Pagan test to see spatial diversity for each year and combination.

   Heterogeneity testing is needed in order to know the diversity of observations. The linear regression model for the explanatory variables is generally written as follows:

   $$y_i = \beta_0 + \sum_{k=1}^{p} \beta_k x_{ik} + \varepsilon_i \qquad (8)$$

   with $i = 1, 2, ..., n$; $\beta_0, \beta_1, ..., \beta_p$ is model parameters and $\varepsilon_1, \varepsilon_2, ..., \varepsilon_n$ is the error that assumed to be identical, independent, and normal distribution with a zero average and a constant variance σ^2 or $(\varepsilon_i \tilde{} iid(0,\sigma^2))$.

   The hypothesis used in the heterogeneity test of observations, namely:

   H_0: $\alpha_1 = \alpha_2 = ... = \alpha_p = 0$ (homoscedasticity)

   H_1: at least one $\alpha_k \neq 0$; $k=1,...,p$ (heteroscedasticity)

   with α is a vector of size $(p + 1) \times 1$ from the β coefficient. If Assumed the $\sigma_i^2 = f(\alpha_0 + \alpha_k Z_{ki})$, and $\alpha_k = 0$, then $\alpha_k Z_{ki} = 0$ so $\sigma_i^2 = f(\alpha_0)$ constant.

   Breusch and Pagan [31] formulated heterogeneity test statistics for cross-section data by differencing the Lagrange Multiplier (LM) formula. Breusch-Pagan test statistics are:

   $$BP = \frac{1}{2} f^T Z (Z^T Z)^{-1} Z^T f \qquad (9)$$

   with $f = (f_1, f_2, ..., f_n)^T$, $f_i = \frac{e_i^2}{\sigma^2} - 1$, $e_i = y_i - \hat{y}_i$, and $Z = (z_1, z_2, ..., z_n)^T$ is a matrix of size n × (p + 1) that contains a vector that has been normalized for each observation. The test

gives a reject decision H_0 if the value $BP > \chi^2_{\alpha;(p-1)}$.

   b. Boxplot method to see temporal diversity.

5. Perform GTWR modeling which includes:

   a. Calculates Euclid distance at coordinates u_i, v_i, t_i.

   b. Get the optimum estimation of parameter τ iteratively with the initial value τ_0 and $b_{ST} = b_S$ or spatial bandwidth by comparing the value of the minimum Cross-validation (CV). Get parameter estimates μ and λ.

   c. Determine spatiotemporal bandwidth (b_{ST}).

   d. Calculates the weighting matrix of the GTWR model with kernel bisquare functions.

   e. Estimation of GTWR parameters.

   f. Outlier detection.

   Outliers are observations that are far or unequal from the overall distribution [32]. Regression modeling is very much influenced by the existence of outliers in the data. The existence of outliers will result in inefficient parameter estimates because the resulting output tends to be large or small.

   Boxplot is one method that is often used to find out the existence of outliers [33]. Moses [34] stated that the calculation of this method uses a quartile value and inter-quartile range (JAK). The JAK value is calculated based on the formula:

   $$JAK = Q_3 - Q_1 \qquad (10)$$

   with Q3 is the 3rd quartile value and Q1 is the 1st quartile value. Observations are said to be an outlier if it meets conditions:

   - Value is smaller than {Q1 - (1.5 x JAK)}, or

   - Value is greater than {Q3 + (1.5 x JAK)}

6. Perform RGTWR modeling which includes:

a. Calculated the M-estimator weighting matrix using Tukey bisquare's objective function.

b. Calculated the weighting matrix of the RGTWR model using the IRLS method.

c. Estimating of RGTWR parameters.

d. Normality test of residuals the RGTWR model.

7. Interpret the results by making maps based on coefficients that have a significant effect on the GRDP of the construction sector in the RGTWR model.

8. Make conclusions and suggestions.

III. RESULTS AND DISCUSSION

Overviews and information from data without general decision making are carried out with data descriptions. Descriptions of the data in this study are shown in Figure 1. Figure 1 describes the average value of the GRDP of the construction sector according to the regencies/municipalities category (Y), and its correlation with other independent variables, namely population (X_1), local revenue (X_2), area (X_3), and the number of construction establishments (X_4).

Regencies/municipalities with the large average of the population and have high the average of GRDP the construction sector, there are 4 or 3.36%, namely South Jakarta City, East Jakarta City, West Jakarta City, and Surabaya City (Figure 1a). Regencies/municipalities that have low the average of value PAD there are 114 or 95.80%, and 2 of them have the average value of GRDP the construction sector is high, namely Semarang City and Surabaya City (Figure 1b). Regencies/municipalities whose average value of GRDP the construction sector is high, but have a small area there are 7 or 5.88%, namely South Jakarta City, East Jakarta City, Central Jakarta City, West Jakarta City, North Jakarta City, Semarang City, and Surabaya City (Figure 1c). Regencies/municipalities that have a large the

number of construction establishments, but the average value of the GRDP the construction sector is small there is 1 or 0.84%, namely Sampang Regency.
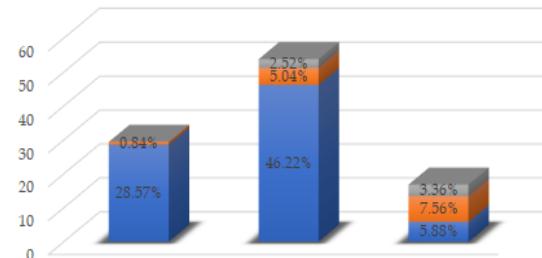
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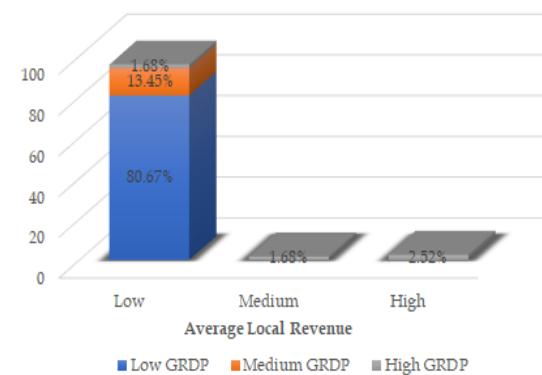
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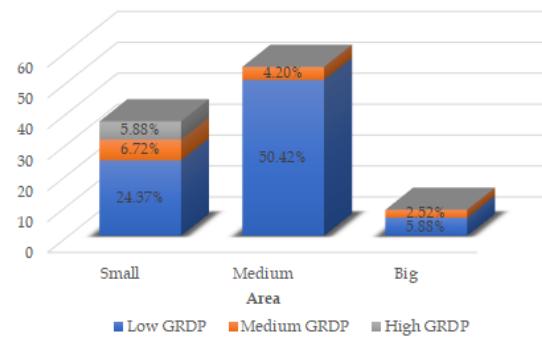
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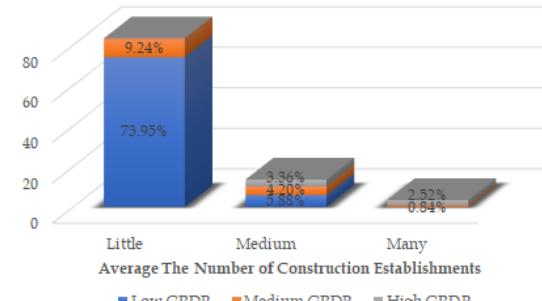
d

Figure 1 The number of regencies/municipalities on Java Island according to the category of

average response variables Y and explanatory variables X_1 (a), X_2 (b), X_3 (c), and X_4 (d)

The boxplot of residuals the GTWR model in Haryanto et al. (2019) research is shown in Figure 2. In general, each year the GTWR modeling produces residuals that are detected as an outlier, either in the form of top or bottom outliers. Outliers were detected in 2010-2012 and 2016 as many as 5 regencies/municipalities, namely the Kepulauan Seribu Regency and East Jakarta City as the bottom outlier and Central Jakarta City, Surakarta City, and Semarang City as the top outliers. East Jakarta City was not detected as an outlier in 2013-2015.
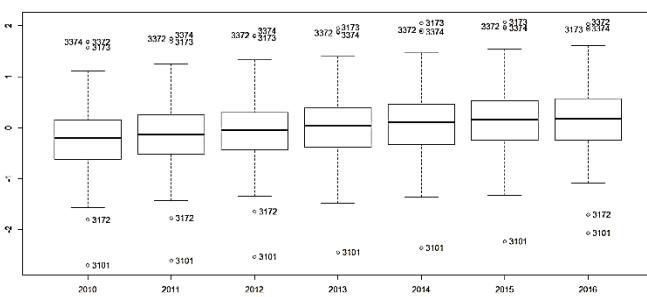
Note: 3101: Kepulauan Seribu Regency; 3172: East Jakarta City; 3173: Central Jakarta City; 3372: Surakarta City; 3374: Semarang City

Figure 2 The boxplot of residuals the GTWR model

RGTWR modeling produced a model as much as the location and time studied. In this study, the resulting model was 119 locations × 7 times = 833 models. Each location has 7 models that are differentiated by year, starting from the 2010 model to the 2016 model. RGTWR estimation is done through an iterative process by utilizing the GTWR parameter estimates as initial values. The iteration process is carried out using an M-estimator until a convergent value ($\beta^m \approx \beta^{m+1}$). is obtained. Each location and time produced an estimate that converges on different iterations. Iteration process until convergent conditions occurs at 107th iteration.

The values of parameters estimation the RGTWR modeling results vary in each location and year. Each variable also has different influences in each regency/municipality and year. For example, the

RGTWR model for Tangerang Regency in 2014 is as follows:

$$\hat{y} = e^{13.34 + 8.01 \times 10^{-7} x_1 + 9.82 \times 10^{-7} x_2 + 7.90 \times 10^{-6} x_3 - 3.02 \times 10^{-4} x_4}$$

Tangerang Regency in 2015 is as follows:

$$\hat{y} = e^{13.21 + 1.16 \times 10^{-6} x_1 + 8.51 \times 10^{-8} x_2 - 1.55 \times 10^{-4} x_3 + 1.20 \times 10^{-4} x_4}$$

Tangerang City in 2014 is as follows:

$$\hat{y} = e^{13.88 + 7.30 \times 10^{-7} x_1 + 5.19 \times 10^{-8} x_2 - 3.17 \times 10^{-4} x_3 + 4.48 \times 10^{-4} x_4}$$

Tangerang City in 2015 is as follows:

$$\hat{y} = e^{13.87 + 7.61 \times 10^{-7} x_1 + 5.18 \times 10^{-8} x_2 - 3.19 \times 10^{-4} x_3 + 4.02 \times 10^{-4} x_4}$$

The four equations showed that the RGTWR model produces different influences between regencies/municipalities and times. This difference is caused by different characteristics from each regency/municipality and between times. Differences in influential factors allow each regency/municipality to make its own policies and differ each year adjusted the conditions and existing needs in increasing the GRDP of the construction sector.

The residuals result from modeling of GTWR and RGTWR can be explained in Figure 4. The figure showed that after processing a RGTWR model has been able to reduce the 4 regencies/municipalities detected as outliers, namely East Jakarta City in 2010-2012 and 2016. However, the residual from Serang Regency emerged as outliers in 2013.
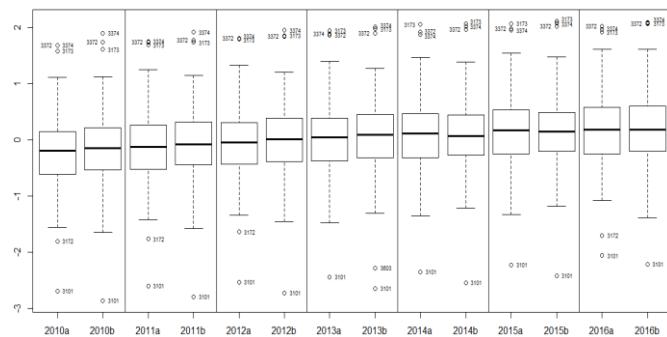
Note: 3101: Kepulauan Seribu Regency; 3172: East Jakarta City; 3173: Central Jakarta City; 3372: Surakarta City; 3374: Semarang City; 3603: Serang Regency; a: GTWR model; b: RGTWR model

Figure 3 The boxplot of residuals the GTWR and RGTWR model

Regencies/municipalities grouping based on influential factors using the GTWR and RGTWR models is illustrated in Figure 4. In the GTWR model there are two groups formed. The first group is the regencies/municipalities whose construction sector GRDP is influenced by the population (X_1), local revenue (X_2), and area (X_3). The second group is regencies/municipalities whose construction sector GRDP is influenced by population (X_1), local revenue (X_2), area (X_3), and the number of construction establishments (X_4).

2010a

2010b

2011a

2011b

2012a

2012b

2013a

2013b

2014a

2014b

2015a

2015b

2016b
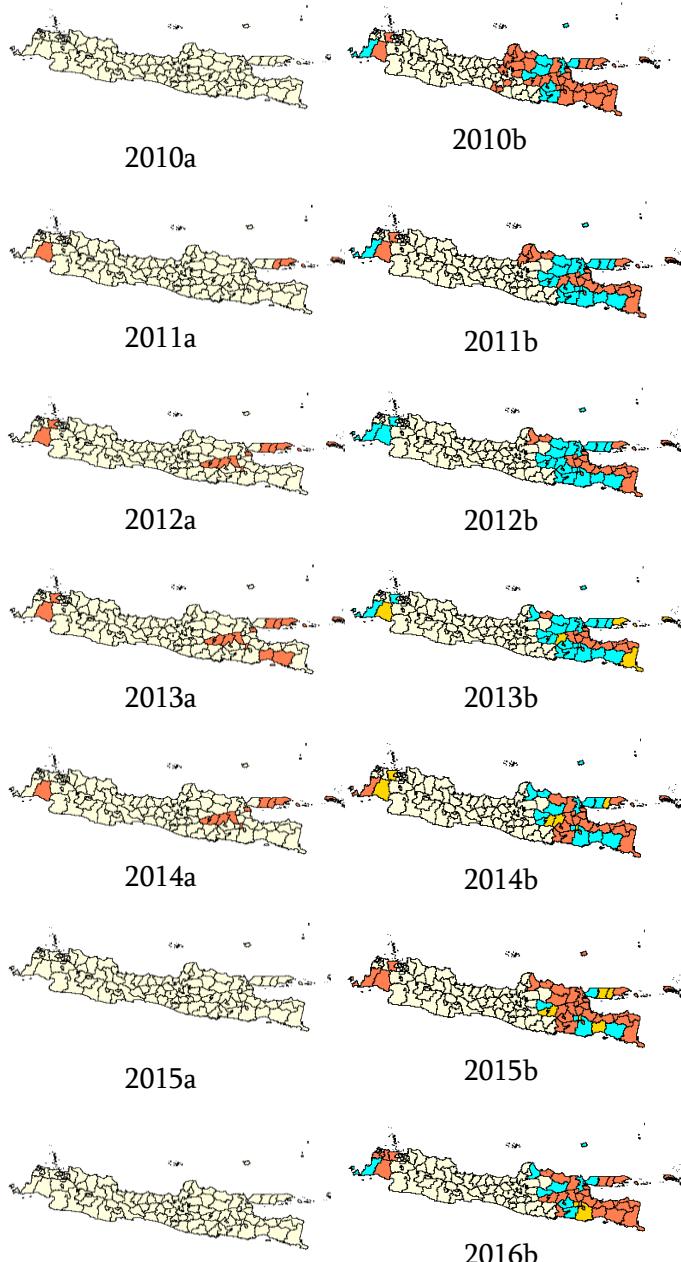
2016a

Note:
a: GTWR model;
b: RGTWR model

Figure 4 Regencies/municipalities grouping based on influential factors

Whereas in the RGTWR model, there are four groups formed. Two groups are the same as the GTWR model group. The first group is the regencies/municipalities whose construction sector GRDP is influenced by the population (X_1) and local revenue (X_2). The second group is regencies/municipalities whose construction sector GRDP is influenced by population (X_1), local revenue (X_2), and area (X_3). The third group is regencies/municipalities whose construction sector GRDP is influenced by population (X_1), local revenue (X_2), and the number of construction establishments (X_4). The fourth group is regencies/municipalities whose construction sector GRDP is influenced by population (X_1), local revenue (X_2), area (X_3), and the number of construction establishments (X_4). Regencies/Municipalities frequency based on influential factors can be seen in Table 2.

Table 2 Regencies/Municipalities frequency based on influential factors

Year	X_1, X_2	X_1, X_2, X_3	X_1, X_2, X_4	X_1, X_2, X_3, X_4
2010	9	42		68
2011	20	23		76
2012	24	16		79
2013	22	13	5	79
2014	13	20	7	79
2015	5	28	7	79
2016	8	32	2	77

IV. CONCLUSION

GTWR modelling still results in residuals detected as outliers. Outlier handling performed with RGTWR M-estimator results in a change in the direction of the parameter estimation coefficient to be more in accordance with the direction of the plot of the relationship, although there are still some locations whose estimated coefficient parameters are not yet appropriate. Factors that influence the GRDP of the construction sector in Java in 2010-2016 vary in each regency/municipality and every year. The explanatory variable population and local revenue have a positive and significant effect on each regency/municipality and every year. The more population and the value of local revenue can encourage the creation of an increase in the GRDP of the construction sector. The explanatory variable area and the number of construction establishments influence vary in each regency/municipality and every year.

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