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Poverty Modeling in Indonesia using Geographically and Temporally Weighted Regression (GTWR)

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Abstract

Poverty is a big problem that must be resolved by the government and the people of Indonesia. Various programs are designed and implemented to alleviate poverty in Indonesia. Research is needed to find out what factors influence the problem of poverty. One statistical method that can be used to analyze this effect is the geographically and temporally weighted regression (GTWR) method. This method combines the effects of spatial and time simultaneously. The formation of the model begins with determining the weighting matrix. In determining the weighting matrix, a fixed kernel function is used where the bandwidth value for each location and time of observation is the same. Weighting matrix with kernel functions used are gaussian, bi-square, exponential and tricube kernel functions. The selection of the best model is done by comparing the GTWR model from each of the weighting matrices of the four kernel functions. The best model is determined by looking at the largest R2 value and the smallest AIC. Based on the results of the data processing, the GTWR model with the weighting matrix of the exponential kernel function has the largest R^2=71,05% value and the smallest AIC=718,5934. Variables that have a significant effect on the model differ in each location and time of observation. Significant predictor variables were determined by comparing the values of t and values t in statistic . The predictor variable is significant when t values are bigger than values t in statistic. The results of data analysis show that the variable life expectancy (UHH) has an influence in most provinces in Indonesia in each year of observation.

1. INTRODUCTION

Poverty is a big problem in developing countries, one of which is Indonesia, because poverty will have an impact on widespread unemployment, higher dropout rates, increasing crime, the emergence of various conflicts in society. Therefore, poverty is the key to the success of a country's economic development. The Badan Pusat Statistik (BPS) (2018) recorded that the number of poor people in Indonesia in March 2020 was 26.42 million. This number has increased by 1.28 million people compared to March 2019. This increase has made the government continue to work through its programs to reduce this number. To reduce poverty in Indonesia, the government has launched several programs that will be realized in 2021. The government hopes that the programs that have been implemented can be right on target. Therefore, the government needs to know what factors influence poverty in Indonesia.

Nurhayati (2007) reveals the factors that influence poverty at a real level of 10 percent in West Java are income and education. Hudaya (2009) conducted a study which resulted in indicators of the open unemployment rate (TPT), income per capita (PP), and life expectancy (UHH) having a significant effect on the poverty rate at a significant level of five percent[4]. These factors can be analyzed using statistical methods, one of which is regression analysis. Research on poverty using the weighted regression method has also been carried out by Rahmawati and Djuraidah [5].

Analysis using the regression method must meet the assumptions ε_i~IIDN(0,σ^2) or errors must be identical (homogeneous), independent and normally distributed (0,σ^2). Independent error indicates no autocorrelation. Homogeneous error indicates that there is no heteroscedasticity. When spatial data is analyzed using the regression method, the error assumption must be identical (homogeneous), independent and normally distributed (0,σ^2) violated. This will result in the estimation of the regression parameters being inefficient and the standard error parameters being underestimated.

To overcome this problem, researchers have developed a method of spatial analysis. One of them is the Geographically Weighted Regression (GWR) method. Geographically and Temporally Weighted Regression (GTWR). This method is the development of the GWR method which is used to analyze the effect of spatial and time series observations simultaneously. By using the GTWR method, results can be obtained from several observation points at once in one analysis. The most important thing from GTWR modeling is determining the weighting matrix using the optimum bandwidth value. Determination of the weighting matrix can be done with kernel functions, namely gaussian, bi-square, exponential and tricube kernel. To find out the most appropriate GTWR model and the factors that affect poverty in poverty cases in Indonesia between 2017 and 2020, the authors are interested in comparing the GTWR model using the four fixed kernel weighting functions. Many researchers have used the GTWR method, including (Wang et al. (2013), Sholihin et al. (2017), and Yasin et al. (2018)).

The factors that will be observed are the Open Unemployment Rate (TPT), Labor Force Participation Rate (TPAK), Per capita Income (GDP/PDRB) based on constant prices and Life Expectancy (UHH) to the Poverty Percentage of provinces in Indonesia.

2. METHOD

2.1 Multiple Linear Regression Analysis

Regression analysis can help in projecting the determination of the characteristics of the relationship of one or more variables. Simple linear regression uses one independent variable and one response variable, while multiple linear regression uses two or more independent variables and two or more response variables. The general equation for the multiple linear regression model is as follows:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \cdots + \beta_k X_{ki} + \varepsilon_i \tag{1}$$

where $i = 1,2,3,\ldots,n$, Y_i are dependent variables for the *i-th* observation, $X_{1i}, X_{2i}, X_{3i}, \ldots, X_{ki}$ are the *k*-th independent variables on i-th observation, $\beta_0, \beta_1, \beta_2, \ldots, \beta_k$ is the regression coefficient or regression parameter, ε_i *error* ($\varepsilon_i \sim IIDN(0, \sigma^2)$).

2.2 Classical Assumption Tests on Multiple Linear Regression Model.

Before conducting a more in-depth analysis of the regression model, the model was tested. The tests carried out were the normality error test using the Kolmogorov-Smirnov test, the multicollinearity assumption test by calculating the value of the variance inflation factor (VIF). The multicollinearity criterion of the VIF value is greater than 10. Test the assumption of autocorrelation using the Durbin-Watson statistic. Test the assumption of heteroscedasticity using the breusch-pagan test statistic.

2.3 Spatial Data

Budiyanto (2009) states that spatial data are measurement data that contains location information and has a certain coordinate system as the basis for reference so as to have geographic information in the data. Spatial data is one item of information in which there is information about the earth, including the earth's surface, below the earth's surface, waters, oceans and under the atmosphere [2].

The first law of geography expressed by W Tobler, that everything is related to one another, but something that is close has more influence than something that is further away. Based on the law above, researchers began to develop an analysis of spatial data. Before conducting an analysis using spatial data, a test is first conducted on the data, whether the data has a spatial effect or not. The test was carried out in two stages, namely:

2.3.1 Spatial Dependence test using Moran's I test.

Anselin (1988) stated that to determine the existence of spatial dependence, the Moran Test I method can be used. Moran Test Statistics I use the following equation[1]:

$$Z_{cal} = \frac{I - E(I)}{\sqrt{Var(I)}} \tag{2}$$

where

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{S_0 \sum_{i=1}^{n} (x_i - \bar{x})^2} \tag{3}$$

The hypothesis criteria used is to reject H_0 if $Z_{cal} > Z_{\frac{\alpha}{2}}$

2.3.2 Spatial Heterogeneity test using Breusch-Pagan test.

To determine the spatial heterogeneity of the data, the Breusch-Pagan test was used. The statistical equation for the Breusch-Pagan test is as follows:

$$BP = \frac{1}{2}\boldsymbol{f}'\boldsymbol{Z}(\boldsymbol{Z}'\boldsymbol{Z})^{-1}\boldsymbol{Z}'\boldsymbol{f} \;\; \sim\chi^2_{(p)} \tag{4}$$

where

$\boldsymbol{f}$ vector element.

2.4 Geographically Weighted Regression (GWR)

The GWR model uses a point approach. The resulting parameter values are different for each observation location. The GWR model is written as follows [6]:

$$y_i = \beta_0(u_i\,,v_i\,) + \sum_{k=1}^{p} \beta_k\,(u_i\,,v_i\,)x_{ik} + \varepsilon_i \tag{5}$$

where y_i is the value of dependent variable at *i*-th location, x_{ik} is the value of *k*-th independent variable at *i*-th location, $(u_i\,,v_i\,)$ is the *i*-th *longitude and latitude or geographical location*, $\beta_k(u_i\,,v_i\,)$ is the k-th regression parameter at each location, and ε_i is the error term of the *i*-th observation or location.
The estimation of the GWR model parameters can be done using the Weighted Least Square (WLS) method.

2.4.1 Spatial Weight.

The most important thing in the GWR model is the determination of the weighting matrix.

$$\boldsymbol{W}(u_i\,,v_i) = \begin{bmatrix} w_{\boldsymbol{i1}} & \boldsymbol{0} & \cdots & \boldsymbol{0} \\ \boldsymbol{0} & w_{\boldsymbol{i2}} & \cdots & \boldsymbol{0} \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{0} & \boldsymbol{0} & \cdots & w_{\boldsymbol{in}} \end{bmatrix} \tag{6}$$

$\boldsymbol{W}(u_i\,,v_i)$ is the $n \times n$ matrix whose diagonal elements indicate the geographic weighting at the *i*-th observation location. The weighting matrix is calculated for each location in the *i*-th observation [6].

The selection of spatial weights in the model is very important. Spatial weighting depends on the distance between observation points or describes the proximity between observation locations. Weighting matrix $\boldsymbol{W}(u_i\,,v_i)$ can be determined using the Kernel function. The Kernel function gives weighting according to the optimum bandwidth whose value depends on the data conditions. The weights formed from the adaptive kernel function are the gaussian, exponential, bisquare and tricube functions. The Gaussian, Exponential, Bisquare, and Tricube functions consecutively are formulated in equation (7), (8), (9), and (10).

$$w_{\boldsymbol{j}}(u_i\,,v_j) = exp\left[-\frac{1}{2}\left(\frac{d_{ij}}{h}\right)^{\boldsymbol{2}}\right] \tag{7}$$

$$w_{\boldsymbol{j}}(u_i\,,v_j) = \sqrt{exp\left[-\left(\frac{d_{ij}}{h}\right)^{\boldsymbol{2}}\right]} \tag{8}$$

$$w_{\boldsymbol{j}}(u_i\,,v_j) = \begin{cases} \left(1-\left(\frac{d_{ij}}{h}\right)^{2}\right)^{\boldsymbol{2}}, & d_{ij} \le h \\ 0, & d_{ij} > h \end{cases} \tag{9}$$

$$w_{\boldsymbol{j}}(u_i\,,v_j) = \begin{cases} \left(1-\left(\frac{d_{ij}}{h}\right)^{2}\right)^{\boldsymbol{3}}, & d_{ij} \le h \\ 0, & d_{ij} > h \end{cases} \tag{10}$$

where d_{ij} determined by the equation (11).

$$d_{ij} = \sqrt{\left(u_i - u_j\right)^2 + \left(v_i - v_j\right)^2} \tag{11}$$

where h is the bandwidth which is a non negative parameter. In a normal distribution, the bandwidth value shows the standard deviation or the distance from the symmetrical point (average point) to the inflection point. When the bandwidth value is getting smaller, then a slight shift in distance will drastically change the w_{ij} weighting function. This causes the variance to be large. As the meeting point of the two problems above, the optimum bandwidth is taken.

One of the methods used to determine the optimum bandwidth is the cross-validation (CV) method, namely by determining the value of h which minimizes the equation *[]:*

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

where y_i is the observed value of the response variable at the i-th location and $\hat{y}_{\neq i}$ estimated value y_i based on the GWR model obtained by using the value of h which does not include the *i*-th location observation.

2.5 Geographically and Temporally Weighted Regression (GTWR)

The GTWR model is an effective approach model to overcome the existence of spatial and temporal diversity [6]. This model is a development of the GWR model which incorporates time (temporal) variables into the model. The GTWR model is written with the following equation:

$$y_i = \beta_0(u_i\,, v_i, t_i\,) + \sum_{k=1}^{p} \beta_k\,(u_i\,, v_i, t_i\,)x_{ik} + \varepsilon_i \tag{13}$$

where y_i is the observed value of the response variable for the observation location $(u_i\,, v_i\,)$ and time t_i, $\beta_0(u_i\,, v_i, t_i\,)$ is the *i*-th location intercept observation and time t_i, $\beta_k(u_i\,, v_i, t_i\,)$ is the k-th parameter regression at location $(u_i\,, v_i\,)$ and time t_i, x_{ik} is the observed value of the *k*-th independent variable at location $(u_i\,, v_i\,)$ and time t_i dan ε_i is the *i*-th error term. The estimated *k*-th parameter or *k*-th regression coefficient $\hat{\beta}_k(u_i\,, v_i, t_i\,)$ at *i*-th location can be obtained using the weighted least squares method as follows:

$$\hat{\boldsymbol{\beta}}_k(u_i\,, v_i, t_i\,) = [\boldsymbol{X}^T\boldsymbol{W}(u_i\,, v_i, t_i)\boldsymbol{X}]^{-1}\boldsymbol{X}^T\boldsymbol{W}(u_i\,, v_i, t_i)\boldsymbol{y} \tag{14}$$

where $\boldsymbol{W}(u_i\,, v_i, t_i)$ is a diagonal matrix $(w_{i1}\,, w_{i2}, \dots, w_{in})$ which is the weighting matrix at the observation location $(u_i\,, v_i\,)$ at time t_i and n observations.
which is a weighting matrix at the observation location. GTWR model is a model that combines the effects of spatial and time series simultaneously, so that the calculated distance is the distance between observed locations (d_{ij}^S) and observed times (d_{ij}^T). Hence, the spasio-temporal distance (d_{ij}^{ST}) is calculated as follows:

$$\begin{aligned}
\left(d_{ij}^S\right)^2 &= \left(u_i - u_j\right)^2 + \left(v_i - v_j\right)^2 \\
\left(d_{ij}^T\right)^2 &= \left(t_i - t_j\right)^2 \\
\left(d_{ij}^{ST}\right)^2 &= \varphi^S\left[\left(u_i - u_j\right)^2 + \left(v_i - v_j\right)^2\right] + \varphi^T\left[\left(t_i - t_j\right)^2\right] \\
\left(d_{ij}^{ST}\right)^2 &= \varphi^S\left(d_{ij}^S\right)^2 + \varphi^T\left(d_{ij}^T\right)^2
\end{aligned}$$

Also, the calculated *bandwidth* used are the combination of spatial bandwidth (h_S) and temporal bandwidth h_T, which is called a spasio-temporal bandwidth (h_{ST}) with the formula:

$$\frac{\left(d_{ij}^{ST}\right)^2}{\varphi^S} = \left[\left(u_i - u_j\right)^2 + \left(v_i - v_j\right)^2\right] + \tau\left[\left(t_i - t_j\right)^2\right] \tag{15}$$

where τ merupakan parameter rasio dari $\tau = \frac{\varphi^T}{\varphi^S}$ dengan $\varphi^S \neq 0$ (*Liu et al. (*2017))

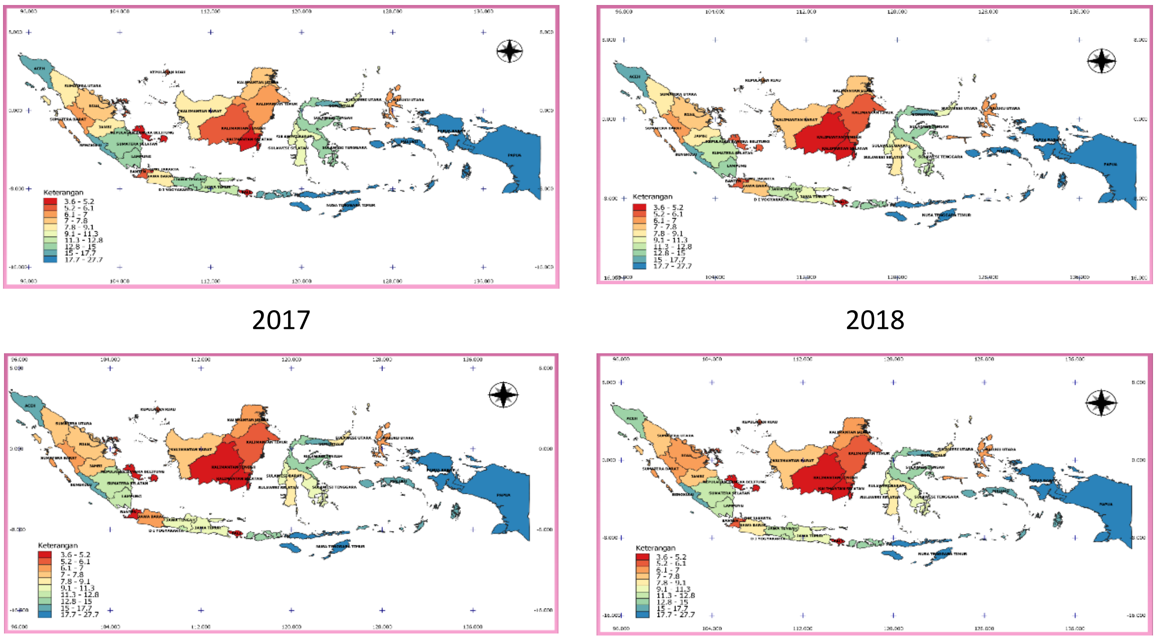
2.6 Model Goodness Criteria

The criteria for the goodness of the model are needed to evaluate the model so that it is known how big the chances of each model formed are whether it is appropriate or not. The best model is a model that provides a sufficient description of the data using the minimum number of parameters. The criteria for the goodness of the model are determined by the largest R^2 value and the smallest Akaike Information Criterion (AIC) value.

The predictor variables used in this study were the open unemployment rate (TPT) in % (X_1), the labor force participation rate (TPAK) in % (X_2),: GDP/GRDP at constant prices in thousand rupiah (X_3), Expected age life (UHH) in numbers (X_4) and the response variable used is the percentage of poverty in % (Y) sourced from BPS RI publication data for the period 2017 to 2020.

3. RESULTS AND DISCUSSION

According to BPS, Indonesia's population in 2020 is 270.20 million, of which 7.88% are poor. The distribution of the percentage of poor people by province in Indonesia in 2017 to 2020 can be seen in the following picture:



2017 2018

2019 2020

Figure 1. Map of the distribution of the percentage of poor people in Indonesia in 2017-2020.

3.1 Multiple Linear Regression Modeling

By using the general equation of the multiple linear regression model (Equation (1)), global multiple linear regression model parameters are estimated for data from 34 provinces in Indonesia from 2017 to 2020 (Table 1)

Table 1. Global Multiple Linear Regression Model.

Variable	Estimate	Standard Error	$t-value$	$p-value$
Y	$7.280e^{1}$	$1.801\ e^{1}$	4.043	$8.94\ e^{-5}$
X_1	$2.918e^{-1}$	$3.374\ e^{-1}$	0.865	0.389
X_2	$-2.442e^{-5}$	$1.512\ e^{-5}$	-1.615	0.109
X_3	$2.455e^{-1}$	$1.604\ e^{-1}$	1.531	0.128
X_4	-1.141	$1.707\ e^{-1}$	-6.686	$6.01\ e^{-10}$
$R^2 = 33.2\%$				
$Sig-level\ of\ the\ test = 0.05$				

The value of determination of the multiple linear regression model is 33.2 percent, this shows the effect of the predictor variables of 33.2 percent used on the model and 66.8 percent is the influence of other variables outside the model. The predictor variable that has a significant effect on the response variable is the variable X_4 with $p-value = 6.01\ e^{-10} < 0.05$.

3.2 Classical Assumption Test of Multiple Linear Regression Model

The results of the normality test using the Kolmogorov-Smirnov test statistic obtained a probability value of $0,265 > \alpha = 0,05$. These results conclude that the error is normally distributed. Multicollinearity detection is done by calculating the VIF value. The data does not occur multicollinearity if the value of VIF <10. The VIF value for all predictor variables (X_1, X_2, X_3, X_4) is less than 10. This means that there is no multicollinearity in the data. The autocorrelation test was carried out using the Durbin-Watson test statistic. The test statistic value is 0.37814 with a probability value of $2.2e^{-16} < \alpha = 0,05$. This shows that there is no correlation between the data in the multiple linear regression model. To see the heteroscedasticity in the multiple linear regression model, the Breusch-Pagan test was performed. The result of the Breusch-Pagan test is 42.295 and the probability value is $1,449e^{-08} < \alpha = 0,05$. This figure shows that there is heteroscedasticity in the model or there is an inequality of variance from the residual of one observation to another observation.

3.3 Spatial Dependence Test

The spatial dependence test uses Moran's I test statistics. The Moran's I test is carried out annually from 2017 to 2020, this aims to see the relationship of spatial dependence between observation locations that occurred in the year of observation. The test results show that the p-value every year observed is smaller than 0.05. This means that the percentage of poverty in the location of a province in Indonesia affects other provinces that are close to each other

3.4 Spatial Heterogeneity Test

Spatial heterogeneity test is carried out for every year of observation. This test aims to see the effect of spatial diversity between observed locations. The spatial heterogeneity test uses the Breusch-Pagan test statistic. The results of the spatial heterogeneity test show that the p-value observed every year is smaller than 0.05, so it can be concluded that there is a spatial diversity of each province in Indonesia which shows that each province has different characteristics.

3.5 GTWR Model

Before doing the modeling, we need a weighting matrix and the bandwidth value of each weighting. The optimum bandwidth value is determined using the cross validation (CV) method.

3.6 Bandwidth Search Process

Bandwidth is a non-negative parameter that can be illustrated as the radius of a circle from the point of observation as an illustration of the maximum distance of the observed location that still affects the nearest location or its neighbors. When the influence of the observed location is greater or greater with its neighbors, the greater the bandwidth value (the shape of the normal curve is more blunt) then the normal curve will be flatter, $\frac{d_{ij}}{h} \cong 1$. So that the weighting function w_{ij} will close to 1, spatial regression will be the same as the global regression. This causes the estimator to be biased. On the other hand, when the bandwidth value is getting smaller or very small, the normal curve will be sharper, $\frac{d_{ij}}{h} = \sim$. This causes the variance to be large. For this reason, the optimum bandwidth value will be sought that can minimize the CV value. This method uses the Golden Section Search algorithm approach [3].

3.6.1 Best Model Selection.

GTWR model with four formed weighting functions are then compared. The purpose of this is to determine the best GTWR model among the four generated GTWR models. The selection of the best model is based on the value of coefficient of determination *(R^2)* and the smallest value of Akaike Information Criterion (AIC).

Table 2. The results of $\boldsymbol{R^2}$ and AIC of each weighting function of the GTWR model.

Weighting Function	$\boldsymbol{R^2}$	*AIC*
bisquare	0.6298816	735.2438
gaussian	0.6729847	727.4856
exponential	0.7105802	718.5934
tricube	0.6818135	723.8864

Based on Table 2, the largest R^2 value and the smallest AIC value are generated by the GTWR model with an exponential weighting function, it can be seen in the figure. better than GTWR models with other weighting functions. The GTWR model with the exponential weighting function has a value of $R^2 = 0.7105802$ or $71{,}05802$ percent. This shows that the variables TPT (X_1), GRDP (X_2), TPAK (X_3) and UHH (X_4) have an effect on the percentage of poverty (Y) of 71.05802 percent. While the remaining 28.94198 percent is influenced by other variables outside the model under study.

3.6.2 Explanation of Variables in the GTWR Model with Exponential Weighting Function.

Furthermore, predictor variables that have a significant effect on the model at each location and time of observation will be determined. Determination is done by comparing the value of t_{calc} with t_{table}. The predictor variable is significant when $t_{calc} > t_{table}$. By comparing the value of t_{calc} with t_{table}, a significant variable is obtained which can be seen in the table below.

Table 3. Variables that have a significant effect in 2017 to 2018.

Variable	2017	2018
X_2	DKI Jakarta	-
X_4	North Sumatra, West Sumatra, Riau, Jambi, Bangka Belitung Islands, Riau Islands, East Java, Bali, West Nusa Tenggara, East Nusa Tenggara, West Kalimantan, Central Kalimantan, South Kalimantan, East Kalimantan, North Kalimantan, North Sulawesi, Central Sulawesi , South Sulawesi, Southeast Sulawesi, Gorontalo, West Sulawesi, North Maluku	North Sumatra, West Sumatra, Riau, Jambi, South Sumatra, Bengkulu, Lampung, Bangka Belitung Islands, Riau Islands, DKI Jakarta, West Java, Central Java, DI Yogyakarta, East Java, Banten, Bali, West Nusa Tenggara, East Nusa Tenggara , West Kalimantan, Central Kalimantan, South Kalimantan, East Kalimantan, North Kalimantan, North Sulawesi, Central Sulawesi, South Sulawesi, Southeast Sulawesi, Gorontalo, West Sulawesi, Maluku, North Maluku, West Papua
X_2, X_4	Aceh	-
X_3, X_4	Maluku	Aceh, Papua
X_1, X_3, X_4	West Papua, Papua	-

Table 4. Variables that have a significant effect in 2019 to 2020.

Variable	2019	2020
	Aceh	-
X_4	South Sumatra, Bengkulu, Bangka Belitung Islands, Riau Islands, East Java, Bali, West Nusa Tenggara, East Nusa Tenggara, West Kalimantan, Central Kalimantan, South Kalimantan, East Kalimantan, North Kalimantan, North Sulawesi, Central Sulawesi, South Sulawesi, Sulawesi Southeast, Gorontalo, West Sulawesi	East Java, Bali, West Nusa Tenggara, East Nusa Tenggara, West Kalimantan, Central Kalimantan, South Kalimantan, East Kalimantan, North Kalimantan, North Sulawesi, Central Sulawesi, South Sulawesi, Southeast Sulawesi, Gorontalo, West Sulawesi
X_2, X_4	-	-
X_3, X_4	North Maluku	North Maluku
X_1, X_3, X_4	Maluku, Papua Barat, Papua	Maluku, West Papua, Papua

The result can also be seen in Figure 2. The GTWR model obtained varies at each location and time of observation, which can be seen in Appendix 9. For example, the GTWR model for the provinces of Aceh and Bengkulu in 2019 is as follows:

$$\widehat{Y_{\text{Aceh}}} = 68{,}934 - 0{,}0000473X_2$$

$$Y_{\widehat{\text{Bengkulu}}} = 46{,}684 - 0{,}590X_4$$

Based on the model above, every 1000 rupiah increase in GRDP (X_2) in Aceh province in 2019 will reduce the percentage value of poverty by 0.00000473 percent. Every increase of 1 unit of UHH (X_4) in Bengkulu province in 2019 will reduce the poverty percentage rate by 0.590 percent.

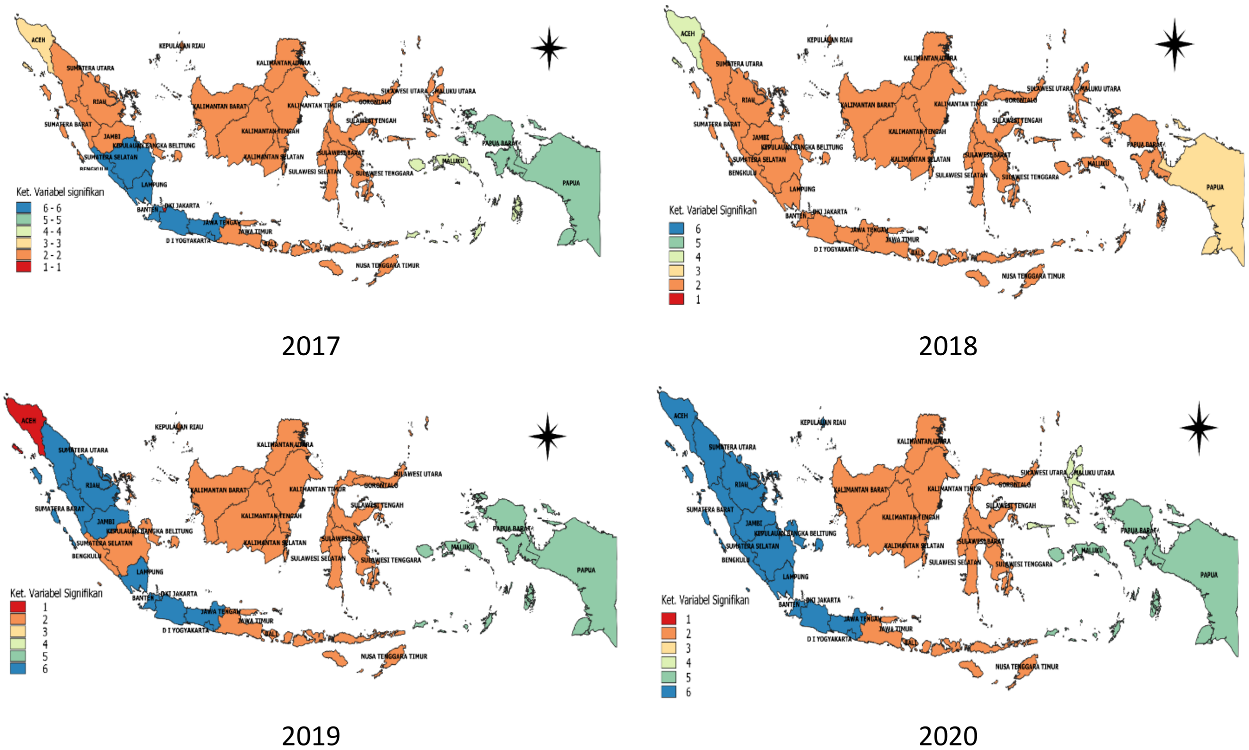


Figure 2. Map of the percentage of poor people distribution in Indonesia from 2017 to 2020.

4. CONCLUSION

Determination of the weighting function begins with calculating (iteration) the bandwidth value using the R program. The results of the data processing show that the highest number of iterations is in the gaussian weighting function, and the least is the bisquare function. Meanwhile, the highest bandwidth value is bisquare and the smallest is the exponential function. Based on the data analysis that has been done, it can be concluded that the GTWR model with the exponential weighting function is the best model.

The GTWR model with an exponential weighting function produces different estimation models at each location and time of observation. The most influential variable in several locations is the variable X_4 (UHH) in each year of observation.

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