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COMPARISON OF GEOGRAPHICALLY WEIGHTED REGRESSION WITH ADAPTIVE GAUSSIAN AND BISQUARE KERNEL ON OPEN UNEMPLOYMENT RATE IN RIAU ISLANDS

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Abstract: *Regression analysis is an analysis to determine the relationship and influence of independent variables on the dependent variable. If the data has a spatial relationship, this analysis has the potential to produce a less accurate model because the regression analysis ignores the influence of the location. One of the data indicated to have a spatial relationship is the open unemployment rate. One spatial analysis that can be used to accommodate spatial relationships is the Geographically Weighted Regression (GWR) model. In the GWR model, a spatial weighting matrix is required whose size depends on the proximity between locations. In this study, two spatial weighting matrix were used: Adaptive Gaussian Kernel and Adaptive Bisquare Kernel. Based on the results of the analysis, it is known that the factors influencing the open unemployment rate in the Riau Islands in 2024 at several locations are the human development index, Economic Growth, and Minimum Wages by Regency/City. Based on the R^2 value and AIC value, the best spatial weight matrix produced is the Adaptive Bisquare Kernel weighting function with an R^2 value of 93.32% and an AIC value of 15.2835.*

Keywords: *Open Unemployment Rate, GWR, Multiple Linear Regression, Spatial Weighting Matrix*

Abstrak: Analisis regresi merupakan analisis untuk mengetahui hubungan dan pengaruh variabel bebas terhadap variabel terikat. Apabila data memiliki hubungan spasial, analisis ini berpotensi menghasilkan model yang kurang akurat karena analisis regresi mengabaikan pengaruh lokasi. Salah satu data yang terindikasi memiliki hubungan spasial adalah tingkat pengangguran terbuka. Salah satu analisis spasial yang dapat digunakan untuk mengakomodasi hubungan spasial adalah model Geographically Weighted Regression (GWR). Dalam model GWR diperlukan matrik pembobot spasial yang besarnya bergantung pada kedekatan antar lokasi. Dalam penelitian ini digunakan dua matrik pembobot spasial yaitu Adaptive Gaussian Kernel dan Adaptive Bisquare Kernel. Berdasarkan hasil analisis diketahui faktor-faktor yang mempengaruhi tingkat pengangguran terbuka di Kepulauan Riau tahun 2024 pada beberapa lokasi yaitu indeks pembangunan manusia, Pertumbuhan Ekonomi, dan Upah Minimum Kabupaten/Kota. Berdasarkan nilai R^2 dan nilai AIC, matriks pembobot spasial terbaik yang dihasilkan adalah matriks pembobot Adaptive Bisquare Kernel dengan nilai R^2 sebesar 93,32% dan nilai AIC sebesar 15,2835.

Kata Kunci: Tingkat Pengangguran Terbuka, GWR, Regresi Linier Berganda, Matriks Pembobot Spasial

INTRODUCTION

Spatial data often exhibits heterogeneity and relationships between variables that vary by location, making global regression models like Ordinary Least Squares (OLS) unable to adequately capture spatial non-stationarity. To address this, Geographically Weighted Regression (GWR) has become a widely used method because it allows each location to have its own regression coefficient based on spatial proximity (Fotheringham, Yang, and Kang 2017; Wheeler 2021). The GWR model is a regression model that takes into account geographic characteristics according to location. (Mahroji and Nurkhasanah 2019; Shahneh, Oymak, and Magdy 2021). The GWR model will produce different parameter values at each observation location. (Wu 2020).

The quality of a GWR model is strongly influenced by the weighting function (kernel) and bandwidth used, as these components determine the contribution of each data point to local parameter estimation. The use of an adaptive kernel is particularly relevant when the spatial distribution of data is uneven, as the bandwidth can adjust the data density, resulting in more stable and representative estimates. Two widely used adaptive kernels with distinct characteristics are the adaptive Gaussian kernel and the adaptive bisquare kernel. The adaptive Gaussian kernel assigns non-zero weights to all observations with a smooth weighting decay, resulting in a smoother estimation surface. Conversely, the adaptive bisquare kernel assigns zero weights to points outside the bandwidth range, making it more sensitive to local variations and better at detecting localized heterogeneous patterns.

Recent research has shown that kernel selection can produce significantly different models, both in terms of accuracy (AIC, R^2), parameter stability, and spatial interpretation. For example, a study of maternal mortality in East Java showed that the adaptive bisquare kernel produced the best model based on a lower AIC value (Safitri and Amaliana 2021). Meanwhile, research on Indonesia's 2021 Gender Development Index (IPG) shows the superiority of the adaptive Gaussian kernel in producing smoother spatial patterns (Krismayanto, Saputra, and Ibad 2023). In the case of open unemployment rate, the adaptive bisquare kernel is also reported to have the best performance compared to several other kernels (Ramadayani, Indiyah, and Hadi 2022) . In addition, regional GRDP modeling in Indonesia also shows how the adaptive Gaussian kernel is able to capture more stable spatial relationships in regions with diverse data distribution patterns (Tangka et al. 2024). These findings indicate that no single kernel is consistently superior for all data types, and kernel selection without comparative evaluation can result in suboptimal models. Therefore, a systematic comparison between GWR models using the adaptive Gaussian kernel and the adaptive bisquare kernel is needed to determine the weighting approach that best suits the data characteristics, improves model accuracy, and produces more valid and reliable spatial interpretations.

Research on the open unemployment rate using the GWR model has been conducted in East Java Province by comparing the multiple linear regression model and the GWR model, which resulted in GWR as the best model (Putra, Wahyuning Tyas, and Fadhlurrahman 2022). In addition, modeling the open unemployment rate in West Java Province also produces the GWR model as the best model compared to multiple linear regression (Sartika and Suryani 2020). In addition, GWR modeling has also been conducted to determine the factors that influence the open unemployment rate and found the GWR model is better than the multiple linear regression model and the results show that the factors that significantly influence the open unemployment rate in East Java are population, GRDP, and the number of workers in the agriculture/forestry/fisheries sector. Furthermore, the analysis of the open unemployment rate with the coverage of districts/cities in Java Island and significant variables in each location are the Human Development Index (HDI), district minimum wages and dependency ratio. (Amalia and Sari 2019).

Although GWR is widely used to capture spatial heterogeneity, this method is not without several limitations that create a gap between ideal conditions and actual conditions of its application. Ideally, GWR is expected to provide stable, accurate, and easily interpretable local parameter estimates for each location. However, in practice, GWR results are highly sensitive to the choice of modeling parameters, particularly the kernel function and bandwidth, which can lead to coefficient instability, local multicollinearity, and overfitting in areas with a limited number of observations (Fotheringham et al. 2017). In addition, GWR is also prone to producing spatial patterns that are difficult to interpret if the kernel used does not match the actual spatial data structure, especially in areas with uneven data density. (Yu et al. 2019).

Ideally, kernel selection in GWR is based on systematic comparative evaluation to ensure that the resulting model accurately reflects the spatial processes occurring. However, in actual practice, many studies still use a single kernel type without adequate comparison, potentially resulting in suboptimal models and biased spatial interpretation (Comber et al. 2022). The characteristic differences between the adaptive Gaussian kernel and the adaptive bisquare kernel, particularly in terms of their range of influence and sensitivity to local variations, are often overlooked, even though these kernel choices can lead to significantly different policy conclusions (Yu et al. 2019). This gap between the ideal approach and actual practice underscores the importance of empirical kernel evaluation and comparison to ensure GWR results are more valid, reliable, and aligned with the spatial characteristics of the study area.

In several previous studies, there has been no discussion about the comparison of GWR models using spatial weighting matrices on the Open Unemployment Rate in the Riau Islands Province, so this study aims to determine the comparison of GWR models using adaptive Gaussian kernel and adaptive bisquare kernel weighting matrices on the Open Unemployment Rate in the Riau Islands Province.

RESEARCH METHODS

The data used in this study is secondary data sourced from the Central Statistics Agency of the Riau Islands Province, in the form of open unemployment rate data and the factors that influence it. This research unit covers 7 districts/cities in the Riau Islands in 2024. The independent variables used in the study are the human development index (x_1), Economic Growth (x_2), Minimum Wages by District/City (x_3), and Government Expenditure/Spending (x_4). The spatial coordinates used in the analysis were obtained from the center points (centroids) of the administrative areas of districts/cities in the Riau Islands Province. These coordinates were extracted from administrative boundary shapefile data sourced from the Geospatial Information Agency (BIG) and/or the Central Statistics Agency (BPS), then projected into a geographic coordinate system (latitude–longitude) before being used in Geographically Weighted Regression (GWR) modeling. The analysis method used in this study is the GWR model with the following analysis stages:

1. Form a multiple linear regression model to determine whether there is an influence of the independent variable on the dependent variable globally with the equation:
$$y_i = \beta_0 + \sum_{k=1}^{p} \beta_k + \varepsilon_i \tag{1}$$
2. Conducting spatial heterogeneity, namely to see whether there are differences in characteristics between observation locations, whether geographically, socio-culturally or other factors. (Munikah, Pramoedyo, and Fitriani 2014). Spatial heterogeneity in GWR modeling can be done using the Breusch Pagan test (BP test) (Runadi, Widyaningsih, and Lestari 2020). The hypothesis used is:
$$H_0: \sigma_1^2 = \sigma_2^2 = \cdots = \sigma_p^2 = \sigma^2$$
$$H_1: there\ is\ at\ least\ one \sigma_i^2 \neq \sigma^2$$
Mathematically, the BP test can be written:
$$BP = \left(\frac{1}{2}\right) \boldsymbol{h^T Z}\left(\boldsymbol{Z^T Z}\right)^{-\mathbf{1}} \boldsymbol{Z^T h} + \left(\frac{1}{tr}\right)\left[\frac{e^T \boldsymbol{W_e}}{\sigma^2}\right]^2 \sim \chi^2_{(p+1)} \tag{2}$$
H_0 will be rejected if the BP test $> \chi^2_{(p+1)}$ which indicates that spatial heterogeneity occurs.
3. Calculate the Euclidean distance with the equation:
$$d_{ij} = \sqrt{\left(u_i - u_j\right)^2 + \left(v_i - v_j\right)^2} \tag{3}$$
4. Determine the optimum bandwidth for each location using the Golden Section Search (GSS) method. The optimum bandwidth value indicates how many observations significantly influence the formation of the GWR model. The optimum bandwidth value used is the one that produces the minimum cross-validation coefficient value. The minimum CV value is determined using the equation:

$$CV(b) = \sum_{i=1}^{n} \left(y_i - \hat{y}_{\neq i}(h)\right)^2 \tag{4}$$

With $\hat{y}_{\neq i}$ (h) eing the estimated value of y_i where observations at location (u_i, v_i) are removed from the estimation process. To obtain the optimal bandwidth, the h that produces the minimum CV is obtained. (Sulekan and Jamaludin 2020).

5. Compile the adaptive Gaussian Kernel weighting matrix with the equation:

$$w_{ij} = exp\left[-\frac{1}{2}\left(\frac{d_{ij}}{h}\right)^2\right] \tag{5}$$

and the adaptive Bisquare Kernel weighting matrix with the equation:

$$w_{ij} = \left[1 - \left(\frac{d_{ij}}{\mathrm{h}}\right)^2\right]^2 \tag{6}$$

6. Performing parameter estimation using weighted least squares (WLS). In estimating parameters at a location, the WLS method assigns unequal weights to all observations. The weighting is based on the distance between the observation locations. The closer the distance to the observation whose parameters are being estimated, the greater the weight in the estimation of $\beta(u_i, v_i)$. The GWR model parameter estimator is obtained as follows: (Comber et al. 2020).

$$\hat{\beta}_{(u_i,v_i)} = (X^T W_i X)^{-1} X^T W_i Y \tag{7}$$

7. Perform GWR modeling with the equation:

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i) x_{ik} + \varepsilon_i\,, \;\; i = 1,2,\dots,n \tag{8}$$

8. Conduct GWR model parameter testing with the equation

$$t = \frac{\hat{\beta}_{k(u_i,v_i)}}{\hat{\sigma}\sqrt{c_{kk}}} \tag{9}$$

9. Testing the goodness of fit of the GWR model by comparing the global regression model and the GWR model using the coefficient of determination (R^2) with the equation:

$$R^2_{(u_i,v_i)} = \frac{JKR_w}{JKT_w} - \frac{\sum_{j=1}^{p}\left(y_j - \hat{y}_j\right)^2}{\sum_{j=1}^{p}(y_i - \bar{y})^2} \tag{10}$$

Additionally, to compare global regression and GWR models, the best model can be selected using the Akaike Information Criterion (AIC). The AIC value equation for the GWR model is as follows:

$$AIC = n\,2\log(\hat{\sigma}) + n\log(2\pi) + n\left\{\frac{n + tr(S)}{n - 2 - tr(S)}\right\} \tag{11}$$

The best model is the model that has the largest coefficient of determination (R^2) value and the smallest AIC value.

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RESULTS AND DISCUSSION

Research Result

Modeling the Open Unemployment Rate with Multiple Linear Regression

Modeling the Open Unemployment Rate using multiple linear regression aims to determine whether the independent variables used have a significant influence on the Open Unemployment Rate in the Riau Islands without considering spatial aspects. The first step taken in multiple linear regression analysis is simultaneous parameter testing. Simultaneous parameter testing shows that all independent variables together have a significant influence on the Open Unemployment Rate as indicated by a P-Value of 0.007 which is smaller than α = 5%.

Table 1. *Analysis of Variance*

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	5	22.2845	4.4569	39.78	0.007

After the simultaneous test. a partial test was conducted using the t-test. as shown in Table 1. Partial testing showed that there was one variable that had an insignificant effect on the Open Unemployment Rate in the Riau Islands Province. namely the variable Government Expenditure/Spending with a p-value of 0.063. which is greater than α = 5%. In addition. three independent variables. namely the HDI. economic growth. and minimum wages. had a significant effect on the HDI in the Riau Islands Province. This result is indicated by a p-value smaller than α = 5% for the three independent variables.

Table 2. *Coefficients*

Term	Coef	SE Coef	*t*-Value	P-Value	VIF
Constant	6.231	0.551	9.290	0.004	
Human Development Index	0.173	0.005	17.880	0.036	2.010
Economic Growth	3.255	0.011	17.960	0.005	2.020
Minimum Wage	-2.000	0.310	11.820	0.004	4.210
Government Expenditure/Spending	0.002	0.001	2.450	0.063	6.430

Based on the significant parameters in the partial test. a multiple linear regression model can be formed. producing the following results:

$$Y = 6.231 + 0.173\,X_1 + 3.255X_2 - 2.000X_3$$

Next. a multicollinearity test is performed by looking at the Variance Inflation Factors (VIF) value. The multicollinearity assumption is met if the VIF value is less than 10. Based on the results of the analysis that has been done. the multicollinearity test value is obtained which can be seen in table 5. The results of the multicollinearity test show that each independent variable has a VIF value of less than 10. This indicates that there is no multicollinearity between independent variables. Next. a normality assumption test is performed using the Anderson Darling test. From the analysis results. the Anderson Darling value is 0.363 with a p-value of

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0.713 where this value is greater than $\alpha = 5\%$ nd it can be concluded that the residuals are normally distributed. Next. a heteroscedasticity test is performed using the Glejser Test. namely by regressing the independent variables against the absolute value of the residuals. The results of the Glejser test show that the data used have met the heteroscedasticity assumption with the p-value of all independent variables greater than $\alpha = 5\%$.

Determining the Spatial Weighting Function

To obtain the GWR model at each location. the optimum bandwidth value is required. obtained using the Cross Validation (CV) method. which is then used to obtain a spatial weighting matrix in the parameter estimation process. From the analysis results. the optimum bandwidth value is 0.3819 with a minimum CV of 0.5915. Furthermore. the optimum bandwidth value obtained is used to determine the spatial weighting matrix. The weighting functions used are the Adaptive Gaussian kernel and the Adaptive Bisquare Kernel.
Based on the optimum bandwidth. the Adaptive Gaussian kernel weighting function is obtained:

$$w_{ij} = exp\left[-\frac{1}{2}\left(\frac{d_{ij}}{0.3819}\right)^2\right]$$

The bandwidth for the Adaptive Bisquare Kernel weighting function is obtained as 0.5147 which results in a minimum CV of 1.7558. so that the weighting function becomes:

$$w_{ij} = \left[1 - \left(\frac{d_{ij}}{0.5147}\right)^2\right]^2$$

The initial step in conducting a GWR analysis is testing for spatial heterogeneity. Because the data used meets the heteroscedasticity assumption. Spatial heterogeneity is suspected. So a test was conducted using the Breusch Pagan (BP) test. Based on the analysis. the BP value was obtained at 1.5326 with a p-value of 0.02873. which is smaller than $\alpha = 5\%$. This indicates that the data experiences spatial heterogeneity. So, modeling with GWR is necessary to determine the independent variables that influence the dependent variable in each district/city in the Riau Islands Province.

Open Unemployment Rate Modeling with GWR Using Adaptive Gaussian Kernel Weighting

After obtaining the weighting function. GWR modeling is then carried out using the Weighted Least Square (WLS) Method. Each GWR coefficient using the Adaptive Gaussian Kernel weighting matrix is $\beta_0(u_1.v_1) = 0.1354$. $\beta_1(u_1.v_1) = 0.2163$. $\beta_2(u_1.v_1) = 0.8749$. $\beta_3(u_1.v_1) = -0.7148$ so that the GWR model equation with Adaptive Gaussian Kernel in Bintan is obtained as follows:

$$\hat{y}_i^* = 0.1354 + 0.2163\, X_{i1}^* + 0.8749\, X_{i2}^* - 0.7148\, X_{i3}^*$$

Model suitability testing was carried out using the F test. which can be seen in Table 3.

Table 3. Anova Adaptive Gaussian Kernel

	d_f	*SS*	F_{hitung}	*P-Value*
GWR Improvement	19.11	6.74		
GWR Residual	31.42	9.71	4.21	0.002

Table 3 shows that spatial factors significantly influence the open unemployment rate in the Riau Islands Province. In addition to the model fit test. partial model parameter testing was also conducted. Partial testing of each parameter was conducted to determine the factors influencing the open unemployment rate at each location $(u_i. v_i)$. The results of the partial testing using the Adaptive Gaussian Kernel weighting function can be seen in Table 4.

Tabel 4. Partial Test of GWR Model with Adaptive Gaussian Kernel Weighting Function

Regency/city	$\hat{\beta}_0$	**P Value**	$\hat{\beta}_1$	**P Value**	$\hat{\beta}_2$	**P Value**	$\hat{\beta}_3$	**P Value**
Bintan	0.1354	0.1036	0.2163	**0.042**	0.8749	**0.0332**	-0.7148	0.0559
Karimun	0.4807	0.1041	1.1029	**0.0419**	1.2375	**0.0334**	0.4608	0.0553
Kepulauan Anambas	0.4133	0.0918	0.9541	**0.0367**	1.4806	**0.0254**	1.3399	**0.0364**
Kota Batam	0.5996	0.1052	1.0076	**0.0427**	1.4148	**0.0345**	-1.4806	0.0586
Kota Tanjungpinang	0.4869	0.1047	2.6309	**0.0425**	1.1081	**0.0341**	1.2385	0.0577
Lingga	0.4424	0.1046	0.9947	**0.0424**	1.4342	**0.034**	1.0407	0.0575
Natuna	0.4476	0.0917	1.0093	**0.0365**	1.4061	**0.0257**	1.0408	**0.0367**

Table 6 shows variations in the influence between regions. In general $\hat{\beta}_1$ and $\hat{\beta}_2$ have a significant effect (p < 0,05) across all districts/cities, meaning that increases in these variables consistently increase the response variable, but with varying spatial strengths. The effect of $\hat{\beta}_1$ is strongest in Tanjungpinang City, while $\hat{\beta}_2$ is relatively high in the Anambas Islands, Batam, Lingga, and Natuna. Meanwhile, $\hat{\beta}_3$ is generally positive but its significance is weaker (p approaching 0.05), indicating a more contextual and uneven influence across regions. The constant $(\hat{\beta}_0)$ is insignificant in most regions, indicating that the variation in response values is explained more by explanatory variables than by underlying regional factors

Open Unemployment Rate Modeling with GWR Using Adaptive Bisquare Kernel Weighting

Based on the analysis results, each GWR coefficient using Adaptive Bisquare Kernel weighting matrix is $\beta_0(u_1. v_1) = 0.3362$. $\beta_1(u_1. v_1) = -0.1654$. $\beta_2(u_1. v_1) = 0.5348$. $\beta_3(u_1. v_1) = 0.9153$ so that the GWR model equation with Adaptive Bisquare Kernel in Bintan is obtained as follows:

$$\hat{y}_i^* = 0.3362 - 0.1654\, X_{i1}^* + 0.5348\, X_{i2}^* + 0.9153\, X_{i3}^*$$

Model suitability testing was carried out using the F test. which can be seen in Table 5.

Table 5. Anova Adaptive Bisquare Kernel

	D_f	SS	F_{hitung}	*P-Value*
GWR Improvement	17.34	5.47		
GWR Residual	28.72	7.98	3.84	0.006

Table 5 shows that the Adaptive Bisquare Kernel weighting method also significantly influences the open unemployment rate in the Riau Islands Province. The results of partial testing using the Adaptive Bisquare Kernel weighting function can be seen in Table 6.

Table 6. Partial Test of GWR Model with Adaptive Bisquare Kernel Weighting

Variabel	$\hat{\beta}_0$	P Value	$\hat{\beta}_1$	P Value	$\hat{\beta}_2$	P Value	$\hat{\beta}_3$	P Value
Bintan	0.3362	0.0876	-0.1654	**0.016**	0.5348	**0.0232**	0.9153	**0.0419**
Karimun	0.5123	0.0881	-1.1438	**0.0259**	1.2599	**0.0254**	0.5217	**0.0423**
Kepulauan Anambas	0.4431	0.0758	-0.9898	**0.0107**	1.6051	**0.0124**	1.3856	**0.0334**
Kota Batam	0.6323	0.0892	-1.0493	**0.0267**	1.5483	**0.0225**	1.5623	0.0516
Kota Tanjungpinang	0.5221	0.0787	-2.6724	**0.0265**	1.2412	**0.0271**	1.3283	0.0527
Lingga	0.4856	0.0786	-1.0361	**0.0264**	1.3672	**0.0283**	1.2821	0.0535
Natuna	0.4742	0.0657	-1.0448	**0.0105**	1.5308	**0.0137**	1.6763	**0.0317**

Based on Table 8, the GWR results show that $\hat{\beta}_1$ and $\hat{\beta}_2$ have a positive and significant effect (p < 0,05) cross all regions, indicating that both variables consistently increase the response variable, but with varying spatial strengths. The effect of $\hat{\beta}_1$ is strongest in Tanjungpinang City, while $\hat{\beta}_2$ is most dominant in the Anambas Islands and Batam City. The coefficient of $\hat{\beta}_3$ is also positive and significant across all regions, with the largest effect in Natuna and Batam, indicating the presence of strong local factors. The constant ($\hat{\beta}_0$) s relatively small and insignificant, so the variation in the response variable is explained more by the explanatory variables than by the regional baseline effect.

Best Model Selection

To determine the best model among GWR models using different weighting functions. the R^2 and Akaike Information Criterion (AIC) criteria were used. The best model was the one with the largest R^2 and the smallest AIC. The R^2 and AIC values for the two models can be seen in Table 7.

Table 7. AIC Value of Geographically Weighted Regression Model

Spatial Weight Matrix	R^2	Nilai AIC
Adaptive Gaussian Kernel	88.93%	16.63416
Adaptive Bisquare Kernel	93.32%	15.2835

Table 7 shows that the model with the largest R^2 value and the smallest AIC is the GWR model with the Adaptive Bisquare Kernel weighting function. So it can be concluded that the GWR method using the Adaptive Bisquare Kernel weighting function is better used to model the open unemployment rate data in the Riau Islands in 2024 compared to the GWR method with the Adaptive Gaussian Kernel weighting function.

Discussion

The results of Geographically Weighted Regression (GWR) modeling on open unemployment rate data in the Riau Islands Province show that socio-economic variables such as the Human Development Index (HDI). economic growth. and minimum wages have a significant influence on the open unemployment rate. with different variations in effects across locations. This spatial significance is proven through the F test and partial tests on models with adaptive kernels (Gaussian and Bi-square). strengthening the argument that global regression is inadequate to capture spatial heterogeneity in employment phenomena. Such findings are consistent with previous studies: in research on Bojonegoro Regency. for example. the GWR model with a Bi-square kernel is able to explain spatial variations in unemployment better than global regression (Kartini 2019).

The variable coefficients in the Gaussian and Bisquare kernel models differ in both magnitude and direction (positive vs. negative signs). particularly for the HDI and minimum wage. This difference indicates that GWR estimates are highly sensitive to the choice of weighting function and the density of observation points (Ningtyas 2019). This implies that interpretation of GWR results requires consideration of local context: what works in one location may not work in another.

The selection of the best model based on the R^2 and AIC values indicates that the GWR model with the Adaptive Bisquare kernel is the most suitable for the Riau Islands data. This is in line with methodological recommendations from the literature that adaptive kernels (especially Bisquare) are superior when observation points are unevenly distributed or when the data exhibits strong spatial heterogeneity (Ningtyas 2019). Thus. the use of the Bisquare adaptive kernel provides more stable and spatially relevant local coefficient estimates.

Substantively, the spatial variation in the influence of the Human Development Index (HDI), economic growth, and minimum wages on the Open Unemployment Rate (TPT) in the Riau Islands Province is inseparable from the characteristics of the region which is an archipelago, strong links to the global economy, and the inequality of economic structures between districts/cities. The Riau Islands have centers of economic growth that are highly concentrated in industrial and international trade areas such as Batam and Karimun City, while other regions such as Natuna, Lingga, and the Anambas Islands are more dependent on the primary sector and government activities (BPS Kepulauan Riau, 2019).

The GWR results show that the HDI coefficient has a significant effect with quite sharp spatial variations, especially with the greatest influence in Tanjungpinang City. This finding reflects Tanjungpinang's characteristics as a center of government administration and services, where improvements in the quality of education, health, and purchasing power are not always accompanied by proportional absorption of the formal sector workforce. This condition indicates educated unemployment, namely the increase in educated unemployment due to the limited job opportunities that match the qualifications of local human resources. (Todaro, M. & Smith 2020).

Meanwhile, economic growth showed a positive and significant impact on the TPT in almost all regions, with relatively high coefficients in the Anambas Islands, Batam, and Natuna. Theoretically, this finding can be explained by the phenomenon of jobless growth, where economic growth supported by capital-intensive sectors such as manufacturing, oil and gas, and international logistics activities does not directly increase employment opportunities for the local population (Kuncoro 2018). In Batam, for example, strong economic growth relies heavily on foreign investment and the export-oriented industrial sector, which tends to absorb skilled labor and fluctuates according to global economic dynamics (BPS 2020).

The minimum wage variable also shows a significant influence with varying direction and strength across regions, particularly with relatively large coefficients in Batam and Natuna in the Adaptive Bisquare Kernel model. This condition reflects the dualism of the labor market in the Riau Islands, where minimum wage increases in industrial areas can drive an increase in the TPT due to company adjustments to labor costs, particularly in the manufacturing and industrial support services sectors (Sukirno 2019). In outermost island regions such as Natuna, minimum wage increases also have the potential to suppress labor absorption due to limited business scale and the dominance of the informal sector.

The superiority of the GWR model with the Adaptive Bisquare Kernel weighting function in explaining the TPT in the Riau Islands indicates that local spatial interactions are more relevant than global influences. The uneven distribution of regions, distances between islands, and differences in local economic structures result in the adaptive Bisquare kernel approach providing more stable and sensitive estimates to local conditions than the Gaussian kernel. These findings strengthen the argument that unemployment management policies in the Riau Islands cannot be standardized but must be designed based on regional characteristics, particularly between industrial areas, government centers, and outermost island regions.

CONCLUSION

Based on the results of the GWR modeling on the Open Unemployment Rate in the Riau Islands Province. it was found that the GWR model with the Adaptive Gaussian Kernel and Adaptive Bisquare Kernel weighting functions showed that spatial factors had a significant effect on variations in the unemployment rate in the region. This was proven through the results of the significant F test. each with a p-value of 0.002 for the Adaptive Gaussian Kernel model and 0.006 for the Adaptive Bisquare Kernel model. So, it can be concluded that the GWR model is better than the non-spatial global model in explaining the Open Unemployment Rate. The results of the partial test on both models showed that the Human Development Index (HDI) variable. economic growth. and minimum wages had a significant effect on the open unemployment rate in each observation location (P-value <0.05). Thus. socio-economic factors have an important role in explaining the spatial variation of the Open Unemployment Rate in the Riau Islands Province.

For the selection of the best model. the coefficient of determination (R^2) and Akaike Information Criterion (AIC) criteria were used. The GWR model with Adaptive Bisquare Kernel weighting has the best performance with an R^2 value 93.32% and an AIC of 15.2835. Compared to the Adaptive Gaussian Kernel model which has an R^2 of 88.93% and an AIC of 16.63416. Therefore. the best model for modeling the Open Unemployment Rate in the Riau Islands Province is the GWR with Adaptive Bisquare Kernel weighting.

This study has a major limitation in the relatively small number of spatial units, covering only seven districts/cities in the Riau Islands Province. In the context of Geographically Weighted Regression (GWR), the limited spatial sample size has the potential to affect the stability of local coefficient estimates, as each observation carries a large weight in the parameter estimation process. This condition also increases the risk of overfitting, especially in models with adaptive Bisquare kernels that produce very high R^2 values. Therefore, although the model shows a good fit, its robustness to other data or periods still needs to be tested. Furthermore, the use of one year of data limits the model's ability to capture the temporal dynamics of the open unemployment rate, which is influenced by economic fluctuations and changes in the structure of the employment sector. Therefore, the results of this study are contextual and need to be interpreted with caution, especially in terms of generalization to other regions.

Future research is recommended to use multi-year data or spatial panel data to improve estimation stability and reduce the potential for overfitting. The addition of more diverse socioeconomic variables, such as the structure of business sectors, labor force participation rate, labor force education level, investment, and the proportion of the informal sector, is also recommended to enrich the modeling and improve its explanatory power. Furthermore, the use of alternative approaches such as Multiscale GWR (MGWR) can be considered to test the consistency and robustness of the estimation results.

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