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A SPATIO-TEMPORAL DESCRIPTION OF COVID-19 CASES IN EAST BORNEO USING IMPROVED GEOGRAPHICALLY AND TEMPORALLY WEIGHTED REGRESSION (I-GTWR)

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Abstract: At the end of 2019, the world was impacted by a deadly viral phenomenon referred to as COVID-19. The Indonesian government quickly implemented Large-Scale Social Restrictions (LSSR) to prevent the spread and transmission of COVID-19. However, various violations are often committed by the community towards LSSR, which are specifically caused by economic inequality. This study was focused on spatial and temporal modelling of the

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COVID-19 cases in East Borneo Province by identifying the contributing factors. This study aimed to develop an analytical program to estimate the parameters of the Improved-Geographically and Temporal Weighted Regression (I-GTWR), which accommodates the interaction of the spatial-temporal distance function. Moreover, this study was also intended to develop an I-GTWR model for the COVID-19 data for each Regency/City of East Borneo Province by considering the spatial-temporal diversity and adding the interaction of the spatial-temporal distance function to the weighting matrix, and determining the factors that influence of COVID-19 cases in East Borneo Province, based on regional variations by applying I-GTWR. Map and model exploration had succeeded in identifying different patterns of factors that affected of COVID-19 cases at each location and time. The I-GTWR method had proven to be more appropriate in describing the contributing factors of COVID-19 cases in East Borneo Province in 2020-2021. This was indicated by a higher R-Square value, a decrease in the Root Means Squared Error (RMSE).

Keywords: improved-geographically and temporally weighted regression (I-GTWR); spatial; spatio-temporal; distance function.

2010 AMS Subject Classification: 92C60.

1. INTRODUCTION

Based on the definition from the World Health Organization (WHO), COVID-19 refers to a virus that infects the respiratory system [1], [2]. Until the present time, 188 countries were reportedly confirmed to be exposed to the Corona virus, including Indonesia. As of March 2, 2020, Depok residents were tested positive for COVID-19, and the virus continues to spread and infect people throughout Indonesia. Consequently, Joko Widodo as a President of Indonesia, issued Government Regulation No. 21/2020 concerning Large-Scale Social Restrictions (LSSR) in response to COVID-19 on March 31, 2020, as well as Presidential Decree No. 11/2020 declaring the coronavirus pandemic as a national disaster [3]. These regulations were stimulated based on Law Number 06/2018 concerning Health Quarantine, which regulates the basic provisions for LSSR.

The COVID-19 pandemic has currently provided a negative impact on various sectors [4], [5]. At the global economic level, the COVID-19 pandemic was found to provide a very significant disruption to the domestic economy of nation-states and the development of Micro, Small, and Medium Enterprises (MSMEs) [6]. The social distancing policy has significantly reduced the level of public physical activity in the Jakarta metropolitan area and other big cities [7], [8]. This may be indicated by the decline in the number of passengers on various means of transportation, including airplanes, commuter trains, buses and busways, taxis, online taxis, bajaj, to motorcycle taxis and online motorcycle taxis [9]. Referring to this, a model is highly required to evaluate the contributing factors of COVID-19.

Viruses that spread rapidly from one location to another are known to indicate a spatial effect in the modelling process. Moreover, the diversity of regional conditions and changes in time that have led to suppression of the total of COVID-19 cases in an area cannot be analyzed by means of the same analytical approach. One approach that may be utilized to analyze an area affected by COVID-19 is the spatial and temporal mapping approach [10]–[12]. The spatial and temporal approach aims to determine the distribution and geographic factors that contribute to influence over a certain period of time [12]. Consequently, a statistical modelling method is urgently needed to analyze geographic location or location factors of observations over a period of time. The Geographically and Temporally Weighted Regression (GTWR) model is regarded as one of the methods that may be utilized in the analysis process. The GTWR model has been commonly defined as a development of the linear regression. The linear regression is only able to produce a globally valid parameter estimator, while the GTWR model produces a local model parameter estimator for each observation location [13], [14].

Studies with GTWR methods are typically conducted by using addition operators to model spatial-temporal distances. Subsequently, this may result in the distance measured in spatial dimensions not having an effect on temporal distance, thus making spatial-temporal interaction modeling less appropriate. This study would be carried out by means of the Improved-Geographically and Temporal Weighted Regression (I-GTWR) method as a development of the GTWR method by adding interactions to the spatial-temporal distance function in the COVID-19 modeling of East Borneo Province in 2020-2021.

This study was objected to develop the Improved-Geographically and Temporal Weighted Regression (I-GTWR) model, which accommodates the interaction of the spatial-temporal distance function. Furthermore, this study also aimed to develop an I-GTWR model for COVID-19 data for each regency/city of East Borneo Province by considering the spatial-temporal diversity and adding the interaction of the spatial-temporal distance function to the weighting matrix as well as determining the contributing factors of COVID-19 in East Borneo Province based on regional variations through the implementation of I-GTWR.

2. PRELIMINARIES

A. The Geographically Temporally Weighted Regression Model (GTWR)

This modeling involves spatial, temporal or time aspects that are used to exploration and data analysis on the distribution of the total of COVID-19 cases in the 2020-2021 timeframe. The GTWR model is defined as an effective approach to dealing with the issue of spatial and temporal non-stationarity [15]. The GTWR model was developed from the GWR model by adding an element of time (temporal) [11], [16], [17]. However, GTWR combines temporal and spatial using a weighted matrix to be able to identify spatial and temporal diversity[18], [19]. The GTWR model with the response variable y_i, the predictor variable p, and location for each observation (u_i, v_i, t_i) is written in Equation (1).

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

Where:

y_i : observational value of the response variable

$\beta_0(u_i, v_i, t_i)$: constant of intercept value

$\beta_k(u_i, v_i, t_i)$: the regression coefficient of the *k*-th predictor variable

x_{ik} : observational value of the predictor variable

ε_i : the error of the *i*-th observation, which is assumed to be identical, independent, and $\varepsilon_i \sim N(0, \sigma^2)$

Regression coefficient of $\hat{\beta}_i(u_i, v_i, t_i)$ at the i-th point can be estimated using the estimation method Weighted Least Square (WLS) as shown in Equation (2).

$$\widehat{\boldsymbol{\beta}}(u_i, v_i, t_i) = [\boldsymbol{X}^T\boldsymbol{W}(u_i, v_i, t_i)\boldsymbol{X}]^{-1}\boldsymbol{X}^T\boldsymbol{W}(u_i, v_i, t_i)\boldsymbol{y} \qquad (2)$$

$\boldsymbol{W}(u_i, v_i, t_i) = diag\big(w_1(u_i, v_i, t_i), w_2(u_i, v_i, t_i), \ldots, w_n(u_i, v_i, t_i)\big)$ is the weighting matrix at the observation location (u_i, v_i) and the t-th time. Diagonal element of $w_{ij}(1 \leq j \leq n)$ is defined as a function of the spatial-temporal distance at the point of observation (u_i, v_i, t_i).

Distance functions of GTWR model $\left(d_{ij}^{ST}\right)$ consist of a combination from spatial distance $\left(d_{ij}^{S}\right)$ and temporal distance $\left(d_{ij}^{T}\right)$, which is formulated [20]:

$$\begin{aligned}
\left(d_{ij}^{S}\right)^2 &= \left(u_i - u_j\right)^2 + \left(v_i - v_j\right)^2 \\
\left(d_{ij}^{T}\right)^2 &= \left(t_i - t_j\right)^2 \\
\left(d_{ij}^{ST}\right)^2 &= \phi^S\left[\left(u_i - u_j\right)^2 + \left(v_i - v_j\right)^2\right] + \phi^T\left[\left(t_i - t_j\right)^2\right]
\end{aligned} \qquad (3)$$

where φ^S and φ^T are used as balancing parameters for the different effects from location and time on spatial-temporal distance measurements. From Equation (3), can be generated as follows:

$$\begin{aligned}
w_{ij} &= exp\left\{-\left(\frac{\phi^S\left[\left(u_i - u_j\right)^2 + \left(v_i - v_j\right)^2\right] + \phi^T\left[\left(t_i - t_j\right)^2\right]}{h_{ST}^2}\right)\right\} \\
w_{ij} &= exp\left\{-\left(\frac{\left[\left(u_i - u_j\right)^2 + \left(v_i - v_j\right)^2\right]}{h_S^2} + \frac{\left[\left(t_i - t_j\right)^2\right]}{h_T^2}\right)\right\}
\end{aligned} \qquad (4)$$

Let $h_S^2 = \frac{h_{ST}^2}{\varphi^S}$ and $h_T^2 = \frac{h_{ST}^2}{\varphi^T}$, then the result of Equation (5) is written as follows:

$$\begin{aligned}
w_{ij} &= exp\left\{-\left(\frac{\left(d_{ij}^S\right)^2}{h_S^2} + \frac{\left(d_{ij}^T\right)^2}{h_T^2}\right)\right\} \\
w_{ij} &= exp\left\{-\left(\frac{\left(d_{ij}^S\right)^2}{h_S^2}\right)\right\} exp\left\{-\left(\frac{\left(d_{ij}^T\right)^2}{h_T^2}\right)\right\} = w_{ij}^S \times w_{ij}^T
\end{aligned} \qquad (5)$$

With $w_{ij}^S = exp\left\{-\left(\frac{\left(d_{ij}^S\right)^2}{h_S^2}\right)\right\}$ and $w_{ij}^T = exp\left\{-\left(\frac{\left(d_{ij}^T\right)^2}{h_T^2}\right)\right\}$

h_S : window width of spatial distance

h_T : window width of temporal distance

h_{ST} : window width of spatial-temporal distance

Allow τ to represent ratio parameter of $\tau = \frac{\varphi^T}{\varphi^S}$ with $\varphi^S \neq 0$, then Equation (6) will be obtained:

$$\frac{\left(d_{ij}^{ST}\right)^2}{\phi^S} = \left[\left(u_i - u_j\right)^2 + \left(v_i - v_j\right)^2\right] + \tau\left[\left(t_i - t_j\right)^2\right] \tag{6}$$

Let $\varphi^S = 1$, to eliminate or reduce the unknown parameters. In this matter, τ is regarded as an unknown parameter. Parameter τ is useful for increasing or decreasing the effect of temporal in spatial distance. Parameter τ can be obtained by minimizing the cross-validation criteria through the initialization process of initial value as in Equation (7).

$$CV(\tau) = \sum_{i=1}^{n} \left(y_{\neq 1} - \hat{y}_{\neq 1}(\tau)\right)^2 \tag{7}$$

The Kernel with Gaussian function is regarded as the most frequently in the GWTR model, which is formulated as in Equation (8).

$$w_{ij} = exp\left(-\left(\frac{d_{ij}^{ST}}{h_{ST}}\right)^2\right) \tag{8}$$

The calculation of window width values may be carried out by means of the GWR model as proposed from Fotheringham et al. [21], [22]. The estimated value of the response variable ($\hat{y}$) can be determined using the formula in Equation (9).

$$\hat{\boldsymbol{y}} = \begin{bmatrix} \hat{y}_1 \\ \hat{y}_2 \\ \cdots \\ \hat{y}_n \end{bmatrix} = \begin{bmatrix} \boldsymbol{x}_1^T[\boldsymbol{X}^T\boldsymbol{W}(u_1, v_1, t_1)\boldsymbol{X}]^{-1}\boldsymbol{X}^T\boldsymbol{W}(u_1, v_1, t_1)\boldsymbol{X} \\ \boldsymbol{x}_2^T[\boldsymbol{X}^T\boldsymbol{W}(u_2, v_2, t_2)\boldsymbol{X}]^{-1}\boldsymbol{X}^T\boldsymbol{W}(u_2, v_2, t_2)\boldsymbol{X} \\ \cdots \\ \boldsymbol{x}_n^T[\boldsymbol{X}^T\boldsymbol{W}(u_n, v_n, t_n)\boldsymbol{X}]^{-1}\boldsymbol{X}^T\boldsymbol{W}(u_n, v_n, t_n)\boldsymbol{X} \end{bmatrix} \tag{9}$$

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

The selection of the goodness of the model may be calculated using the Akaike Information Criterion (AIC) [23]. Regarding to the effect of spatial-temporal diversity, the corrected from Akaike Information Criterion (AICc) is used in the selection of the goodness of the model as formulated in Equation (10):

$$AICc = 2n\,ln(\hat{\sigma}) + n\,ln(2\pi) + n\left(\frac{n + tr(\boldsymbol{S})}{n - 2 - tr(\boldsymbol{S})}\right) \tag{10}$$

Where:

$$\hat{\sigma}^2 = \frac{\boldsymbol{y}^T(\boldsymbol{I}-\boldsymbol{S})^T(\boldsymbol{I}-\boldsymbol{S})\boldsymbol{y}}{n}$$

B. The Improved-Geographically Temporally Weighted Regression (I-GTWR) Model

The weighted involved in the GTWR model uses a simple operator, particularly addition operator, which is used to calculate the spatial-temporal with a linear combination between the spatial and the temporal distance as shown in Equation (11):

$$d_{ST}^2 = \varphi^s d_s^2 + \varphi^T d_T^2 \tag{11}$$

where φ^S and φ^T are regarded as parameters adjusted to balance the effects of the scale used to calculate the spatial and temporal distances in each of the coordinate. According to this specification, the spatial-temporal coordinate system is considered perpendicular. Thus, the distance measured in the spatial dimension does not indicate any influence on the temporal distance, thus causing it to be inappropriate for use in modeling spatial-temporal interactions. A more complex operator is defined as the compiler of the Improved-Geographically and Temporally Weighted Regression (I-GTWR) model as indicated in Equation (12):

$$d_{ij}^{ST} = \varphi^s d_{ij}^s + \varphi^T d_{ij}^T + \varphi^s \varphi^T d_{ij}^s d_{ij}^T + 2\sqrt{\varphi^s \varphi^T d_{ij}^s d_{ij}^T}\, Cos(\xi) \tag{12}$$

where t_i and t_j are defined as the time of observation at the *i*-th and *j*-th locations. Parameters φ^s, φ^T and $\xi \epsilon [0, \pi]$ are considered as balancing parameters derived by means of the coefficient of determination optimization method through cross-validation procedures. The parameters may be used to measure the interaction effect of location and time

C. The Geographically Weighted Regression (GWR) Model Parameter Testing

The Geographically Weighted Regression (GWR) parameter testing is used to evaluate the parameters that are able to provide a significant influence on the response variable [24]. Parameter testing at each location is conducted partially. The hypotheses of parameters testing are as follows:

$H_0 : \beta_k(u_i, v_i) = 0$

$H_1 : \beta_k(u_i, v_i) \neq 0$ with $k = 1,2, \ldots,$

Therefore, the form of the standard normal distribution has been successfully obtained equation

(13)

$$\frac{\hat{\beta}_k(u_i,v_i)-\beta_k(u_i,v_i)}{\sigma\sqrt{c_{kk}}}\sim N(0,1) \tag{13}$$

where c_{kk} is the diagonal element from $\boldsymbol{C}_i\boldsymbol{C}_i^T$, and $\boldsymbol{C}_i=[\boldsymbol{X}^T\boldsymbol{W}(u_i,v_i)]^{-1}\boldsymbol{X}^T\boldsymbol{W}(u_i,v_i)$.

In alternative hypothesis (H_1), the various regression coefficients are partially determined by the GWR model. The Sum of Squares for Error (SSE) obtained from the GWR model is shown as follows:

$$SSE(H_1)=\hat{\varepsilon}^T\hat{\varepsilon}=\boldsymbol{y}^T(\boldsymbol{I}-\boldsymbol{L})^T(\boldsymbol{I}-\boldsymbol{L})\boldsymbol{y} \tag{14}$$

with the matrix **L** is obtained as in Equation (4). Thus, the test statistics used in partial parameter testing are written as follows [25]:

$$t_{hit}=\frac{\hat{\beta}_k(u_i,v_i)}{\hat{\sigma}\sqrt{c_{kk}}} \tag{15}$$

Where $\hat{\sigma}=\sqrt{\frac{SSE(H_1)}{\delta_i}}$ and follow the distribution with degrees of freedom (*df*) = $\left(\frac{\delta_1^2}{\delta_2^2}\right)$. The value of $SSE(H_1)$ is obtained as in Equation (14), while the value of δ_1 is calculated by utilizing the formula: $\delta_i=tr\left([(\boldsymbol{I}-\boldsymbol{L})^T(\boldsymbol{I}-\boldsymbol{L})]^i\right)$.

3. RESEARCH METHODOLOGY

A. Data Source

This study was conducted by using panel data, which is referred to as a combination of cross section data and time series data. The crosssection data were derived from data on health aspects, which included data on the total of Tuberculosis (TB) cases, the total of hospitals, and the total of health care centers. Meanwhile, data on aspects of human development were obtained based on population density data and economic aspects consisting of data on gross regional domestic product (GRDP). The data were successfully collected in different time periods between 2020-2021, in each Regency/City in East Borneo. The variables in this study are shown in Table 1.

Variables	Notation	Descriptions	Unit
Response	Y	Total of Confirmed COVID-19 Positive Cases	People
Predictor	X_1	Total of Tuberculosis (TB) Cases	Cases
	X_2	Population Density	People/Km^2
	X_3	Gross Regional Domestic Product (GRDP)	Billion Rupiah
	X_4	Total of Hospitals	Unit
	X_5	Total of Health Care Centers	Unit

TABLE 1. Research Variable

B. Data Analysis

The modeling processes was carried out using the R-Studio version 2022.02.2 Build 485. The Steps and Data Analysis of the Distance Function in the I-GTWR Model:

1. Determination of spatial-temporal ratio parameter (τ) by utilizing a cross-validation.
   a. Inserting $\boldsymbol{X}$, $\boldsymbol{y}$, and location-time coordinates of observations (u_i, v_i, t_i)
   b. Specifying the initial value of the spatial window width (h_S) and supposing $\xi = 0$.
   c. Determining the constant in a measure of distance between observed locations and time

   $$d_{ij}^{ST} = d_{ij}^{S} + \tau d_{ij}^{T} + 2\sqrt{\tau d_{ij}^{S} d_{ij}^{T}} \quad , \ t_j < t_i$$

   $$d_{ij}^{ST} = \alpha \quad , \ t_j > t_i$$

   d. Defining the weighting function of GTWR model. This study used a Gaussian weighting function

   $$w_{ij} = exp\left(-\frac{1}{2}\left(\frac{d_{ij}}{h}\right)^2\right) \text{ where } i = 1,2,\dots,n \text{ and } j = 1,2,\dots,n$$

   e. Calculating the weighting matrix $\boldsymbol{W}(u_i, v_i, t_i) = diag(w_{i1}, w_{i2}, \dots, w_{in})$.
   f. Calculating $\widehat{\boldsymbol{\beta}}(u_i, v_i, t_i) = [\boldsymbol{X}^T \boldsymbol{W}(u_i, v_i, t_i)\boldsymbol{X}]^{-1}\boldsymbol{X}^T \boldsymbol{W}(u_i, v_i, t_i)\boldsymbol{y}$
   g. Calculating $\hat{y}_{\neq i}(\tau) = \boldsymbol{x}_i \widehat{\boldsymbol{\beta}}(u_i, v_i, t_i)$ by utilizing the value of τ without entering the location of the i-th observation.

h. Minimizing cross-validation (CV) values based on τ with the following formula:

$$CV(\tau) = \sum_{i=1}^{n} (y_{\neq i} - \hat{y}_{\neq i}(\tau))^2$$

2. Determination of spatial parameter (φ^S) and temporal parameter (φ^T) by utilizing a cross-validation.

a. Inserting $\boldsymbol{X}$, $\boldsymbol{y}$, spatial window width (h_S), constant τ, and location-time coordinates of observations (u_i, v_i, t_i).

b. supposing $\xi = 0$.

c. Determining the constants of (φ^S) and (φ^T) in a measure of distance between observed locations and time with $\varphi^T = \varphi^S \times \tau$

$$d_{ij}^{ST} = \varphi^S d_{ij}^S + (\varphi^S \tau) d_{ij}^T + 2\sqrt{\varphi^S(\varphi^S\tau) d_{ij}^S d_{ij}^T} \quad , \ t_j < t_i$$

$$d_{ij}^{ST} = \alpha \quad , \ t_j > t_i$$

f. Determining the spatial-temporal weighting function by using the Gaussian weighting function.

g. Calculating the weighting matrix $\boldsymbol{W}(u_i, v_i, t_i) = diag(w_{i1}, w_{i2}, \ldots, w_{in})$.

h. Calculating $\hat{\boldsymbol{\beta}}(u_i, v_i, t_i) = [\boldsymbol{X}^T \boldsymbol{W}(u_i, v_i, t_i) \boldsymbol{X}]^{-1} \boldsymbol{X}^T \boldsymbol{W}(u_i, v_i, t_i) \boldsymbol{y}$.

i. Calculating $\hat{y}_{\neq i}(\tau) = \boldsymbol{x}_i \hat{\boldsymbol{\beta}}(u_i, v_i, t_i)$ by utilizing the value of φ^s without entering the location of the *i*-th observation.

j. Minimizing cross-validation values based on φ^s with the formula as follows:

$$CV(\varphi^S) = \sum_{i=1}^{n} (y_{\neq i} - \hat{y}_{\neq i}(\varphi^S))^2$$

3. Determination of parameter ξ by means of a cross-validation.

a. Inserting $\boldsymbol{X}$, $\boldsymbol{y}$, spatial window width (h_s), constants of τ, φ^S, φ^T and location-time coordinates of observations (u_i, v_i, t_i).

b. Determining the constant ξ in a measure of distance between the observed locations and time.

$$d_{ij}^{ST} = \varphi^S d_{ij}^S + \varphi^T d_{ij}^T + 2\sqrt{\varphi^S \varphi^T d_{ij}^S d_{ij}^T} \qquad , \ t_j < t_i$$

$$d_{ij}^{ST} = \alpha \qquad , \ t_j > t_i$$

c. Determining the spatial-temporal weighting function by using the Gaussian weighting function.

d. Calculating the weighting matrix $\boldsymbol{W}(u_i, v_i, t_i) = diag(w_{i1}, w_{i2}, \ldots, w_{in})$.

e. Calculating $\widehat{\boldsymbol{\beta}}(u_i, v_i, t_i) = [\boldsymbol{X}^T \boldsymbol{W}(u_i, v_i, t_i)\boldsymbol{X}]^{-1} \boldsymbol{X}^T \boldsymbol{W}(u_i, v_i, t_i)\boldsymbol{y}$.

f. Calculating $\hat{y}_{\neq i}(\tau) = \boldsymbol{x}_i \widehat{\boldsymbol{\beta}}(u_i, v_i, t_i)$ by utilizing the value of ξ without entering the location of the *i*-th observation.

g. Minimizing cross-validation values based on ξ with the formula as follows:

$$CV(\xi) = \sum_{i=1}^{n} (y_{\neq i} - \hat{y}_{\neq i}(\xi))^2$$

4. Determination of parameter (h_{ST}) by means of a cross-validation.

a. Inserting $\boldsymbol{X}$, $\boldsymbol{y}$, spatial window width (h_s), constants of τ, φ^S, φ^T and location-time coordinates of observations (u_i, v_i, t_i).

b. Determining the location and time of observation in a measure of Euclidean distance.

c. Determining the spatial-temporal weighting function. This study used a Gaussian weighting function.

d. Calculating the weighting matrix $\boldsymbol{W}(u_i, v_i, t_i) = diag(w_{i1}, w_{i2}, \ldots, w_{in})$.

e. Calculating $\widehat{\boldsymbol{\beta}}(u_i, v_i, t_i) = [\boldsymbol{X}^T \boldsymbol{W}(u_i, v_i, t_i)\boldsymbol{X}]^{-1} \boldsymbol{X}^T \boldsymbol{W}(u_i, v_i, t_i)\boldsymbol{y}$.

f. Calculating $\hat{y}_{\neq i}(h_{ST}) = \boldsymbol{x}_i^T \widehat{\boldsymbol{\beta}}(u_i, v_i, t_i)$ by using the value of h_{ST} without entering the location of the *i*-th observation.

g. Minimizing cross-validation values based on h_{ST} with the following formula:

$$CV(h_{ST}) = \sum_{i=1}^{n} (y_{\neq i} - \hat{y}_{\neq i}(h_{ST}))^2$$

5. Estimation of Parameter $\widehat{\boldsymbol{\beta}}(u_i, v_i, t_i)$ of the I-GTWR model.
   a. Inserting $\boldsymbol{X}$, $\boldsymbol{y}$, and weighting matrix $\boldsymbol{W}(u_i, v_i, t_i)$.
   b. Determining $\widehat{\boldsymbol{\beta}}(u_i, v_i, t_i) = [\boldsymbol{X}^T\boldsymbol{W}(u_i, v_i, t_i)\boldsymbol{X}]^{-1}\boldsymbol{X}^T\boldsymbol{W}(u_i, v_i, t_i)\boldsymbol{y}$.
   c. Calculating $\widehat{\boldsymbol{y}}_i = \boldsymbol{x}_i^T([\boldsymbol{X}^T\boldsymbol{W}(u_i, v_i, t_i)\boldsymbol{X}]^{-1}\boldsymbol{X}^T\boldsymbol{W}(u_i, v_i, t_i)\boldsymbol{y})$.

6. Determination of the Best I-GTWR Model.
   a. Inserting $\boldsymbol{X}$, $\boldsymbol{y}$, and weighting matrix $\boldsymbol{W}(u_i, v_i, t_i)$.
   b. Calculating matrix $\boldsymbol{S}_{IGTWR}$
   c. Calculating Sum of Squares for Error (SSE) of the I-GTWR model with the formula as follows:

$$SSE_{IGTWR} = \boldsymbol{y}^T(\boldsymbol{I} - \boldsymbol{S}_{IGTWR})^T(\boldsymbol{I} - \boldsymbol{S}_{IGTWR})\boldsymbol{y}$$

   d. Calculating Sum of Squares for Total (SST) of the I-GTWR model by utilizing the following formula:

$$SST_{IGTWR} = \boldsymbol{y}^T\boldsymbol{y} - \frac{1}{n}(\boldsymbol{y}^T\boldsymbol{J}\boldsymbol{y})$$

   e. Calculating R^2, AIC_{IGTWR}, $RMSE_{IGTWR}$ of the I-GTWR model.

7. Partial testing of each parameter in I-GTWR Model
   a. Inserting $\boldsymbol{X}$, $\boldsymbol{y}$, weighting matrix $\boldsymbol{W}(u_i, v_i, t_i)$, SSE_{IGTWR}, $\widehat{\boldsymbol{\beta}}(u_i, v_i, t_i)$, and hat matrix of the I-GTWR model $\boldsymbol{S}_{IGTWR}$
   b. Calculating δ_1 dan δ_2 through the formula as follows:

$$\delta_i = tr\left([(\boldsymbol{I} - \boldsymbol{S}_{\boldsymbol{IGTWR}})^T(\boldsymbol{I} - \boldsymbol{S}_{\boldsymbol{IGTWR}})]^i\right) \quad \text{, where } i = 1,2$$

   c. Calculating $\hat{\sigma} = \sqrt{\frac{SSE_{IGTWR}}{\delta_i}}$
   d. Calculating matrix $\boldsymbol{C}_i\boldsymbol{C}_i^T$ by using the following formula:

$$\boldsymbol{C}_i = (\boldsymbol{X}^T\boldsymbol{W}(u_i, v_i, t_i))^{-1}\boldsymbol{X}^T\boldsymbol{W}(u_i, v_i, t_i) \quad \text{, where } i = 1,2,\ldots,n$$

   e. Determining c_{kk} as the *k*-th diagonal element of the matrix $\boldsymbol{C}_i\boldsymbol{C}_i^T$
   f. Calculating degrees of freedom (df) = $\left(\frac{\delta_1^2}{\delta_2^2}\right)$
   g. Calculating *t*-test for each observation through the following formula:

$$t_i = \frac{\hat{\beta}_k(u_i, v_i, t_i)}{\sigma\sqrt{c_{kk}}} \text{ , where } i = 1,2,\ldots,n$$

The next stage is to conduct an analysis through the I-GTWR method by using COVID-19 data from the Regency/City of East Borneo Province in December 2019 – August 2021. The stages of analysis in this study are as follows:

1. Conducting an exploration of the linear relationship between predictor variables and testing the assumption of multicollinearity by considering the value of VIF (Variance Inflation Factor).
2. Testing the spatial diversity by means of the Breusch-Pagan test.
3. Constructing the weighting matrix ($\boldsymbol{W}$) of the I-GTWR method as follows:
   a. Calculating the optimal spatial window width (h_s) using a cross-validation.
   b. Calculating the optimal spatial-temporal ratio parameter (τ) using a cross-validation
   c. Calculating parameters φ^S and φ^T by means of a cross-validation approach. The parameters are based on the spatial-temporal distance function by using the interaction, and assumes the value of $\xi = 0$
   d. Calculating the parameter ξ through a cross-validation approach.
   e. Calculating the optimum spatial-temporal window width (h_{ST}) using a cross-validation.
   f. Determining the weighting matrix ($\boldsymbol{W}$) using a measure of the spatial-temporal distance with interactions.
4. Comparing the goodness of several models, including Global Regression, GTWR and I-GTWR.

4. MAIN RESULTS

A. Multicollinearity Test

The multicollinearity checking was performed with the Variance Inflation Factor (VIF) test to identify the correlation between the predictor variables used in the study. VIF values are shown in Table 2. VIF values less than 10 are often regarded as showing multicollinearity in the predictor variables used. Panel data were used in this study. Therefore, the VIF value was calculated each year and on a combined basis.

Year	**Variables**				
	X_1	X_2	X_3	X_4	X_5
Combination	7.833	9.958	3.159	5.868	6.470
2020	44.560	25.143	4.048	16.603	10.210
2021	55.357	60.873	3.230	7.304	19.334

TABLE 2. Value of VIF (Variance Inflation Factor) of The Predictor Variables

B. Spatial and Temporal Heterogeneity Test

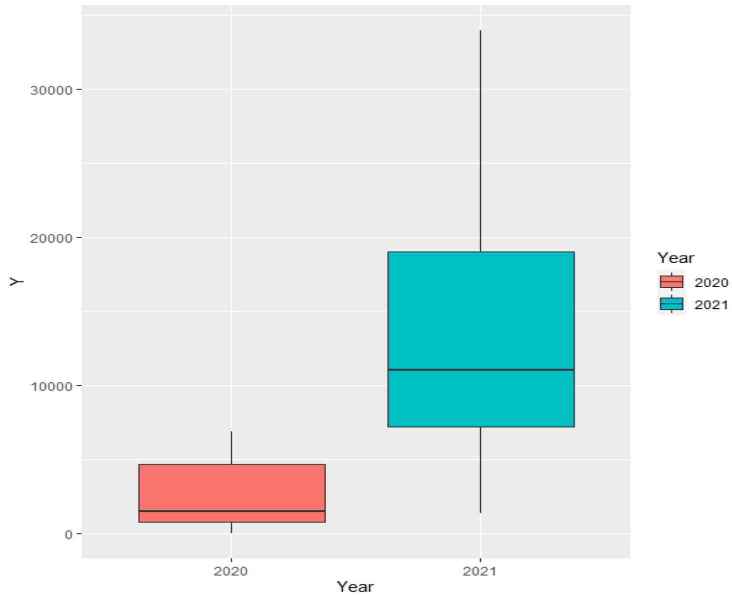
The Breusch-Pagan test based on a combined annual or per year basis are presented in Table 3. Referring to the results, all data were found to show significance at the 5% level of significance, thus spatial heterogeneity was found generally in the data on the total of COVID-19 cases. The spatial heterogeneity included the diversity of data between regions and time in East Borneo. Consequently, the total of COVID-19 cases in East Borneo might be affected by region and time.

Year	**Breusch-Pagan Value**	**p-value**
Combination	11.599	0.041
2020	6.067	0.299
2021	6.781	0.237

TABLE 3. Results of the Breusch-Pagan Test

Figure 1 show the distribution of the total of COVID-19 in East Borneo is likely to increase every year. Figure 1 shows that the boxplot size tends to widen each year. The width of the boxplot describes the diversity of the data. No outliers are found for each year, thus indicating that no region in Regency/City was reported to have a very high total of COVID-19 cases compared to other regions.

FIGURE 1. Boxplot of Temporal Diversity in Each Year



C. Parameter Estimation

Table 4 shows the parameter estimator by using I-GTWR model. The variable (X_4) provided the highest average compared to other variables, so the variable of the total of hospitals (X_4) had a greater influence on the total of COVID-19 cases in Regencies/Cities, followed by the variables of the total of health care centers (X_5), the density population (X_2), the total of tuberculosis (TB) cases (X_1), and the least influence were provided by the variable of Gross Regional Domestic Product (GRDP) (X_3).

Variable	Minimum	Maximum	Mean	Standard Deviation
Constant	-5392.300	-4463.556	-4873.25	318.445
$\hat{\beta}_1$	-39.634	-36.741	-38.195	1.077
$\hat{\beta}_2$	21.770	25.076	23.433	1.346
$\hat{\beta}_3$	0.084	0.111	0.098	0.008
$\hat{\beta}_4$	1600.100	1802.590	1686.93	65.063
$\hat{\beta}_5$	93.679	114.508	103.241	7.654

TABLE 4. Summary from the Estimated Values of the I-GTWR Model Parameters

D. Kernel Functions on Fixed Bandwidth

Based on Table 5, the implementation of the goodness-of-fit, particularly AICc was capable of causing the Gaussian kernel function to have the smallest value compared to other kernel functions. Meanwhile, for the R-Square value, the Exponential kernel function provided a higher value than other kernel functions. However, the R-Square values in the Gaussian kernel function and the Exponential kernel function were not found to be significantly different. Therefore, the Kernel Gaussian function could be considered as a function that was generally able to generate better the I-GTWR modeling results in this study data.

Kernel Function	Bandwidth	AICc	R^2
Gaussian	1.346	714.263	0.981
Bisquare	1.584	733.663	0.816
Exponential	0.665	1649.417	0.998

TABLE 5. Comparison of Kernel Functions on Fixed Bandwidth

E. Comparison of Models

The global regression model, the GTWR model and the I-GTWR model were compared to identify a better model to describe the distribution of COVID-19 cases in East Borneo. Based on Table 6, the I-GTWR model accompanied by the Gaussian kernel function weighting was observed to be better for modeling the distribution of the total of COVID-19 cases in East Borneo, because it had a larger value of R^2, and smaller RMSE values than the global regression method.

Method	R^2	RMSE
Global Regression	0.634	6232.002
GTWR	0.834	4205.785
I-GTWR	0.981	2270.671

TABLE 6. Comparison of Models

F. Spatial and Temporal Pattern of Contributing Factors for COVID-19 Cases

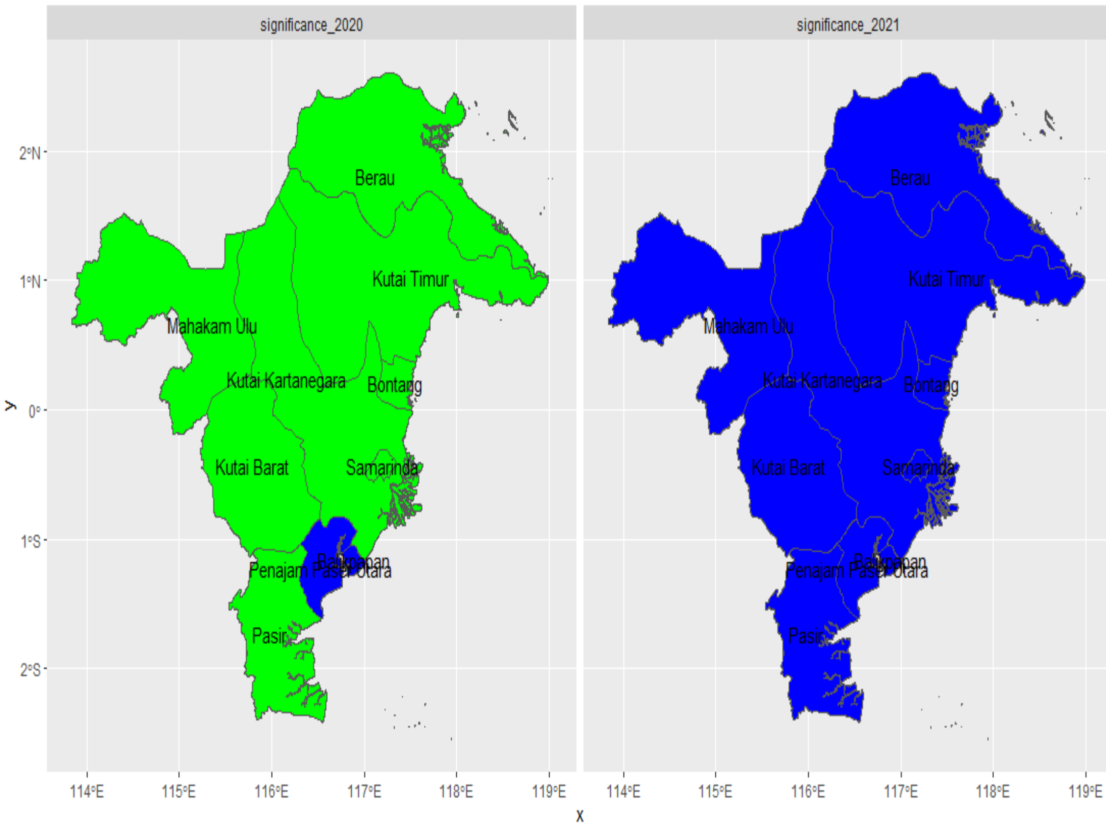
In each Regency/City, the predictor variables that significantly affect the total of COVID-19 cases could be different between years. The mapping process was capable of indicating significant movement of response variables between Regencies/Cities and between years at Figure 2. The mapping was successfully carried out by dividing four maps based on a single variable and one map based on a combination variable. The maps were explored based on a single variable that significantly influenced changes in the total of COVID-19 cases by region and time as shown in Table 8. Referring to Table 7, each variable was found to affect the total of COVID-19 cases in each region and at different times. In 2020, the GRDP variable (X_3) was identified as not significantly affecting the total of COVID-19 cases in several Regencies/cities, while the variables for the total of tuberculosis (TB) cases (X_1), the population density (X_2), the total of hospitals (X_4), and the total of health care centers (X_5) were found to have an effect on changes in the total of COVID-19 cases in all Regencies/Cities in East Borneo Province.

Variables	**2020**	**2021**
X_1	Kutai Barat, Kutai Timur, Kutai Kartanegara, Penajam Paser Utara, Paser, Berau, Mahakam Ulu, Balikpapan, Bontang, Samarinda	Kutai Barat, Kutai Timur, Kutai Kartanegara, Penajam Paser Utara, Paser, Berau, Mahakam Ulu, Balikpapan, Bontang, Samarinda
X_2	Kutai Barat, Kutai Timur, Kutai Kartanegara, Penajam Paser Utara, Paser, Berau, Mahakam Ulu, Balikpapan, Bontang, Samarinda	Kutai Barat, Kutai Timur, Kutai Kartanegara, Penajam Paser Utara, Paser, Berau, Mahakam Ulu, Balikpapan, Bontang, Samarinda
X_3	Penajam Paser Utara, Balikpapan	Kutai Barat, Kutai Timur, Kutai Kartanegara, Penajam Paser Utara, Paser, Berau, Mahakam Ulu, Balikpapan, Bontang, Samarinda
X_4	Kutai Barat, Kutai Timur, Kutai Kartanegara, Penajam Paser Utara, Paser, Berau, Mahakam Ulu, Balikpapan, Bontang, Samarinda	Kutai Barat, Kutai Timur, Kutai Kartanegara, Penajam Paser Utara, Paser, Berau, Mahakam Ulu, Balikpapan, Bontang, Samarinda
X_5	Kutai Barat, Kutai Timur, Kutai Kartanegara, Penajam Paser Utara, Paser, Berau, Mahakam Ulu, Balikpapan, Bontang, Samarinda	Kutai Barat, Kutai Timur, Kutai Kartanegara, Penajam Paser Utara, Paser, Berau, Mahakam Ulu, Balikpapan, Bontang, Samarinda

TABLE 7. Variables that Provide Significant Influence

Based on the simultaneous analysis, two groups of Regencies/Cities were found based on a model of a combination of contributing factors for the total of COVID-19 cases.

FIGURE 2. Location of COVID-19 Cases based on Significant Influencing Factors



The first group was the total of COVID-19 influenced by the variables of the total of tuberculosis (TB) cases (X_1), population density (X_2), the GRDP (X_3), the total of hospitals (X_4), and the total of health care centers (X_5); and the second group was the total of COVID-19 cases influenced by the total of tuberculosis (TB) cases (X_1), population density (X_2), the total of hospitals (X_4), and the total of health care centers (X_5). The complete grouping of Regencies/Cities based on the combination model that causes an increase in the total of COVID-19 cases is shown in Table 8.

Group	Variables	Regency/City	
		2020	2021
1	X_1, X_2, X_3, X_4, X_5	Penajam Paser Utara, Balikpapan	Paser, Kutai Barat, Kutai Kartanegara, Kutai Timur, Berau, Penajam Paser Utara, Mahakam Ulu, Balikpapan, Samarinda, Bontang
2	X_1, X_2, X_4, X_5	Kutai Barat, Kutai Timur, Kutai Kartanegara, Paser, Berau, Mahakam Ulu, Bontang, Samarinda	-

TABLE 8. Grouping of Regencies/Cities Based on The Combination Model

5. CONCLUSION

Based on the study that had been conducted, it may be inferred that the Improved-Geographically Temporally Weighted Regression (I-GTWR) modeling had proven to be more effective in describing the spread of the total of COVID-19 in East Borneo. Referring to the results of the parameter estimation of the total of COVID-19 cases in East Borneo by means of the I-GTWR method, the factors found to provide an influence on the total of COVID-19 cases included the total of tuberculosis (TB) cases (X_1), the population density (X_2), the GRDP (X_3), the total of hospitals (X_4), and the total of health care centers (X_5). These five factors significantly affected the total of COVID-19 cases East Borneo based on region and time (spatial temporary). The I-GTWR method could also be used to classify the spread of the total of COVID-19 in Regency/City that was influenced by certain variables in combination or single variables based on region and time. The variable of gross regional domestic product (GRDP) (X_3) was identified as a single variable that had no effect on the total of COVID-19 cases in East Borneo Province in 2020. The combination factors that provided a significant influence in this study consisted of the total of tuberculosis (TB) cases (X_1), the population density (X_2), the total of Hospitals (X_4), and the total of health care centers (X_5).

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CONFLICT OF INTERESTS

The author(s) declare that there is no conflict of interests.

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