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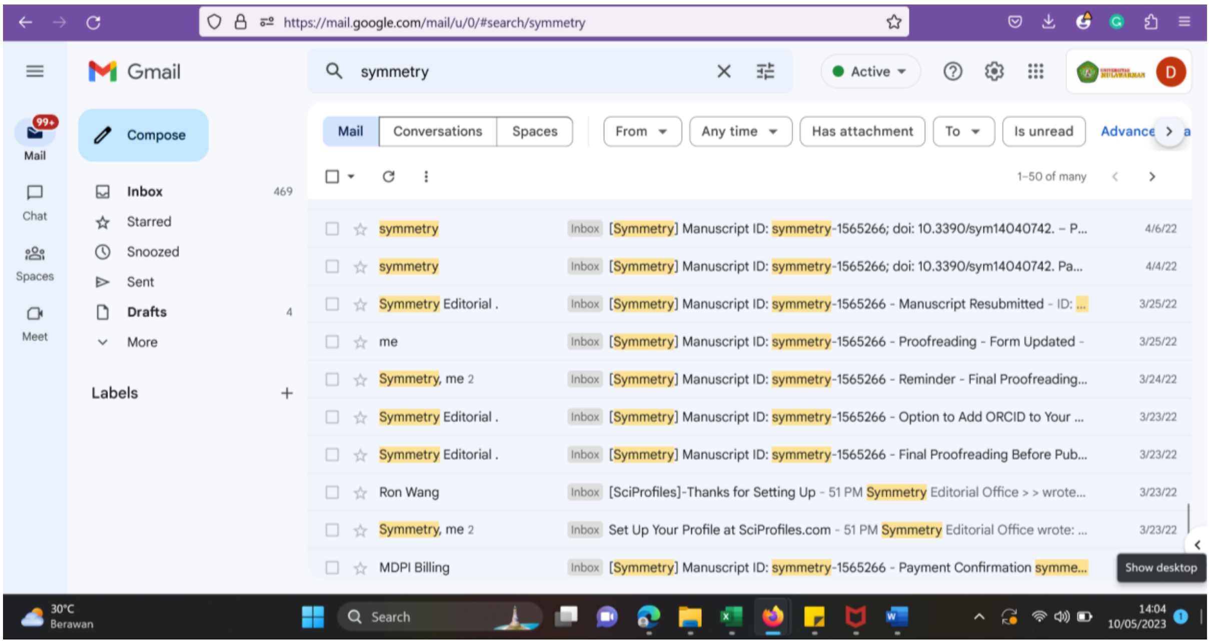

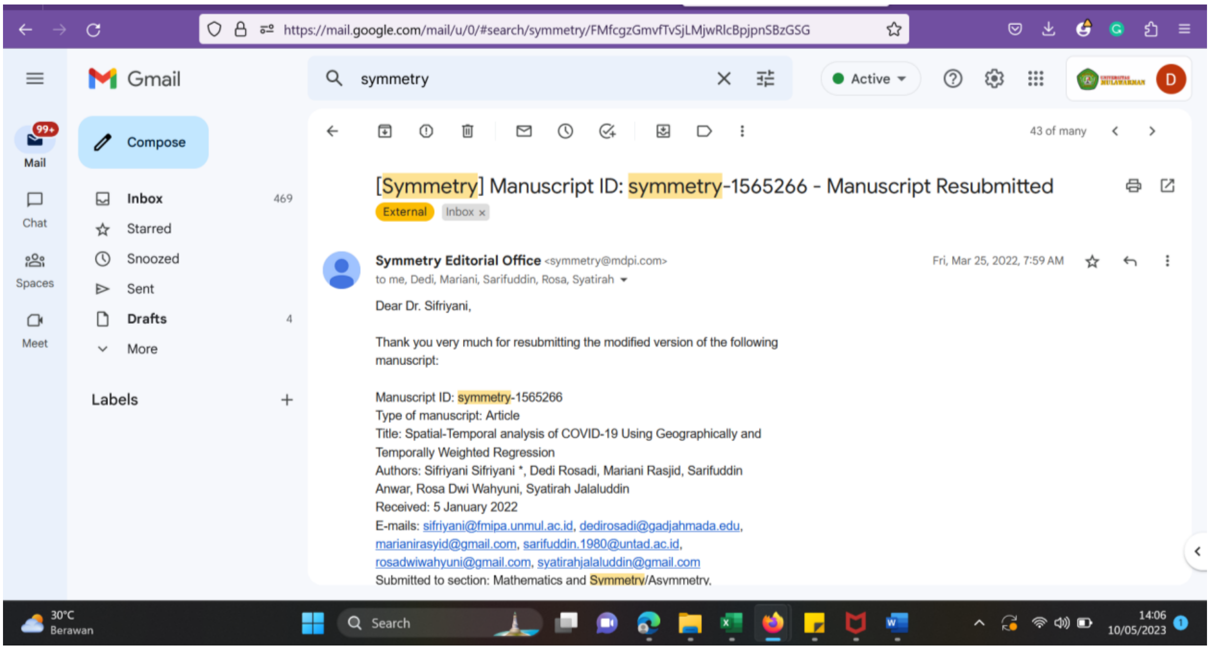

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to me, Dedi, Mariani, Sarifuddin, Rosa, Syatirah

Dear Dr. Sifriyani,

Thank you very much for resubmitting the modified version of the following manuscript:

Manuscript ID: symmetry-1565266
Type of manuscript: Article
Title: Spatial-Temporal analysis of COVID-19 Using Geographically and Temporally Weighted Regression
Authors: Sifriyani Sifriyani *, Dedi Rosadi, Mariani Rasjid, Sarifuddin Anwar, Rosa Dwi Wahyuni, Syatirah Jalaluddin
Received: 5 January 2022
E-mails: sifriyani@fmipa.unmul.ac.id, dedirosadi@gadjahmada.edu, marianirasyid@gmail.com, sarifuddin.1980@untad.ac.id, rosadwiwahyuni@gmail.com, syatirahjalaluddin@gmail.com
Submitted to section: Mathematics and Symmetry/Asymmetry,

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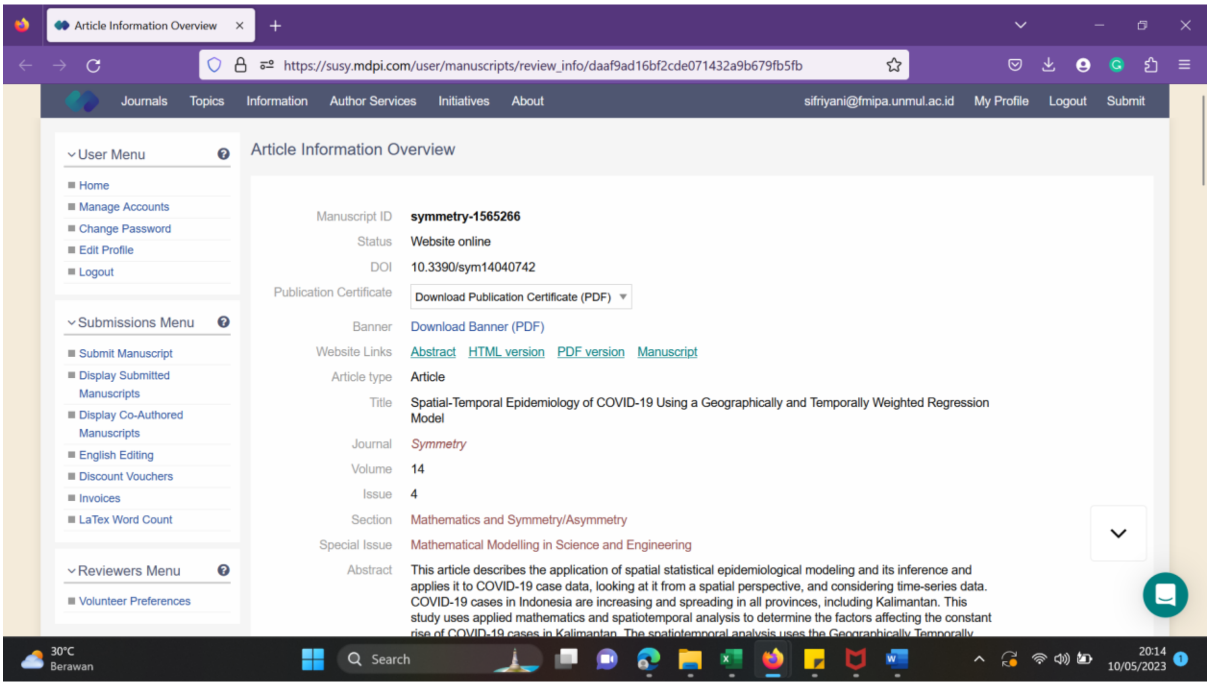

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Article type	Article
Title	Spatial-Temporal Epidemiology of COVID-19 Using a Geographically and Temporally Weighted Regression Model
Journal	*Symmetry*
Volume	14
Issue	4
Section	Mathematics and Symmetry/Asymmetry
Special Issue	Mathematical Modelling in Science and Engineering
Abstract	This article describes the application of spatial statistical epidemiological modeling and its inference and applies it to COVID-19 case data, looking at it from a spatial perspective, and considering time-series data. COVID-19 cases in Indonesia are increasing and spreading in all provinces, including Kalimantan. This study uses applied mathematics and spatiotemporal analysis to determine the factors affecting the constant rise of COVID-19 cases in Kalimantan. The spatiotemporal analysis uses the Geographically Temporally

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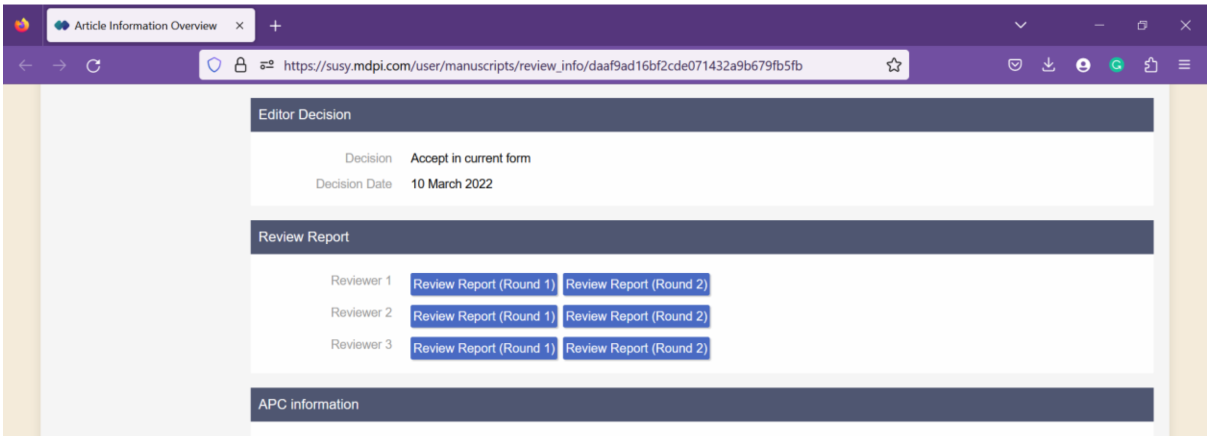

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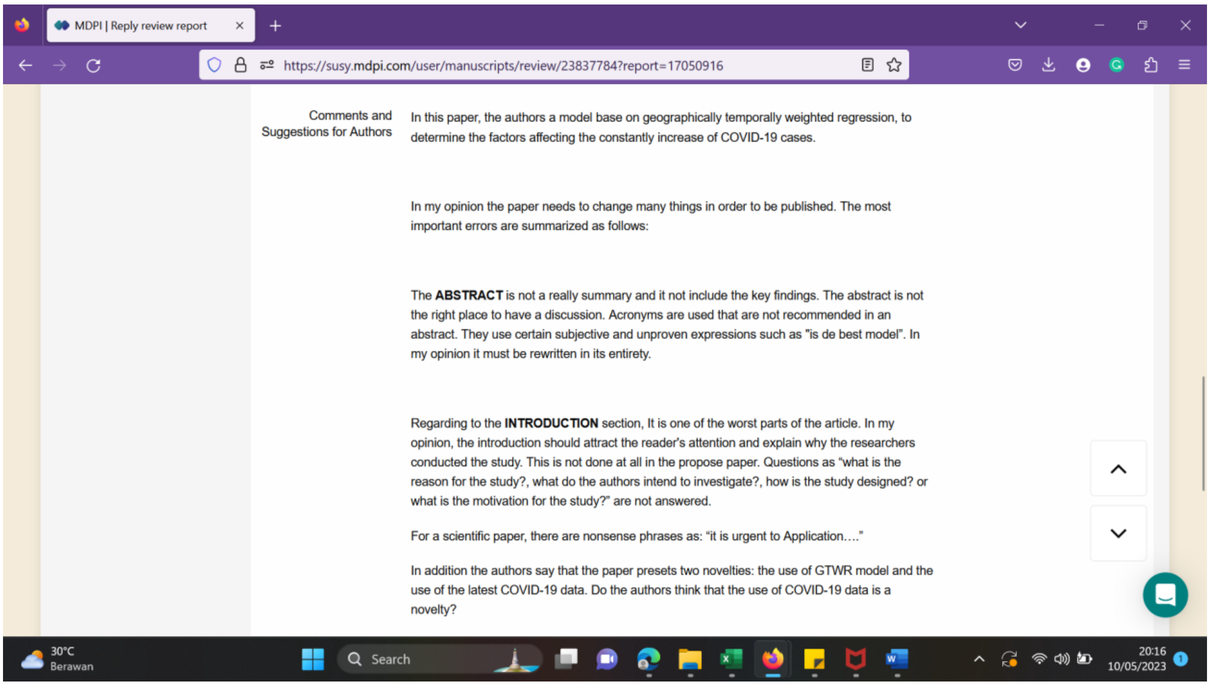


Comments and Suggestions for Authors

In this paper, the authors a model base on geographically temporally weighted regression, to determine the factors affecting the constantly increase of COVID-19 cases.

In my opinion the paper needs to change many things in order to be published. The most important errors are summarized as follows:

The **ABSTRACT** is not a really summary and it not include the key findings. The abstract is not the right place to have a discussion. Acronyms are used that are not recommended in an abstract. They use certain subjective and unproven expressions such as "is de best model”. In my opinion it must be rewritten in its entirety.

Regarding to the **INTRODUCTION** section, It is one of the worst parts of the article. In my opinion, the introduction should attract the reader's attention and explain why the researchers conducted the study. This is not done at all in the propose paper. Questions as “what is the reason for the study?, what do the authors intend to investigate?, how is the study designed? or what is the motivation for the study?” are not answered.

For a scientific paper, there are nonsense phrases as: “it is urgent to Application….”

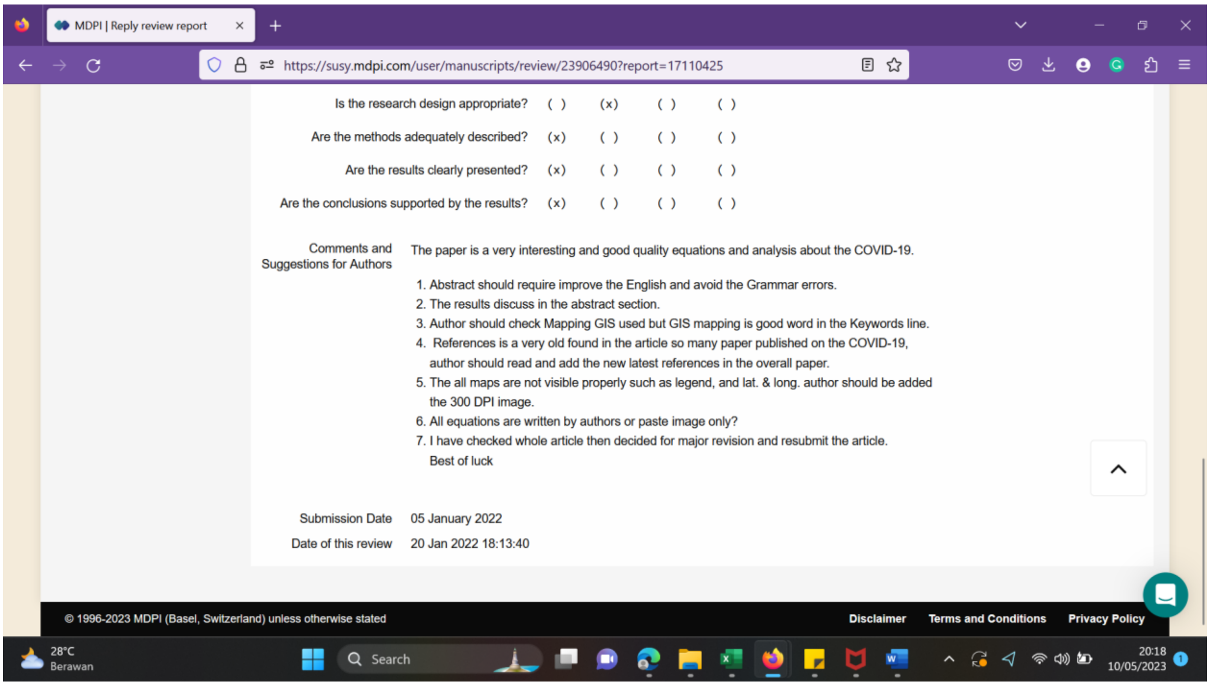
In addition the authors say that the paper presets two novelties: the use of GTWR model and the use of the latest COVID-19 data. Do the authors think that the use of COVID-19 data is a novelty?

In short, superfluous and unnecessary information is added but the main information is omitted. It must be changed.

In section two there are some preliminaries and data (subsections 2., 2.2, 2.3 and 2.4.1) and the main part of the paper, the methodology used in the model (subsection 2.4.2). The authors must divide this section in two: 3. Preliminaries and Data; 4. Methodology.

In section 2.4.2 de the author must to include a flowchart, this helps to describe how the paper works.

RESULTS and DISCUSSION section is, without a doubt, the best of the paper, but even so, it must be improved. In my opinion, the section must be divided into two parts: Experimental Results and Discussion. In the first part, the results of the different parts of the model should be shown: Spatial distribution mapping, description of covid-19 cumulative data..., GTWR. In the Discussion section a study and analysis of the results should be carry out with their advantages over other existing models. In fact, a comparison with other models is not made, and this makes the paper a bit weak.



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Are the conclusions supported by the results?	(x)	( )	( )	( )

Comments and Suggestions for Authors

The paper is a very interesting and good quality equations and analysis about the COVID-19.

1. Abstract should require improve the English and avoid the Grammar errors.
2. The results discuss in the abstract section.
3. Author should check Mapping GIS used but GIS mapping is good word in the Keywords line.
4. References is a very old found in the article so many paper published on the COVID-19, author should read and add the new latest references in the overall paper.
5. The all maps are not visible properly such as legend, and lat. & long. author should be added the 300 DPI image.
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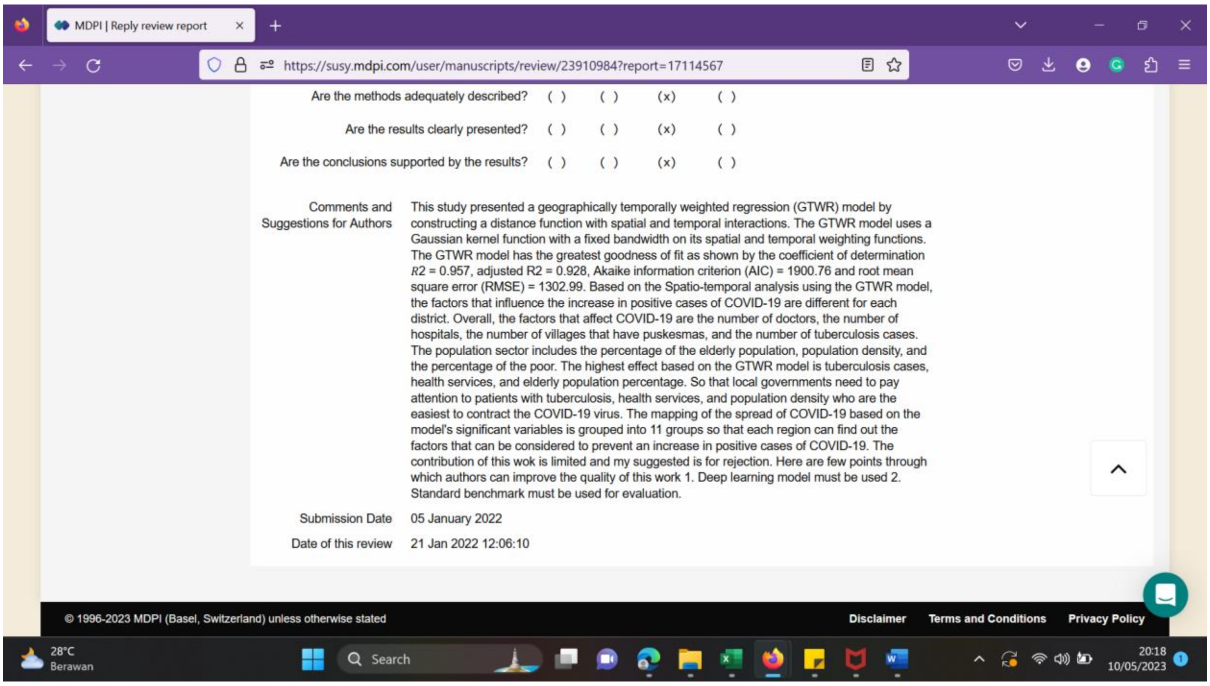
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Comments and Suggestions for Authors: This study presented a geographically temporally weighted regression (GTWR) model by constructing a distance function with spatial and temporal interactions. The GTWR model uses a Gaussian kernel function with a fixed bandwidth on its spatial and temporal weighting functions. The GTWR model has the greatest goodness of fit as shown by the coefficient of determination $R2$ = 0.957, adjusted R2 = 0.928, Akaike information criterion (AIC) = 1900.76 and root mean square error (RMSE) = 1302.99. Based on the Spatio-temporal analysis using the GTWR model, the factors that influence the increase in positive cases of COVID-19 are different for each district. Overall, the factors that affect COVID-19 are the number of doctors, the number of hospitals, the number of villages that have puskesmas, and the number of tuberculosis cases. The population sector includes the percentage of the elderly population, population density, and the percentage of the poor. The highest effect based on the GTWR model is tuberculosis cases, health services, and elderly population percentage. So that local governments need to pay attention to patients with tuberculosis, health services, and population density who are the easiest to contract the COVID-19 virus. The mapping of the spread of COVID-19 based on the model's significant variables is grouped into 11 groups so that each region can find out the factors that can be considered to prevent an increase in positive cases of COVID-19. The contribution of this wok is limited and my suggested is for rejection. Here are few points through which authors can improve the quality of this work 1. Deep learning model must be used 2. Standard benchmark must be used for evaluation.

Submission Date: 05 January 2022

Date of this review: 21 Jan 2022 12:06:10

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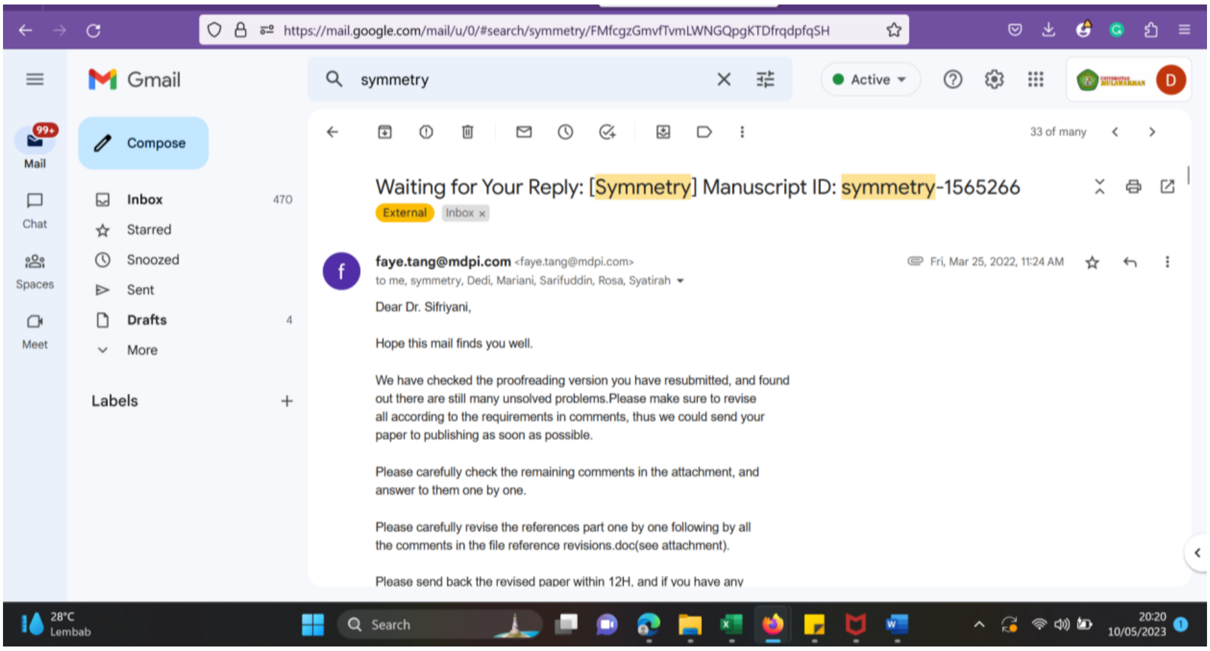
Comments and Suggestions for Authors

This study presented a geographically temporally weighted regression (GTWR) model by constructing a distance function with spatial and temporal interactions. The GTWR model uses a Gaussian kernel function with a fixed bandwidth on its spatial and temporal weighting functions. The GTWR model has the greatest goodness of fit as shown by the coefficient of determination $R2$ = 0.957, adjusted R2 = 0.928, Akaike information criterion (AIC) = 1900.76 and root mean square error (RMSE) = 1302.99. Based on the Spatio-temporal analysis using the GTWR model, the factors that influence the increase in positive cases of COVID-19 are different for each district. Overall, the factors that affect COVID-19 are the number of doctors, the number of hospitals, the number of villages that have puskesmas, and the number of tuberculosis cases. The population sector includes the percentage of the elderly population, population density, and the percentage of the poor. The highest effect based on the GTWR model is tuberculosis cases, health services, and elderly population percentage. So that local governments need to pay attention to patients with tuberculosis, health services, and population density who are the easiest to contract the COVID-19 virus. The mapping of the spread of COVID-19 based on the model's significant variables is grouped into 11 groups so that each region can find out the factors that can be considered to prevent an increase in positive cases of COVID-19. The contribution of this wok is limited and my suggested is for rejection. Here are few points through which authors can improve the quality of this work 1. Deep learning model must be used 2. Standard benchmark must be used for evaluation.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Hope this mail finds you well.
We have checked the proofreading version you have resubmitted, and found out there are still many unsolved problems.Please make sure to revise all according to the requirements in comments, thus we could send your paper to publishing as soon as possible.
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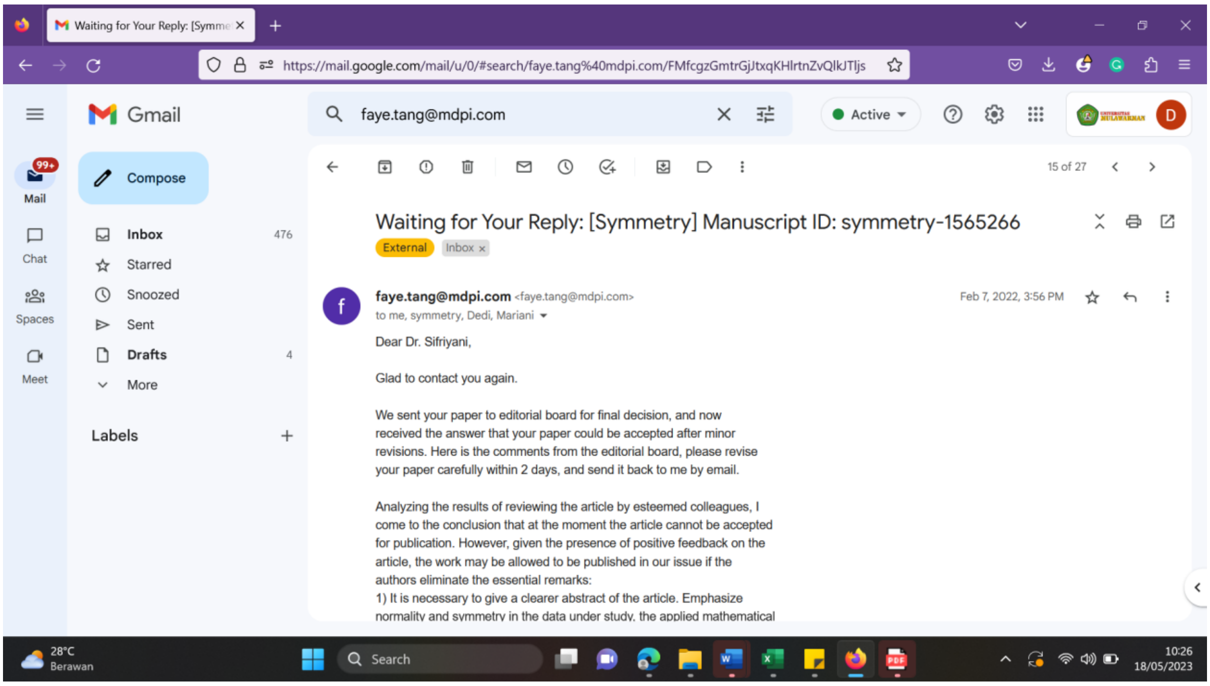
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Analyzing the results of reviewing the article by esteemed colleagues, I come to the conclusion that at the moment the article cannot be accepted for publication. However, given the presence of positive feedback on the article, the work may be allowed to be published in our issue if the authors eliminate the essential remarks:
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2) Add a citation to study 10.1109/ITNT52450.2021.9649210, dedicated to the analysis of restrictive measures during the pandemic.
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4) You need to beautifully design the formulas. No need to wrap where the formula fits on the page.
5) Make the text in figure 2 readable. (Remove unnecessary inscriptions so that they do not run into each other).
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7) Improve the quality of drawings.
8) Design the formulas in accordance with the template.

If you have any questions, please do not hesitate to contact me.

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Article

Spatial-Temporal Epidemiology of COVID-19 Using a Geographically and Temporally Weighted Regression Model

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Abstract: This article describes the application of spatial statistical epidemiological modeling and its inference and applies it to COVID-19 case data, looking at it from a spatial perspective, and considering time-series data. COVID-19 cases in Indonesia are increasing and spreading in all provinces, including Kalimantan. This study uses applied mathematics and spatiotemporal analysis to determine the factors affecting the constant rise of COVID-19 cases in Kalimantan. The spatiotemporal analysis uses the Geographically Temporally Weighted Regression (GTWR) model by developing a spatial and temporal interaction distance function. The GTWR model was applied to data on positive COVID-19 cases at a scale of 56 districts/cities in Kalimantan between the period of January 2020 and August 2021. The purpose of the study was to determine the factors affecting the cumulative increase in COVID-19 cases in Kalimantan and map the spatial distribution for 56 districts/cities based on the significant predictor variables. The results of the study show that the GTWR model with the development of a spatial and temporal interaction distance function using the kernel Gaussian fixed bandwidth function is a better model compared to the Ordinary Least Squares (OLS) model. According to the significant variables, there are various factors affecting the rise in cases of COVID-19 in the region of Kalimantan, including the number of doctors, the number of TB cases, the percentage of elderly population, GRDP, and the number of hospitals. The highest factors that affect COVID-19 cases are the high number of TB cases, population density, and the lack of health services. Furthermore, an area map was produced on the basis of the significant variables affected by the rise in COVID-19 cases. The results of the study provide local governments with decision-making recommendations to overcome COVID-19-related issues in their respective regions.

Keywords: COVID-19 outbreak; spatio-temporal; geographically and temporally weighted regression model; statistical modeling; time series analysis; statistical inference; GIS mapping

1. Introduction

The spread of active cases of COVID-19 has significantly increased in a number of countries in 2021, including Indonesia. As of 7 September 2021, COVID-19 had spread to 204 countries and had infected more than 220 million people, resulting in nearly 4.5 million deaths [1]. Moreover, Indonesia was also reported to have more than 4 million confirmed positive cases of COVID-19, with over 130 thousand deaths [2]. The transmission of COVID-19 was also found to have increased in one of the provinces of Indonesia, specifically in Kalimantan, with a total number of accumulative cases of 245,205 in August 2021. Based on the increasing number of COVID-19 cases in Kalimantan, it is necessary to conduct research to identify the reasons and factors which led to this increase in COVID-19 cases. This purpose of this research was to determine contributing factors to the increase in COVID-19 cases based on the Improved Geographically and Temporally Weighted Regression model.

Spatial data were modeled using spatial regression with geographic weighting, also known as the geographically weighted regression (GWR) model. GWR was first introduced by Fotheringham in 1967 [3-4]. The GWR model is the development of Linear Regression Analysis with the addition of geographic weighting for each regression parameter to handle emerging spatial diversity. GWR theory has been widely used by researchers, including [5-8]. However, the GWR model only uses spatial data (location) in one time period, while spatial data is usually influenced by the time series. Spatial data should be analyzed by involving several time observations (temporal), thus demanding a more accurate parameter estimation. Therefore, to increase the precision of the parameter estimator on the GWR model, observations should be highly carried out for each location at a certain time. Referring to that matter, a Geographically Temporally Weighted Regression (GTWR) model was developed to overcome the weaknesses of the GWR model [9], by considering the elements of location and time.

The GTWR model is a development of the GWR model, but it is not able to handle non-stationary data both spatially and temporally at the same time. Consequently, this research was conducted by applying the Improved Geographically Temporally Weighted Regression model with the development of the distance function. This model is expected to be capable of generating local models at any location and time, resulting in a more representative model. Furthermore, the spatial and temporal information in the GTWR model is regarded as a crucial element in creating the weighting matrix. Thus, the improved model is expected to be succeed in identifying spatial and temporal variability. The GTWR model, one of the spatio-temporal models, has been widely used in various fields. As stated by Fotheringham, the 2015 GTWR model is generally used to handle issues of spreading infectious diseases, water pollution, hydrology, and urban planning. In this research, the GTWR model was used to address the issue of the spread of the COVID-19 disease. The COVID-19 virus has spread globally in various countries, including in Indonesia.

Indonesia is an archipelagic country, consisting of various large and small islands. Kalimantan represents the largest island in Indonesia, and consists of five provinces—East Kalimantan, North Kalimantan, South Kalimantan, Central Kalimantan, and West Kalimantan Provinces—all with an increasing daily spread of COVID-19. Data from the official COVID-19 website of the five provinces on the island of Kalimantan showed that the highest cumulative number of positive COVID-19 cases, as of 10 August 2021, was East Kalimantan Province with 133,826 cases [10], followed by South Kalimantan Province with 55,257 cases [11], Central Kalimantan Province with 38,123 cases [12], North Kalimantan Province with 26,050 cases [13], and West Kalimantan Province with 17,999 cases [14]. Based on this, it is important to undertake a study to understand the factors causing such an increase from a spatial and temporal point of view. The present study offers local governments information with regard to overcoming the increase in COVID-19 cases in their respective regions.

COVID-19 modeling studies using spatiotemporal analysis include: Pearson's correlation methods for spatiotemporal analysis in regions of China [15]; Levy's flight to explain the spatiotemporal dynamics of the pandemic regions in China [16]; prospective space–time statistics to identify active and emerging COVID-19 groups at a county level in the USA [17]; and an online questionnaire for the geographical identification of possible symptomatic regions in Israel [18]. Studies predicting the global spread of COVID-19 based on geographic and climatic data regions include: the Caribe Basin [19]; geographical characteristics and spatiotemporal analysis of infection regions in the USA [20]; analysis by province of the effectiveness of quarantine on the spread of the pandemic in Spain [21]; spatiotemporal analysis of COVID-19 at national and provincial levels in India [22]; the Poisson segmented model for the analysis of changing patterns in different geographic areas in China [23]; spatiotemporal analysis and reflections on health geography in Argentina [24]; spatiotemporal analysis of COVID-19 at national and provincial levels in Mexico [25]; spatiotemporal analysis and reflections on the usefulness of GIS in the pandemic [26]; and the analysis of restrictive measures during the pandemic [27]. A Susceptible–Infected–Recovered (SIR) model for estimating COVID-19 reproduction number in East Kalimantan and Samarinda [28].

Based on the background description above, this research was carried out using the Improved Geographically Temporally Weighted Regression model with the development of the distance function and the application of COVID-19 cumulative data in Kalimantan, Indonesia. The first objective of this research was to identify the factors that influenced the cumulative increase in COVID-19 at a region/city scale in Kalimantan, Indonesia—which consists of 56 regions/cities—by using data from 2020 and 2021. The second objective of this research was to map the spatial distribution for the 56 regions/cities based on significant predictor variables.

2. Materials and Methods

2.1. Geographically and Temporally Weighted Regression

The Geographically and Temporally Weighted Regression (GTWR) model represents an effective approach to dealing with the problem of spatial and temporal non-stationarity [9]. The GTWR model is a development of the GWR model, adding the time (temporal) element. In contrast to the GWR model, GTWR combines temporal and spatial information in a weighted matrix to identify spatial and temporal variability. The GTWR model in Equation (1) is for the independent variable *p* with the response variable at the location (u_i, v_i, t) for each observation:

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

where y_i is the observed value of the response variable for the observation location (u_i, v_i) and time t_i; the parameter $\beta_0(u_i, v_i, t_i)$ is the constant of the intercept value; the parameter $\beta_k(u_i, v_i, t_i)$ is the regression coefficient of the *k*-th independent variable at the observation location (u_i, v_i) and time t_i; the variable x_{ik} is the observed value of the *k*-th explanatory variable at the observation location (u_i, v_i) and time t_i; and ε_i is error the *i*-th observations which are assumed to be identical, independent, and $\varepsilon_i \sim N(0, \sigma^2)$.

2.2. GTWR Model Parameter Estimation

The regression coefficient $\hat{\beta}_i(u_i, v_i, t_i)$ at the *i*-th point can be obtained by using the Weighted Least Square. The estimated parameters of the GTWR model are given in Equation (2):

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

where the weight $\boldsymbol{W}(u_i, v_i, t_i) = diag(w_{i1}, w_{i2}, \ldots, w_{in})$ is the weighting matrix at the observation location (u_i, v_i) and time t_i. The diagonal element $w_{ij} (1 \leq j \leq n)$ is the spatiotemporal distance function at the observation point (u_i, v_i, t_i). In the modeling stage, it is assumed that the proximity of the data observation point to the *i* point in the spatiotemporal coordinate system has a greater effect on the parameter estimator $\widehat{\boldsymbol{\beta}}(u_i, v_i, t_i)$ than that of the data located further from the *i* point. The proximity has two elements, spatial proximity and temporal proximity; thus, the definition and measurement of spatiotemporal proximity in the coordinate system constitute major problems in the construction of the GTWR model.

The present study used a date located at three dimensions in the spatiotemporal coordinate system and it was known that the observations were close to the *i* point. Therefore, [9] used an ellipsoidal coordinate system to measure the proximity of the regression point to the observation points that surround it.

2.3. Distance Function and Geographical Weight of the GTWR Model

The spatiotemporal distance function consists of a combination of the spatial distance function and the temporal distance function, which are given as follows [9,14]:

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

where φ^S and φ^T are the affecting factors that balance the different effects used to measure the spatiotemporal distance. Based on the distance function in Equation (3), the geographical weighting function according to Equation (4) is obtained:

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

The value of $h_S^2 = \frac{h_{ST}^2}{\varphi^S}$ and $h_T^2 = \frac{h_{ST}^2}{\varphi^T}$, then Equation (5) is obtained:

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

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

h_S is a parameter of the spatial window width, h_T is a parameter of the temporal window width, and h_{ST} is a parameter of the spatial-temporal window width.

In most cases, the value of φ^S and φ^T is not equal to zero. Let τ be the ratio parameter of $= \frac{\varphi^T}{\varphi^S}$ with $\varphi^S \neq 0$; then, Equation (6) [30] is obtained:

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

Let $\varphi^S = 1$ in order to reduce unknown parameters. In this problem, there is only one unknown parameter, τ. The parameter τ serves to increase or decrease the effect of temporal distance on spatial distance. This parameter is obtained from the minimum cross-validation criteria by initializing the initial τ value, as given in Equation (7).

$$(\tau) = \sum_i \left(y_i - \hat{y}_{\neq i}(\tau)\right)^2 \tag{7}$$

The Gaussian kernel function is a weighting function which is used in the GTWR model, as given in Equation (8).

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

The weighting matrix is $\boldsymbol{W}_{ij}$ determined by the spatiotemporal distance (d_{ij}^{ST}) and the window width h_{ST}. The window width value can be calculated using the geographic weighted regression model, as proposed by [3]. The estimator value of the response variable is determined by Equation (9).

$$\hat{y} = \begin{bmatrix} \hat{y}_1 \\ \hat{y}_2 \\ \dots \\ \hat{y}_n \end{bmatrix} = \begin{bmatrix} X_1^T(X^TW(u_1,v_1,t_1)X)^{-1}X^TW(u_1,v_1,t_1) \\ X_2^T(X^TW(u_2,v_2,t_2)X)^{-1}X^TW(u_2,v_2,t_2) \\ \dots \\ X_n^T(X^TW(u_n,v_n,t_n)X)^{-1}X^TW(u_n,v_n,t_n) \end{bmatrix} y = Sy \tag{9}$$

The selection of the model's goodness of fit can be calculated using the AIC (Akaike information criterion) value. The corrected AIC value [30] is used to overcome the spatio-temporal variability, as given in Equation (10).

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

2.4. *Research Methodology*

2.4.1. Data and Data Sources

Data and data sources are described in Table 1.

Table 1. Description of Resesarch Variables and Data Sources.

Variable	Symbol	Variable Description	Observation Data Source	Unit	Scale
Response	y	Cumulative positive cases of COVID-19	Official websites www.covid19.kaltimprov.go.id www.corona.kalselprov.go.id www.corona.kalteng.go.id www.coronainfo.kaltaraprov.go.id www.corona.kalbarprov.go.id (accessed on 10 August 2021) [10-14]	People	56 regions/cities in the island of Kalimantan
Predictor	x_1	Number of doctors	Statistics Indonesia of East Kalimantan Province, North Kalimantan Province, South Kalimantan Province, Central Kalimantan Province, West Kalimantan Province, 2020–2021 [41-50]	People	56 regions/cities in the island of Kalimantan
	x_2	Number of TB cases	Public Health Office of East Kalimantan Province, North Kalimantan Province, South Kalimantan Province, Central Kalimantan Province, West Kalimantan Province, 2020–2021 [31-40]	Cases	56 regions/cities in the island of Kalimantan
	x_3	Percentage of elderly population	Statistics Indonesia of East Kalimantan Province, North Kalimantan Province, South Kalimantan Province, Central Kalimantan Province, West Kalimantan Province, 2020–2021 [41-50]	Percentage	56 regions/cities in the island of Kalimantan
	x_4	Population density	Statistics Indonesia of East Kalimantan Province, North Kalimantan Province, South Kalimantan	People/Km^2	56 regions/cities in the island of Kalimantan

		Province, Central Kalimantan Province, West Kalimantan Province, 2020–2021 [41-50]		
x_5	Gross Regional Domestic Product at Market Price	Statistics Indonesia of East Kalimantan Province, North Kalimantan Province, South Kalimantan Province, Central Kalimantan Province, West Kalimantan Province, 2020–2021 [41-50]	Billion Rupiah	56 regions/cities in the island of Kalimantan
x_6	Number of hospitals	Public Health Office of East Kalimantan Province, North Kalimantan Province, South Kalimantan Province, Central Kalimantan Province, West Kalimantan Province, 2020–2021 [31-40]	Units	56 regions/cities in the island of Kalimantan
x_7	Number of villages/ kelurahan with public health centers	Public Health Office of East Kalimantan Province, North Kalimantan Province, South Kalimantan Province, Central Kalimantan Province, West Kalimantan Province, 2020–2021 [31-40]	Units	56 regions/cities in the island of Kalimantan
x_8	Percentage of poor population	Statistics Indonesia of East Kalimantan Province, North Kalimantan Province, South Kalimantan Province, Central Kalimantan Province, West Kalimantan Province, 2020–2021 [41-50]	%	56 regions/cities in the island of Kalimantan

2.4.2. Stages of Analysis

The analysis and modeling processes were carried out by using the R-Studio version 2021.09.1 Build 372. The analysis stages are shown in Figure 1.

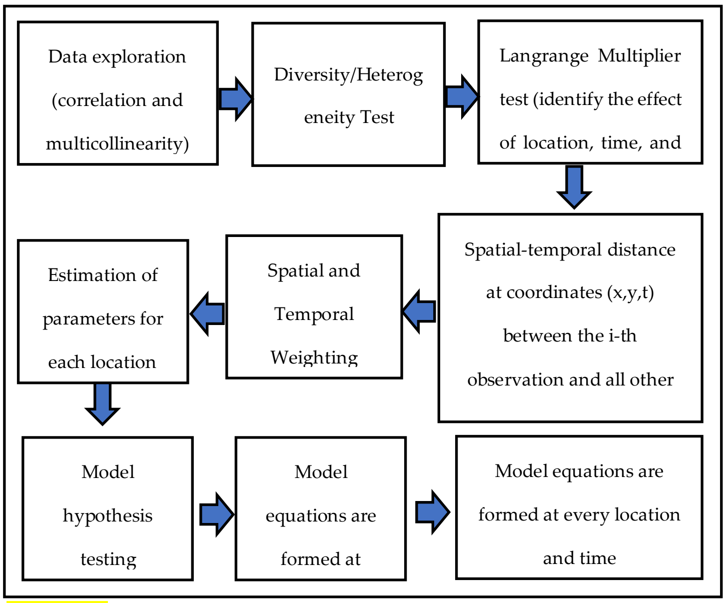


Figure 1. Improved GTWR Model Flowchart.

Based on the objectives of the study, the following are the stages of data analysis using the GTWR model to determine factors affecting the cumulative increase in COVID-19 cases and to map the spatial distribution based on significant predictor variables.

1. Explore the distribution of response variables and predictor variables for the period of 2020–2021 using a spatial distribution mapping;
2. Describe cumulative data of COVID-19 cases and the predictor variables;
3. Perform a multicollinearity test by taking the value of VIF (variance inflation factor) into account;
4. Explore temporal variability using a boxplot of response variables for each year;
5. Perform an analysis using the GTWR method as follows:

a. Calculate the optimum spatial bandwidth (h_S) using cross-validation based on the GWR optimization approach with the formula as given by Equation (11):

$$CV(h_S) = \sum_i \left(y_i - \hat{y}_{\neq i}(h_S)\right)^2 \tag{11}$$

b. Calculate the optimum spatiotemporal ratio parameter $(\tau)(\tau)$ using cross-validation based on the GTWR optimization approach with the formula as given by Equation (7);

c. Calculate parameters φ^S and φ^T using the cross-validation approach with the formula given in point b. Both parameters are based on the spatiotemporal distance function with the formula as given by Equation (12):

$$(d_{ij}^{ST})^2 = \varphi^S[(u_i - u_j)^2 + (v_i - v_j)^2] + \varphi^T(t_i - t_j)^2 \tag{12}$$

d. Determine the weighting matrix $(W)(W)$ using the spatiotemporal distance measure for each observation location based on the Gaussian kernel function with the formula given by Equation (8).

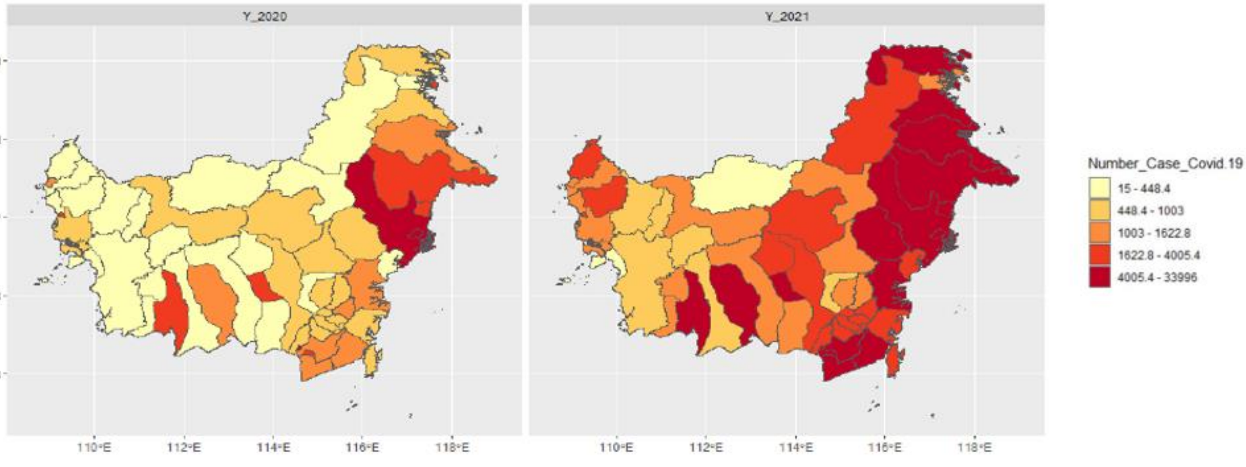
6. Estimate parameters in the GTWR model at each location using the weighted least square (WLS) according to Equation (2);
7. Perform a parameter significance test for the GTWR model;
8. Map the variable significance for each region.

3. Results and Discussion

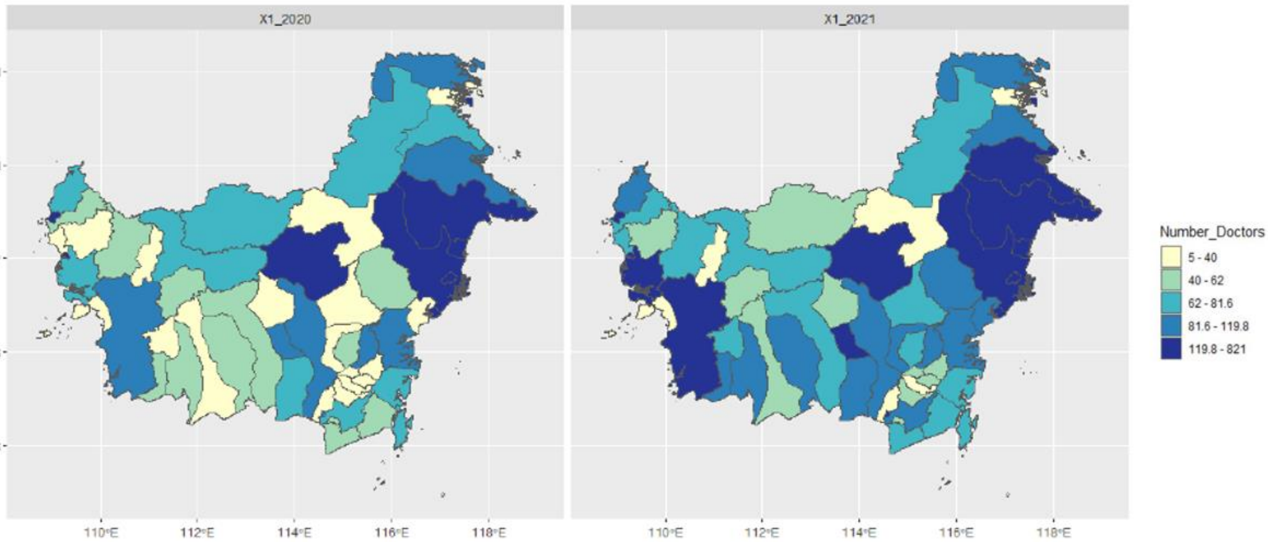
This section begins by providing information on descriptive statistics, especially the presentation of data using a spatial distribution map, followed by information on the measure of concentration and the measure of data distribution. The results of the statistical inference research begin with regression analysis and a test of spatial effects, GTWR modeling, GTWR model estimation, the GTWR model significance test, and spatial mapping based on the GTWR model results. The analysis to determine factors affecting the increase in confirmed COVID-19 cases is based on the region/city scale on the island of Kalimantan, Indonesia.

3.1. Spatial Distribution Mapping

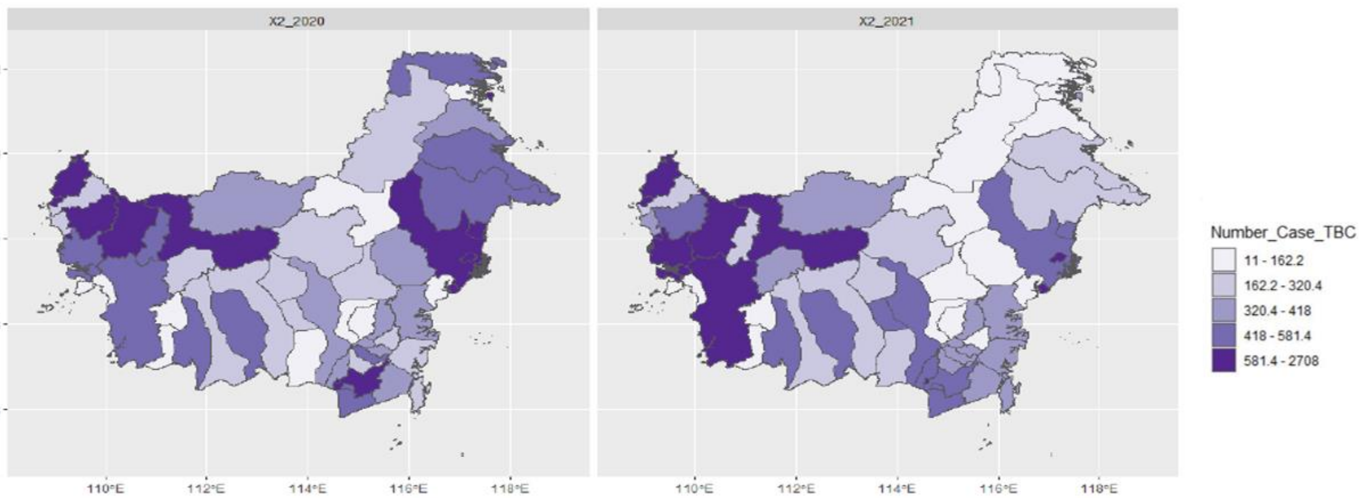
The observation data in Table 1 were subjected to descriptive statistical analysis and statistical inference. Observation data were categorized based on variables and are described in Figures 2 and 3.


Y_2020
Y_2021
Number_Case_Covid.19
15 - 448.4
448.4 - 1003
1003 - 1622.8
1622.8 - 4005.4
4005.4 - 33996

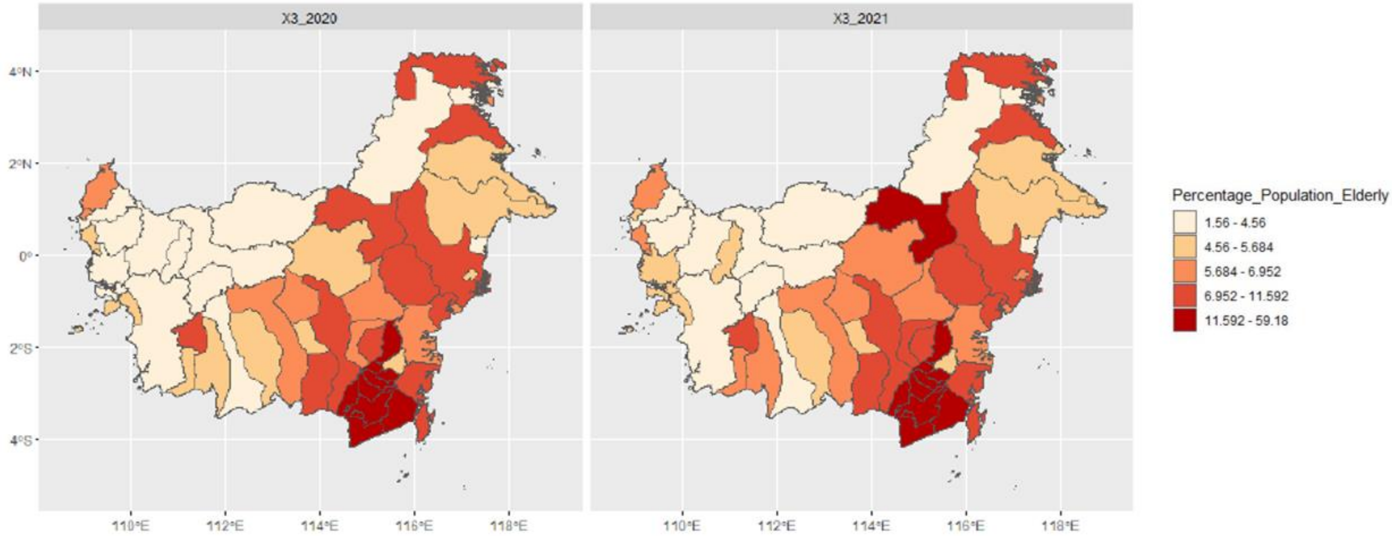
(**a**)


X1_2020
X1_2021
Number_Doctors
5 - 40
40 - 62
62 - 81.6
81.6 - 119.8
119.8 - 821

(**b**)


X2_2020
X2_2021
Number_Case_TBC
11 - 162.2
162.2 - 320.4
320.4 - 418
418 - 581.4
581.4 - 2708

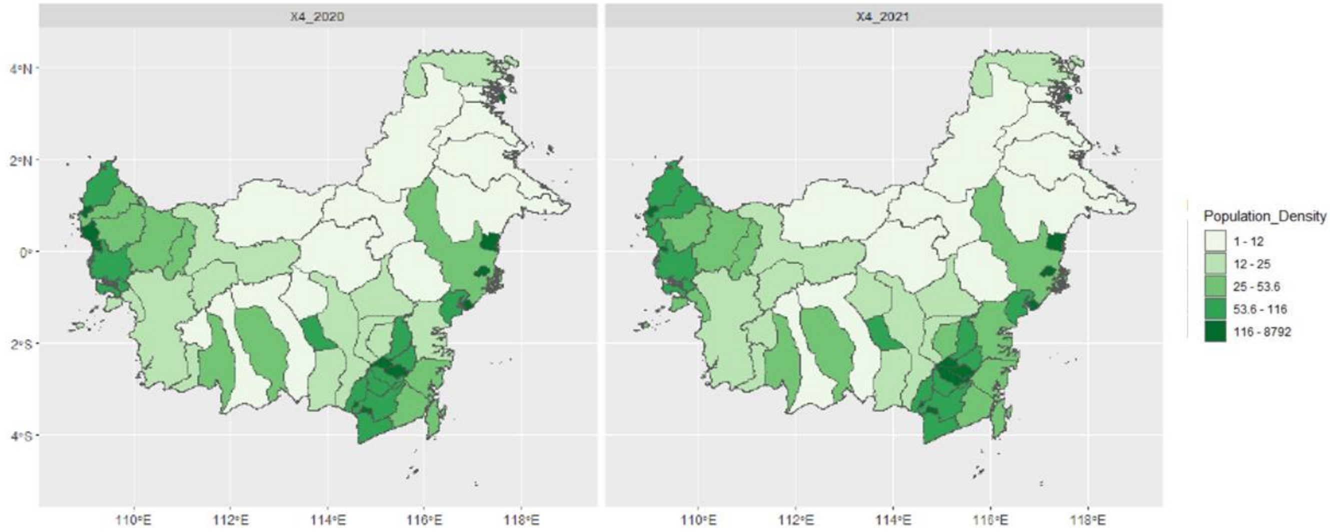
(**c**)



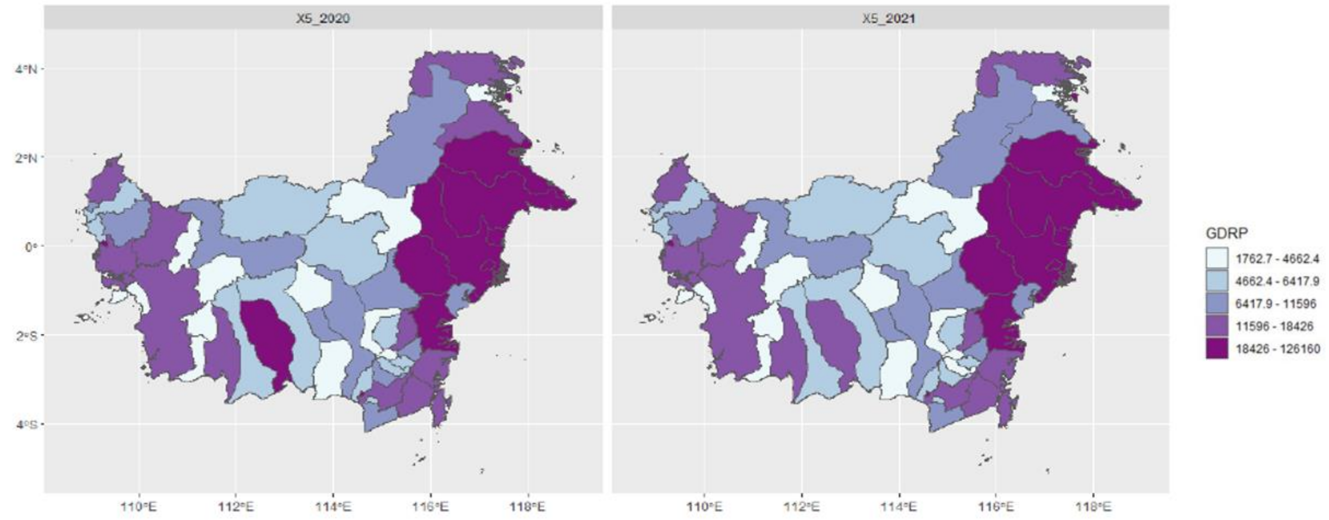
(**d**)

Figure 2. Spatial Distribution Mapping of $x_1 - x_4$. (**a**) Map of the number of confirmed positive COVID-19 cases 2020–2021; (**b**) map of the number of doctors 2020–2021; (**c**) map of the number of TB cases 2020–2021; (**d**) map of the percentage of elderly population in 2020–2021.

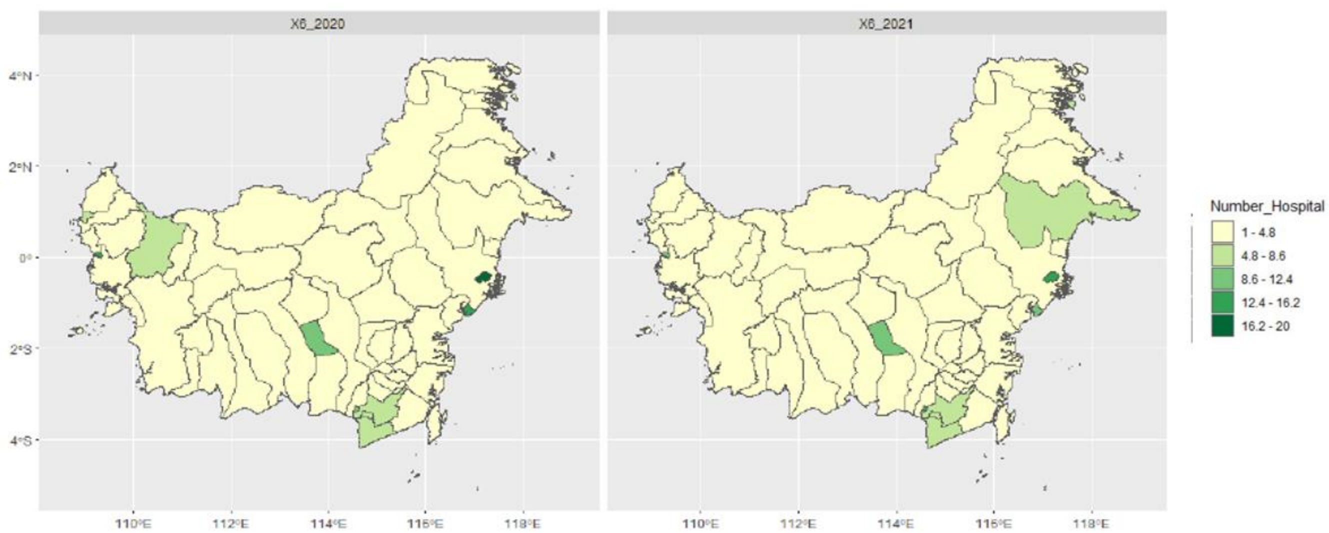
Figure 2a shows that the number of confirmed positive COVID-19 cases in 2020 spread evenly across the regions/cities in Kalimantan, as indicated by the similar distribution colors. However, in comparison, in 2020 the number of confirmed cases was relatively scant, while the number of positive COVID-19 cases increased in 2021. This is clearly shown by the color changes for regions/cities in East Kalimantan Province. Figure 2b shows the distribution of the number of doctors at the region/city scale in Kalimantan 2020–2021. Most regions/cities in Kalimantan had a small and evenly distributed number of doctors. In 2021, the number of doctors increased quite significantly in Samarinda and Balikpapan. This is shown by the dark color contrast, indicating a large number of doctors in these areas. This is commensurate with the increasing number of COVID-19 cases. Figure 2c shows the distribution of the number of TBC cases in 2020–2021. In general, there was no increase in the number of TBC cases in each region/city in Kalimantan. This is shown by the almost similar and evenly distributed color pattern in each area. However, the City of Banjarmasin had higher TB cases than that of other region/cities, as indicated by its darker color. Figure 3a shows the distribution of population density in 2020–2021. In general, there was no increase in population density in every region/city in Kalimantan. This is shown by the almost similar and evenly distributed color pattern in each area. However, the city of Samarinda had a higher population density than that of other regions/cities, as indicated by the darker color. Furthermore, the city of Samarinda had a decrease in population density from 2020 to 2021, as indicated by the color difference, which gets brighter.


X4_2020
X4_2021
4°N
2°N
0°
2°S
4°S
110°E
112°E
114°E
116°E
118°E
Population_Density
1 - 12
12 - 25
25 - 53.6
53.6 - 116
116 - 8792

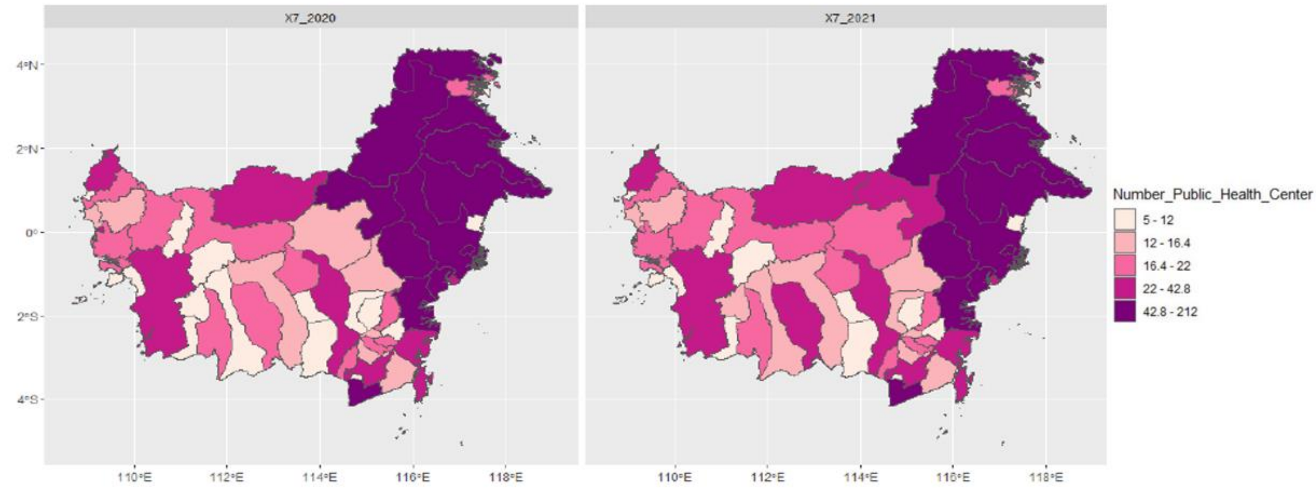
(**a**)


X5_2020
X5_2021
4°N
2°N
0°
2°S
4°S
110°E
112°E
114°E
116°E
118°E
GDRP
1762.7 - 4662.4
4662.4 - 6417.9
6417.9 - 11596
11596 - 18426
18426 - 126160

(**b**)


X6_2020
X6_2021
4°N
2°N
0°
2°S
4°S
110°E
112°E
114°E
116°E
118°E
Number_Hospital
1 - 4.8
4.8 - 8.6
8.6 - 12.4
12.4 - 16.2
16.2 - 20

(**c**)



(**d**)

Figure 3. Spatial Distribution Mapping of $x_5 - x_8$. (**a**) Map of population density in 2020–2021; (**b**) map of Gross Regional Domestic Product (GRDP) 2020–2021; (**c**) map of the number of hospitals in 2020–2021; (**d**) map of the number of public health centers in 2020–2021.

3.2. Description of COVID-19 Cumulative Data and Predictor Variables

The descriptions of the COVID-19 cumulative data and predictor variables for the observation data in Table 1 are shown in Table 2.

Table 2. Summary of Variable Statistics.

Descriptive Statistics	Confirmed Positive Cases of COVID-19	Number of Doctors (x_1)	Number of TB Cases (x_2)	Percentage of Elderly Population (x_3)	Population Density (x_4)	GRDP (x_5)	Number of Hospitals (x_6)	Number of Public Health Centers (x_7)	Percentage of Poor Population (x_8)
Minimum	15	5	11	2	1	1763	1	5	2
Maximum	33,996	821	2708	59	8792	126,160	20	212	12
Range	33,981	816	2697	58	8791	124,397	19	207	10
Sum	332,489	12,084	49,283	1149	45,054	1,818,623	382	3861	675
Median	1183	73	355	6	31	8512	2	20	5
Mean	2969	108	440	10	402	16,238	3	34	6
SE.Mean	464	12	39	1	133	2122	0	4	0
Variance	24,119,005	16,810	166,245	118	1,969,598	504,525,521	11	1609	5
Std.dev	4911	130	408	11	1403	22,462	3	40	2

Correlation between the variable y and each variable $x_1, x_2, x_3, x_4, x_5, x_6, x_7$, and x_8 is given in Table 3.

Table 3. Correlation of independent variables to the number of positive COVID-19 cases.

Variable	Correlation	p-Value
x_1	0.684	0.000 *
x_2	0.255	0.006 *
x_3	0.048	0.612
x_4	0.232	0.013 *
x_5	0.628	0.000 *
x_6	0.501	0.000 *
x_7	0.353	0.000 *
x_8	−0.144	0.129

Note: (*) = significant at 5% significance level.

The value of the correlation of the explanatory variable to the response variable shows that the variable x_1 had a high and positive correlation to the variable y. In addition, the variable x_1 had a significant correlation to the variable y. It can be concluded that the higher the number of positive COVID-19 cases, the higher the number of doctors will be.

The results of the multicollinearity test in Table 4 show that all variables had a VIF value of < 5; thus, all independent variables had no multicollinearity.

Table 4. Multicollinearity Test.

Predictor Variable	VIF
x_1	2.521
x_2	2.481
x_3	1.294
x_5	1.455
x_6	3.557

The results of the spatial variability test using the Breusch–Pagan test are shown in Table 5. It shows a p-value of $4.642 \times 10^7 < 0.05$; thus, there was spatial variability in the multiple linear regression model.

Table 5. Spatial variability test value.

Breusch–Pagan	p-Value
0.90079	4.642×10^7

Figure 4 shows the visualization results of the number of positive COVID-19 cases from 2020 to 2021 using a boxplot. Figure 4 shows that, in 2021, the variability in the number of positive COVID-19 cases was larger than that of 2020. This difference in variability indicates a variability between years, or so-called temporal variability. The results of the analysis of the Breusch–Pagan and boxplot tests leads us to the conclusion that GTWR modeling can effectively be performed in the study of the 56 regions/cities in Kalimantan.

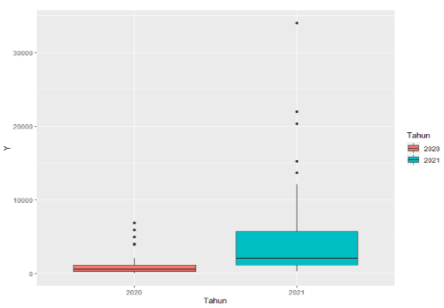


Figure 4. Boxplot of temporal variability for each year.

3.3. Geographically Temporally Weighted Regression (GTWR) Modeling for 56 Regencies/Cities in Kalimantan

3.3.1. Estimation of GTWR Model

The analysis of the GTWR model estimation uses Equation (2) at the i-th location where the location $i = 1,2,\cdots,56$ is the initials for 56 regions/cities in Kalimantan, and the t time is 1 for 2020 and 2 for 2021. The estimation results of the GTWR model are given in Equation (13).

$$\hat{y}_{it} = \hat{\beta}_0(u_i, v_i, t_i) + \hat{\beta}_1(u_i, v_i, t_i)x_{it1} + \hat{\beta}_2(u_i, v_i, t_i)x_{it2} + \hat{\beta}_3(u_i, v_i, t_i)x_{it3} + \hat{\beta}_5(u_i, v_i, t_i)x_{it5} + \hat{\beta}_6(u_i, v_i, t_i)x_{it6} \quad, i = 1,2, \ldots ,56 \ ; \ t = 1,2 \tag{13}$$

Table 6 shows the summary results of GTWR modeling using the Gaussian kernel function with a fixed bandwidth on the spatial and temporal weighting function. The variable number of doctors (x_1) has a coefficient value ranging from –3.750 to 23.5555. The variable number of TB cases (x_2) has a coefficient value ranging from –4869 to 2702. The variable percentage of elderly population has a coefficient value ranging from –20,633 to 110,781. The variable GRDP (x_5) has a coefficient value ranging from 0.0303 to 0.2104. The variable number of hospitals (x_6) has a coefficient value ranging from –308.44 to 1024,983. The coefficient values for each of these variables are spread across all regions/cities in Kalimantan.

Table 6. Summary of the estimated values of the GTWR model parameters.

Parameter Estimator	Minimum	Q_1	Median	Q_3	Maximum
$\hat{\beta}_0$	−1612.200	−886.460	−282.050	−64.537	1206.736
$\hat{\beta}_1$	−3.750	−0.609	0.033	5.815	23.556
$\hat{\beta}_2$	−4.870	−0.634	−0.197	0.560	2.702
$\hat{\beta}_3$	−20.633	−4.809	5.696	29.529	110.782
$\hat{\beta}_5$	0.030	0.033	0.086	0.170	0.210
$\hat{\beta}_6$	−308.440	170.570	220.270	849.960	1024.984

The results of parameter estimation provide GTWR model estimators which state the correlation of the independent variables of number of doctors (x_1), number of TB cases (x_2), percentage of elderly population (x_3), GRDP (x_5), and number of hospitals (x_6) to the percentage of positive COVID-19 cases in the Kalimantan provinces. Four GTWR models are given for four region/city locations in Equations (14)–(17).

Samarinda City, East Kalimantan Province 2020:

$$\hat{y}_{it} = -206.539 - 0.898X_{it1} + 0.248X_{it2} - 2.802X_{it3} + 0.034X_{it5} + 264.725X_{it6} \tag{14}$$

Samarinda City, East Kalimantan Province 2021:

$$\hat{y}_{it} = -515.123 + 12.700X_{it1} + 1.194X_{it2} + 4.734X_{it3} + 0.149X_{it5} + 432.961X_{it6} \tag{15}$$

Kapuas Hulu Regency, West Kalimantan Province 2020:

$$\hat{y}_{it} = -405.751 - 0.096X_{it1} - 0.149X_{it2} + 19.508X_{it3} + 0.04X_{it5} + 188.398X_{it6} \tag{16}$$

Kapuas Hulu Regency, West Kalimantan Province 2021:

$$\hat{y}_{it} = -1382.853 + 5.676X_{it1} - 4.156X_{it2} + 74.872X_{it3} + 0.185X_{it5} + 903.160X_{it6} \tag{17}$$

3.3.2. Measure of Model's Goodness of Fit

The measure of the goodness used to compare the OLS model and GTWR model is the coefficient of determination (R^2), adjusted R^2, Akaike information criterion (AIC), and the root mean square error (RMSE). The results of the comparison of the value of the goodness-of-fit measure are shown in Table 7.

Table 7. Comparison of models in terms of the number of positive COVID-19 cases.

Criteria	OLS	GTWR
R^2	0.6134	0.95713
Adjusted R^2	0.5952	0.92855

AIC	2128.229	1900.76
RMSE	3039.91	1302.99

The above comparison of models shows that the GTWR model is better than the OLS model. This is indicated by the higher values of R^2 and adjusted R^2, as well as the smaller values of AIC and RMSE criteria.

3.3.3. Simultaneous Significance Test of GTWR Model Parameters

The first hypothesis testing conducted were the simultaneous tests of the model in order to test the goodness of fit of the GTWR model. The hypothesis testing for the goodness of fit of the GWPR model was as follows:

H_0: $\hat{\beta}_k(u_i, v_i, t_i) = \hat{\beta}_k \quad , k = 1,2,\ldots,5 \ ; i = 1,2,\ldots,56 \ ; t = 1,2$
(There is no significant difference between multiple linear regression models and GTWR models.)

H_1: There is at least one $\hat{\beta}_k(u_i, v_i, t_i) \neq \hat{\beta}_k \quad k = 1,2,\ldots,5 \ ; i = 1,2,\ldots,56 \ ; t = 1,2$

Table 8 shows that F-Statistics = 14,440 > F-table = 1537 or p-value = 0.000 < α = 0.05. Thus, H_0 was rejected and there was a significant difference between the multiple linear regression model and the GTWR model.

Table 8. Values of simultaneous hypotheses testing of the model's goodness of fit.

F-Statistics	F Table	p-Value	Keputusan Uji
14.440	1.537	0.000	Tolak Ho

3.3.4. Partial Significance Test of GTWR Model Parameters

Partial parameter tests aim to determine the partial effects of the independent variables on the dependent variable. The hypothesis for the partial tests of the regression model parameters for the parameter $\hat{\beta}_k(u_i, v_i, t_i)$ was as follows:

H_0: $\hat{\beta}_k(u_i, v_i, t_i) = 0 \quad , k = 1,2,\ldots,5 \ ; i = 1,2,\ldots,56 \ ; t = 1,2$
(The independent variable X_{kt} has no effect on the number of positive COVID-19 cases in Kalimantan Provinces.)

H_1: $\hat{\beta}_k(u_i, v_i, t_i) \neq 0 \quad , k = 1,2,\ldots,5 \ ; i = 1,2,\ldots,56 \ ; t = 1,2$
(The independent variable X_{kt} has an effect on the number of positive COVID-19 cases in Kalimantan Provinces.)

The test statistic of the partial parameter testing was the statistic of the t-test. The criteria for rejecting H_0 at the significance level of α = 0.05 was to reject H_0 if the p-value < 0.05. The results of the partial test of parameters are shown in Table 9. The table above shows that the factors affecting the number of positive COVID-19 cases in the Berau region were the human development index, life expectancy, gross regional domestic income, population growth rate, and so on, for all observation locations in the Kalimantan provinces. This is shown by the p-value of those variables that is lower than 0.05.

Table 9. The test statistical value of partial hypothesis testing of the GTWR model parameters.

Location	Year	Parameter	Estimator Value	Standard Error	T-Value	p-Value
Samarinda	2020	β_0	−206.539	421.063	−0.491	0.625
		β_1	−0.898	4.825	−0.186	0.853
		β_2	0.248	0.859	0.289	0.773

		β_3	−2.802	21.995	−0.127	0.899
		β_5	0.034	0.011	3.016	0.003 *
		β_6	264.725	129.780	2.040	0.044 *
	2021	β_0	−515.123	422.710	−1.219	0.226
		β_1	12.700	2.200	5.773	0.000 *
		β_2	1.194	1.109	1.076	0.284
		β_3	4.734	24.235	0.195	0.845
		β_5	0.149	0.011	13.838	0.000 *
		β_6	432.961	142.856	3.031	0.003 *
Kapuas Hulu	2020	β_0	−405.751	388.938	−1.043	0.299
		β_1	−0.096	3.698	−0.026	0.979
		β_2	−0.149	0.770	−0.194	0.846
		β_3	19.508	20.966	0.930	0.354
		β_5	0.040	0.010	4.088	0.000 *
		β_6	188.398	111.859	1.684	0.095
	2021	β_0	−1382.853	400.964	−3.449	0.001 *
		β_1	5.676	2.290	2.478	0.015 *
		β_2	−4.156	0.738	−5.631	0.000 *
		β_3	74.872	22.760	3.290	0.001 *
		β_5	0.185	0.010	17.661	0.000 *
		β_6	903.160	117.218	7.705	0.000 *

Note: (*) Significant at the 5% significance level.

3.3.5. Mapping Based on the Significance of GTWR Model Parameters

Figure 5 shows the result of a GTWR model analysis, indicating variables significantly affecting the number of positive COVID-19 cases in Kalimantan in 2020–2021. In 2020, GRDP (x_5) and number of hospitals (x_6) had a significant effect on the number of positive COVID-19 cases in the majority of regions/cities. Meanwhile, in 2021, x_2, x_3, x_5 and x_6 were those variables with a significant effect on the number of positive COVID-19 cases in West Kalimantan Province. In North Kalimantan Province, the variables x_1, x_3 and x_5 had a significant effect on the number of positive COVID-19 cases. Furthermore, in South Kalimantan Province, the variables with a significant effect on the number of positive COVID-19 cases were x_1, x_5, and x_6.

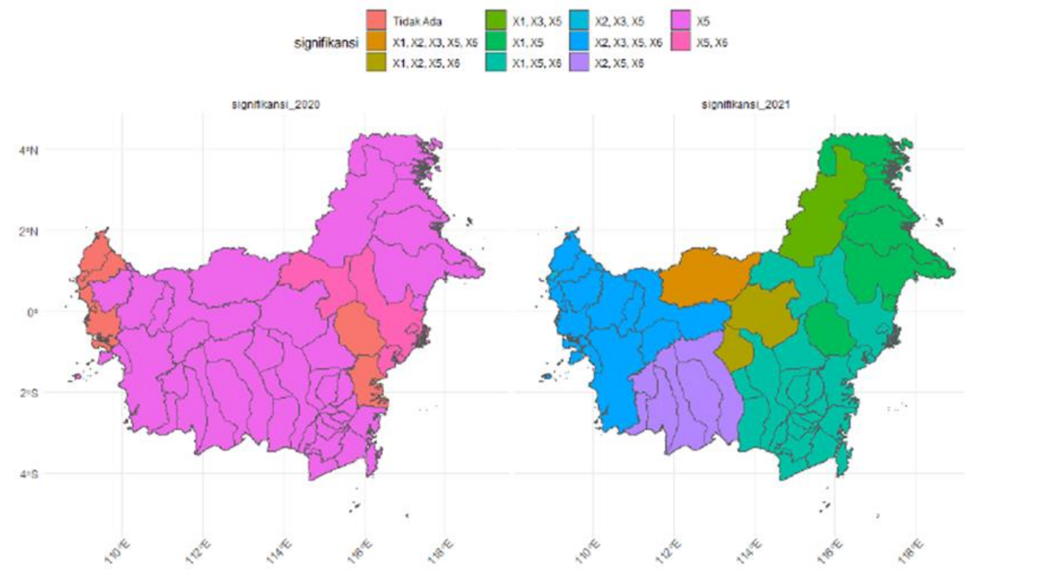


Figure 5. Significance of variables at 5% significance level.

4. Conclusions

The present study developed a geographically temporally weighted regression (GTWR) model by constructing a distance function with spatial and temporal interactions. The GTWR model uses a Gaussian kernel function with a fixed bandwidth on its spatial and temporal weighting functions. The GTWR model had the greatest goodness of fit, as shown by the coefficient of determination R^2 = 0.957, adjusted R^2 = 0.928, Akaike information criterion (AIC) = 1900.76, and root mean square error (RMSE) = 1302.99. Based on the spatio-temporal analysis using the GTWR model, the factors that influenced the increase in positive cases of COVID-19 were different for each district/city in Kalimantan. Overall, the factors that affected COVID-19 were the number of doctors, the number of hospitals, the number of villages that had puskesmas, and the number of tuberculosis cases. The population sector included the percentage of elderly population, population density, and the percentage of the poor. The highest effects, based on the GTWR model, were tuberculosis cases, health services, and elderly population percentage. Therefore, local governments need to pay attention to patients with tuberculosis, health services, and population density, considering those who are most vulnerable to contracting the COVID-19 virus. The mapping of the spread of COVID-19 based on the model's significant variables was grouped into 11 groups, so that each region can identify the factors that can be considered to prevent an increase in positive cases of COVID-19.

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Spatial-Temporal Epidemiology of COVID-19 Using Geographically and Temporally Weighted Regression Model

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Spatial-Temporal Epidemiology of COVID-19 Using a Geographically and Temporally Weighted Regression Model

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Abstract: This article describes the application of spatial statistical epidemiological modeling and its inference and applies it to COVID-19 case data, looking at it from a spatial perspective, and considering time-series data. COVID-19 cases in Indonesia are increasing and spreading in all provinces, including Kalimantan. This study uses applied mathematics and spatiotemporal analysis to determine the factors affecting the constant rise of COVID-19 cases in Kalimantan. The spatiotemporal analysis uses the Geographically Temporally Weighted Regression (GTWR) model by developing a spatial and temporal interaction distance function. The GTWR model was applied to data on positive COVID-19 cases at a scale of 56 districts/cities in Kalimantan between the period of January 2020 and August 2021. The purpose of the study was to determine the factors affecting the cumulative increase in COVID-19 cases in Kalimantan and map the spatial distribution for 56 districts/cities based on the significant predictor variables. The results of the study show that the GTWR model with the development of a spatial and temporal interaction distance function using the kernel Gaussian fixed bandwidth function is a better model compared to the Ordinary Least Squares (OLS) model. According to the significant variables, there are various factors affecting the rise in cases of COVID-19 in the region of Kalimantan, including the number of doctors, the number of TB cases, the percentage of elderly population, GRDP, and the number of hospitals. The highest factors that affect COVID-19 cases are the high number of TB cases, population density, and the lack of health services. Furthermore, an area map was produced on the basis of the significant variables affected by the rise in COVID-19 cases. The results of the study provide local governments with decision-making recommendations to overcome COVID-19-related issues in their respective regions.

Keywords: COVID-19 outbreak; spatio-temporal; geographically and temporally weighted regression model; statistical modeling; time series analysis; statistical inference; GIS mapping

1. Introduction

The spread of active cases of COVID-19 has significantly increased in a number of countries in 2021, including Indonesia. As of 7 September 2021, COVID-19 had spread to 204 countries and had infected more than 220 million people, resulting in nearly 4.5 million deaths [1]. Moreover, Indonesia was also reported to have more than 4 million confirmed positive cases of COVID-19, with over 130 thousand deaths [2]. The transmission of COVID-19 was also found to have increased in one of the provinces of Indonesia, specifically in Kalimantan, with a total number of accumulative cases of 245,205 in August 2021. Based on the increasing number of COVID-19 cases in Kalimantan, it is necessary to conduct research to identify the reasons and factors which led to this increase in COVID-19 cases. This purpose of this research was to determine contributing factors to the increase in COVID-19 cases based on the Improved Geographically and Temporally Weighted Regression model.

Spatial data were modeled using spatial regression with geographic weighting, also known as the geographically weighted regression (GWR) model. GWR was first introduced by Fotheringham in 1967 [3-4]. The GWR model is the development of Linear Regression Analysis with the addition of geographic weighting for each regression parameter to handle emerging spatial diversity. GWR theory has been widely used by researchers, including [5-8]. However, the GWR model only uses spatial data (location) in one time period, while spatial data is usually influenced by the time series. Spatial data should be analyzed by involving several time observations (temporal), thus demanding a more accurate parameter estimation. Therefore, to increase the precision of the parameter estimator on the GWR model, observations should be highly carried out for each location at a certain time. Referring to that matter, a Geographically Temporally Weighted Regression (GTWR) model was developed to overcome the weaknesses of the GWR model [9], by considering the elements of location and time.

The GTWR model is a development of the GWR model, but it is not able to handle non-stationary data both spatially and temporally at the same time. Consequently, this research was conducted by applying the Improved Geographically Temporally Weighted Regression model with the development of the distance function. This model is expected to be capable of generating local models at any location and time, resulting in a more representative model. Furthermore, the spatial and temporal information in the GTWR model is regarded as a crucial element in creating the weighting matrix. Thus, the improved model is expected to be succeed in identifying spatial and temporal variability. The GTWR model, one of the spatio-temporal models, has been widely used in various fields. As stated by Fotheringham, the 2015 GTWR model is generally used to handle issues of spreading infectious diseases, water pollution, hydrology, and urban planning. In this research, the GTWR model was used to address the issue of the spread of the COVID-19 disease. The COVID-19 virus has spread globally in various countries, including in Indonesia.

Indonesia is an archipelagic country, consisting of various large and small islands. Kalimantan represents the largest island in Indonesia, and consists of five provinces—East Kalimantan, North Kalimantan, South Kalimantan, Central Kalimantan, and West Kalimantan Provinces—all with an increasing daily spread of COVID-19. Data from the official COVID-19 website of the five provinces on the island of Kalimantan showed that the highest cumulative number of positive COVID-19 cases, as of 10 August 2021, was East Kalimantan Province with 133,826 cases [10], followed by South Kalimantan Province with 55,257 cases [11], Central Kalimantan Province with 38,123 cases [12], North Kalimantan Province with 26,050 cases [13], and West Kalimantan Province with 17,999 cases [14]. Based on this, it is important to undertake a study to understand the factors causing such an increase from a spatial and temporal point of view. The present study offers local governments information with regard to overcoming the increase in COVID-19 cases in their respective regions.

COVID-19 modeling studies using spatiotemporal analysis include: Pearson's correlation methods for spatiotemporal analysis in regions of China [15]; Levy's flight to explain the spatiotemporal dynamics of the pandemic regions in China [16]; prospective space–time statistics to identify active and emerging COVID-19 groups at a county level in the USA [17]; and an online questionnaire for the geographical identification of possible symptomatic regions in Israel [18]. Studies predicting the global spread of COVID-19 based on geographic and climatic data regions include: the Caribe Basin [19]; geographical characteristics and spatiotemporal analysis of infection regions in the USA [20]; analysis by province of the effectiveness of quarantine on the spread of the pandemic in Spain [21]; spatiotemporal analysis of COVID-19 at national and provincial levels in India [22]; the Poisson segmented model for the analysis of changing patterns in different geographic areas in China [23]; spatiotemporal analysis and reflections on health geography in Argentina [24]; spatiotemporal analysis of COVID-19 at national and provincial levels in Mexico [25]; spatiotemporal analysis and reflections on the usefulness of GIS in the pandemic [26]; and the analysis of restrictive measures during the pandemic [27]. A Susceptible–Infected–Recovered (SIR) model for estimating COVID-19 reproduction number in East Kalimantan and Samarinda [28].

Based on the background description above, this research was carried out using the Improved Geographically Temporally Weighted Regression model with the development of the distance function and the application of COVID-19 cumulative data in Kalimantan, Indonesia. The first objective of this research was to identify the factors that influenced the cumulative increase in COVID-19 at a region/city scale in Kalimantan, Indonesia—which consists of 56 regions/cities—by using data from 2020 and 2021. The second objective of this research was to map the spatial distribution for the 56 regions/cities based on significant predictor variables.

2. Materials and Methods

2.1. Geographically and Temporally Weighted Regression

The Geographically and Temporally Weighted Regression (GTWR) model represents an effective approach to dealing with the problem of spatial and temporal non-stationarity [9]. The GTWR model is a development of the GWR model, adding the time (temporal) element. In contrast to the GWR model, GTWR combines temporal and spatial information in a weighted matrix to identify spatial and temporal variability. The GTWR model in Equation (1) is for the independent variable p with the response variable at the location (u_i, v_i, t) for each observation:

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

where y_i is the observed value of the response variable for the observation location (u_i, v_i) and time t_i; the parameter $\beta_0(u_i, v_i, t_i)$ is the constant of the intercept value; the parameter $\beta_k(u_i, v_i, t_i)$ is the regression coefficient of the k-th independent variable at the observation location (u_i, v_i) and time t_i; the variable x_{ik} is the observed value of the k-th explanatory variable at the observation location (u_i, v_i) and time t_i; and ε_i is error the i-th observations which are assumed to be identical, independent, and $\varepsilon_i \sim N(0, \sigma^2)$.

2.2. GTWR Model Parameter Estimation

The regression coefficient $\hat{\beta}_i(u_i, v_i, t_i)$ at the i-th point can be obtained by using the Weighted Least Square. The estimated parameters of the GTWR model are given in Equation (2):

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

where the weight $\boldsymbol{W}(u_i, v_i, t_i) = diag(w_{i1}, w_{i2}, \dots, w_{in})$ is the weighting matrix at the observation location (u_i, v_i) and time t_i. The diagonal element $w_{ij} (1 \leq j \leq n)$ is the spatiotemporal distance function at the observation point (u_i, v_i, t_i). In the modeling stage, it is assumed that the proximity of the data observation point to the i point in the spatiotemporal coordinate system has a greater effect on the parameter estimator $\widehat{\boldsymbol{\beta}}(u_i, v_i, t_i)$ than that of the data located further from the i point. The proximity has two elements, spatial proximity and temporal proximity; thus, the definition and measurement of spatiotemporal proximity in the coordinate system constitute major problems in the construction of the GTWR model.

The present study used a date located at three dimensions in the spatiotemporal coordinate system and it was known that the observations were close to the i point. Therefore, [9] used an ellipsoidal coordinate system to measure the proximity of the regression point to the observation points that surround it.

2.3. Distance Function and Geographical Weight of the GTWR Model

The spatiotemporal distance function consists of a combination of the spatial distance function and the temporal distance function, which are given as follows [9,14]:

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

where φ^S and φ^T are the affecting factors that balance the different effects used to measure the spatiotemporal distance. Based on the distance function in Equation (3), the geographical weighting function according to Equation (4) is obtained:

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

The value of $h_S^2 = \frac{h_{ST}^2}{\varphi^S}$ and $h_T^2 = \frac{h_{ST}^2}{\varphi^T}$, then Equation (5) is obtained:

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

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

h_S is a parameter of the spatial window width, h_T is a parameter of the temporal window width, and h_{ST} is a parameter of the spatial-temporal window width.

In most cases, the value of φ^S and φ^T is not equal to zero. Let τ be the ratio parameter of $= \frac{\varphi^T}{\varphi^S}$ with $\varphi^S \neq 0$; then, Equation (6) [29] is obtained:

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

Let $\varphi^S = 1$ in order to reduce unknown parameters. In this problem, there is only one unknown parameter, τ. The parameter τ serves to increase or decrease the effect of temporal distance on spatial distance. This parameter is obtained from the minimum cross-validation criteria by initializing the initial τ value, as given in Equation (7).

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

The Gaussian kernel function is a weighting function which is used in the GTWR model, as given in Equation (8).

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

The weighting matrix is $\boldsymbol{W}_{ij}$ determined by the spatiotemporal distance (d_{ij}^{ST}) and the window width h_{ST}. The window width value can be calculated using the geographic weighted regression model, as proposed by [3]. The estimator value of the response variable is determined by Equation (9).

$$\hat{y} = \begin{bmatrix} \hat{y}_1 \\ \hat{y}_2 \\ \dots \\ \hat{y}_n \end{bmatrix} = \begin{bmatrix} X_1^T (X^T W(u_1, v_1, t_1) X)^{-1} X^T W(u_1, v_1, t_1) \\ X_2^T (X^T W(u_2, v_2, t_2) X)^{-1} X^T W(u_2, v_2, t_2) \\ \dots \\ X_n^T (X^T W(u_n, v_n, t_n) X)^{-1} X^T W(u_n, v_n, t_n) \end{bmatrix} y = Sy \tag{9}$$

The selection of the model's goodness of fit can be calculated using the AIC (Akaike information criterion) value. The corrected AIC value [30] is used to overcome the spatio-temporal variability, as given in Equation (10).

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

2.4. Research Methodology

2.4.1. Data and Data Sources

Data and data sources are described in Table 1.

Table 1. Description of Resesarch Variables and Data Sources.

Variable	Symbol	Variable Description	Observation Data Source	Unit	Scale
Response	y	Cumulative positive cases of COVID-19	Official websites www.covid19.kaltimprov.go.id www.corona.kalselprov.go.id www.corona.kalteng.go.id www.coronainfo.kaltaraprov.go.id www.corona.kalbarprov.go.id (accessed on 10 August 2021) [10-14]	People	56 regions/cities in the island of Kalimantan
Predictor	x_1	Number of doctors	Statistics Indonesia of East Kalimantan Province, North Kalimantan Province, South Kalimantan Province, Central Kalimantan Province, West Kalimantan Province, 2020–2021 [31-40]	People	56 regions/cities in the island of Kalimantan
	x_2	Number of TB cases	Public Health Office of East Kalimantan Province, North Kalimantan Province, South Kalimantan Province, Central Kalimantan Province, West Kalimantan Province, 2020–2021 [41-50]	Cases	56 regions/cities in the island of Kalimantan
	x_3	Percentage of elderly population	Statistics Indonesia of East Kalimantan Province, North Kalimantan Province, South Kalimantan Province, Central Kalimantan Province, West Kalimantan Province, 2020–2021 [31-40]	Percentage	56 regions/cities in the island of Kalimantan
	x_4	Population density	Statistics Indonesia of East Kalimantan Province, North Kalimantan Province, South Kalimantan	People/Km^2	56 regions/cities in the island of Kalimantan

Commented [M1]: [41-50] should be put after [31-40]

Commented [SS2R1]: Please chek Reference

Commented [M3R1]: **The first citation of references number should be in numerical order, such as 31-40,40-50. Otherwise, it can't be sent to publishing since it does not meet the standard requirements. Please kindly revise them.**

		Province, Central Kalimantan Province, West Kalimantan Province, 2020–2021 [31-40]		
x_5	Gross Regional Domestic Product at Market Price	Statistics Indonesia of East Kalimantan Province, North Kalimantan Province, South Kalimantan Province, Central Kalimantan Province, West Kalimantan Province, 2020–2021 [31-40]	Billion Rupiah	56 regions/cities in the island of Kalimantan
x_6	Number of hospitals	Public Health Office of East Kalimantan Province, North Kalimantan Province, South Kalimantan Province, Central Kalimantan Province, West Kalimantan Province, 2020–2021 [41-50]	Units	56 regions/cities in the island of Kalimantan
x_7	Number of villages/ kelurahan with public health centers	Public Health Office of East Kalimantan Province, North Kalimantan Province, South Kalimantan Province, Central Kalimantan Province, West Kalimantan Province, 2020–2021 [41-50]	Units	56 regions/cities in the island of Kalimantan
x_8	Percentage of poor population	Statistics Indonesia of East Kalimantan Province, North Kalimantan Province, South Kalimantan Province, Central Kalimantan Province, West Kalimantan Province, 2020–2021 [31-40]	%	56 regions/cities in the island of Kalimantan

2.4.2. Stages of Analysis

The analysis and modeling processes were carried out by using the R-Studio version 2021.09.1 Build 372. The analysis stages are shown in Figure 1.

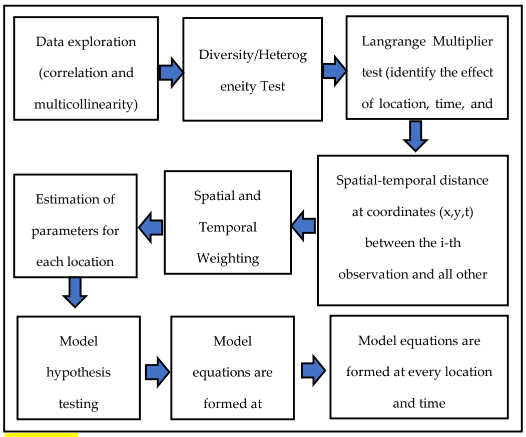


Figure 1. Improved GTWR Model Flowchart.

Based on the objectives of the study, the following are the stages of data analysis using the GTWR model to determine factors affecting the cumulative increase in COVID-19 cases and to map the spatial distribution based on significant predictor variables.

1. Explore the distribution of response variables and predictor variables for the period of 2020–2021 using a spatial distribution mapping;
2. Describe cumulative data of COVID-19 cases and the predictor variables;
3. Perform a multicollinearity test by taking the value of VIF (variance inflation factor) into account;
4. Explore temporal variability using a boxplot of response variables for each year;
5. Perform an analysis using the GTWR method as follows:

a. Calculate the optimum spatial bandwidth (h_S) using cross-validation based on the GWR optimization approach with the formula as given by Equation (11):

$$CV(h_S) = \sum_i (y_i - \hat{y}_{\neq i}(h_S))^2 \quad (11)$$

b. Calculate the optimum spatiotemporal ratio parameter $(\tau)(\tau)$ using cross-validation based on the GTWR optimization approach with the formula as given by Equation (7);

c. Calculate parameters φ^S and φ^T using the cross-validation approach with the formula given in point b. Both parameters are based on the spatiotemporal distance function with the formula as given by Equation (12):

$$(d_{ij}^{ST})^2 = \varphi^S[(u_i - u_j)^2 + (v_i - v_j)^2] + \varphi^T(t_i - t_j)^2 \quad (12)$$

d. Determine the weighting matrix $(W)(W)$ using the spatiotemporal distance measure for each observation location based on the Gaussian kernel function with the formula given by Equation (8).

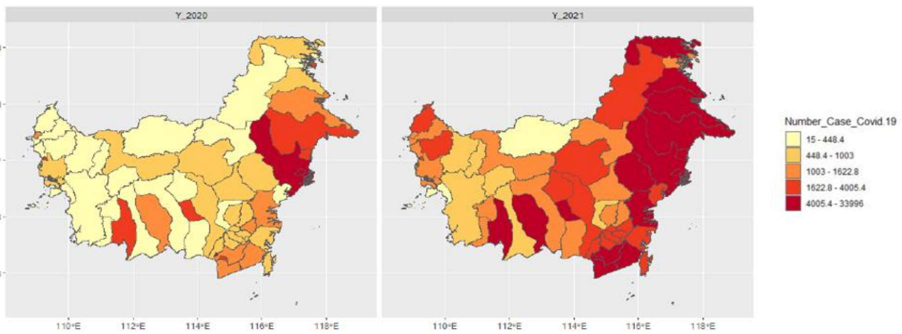
6. Estimate parameters in the GTWR model at each location using the weighted least square (WLS) according to Equation (2);
7. Perform a parameter significance test for the GTWR model;
8. Map the variable significance for each region.

3. Results and Discussion

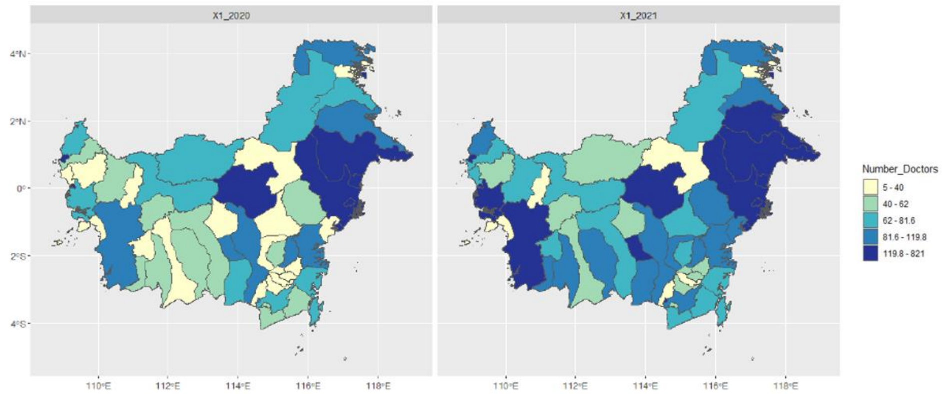
This section begins by providing information on descriptive statistics, especially the presentation of data using a spatial distribution map, followed by information on the measure of concentration and the measure of data distribution. The results of the statistical inference research begin with regression analysis and a test of spatial effects, GTWR modeling, GTWR model estimation, the GTWR model significance test, and spatial mapping based on the GTWR model results. The analysis to determine factors affecting the increase in confirmed COVID-19 cases is based on the region/city scale on the island of Kalimantan, Indonesia.

3.1. Spatial Distribution Mapping

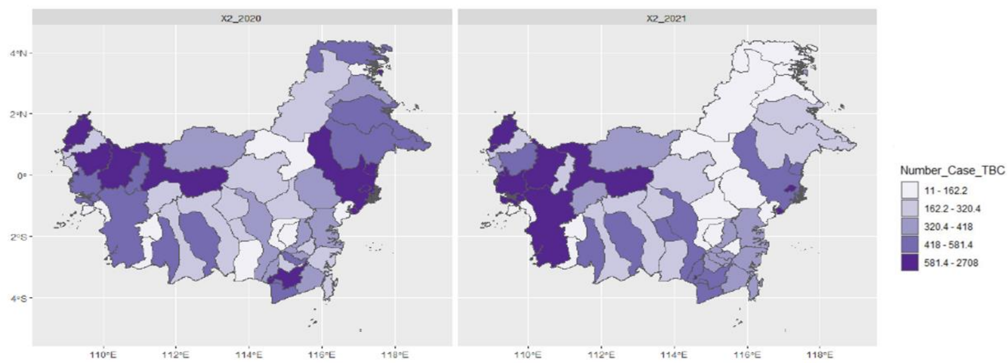
The observation data in Table 1 were subjected to descriptive statistical analysis and statistical inference. Observation data were categorized based on variables and are described in Figures 2 and 3.


Y_2020
Y_2021
4°N
2°N
0°
2°S
4°S
110°E
112°E
114°E
116°E
118°E
Number_Case_Covid.19
15 - 448.4
448.4 - 1003
1003 - 1622.8
1622.8 - 4005.4
4005.4 - 33996

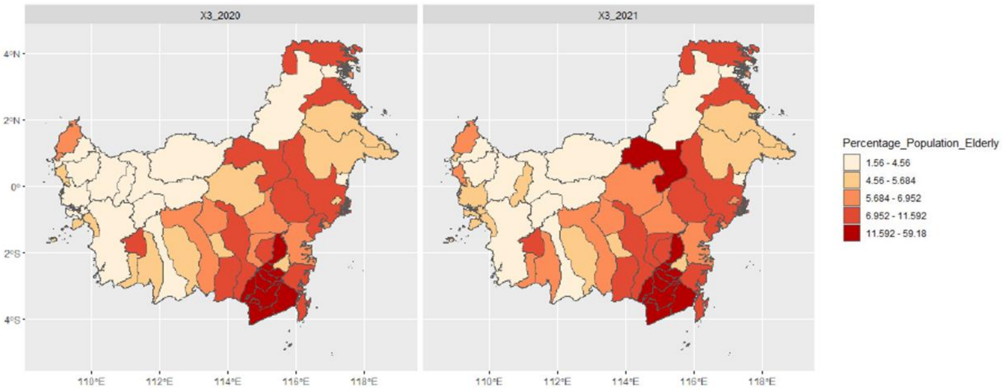
(**a**)


X1_2020
X1_2021
4°N
2°N
0°
2°S
4°S
110°E
112°E
114°E
116°E
118°E
Number_Doctors
5 - 40
40 - 62
62 - 81.6
81.6 - 119.8
119.8 - 821

(**b**)


X2_2020
X2_2021
4°N
2°N
0°
2°S
4°S
110°E
112°E
114°E
116°E
118°E
Number_Case_TBC
11 - 162.2
162.2 - 320.4
320.4 - 418
418 - 581.4
581.4 - 2708

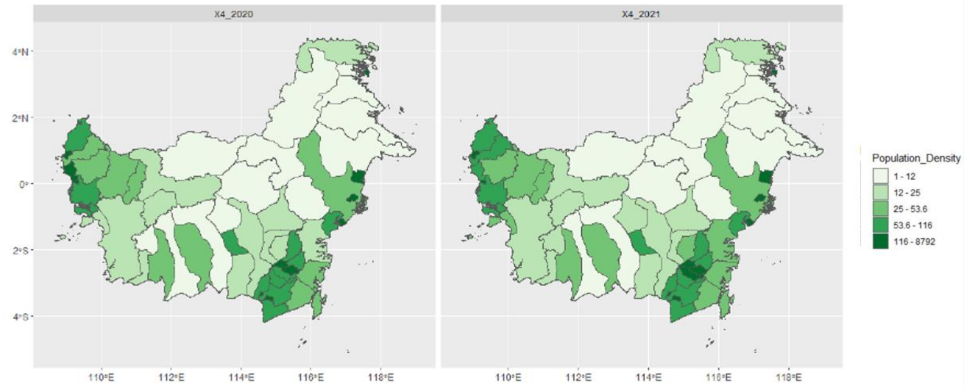
(**c**)



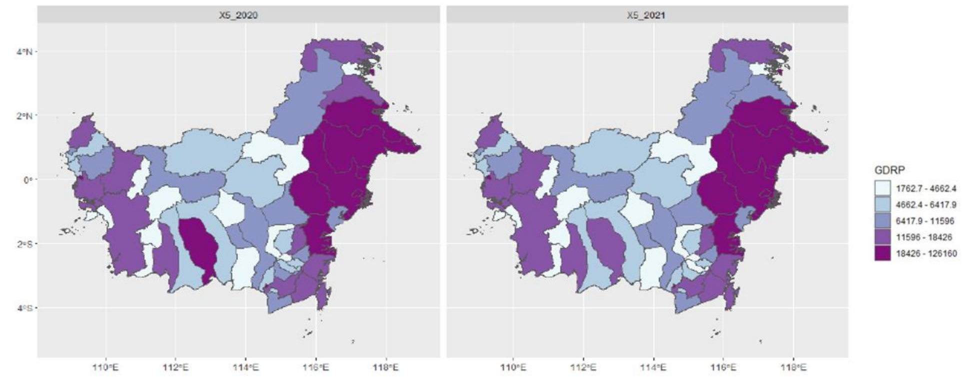
(**d**)

Figure 2. Spatial Distribution Mapping of $x_1 - x_4$. (**a**) Map of the number of confirmed positive COVID-19 cases 2020–2021; (**b**) map of the number of doctors 2020–2021; (**c**) map of the number of TB cases 2020–2021; (**d**) map of the percentage of elderly population in 2020–2021.

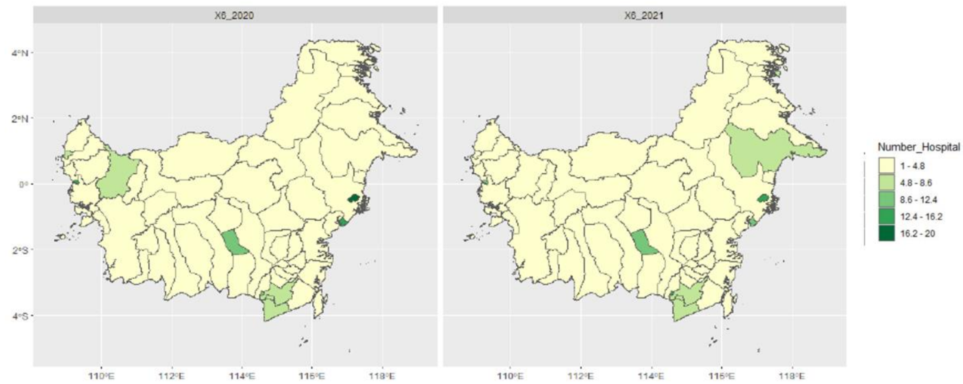
Figure 2a shows that the number of confirmed positive COVID-19 cases in 2020 spread evenly across the regions/cities in Kalimantan, as indicated by the similar distribution colors. However, in comparison, in 2020 the number of confirmed cases was relatively scant, while the number of positive COVID-19 cases increased in 2021. This is clearly shown by the color changes for regions/cities in East Kalimantan Province. Figure 2b shows the distribution of the number of doctors at the region/city scale in Kalimantan 2020–2021. Most regions/cities in Kalimantan had a small and evenly distributed number of doctors. In 2021, the number of doctors increased quite significantly in Samarinda and Balikpapan. This is shown by the dark color contrast, indicating a large number of doctors in these areas. This is commensurate with the increasing number of COVID-19 cases. Figure 2c shows the distribution of the number of TBC cases in 2020–2021. In general, there was no increase in the number of TBC cases in each region/city in Kalimantan. This is shown by the almost similar and evenly distributed color pattern in each area. However, the City of Banjarmasin had higher TB cases than that of other region/cities, as indicated by its darker color. Figure 3a shows the distribution of population density in 2020–2021. In general, there was no increase in population density in every region/city in Kalimantan. This is shown by the almost similar and evenly distributed color pattern in each area. However, the city of Samarinda had a higher population density than that of other regions/cities, as indicated by the darker color. Furthermore, the city of Samarinda had a decrease in population density from 2020 to 2021, as indicated by the color difference, which gets brighter.


X4_2020
X4_2021
Population_Density
1 - 12
12 - 25
25 - 53.6
53.6 - 116
116 - 8792
4°N
2°N
0°
2°S
4°S
110°E
112°E
114°E
116°E
118°E

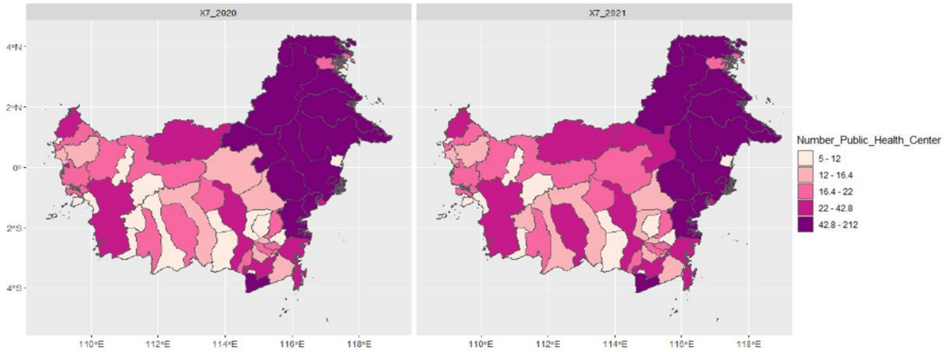
(**a**)


X5_2020
X5_2021
GDRP
1762.7 - 4662.4
4662.4 - 6417.9
6417.9 - 11596
11596 - 18426
18426 - 126160
4°N
2°N
0°
2°S
4°S
110°E
112°E
114°E
116°E
118°E

(**b**)


X6_2020
X6_2021
Number_Hospital
1 - 4.8
4.8 - 8.6
8.6 - 12.4
12.4 - 16.2
16.2 - 20
4°N
2°N
0°
2°S
4°S
110°E
112°E
114°E
116°E
118°E

(**c**)



(**d**)

Figure 3. Spatial Distribution Mapping of $x_5 - x_8$. (**a**) Map of population density in 2020–2021; (**b**) map of Gross Regional Domestic Product (GRDP) 2020–2021; (**c**) map of the number of hospitals in 2020–2021; (**d**) map of the number of public health centers in 2020–2021.

3.2. *Description of COVID-19 Cumulative Data and Predictor Variables*

The descriptions of the COVID-19 cumulative data and predictor variables for the observation data in Table 1 are shown in Table 2.

Table 2. Summary of Variable Statistics.

Descriptive Statistics	Confirmed Positive Cases of COVID-19	Number of Doctors (x_1)	Number of TB Cases (x_2)	Percentage of Elderly Population (x_3)	Population Density (x_4)	GRDP (x_5)	Number of Hospitals (x_6)	Number of Public Health Centers (x_7)	Percentage of Poor Population (x_8)
Minimum	15	5	11	2	1	1763	1	5	2
Maximum	33,996	821	2708	59	8792	126,160	20	212	12
Range	33,981	816	2697	58	8791	124,397	19	207	10
Sum	332,489	12,084	49,283	1149	45,054	1,818,623	382	3861	675
Median	1183	73	355	6	31	8512	2	20	5
Mean	2969	108	440	10	402	16,238	3	34	6
SE.Mean	464	12	39	1	133	2122	0	4	0
Variance	24,119,005	16,810	166,245	118	1,969,598	504,525,521	11	1609	5
Std.dev	4911	130	408	11	1403	22,462	3	40	2

Correlation between the variable *y* and each variable $x_1, x_2, x_3, x_4, x_5, x_6, x_7$, and x_8 is given in Table 3.

Table 3. Correlation of independent variables to the number of positive COVID-19 cases.

Variable	Correlation	*p*-Value
x_1	0.684	0.000 *
x_2	0.255	0.006 *
x_3	0.048	0.612
x_4	0.232	0.013 *
x_5	0.628	0.000 *
x_6	0.501	0.000 *
x_7	0.353	0.000 *
x_8	−0.144	0.129

Note: (*) = significant at 5% significance level.

The value of the correlation of the explanatory variable to the response variable shows that the variable x_1 had a high and positive correlation to the variable y. In addition, the variable x_1 had a significant correlation to the variable y. It can be concluded that the higher the number of positive COVID-19 cases, the higher the number of doctors will be.

The results of the multicollinearity test in Table 4 show that all variables had a VIF value of < 5; thus, all independent variables had no multicollinearity.

Table 4. Multicollinearity Test.

Predictor Variable	VIF
x_1	2.521
x_2	2.481
x_3	1.294
x_5	1.455
x_6	3.557

The results of the spatial variability test using the Breusch–Pagan test are shown in Table 5. It shows a p-value of $4.642 \times 10^7 < 0.05$; thus, there was spatial variability in the multiple linear regression model.

Table 5. Spatial variability test value.

Breusch–Pagan	p-Value
0.90079	4.642×10^7

Figure 4 shows the visualization results of the number of positive COVID-19 cases from 2020 to 2021 using a boxplot. Figure 4 shows that, in 2021, the variability in the number of positive COVID-19 cases was larger than that of 2020. This difference in variability indicates a variability between years, or so-called temporal variability. The results of the analysis of the Breusch–Pagan and boxplot tests leads us to the conclusion that GTWR modeling can effectively be performed in the study of the 56 regions/cities in Kalimantan.

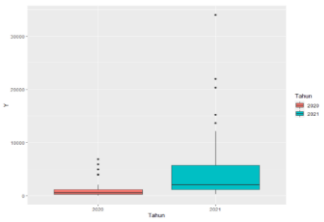


Figure 4. Boxplot of temporal variability for each year.

3.3. Geographically Temporally Weighted Regression (GTWR) Modeling for 56 Regencies/Cities in Kalimantan

3.3.1. Estimation of GTWR Model

The analysis of the GTWR model estimation uses Equation (2) at the i-th location where the location $i = 1,2,\cdots,56$ is the initials for 56 regions/cities in Kalimantan, and the t time is 1 for 2020 and 2 for 2021. The estimation results of the GTWR model are given in Equation (13).

$$\hat{y}_{it} = \hat{\beta}_0(u_i, v_i, t_i) + \hat{\beta}_1(u_i, v_i, t_i)x_{it1} + \hat{\beta}_2(u_i, v_i, t_i)x_{it2} + \hat{\beta}_3(u_i, v_i, t_i)x_{it3} + \hat{\beta}_5(u_i, v_i, t_i)x_{it5} + \hat{\beta}_6(u_i, v_i, t_i)x_{it6} \quad, i = 1,2, \ldots ,56 \; ; \; t = 1,2 \tag{13}$$

Table 6 shows the summary results of GTWR modeling using the Gaussian kernel function with a fixed bandwidth on the spatial and temporal weighting function. The variable number of doctors (x_1) has a coefficient value ranging from −3.750 to 23.5555. The variable number of TB cases (x_2) has a coefficient value ranging from −4869 to 2702. The variable percentage of elderly population has a coefficient value ranging from −20,633 to 110,781. The variable GRDP (x_5) has a coefficient value ranging from 0.0303 to 0.2104. The variable number of hospitals (x_6) has a coefficient value ranging from −308.44 to 1024,983. The coefficient values for each of these variables are spread across all regions/cities in Kalimantan.

Table 6. Summary of the estimated values of the GTWR model parameters.

Parameter Estimator	Minimum	Q_1	Median	Q_3	Maximum
$\hat{\beta}_0$	−1612.200	−886.460	−282.050	−64.537	1206.736
$\hat{\beta}_1$	−3.750	−0.609	0.033	5.815	23.556
$\hat{\beta}_2$	−4.870	−0.634	−0.197	0.560	2.702
$\hat{\beta}_3$	−20.633	−4.809	5.696	29.529	110.782
$\hat{\beta}_5$	0.030	0.033	0.086	0.170	0.210
$\hat{\beta}_6$	−308.440	170.570	220.270	849.960	1024.984

The results of parameter estimation provide GTWR model estimators which state the correlation of the independent variables of number of doctors (x_1), number of TB cases (x_2), percentage of elderly population (x_3), GRDP (x_5), and number of hospitals (x_6) to the percentage of positive COVID-19 cases in the Kalimantan provinces. Four GTWR models are given for four region/city locations in Equations (14)–(17).

Samarinda City, East Kalimantan Province 2020:

$$\hat{y}_{it} = -206.539 - 0.898X_{it1} + 0.248X_{it2} - 2.802X_{it3} + 0.034X_{it5} + 264.725X_{it6} \tag{14}$$

Samarinda City, East Kalimantan Province 2021:

$$\hat{y}_{it} = -515.123 + 12.700X_{it1} + 1.194X_{it2} + 4.734X_{it3} + 0.149X_{it5} + 432.961X_{it6} \tag{15}$$

Kapuas Hulu Regency, West Kalimantan Province 2020:

$$\hat{y}_{it} = -405.751 - 0.096X_{it1} - 0.149X_{it2} + 19.508X_{it3} + 0.04X_{it5} + 188.398X_{it6} \tag{16}$$

Kapuas Hulu Regency, West Kalimantan Province 2021:

$$\hat{y}_{it} = -1382.853 + 5.676X_{it1} - 4.156X_{it2} + 74.872X_{it3} + 0.185X_{it5} + 903.160X_{it6} \tag{17}$$

3.3.2. Measure of Model's Goodness of Fit

The measure of the goodness used to compare the OLS model and GTWR model is the coefficient of determination (R^2), adjusted R^2, Akaike information criterion (AIC), and the root mean square error (RMSE). The results of the comparison of the value of the goodness-of-fit measure are shown in Table 7.

Table 7. Comparison of models in terms of the number of positive COVID-19 cases.

Criteria	OLS	GTWR
R^2	0.6134	0.95713
Adjusted R^2	0.5952	0.92855
AIC	2128.229	1900.76

RMSE	3039.91	1302.99

The above comparison of models shows that the GTWR model is better than the OLS model. This is indicated by the higher values of R^2 and adjusted R^2, as well as the smaller values of AIC and RMSE criteria.

3.3.3. Simultaneous Significance Test of GTWR Model Parameters

The first hypothesis testing conducted were the simultaneous tests of the model in order to test the goodness of fit of the GTWR model. The hypothesis testing for the goodness of fit of the GWPR model was as follows:

H_0: $\hat{\beta}_k(u_i, v_i, t_i) = \hat{\beta}_k$, $k = 1,2,\ldots,5$; $i = 1,2,\ldots,56$; $t = 1,2$
(There is no significant difference between multiple linear regression models and GTWR models.)

H_1: There is at least one $\hat{\beta}_k(u_i, v_i, t_i) \neq \hat{\beta}_k$ $k = 1,2,\ldots,5$; $i = 1,2,\ldots,56$; $t = 1,2$

Table 8 shows that F-Statistics = 14,440 > F-table = 1537 or p-value = 0.000 < α = 0.05. Thus, H_0 was rejected and there was a significant difference between the multiple linear regression model and the GTWR model.

Table 8. Values of simultaneous hypotheses testing of the model's goodness of fit.

F-Statistics	F Table	p-Value	Keputusan Uji
14.440	1.537	0.000	Tolak Ho

3.3.4. Partial Significance Test of GTWR Model Parameters

Partial parameter tests aim to determine the partial effects of the independent variables on the dependent variable. The hypothesis for the partial tests of the regression model parameters for the parameter $\hat{\beta}_k(u_i, v_i, t_i)$ was as follows:

H_0: $\hat{\beta}_k(u_i, v_i, t_i) = 0$, $k = 1,2,\ldots,5$; $i = 1,2,\ldots,56$; $t = 1,2$
(The independent variable X_{kt} has no effect on the number of positive COVID-19 cases in Kalimantan Provinces.)

H_1: $\hat{\beta}_k(u_i, v_i, t_i) \neq 0$, $k = 1,2,\ldots,5$; $i = 1,2,\ldots,56$; $t = 1,2$
(The independent variable X_{kt} has an effect on the number of positive COVID-19 cases in Kalimantan Provinces.)

The test statistic of the partial parameter testing was the statistic of the t-test. The criteria for rejecting H_0 at the significance level of α = 0.05 was to reject H_0 if the p-value < 0.05. The results of the partial test of parameters are shown in Table 9. The table above shows that the factors affecting the number of positive COVID-19 cases in the Berau region were the human development index, life expectancy, gross regional domestic income, population growth rate, and so on, for all observation locations in the Kalimantan provinces. This is shown by the p-value of those variables that is lower than 0.05.

Table 9. The test statistical value of partial hypothesis testing of the GTWR model parameters.

Location	Year	Parameter	Estimator Value	Standard Error	T-Value	p-Value
Samarinda	2020	β_0	−206.539	421.063	−0.491	0.625
		β_1	−0.898	4.825	−0.186	0.853
		β_2	0.248	0.859	0.289	0.773
		β_3	−2.802	21.995	−0.127	0.899

		β_5	0.034	0.011	3.016	0.003 *
		β_6	264.725	129.780	2.040	0.044 *
	2021	β_0	−515.123	422.710	−1.219	0.226
		β_1	12.700	2.200	5.773	0.000 *
		β_2	1.194	1.109	1.076	0.284
		β_3	4.734	24.235	0.195	0.845
		β_5	0.149	0.011	13.838	0.000 *
		β_6	432.961	142.856	3.031	0.003 *
Kapuas Hulu	2020	β_0	−405.751	388.938	−1.043	0.299
		β_1	−0.096	3.698	−0.026	0.979
		β_2	−0.149	0.770	−0.194	0.846
		β_3	19.508	20.966	0.930	0.354
		β_5	0.040	0.010	4.088	0.000 *
		β_6	188.398	111.859	1.684	0.095
	2021	β_0	−1382.853	400.964	−3.449	0.001 *
		β_1	5.676	2.290	2.478	0.015 *
		β_2	−4.156	0.738	−5.631	0.000 *
		β_3	74.872	22.760	3.290	0.001 *
		β_5	0.185	0.010	17.661	0.000 *
		β_6	903.160	117.218	7.705	0.000 *

Note: (*) Significant at the 5% significance level.

3.3.5. Mapping Based on the Significance of GTWR Model Parameters

Figure 5 shows the result of a GTWR model analysis, indicating variables significantly affecting the number of positive COVID-19 cases in Kalimantan in 2020–2021. In 2020, GRDP (x_5) and number of hospitals (x_6) had a significant effect on the number of positive COVID-19 cases in the majority of regions/cities. Meanwhile, in 2021, x_2, x_3, x_5 and x_6 were those variables with a significant effect on the number of positive COVID-19 cases in West Kalimantan Province. In North Kalimantan Province, the variables x_1, x_3 and x_5 had a significant effect on the number of positive COVID-19 cases. Furthermore, in South Kalimantan Province, the variables with a significant effect on the number of positive COVID-19 cases were x_1, x_5, and x_6.

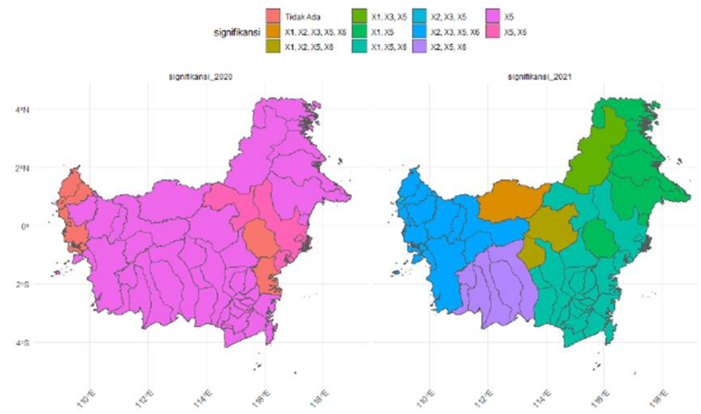


Figure 5. Significance of variables at 5% significance level.

4. Conclusions

The present study developed a geographically temporally weighted regression (GTWR) model by constructing a distance function with spatial and temporal interactions. The GTWR model uses a Gaussian kernel function with a fixed bandwidth on its spatial and temporal weighting functions. The GTWR model had the greatest goodness of fit, as shown by the coefficient of determination R^2 = 0.957, adjusted R^2 = 0.928, Akaike information criterion (AIC) = 1900.76, and root mean square error (RMSE) = 1302.99. Based on the spatio-temporal analysis using the GTWR model, the factors that influenced the increase in positive cases of COVID-19 were different for each district/city in Kalimantan. Overall, the factors that affected COVID-19 were the number of doctors, the number of hospitals, the number of villages that had puskesmas, and the number of tuberculosis cases. The population sector included the percentage of elderly population, population density, and the percentage of the poor. The highest effects, based on the GTWR model, were tuberculosis cases, health services, and elderly population percentage. Therefore, local governments need to pay attention to patients with tuberculosis, health services, and population density, considering those who are most vulnerable to contracting the COVID-19 virus. The mapping of the spread of COVID-19 based on the model's significant variables was grouped into 11 groups, so that each region can identify the factors that can be considered to prevent an increase in positive cases of COVID-19.

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Conflicts of Interest: The authors have no conflict of interest related to this research.

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