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Spatial-Temporal Epidemiology of COVID-19 in Aceh, Indonesia: A Statistical Perspective

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Abstract

The development of COVID-19 cases in Aceh for each region based on spatio-temporal is vital information to know. Spatio-temporal mapping is carried out to know the distribution of cases in diversity based on regional and time conditions. The time series design study was used as the research design in this study. This study aims to obtain factors that influence the incidence of COVID-19 cases in Aceh using panel data regression analysis and the GTWR model for more accurate results. There are nine variables from 23 districts/cities in Aceh Province in 2020 and 2021. Based on partial panel data regression analysis, of the eight independent variables that are factors for analysis, it shows that only the variable number of doctors ($p < 0.000$), number of Tuberculosis Cases ($p < 0.000$), Number of Villages with Puskesmas ($p < 0.026$), and Number of Poor population ($p < 0.035$) have a significant effect on the increase in COVID-19 cases in Aceh. The number of Tuberculosis Cases is a very dominant variable. Then, the results of the GTWR analysis using the Adaptive Kernel Exponential weighting function show that regional and time diversity affect the factors that cause an increase in COVID-19 cases in Aceh. These factors need to be a concern in controlling COVID-19 cases in Aceh in the future.

INTRODUCTION

Indonesia reported its first COVID-19 case on March 2, 2020, when two Indonesian citizens were confirmed with COVID-19 after traveling from Japan (Sasmita et al., 2020; Yuliarti, 2021). COVID-19 cases in Indonesia are spreading rapidly; based on data as of December 1, 2020, COVID-19 cases have grown to 549,508 cases. Furthermore, the first case of COVID-19 in Aceh Province was found in a Patient Under Supervision (PDP) who died during treatment at the Respiratory Intensive Care Unit (RICU) of Zainoel Abidin Hospital (Sufri et al., 2021). In accumulation, the prevalence of COVID-19 cases in Aceh was 157.56 per 100,000 people, with a Case Fatality Rate of 3.84% as of December 1, 2020. (Kartikasari & Kurniawati, 2020).

Then, the diversity of regional conditions

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and communities also influences the spread of this virus. People from various backgrounds have different levels of susceptibility to COVID-19 disease (Fadly & Sari, 2020). In addition, economic differences can also affect the spread of this virus. People with lower economic capabilities are less likely to access good health care, making them more vulnerable to COVID-19 (Azharuddin et al., 2023; Yang et al., 2020).

The spatial and temporal mapping approach can analyze an area affected by diseases such as COVID-19 (Rahayu et al., 2023; Sasmita et al., 2024). Spatial data is modeled using geographically weighted spatial regression, also known as the Geographically Weighted Regression (GWR) model. GWR is a spatial statistical technique that allows for modeling spatial relationships by considering local variations in the data. Unlike traditional global regression models, GWR recognizes that relationships between variables can vary across different locations, making it a valuable tool for analyzing spatially heterogeneous data (Oshan et al., 2019). GWR is an extension of linear regression that focuses on local relationships, allowing for a more nuanced understanding of how variables interact within specific geographic areas (G. Li et al., 2020).

The Geographically and Temporally Weighted Regression (GTWR) model represents an advancement over the Geographically Weighted Regression (GWR) model by incorporating both spatial and temporal dimensions into the analysis. GTWR addresses the limitations of GWR by considering the elements of location and time simultaneously, allowing for a more comprehensive understanding of spatial-temporal relationships (Wei et al., 2019) (Wei, Zhang, Duan, and Zhen 2019, 5107). This model integrates GWR, which focuses on spatial non-stationarity, and Temporally Weighted Regression (TWR), which addresses temporal non-stationarity, into a unified framework to capture the complexities of both dimensions (Wei et al., 2019).

Mapping the number of COVID-19 cases in Aceh requires considering factors that could affect the spread of the virus. The COVID-19 crisis has strained healthcare systems worldwide and highlighted disparities in access to medical services, which can have direct implications for disease management and outcomes (Joode et al., 2020). The number of doctors available in Aceh may affect people's access to adequate medical care, which could affect the number of COVID-19 cases in the area (Cox et al., 2023).

In addition, factors such as the number of tuberculosis (TB) cases, percentage of the population with health complaints, population density, gross regional domestic product (GRDP), number of hospitals, number of villages with health centers, and number of poor people can also affect the spread of COVID-19 in Aceh Province. Areas with high population density and lack of access to adequate health facilities can accelerate the spread of the virus. Several studies have explored the impact of population density on the spread of COVID-19, highlighting the higher probability of disease transmission in densely populated areas (Zakianis et al., 2021). The close contact opportunities in densely populated regions, such as metropolitan cities, increase the likelihood of rapid disease spread (Bhadra et al., 2021). Thus, the trends and patterns of the spread of the virus in Acehare traceable. This information is vital in determining effective prevention and control measures to minimize the spread of COVID-19 in Aceh.

Many previous studies have analyzed the incidence of COVID-19 spatio-temporally using Geographically and Temporally Weighted Regression (GTWR), including research conducted by (Chen et al., 2021) on modeling the Spatiotemporal Association Between COVID-19 Transmission and Population Mobility Using Geographically and Temporally Weighted Regression (GTWR). The results of this study state that the GTWR model can show how COVID-19 and population mobility are spatially-temporally variable. In addition, the correlation between the number of COVID-19 cases and population movement shows three stages of temporally variable features due to the virus incubation time and the implementation of strict regional quarantine measures.

Then, a similar study was also conducted by (Park et al., 2021) regarding deaths due to COVID-19 in the United States. The results of this study state that COVID-19 mortality rates are significantly correlated with local infection rates and testing rates, social distancing interventions, social variables, the environment, and other health risks. Furthermore, another study conducted by (Sifriyani et al., 2022) on the Geographically and temporally weighted regression model for GIS mapping of the influence of COVID-19 in East Kalimantan mentioned the results that the number of tuberculosis cases, population density, GDP, the number of hospitals, and the number of villages that have public health centers affect the cumulative positive cases of COVID-19 in East Kalimantan.

By using other analyses to get better results in the case of COVID-19 using GTWR, Sifriyani has selected significant variables using correlation analysis (Sifriyani et al., 2022). The correlation analysis in this study aims to select significant variables to be included in the GTWR model. The study states that the number of hospitals, the number of doctors, the percentage of the elderly, the number of TB cases, and the Gross Regional Domestic Product (GRDP) are several variables influencing the increase of COVID-19 cases in Kalimantan Island.

Furthermore, this study uses panel data regression and GTWR. Panel data regression is used to analyze variables that affect the incidence of COVID-19 in Aceh Province and model the incidence of COVID-19 cases based on panel data models by combining elements from cross-sectional regression and time series regression. This analysis technique is carried out to ensure the results of the GTWR analysis are more accurate and realistic. This study aims to obtain factors that influence the incidence of COVID-19 cases in Aceh using panel data regression analysis and the GTWR model for more accurate results.

METHOD

Data and Research Variables

The data used in this study are secondary data obtained from the Aceh Provincial Health Office and the Aceh Provincial Statistics Agency (BPS) in the official publication of Aceh in Figures for 2021 and 2022. This study uses data from Aceh Province, which consists of 23 districts/cities in 2020 and 2021. The data consists of independent and dependent variables and numerical data with a ratio measurement scale. The number of COVID-19 cases (people) is the dependent variable, while the number of doctors (people), the number of TB cases (people), the percentage of the population who have health complaints (percent), population density (people/km2), gross regional domestic product (billion rupiah), the number of hospitals (units), the number of villages that have health centers (units), and the number of poor people (thousand) are independent variables in this study. Time series design study was used as the research design in this study.

Statistical Methods

In this study, statistics is the primary method used to generalize the results (Agustia et al., 2022; Nadia et al., 2019; Noviandy et al., 2022; Sasaki et al., 2021). The statistical methods used in this study consist of mean, minimum, maximum, and quartiles 1, 2, and 3 as part of descriptive statistical analysis (Idroes et al., 2020). Panel data regression and GTWR were applied in this study. Descriptive statistical analysis is used to understand the essential characteristics of the data and provide basic information about the data (Earlia et al., 2021; Sofyan et al., 2023). Panel data regression is used to simultaneously analyze the significance of variables and model the incidence of COVID-19 cases based on panel data models by combining elements from cross-sectional and time series regression. By utilizing panel data models, researchers can account for both individual-specific effects and time-specific effects, providing a more robust analysis of the relationships between independent and dependent variables (Idroes, Husna, et al., 2019; X. Li et al., 2022). Then, GTWR is used to model the relationship between dependent variables and independent variables that can vary spatially and temporally in the context of geographic and time data.

Data Analysis Procedure

Data analysis in this study used R 4.3.0 and QGIS 3.20.3 software. The first step was to perform descriptive statistics on the independent and dependent variables and map the spatial distribution of both types of variables. Then, conduct a panel data regression analysis to see what variables affect the incidence of COVID-19 cases in Aceh Province in 2020 and 2021 and create a panel data regression model. Panel data regression analysis was chosen because the data used is panel data consisting of cross-sectional and time series data. The detailed stages of the initial analysis are, estimating the test parameters of the Common Effect Model (CEM), Fixed Effect Model (FEM), and Random Effect Model (REM). The estimated parameter results were then analyzed using the Chow test to select the best model between CEM and FEM. If the best model is CEM, the Lagrange Multiplier (LM) test will be applied to compare with the REM model, but if the best model is FEM, the Hausman test will be applied to compare with the REM model. The next stage tests the assumptions of autocorrelation, heteroscedasticity, and multicollinearity of the selected model. In the final stage of panel data regression analysis, simultaneous test (F test), partial test (t test), and coefficient of determination are applied to test the model specification.

In the GTWR analysis, a spatial heterogeneity test using the Breusch Pagan test is conducted to determine whether there is spatial diversity. Data visualization through boxplots was applied to see the diversity of temporal variability in the dependent variable for each year. Furthermore, goodness of fit testing is also applied to determine whether there is a significant difference between the GTWR model and the panel data regression model, which aims to determine the weighting function that can be used. Furthermore, the best GTWR model function is determined based on the criteria of the smallest AIC and the largest Adjusted R2 (Idroes et al., 2021; Mahmood et al., 2020). The Euclidean distance between observation locations at coordinates (u_i,v_i)) and locations at coordinates (u_j,v_j) are calculated. Then, the optimum bandwidth is determined using the Cross Validation (CV) method on the best kernel function weighting type. The GTWR model equation is formed in each region and time by examining what variables affect each observation. In the final stage, a distribution map of significant variables for each region and time is created to visualize how the variables change in different regions and impact over time.

RESULT AND DISCUSSION

Descriptive Analysis of Variables

To better understand the factors influencing COVID-19 cases in Aceh Province, we conducted a comprehensive descriptive analysis of key variables. This analysis provides a summary of the central tendencies and dispersions of the data, offering insights into the distribution and variability of COVID-19 incidence and its associated factors across the region. The table below presents the minimum, first quartile (Q1), median (Q2), mean, third quartile (Q3), maximum, and standard deviation for each variable under study. These statistics help elucidate the range and variability of the data, highlighting potential disparities and areas of concern that may require targeted public health interventions.

Table 1. Descriptive statistics of variables affecting COVID-19 case rates

No	Variable	Min	Q1	Q2	Mean	Q3	Max	Std. Deviation
1	COVID-19 Cases (y)	86.0	198.2	353.5	818.9	794.5	9503.0	1,462.1
2	Number of Doctors (x_1)	24.0	56.5	75.0	99.1	112.7	718.0	104.3
3	Number of TB Cases (x_2)	11.0	143.0	226.0	310.0	445.0	973.0	113.1
4	Percentage of Population with Health Complaints (x_3)	13.5	20.8	27.2	26.2	30.6	36.1	6.3
5	Population Density (x_4)	17.0	54.2	101.5	345.3	177.5	4156.0	850.9
6	Gross Regional Domestic Product (GRDP) (x_5)	1,531	3,015	5,866	7,625	10,451	23,192	5,391.9
7	Number of Hospitals (x_6)	1.0	1.0	2.0	2.9	3.7	15.0	2.9
8	Number of Villages with Health Centers (x_7)	4.0	12.0	14.0	16.0	23.0	41.0	9.1
9	Number of Poor People (x_8)	5.3	19.2	29.1	35.8	39.6	109.5	24.6

Table 1. shows the statistics for the variables in this study. The number of COVID-19 cases ranges from 86 to 9,503, with a mean of 818.9 and a standard deviation of 1,462.1. This wide range indicates significant disparities in infection rates across different districts. Such disparities could be attributed to variations in population density, healthcare infrastructure, and socioeconomic conditions. The number of doctors ranges from 24 to 718, with a mean of 99.1. Regions with more doctors likely have better healthcare access and higher capacity to manage and treat COVID-19 cases. However, areas with fewer doctors are at a disadvantage, potentially leading to higher infection and mortality rates. This disparity highlights the need for equitable distribution of healthcare resources.

The number of TB cases ranges from 11 to 973, with a mean of 310. TB is a significant comorbidity with COVID-19, as both diseases affect the respiratory system. Patients with TB are more susceptible to severe outcomes if they contract COVID-19 (Ong, 2022; Togun et al., 2020). The co-infection of TB and COVID-19 can exacerbate clinical outcomes, making it essential to address TB prevalence to mitigate COVID-19's impact. The intersection of COVID-19 and TB poses unique public health challenges. Both diseases share similar clinical symptoms, such as cough, fever, and difficulty breathing, complicating diagnosis and treatment (Song et al., 2021). Co-infected patients require specialized care to manage both conditions simultaneously. High TB prevalence in certain regions exacerbates the burden on healthcare systems already strained by COVID-19. Integrated disease management strategies are essential to address this dual threat effectively.

Further, The percentage of population with Health Complaints ranges from 13.5% to 36.1%, indicating varying levels of general health across the population. Higher percentages may reflect underlying health vulnerabilities, which can increase susceptibility to COVID-19. Public health initiatives should focus on improving overall health and managing chronic conditions to reduce COVID-19 risk.

Population density ranges from 17 to 4,156 people per km², with a mean of 345.3. Densely populated areas facilitate faster transmission of COVID-19 due to closer human contact (Ezeibe et al., 2020; Gaano et al., 2024). These areas require stringent public health measures, such as social distancing and robust healthcare services, to control the spread. Gross Regional Domestic Product (GRDP) (x□): GRDP ranges from 1,531 to 23,192 billion rupiah, with a mean of 7,625 billion rupiah. Economic conditions significantly influence healthcare access and quality. Regions with lower GRDP may struggle to provide adequate healthcare, making them more vulnerable to COVID-19 outbreaks (Rieckert et al., 2021; Zhang et al., 2020).

The number of hospitals ranges from 1 to 15, with a mean of 2.9. Adequate hospital facilities are crucial for managing severe COVID-19 cases. Regions with fewer hospitals may face challenges in providing necessary care, leading to higher mortality rates. Increasing hospital capacity in underserved areas is vital for effective disease management. Next, The number of Villages with Health Centers ranges from 4 to 41, with a mean of 16. Health centers provide primary healthcare services and are essential for early detection and treatment of COVID-19. Regions with more health centers are better positioned to manage the pandemic through timely interventions and preventive measures.

The number of poor people ranges from 5.3 to 109.5 thousand, with a mean of 35.8 thousand. Poverty is a significant determinant of health outcomes, as it limits access to healthcare, nutritious food, and other essentials. Due to these limitations, poorer regions are more vulnerable to COVID-19 (Pereira & Oliveira, 2020; Tian, 2024). Due to their geographic isolation and limited healthcare infrastructure, remote areas in Aceh face distinct public health challenges. These regions often have higher poverty rates and lower healthcare access, making them particularly vulnerable to COVID-19. The variability in healthcare facilities, as shown by the number of hospitals and health centers, highlights the need for targeted interventions.

Panel Data Regression Analysis

The panel data regression analysis was conducted to identify variables that significantly impact the incidence of COVID-19 and to determine the most suitable model. Initially, the Chow test was used to compare the Constant Effects Model (CEM) with the Fixed Effects Model (FEM), and it was found with a p-value of 0.011. Subsequently, a Hausman test comparing the Fixed Effects Model (FEM) with the Random Effects Model (REM) resulted in a p-value of 0.396, indicating that the Random Effects Model (REM) was the best model for this analysis.

Classical Assumption Test

The classical assumption tests on the panel data model are autocorrelation and heteroscedasticity. Based on the analysis, REM is the selected model, so it is not required to carry out a classical assumption test. REM uses the Generalized Least Squares (GLS) estimation approach, where each estimate can give equal weight or importance to each observation. GLS can produce an optimal and unbiased estimator so that it is the Best Linear Unbiased Estimator (BLUE) (Gujarati, 2021).

In GTWR analysis, a multicollinearity test is required in the initial analysis. Multicollinearity in GTWR analysis is used to identify and handle excessive relationships between predictor variables in the regression model, which can cause instability of parameter estimates and affect the accuracy and interpretation of the model geographically. Based on multicollinearity testing, the VIF values for variables x_1 to x_8 are 2.778, 1.579, 1.102, 6.312, 9.241, 3.401, 3.558, and 7.353, respectively. Based on this value, where all variable values are ≤ 10, it can be concluded that there is no multicollinearity.

Panel Data Regression Model

The panel data regression model formed using REM is:

$$\hat{y} = -365,73 + 12.71x_1 + 3.26x_2 - 11.42x_3 - 0.11x_4 - 0.005x_5 + 19.66x_6 + 42.11x_7 - 22.35x_8 \quad (1)$$

The coefficient on the variable number of doctors (x_1) is 12.70, which indicates that as the number of doctors (x_1) increases, the incidence of COVID-19 (y) will increase by 12.71 cases. Furthermore, the coefficient on the variable number of TB cases (x_2) is 3.26, which indicates that as the number of TB cases (x_2) increases, the incidence of COVID-19 (y) will also increase by 3.26 cases. In the variable percentage of the population who have health complaints(x_3), the resulting coefficient is -11.42, indicating that as the percentage of the population who have health complaints (x_3) increases, the incidence of COVID-19 (y) will decrease by 11.42 cases. Likewise, for the coefficients on variables x_4, x_5, x_6, x_7, and x_8.

F Test

The F test determines whether all independent variables in the model simultaneously significantly affect the dependent variable. This test is helpful for evaluating the reliability of the entire model. Based on the results of the F test, it is obtained that the p-value < α, namely 2.22 × 10-16 < 0.05, so it can be concluded that the independent variables jointly affect the dependent variable. The panel data regression model shows an Adjusted R^2 value of 0.9067, which means that the independent variables in the model can explain 90.67% of the variation in the dependent variable, indicating that the level of fit of the model is very good. In contrast, the remaining 9.33% is explained by other variables that are outside the model.

Partial Test

Based on partial testing in the panel data regression analysis using the t-test, variable x_1 has a significant effect on the incidence of COVID-19, indicated by a p-value of 2.20×10-16 which is lower than 0.05. The same is found for variables x_2, x_7, and x_8, with p-values of 7.57×10-8, 0.026, and 0.036, respectively, indicating that they significantly affect the incidence of COVID-19. Meanwhile, variables x_3, x_4, x_5, and x_6 do not have a significant effect, as indicated by their p-values that are higher than 0.05, namely 0.389, 0.695, 0.925, and 0.719.

Test of Spatial and Temporal Heterogeneity

In testing spatial heterogeneity using Breusch-Pagan, the Breusch-Pagan value is 19.132 with a p-value of 2.2×10^{-16} , so there is spatial heterogeneity in the data--meanwhile, the results of testing temporal diversity using boxplots obtained visualization as in Figure 3.1. The figure shows a change in COVID-19 cases from 2020 to 2021. This can be seen from the extreme outliers and the significant difference from the interquartile of 2020 of 200.5 and 2021 of 827.5 compared to both years. This result explains that each year, there is a significant increase in COVID-19 cases. Based on this information, temporal heterogeneity occurs in the data and has met the assumptions.

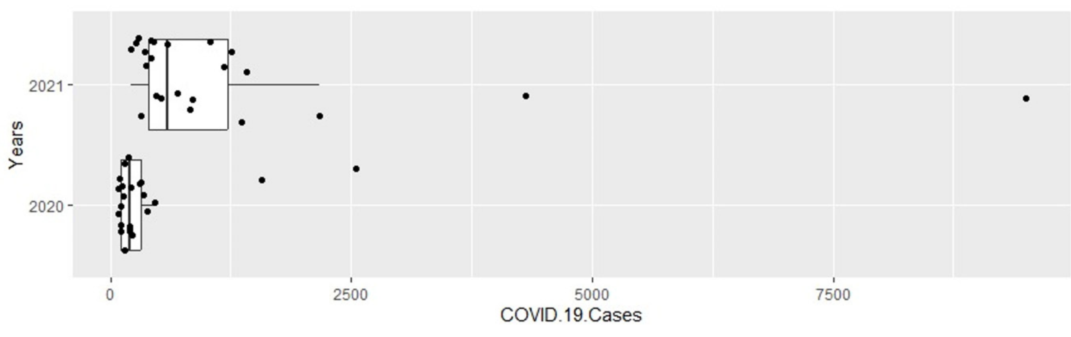

Figure 1. Temporal diversity test for COVID-19 data in Aceh Province

GTWR Modeling

Euclidean distance is used in GTWR modeling to calculate the distance between each observation. In addition, the search for optimum bandwidth is carried out using one method, including a kernel function. Two types of bandwidth are used in GTWR: adaptive and fixed. Four types of kernel functions are used in this study's weighted regression: Gaussian, Exponential, Bisquare, and Tricube.

Table 3. shows that each type of weighting function is applicable. The Fvalue indicates this

Table 2. Results of the goodness of fit test on each kernel function

Weighting Function	**Fvalue**	**Ftable**	**Adjusted R^2**	**AIC**
Adaptive Kernel Gaussian	2.801	0.583	0.945	666.560
Fixed Kernel Gaussian	4.958	0.584	0.913	687.470
Adaptive Kernel Exponential	1.424	0.576	0.955	654.150
Fixed Kernel Exponential	4.958	0.584	0.913	687.470
Adaptive Kernel Tricube	7.797	0.588	0.898	697.247
Fixed Kernel Tricube	10.032	0.590	0.896	698.556
Adaptive Kernel Bisquare	7.724	0.588	0.897	697.354
Fixed Kernel Bisquare	10.033	0.590	0.896	698.556

for all weighting functions exceeding the F-table value. This result indicates that at least one variable significantly differs between the panel data regression model and the GTWR model. Therefore, the GTWR model performs better than the panel data regression model when applied to this data. Through the same table, the selection of the best GTWR model with a weighting function is determined based on the highest Adjusted R^2 value and the lowest AIC value (Idroes, Noviandy, et al., 2019; Zhou & Zhou, 2021). Considering these criteria, the Adaptive Kernel Exponential model is the best choice.

Parameter Estimation of GTWR Model

The estimation of the GTWR model was applied to each of the 23 districts/cities for two different years. At the i-th location where the i-th location = 1, 2, ..., 23 is the initial for 23 districts/cities in Aceh Province, and the t-th time is 1 for 2020 and 2 for 2021. The estimation results of the GTWR model are given in Equation (2).

$$\hat{y}_{it} = \hat{\beta}_0(u_i,v_i,t_i) + \hat{\beta}_1(u_i,v_i,t_i)x_{it1} + \hat{\beta}_2(u_i,v_i,t_i)x_{it2} + \hat{\beta}_3(u_i,v_i,t_i)x_{it3} + \hat{\beta}_4(u_i,v_i,t_i)x_{it4}, i = 1,2,\ldots,46\,; t = 1,2 \quad (2)$$

Table 4. Shows a summary of parameter estimation data formed from the Adaptive Kernel Exponential kernel function in the GTWR model. The variable number of doctors (x_1) ranges from 1.69 to 12.09. The variable number of TB cases (x_2) ranges from 1.38 to 4.17. The variable number of villages with a health center (x_7) ranges from -14.93 to 70.2. Furthermore, the variable number of poor people (x_8) has a value range from -26.33 to 0.47. The coefficient on each variable has a different value for each district/city in Aceh Province.

Table 3. GTWR model parameter results

Parameter	**Min**	**Q1**	**Median**	**Q3**	**Max**
β_0	-864.87	-567.68	-339.13	78.71	238.54
β_1	1.69	3.61	10.04	11.86	12.09
β_2	1.38	2.04	2.94	3.43	4.17
β_3	-14.93	-7.51	12.78	33.05	70.2
β_4	-26.33	-19.71	-9.97	-1.61	0.47

GTWR Model Formation

The GTWR model estimator generated from the parameter estimation process shows the relationship between the independent variables of the number of doctors (x_1), the number of TB cases (x_2), the number of villages equipped with Puskesmas (x_7), and the number of poor people (x_8) to the incidence of COVID-19 cases in Aceh Province. The four examples of GTWR models generated for four regional locations and times are as follows.

Simeulue Regency in 2020:

$$\hat{y}_{Simeulue2020} = -579.13 + 11.83x_1 + 3.76x_2 + 33.54x_7 - 19.72x_8 \quad (3)$$

Simeulue Regency in 2021:

$$\hat{y}_{Simeulue2021} = -135.13 + 9.13x_1 + 2.83x_2 + 7.07x_7 - 6.43x_8 \quad (4)$$

Aceh Singkil Regency in 2020:

$$\hat{y}_{AcehSingkil2020} = -577.34 + 12{,}05x_1 + 3.15x_2 + 35.37x_7 - 19.69x_8 \quad (5)$$

Aceh Singkil Regency in 2021:

$$\hat{y}_{AcehSingkil2021} = 203.86 + 3.53x_1 + 1.94x_2 + 13.55x_7 - 1.09x_8 \quad (6)$$

For example, the GTWR model interpretation for Simeulue District 2020 shows a positive correlation between the number of doctors (x_1) and TB cases (x_2), as well as the number of villages with Puskesmas (x_7) on COVID-19 cases. Specifically, an increase of one doctor or one TB case or one number of villages with Puskesmas will increase COVID-19 cases by 11.83, 3.76, and 33.54, respectively. On the other hand, an increase of 1 poor person (x_8) will reduce COVID-19 cases by 9.73.

Partial Significance Test of GTWR Model Parameters

Following the previously formed model, partial testing by comparing the t-value against the t-table in this study is used to determine the independent variables that significantly affect the model based on region and year.

Table 4. The test statistical value of partial hypothesis testing of the GTWR model parameters

No	Location	Year	Variable	t value	No	Location	Year	Variable	t value
1	Simeulue	2020	X_1	23.04*	3	Aceh Singkil	2020	X_1	22.88*
			X_2	7.44*				X_2	5.72*
			X_7	3.53*				X_7	3.44*
			X_8	-5.70*				X_8	-5.26*
2	Simeulue	2021	X_1	5.28*	4	Aceh Singkil	2021	X_1	1.07
			X_2	3.90*				X_2	2.02
			X_7	-0.45				X_7	-0.95
			X_8	-0.24				X_8	-0.17

Note: (*) Significant because more than t tabel value (t table = 2.02).

Grouping of Significant Variables

This research has identified several variables that have a significant influence, forming five groups in each district/city in Aceh Province. This grouping is based on an in-depth analysis of the variables that influence events or situations related to COVID-19.

Based on the results of the analysis, it is obtained that the variables of the number of doctors (x_1), the number of TB cases (x_2), the number of villages with Puskesmas (x_7), and the number of poor people (x_8) have a spatial influence in two consecutive years on the incidence rate of COVID-19 in Aceh Tengah, Aceh Barat, and Aceh Besar. Then, the variables of the number of doctors (x_1) and the number of TB cases (x_2), also have a spatial influence in two consecutive years on the incidence rate of COVID-19 in South Aceh and Langsa. Visualization of significant variables on COVID-19 is presented in Figure 2.

Table 5. Grouping of significant variables

Year	District/city	Significant variable
2020	Simeulue, Aceh Singkil, Southeast Aceh, East Aceh, Central Aceh, West Aceh, Aceh Besar, North Aceh, Gayo Lues, Nagan Raya, Aceh Jaya	x_1, x_2, x_7, x_8
	South Aceh, Langsa, Lhokseumawe	x_1, x_2
	Banda Aceh	x_1, x_2, x_8
	Pidie	x_2
	Bireuen, Southwest Aceh, Aceh Tamiang, Sabang, Subulussalam	No significant variables
2021	Aceh Tengah, West Aceh, Aceh Besar, Bireuen, Aceh Tamiang, Banda Aceh, Lhokseumawe, Subulussalam	x_1, x_2, x_7, x_8
	Simeulue, South Aceh, Southeast Aceh, North Aceh, Southwest Aceh, Langsa	x_1, x_2
	Pidie	x_1, x_2, x_8
	Pidie Jaya	x_2
	Aceh Singkil, East Aceh, Gayo Lues, Nagan Raya, Aceh Jaya, Bener Meriah, Sabang	No significant variables

Based on the results of the analysis, the distribution of COVID-19 cases in this study period is quite large and does not center around the average value. These foundings mean that

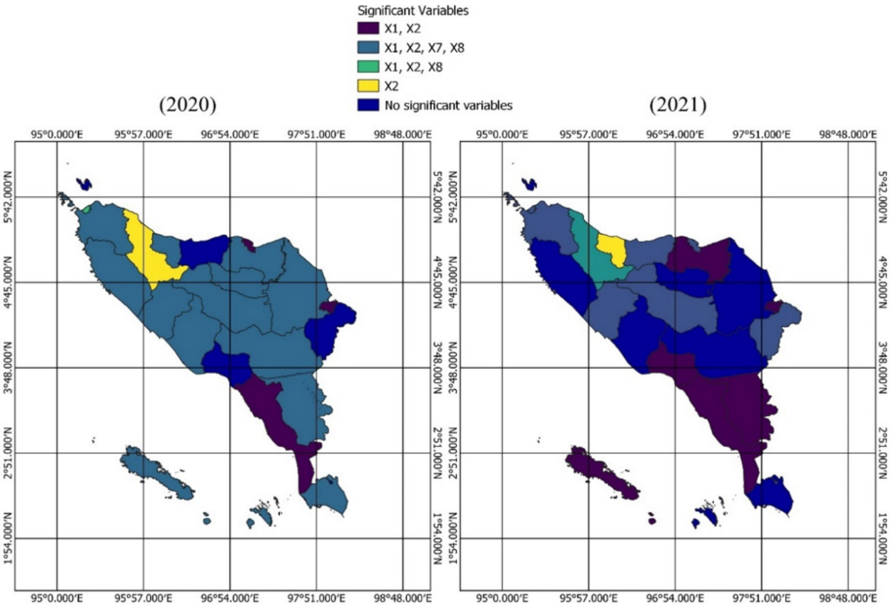

Figure 2. Map of district/city distribution based on significant variables

the incidence of COVID-19 in districts/cities in Aceh Province varies greatly. The same condition also occurs in several other regions (Messner & Payson, 2020), where some events can cause the number of COVID-19 cases to exceed the average value, and some events cause the number of cases to be lower than the average value. Factors such as variations in testing rates, prevention and control policies, and community response may contribute to these significant variations (Haldar & Sethi, 2020; Wallis, 2024).

Based on the selection of variables, TB has the most dominant influence on the incidence of COVID-19. The higher the TB cases in an area, the higher the COVID-19 cases. The same happened in China (Gao et al., 2021; Khurana & Aggarwal, 2020). Then, individually, a person suffering from TB and COVID-19 simultaneously can exacerbate each other and pose unique challenges in management and treatment. In the context of transmission, an increase in TB cases may increase the number of COVID-19 cases and vice versa, especially if co-infection occurs. Patients with TB may be more susceptible to COVID-19 infection and may show more severe symptoms (Singh et al., 2020).

The research data's short duration and the analysis area's small scale are limitations. A longer duration and a larger scale of analysis area, such as covering provinces or even countries, would be better used.

CONCLUSION

This study develops a panel data regression model as a variable selection feature and geographically temporally weighted regression (GTWR) to model the relationship between variables that can vary spatially and temporally in the context of geographic and time data. Of the eight variables analyzed, four variables were influential. Based on spatio-temporal analysis using the GTWR model, the factors influencing the increase in positive COVID-19 cases differ for each district/city in Aceh Province. Overall, the factors that influence COVID-19 are the number of doctors, the number of TB cases, the number of villages with health centers, and the number of poor people. However, the number of TB cases is the most dominant variable that influences the incidence rate of COVID-19 in Aceh Province. Therefore, handling the decline in TB cases will have implications for reducing COVID-19 cases so that the strategy to overcome COVID-19 becomes a priority for the government.

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