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Looking at GDP from a Statistical Perspective: Spatio-Temporal GSTAR(1;1) Model

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ABSTRACT

The gross domestic product (GDP) is a significant indicator for evaluating the performance of an economy. The GDP of a nation can be used to get a sense of the size and health of that nation's economy. Indonesia is the only nation from Southeast Asia to be represented in the G20. All G20's countries play vital roles in creating the economic landscape of the region, the world, and everything in between. This research is focused on the increase of the GDP in Indonesia, Malaysia, Singapore, Thailand, and Brunei Darussalam. The spatial influence of GDP can be seen in the growth of each nation's infrastructure and industrial sector, for example. at the regional level, the increase of a country's GDP can also have an effect on the countries that are its neighbors. Using the GSTAR model, the aim of this study is to investigate the spatial and temporal influences on the GDP statistics of five different countries. The GSTAR model is distinguished by the presence of a weight matrix, which is one of its distinguishing features. In addition, the aim of this research is to select the most appropriate weight matrix for the purpose of representing the spatial effect on GDP statistics. Uniform, queen contiguity, and inverse distance weight matrices are the types of weight matrices that are utilized. Calculating each weight matrix, estimating relevant parameters, and performing diagnostic tests are the primary activities involved in this investigation. As a consequence of this, a weight matrix that is uniform in its distribution is the one that performs the best. The spatial and temporal correlations of GDP data may be accurately represented by the GSTAR model when it is equipped with a uniform weight matrix. This model is applied to five different countries.

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A. INTRODUCTION

The value of a country's products and services that are produced there by the factors of production that are owned by people of that country as well as citizens of other countries is referred to as the country's Gross Domestic Product (GDP) (Fan et al., 2018). This indicates that the GDP can also be defined as a mechanism for determining national revenue. The production, the income, and the expenditure approach are the three ways that one might look at the size of the GDP (Konchitchki & Patatoukas, 2014). The production method defines GDP as the sum of all final goods and services generated by all of the different production units located inside a country's borders within a given year (Onuoha et al., 2015). The income method states that the amount of compensation received by the factors of production that participate in the production process inside the territory of a country within one year is the amount that constitutes a country's GDP (Aitken, 2019). In the meantime, according to the expenditure method, GDP is the sum of all final components, which comprise the following: (1) Expenditures made by households on their own consumption and by private entities that are not for profit; (2) the emergence of gross domestic fixed capital and the evolution of stock; (3) government consumption expenditure; and (4) annualized "Nettom" exports, or total exports minus total imports for the previous year (Kahoun & Sixta, 2013). The following is a list of the advantages that come with using GDP as a concept of national income: (1) Contrasting the economic development achieved by a nation at different points in time; (2) Evaluating the level of economic performance achieved by a nation; (3) serving as a blueprint for the development of official policies; (4) Having an understanding of the components or framework of the economy; (5) Making comparisons between the economies of different regions or countries; and (6) Being aware of the rate of economic growth and the average income per person (Hagerty & Veenhoven, 2003).

The value of a country's gross domestic product is the primary qualification for becoming a member of the G20 forum (Pérez-Moreno et al., 2016). This is since members of the G20 forum are thought to be capable of making a significant contribution to the economy while also maintaining the financial stability of their respective countries. The Group of Twenty, or G20 for short, is an essential platform for international economic cooperation that is made up of the countries that have the world's twenty largest economies. It is also commonly referred to as the G20 (Nguyen et al., 2020). Currently, the G20 consists of 19 countries and one institution from the European Union. The primary goal of the G20 is to convene the heads of government from the world's most significant established and emerging nations for with the aim of having a discussion about potential solutions to the challenges that are currently being faced by the global economy. Indonesia is considered a member of the G20 because it is regarded as experienced in resolving economic crises and because it is believed to be a rising country that has enormous size and economic potential in the Asian area (Saputra & Hapzi Ali, 2021). These factors combine to make Indonesia a candidate for membership in the G20. As a result, Indonesia is a member of the G20, where it represents a coalition of developing nations, the Southeast Asian region, and nations where Muslims make up most of the population. In this analysis, the effects of Indonesia's participation in the G20 will be compared spatially with those of its four immediate neighbors, namely Malaysia, Thailand, Brunei Darussalam and Singapore.

The GDP is often regarded as one of the most important measures of a nation's overall monetary activity (Wan & Sheng, 2022). The strategic forecasting of economic indicators holds an enormous amount of value, both theoretically and practically, when it comes to the formulation of objectives for the expansion of the economy. In addition to this, having a good understanding of the dynamics involved in the interaction between the mechanisms of economic development in a country and the development of that country is of the utmost importance. This is because the interaction can have a significant impact on the future of the country. It is possible that this will be of great assistance in the process of developing new policies and programs regarding economic policy and budgeting. As a result, the data on GDP can be interpreted as time series data, which can be used to make forecasts on the GDP of each country in the future (Hasan & Barua, 2015). The data on GDP can be viewed in a variety of different ways, including as a time series, as spatial data, or as both of these at the same time. It is generally accepted that the GDP data of a country has an effect on the countries that are nearby. In the course of this study, Indonesia, which is a member nation of the G20, will evaluate the temporal and spatial effects of its influence on the countries that are immediately adjacent to it. In a similar vein, each of these countries may also be understood by looking at the effect that space and time have had on other nations. One of the various space-time studies that can be engaged to use is the investigation of a model known as the Generalized Space Time Autoregressive, or GSTAR. Recent research on GSTAR has been carried out a lot,

1. Modeling GSTAR for discrete cases (Huda et al., 2021).
2. Modeling GSTAR if there are outliers detected (Huda et al., 2022).
3. Comparing some of weight matrix for GSTAR (1;1) model (Huda & Imro'ah, 2023).
4. Applying GSTAR (1;1) model with outlier factor to dengue fever cases (Mukhaiyar et al., 2019).
5. Modifying the weight matrix for GSTAR (1;1) model (Pasaribu et al., 2021).
6. Proposing the new weight matrix for GSTAR (1;1) model: Spatial weight with kernel function (Yundari et al., 2018).
7. Checking the stationary process for spatial weight with kernel function (Yundari et al., 2020).

The GSTAR models take into explicit consideration the spatial dependencies that exist between observations. This is of particular utility in contexts in which the data points are not independent from one another, such as in the collection of geographic data or the monitoring of environmental conditions. The GSTAR models include lag factors for both the spatial and the temporal components. According to the findings of the research that was discussed earlier, various studies demonstrate that research concentrates on the weight matrix. When describing the spatial dependencies that exist between various places or areas in a spatiotemporal dataset, the weight matrix is the component of a GSTAR model that is responsible for making such description. The spatial weights matrix, or simply the W matrix, is another name for this particular matrix. It provides assistance in defining the relationship between observations made in one area and observations made in locations that are nearby. In addition, the purpose of this research is to select the weight matrix that will 978os o978 most accurate representation of the geographical effect on GDP data, and the goal is to 978os o by choosing the most appropriate weight matrix.

B. METHODS

1. GSTAR(1;1) Model

A subset of the more comprehensive GSTAR model is referred to as the GSTAR (1;1) model. Generalized Space-Time Autoregressive model with a first-order spatial lag and a first-order temporal lag is the definition of what is known as a GSTAR (1,1) model. In terms of the geographic component, the 1st-order spatial lag represents spatial dependence, which indicates that observations made in one area are influenced by observations made in locations that are adjacent to the one in issue. In terms of the temporal component, the 1st-order temporal lag represents temporal dependency. This means that the current value of the variable is influenced by its previous values at the same place, and this is indicated by the fact that the variable has a temporal dependence. Let $\boldsymbol{Y}_t$ is random variable following the GSTAR (1;1) model (Ruchjana et al., 2012),

$$\boldsymbol{Y}_t = \Phi_{10}\boldsymbol{Y}_{t-1} + \Phi_{11}\boldsymbol{W}_{(*)}\boldsymbol{Y}_{t-1} + \boldsymbol{e}_t \tag{1}$$

where

$$\boldsymbol{Y}_t = \begin{bmatrix} Y_t^{(1)} \\ Y_t^{(2)} \\ \vdots \\ Y_t^{(n)} \end{bmatrix}; \Phi_{10} = \begin{bmatrix} \phi_{10}^{(1)} & 0 & \dots & 0 \\ 0 & \phi_{10}^{(2)} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \phi_{10}^{(n)} \end{bmatrix}; \Phi_{11} = \begin{bmatrix} \phi_{11}^{(1)} & 0 & \dots & 0 \\ 0 & \phi_{11}^{(2)} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \phi_{11}^{(n)} \end{bmatrix}; \boldsymbol{e}_t = \begin{bmatrix} e_t^{(1)} \\ e_t^{(2)} \\ \vdots \\ e_t^{(n)} \end{bmatrix}$$

$\boldsymbol{W}_{(*)}$ is the weight matrix, $(*)$ is either U, Q, or I, $\phi_{10}^{(i)}$ and $\phi_{11}^{(i)}$ are the autoregressive parameters for $i = 1,2,\dots,n$ and n is the number of location. Noted that eq.1 can be stated as

$$\boldsymbol{Y}_t = (\Phi_{10} + \Phi_{11}\boldsymbol{W}_{(*)})\boldsymbol{Y}_{t-1} + \boldsymbol{e}_t \tag{2}$$

The model shown in eq.(2) can be interpreted as an extension of the 1st-order Autoregressive (AR(1)) model known as a 1st-order Vector AR (VAR(1)) time series model. This model can be viewed as a time series model. As a result, modelling on the GSTAR space-time model is likewise comparable to modelling on the AR time series model, specifically through the same three steps (Mukhaiyar & Pasaribu, 2012). Here the procedure of modeling GSTAR model shown in Figure 1.

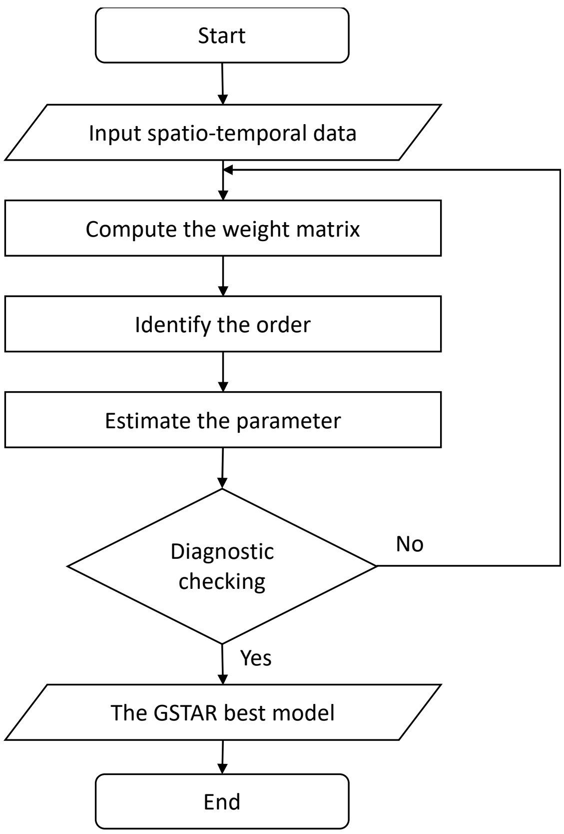


Figure 1. Flowchart

The following are the explanation based on Figure 1:

a. **Identify the order** by reviewing the plots of the Space-Time Auto Correlation Function (STACF) and the Space-Time Partial Auto Correlation Function (STPACF).
b. The Maximum Likelihood Estimation (MLE) method is utilised in the process of **parameter estimation**.
c. The residual **diagnostic test**, specifically the residual independency and normality test.

2. Weight Matrix

The weight matrix that is characteristic of the GSTAR spacetime model can be used to identify the model. The relationship that occurs between a variety of geographical locations is depicted by this matrix (Huda & Imro'ah, 2023).

a. Uniform weight matrix is generated by counting how many distinct sites fall inside a specified distance interval. This value is derived from the presumption that all of the locations are interconnected and share the same qualities (are homogeneous). The formula for the uniform weight is as follows:

$$\boldsymbol{W}_{(\boldsymbol{U})} = \left[w_{(U)ij}\right] = \begin{bmatrix} 0 & \frac{1}{m} & \cdots & \frac{1}{m} \\ \frac{1}{m} & 0 & \cdots & \frac{1}{m} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{1}{m} & \frac{1}{m} & \cdots & 0 \end{bmatrix} \tag{3}$$

where $m = n - 1, n$ is the number of location.

b. Queen Contiguity weight matrix is a concept of intersection in which areas that intersect and the corners meet are given a value of $n_{ij} = 1$, while other areas are given a value of $n\_ij = 0$. This gives areas that intersect and the corners meet a value of 1. Neighborhood matrix is defined as $\boldsymbol{N} = [n_{ij}]$. Therefore, in order to determine this weight, a grid map that describes the location of the place is required. The calculation of this matrix is finished when each row is normalized in such a way that the sum of each row is equal to one. This brings each row's total up to the same value. After the neighbors of each place have been determined, this step can then be taken.

$$\boldsymbol{W}_{(\boldsymbol{Q})} = \left[w_{(Q)ij}\right] = \begin{bmatrix} 0 & \frac{n_{12}}{\sum_{j=1}^{N} n_{1j}} & \cdots & \frac{n_{1N}}{\sum_{j=1}^{N} n_{1j}} \\ \frac{n_{21}}{\sum_{j=1}^{N} n_{2j}} & 0 & \cdots & \frac{n_{2N}}{\sum_{j=1}^{N} n_{2j}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{n_{N1}}{\sum_{j=1}^{N} n_{Nj}} & \frac{n_{N2}}{\sum_{j=1}^{N} n_{Nj}} & \cdots & 0 \end{bmatrix} \tag{4}$$

c. Inverse Distance (ID) weight matrix is used for weighting depending on the actual distance between sites. When using the inverse distance weighting, a larger value is assigned to shorter distances, while a smaller weight is assigned to greater distances. Eucli's formula for measuring distance is the one that is utilised in calculations.

$$\boldsymbol{W}_{(I)} = \left[w_{(I)_{ij}}\right] = \begin{bmatrix} 0 & \dfrac{\frac{1}{d_{12}}}{\sum_{j=1}^{N}\frac{1}{d_{ij}}} & \cdots & \dfrac{\frac{1}{d_{1N}}}{\sum_{j=1}^{N}\frac{1}{d_{ij}}} \\ \dfrac{\frac{1}{d_{21}}}{\sum_{j=1}^{N}\frac{1}{d_{ij}}} & 0 & \cdots & \dfrac{\frac{1}{d_{2N}}}{\sum_{j=1}^{N}\frac{1}{d_{ij}}} \\ \vdots & \vdots & \ddots & \vdots \\ \dfrac{\frac{1}{d_{N1}}}{\sum_{j=1}^{N}\frac{1}{d_{ij}}} & \dfrac{\frac{1}{d_{N2}}}{\sum_{j=1}^{N}\frac{1}{d_{ij}}} & \cdots & 0 \end{bmatrix} \tag{5}$$

where $\boldsymbol{D} = \left[d_{ij}\right]$ is distance matrix.

C. RESULT AND DISCUSSION

1. Descriptive Statistics

The data utilised in this research are annual GDP growth (percent) figures. The period (t) range considered is from 1975 to 2021 (47 observations). Indonesia, Malaysia, Singapore, Thailand, and Brunei Darussalam are the five locations comprising up the locations (i) used. The plot of time series data for each nation is displayed in Figure 3, and the geographical mapping of the countries that were used is displayed in Figure 2. In addition, descriptive statistics of the data are presented in Table 1, which can be found here.

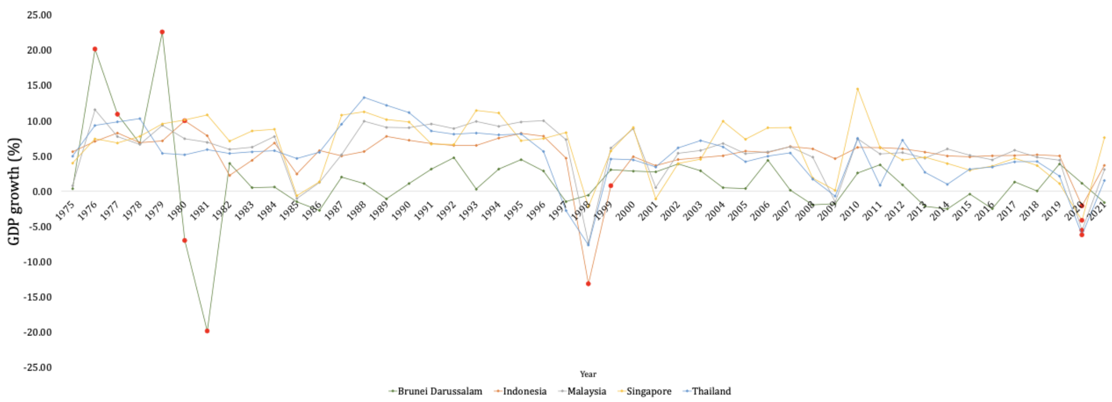


Figure 2. Time series plot of GDP growth (%) in five countries

Figure 3. Geographical map of five countries

Table 1. Descriptive statistics

Country	Not.	Min.	Max.	Mean	Var.	Out.
Brunei 	$Y^{(1)}$	-19.83	22.56	1.62	35.65	1976, 1977, 1979, 1980, 1981
Indonesia 	$Y^{(2)}$	-13.13	10.00	5.17	11.47	1980, 1998, 2009, 2020
Malaysia 	$Y^{(3)}$	-7.36	11.56	5.67	14.96	1985, 1998, 2009, 2020
Singapore 	$Y^{(4)}$	-4.14	14.52	6.24	16.13	2020
Thailand 	$Y^{(5)}$	-7.63	13.29	5.10	16.96	1998, 2020

The maximum GDP growth (%) is also in Brunei Darussalam, which is 22.56 (1979). Brunei's gross domestic product (GDP) in 1981. In terms of average, the other four countries, with the exception of Brunei Darussalam, have an average that falls somewhere in the region of 5.00–6.00%. Brunei Darussalam, on the other hand, has an exceptionally low average of 1.62%. In contrast, Brunei Darussalam recorded both the maximum and minimum values. Because of this, it is necessary to identify outliers in the data collected in each country. The detection findings that are presented in Table 1 demonstrate that, in comparison to other nations, Brunei Darussalam has the highest number of outliers, namely as many as five outliers at five separate times. Singapore, on the other hand, will only have outliers in the year 2020. The presence of red dots in Fig. 1 indicates the outliers for each nation. Based on the information presented in Fig. 1, the year 2020 will mark the occurrence of outliers in almost all of these countries, with the exception of Brunei Darussalam. This was brought about as a direct result of the effects of the COVID-19 epidemic, which swept the globe and caused significant disruptions in economic activity. In the year 2020, the gross domestic product (GDP) of Indonesia, Malaysia, Singapore, and Thailand all saw a decline and a negative growth rate for a number of different causes, including the following: (1) The impact of the epidemic brought on by COVID-19; (2) The decline in the price of oil; (3) The decrease in the amount of food consumed by individual homes; and (4) Dependence on specific businesses. In addition, the connection between locales' respective rates of GDP growth is symbolic of the relationship that exists between the two locations. This correlation is used as an initial assumption about the relationship between these areas' GDP growth, which is shown in Table 2.

Table 2. Correlation of GDP growth

	$\boldsymbol{Y_1}$	$\boldsymbol{Y_2}$	$\boldsymbol{Y_3}$	$\boldsymbol{Y_4}$	$\boldsymbol{Y_5}$
Y_1	1.000	0.068	0.283	0.071	0.230
Y_2	0.068	1.000	0.752	0.573	0.669
Y_3	0.283	0.752	1.000	0.799	0.736
Y_4	0.071	0.573	0.799	1.000	0.649
Y_5	0.230	0.669	0.736	0.649	1.000

2. Data Analysis

The first thing that is done in this modeling process is to compute the weight matrix, which is supposed to be a representation of the spatial link that already exists between the different sites. This experiment made use of three distinct kinds of weight matrices: uniform, queen contiguity, and inverse distance. In order to compute the uniform weight matrix, equation (3) is utilized in the process. The value of n in the equation, which is m, is equal to five minus one, which is four, because there are five locations. In addition, the computation of the queen contiguity weight matrix is controlled by the closeness between sites (the neighborhood), precisely whether or not these locations are physically near to one another or not. This proximity between sites is what is referred to as the neighborhood. The value of n_{ij} is 1 if the two sites are located next to each other, and it is 0 in any other circumstance. The matrix, N, is used to indicate adjacency between places.

$$\boldsymbol{N} = \left[n_{ij}\right] = \begin{bmatrix} 0 & 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 \\ 1 & 1 & 0 & 1 & 1 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix}; \boldsymbol{D} = \left[d_{ij}\right] = \begin{bmatrix} 0 & 599 & 1414 & 1262 & 1959 \\ 599 & 0 & 1439 & 1148 & 2334 \\ 1414 & 1439 & 0 & 378 & 1301 \\ 1262 & 1148 & 378 & 0 & 1644 \\ 1959 & 2334 & 1301 & 1644 & 0 \end{bmatrix} \quad (6)$$

The next weight matrix that will be spoken about is the one called the Inverse Distance weight matrix. The distance between each of these sites is the criterion that should be given the most weight in this matrix. The component of Google Maps that determines the length of time it takes to get from one location to another is denoted by the matrix D that is presented below and can be located in equation (6). The three different weight matrices that were applied are presented in Table 3.

Table 3. Weight matrix used

Weight	Not.	Matrix
Uniform	$\boldsymbol{W}_{(U)}$	$\begin{bmatrix} 0.00 & 0.25 & 0.25 & 0.25 & 0.25 \\ 0.25 & 0.00 & 0.25 & 0.25 & 0.25 \\ 0.25 & 0.25 & 0.00 & 0.25 & 0.25 \\ 0.25 & 0.25 & 0.25 & 0.00 & 0.25 \\ 0.25 & 0.25 & 0.25 & 0.25 & 0 \end{bmatrix}$
Queen Contiguity	$\boldsymbol{W}_{(Q)}$	$\begin{bmatrix} 0.00 & 0.00 & 1.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 1.00 & 0.00 & 0.00 \\ 0.25 & 0.25 & 0.00 & 0.25 & 0.25 \\ 0.00 & 0.00 & 1.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 1.00 & 0.00 & 0.00 \end{bmatrix}$

Weight	**Not.**	**Matrix**
Inverse Distance	$\boldsymbol{W}_{(I)}$	$\begin{bmatrix} 0.00 & 0.45 & 0.19 & 0.22 & 0.14 \\ 0.46 & 0.00 & 0.19 & 0.24 & 0.12 \\ 0.15 & 0.14 & 0.00 & 0.55 & 0.16 \\ 0.16 & 0.18 & 0.54 & 0.00 & 0.12 \\ 0.22 & 0.19 & 0.33 & 0.26 & 0.00 \end{bmatrix}$

Test the stationarity of the data at each location as the next step. The visual plot that is presented in Fig. 1 can serve as a basis for this stationary test. It is possible to draw the conclusion that the data is not stationary because all five countries exhibit significant fluctuations. Because of this, the data for each country are differentiate. Afterward, the outcomes of the differentiation are depicted in Figure 4, as shown.

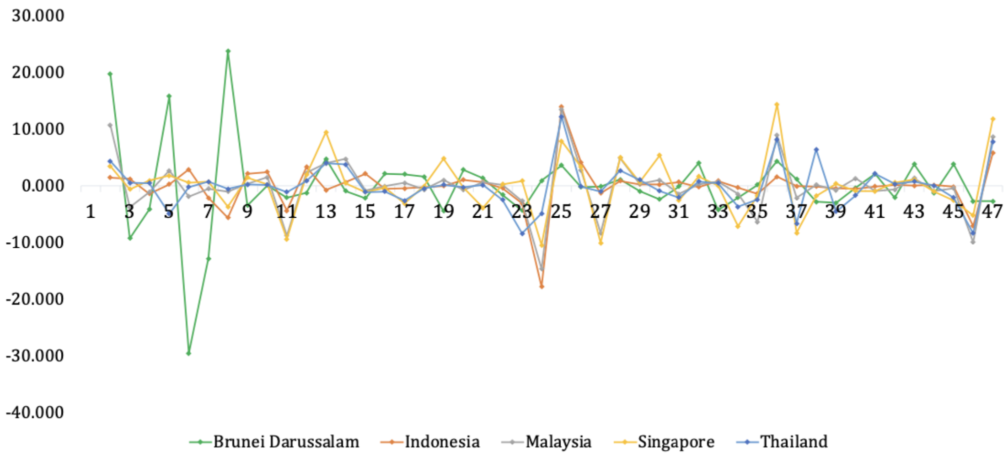
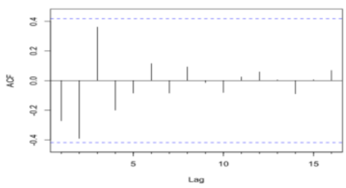
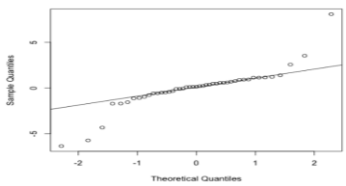
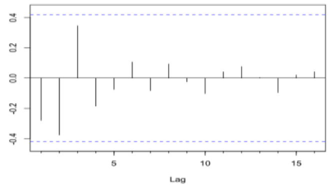
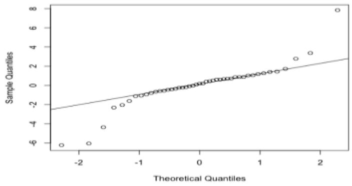
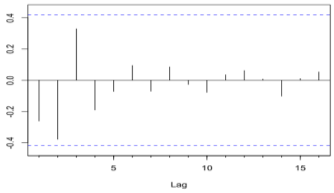
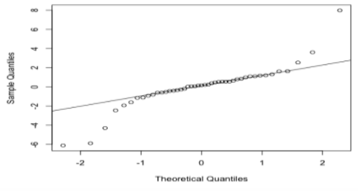


Figure 4. Differencing plot

In the present study, the order of the GSTAR model is restricted to the (1,1). Following this, parameter estimation is carried out for the GSTAR (1,1) model using a variety of weight matrices, as outlined in Table 4. The columns labelled "independence" and "normality" have been placed in Table 4 and assigned to the residuals of each GSTAR (1;1) model. This stage falls under the diagnostic test category so that a comparison may be made to determine whether the data are suitable for the model, as shown in Table 4.

Table 4. Parameter estimation and diagnostic test of GSTAR(1;1) model for each weight

Weight	**Parameter**				**Independency**	**Normality**	**MSE**
$\boldsymbol{W}_{(U)}$	$\phi_{10}^{(1)}$	- 0.274	$\phi_{11}^{(1)}$	- 0.061			334.444
	$\phi_{10}^{(2)}$	- 0.436	$\phi_{11}^{(2)}$	0.275			
	$\phi_{10}^{(3)}$	- 0.970	$\phi_{11}^{(3)}$	0.958			
	$\phi_{10}^{(4)}$	- 0.308	$\phi_{11}^{(4)}$	- 0.060			
	$\phi_{10}^{(5)}$	- 0.064	$\phi_{11}^{(5)}$	- 0.318			
$\boldsymbol{W}_{(Q)}$	$\phi_{10}^{(1)}$	- 0.259	$\phi_{11}^{(1)}$	- 0.408			375.423
	$\phi_{10}^{(2)}$	- 0.261	$\phi_{11}^{(2)}$	0.262			
	$\phi_{10}^{(3)}$	-0.97	$\phi_{11}^{(3)}$	0.239			

Weight	Parameter				Independency	Normality	MSE
	$\phi_{10}^{(4)}$	-0.022	$\phi_{11}^{(4)}$	-1.588			
	$\phi_{10}^{(5)}$	0.125	$\phi_{11}^{(5)}$	-1.739			
$W_{(I)}$	$\phi_{10}^{(1)}$	-0.274	$\phi_{11}^{(1)}$	-0.119			356.769
	$\phi_{10}^{(2)}$	-0.367	$\phi_{11}^{(2)}$	0.234			
	$\phi_{10}^{(3)}$	-1.157	$\phi_{11}^{(3)}$	0.950			
	$\phi_{10}^{(4)}$	-0.246	$\phi_{11}^{(4)}$	-0.128			
	$\phi_{10}^{(5)}$	-0.073	$\phi_{11}^{(5)}$	-0.557			

According to Table 4, the GSTAR(1;1) model that utilises uniform weights is the most accurate representation of the data because it has the lowest MSE value. eq. (7) shows the best GSTAR(1,1) model for annual GDP data (%) using uniform weights,

$$\begin{bmatrix} Y_t^{(1)} \\ Y_t^{(2)} \\ Y_t^{(3)} \\ Y_t^{(4)} \\ Y_t^{(5)} \end{bmatrix} = \left(\begin{bmatrix} -0.274 & 0 & 0 & 0 & 0 \\ 0 & -0.436 & 0 & 0 & 0 \\ 0 & 0 & -0.970 & 0 & 0 \\ 0 & 0 & 0 & -0.308 & 0 \\ 0 & 0 & 0 & 0 & -0.064 \end{bmatrix} + \begin{bmatrix} -0.061 & 0 & 0 & 0 & 0 \\ 0 & 0.275 & 0 & 0 & 0 \\ 0 & 0 & 0.958 & 0 & 0 \\ 0 & 0 & 0 & -0.060 & 0 \\ 0 & 0 & 0 & 0 & -0.318 \end{bmatrix} \begin{bmatrix} 0.00 & 0.25 & 0.25 & 0.25 & 0.25 \\ 0.25 & 0.00 & 0.25 & 0.25 & 0.25 \\ 0.25 & 0.25 & 0.00 & 0.25 & 0.25 \\ 0.25 & 0.25 & 0.25 & 0.00 & 0.25 \\ 0.25 & 0.25 & 0.25 & 0.25 & 0 \end{bmatrix} \right) \begin{bmatrix} Y_{t-1}^{(1)} \\ Y_{t-1}^{(2)} \\ Y_{t-1}^{(3)} \\ Y_{t-1}^{(4)} \\ Y_{t-1}^{(5)} \end{bmatrix}$$

by solving eq. (7), a model for each is obtained

$$\begin{aligned} Y_t^{(1)} &= -0.274Y_{t-1}^{(1)} - 0.015Y_{t-1}^{(2)} - 0.015Y_{t-1}^{(3)} - 0.015Y_{t-1}^{(4)} - 0.015Y_{t-1}^{(5)} \\ Y_t^{(2)} &= 0.069Y_{t-1}^{(1)} - 0.436Y_{t-1}^{(2)} + 0.069Y_{t-1}^{(3)} + 0.069Y_{t-1}^{(4)} + 0.069Y_{t-1}^{(5)} \\ Y_t^{(3)} &= 0.239Y_{t-1}^{(1)} + 0.239Y_{t-1}^{(2)} - 0.970Y_{t-1}^{(3)} + 0.239Y_{t-1}^{(4)} + 0.239Y_{t-1}^{(5)} \\ Y_t^{(4)} &= -0.015Y_{t-1}^{(1)} - 0.015Y_{t-1}^{(2)} - 0.015Y_{t-1}^{(3)} - 0.308Y_{t-1}^{(4)} - 0.015Y_{t-1}^{(5)} \\ Y_t^{(5)} &= -0.079Y_{t-1}^{(1)} - 0.079Y_{t-1}^{(2)} - 0.079Y_{t-1}^{(3)} - 0.079Y_{t-1}^{(4)} - 0.064Y_{t-1}^{(5)} \end{aligned} \tag{8}$$

According to equation (8), the country that has the highest impact (look at the parameter coefficients in $Y_t^{(3)}$) in GDP value is Malaysia, which is represented by the blue figures. This is due to the fact that in the year prior, the value of Malaysia's GDP was greatly influenced by the GDP values of the four nations that were located immediately surrounding it. These countries were Brunei (0.239), Indonesia (0.239), Singapore (0.239), and Thailand (by 0.239). Aside from that, the GDP value in Malaysia is of obviously also influenced by the GDP in the previous year, which was -0.97, and this influences the GDP value in Malaysia. Despite Thailand is the only nation in the region to have a GDP value in the current year, this value is, as a matter of course, affected by the four countries that surround it; nevertheless, this influence is not significant. By looking at the parameter coefficients in eq. (8), specifically the parameter coefficients for the independent variables $Y_{t-1}^{(i)}$ whose locations are not the same as the locations on the dependent variable $\left(Y_t^{(j)}\right)$ $(i \neq j)$, as a result will see that the parameter coefficient values are the same for all locations. If it's taken a look at the equation for $Y_t^{(1)}$, for example, it's apparent that the parameter coefficients for $Y_{t-1}^{(2)}$, $Y_{t-1}^{(3)}$, $Y_{t-1}^{(4)}$ and $Y_{t-1}^{(5)}$ are all the same value: -0.015. The same may be said for the remaining equations, which are $Y_t^{(2)}$, $Y_t^{(3)}$, $Y_t^{(4)}$ and $Y_t^{(5)}$. This occurs because the weights that are used are all uniform value. The assumption underlying this weight is that the effect of other places on the location of the object is not different from what it would be ordinarily. The correlation between Malaysia and Singapore is particularly high because of the tight economic ties that exist between the two countries and the mutual effect that they exert on one another. There are a number of explanations for a correlation between the GDP rates in Malaysia and Singapore, including the following:

a. Economic Dependence (Malaysia is one of Singapore's largest trading partners, and both countries enjoy tight trade links). Malaysia is one of Singapore's largest commercial partners.
b. Industrial Linkages (Singapore has a developed and fast-growing manufacturing sector, while Malaysia has abundant natural resources, such as oil and natural gas. The processing and distribution of Malaysian goods takes place mostly in Singapore, which plays a key role in this regard).
c. Cross-Investment (businesses based in Singapore frequently make investments in Malaysia, and companies based in Malaysia frequently use Singapore as a regional center for finance and business).

Sustainability in the Region (Both Malaysia and Singapore are members of ASEAN, which stands for the Association of Southeast Asian Nations, and both countries have made a commitment to create a region that is more economically linked). Determining the weight matrix is indeed an important part of the process if it is connected to the pertinent research that was discussed at the beginning of the discussion. Because the conditions under which the data were collected have a significant impact on the process of determining the weight matrix, modeling GSTAR requires analyzing multiple distinct weight matrices side by side.

D. CONCLUSION AND SUGGESTIONS

The GDP rates of the five countries have mutually influential relationships, both historically and geographically. This is something that can be determined by looking at the original assumption, which is the correlation value between various locations. In order to conduct additional research and analysis addressing the association between time and location in terms of GDP, the GSTAR model is used. The GSTAR model's order is constrained to order 1 over the length of this inquiry, which encompasses autoregressive time as well as location. This restriction will remain in place until further notice. To put it another way, it is generally accepted as fact that the GDP of a nation at any given point in time is entirely determined by the GDP of the countries that bordered it in the preceding year. This is how the GDP calculation works. The order of the GSTAR model is not what is addressed in this study; rather, the weight matrix that was utilized is highlighted. When utilizing the GSTAR (1; 1) model to describe the temporal and spatial correlation of GDP cases among nations, a uniform weight matrix is obtained from the three different weight matrices. This uniform weight matrix is the one that is most appropriate to characterize the time and spatial correlation. The fact that the MAPE is the smallest among the other two weight matrices is an indication of this fact. The concept behind the uniform weight matrix is that the Gross Domestic Product (GDP) of any country has the same effect on the countries that surround it. This indicates that whenever there is a rise or drop in Indonesia's GDP, there is a corresponding increase or decrease in the GDP of Indonesia's bordering countries.

REFERENCES

Aitken, A. (2019). Measuring Welfare Beyond GDP. *National Institute Economic Review*, *249*, R3–R16. https://doi.org/10.1177/002795011924900110

Fan, V. Y., Bloom, D. E., Ogbuoji, O., Prettner, K., & Yamey, G. (2018). Valuing health as development: going beyond gross domestic product. *BMJ*, k4371. https://doi.org/10.1136/bmj.k4371

Hagerty, M. R., & Veenhoven, R. (2003). Wealth and Happiness Revisited – Growing National Income Does Go with Greater Happiness. *Social Indicators Research*, *64*(1), 1–27. https://doi.org/10.1023/A:1024790530822

Hasan, R., & Barua, S. (2015). Financial Development and Economic Growth: Evidence from a Panel Study on South Asian Countries. *Asian Economic and Financial Review*, *5*(10), 1159–1173.

Huda, N. M., & Imro'ah, N. (2023). Determination of the best weight matrix for the Generalized Space Time Autoregressive (GSTAR) model in the Covid-19 case on Java Island, Indonesia. *Spatial Statistics*, *54*, 100734. https://doi.org/10.1016/j.spasta.2023.100734

Huda, N. M., Mukhaiyar, U., & Imro'ah, N. (2022). An Iterative Procedure For Outlier Detection In GSTAR (1;1) MODEL. *BAREKENG: Jurnal Ilmu Matematika Dan Terapan*, *16*(3), 975–984. https://doi.org/10.30598/barekengvol16iss3pp975-984

Huda, N. M., Mukhaiyar, U., & Pasaribu, U. S. (2021). The Approximation of GSTAR Model for Discrete Cases through INAR Model. *Journal of Physics: Conference Series*, *1722*(1), 012100. https://doi.org/10.1088/1742-6596/1722/1/012100

Kahoun, J., & Sixta, J. (2013). Regional GDP Compilation: Production, Income and Expediture Approach. *Statistika: Statistics and Economy Journal*, *93*(4), 24–36.

Konchitchki, Y., & Patatoukas, P. N. (2014). Taking the Pulse of the Real Economy Using Financial Statement Analysis: Implications for Macro Forecasting and Stock Valuation. *The Accounting Review*, *89*(2), 669–694. https://doi.org/10.2308/accr-50632

Mukhaiyar, U., Huda, N. M., Novita Sari, R. K., & Pasaribu, U. S. (2019). Modeling Dengue Fever Cases by Using GSTAR(1;1) Model with Outlier Factor. *Journal of Physics: Conference Series*, *1366*(1), 012122. https://doi.org/10.1088/1742-6596/1366/1/012122

Mukhaiyar, U., & Pasaribu, U. S. (2012). A New Procedure of Generalized STAR Modeling using IAcM Approach. *ITB Journal of Sciences*, *44*(2), 179–192. https://doi.org/10.5614/itbj.sci.2012.44.2.7

Nguyen, T. T., Pham, T. A. T., & Tram, H. T. X. (2020). Role of information and communication technologies and innovation in driving carbon emissions and economic growth in selected G-20 countries. *Journal of Environmental Management*, *261*, 110162. https://doi.org/10.1016/j.jenvman.2020.110162

Onuoha, D. O., Ibe, A., Njoku, C. U., & Onuoha, J. I. (2015). Analysis of The Gross Domestic Product (G.D.P) of Nigeria:1960-2012. *West African Journal of Industrial and Academic Research*, *14*(1).

Pasaribu, U. S., Mukhaiyar, U., Huda, N. M., Sari, K. N., & Indratno, S. W. (2021). Modelling COVID-19 Growth Cases of Provinces in Java Island by Modified Spatial Weight Matrix GSTAR through Railroad Passenger's Mobility. *Heliyon*, *7*(2), e06025. https://doi.org/10.1016/j.heliyon.2021.e06025

Pérez-Moreno, S., Rodríguez, B., & Luque, M. (2016). Assessing global competitiveness under multi-criteria perspective. *Economic Modelling*, *53*, 398–408. https://doi.org/10.1016/j.econmod.2015.10.030

Ruchjana, B. N., Borovkova, S. A., & Lopuhaa, H. P. (2012). *Least Squares Estimation of Generalized Space Time AutoRegressive (GSTAR) Model and Its Properties*. 61–64. https://doi.org/10.1063/1.4724118

Saputra, F., & Hapzi Ali. (2021). The Impact of Indonesia's Economic and Political Policy Regarding Participation in Various International Forums: G20 Forum (Literature Review of Financial

Management). *Journal of Accounting and Finance Management*, *2*(1), 40–51. https://doi.org/10.38035/jafm.v2i1.50

Wan, Y., & Sheng, N. (2022). Clarifying the relationship among green investment, clean energy consumption, carbon emissions, and economic growth: a provincial panel analysis of China. *Environmental Science and Pollution Research*, *29*(6), 9038–9052. https://doi.org/10.1007/s11356-021-16170-w

Yundari, Pasaribu, U. S., Mukhaiyar, U., & Heriawan, M. N. (2018). Spatial Weight Determination of GSTAR(1;1) Model by Using Kernel Function. *Journal of Physics: Conference Series*, *1028*, 012223. https://doi.org/10.1088/1742-6596/1028/1/012223

Yundari, Y., Huda, N. M., Pasaribu, U. S., Mukhaiyar, U., & Sari, K. N. (2020). *Stationary Process in GSTAR(1;1) through Kernel Function Approach*. 020010. https://doi.org/10.1063/5.0016808