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Modelling of Forecasting ASEAN-5 Stock Price Index Using GSTAR Model

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ABSTRACT

This research aims to apply the Generalized Space-Time Autoregressive (GSTAR) model to predict stock price indices in ASEAN-5 countries. Generalized Space Time Autoregressive (GSTAR) model is one of the most common used space-time model to modeling and predicting spatial and time series data. The GSTAR model produces a space-time model that adopts the stages of the Autoregressive Integrated Moving Average (ARIMA) model. This research uses parameter estimation using the Maximum Likelihood method, which is a method used to estimate parameter values by maximizing the probability function seen based on observations. This research uses secondary data in the form of Stock Price Index data from 5 countries in Asia, namely the Composite Stock Price Index (JCI), Philippine Stock Exchange (PSEi), Strait Time Index (STI), Kuala Lumpur Composite Index (KLCI), and Thailand Stock Exchange Index (SETI). Stock Price Index data was divided into in-sample data for Generalized Space-Time Autoregressive (GSTAR) modelling and out-sample data used to validate presumptive results. In-sample data was taken from January 4, 2021, to December 29, 2023, and then out-sample data for presumptive was as many as 5 from January 2, 2024, to January 8, 2024. From the modeling results, it was found that the mean MAPE value of the GSTAR model was smaller than that of the ARIMA model. Moreover, based on the presumptive results for the following 5 periods using the GSTAR (2.1) I(1) model, a Mean Absolute Percentage Error (MAPE) of less than 10% in each location. The values shows that GSTAR model is more accurate than the ARIMA model.

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A. INTRODUCTION

The weakening of the Chinese economy due to the Covid-19 pandemic caused great changes not only in the Chinese stock market but also had an impact on the ASIAN stock market, especially ASEAN-5. The capital market performance during the COVID-19 in ASEAN-5 during pandemic have decreased generally. Several companies on the LQ 45 index experienced an increase in share prices during the COVID-19 pandemic, such as Erajaya Self-Sufficiency, Bank Central Asia, Sarana Menara Nusantara, Charoen Pokphand Indonesia, Vale Indonesia, Bank BTPN Syariah, Surya Citra Media, Indah Kiat Pulp & Paper, and United Tractors Tbk (Sayadi & Sari, 2021). In fact, until the end of August 2023, Asian stock markets weakened, causing record losses for some investors. Using a causality test, Huang et al. (2023)argue that the ASEAN and Chinese stock markets have a two-way Granger causation relation to evolving features. During the COVID-19 pandemic, Fatah et al. (2023) used the Vector Autoregressive (VAR) model to find correlations between the ASEAN-5 stock markets. The study's findings demonstrate a relationship between the ASEAN-5 stock markets, as seen by a series of price index declines. The capital market reaction can also be seen in the decline in world oil prices due to the Russian invasion Ukraine in 2022. The atypical return of the ASEAN-5 stock index exhibited a major negative reaction before to the decrease in world oil prices, but at the time of the occurrence, it created a substantial positive reaction (Agung et al., 2023).

Changes in a stock price index followed by another stock price index occur because there is an integration between one stock price index and another (Patel, R., et al., 2022). Capital market integration is a topic of interest to stock market researchers Jacob et al. (2021) because the phenomenon of financial integration is closely related to financial markets in neighboring, regional and global countries. Moreover, the stock market is an essential component in a country's economy, where most of the capital presence of stock markets is exchanged worldwide. Therefore, stock market performance significantly influences the national economy (Gao et al., 2020). It is called capital market integration (Cahyaningrum & Robiyanto, 2021). In addition, there is also a segmented capital market. A segmented capital market has the opposite meaning of capital market integration (Sella et al., 2021). In a segmented capital market, there are restrictions on capital flows, and stock prices with the same risk have returns that are not interrelated between capital markets. This is related to Behavior Finance. Therefore, strange phenomena are created that will not be captured by the Capital Asset Pricing Model alone.

Stock indices or stock market indices are not only useful for helping investors compare current price levels with previous values but can also be used to measure the performance of the stock market in a country. There are various statistical models for calculating stock market indices (Verma et al., 2021). This statistical measurement is critical in determining the trend of stock price movements Orimoloye et al. (2020) with a series of calculations that combine the index calculation methodology with a choice of capital market and financial instruments. Investors and portfolio managers can benefit by predicting when stock prices will rise or fall (Yıldız et al., 2022). One of the things an investor often does before making a decision is to use a model to presumptive future stock prices. Accurately predicting stock price indices is very important for all financial market stakeholders. This is important not only for the success of risk-al streaming investors but also for the policy-making of monetary regulatory authorities. The effectiveness of financial market risk management will increase significantly if stock price index fluctuations can be predicted accurately (Huang et al., 2022).

The accuracy of predictions and the complexity of appropriate modeling stimulated much research especially in financial presumptive. Presumptive the stock market price index is a challenging task (Niu et al., 2020). Many models have been developed from this process of presumptive stock prices. One of them is time series analysis and presumptive is an active field of research. Time series data prediction is a crucial topic in business, finance, and economics. Due to insufficient information on the one hand and unforeseen changes in economic trends and conditions on the other, predicting financial and economic time series data is a difficult assignment (Siami-Namini & Namin, 2018). The accuracy of time series analysis and presumptive is fundamental in the decision-making process. Time series analysis in the observation process can be classified into univariate and multivariate models. One of the time series analyzes that supports univariate model-based forecasting that is often used is ARIMA.

Many studies in the financial sector use ARIMA methods such as forecasting volatility risk in the industrial sector (Wadi, 2017), forecasting of Chinese E-Commerce sales(Li et al., 2018), and forecasting the deposit interest rate (Sahin, 2023). The ARIMA methods is a classic time series model for predictions in the financial sector. This model has the main weakness, namely that it only utilizes time effects and ignores economic interactions between regions. The ARIMA model is a classic time series model for predictions in the financial sector. This model has the main weakness, namely that it only utilizes time effects and ignores economic interactions between regions. Therefore, the GSTAR multivariate time series method is currently being developed which not only takes into account time effects, but also location effects. Some applications of the GSTAR method in the field of financial economics are determination of consumer price index (Harini & Nuronia, 2020), forecasting house prices in metropolises (Chini, 2020), and inflation forecasting models (Hestuningtias & Kurniawan, 2023). Multivariate time series based forecasting is a type of forecasting that has more than one criterion that changes from time to time so that it can make more accurate predictions than univariate based forecasting (Yin & Shang, 2016). The prediction results of the GSTAR method have an accuracy rate of 7% -38% higher than the ARIMA model (Ji et al., 2019). On the other hand, research by Hamsyah (2015) shows that modeling results using the ARIMA univariate time series model produce smaller MAPE values compared to the GSTAR multivariate model. Based on the differences in accuracy results of time series models in previous research, this research aims to select the best time series model between the ARIMA or GSTAR models to predict financial data for the ASEAN-5 stock price index.

B. METHODS

This research uses secondary data from the financial website finance.yahoo.com. There are five variables used, Strait Time Index/STI (Singapore), Jakarta Composite Index/JCI (Indonesia), Securities Exchange of Thailand Index/SETI (Thailand), Philippine Stock Exchange/PSE (Philippines), and Kuala Composite Stock Price Index Mud/KLCI (Malaysia). The data collection period is from 4 January 2021 to 8 January 2024 and divided into sample data as January 2021-December 2023 and out sample data as January 2024.

In this research, data was processed using R software. R software was chosen because it has many advantages such as being multiplatform (available for Windows, Linux, Macintosh and Unix operating systems), good software reliability, availability of complete updates and libraries, as well as help facilities for free of charge users. GSTAR model analysis using R starts from inputting data, plotting data, estimating parameters, creating models, to diagnostic tests. For the purposes of analyzing the GSTAR model with R Studio, use the GSTAR package including Library (gstar) and library (xts). The steps for forming the GSTAR model are as follows (Talungke et al., 2015)(Zaenal & Revadiansyah, 2022):

1. Explore share price data in five Southeast Asian countries and calculate the Gini index to check for location heterogeneity. The Gini index is a coefficient that shows an observation's unevenness level to test the heterogeneity of locations. Gini index values range from 0 to 1. A location is said to have perfect evenness (homogeneous) if the Gini index value is close to 0 and vice versa. The Gini index is calculated based on the formula below:

$$G=1+\frac{1}{T}-\frac{2}{T^2\bar{Z}_t}\sum_{i=1}^{N}\sum_{i=1}^{T}Z_t$$

Information: Z_t is the value of the observed variable based on the sample index t; $\bar{Z}_t$ *is* Average of the values of all observed variables; T is Many observations (time) $N$is Many lookouts.

2. The formation of weighting matrices use distance inverse location weights.
3. Perform autocorrelation tests using Pearson's correlation coefficient. Testing using the Pearson test was chosen because the calculations are relatively simple and suitable for interval and ratio data types. The Pearson correlation test was used to determine the relationship between variables. The greater the absolute value of the Pearson correlation coefficient, the stronger the relationship.
4. Conducting a stationary test of stock price data is the same both on variety and average. Testing can be through Augmented Dickey-Fuller (ADF) tests or data plots. Log transformation and differencing are carried out if the data is not stationary until fixed data is obtained on variety and average.
5. Identify the GSTAR model by determining spatial order and time order. Spatial orders are limited to one order only, while time orders can be identified based on the significant lag in MACF plots as order vector moving averages and autoregressive order vectors can be identified through MPACF plots based on significant lag.
6. Estimating GSTAR model parameters with the Ordinary Least Square (OLS) method.
7. Selection of the smallest MAPE, AIC and BIC as the basis for selecting the best model.
8. Make predictions based on the best model.

C. RESULT AND DISCUSSION

1. Data Exploration

In this section, data exploration uses descriptive analysis to illustrate stock price index data in five countries in ASEAN. Figure 1 displays the time series plot of the stock price index data.

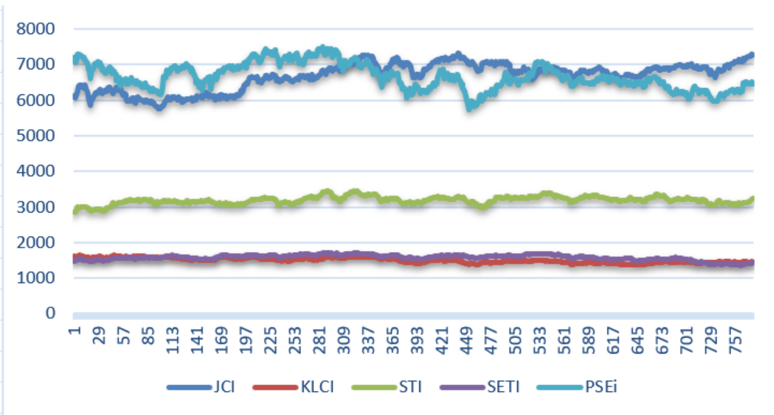


Figure 1. Stock Price Indices Data Plot of ASEAN-5

Based on Figure 1, the stock proce indices in the five country on ASEAN fluctuated. From January 2021 to April 2022, PSEi Index saw the highest levels of stock price indices among the five country on ASIA. Meanwhile, starting April 2022, the Indonesian stock price index JCI will move up and occupy the top position among the five ASEAN-5 countries. The lowest position is occupied by the Malaysian stock price index KLCI, as shown in Table 1.

Table 1. Descriptive Statistics of Stock Price Index Data of ASEAN-5

	JCI ($Z_t^{(1)}$)	**KLCI** ($Z_t^{(2)}$)	**STI** ($Z_t^{(3)}$)	**SETI** ($Z_t^{(4)}$)	**PSEi** ($Z_t^{(5)}$)
Min	5761	1373	2859	1358	5741
1 st Qu	6428	1447	3121	1540	6404
Median	6791	1495	3193	1591	6607
Mean	6681	1503	3189	1581	6666
3 rd Qu	6952	1570	3257	1635	6951
Max	7318	1640	3445	1713	7502

2. Inflation Data Correlation Between Locations

The assumption of GSTAR model is the correlation between observation locations. The relationship between one location and another can be used to test the correlation between locations. With a confidence level of 95%, the existing data rejects H0. The t-value and p-value are given to test the correlation between the stock indices of the other two countries in Table 2 below:

Table 2. ASEAN-5 Country Correlation Test Results

	JCI	**KLCI**	**STI**	**SETI**	**PSEi**
JCI		-15.434 [2.2e-16]	15.31 [2.2e-16]	2.1476 [0.03205]	-5.1523 [3.267e-07]
KLCI	-15.434 [2.2e-16]		-2.5714 [0.01031]	11.201 [2.2e-16]	20.424 [2.2e-16]
STI	15.31 [2.2e-16]	-2.5714 [0.01031]		17.146 [2.2e-16]	5.336 [1.248e-07]
SETI	2.1476 [0.03205]	11.201 [2.2e-16]	17.146 [2.2e-16]		19.152 [2.2e-16]
PSEi	-5.1523 [3.267e-07]	20.424 [2.2e-16]	5.336 [1.248e-07]	19.152 [2.2e-16]	

The value of the correlation coefficient can also be used to determine the strength or weakness of a relationship between these countries. The correlation coefficients between countries are shown in Table 3.

Table 3. Correlation of Stock Price Index between Country on ASEAN-5

	JCI	**KLCI**	**STI**	**SETI**	**PSEi**
JCI	1	-0.48488577	0.48187447	0.07691664	-0.1819857
KLCI		1	-0.09197687	0.37325929	0.5915328
STI			1	0.52442167	0.1882491
SETI				1	0.5667887
PSEi					1

Based on Table 3, it can be seen that the correlation value between the stock price index of Malaysia and the Philippines has the highest number compared to the correlation between the other two countries. This shows a reasonably strong relationship between KLCI and PSEi compared to other stock indices for the correlation value of the other two countries. Based on the correlation test results, it can be concluded that the data meets the assumptions of the GSTAR model, where each observation location is interconnected.

3. Spatial Heterogeneity Test

The heterogeneous characteristics assumption must be satisfied by the implementation of the GSTAR data model. The characteristics of each observation location were estimated using the Gini Index test statistic in order to perform the spatial heterogeneity test, as shown in Table 4.

Table 4. Spatial Heterogeneity Test

Country	Gini Index Value
Indonesia	1.000154
Malaysia	1.000154
Singapore	1.000154
Thailand	1.000154
Philippines	1.000154

The decision to reject H0 is based on Table 4, which indicates that there is variability between locations in the stock price index data in the ASEAN-5 countries. Each country's computed Gini Index value is more than 1.

4. Data Stasionecity Test

In time-series models, the data used must be stationary. If testing the resulting data is not stationary, it must be overcome by carrying out a different process until it is stationary to proceed to the subsequent analysis process. One test that can be used to determine data stationarity is the ADF test. The next is Table 5, which shows ADF test results at level levels for stock price index data in five ASEAN-5 countries.

Table 5. ADF Level Level Test

Index	p-value		α
JCI	0,747	>	0,05
KLCI	0,370	>	0,05
STI	0,794	>	0,05
SETI	0,681	>	0,05
PSEi	0,502	>	0,05

Table 5 shows that none of the Stock Price Index data of the five ASEAN-5 countries are stationary at the Level using a significance level of $\alpha = 5\%$. Furthermore, the first differencing was done for the five stock price data. The results of 1st differencing are given in Table 6.

Table 6. ADF 1st differencing test

Index	p-value		α
JCI	0,01	<	0,05
KLCI	0,01	<	0,05
STI	0,01	<	0,05
SETI	0,01	<	0,05
PSEi	0,01	<	0,05

According to Table 6, the p-value for each of the five locales is less than α = 5 so H0 is rejected. Based on the 95 confidence position, it can be deduced that the ASEAN-5 stock price indicator data were either previously stationary or did not contain a unit root, which would allow for future analysis with GSTAR models.

5. ARIMA ultivariate Modeling

In determining the best ARIMA model for each ASEAN-5 stock price index use the auto.Arima function available in R Studio. The best model results are given in the following Table 7.

Table 7. Best ARIMA Model for ASEAN-5

Index	Univariat ARIMA modeling
JCI	ARIMA (3,1,2)
KLCI	ARIMA (0,1,0)
STI	ARIMA (0,1,2)
SETI	ARIMA (4,1,0)
PSEi	ARIMA (0,1,0)

6. GSTAR Multivariate Modeling

In determining the order of time (autoregressive) in the GSTARIMA model, the order of the VAR model (p) can be used. The identification of the order of the VAR model is determined by the optimal lag length, i.e., by looking at the smallest AIC values of the lag range, as shown in Table 8.

Table 8. AIC Value in the VAR Model

Lag	1	2	3	4	5
AIC	7.5070	7.5064	7.5068	7.5069	7.5071
Lag	6	7	8	9	10
AIC	7.5074	7.5078	7.5081	7.5085	7.5085

Table 8 explains that the smallest AIC value is at the 2nd lag. Thus, it can be concluded that the autoregressive order of the GSTARIMA model is 2. Based on the AIC value, the GSTAR model obtained is GSTAR (2,1) I(1).

7. Calculation of Location Weights for the GSTAR Model

The GSTAR model is part of the space-time model. Where in constructing models and forecasting, we do not only look at the element of time but also use location as a consideration. In this study, the inverse distance location weights were used. The inverse distance weight is determined based on the real distance between observation locations by considering latitude and longitude. The distance between observation locations based on latitude and longitude is given in the form of a distance matrix as follows:

$$d_{ij} = \begin{vmatrix} 0 & 10{,}78 & 8{,}23 & 20{,}99 & 25{,}13 \\ 10{,}76 & 0 & 2{,}70 & 10{,}66 & 22{,}54 \\ 8{,}23 & 2{,}70 & 0 & 12{,}82 & 21{,}91 \\ 20{,}99 & 10{,}66 & 12{,}82 & 0 & 20{,}65 \\ 25{,}13 & 22{,}54 & 21{,}91 & 20{,}65 & 0 \end{vmatrix}$$

Based on the matrix above, the farthest distance can be obtained from Indonesia to the Philippines, namely 25.13 km, while the closest distance between the two observation locations is between Malaysia and Singapore, 2.70 km. And then we will obtain an inverse distance weighting matrix for the five countries of observation.

$$W_{ij} = \begin{vmatrix} 0 & 0{,}278 & 0{,}291 & 0{,}226 & 0{,}205 \\ 0{,}256 & 0 & 0{,}314 & 0{,}257 & 0{,}172 \\ 0{,}273 & 0{,}314 & 0 & 0{,}239 & 0{,}173 \\ 0{,}226 & 0{,}279 & 0{,}268 & 0 & 0{,}228 \\ 0{,}240 & 0{,}250 & 0{,}252 & 0{,}257 & 0 \end{vmatrix}$$

From the inverse distance weight values obtained, the distance between two locations that is further away is given a smaller weight value compared to the distance that is closer.

8. GSTAR Model Parameter Estimation (2,1) I(1)

Adding location weights will produce different estimated parameter values at each observation location. GSTAR model parameter estimation was carried out on location weights using the least squares method. At the identification stage, a GSTAR (2,1) I(1) model was formed with the location weights used, namely the inverse distance weights. The values of all parameters of the GSTAR (2,1) I(1) model with inverse distance weighting were estimated to produce 20 parameters which are presented in Table 9.

Table 9. GSTAR Model Parameter Estimation (2,1) I(1)

Parameter	Estimate	Parameter	Estimate
$\hat{\phi}_{10}^{(1)}$	-0.097405	$\hat{\phi}_{11}^{(1)}$	0.092515
$\hat{\phi}_{10}^{(2)}$	-0.056846	$\hat{\phi}_{11}^{(2)}$	0.034195
$\hat{\phi}_{10}^{(3)}$	0.006250	$\hat{\phi}_{11}^{(3)}$	0.042866
$\hat{\phi}_{10}^{(4)}$	0.030342	$\hat{\phi}_{11}^{(4)}$	0.038440
$\hat{\phi}_{10}^{(5)}$	-0.115330	$\hat{\phi}_{11}^{(5)}$	0.862990
$\hat{\phi}_{20}^{(1)}$	-0.046501	$\hat{\phi}_{21}^{(1)}$	0.325535
$\hat{\phi}_{20}^{(2)}$	0.066933	$\hat{\phi}_{21}^{(2)}$	-0.016676
$\hat{\phi}_{20}^{(3)}$	0.113655	$\hat{\phi}_{21}^{(3)}$	0.009457
$\hat{\phi}_{20}^{(4)}$	-0.076815	$\hat{\phi}_{21}^{(4)}$	0.021081
$\hat{\phi}_{20}^{(5)}$	-0.059560	$\hat{\phi}_{21}^{(5)}$	-0.097313

The results of estimating the GSTAR (2,1) I(1) parameters using the inverse distance weights are given in the equations below:

$$Z_t^{(1)} = -0.097\ Z^1_{(t-1)} + 0.026\ Z^2_{(t-1)} + 0.027\ Z^3_{(t-1)} + 0.021\ Z^4_{(t-1)} + 0.019\ Z^5_{(t-1)} - 0.047\ Z^1_{(t-2)} + 0.091\ Z^2_{(t-2)} + 0.095\ Z^3_{(t-2)} + 0.074\ Z^4_{(t-2)} + 0.067\ Z^5_{(t-2)} + e_1(t)$$

$$Z_t^{(2)} = -0.057\ Z^2_{(t-1)} + 0.009\ Z^1_{(t-1)} + .011\ Z^3_{(t-1)} + 0.009\ Z^4_{(t-1)} + 0.006\ Z^5_{(t-1)} + 0.067\ Z^2_{(t-2)} - 0.004\ Z^1_{(t-2)} - 0.005\ Z^3_{(t-2)} - 0.004\ Z^4_{(t-2)} - 0.003\ Z^5_{(t-2)} + e_2(t)$$

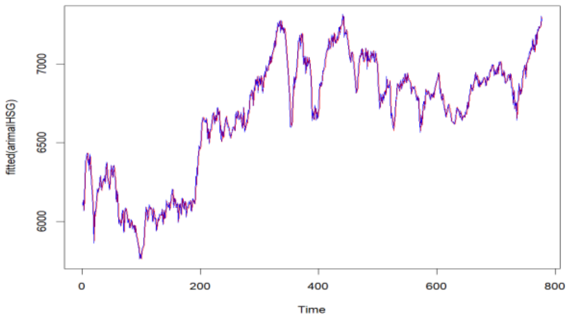
$$Z_t^{(3)} = 0.006\ Z^3_{(t-1)} + 0.012\ Z^1_{(t-1)} + 0.013\ Z^2_{(t-1)} + 0.010\ Z^4_{(t-1)} + 0.007\ Z^5_{(t-1)} + 0.114\ Z^3_{(t-2)} + 0.003\ Z^1_{(t-2)} + 0.003\ Z^2_{(t-2)} + 0.002\ Z^4_{(t-2)} + 0.002\ Z^5_{(t-2)} + e_3(t)$$

$$Z_t^{(4)} = 0.030\ Z^4_{(t-1)} + 0.009\ Z^1_{(t-1)} + 0.011\ Z^2_{(t-1)} + 0.010\ Z^3_{(t-1)} + 0.009\ Z^5_{(t-1)} - 0.077\ Z^4_{(t-2)} + 0.005\ Z^1_{(t-2)} + 0.006\ Z^2_{(t-2)} + 0.006\ Z^3_{(t-2)} + 0.005\ Z^5_{(t-2)} + e_4(t)$$

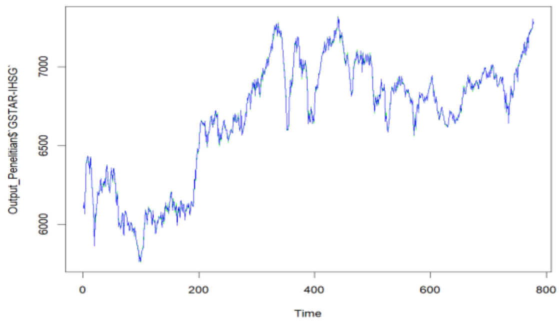
$$Z_t^{(5)} = -0.110\ Z^5_{(t-1)} + 0.207\ Z^1_{(t-1)} + 0.216\ Z^2_{(t-1)} + 0.218\ Z^3_{(t-1)} + 0.222\ Z^4_{(t-1)} - 0.060\ Z^5_{(t-2)} - 0.023\ Z^1_{(t-2)} - 0.024\ Z^2_{(t-2)} - 0.025\ Z^3_{(t-2)} - 0.025\ Z^4_{(t-2)} + e_5(t)$$

9. Best GSTAR Model Selection

After analysis using univariate ARIMA and multivariate GSTAR, model validation or selection of the best model to forecast the ASEAN-5 stock price index for the following 5 periods, the best model chosen is the model with the smallest MSE value using training data. The following prediction results are given using the ARIMA and GSTAR models as comparison graphs of actual and fitted value data, as shown in Figure 2, Figures 3, Figures 4, Figures 5 and Figures 6.

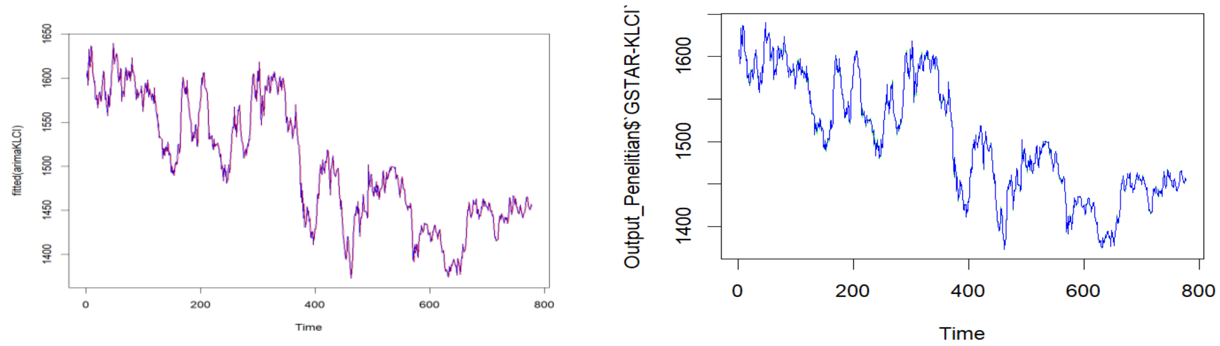


(a)



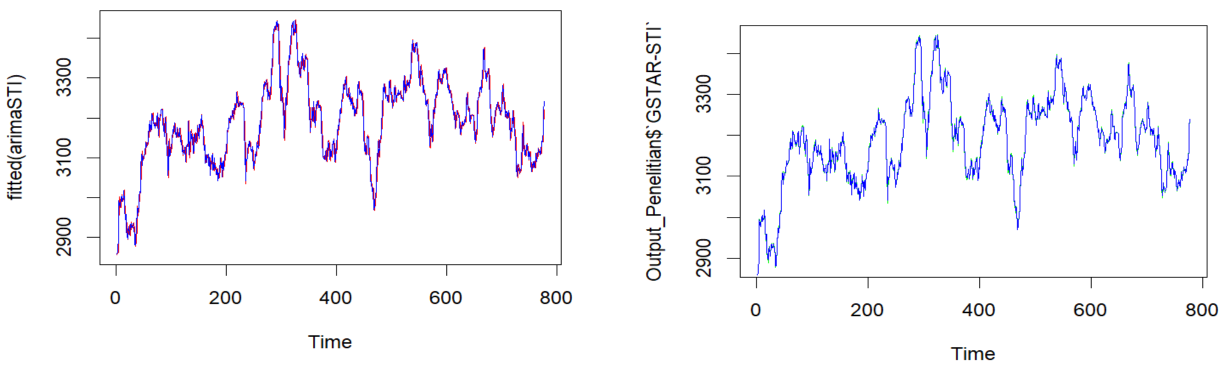
(b)

Figure 2. Data JCI: (a) Comparison of Actual Data with ARIMA Model Predictions; and (b)Comparison of Actual Data with GSTAR Model Predictions



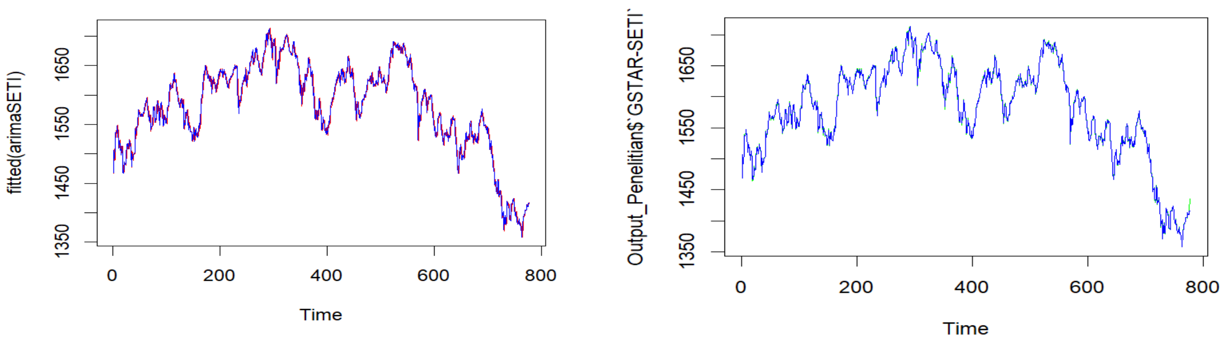
(a) (b)

Figure 3. Data KLCI: (a) Comparison of Actual Data with ARIMA Model Prediction; and (b)Comparison of Actual Data with GSTAR Model Predictions



(a) (b)

Figure 4. Data STI: (a) Comparison of Actual Data with ARIMA Model Predictions; and (b) Comparison of Actual Data with GSTAR Model Predictions



(a) (b)

Figure 5. Data SETI; (a) Comparison of Actual Data with ARIMA Model Predictions; and (b) Comparison of Actual Data with GSTAR Model Predictions

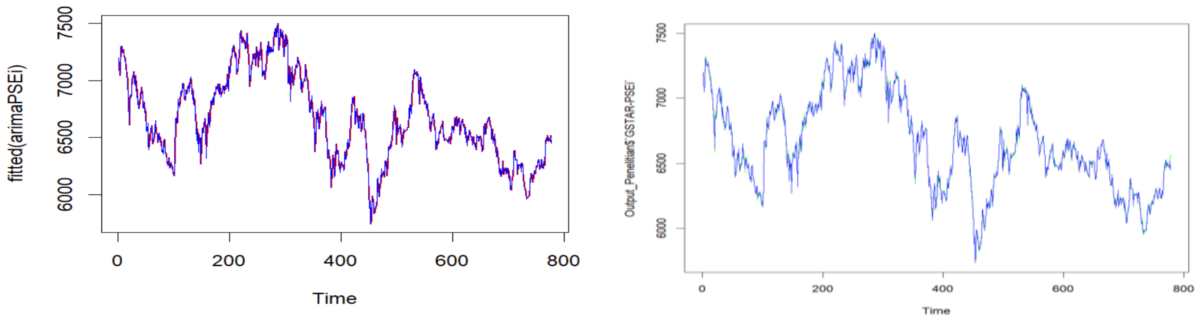


Figure 6. Data PSEi: (a) Comparison of Actual Data with ARIMA Model Predictions; and (b) Comparison of Actual Data with GSTAR Model Predictions

Figures 2 to Figures 6 describe the comparison graph between the analysis results using the ARIMA and GSTAR models with actual data from January 2021 to December 2023. In the graph, the blue line shows the actual data, the red line shows the predicted data of the ARIMA model, and the green colour indicates the prediction data of the GSTAR model. From the overall graph, the GSTAR model prediction results have a pattern that more closely resembles actual data than the ARIMA model prediction results. This can be seen from the tendency to overlap or overlap each other in real data and predictions. The same results can also be seen from the MAPE values of the GSTAR model for the five ASEAN-5 countries, as shown in Table 10.

Table 10. MAPE Value of ASEAN-5 Stock Price Index

Index	$MAPE_{ARIMA}$	$MAPE_{GSTAR}$
JCI	0,547	0,092
KLCI	0,461	0,057
STI	0,512	0,071
SETI	0,512	0,067
PSEi	0,824	0,148

From Table 10, MAPE values of both ARIMA and GSTAR models are obtained for all observation locations below 10%. According to Lewis (1982), MAPE values below 10% indicate that the prediction model has excellent presumptive ability. Furthermore, the MAPE value of the GSTAR model is smaller than that of the ARIMA model. It can be concluded that the GSTAR multivariate model is more accurate than the ARIMA univariate model. In other words, adding weight to the distance between observation locations can increase the accuracy value in time series data modelling.

10. Stock Price Index Data Forecasting

After getting the best model that matches the characteristics of the data, then presumptive are made with the GSTAR model. The following are given the results of the presumptive data for the following 5 periods, as shown in Table 11.

Table 11. GSTAR Model (2,1)I(1) Predictions

Periode	JCI	KLCI	STI	SETI	PSEi
2 January 2024	7280,27	1455,11	3249,87	1417,294	6463,128
3 January 2024	7278,50	1455,47	3253,29	1416,956	6469,073
4 January 2024	7278,84	1455,38	3253,88	1417,111	6468,275
5 January 2024	7279,67	1455,38	3254,28	1417,185	6468,157
8 January 2024	7279,57	1455,39	3254,36	1417,184	6468,419
MAPE	0,544	1,390	1,825	0,814	1,689

From the forecasting results for the next 5 periods using the GSTAR model (2,1) I(1), MAPE values were obtained below 10% for all observed locations. This shows that the GSTAR model is not only accurate for modeling ASEAN-5 stock price index data but also very well applied for forecasting in next period.

D. CONCLUSION AND SUGGESTIONS

The research results show that time series modeling on stock price index data using the multivariate GSTAR (2,1) I(1) is better implemented than the univariate ARIMA time series model. The best model is chosen by the lowest the AIC value. The forecasting results from the selected model have high accuracy with MAPE values for each observation country in ASEAN-5 below 10%. The results of the GSTAR modeling provide an indication that there is influence between countries in the formation of the stock price index. This can be taken into consideration by investors in making investment policies, namely, apart from observing share prices in one country, they also need to observe share prices in related countries. This research provides good accuracy, so it is recommended that future research use a more complex research model such as GSTARIMA or hybrid Arima-ANN.

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