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COMPARISON OF MODELLING AND PREDICTION OF EXPORT VALUES IN WEST JAVA, BANTEN, AND CENTRAL JAVA USING THE STIMA AND GSTIMA (1,1,1)

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Abstract: Export is the delivery and sale of goods from a country to abroad. The growth of export values can be seen from time to time and it differs between locations which are influenced by spatial interactions. The Space-Time Autoregressive Moving Average (STARMA) model is a model that combines the interdependence of time and location. However, the STARMA model is sometimes seen unrealistic as it assumes all parameters in all locations to be the same. Meanwhile, The Generalized Space-Time Autoregressive Moving Average (GSTARMA) model is more realistic because it produces different parameters for each location. This study aims to compare the STIMA

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and GSTIMA models and to forecast export values. The STIMA and GSTIMA models are the models with zero-order for AR and apply First Difference. In this study, the STIMA and GSTIMA models with weighted inverse distance are used to predict the value of exports in three interacting provinces that have dominant superior sectors in the industrial sector, namely the Provinces of West Java, Banten, and Central Java. The data used is export values from January 2014 – December 2018. The identification of the model revealed the 1st order cut-off on lag 1 of the STACF plot with the first data differencing. The selected order of spatial lag is lag 1 because these three provinces are located on the same island. This is confirmed through the VARMA approach where the AR(0) and MA(1) models have the smallest AIC values so that the models constructed are the STIMA(1,1,1) and GSTIMA(1,1,1). The results of this study indicated that the GSTIMA(1,1,1) model produce better prediction than the STIMA(1,1,1) as it has a smaller MAPE value, where each MAPE value is 14.23% for STIMA and 11.38% for GSTIMA. This result indicates the fulfillment of different parameter assumptions at each location under the existing phenomenon that the export management of each location has different characteristics.

Keywords: space-time; STIMA; GSTIMA; export.

2010 AMS Subject Classification: 37M10.

1. INTRODUCTION

Export can be defined as the delivery and sale of goods from a country to overseas. The advantages of exports involve market expansion, improvement in the country's foreign exchange, and allowing wider job opportunities [1]. The increase in exports will raise the demand for domestic currency so that the exchange rate of the Rupiah strengthens and can also absorb more workers, thereby reducing unemployment and increasing per capita income. The export base theory was first introduced by Tiebout [2] in the pure regional science of economic growth. The difference between Tiebout and Richardson on an exports basis is that Tiebout focuses on production-side analysis, while Richardson focuses his analysis on the output side. Furthermore, on the classical view of exports, Krugman [3] believes that exports are due to absolute advantage and competitive advantage through specialization production. In developing countries, the role of exports to economic growth was observed by Heizer and Nowak-Lehman [4] who conducted a study in Chile, that the horizontal export diversification contributed to the economic growth through a positive externality, a benefit for foreign buyers, and creating a competitive market. The value of exports can be seen from time to time, both monthly and annually so that time series analysis can be carried out. In addition, the export value in each province also has different developments. The difference in export value in each province is also influenced by spatial interactions.

Time series analysis is a data analysis method that is intended to estimate or forecast the future. Modeling and forecasting using time series methods can be performed on both of univariate and multivariate data. Multivariate time series data can be modeled using the Vector Autoregressive Moving Average (VARMA) model which is an extension of the Autoregressive Moving Average (ARMA) model. A certain type of the VARMA model is a model that combines the interdependence of time and location known as the STARMA (Space-Time Autoregressive Moving Average) model which was first introduced by Pfeifer and Deutsch [5]. The STARMA model is sometimes seen unrealistic because it the parameters are assumed to be the same for all location. This assumption does not have a strong theoretical basis and cannot accommodate heterogeneity location. Borovkova, et al [6] suggested that the GSTARMA (Generalized Space-Time Autoregressive Moving Average) model can also incorporate the interdependence of time and location and is considered more realistic because it produces different parameters for each location. The STARMA and GSTARMA models with zero-order for AR and with the application of the first difference is called STIMA and GSTIMA models.

The export value is one of the phenomena that can be modeled using STIMA and GSTIMA. The effect of spatial interactions related to the value of exports between provinces can be seen from the proximity of one province to another. This study uses three interacting provinces, namely West Java, Banten, and Central Java because they have dominant superior sectors in the industrial sector so that they are considered to affect the export value of the three provinces.

The purpose of this study is to model the export value in the provinces of West Java, Banten, and Central Java using the STIMA and GSTIMA models. The GSTIMA model is more solid theoretically and complex than the STIMA model. Nevertheless, Siregar [7] found that the STIMA model is more accurate for predicting sugar prices in eight provincial capitals of Sumatra than the GSTIMA model so that it remains unclear whether the GSTIMA model is better than the STIMA model in forecasting the value of exports in the provinces of West Java, Banten, and Central Java. This study compares the models and predicts export values using the inverse distance as weighted space.

2. PRELIMINARIES

2.1. Stationarity. The principal assumption in the time series model is stationary data [8]. Stationarity is a condition where the data does not form a certain pattern (trend) and is constant over time concerning the mean and variance. Respecification of stationary data can be seen from the data distribution plot between the observation value and time. In addition, a formal test can be used using the Augmented Dickey-Fuller (ADF) test with the following hypothesis:

$H_0 : \alpha = 1$ (data contains unit root) non-stationary data

$H_1 : |\alpha| < 1$ (data does not contain unit root) stationary data

with the statistical test:

$$ADF_t = \frac{\hat{\alpha} - 1}{sd(\hat{\alpha})} \tag{1}$$

H_0 is rejected when ADF > *t*-table, indicating stationary data, while in contrast if ADF < *t*-table data is non stationary. If the data is not stationary to the mean, the differencing process should be performed to the original data. If the data is not stationary concerning the variance, data transformation should be conducted.

2.2. Space-Time Autoregressive Integrated Moving Average (STARIMA) Model. The STARIMA model is a STARMA model that has gone through the differencing process which can accommodate the influence of location on a time series [5]. The STARIMA model is a VARIMA model to which a location weighting matrix has been added. The STARIMA model is defined as:

$$\nabla \boldsymbol{Z}_t = \sum_{k=1}^{p} \sum_{l=0}^{a_k} \phi_{k,l} \boldsymbol{W}^{(l)} \nabla \boldsymbol{Z}_{t-k} - \sum_{k=1}^{p} \sum_{l=0}^{v_k} \theta_{k,l} \boldsymbol{W}^{(l)} \boldsymbol{e}_{t-k} + \boldsymbol{e}_t \tag{2}$$

where a_k and v_k indicate the spatial order of k from autoregressive and moving average, $\phi_{k,l}$ autoregressive parameters of time lag at k and spatial lag at l, $\theta_{k,l}$ moving average parameters at time lag at k and spatial lag at l, and $\boldsymbol{W}^{(l)}$ is the location weighting matrix sized $m\, x\, m$ on lag $l = 0,1,2,\dots,m$. The model that contains no autoregressive terms $(p = 0)$ is referred to as STMA models [5].

2.3. Generalized Space Time Autoregressive Integrated Moving Average (GSTARIMA) Model. The GTARMA model is the improved STARMA model, wherein the STARMA model the parameters are assumed to be the same at each location. However, this assumption is considered unrealistic in describing the characteristics of heterogeneity of locations, so that the GSTARMA emerges as the proceeding of STARMA where the parameters are assumed to be different at each location [6]. On STARMA $\phi_{k,l}$ and $\theta_{k,l}$ is a scalar value, while in the GSTARMA model it is a matrix. The GSTARMA model that goes through the differencing process is called the GSTARIMA model which is defined as follows [9]:

$$\nabla \boldsymbol{Z}_t = \sum_{k=1}^{p} \sum_{l=0}^{a_k} \boldsymbol{\Phi}_{k,l} \boldsymbol{W}^{(l)} \nabla \boldsymbol{Z}_{t-k} - \sum_{k=1}^{p} \sum_{l=0}^{v_k} \boldsymbol{\Theta}_{k,l} \boldsymbol{W}^{(l)} \boldsymbol{e}_{t-k} + \boldsymbol{e}_t \tag{3}$$

where,

$$\boldsymbol{\Phi}_{k,l} = \mathrm{diag}\left(\phi_{k,l}{}^{(1)}, \dots, \phi_{k,l}{}^{(N)}\right) = \begin{bmatrix} \phi_{k,l}{}^{(1)} & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \phi_{k,l}{}^{(N)} \end{bmatrix},$$

$$\boldsymbol{\Theta}_{k,l} = \mathrm{diag}\left(\theta_{k,l}{}^{(1)}, \dots, \theta_{k,l}{}^{(N)}\right) = \begin{bmatrix} \theta_{k,l}{}^{(1)} & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \theta_{k,l}{}^{(N)} \end{bmatrix},$$

2.4. Inverse Distance Weight. Weighting using the inverse distance method is based on the actual distance between locations. The calculation of the distance between these locations can use the coordinates of the observed location. Locations that are close to each other have a greater weight than those that are far apart. As an illustration, suppose *m* location with $x_i(u_{i,}v_i)$, where x_i is a location at *i* with *i*= 1,2,.., *m* and (*u,v*) shows the latitude and longitude coordinates of the location, d_{ij} is the distance between the locations *i* to *j*, and w^*_{ij} is the value of inverse from d_{ij}, thus it was formulated as follows:

(4) $$d_{ij} = d_{ji} = \sqrt{\left(\left[x_i(u_i) - x_j(u_j)\right]^2 + \left[x_i(v_i) - x_j(v_j)\right]^2\right)}$$

(5) $$w^*_{ij} = w^*_{ji} = {}^1/_{d_{ij}} = {}^1/_{d_{ji}}$$

with inverse distance weight is formulated as follows:

(6) $$w_{ij} = \begin{cases} \dfrac{w^*_{ij}}{\sum_{j=1}^{m} w^*_{ij}} \; for\ i \neq j \\ 0, \end{cases}$$

2.5. Parameter Estimation. Identification of optimal lag in the STARIMA and GSTARIMA models is performed through inspection on STACF and STPACF plots to select the best model according to the minimum AIC [10]. The minimum AIC value indicates the minimum difference between the estimator and the parameter such that the smaller the AIC value, the closer the estimator to the parameter value, and the better the model can be obtained. The AIC value is determined using the following formula [11] :

(7) $$AIC(M) = -n \ln \hat{\sigma}_a^2 + 2M$$

M is the number of estimated model parameters and *n* is the number of observations. The minimum AIC (M) is produced from the model with the optimal order based on the value of *M* which is the functions of *p* and *q* as the order of autoregressive and moving average, where *M* is the number of estimated model parameters. Generally, the value of sum of square is approached by extending the least-squares as follows:

(8) $$S(\boldsymbol{\Phi}, \boldsymbol{\Theta}) = S(\hat{\boldsymbol{\delta}}) + (\boldsymbol{\delta} - \hat{\boldsymbol{\delta}})'\boldsymbol{Q}(\boldsymbol{\delta} - \hat{\boldsymbol{\delta}})$$

For $i = 1,2, \ldots, K$and *K* is a dimension of $\boldsymbol{\delta}$ which is the number of parameters with:

(9) $$S(\boldsymbol{\delta}) = \sum_{t=1}^{T} \boldsymbol{e}(t)\boldsymbol{e}(t)'$$

confidence interval estimate for $[\boldsymbol{\Phi}, \boldsymbol{\Theta}]' = \boldsymbol{\delta}$ is obtained:

(10) $$S(\boldsymbol{\delta}) = S(\hat{\boldsymbol{\delta}}) + \frac{K}{TN-K} S(\hat{\boldsymbol{\delta}}) \sim F_{K,TN-K,\alpha}$$

The exact function of sum of square $S(\boldsymbol{\delta})$ is replaced with conditional sum of square $S_*(\boldsymbol{\delta})$ if the conditional maximum likelihood is used so that the confidence interval in $(\sigma^2 | Z(1), Z(2), \dots, Z(T)) \sim S_*(\hat{\boldsymbol{\delta}})\chi_{TN-K^{-2}})$.

2.6. Diagnostic tests of the model. A model diagnostic test is a test to prove that the model is adequate and to determine the best forecasting model [12]. The first step of the diagnostic test is the inspection of residuals of the model. The residuals are said to be white noise if it is normally distributed with mean = 0 and the variance-covariance matrix is equal to $\sigma^2 \boldsymbol{I}_N$ where off-diagonal equals 0 [13]. A statistical hypothesis to tests the assumption of white noise of residuals is as follows:

H_0: $\rho_1 = \rho_2 = \cdots = \rho_m = 0$ (white noise)

H_1: at a minimum, there is one $\rho_k \neq 0$ (non-white noise)

(11) $$Q_n(m) = T^2 \sum_{k-1}^{m} \frac{1}{T-k} tr(\hat{\boldsymbol{\Gamma}}_k \hat{\boldsymbol{\Gamma}}_0^{-1} \hat{\boldsymbol{\Gamma}}_k \hat{\boldsymbol{\Gamma}}_0^{-1}) \sim \chi^2_{(N^2 m)}$$ Sta

tistical testing:

where $\hat{\boldsymbol{\Gamma}}_k = \frac{1}{T-k} \sum_{k=1-k}^{T} \hat{e}_i(t-k)\, \hat{e}_j(t)$

H_0 is not rejected if $Q_n(m) < \chi^2_{(N^2 m)}$ or *p*-value $> \alpha$ which means that the model fulfills the assumption of white noise residuals.

2.7. Selection of the best model. In this study, the selection of the best model is based on Mean Absolute Percentage Error (MAPE). A model with smaller MAPE values is the more accurate model. The MAPE equation is as follows [14].

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Z_i - \hat{Z}_i}{Z_i}\right| \times 100\% \tag{12}$$

where Z_i is the observed value, $\hat{Z}_i$ is the predicted value, and *n* is the number of observations.

3. MAIN RESULTS

3.1. Data and Source of Data. The data is monthly export value data of 72 observations from January 2014 to December 2019 for three locations, namely West Java, Banten, and Central Java, collected from the website of the Central Bureau of Statistics (BPS) of each province. In this study, the data used for the space-time model is in sample data with a total of 60 observation locations during January 2014-December 2018 and out sample data as many as 12 observations during January 2019-December 2019 which are used for prediction.

3.2. Descriptive Analysis. Descriptive statistics of export values of West Java, Banten, and Central Java can be seen in Table 1.

TABLE 1. Descriptive statistics of export value of West Java, Central Java, and Banten

Location	Min.	Max.	Mean	SD
West Java	1557.47	2907.26	2337.74	262.8
Banten	600.75	1148.39	872.35	118.8
Central Java	287.33	960.41	523.08	112.7

Based on Table 1, it can be seen that from 2014 to December 2019 the highest average export value was in the province of West Java and the lowest was in the province of Central Java. In addition to the average value, the standard deviation of the data for the three locations is also quite heterogeneous and fairly large. The growth of exports of the three provinces in Java can be seen in the following graph:

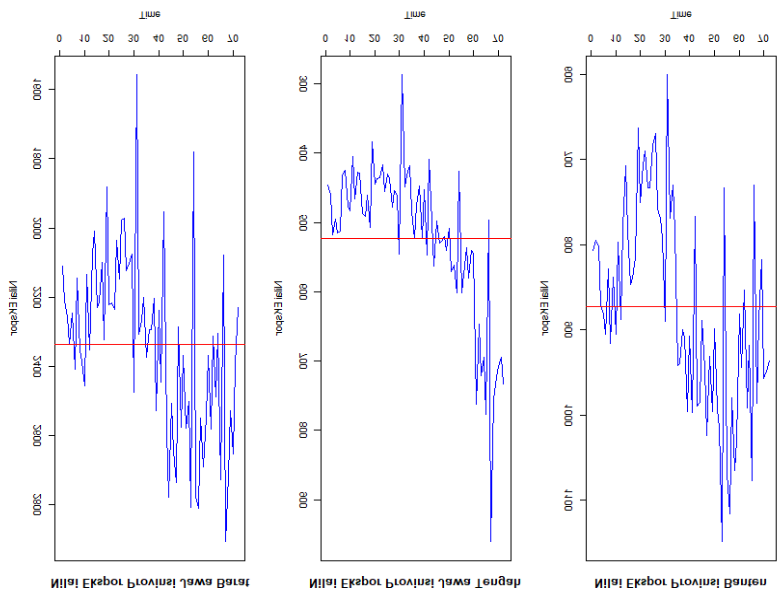

FIGURE 1. The growth of export of West Java, Central Java, and Banten

Based on Figure 1, it can be seen that the values of exports during January 2014-December 2019 in West Java, Banten, and Central Java fluctuated. The relationship between export values in the three research locations can be seen from the correlation coefficient. Table 2 below presents the Pearson correlation coefficients between the provinces.

TABLE 2. Coefficient correlation of exports among the provinces

Location	West Java	Banten	Central Java
West Java	1	0.861	0.7
Banten	0.861	1	0.605
Central Java	0.7	0.605	1

From the Pearson correlation coefficients, the values of exports in the three provinces on the island of Java are related in the same order of time. This indicates that the dynamics of export values in the Java island interact with each other so that can be analyzed using multivariate analysis [15].

3.3. Testing Stationarity data based on the means. To test stationarity in the mean, this study used the Augment Dickey-Fuller (ADF) unit root test. The results of the ADF test are presented in Table 3 below:

TABLE 3. Results of stationary test in the mean

Locations	Data Condition	*ADF-test*	
		p-value	Conclusion
West Java	Original (level)	0.4214	Non-stationary
	First difference	<0.01	Stationary
Central Java	Original (level)	0.2934	Non-Stationary
	First difference	<0.01	Stationary
Banten	Original (level)	0.5969	Non-stationary
	First difference	<0.01	Stationary

Based on Table 3, the data of export values in the three provinces had a p-value greater than 0.05, so it can be concluded that the data was not stationary in the mean. After the first differencing process, each location had a p-value of less than 0.05, so that the data was stationary.

3.4. Identifying the Model using Plot Space-Time Autocorrelation Function (STACF). The model identification process is conducted to find out the optimum order of time lag and spatial lag. The STACF plot for identifying the space-time model with differencing export value data and distance inverse weight can be seen in Figure 2.

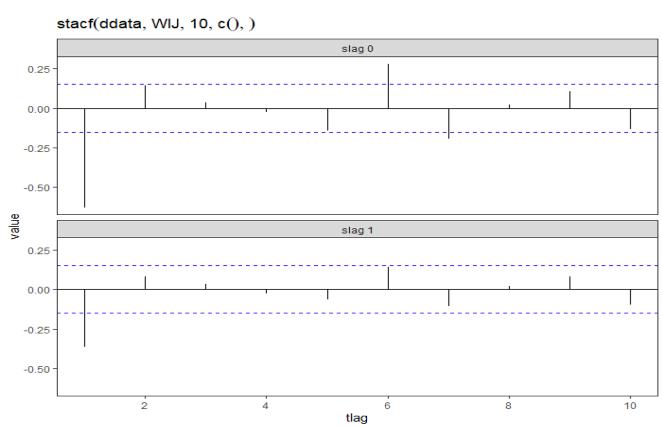

FIGURE 2. STACF plot with inverse distance weight

Based on the STACF plot, the order of spatial lag that may be selected is order 1 (λp=1) because the three provinces are on the same island and order lag time of Moving Average (MA) *cut-off* on order 1 [16, 17]. To ensure the selection of the optimum order the VARMA approach by looking at the smallest Akaike's Information Criterion (AIC) value from the stationary data can be used. The AIC value is shown in Table 4 below:

TABLE 4. The value of AIC VARMA model

Lag	MA(0)	MA(1)	MA(2)
AR (0)	25.64724	**25.11019**	25.50934
AR (1)	25.64724	25.43398	25.40658
AR (2)	25.28135	25.12984	26.87036

The smallest AIC value in Table 4 above is in AR(0) and MA(1), so that the models to be formed are STIMA(1,1,1) and GSTIMA(1,1,1) models.

3.5. The Result of Parameter Estimation. The STIMA model is a certain type of VIMA that involves spatial elements. Parameter estimates of STIMA(1,1,1) using inverse distance weighting that obtains $\hat{\theta}_{10} = -0.9451599$ and $\hat{\theta}_{11} = -0.008166$. Based on these parameters, the equation of STIMA(1,1,1) matrix equation can be formed as follows:

$$\begin{bmatrix} \widehat{\nabla Z_1(t)} \\ \widehat{\nabla Z_2(t)} \\ \widehat{\nabla Z_3(t)} \end{bmatrix} = 0.9451599 \begin{bmatrix} e_1(t-1) \\ e_2(t-1) \\ e_3(t-1) \end{bmatrix} + 0.008166 \begin{bmatrix} 0 & 0.3694308 & 0.6305692 \\ 0.6081602 & 0 & 0.3918398 \\ 0.7259648 & 0.2740352 & 0 \end{bmatrix} \begin{bmatrix} e_1(t-1) \\ e_2(t-1) \\ e_3(t-1) \end{bmatrix}$$

The GSTIMA model is developed from the STIMA and VIMA model. The difference between the STIMA and GSTIMA lies in its parameters. In the STIMA model, parameter ϕ_{kl} and θ_{kl} are scalar, while on the GSTIMA model the parameters of $\mathbf{\Phi}_{kl}$ and $\mathbf{\Theta}_{kl}$ are matrices, so that the GSTIMA model has more parameters to be estimated than the STIMA model. The estimated parameters of GSTIMA(1,1,1) can be seen in Table 5 below:

TABLE 5. The results of parameter estimates of GSTIMA(1,1,1)

Location	Parameter	Estimates
West Java	$\hat{\theta}_{10}^{(1)}$	0.05345
	$\hat{\theta}_{11}^{(1)}$	0.24654
Central Java	$\hat{\theta}_{10}^{(2)}$	0.63172
	$\hat{\theta}_{11}^{(2)}$	-0.06101
Banten	$\hat{\theta}_{10}^{(3)}$	-0.03737
	$\hat{\theta}_{11}^{(3)}$	-0.06115

The estimated value of the parameters above can be written in the matrix as follows:

$$\begin{bmatrix} \widehat{\nabla Z_1(t)} \\ \widehat{\nabla Z_2(t)} \\ \widehat{\nabla Z_3(t)} \end{bmatrix} = -\begin{bmatrix} 0{,}05345 & 0 & 0 \\ 0 & 0{,}63172 & 0 \\ 0 & 0 & -0{,}03737 \end{bmatrix} \begin{bmatrix} e_1(t-1) \\ e_2(t-1) \\ e_3(t-1) \end{bmatrix} - \begin{bmatrix} 0{,}24654 & 0 & 0 \\ 0 & -0{,}06101 & 0 \\ 0 & 0 & -0{,}06115 \end{bmatrix}$$
$$\begin{bmatrix} 0 & 0{,}3694308 & 0{,}6305692 \\ 0{,}6081602 & 0 & 0{,}3918398 \\ 0{,}7259648 & 0{,}2740352 & 0 \end{bmatrix} \begin{bmatrix} e_1(t-1) \\ e_2(t-1) \\ e_3(t-1) \end{bmatrix}$$

3.6. Checking assumption of white noise residual. After the STIMA and GSTIMA parameters and models were obtained, the subsequent step was to check the white noise assumptions of residuals. In conducting the white noise test, the Ljung-Box statistical test was used with the results presented in Table 6.

TABLE 6. Result Ljung-Box statistical test

Location	STIMA (p-value)	GSTIMA (p-value)	Conclusion
West Java	0.69826	0.077357	*White Noise*
Central Java	0.353906	0.156038	*White Noise*
Banten	0.050404	0.215184	*White Noise*

3.7. Comparison of the STIMA and GSTIMA model. To compare a model, the Mean Absolute Percentage Error (MAPE) can be used. The smaller MAPE value is the more accurate the model. The results of MAPE calculation from the STIMA and GSTIMA models on the sample data are presented in Table 7.

TABLE 7. Result MAPE test STIMA and GSTIMA model

Location	STIMA	Overall STIMA	GSTIMA	Overall GSTIMA
West Java	9.47		11.35	
Banten	19.32	14.23	10.52	11.38
Central Java	13.88		12.27	

Based on the MAPE value, it is found that the GSTIMA model has a better forecasting ability than the STIMA model because it has a smaller MAPE value, so that forecasting can be performed on the data of out sample. This finding shows the fulfillment of the assumption of different parameters at each location as the existing phenomenon that the export management of each location has different characteristics. Prediction graphs of out sample data are shown in figure 3.

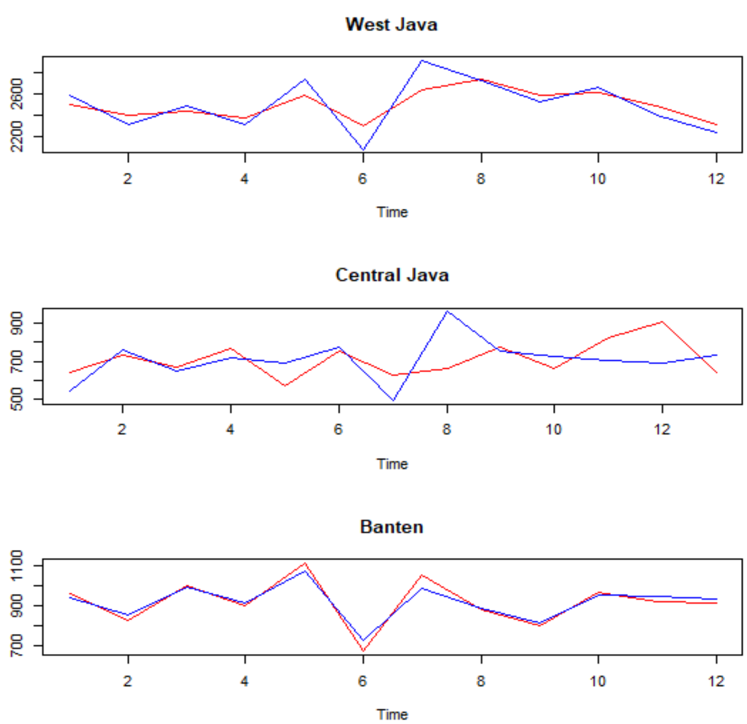

FIGURE 3: Prediction graph of the out sample data of GSTIMA(1,1,1)

Notes: —— Actual —— Predicted

The results of prediction show that the GSTIMA model has a good forecasting ability because the graph of the predicted value and the actual value is almost intersects and almost the same. The MAPE value for the prediction of out-sample data is 8.64% which shows that the prediction of export values using GSTIMA has good prediction ability.

4. CONCLUSION

The export values during January 2014-December 2019 in the provinces of West Java, Banten, and Central Java widely fluctuate. The highest average export value is in the province of West Java, while the lowest is in the province of Central Java. The standard deviation of the data for the three locations is also quite heterogeneous with a fairly large value. Based on the STACF plot, the selected spatial lag order is lag 1 because the three provinces are located on the same island and the cut-off time lag order Moving Average (MA) is in order 1. These results were confirmed through the VARMA approach by looking at the smallest AIC value and obtaining the orders of AR(0) and MA(1) using first differencing so that the models formed are STIMA(1,1,1) and GSTIMA(1,1,1) models. Based on the MAPE value, it is found that the GSTIMA model has a better forecasting ability than the STIMA model because it has a smaller MAPE, 14.23% for STIMA and 11.38% for GSTIMA so that forecasting can be performed on the data of out samples. This also indicates that with the existing export management, each location has different characteristics.

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CONFLICT OF INTERESTS

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

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