Comparison of GSTARIMA and GSTARIMA-X Model by using Transfer Function Model Approach to Rice Price Data

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Abstract. GSTARIMA-X model is a development of the GSTARIMA model involving exogenous variables. The approach of transfer function model in the GSTARIMA-X model produces a dynamic space-time model. The influence of exogenous variables in a GSTARIMA model can assist in better estimation of response values. In this study, GSTARIMA model will be compared with GSTARIMAX model by using transfer function model approach. Both models are applied to data of medium rice price at the market level in six provinces of Java Island, Indonesia. The exogenous variables in the GSTARIMA-X model use data of dried grain price at the milling level at the same location. The best model of GSTARIMA was GSTARIMA(2,1,1,0) and GSTARIMA-X with transfer function approach was GSTARIMA-X(0,2,1,0,0,0). The performance of comparison model showed that GSTARIMA-X model with a transfer function approach was better model than GSTARIMA model. The RMSEP and MAPE values of GSTARIMA-X model by using transfer function model approach for training and testing data had tendency of lower value compared to GSTARIMA model.

1. Introduction

Currently, data modeling has grown very rapidly. Data is not only analyzed on one type of information, but it can be two type of information as well. They are the time series information and spatial information. This data is called space-time data. The space-time data modeling that has been evolving until now uses time series model approach by adding the spatial effect in it. One of space-time model is the GSTARIMA (Generalized Space-Time Autoregressive Integrated Moving Average) model. The GSTARIMA model is a generalized STARMA (Space-Time Autoregressive Moving Average) model. The STARMA model has been introduced by [1][2]. For some cases, STARMA model has lack in capture heterogeneity characteristics in the locations. The weakness of the STARMA model is studied by [3]. They were proposing a model that could handle the heterogeneity characteristics of each location, it was called GSTAR (Generalized Space-Time Autoregressive) model. GSTAR model has not only evolved in autoregressive in model, but also in non-stationary time series and moving average pattern. That model is called GSTARIMA (Generalized Space-Time Autoregressive Integrated Moving Average) model. GSTARIMA model has been used in [5]. For some conditions, exogenous variables are required in a model as explanatory variables for response variables. GSTARIMA model with exogenous variables is known as GSTARIMA-X model. The
GSTARIMA-X model by using transfer function approach has been introduced in [8]. They research showed that GSTARIMA-X model by using transfer function approach was good enough to model space-time data with exogenous variables on rice price data, Indonesia. The model could dynamically connect exogenous variables to response variables and could capture the heterogeneity of characteristics between locations. However, exogenous variables are sometimes considered unnecessary in some cases in time series model. This is due to the events in the response variable are only influenced by the occurrence of the variable from the previous time period. This is why, it is necessary to compare the goodness model on a model that does not involve exogenous variables from which it involves.

One of the applications of space-time model is in the economic field, for example rice price data in Indonesia. Rice is a very important food commodity for the Indonesian people. It was not only caused as a staple food but also a social commodity, a role in political stability and economic growth [6]. Therefore, any occurrence of rice, especially on rice prices, will have an impact on the socio-economic life of Indonesians. This rice price policy is also an important instrument to create a national food security in Indonesia. According to [4], the price of rice in the domestic market was influenced by the real exchange rate, domestic corn prices, and the base price of grain. Meanwhile, according to [7], the price of rice in the domestic market at the national level was influenced by the basic price of rice and world rice price. From both studies indicate that the price of grain has an influence in increasing or decreasing the price of rice in the domestic market.

Based on the description, the research will discuss about comparison of GSTARIMA and GSTARIMA-X model by using transfer function approach. Data in this research will use rice price data as a response variable and price of dry milled grain data in six provinces of Java Island, Indonesia.

2. Materials and Methods

2.1. GSTARIMA Model

Suppose \( z_{i(t)} \) is an observation which follow stochastic process in location \( i \) at time period, where \( i = 1, 2, \ldots, N \) and \( t = 1, 2, \ldots, T \). If \( z_{i(t)} \) is not following stationary process in mean, it will need differencing process. The spatial lag operator of spatial order \( l \) is defined as:

\[
L^{(0)} z_{i(t)} = z_{i(t)},
\]

\[
L^{(l)} z_{i(t)} = \sum_{j=1}^{N} w_{ij}^{(l)} z_{j(t)},
\]

where \( N \) is the number of locations and the weights \( (w_{ij}^{(l)}) \) are such that \( \sum_{l=1}^{N} w_{ij}^{(l)} = 1 \). For all \( i \), \( w_{ij}^{(l)} \) will not zero value if \( i^{th} \) and \( j^{th} \) are neighbors at \( l^{th} \) order.

The GSTARIMA model by [8] with differencing process can be shown as follows:

\[
\nabla^d z_{i(t)} = \sum_{k=1}^{p} \lambda_k L^{(l)} \nabla^d z_{i(t-k)} - \sum_{k=1}^{q} \theta_{kl} L^{(l)} a_{i(t-k)} + a_{i(t)}
\]

(1)

Where \( \nabla^d \) is a differencing process of \( d \); \( a_{i(t)} \) is a zero mean white noise process of \( i^{th} \) location and \( k^{th} \) time order; \( \phi_{ikl} \) is a autoregressive parameter of \( i^{th} \) location, \( k^{th} \) time order, and \( l^{th} \) spatial order; \( \theta_{ikl} \) is a moving average parameter of \( i^{th} \) location, \( k^{th} \) time order, and \( l^{th} \) spatial order; \( p \) is autoregressive order; and \( q \) is moving average order. The order of \( \lambda_k \) is \( \phi_{ikl} \) spatial order at \( k^{th} \) time lag and \( \gamma_k \) is \( \theta_{ikl} \) spatial order at \( k^{th} \) time lag. Equation (1) can also shown as matrix form as:

\[
\nabla^d z_t = \sum_{k=1}^{p} \Phi_{kl} W^{(l)} \nabla^d z_{t-k} - \sum_{k=1}^{q} \Theta_{kl} W^{(l)} a_{t-k} + a_t
\]

(2)

where \( z_t \) is a vector of \( z_{i(t)} \) for \( N \) locations; \( a_{t-k} \) is a vector of \( a_{i(t-k)} \) for \( N \) locations; \( \Phi_{kl} \) is an \( N \times N \) diagonal matrix of autoregressive parameter for each location; \( \Theta_{kl} \) is an \( N \times N \) diagonal matrix...
of moving average parameter for each location; and $W^{(i)}$ is a $N \times N$ square matrix of $w^{(i)}$. Models in equation (1) and (2) can be defined as GSTARIMA $(p_1,p_2,\ldots,p_q,d,q_1,q_2,\ldots,q_q)$ model.

2.2. GSTARIMA-X Model by using transfer function approach

GSTARIMA-X model by using transfer function approach is a development of GSTARIMA model by involving exogenous variable. The model has been introduced by [8]. Let $z_{i(t)}$ is an observation of output series (response variable) and $x_{i(t)}$ is an observation of input series (exogenous variable). The spatial lag operator of $z_{i(t)}$ and $x_{i(t)}$ can be defined as:

$$L^{(i)}z_{i(t)} = \sum_{j=1}^{N} W^{(i)}_{lj} z_{j(t)}$$

and

$$L^{(i)}x_{i(t)} = \sum_{j=1}^{N} W^{(i)}_{lj} x_{j(t)}$$

The spatial lag operator of $z_{i(t)}$ can also be defined in the matrix form as:

$$L^{(0)}z_{t} = W^{(0)}z_{t} = I_Nz_{t},$$

$$L^{(i)}z_{t} = W^{(i)}z_{t}$$

for $l > 0$.

And the matrix form of spatial lag operator for input series $x_{i(t)}$ is defined by:

$$L^{(0)}x_{t} = W^{(0)}x_{t} = I_Nx_{t},$$

$$L^{(i)}x_{t} = W^{(i)}x_{t}$$

for $l > 0$.

The transfer function model with spatial lag operator for $t^{th}$ is defined as follows:

$$z_{i(t)} = \sum_{k=1}^{r} \sum_{l=0}^{\xi_k} \delta_{ikl} L^{(i)}z_{j(t-k)} + \sum_{l=0}^{\zeta_0} \omega_{0l} L^{(i)}x_{i(t-b)} - \sum_{k=1}^{\xi_k} \sum_{l=0}^{s} \omega_{lk} L^{(i)}x_{i(t-b-k)} + \epsilon_{i(t)}^{*}$$

(3)

where $\delta_{ikl}$ is an output series autoregressive for $i^{th}$ location, $k^{th}$ time lag, and $l^{th}$ spatial lag; $\omega_{0l}$ is a parameter that is representing the length series $x_{i(t-b)}$ affecting series $z_{i(t)}$ at the same period time for $i^{th}$ location, zero time lag, and $l^{th}$ spatial lag; $\omega_{ikl}$ is a parameter that is representing the length of series $x_{i(t-b)}$ affecting series $z_{i(t)}$ for $i^{th}$ location, zero time lag, and $l^{th}$ spatial lag; $r$ represents autoregressive order of output series ($z_{i(t)}$); $s$ represents the length of input series affecting output series; $b$ represents time order when the input series start affecting the output series; $\xi_k$ is an autoregressive spatial order of $z_{i(t)}$ at the $k^{th}$ time lag; $\zeta_0$ is an $\omega_{0l}$ spatial; $\xi_k$ is an $\omega_{ikl}$ spatial order at $k^{th}$ time lag; and $\epsilon_{i(t)}^{*}$ is a noise series at the $i^{th}$ location and $t = 1, \ldots, T$ where $\epsilon_{i(t)}^{*} = \epsilon_{i(t)}^{*} - \sum_{k=1}^{\hat{\xi}} \sum_{l=0}^{\hat{s}} \delta_{ikl} L^{(i)}\epsilon_{i(t-k)}$. The noise series $\epsilon_{i(t)}$ is an uncorrelated series, uncorrelated to the input series, and having normally distributed with mean zero and,

$$E(\epsilon_{i(t)}, \epsilon_{i(t+k)}) = \begin{cases} \sigma^2 & \text{if } k = 0 \\ 0 & \text{otherwise} \end{cases}$$

According to definition of spatial lag operator, equation (3) can be written:

$$z_{i(t)} = \sum_{k=1}^{r} \sum_{l=0}^{\xi_k} \delta_{ikl} W^{(i)}_{lj} z_{j(t-k)} + \sum_{l=0}^{\zeta_0} \omega_{0l} W^{(i)}_{lj} x_{i(t-b)} - \sum_{k=1}^{\xi_k} \sum_{l=0}^{s} \omega_{lk} W^{(i)}_{lj} x_{i(t-b-k)} + \epsilon_{i(t)}^{*}$$

(4)

The matrix form of (4) can be written:

$$Z_{t} = \sum_{k=1}^{r} \sum_{l=0}^{\xi_k} \Delta_{kl} W^{(i)}_{lj} Z_{j(t-k)} + \sum_{l=0}^{\zeta_0} \Omega_{0l} W^{(i)}_{lj} X_{i(t-b)} - \sum_{k=1}^{\xi_k} \sum_{l=0}^{s} \Omega_{lk} W^{(i)}_{lj} X_{i(t-b-k)} + \epsilon_{t}^{*}$$

(5)

where $\Delta_{kl}$, $\Omega_{0l}$, and $\Omega_{kl}$ are $N \times N$ diagonal matrix of parameter $\delta_{ikl}$, $\omega_{0l}$, and $\omega_{ikl}$; and $Z_{t} = (z_{1(t)}, z_{2(t)}, \ldots, z_{N(t)})^{'}$; $X_{t} = (x_{1(t)}, x_{2(t)}, \ldots, x_{N(t)})^{'}$; and $\epsilon_{t}^{*} = (\epsilon_{1(t)}^{*}, \epsilon_{2(t)}^{*}, \ldots, \epsilon_{N(t)}^{*})^{'}$ where $\epsilon_{t}^{*}$ =
\[ \mathbf{e}_t = \sum_{k=1}^{\nu} \sum_{l=0}^{\omega} \Delta_{kl} \mathbf{W}^{(l)} \mathbf{e}_{t-k} \]  

The vector of noise series \( \mathbf{e}_t \) has normally distributed with mean zero, and 

\[
E(\mathbf{e}_t , \mathbf{e}_{t-k}) = \begin{cases} 
\sigma^2 I_N & \text{if } k = 0 \\
0 & \text{otherwise} 
\end{cases}
\]

Model in equation (4) or (5) can be called GSTARMA-X model by using transfer function approach with order \( b, r, s, \xi_1, \xi_2, \ldots, \xi_p, \zeta_0, \zeta_1, \ldots, \zeta_q \). In some cases, uncorrelated assumption in noise series can be not fulfilled. One way to overcome autocorrelation in noise series is using the ARMA (Autoregressive Moving Average) model approach. Let \( \mathbf{e}_{i(t)}^{(e)} \) follows ARMA model as below:

\[
\mathbf{e}_{i(t)}^{(e)} = \theta_{i(t)}(B) \phi_{i(t)}(B) \mathbf{a}_{i(t)}(t)
\]

If the noise series has various characteristics in each location, so it requires a spatial lag operator. The noise series with spatial lag operator is shown as below:

\[
L^{(l)} \mathbf{e}_{i(t)}^{(e)} = \theta_{i(t)}(B) \phi_{i(t)}(B) L^{(l)} \mathbf{a}_{i(t)}(t)
\]

Equation (7) causes equation (4) to be following:

\[
Z_{i(t)} = \sum_{k=1}^{\nu} \sum_{l=0}^{\omega} \sum_{j=1}^{N} \delta_{kl} W_{ij} \mathbf{z}_{i(t-k)} + \sum_{l=0}^{\omega} \sum_{j=1}^{N} \omega_{l0} W_{ij} \mathbf{x}_{i(t-b)} - \sum_{k=1}^{\nu} \sum_{l=0}^{\omega} \sum_{j=1}^{N} \omega_{lk} W_{ij} \mathbf{x}_{i(t-b-k)} + \left( \mathbf{e}_{i(t)}^{(e)} - \sum_{k=1}^{\nu} \sum_{l=0}^{\omega} \sum_{j=1}^{N} \phi_{lk} W_{ij} \mathbf{e}_{i(t-k)}^{(e)} \right) + \mathbf{a}_{i(t)} - \sum_{k=1}^{\nu} \sum_{l=0}^{\omega} \sum_{j=1}^{N} \theta_{lk} W_{ij} \mathbf{a}_{i(t-k)}
\]

or in matrix representation below:

\[
z_t = \sum_{k=1}^{\nu} \sum_{l=0}^{\omega} \Delta_{kl} \mathbf{W}^{(l)} \mathbf{z}_{t-k} + \sum_{l=0}^{\omega} \Omega_{l0} \mathbf{W}^{(l)} \mathbf{x}_{t-b} - \sum_{k=1}^{\nu} \sum_{l=0}^{\omega} \Omega_{lk} \mathbf{W}^{(l)} \mathbf{x}_{t-b-k} + \mathbf{e}_t^{(e)}
\]

\[
- \sum_{k=1}^{\nu} \sum_{l=0}^{\omega} \Phi_{kl} \mathbf{W}^{(l)} \mathbf{e}_{t-k}^{(e)} + \mathbf{a}_t - \sum_{k=1}^{\nu} \sum_{l=0}^{\omega} \Theta_{kl} \mathbf{W}^{(l)} \mathbf{a}_{t-k}
\]

Model in equation (8) or (9) can be called GSTARMA-X model by using transfer function approach with noise model which order \( b, r, s, \xi_1, \xi_2, \ldots, \xi_p, \zeta_0, \zeta_1, \ldots, \zeta_q \). \( \mathbf{a}_t \) must be satisfied independent and normal distribution with zero mean and

\[
E(\mathbf{a}_t , \mathbf{a}_{t-k}) = \begin{cases} 
\sigma^2 I_N & \text{if } k = 0 \\
0 & \text{otherwise} 
\end{cases}
\]

2.3. Data

This research used rice price (medium level) data in six province of Java Island, Indonesia. Data was taken from Ministry of Trade, The Republic of Indonesia from January, 2007 until December, 2014. Data of rice price was used for response variable (output series). The exogenous variable (input series) in this research used price of dry milled grain data in five provinces of Java Island, Indonesia. Data of dry milled grain data was taken from BPS-Statistics Indonesia from January, 2007 until December, 2014. The six provinces of rice price data were DKI Jakarta, West Java, Central Java, DI Yogyakarta, East Java, and Banten. The five provinces of dry milled grain price were West Java, Central Java, DI Yogyakarta, East Java, and Banten.

Before data processing, this research divided data into two parts: training data and testing data. Training data was taken from January, 2007 until December, 2013 and testing data was taken from January, 2014 until December, 2014. Each data applied to the GSTARIMA and GSTARIMA-X model.
2.4. Methods

The process of analysis in this study is described in the following stages:

1. Model Identification
   a. Determine locations weights. In this research, the location weights use Queen Contiguity approach.
   b. Determine order of GSTARIMA and GSTARIMA-X model by using space-time cross-correlation function [8] and partial autoregressive correlation function (PACF) for stationary data of output series after pre-whitening process. If data is not stationary in mean, then it needs a differencing process.

2. Forecasting. Forecasting is used to predict rice prices for 12 months ahead. The data used in this stage is testing data. Forecasting is done for GSTARIMA and GSTARIMA-X model.

3. Evaluation model performance. This stage is done to be able determining the better model, whether GSTARIMA or GSTARIMA-X. The better model will produce a smaller RMSEP (Root Mean Square Error Predictor) and MAPE (Mean Absolute Percentage Error) values in both data (training and testing data).

3. Results and Discussion

3.1. Model Identification

Space-time Cross Correlation function required the weighting of locations in it calculations. The location weights used Queen Contiguity \((W)\). Determination of weighted Queen Contiguity based on locations of provinces in Java Island as shown in Figure 1.

![Figure 1. Six province in Java Island, Indonesia](image)

The description in Figure 1 had been described by [8] that number 1 is province of DKI Jakarta, number 2 is province of West Java, number 3 is province of Central Java, number 4 is province of DI Yogyakarta, number 5 is province of East Java, and number 6 is province of Banten. The spatial relationship as shown in Figure 1 was stated in form of location-weighted matrix with spatial order \(l = 1\) below:

\[
W_q^{(1)} = \begin{bmatrix}
0 & 0.5 & 0 & 0 & 0 & 0.5 \\
0.3 & 0 & 0.3 & 0 & 0 & 0.3 \\
0 & 0.3 & 0 & 0.3 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 \\
0.5 & 0.5 & 0 & 0 & 0 & 0 \\
\end{bmatrix}
\]
The predetermined of location-weighted matrix would be used to calculation of space-time cross-correlation function. Rice price data and price of dry milled grain data were nonstationary data in mean. Therefore, the data required differencing process. In this study, we needed differencing process with lag equal to 1 \((d = 1)\). The data that had been stationary would be continued to identification process.

![Cross-Correlation Function Input and Output Series with Spatial Lag](image)

**Figure 2.** Cross-correlation function with spatial lag

Identification process to GSTARIMA-X model by using transfer function approach can use the pattern of space-time cross-correlation function. The variables used in the function were rice price and price of dry milled grain for six provinces in Java, Indonesia. The space-time cross-correlation function in Figure 2 shows that the spatial lag at 1\(^{st}\) order tended to be higher than 2\(^{nd}\) and 3\(^{rd}\) order. According to the pattern of spatial order, the spatial order for this data was \(l = 1\). The highest correlation began at the 0\(^{th}\) time lag. It indicated the order of \(b\) equal to zero \((b = 0)\), which means the price of dry milled grain started to affect the rice at the market level at the same time period.

The pattern of sine wave in cross correlation function showed the tendency of the autoregressive pattern of the output series. The autoregressive of output series had order 2 \((r = 2)\). The autoregressive pattern could use pattern of PACF plot from output series (rice price) after pre-whitening process. Explanation about pre-whitening process for this study could be seen at [8]. PACF plot of pre-whitening process of output series had been shown in Figure 3. The PACF plots of rice price at the market level tend to have autoregressive order at the order 2. Order \(r = 2\) shows that rice price at the market level in one province on Java affected to rice price at the market level in the same location and other locations up to two previous time periods.

According Figure 2, the correlation decreased after the 0\(^{th}\) time lag indicates that the length of the input series affecting the output series is 0 time period \((s = 0)\). It means that the dry milled grain price affected rice price at the market level at the same time period and had no effect on the next periods of rice price. The pattern of space-time cross-correlation function was useful to determine the order of GSTARIMA-X model by using transfer function approach. GSTARIMA-X model with model transfer function approach could be written by order \((b, r, s, p, q) = (0, 2, 1, 1, 0, 0, 0)\).
The order of GSTARIMA model could use ACF and PACF plots of original stationary data of rice price in six provinces, Java Island, Indonesia. The PACF plots (Figure 5) showed that rice price in six provinces of Java Island, Indonesia had autoregressive order $p = 2$. And according to ACF plots (Figure 6) showed that rice price in six province of Java had no moving average order ($q = 0$). The
PACF plots had the same interpretation to the order $r$ in GSTARIMA-X model by using transfer function approach. GSTARIMA model could be written by order $(p, d, q) = (2, 1, 1)$. 

![Figure 5. ACF plot of rice price at market level (original after = 1 )](image)

3.2. Model Evaluation

Performance model of GSTARIMA-X by using transfer function approach was compared to GSTARIMA model. Model identification yielded model order for model GSTARIMA and GSTARIMA-X by using transfer function approach. The order in the designated model was used in the forecasting process. The model performance in this research was done for data that used in model and forecasting. The result of model performance showed in Table 1.

| Province          | RMSEP Training Data | GSTAR IMA model | IMA-X model | GSTAR IMA-X model | IMA-X model | MAPE Testing Data | GSTAR IMA model | IMA-X model | GSTAR IMA-X model | IMA-X model |
|-------------------|---------------------|------------------|-------------|-------------------|-------------|-------------------|------------------|-------------|-------------------|-------------|
| DKI Jakarta       | 157.710             | 152.439          | 455.973     | 243.851           | 1.709       | 1.703             | 4.240            | 1.796       |
| West Java         | 166.787             | 148.087          | 184.236     | 151.515           | 1.805       | 1.585             | 1.328            | 1.470       |
| Central Java      | 154.446             | 126.811          | 284.781     | 359.858           | 1.503       | 1.291             | 2.102            | 3.991       |
| DI Yogyakarta     | 227.549             | 199.372          | 288.515     | 614.478           | 2.623       | 2.472             | 2.106            | 7.043       |
| East Java         | 201.217             | 186.140          | 315.382     | 286.938           | 2.196       | 2.164             | 3.489            | 3.409       |
| Banten            | 255.228             | 220.869          | 384.342     | 67.255            | 3.212       | 2.761             | 3.244            | 0.646       |
| Average           | 193.823             | 172.286          | 313.872     | 287.316           | 2.175       | 1.996             | 2.752            | 3.059       |

Table 1 showed that RMSEP and MAPE values of training data from GSTARIMA-X model in six provinces of Java had smaller than RMSEP and MAPE values of GSTARIMA model. The average of RMSE values of testing data from GSTARIMA-X model in six provinces of Java had smaller than...
average of RMSEP values of GSTARIMA model. There were two provinces that have greater RMSEP and MAPE values. They were Central Java and DI Yogyakarta. It might be due to rice price patterns in both provinces tended not to be influenced by the price of dry milled grain. According to RMSEP and MAPE values of training and testing data, those showed that GSTARIMA-X by using transfer function approach was better model than GSTARIMA for rice price data at the market level in six provinces of Java Island, Indonesia.

4. Conclusion
The GSTARIMA-X model by using transfer function approach could be used as an appropriate alternative model for space-time data modeling with exogenous variables. The space-time cross-correlation function could simplify and ease the identification proses in GSTARIMA-X model by using transfer function approach. Based on comparisons of RMSE and MAPE values in both data showed that GSTARIMA-X model by using transfer function approach had a better model performance than GSTARIMA model.

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