

Application of Spatial Weighting Matrix of GSTAR by Using CLARANS Clustering on Farmer Exchange Rates in 32 Provinces in Indonesia

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Abstract

Generalized Space Time Autoregressive (GSTAR) model was used to model the time series data that had correlation inter-location (space time). In the stage of model identification, spatial weight on GSTAR model shown relations of inter-location, which were weight normalized cross-correlation, binary, uniform, and inverse of distance. Data grouping uses the CLARANS (Clustering Large Application based on Randomized Search) Cluster analysis method, which is a clustering method that involves spatial elements by determining the number of clusters at the beginning where each object has the opportunity to be selected as a cluster center. The data used was secondary data of Farmer Exchange Rates in 32 provinces for 71 months from year 2005 to 2013, which has been obtained from the Economic Indicators published by BPS every month. Model candidates that have been obtained of the data were GSTAR(1;1) and GSTAR(2;1;1).

Keywords

Space-time Model, GSTAR, CLARANS, Weight Matrix.

1. Introduction

Farmer Exchange Rate (FER) is a price comparison received by farmers at the price paid by farmers, which is one indicator measure the welfare of farmers. The analysis of FER research has been conducted (Budi, 2015; BPS, 2013;

Simatupang, 2007; Mokuwa, 2013; Jhung Ahn, 2016) note that low FER is affected by production, household consumption, selling of rice and the use of superior seeds (Nursida K. Bantilan, 2107).

Based on Census of Agriculture 2013 that held Central Bureau of Statistics (CBS), it show that the number of farmer households reached 26.13 million or 42.7 percent of households nationwide. Meanwhile from the aspect of employment in 2011, the number of labor in the agricultural sector amounted to 39.3 million people or 35.9 percent of the total labor. In order to fulfill the agricultural necessity, each province needs its surrounding area to provide what cannot be fulfilled alone. It appears a dependency between provinces in the fulfillment of the needs in the agricultural sector. Thus the movement of FER in addition to having linkages on a previous time, also has linkages with other provinces called spatial relationships. Related to the above problems, it is necessary to conduct research that aims to develop a model for forecasting FER data according to time and location, both locations are considered the same or all locations have different characters.

In this research, a forecasting model was made which takes into account the aspects of time and location. The model that will be developed is *Generalized Space Time Autoregressive* (GSTAR). In order to find the best model, GSTAR has several stage that is model identification, parameter estimation, and diagnostic check. At the identification stage of the model, the linkages between the research locations in the GSTAR model are expressed by the \mathbf{W} spatial weight matrix. This location weight matrix provides all possible forms of relationships between multiple locations and provides a characteristic description of each location. So that, it produce a model candidate that describes the relationship of time and location by using four kinds of location spatial matrices for the GSTAR model including inverse spatial matrix, uniform, binary, and cross correlation normalization matrix.

2. Material and Methods

2.1 Generalized Space Time Autoregressive (GSTAR) Model

The GSTAR model is one model that is widely used to model and forecast time series and spatial data that are heterogeneous. The GSTAR model was introduced by Ruchjana as an extension of the STAR model introduced by Pfeifer and Deutsch. The GSTAR model ($p; \lambda_1, \lambda_2, \dots, \lambda_p$) is a space time model $\mathbf{z}(t)$ that fulfills (Ruchjana et al., 2012):

$$\mathbf{z}(t) = \sum_{k=1}^p \sum_{l=0}^{\lambda_k} \boldsymbol{\phi}_{kl} W^{(l)} \mathbf{z}(t-k) + \mathbf{e}(t)$$

where:

- $\mathbf{z}(t)$ = Random vector ordo $N \times 1$ at time t
- p, λ_k = Autoregressive order, spatial order of autoregressive term in-k
- $\boldsymbol{\phi}_{kl}$ = Autoregressive parameter at time lag k and spatial lag l
- $W^{(l)}$ = Weight matrix ordo $N \times N$ of spatial order l ($l = 0, 1, \dots, N$)
- $\mathbf{e}(t)$ = Error vector time t ordo $N \times 1$ assumed normally distributed with zero mean and constant variance

2.2 Spatial Weight Matrices in the Stage of Identification GSTAR Model

Cross Correlation Normalization Weight Matrix

In general, the cross correlation between two variables or locations i and j at the k -th time lag, $kor[z_i(t), z_j(t-k)]$ defined as [3,12] $\rho_{ij}(k) = \frac{\gamma_{ij}(k)}{\sigma_i \sigma_j}$, $k = 0, \pm 1, \pm 2, \pm 3, \dots$ where $\gamma_{ij}(k)$ is the cross covariance between observation at the i and j locations when the time lags to k and $\sigma_i \sigma_j$ are the standard deviations in observations at location i and j . Estimation of cross correlation on sample data is: (Abdullah AS, et al., 2018)

$$r_{ij}(k) = \frac{\sum_{t=k+1}^n [z_i(t) - \bar{z}_i][z_j(t-k) - \bar{z}_j]}{\sqrt{\left(\sum_{t=1}^n [z_i(t) - \bar{z}_i]^2\right) \left(\sum_{t=1}^n [z_j(t) - \bar{z}_j]^2\right)}}$$

To determine the spatial weight by normalizing the cross-correlation between locations at the corresponding time, this process generally generates spatial weights for the GSTAR model as $w_{ij} = \frac{r_{ij}(k)}{\sum_{k \neq i} |r_{ik}(k)|}$ with $i \neq j, k = 1, \dots, p$ and the spatial weight fulfilled $\sum_{k \neq i} |w_{ij}| = 1$.

Binary Weight Matrix

Binary weight matrix is a form of weight matrix whose elements are 0 or 1. The concept of a binary weight matrix is to use the closest friend, so to determine the larger or smaller is determined by the distance between locations. For

short distances, w_{ij} is worth 1 because the proximity of a location has a strong correlation, and in addition it is 0 because it does not have a strong correlation (Ruchjana et al., 2003).

Uniform Weight Matrix

Uniform weight matrix is a form of weight matrix that gives the same weight value for each location. The value of the Uniform weight can be calculated by the formula $w_{ij} = \frac{1}{n_i}$ with n_i is the number of locations adjacent to location with $i \neq j, k = 1, \dots, p$ and the weight fulfills $\sum_{k \neq i} |w_{ij}| = 1$ (Ruchjana et al., 2003).

Inverse Distance Weight Matrix

Inverse distance weight matrix is a form of weight matrix whose weight value is obtained from the calculation based on the actual distance between locations. Locations that have the closest distance will have a greater weight value than far-flung locations. The following calculation of the weight:

$$w_{ij} = \frac{(\sum_j^k X_{ij} - X_{ij})}{\sum_i^k (\sum_j^k X_{ij} - X_{ij})} \text{ with } X_{ij} \text{ is the distance of location-}i \text{ to location-}j \text{ (Ruchjana et al., 2003).}$$

2.3 Clustering Large Applications based on Randomized Search (CLARANS)

CLARANS is a type of clustering by dividing a data object into a non-overlapping (cluster) subset so that each data object is exactly one cluster (Wutsqa DU, et al., 2010). CLARANS starts the process by randomly taking several objects from n objects that were previously described as a *graph* denoted by $G_{n,k}$. These random objects are considered medoid on a *node*. So a *node* in the *graph* contains k -medoid, where k is the number of clusters. A *node* has a neighbor, and two *nodes* can be said to be neighboring if the difference between their medoid members is only one object. In other words, if there is k medoid on each node, then the difference between two nodes is only $(k-1)$ medoid object, so it can be concluded that one node has a $k(n-k)$ neighbor. And from this node, the total cost equation will be calculated by calculating the distance (*dissimilarity*) between medoid and each object (Arora P, et al., 2016).

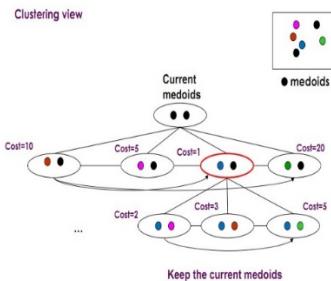


Figure 2.1 CLARANS algorithm illustration

CLARANS is the development of PAM, so the formula used in calculating the cost of each node comes from the PAM algorithm, namely:

$$TC_{ih} = \sum_j C_{jih}, \text{ where } C_{jih} = d(O_j, O_h) - d(O_j, O_i)$$

with O_h, O_i are two medoid candidate data objects that are compared and O_j is a non medoid data object (Aboubi Y, et al., 2016).

3. Result and Discussion

3.1 Selection of Location using CLARANS

The purpose of this experiment is to find the best cluster number (k). A good number of clusters can be seen from the high silhouette index (Nguyen T, et al., 2015). Clustering results in this experiment are presented in the table below:

Table 1. Clustering Results of Farmer Exchange Rate data in Indonesia

No. Test	1	2	3	4	5	6	7	8
k	2	3	4	5	6	7	8	9
$Mincost$	110.9786	95.3743	85.9398	79.8847	74.079	68.6817	64.0618	59.9077
<i>Best node</i>	[11, 19]	[2, 8, 22]	[19, 2, 31, 8]	[31, 23, 8, 2, 19]	[23, 8, 19, 2, 31, 32]	[32, 23, 11, 26, 2, 31, 19]	[29, 8, 32, 19, 2, 10, 31, 1]	[6, 2, 24, 19, 31, 29, 8, 10, 32]

Silhouette	0.4555	0.3333	0.2643	0.2345	0.2759	0.2707	0.0807	0.0502
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Based on Table 1, it is found that the best number of clusters for classifying Farmer Exchange Rate data in Indonesia is 2 with silhouette index 0.4555. Then from the results of this cluster selected clusters in which there are provinces that have Farmer Exchange Rates are quite large and have good data density.

The geographical plot and silhouette results are as below:

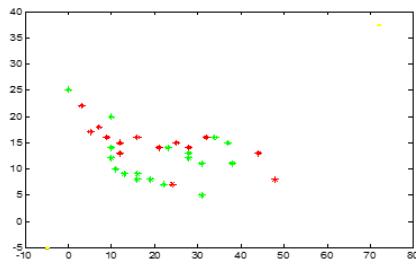


Figure 1.a Cluster plot with $k = 2$

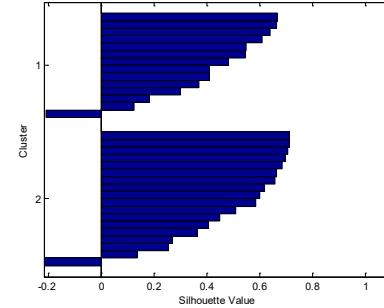


Figure 1.b Silhouette cluster results with $k = 2$

From these results a cluster can be taken with the provinces that have the most stable NTP data, namely clusters that are given a red color totaling fourteen provinces. The fourteen provinces include North Sumatra Z_1 , West Sumatra Z_2 , Riau Z_3 , Jambi Z_4 , Bangka Belitung Islands Z_5 , West Kalimantan Z_6 , Central Kalimantan Z_7 , South Kalimantan Z_8 , Kalimantan Timur Z_9 , Sulawesi Utara Z_{10} , Gorontalo Z_{11} , Sulawesi Barat Z_{12} , West Papua Z_{13} , and Papua Z_{14} .

3.2 Heterogeneity Test

One test to see the heterogeneity or homogeneity of the data auto regression parameter is to use the Gini index method. The results of the Gini Index calculation which states that the fourteen provinces selected are heterogeneous data, with the Gini index of 1,000862317.

3.3 Spatial Weight Matrix

Cross Correlation Normalization Weight Matrix

Cross Correlation Normalization Weight Matrix spatial lag 1, 2, and 3 with $N = 14$.

$$\mathbf{W}^{(1)} = \begin{bmatrix} Z_1 & 0 & 0.1238 & 0.1333 & 0.1380 & 0.0420 & 0.1262 & 0.1449 & 0.0590 & 0.0379 & 0.0868 & 0.0405 & 0.0239 & -0.0032 & 0.0469 \\ Z_2 & 0.1483 & 0 & 0.1398 & 0.1271 & 0.0974 & 0.1147 & 0.1408 & 0.0743 & 0.0100 & 0.1326 & 0.0501 & -0.0264 & -0.0465 & 0.0379 \\ Z_3 & 0.1474 & 0.1291 & 0 & 0.1080 & 0.0960 & 0.0992 & 0.1735 & 0.1349 & -0.0380 & 0.0793 & 0.0745 & 0.0172 & -0.0815 & 0.0604 \\ Z_4 & 0.1596 & 0.1227 & 0.1130 & 0 & 0.0123 & 0.1653 & 0.1481 & -0.0382 & 0.1092 & 0.0758 & 0.0274 & -0.0257 & 0.0575 & 0.0730 \\ Z_5 & 0.4510 & 0.8736 & 0.9328 & 0.1147 & 0 & 0.2806 & 0.4065 & 0.7656 & -1.2045 & 0.7390 & 0.2577 & -0.8587 & -1.5086 & -0.2497 \\ Z_6 & 0.1474 & 0.1118 & 0.1048 & 0.1669 & 0.0305 & 0 & 0.1292 & -0.0309 & 0.1110 & 0.0962 & 0.0617 & -0.0550 & 0.0547 & 0.0718 \\ Z_7 & 0.1598 & 0.1296 & 0.1730 & 0.1412 & 0.0417 & 0.1219 & 0 & 0.0884 & 0.0071 & 0.0373 & 0.0131 & 0.0746 & -0.0320 & 0.0441 \\ Z_8 & 0.2054 & 0.2160 & 0.4250 & -0.1152 & 0.2483 & -0.0923 & 0.2792 & 0 & -0.3665 & 0.1396 & 0.1452 & 0.3292 & -0.3298 & -0.0842 \\ Z_9 & 0.1767 & 0.0390 & -0.1604 & 0.4404 & -0.5231 & 0.4437 & 0.0300 & -0.4908 & 0 & 0.0947 & 0.0533 & -0.1194 & 0.6986 & 0.3174 \\ Z_{10} & 0.1534 & 0.1957 & 0.1266 & 0.1158 & 0.1215 & 0.1455 & 0.0598 & 0.0708 & 0.0359 & 0 & 0.0437 & -0.0200 & 0.0072 & -0.0559 \\ Z_{11} & 0.0990 & 0.1024 & 0.1648 & 0.0581 & 0.0587 & 0.1293 & 0.0291 & 0.1020 & 0.0279 & 0.0605 & 0 & -0.0888 & 0.0443 & 0.2128 \\ Z_{12} & -0.5651 & 0.5223 & -0.3684 & 0.5263 & 1.8910 & 1.1135 & -1.6017 & -2.2354 & 0.6054 & 0.2674 & 0.8591 & 0 & -0.4648 & 0.4505 \\ Z_{13} & 0.0873 & 1.0629 & 2.0171 & -1.3604 & 3.8429 & -1.2809 & 0.7930 & 2.5907 & -4.0972 & -0.1108 & -0.4954 & -0.5376 & 0 & -1.5117 \\ Z_{14} & 0.1143 & 0.0771 & 0.1332 & 0.1541 & -0.0567 & 0.1500 & 0.0976 & -0.0590 & 0.1660 & -0.0772 & 0.2123 & -0.0465 & 0.1348 & 0 \end{bmatrix}$$

$$\mathbf{W}^{(2)} = \begin{bmatrix} Z_1 & 0 & 0.1297 & 0.1347 & 0.1355 & 0.0267 & 0.1208 & 0.1675 & 0.0761 & 0.0398 & 0.0896 & 0.0046 & 0.0389 & -0.0175 & 0.0537 \\ Z_2 & 0.1702 & 0 & 0.1503 & 0.1250 & 0.1048 & 0.1066 & 0.1720 & 0.1090 & -0.0147 & 0.1333 & 0.0157 & -0.0140 & -0.0807 & 0.0224 \\ Z_3 & 0.1441 & 0.1226 & 0 & 0.1068 & 0.1057 & 0.0875 & 0.2080 & 0.1739 & -0.0599 & 0.0990 & 0.0336 & 0.0344 & -0.1140 & 0.0582 \\ Z_4 & 0.1622 & 0.1140 & 0.1195 & 0 & 0.0025 & 0.1703 & 0.1736 & -0.0551 & 0.1323 & 0.0848 & -0.0273 & -0.0215 & 0.0569 & 0.0877 \\ Z_5 & 1.3676 & 4.0874 & 5.0529 & 0.1079 & 0 & 0.2753 & 2.6068 & 5.8022 & -8.0714 & 3.7508 & 1.0441 & -4.1172 & -9.3935 & -1.5126 \\ Z_6 & 0.1469 & 0.0988 & 0.0995 & 0.1730 & 0.0065 & 0 & 0.1701 & -0.0414 & 0.1288 & 0.1056 & 0.0282 & -0.0563 & 0.0564 & 0.0839 \\ Z_7 & 0.1663 & 0.1301 & 0.1929 & 0.1440 & 0.0506 & 0.1388 & 0 & 0.0999 & 0.0003 & 0.0301 & -0.0409 & 0.0985 & -0.0496 & 0.0391 \\ Z_8 & 0.1850 & 0.2020 & 0.3952 & -0.1119 & 0.2757 & -0.0828 & 0.2447 & 0 & -0.3196 & 0.1015 & 0.1206 & 0.3312 & -0.2698 & -0.0718 \\ Z_9 & 0.3344 & -0.0943 & -0.4707 & 0.9296 & -1.3264 & 0.8906 & 0.0021 & -1.1054 & 0 & 0.1071 & -0.0064 & -0.3909 & 1.5699 & 0.5604 \\ Z_{10} & 0.1537 & 0.1744 & 0.1587 & 0.1215 & 0.1257 & 0.1490 & 0.0521 & 0.0716 & 0.0219 & 0 & 0.0713 & -0.0056 & 0.0075 & -0.1018 \\ Z_{11} & 0.0328 & 0.0849 & 0.2220 & -0.1616 & 0.1444 & 0.1641 & -0.2919 & 0.3511 & -0.0054 & 0.2944 & 0 & -0.4756 & -0.0680 & 0.7087 \\ Z_{12} & 1.5075 & -0.4142 & 1.2471 & -0.6955 & -3.1169 & -1.7934 & 3.8431 & 5.2770 & -1.8010 & -0.1274 & -2.6028 & 0 & 1.1658 & -1.4893 \\ Z_{13} & 0.1175 & 0.4115 & 0.7130 & -0.3182 & 1.2288 & -0.3107 & 0.3345 & 0.7429 & -1.2496 & -0.0294 & 0.0643 & -0.2014 & 0 & -0.5031 \\ Z_{14} & 0.1369 & 0.0436 & 0.1389 & 0.1870 & -0.0754 & 0.1761 & 0.1006 & -0.0753 & 0.1700 & -0.1513 & 0.2554 & -0.0981 & 0.1918 & 0 \end{bmatrix}$$

	$\mathbf{W}^{(3)} =$															
Z_1	0	0.1346	0.1438	0.1393	0.0082	0.1125	0.2185	0.1219	0.0435	0.1243	-0.0832	0.0648	-0.0535	0.0254		
Z_2	0.1613	0	0.1852	0.1012	0.1045	0.0919	0.1980	0.1823	-0.0449	0.1241	-0.0247	0.0389	-0.1403	0.0226		
Z_3	0.1307	0.1405	0	0.0919	0.1173	0.0572	0.2494	0.2502	-0.0979	0.1272	-0.0212	0.0852	-0.1693	0.0388		
Z_4	0.1750	0.1061	0.1269	0	-0.0180	0.2003	0.2206	-0.0900	0.1957	0.1169	-0.1483	-0.0263	0.0490	0.0921		
Z_5	-0.1102	-1.1674	-1.7261	0.1917	0	0.4391	-1.0273	-2.9448	3.5733	-1.2805	-0.3110	0.9544	3.9992	0.4096		
Z_6	0.1428	0.0974	0.0799	0.2025	-0.0417	0	0.2418	-0.0639	0.1761	0.1410	-0.0424	-0.0932	0.0532	0.1064		
Z_7	0.1762	0.1332	0.2212	0.1417	0.0619	0.1536	0	0.1281	-0.0080	0.0297	-0.1262	0.1400	-0.0705	0.0191		
Z_8	0.1632	0.2036	0.3684	-0.0959	0.2946	-0.0674	0.2126	0	-0.2721	0.0742	0.0841	0.3203	-0.2203	-0.0653		
Z_9	-3.1552	2.7126	7.8072	-11.2939	19.3532	-10.0527	0.7225	14.7306	0	0.4925	0.8756	6.5717	-21.2560	-6.5082		
Z_{10}	0.1494	0.1245	0.1682	0.1120	0.1151	0.1336	0.0444	0.0667	-0.0082	0	0.1270	0.0168	0.0232	-0.0727		
Z_{11}	0.3036	0.0753	0.0850	0.4307	-0.0848	0.1217	0.5706	-0.2292	0.0441	-0.3852	0	0.3605	0.2559	-0.5481		
Z_{12}	0.2251	0.1126	0.3253	-0.0726	-0.2478	-0.2549	0.6032	0.8312	-0.3150	0.0485	-0.3435	0	0.2939	-0.2061		
Z_{13}	0.1329	0.2906	0.4621	-0.0968	0.7419	-0.1040	0.2171	0.4085	-0.7280	-0.0478	0.1742	-0.2100	0	-0.2407		
Z_{14}	1	0.0627	0.0464	0.1051	0.1808	-0.0754	0.2065	0.0585	-0.1202	0.2213	-0.1489	0.3705	-0.1462	0.2390	0	

Binary Weight Matrix

Binary weight matrix spatial lag 1, 2, and 3 with $N = 14$.

$$\mathbf{W}^{(1)} = \begin{array}{|c|cccccccccccccc|} \hline Z_1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline Z_2 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline Z_3 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline Z_4 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline Z_5 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline Z_6 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline Z_7 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline Z_8 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline Z_9 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ \hline Z_{10} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ \hline Z_{11} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ \hline Z_{12} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ \hline Z_{13} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ \hline Z_{14} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ \hline \end{array}$$

$$\mathbf{W}^{(2)} = \begin{array}{|c|cccccccccccccc|} \hline Z_1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline Z_2 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline Z_3 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline Z_4 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline Z_5 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline Z_6 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline Z_7 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline Z_8 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline Z_9 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline Z_{10} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline Z_{11} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ \hline Z_{12} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ \hline Z_{13} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline Z_{14} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ \hline \end{array}$$

$$\mathbf{W}^{(3)} = \begin{array}{|c|cccccccccccccc|} \hline Z_1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline Z_2 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline Z_3 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline Z_4 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline Z_5 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline Z_6 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline Z_7 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline Z_8 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline Z_9 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline Z_{10} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline Z_{11} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ \hline Z_{12} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ \hline Z_{13} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline Z_{14} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ \hline \end{array}$$

Uniform Weight Matrix

Uniform weight matrix spatial lag 1, 2, and 3 with $N = 14$.

$$\mathbf{W}^{(1)} = \begin{bmatrix} Z_1 & 0 & 0.25 & 0.25 & 0.25 & 0.25 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ Z_2 & 0.25 & 0 & 0.25 & 0.25 & 0.25 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ Z_3 & 0 & 0.25 & 0 & 0.25 & 0.25 & 0.25 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ Z_4 & 0 & 0.25 & 0.25 & 0 & 0.25 & 0.25 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ Z_5 & 0 & 0.25 & 0.25 & 0.25 & 0 & 0.25 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ Z_6 & 0 & 0 & 0 & 0.25 & 0.25 & 0 & 0.25 & 0.25 & 0 & 0 & 0 & 0 & 0 & 0 \\ Z_7 & 0 & 0 & 0 & 0 & 0 & 0.25 & 0 & 0.25 & 0.25 & 0 & 0 & 0.25 & 0 & 0 \\ Z_8 & 0 & 0 & 0 & 0 & 0 & 0.25 & 0.25 & 0 & 0.25 & 0 & 0 & 0.25 & 0 & 0 \\ Z_9 & 0 & 0 & 0 & 0 & 0 & 0 & 0.25 & 0.25 & 0 & 0 & 0.25 & 0.25 & 0 & 0 \\ Z_{10} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.25 & 0 & 0.25 & 0.25 & 0 & 0.25 \\ Z_{11} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.25 & 0.25 & 0.25 & 0 & 0.25 & 0 & 0 \\ Z_{12} & 0 & 0 & 0 & 0 & 0 & 0 & 0.25 & 0.25 & 0.25 & 0 & 0.25 & 0 & 0 & 0 \\ Z_{13} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.25 & 0.25 & 0.25 & 0 & 0.25 \\ Z_{14} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.25 & 0.25 & 0.25 & 0.25 & 0 \end{bmatrix}$$

$$W^{(2)} = \begin{bmatrix} Z_1 & 0 & 0 & 0 & 0 & 0 & 0.25 & 0.25 & 0.25 & 0.25 & 0 & 0 & 0 & 0 & 0 \\ Z_2 & 0 & 0 & 0 & 0 & 0 & 0.25 & 0.25 & 0.25 & 0.25 & 0 & 0 & 0 & 0 & 0 \\ Z_3 & 0 & 0 & 0 & 0 & 0 & 0.25 & 0.25 & 0.25 & 0.25 & 0 & 0 & 0 & 0 & 0 \\ Z_4 & 0.25 & 0 & 0 & 0 & 0 & 0 & 0.25 & 0.25 & 0.25 & 0 & 0 & 0 & 0 & 0 \\ Z_5 & 0.25 & 0 & 0 & 0 & 0 & 0.25 & 0.25 & 0.25 & 0.25 & 0 & 0 & 0 & 0 & 0 \\ Z_6 & 0 & 0.25 & 0.25 & 0 & 0 & 0 & 0 & 0 & 0.25 & 0 & 0 & 0.25 & 0 & 0 \\ Z_7 & 0 & 0 & 0 & 0.25 & 0.25 & 0 & 0 & 0 & 0 & 0.25 & 0.25 & 0 & 0 & 0 \\ Z_8 & 0 & 0 & 0 & 0.25 & 0.25 & 0 & 0 & 0 & 0 & 0.25 & 0.25 & 0 & 0 & 0 \\ Z_9 & 0 & 0 & 0 & 0.25 & 0.25 & 0.25 & 0 & 0 & 0 & 0.25 & 0 & 0 & 0 & 0 \\ Z_{10} & 0 & 0 & 0 & 0 & 0 & 0.25 & 0.25 & 0.25 & 0.25 & 0 & 0 & 0 & 0.25 & 0 \\ Z_{11} & 0 & 0 & 0 & 0 & 0.25 & 0.25 & 0.25 & 0.25 & 0 & 0 & 0 & 0 & 0 & 0.25 \\ Z_{12} & 0 & 0 & 0 & 0 & 0.25 & 0.25 & 0.25 & 0 & 0 & 0.25 & 0 & 0 & 0.25 & 0.25 \\ Z_{13} & 0 & 0 & 0 & 0 & 0 & 0.25 & 0.25 & 0.25 & 0.25 & 0 & 0 & 0 & 0 & 0 \\ Z_{14} & 0 & 0 & 0 & 0 & 0 & 0.25 & 0.25 & 0.25 & 0.25 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Inverse Distance Weight Matrix

Inverse Distance weight matrix spatial lag 1 and 2 with $N = 4$.

$$W^{(1)} = \begin{bmatrix} Z_1 & 0 & 0.0817 & 0.0819 & 0.0808 & 0.0801 & 0.07940 & 0.0777 & 0.0773 & 0.0768 & 0.0742 & 0.0748 & 0.0758 & 0.0686 & 0.0709 \\ Z_2 & 0.0814 & 0 & 0.0826 & 0.0820 & 0.0810 & 0.0798 & 0.0779 & 0.0776 & 0.0767 & 0.0736 & 0.0743 & 0.0758 & 0.0673 & 0.0700 \\ Z_3 & 0.0816 & 0.0826 & 0 & 0.0821 & 0.0811 & 0.0801 & 0.0780 & 0.0776 & 0.0768 & 0.0736 & 0.0743 & 0.0755 & 0.0670 & 0.0698 \\ Z_4 & 0.0800 & 0.0818 & 0.0819 & 0 & 0.0822 & 0.0806 & 0.0786 & 0.0782 & 0.0771 & 0.0735 & 0.0743 & 0.0761 & 0.0663 & 0.0693 \\ Z_5 & 0.0786 & 0.0804 & 0.0806 & 0.0821 & 0 & 0.0814 & 0.0794 & 0.0791 & 0.0778 & 0.0738 & 0.0748 & 0.0767 & 0.0660 & 0.0693 \\ Z_6 & 0.0773 & 0.0785 & 0.0791 & 0.0801 & 0.0806 & 0 & 0.0806 & 0.0800 & 0.0791 & 0.0749 & 0.0759 & 0.0778 & 0.0663 & 0.0699 \\ Z_7 & 0.0741 & 0.0756 & 0.0761 & 0.0775 & 0.0777 & 0.0804 & 0 & 0.0826 & 0.0812 & 0.0768 & 0.0779 & 0.0802 & 0.0681 & 0.0718 \\ Z_8 & 0.0737 & 0.0753 & 0.0757 & 0.0772 & 0.0772 & 0.0799 & 0.0826 & 0 & 0.0812 & 0.0770 & 0.0782 & 0.0807 & 0.0688 & 0.0724 \\ Z_9 & 0.0729 & 0.0740 & 0.0746 & 0.0758 & 0.0763 & 0.0790 & 0.0813 & 0.0812 & 0 & 0.0789 & 0.0800 & 0.0817 & 0.0702 & 0.0740 \\ Z_{10} & 0.0722 & 0.0729 & 0.0734 & 0.0743 & 0.0747 & 0.0767 & 0.0785 & 0.0785 & 0.0800 & 0 & 0.0825 & 0.0805 & 0.0764 & 0.0793 \\ Z_{11} & 0.0721 & 0.0729 & 0.0734 & 0.0744 & 0.0748 & 0.0770 & 0.0789 & 0.0791 & 0.0806 & 0.0824 & 0 & 0.0811 & 0.0751 & 0.0782 \\ Z_{12} & 0.0722 & 0.0736 & 0.0736 & 0.0752 & 0.0755 & 0.0780 & 0.0805 & 0.0809 & 0.0818 & 0.0798 & 0.0809 & 0 & 0.0723 & 0.0757 \\ Z_{13} & 0.0737 & 0.0741 & 0.0744 & 0.0749 & 0.0750 & 0.0762 & 0.0772 & 0.0774 & 0.0780 & 0.0796 & 0.0793 & 0.0785 & 0 & 0.0818 \\ Z_{14} & 0.0729 & 0.0735 & 0.0738 & 0.0745 & 0.0747 & 0.0761 & 0.0774 & 0.0776 & 0.0784 & 0.0806 & 0.0801 & 0.0790 & 0.0813 & 0 \end{bmatrix}$$

$$W^{(1)} = \begin{bmatrix} Z_1 & 0 & 0.076954 & 0.076956 & 0.076945 & 0.076935 & 0.076925 & 0.076903 & 0.076901 & 0.076895 & 0.076891 & 0.076889 & 0.076891 & 0.076900 & 0.076895 \\ Z_2 & 0.076956 & 0 & 0.076962 & 0.076957 & 0.076947 & 0.076934 & 0.076914 & 0.076912 & 0.076903 & 0.076895 & 0.076895 & 0.076900 & 0.076904 & 0.076899 \\ Z_3 & 0.076958 & 0.076963 & 0 & 0.076958 & 0.076949 & 0.076938 & 0.076917 & 0.076915 & 0.076907 & 0.076899 & 0.076899 & 0.076900 & 0.076905 & 0.076902 \\ Z_4 & 0.076950 & 0.076968 & 0.076959 & 0 & 0.076959 & 0.076945 & 0.076927 & 0.076925 & 0.076915 & 0.076905 & 0.076905 & 0.076911 & 0.076909 & 0.076906 \\ Z_5 & 0.076945 & 0.076951 & 0.076952 & 0.076959 & 0 & 0.076949 & 0.076928 & 0.076925 & 0.076919 & 0.076908 & 0.076908 & 0.076913 & 0.076910 & 0.076908 \\ Z_6 & 0.076940 & 0.076943 & 0.076945 & 0.076949 & 0.076954 & 0 & 0.076948 & 0.076944 & 0.076937 & 0.076922 & 0.076924 & 0.076931 & 0.076918 & 0.076917 \\ Z_7 & 0.076929 & 0.076930 & 0.076931 & 0.076935 & 0.076941 & 0.076949 & 0 & 0.076963 & 0.076953 & 0.076953 & 0.076934 & 0.076937 & 0.076948 & 0.076925 & 0.076927 \\ Z_8 & 0.076926 & 0.076928 & 0.076928 & 0.076932 & 0.076938 & 0.076944 & 0.076962 & 0 & 0.076953 & 0.076944 & 0.076938 & 0.076950 & 0.076950 & 0.076926 & 0.076928 \\ Z_9 & 0.076922 & 0.076921 & 0.076922 & 0.076924 & 0.076929 & 0.076938 & 0.076953 & 0.076953 & 0 & 0.076961 & 0.076948 & 0.076957 & 0.076930 & 0.076933 \\ Z_{10} & 0.076904 & 0.076900 & 0.076900 & 0.076899 & 0.076901 & 0.076909 & 0.076922 & 0.076924 & 0.076937 & 0 & 0.076961 & 0.076943 & 0.076942 & 0.076948 & 0.076948 \\ Z_{11} & 0.076908 & 0.076905 & 0.076905 & 0.076905 & 0.076908 & 0.076916 & 0.076930 & 0.076932 & 0.076945 & 0.076962 & 0 & 0.076950 & 0.076939 & 0.076945 & 0.076945 \\ Z_{12} & 0.076916 & 0.076915 & 0.076913 & 0.076917 & 0.076922 & 0.076929 & 0.076946 & 0.076949 & 0.076956 & 0.076948 & 0.076952 & 0 & 0.076934 & 0.076938 & 0.076938 \\ Z_{13} & 0.076865 & 0.076856 & 0.076854 & 0.076849 & 0.076847 & 0.076849 & 0.076862 & 0.076867 & 0.076877 & 0.076920 & 0.076910 & 0.076891 & 0 & 0 & 0.076954 \\ Z_{14} & 0.076682 & 0.076875 & 0.076873 & 0.076870 & 0.076870 & 0.076875 & 0.076888 & 0.076892 & 0.076902 & 0.076940 & 0.076932 & 0.076915 & 0.076957 & 0 & 0 \end{bmatrix}$$

3.4 Identifying stationary and model candidates using STACF and STPACF

The initial stage of the formation of the candidate model is the identification of the model by looking at the value of STACF and STPACF. Here are the STACF and STPACF values of the number of migrant workers with N = 4 and T = 71 with the cross correlation matrix of binary, uniform, and inverse distance weights:

Table 2. STACF Value (Space Time Autocorrelation Function)

Weight	Time lag (s) Spatial lag (t)	STACF Value (Space Time Autocorrelation Function)					
		1	2	3	4	5	6
Cross Correlation	0	0.9862	0.9724	0.9584	0.9445	0.9304	0.9162
	1	0.43	0.4238	0.4176	0.4114	0.4051	0.3987
	2	0.2036	0.2006	0.1977	0.1947	0.1917	0.1886
	3	0.0998	0.0982	0.0966	0.095	0.0933	0.0917
Binary	0	0.9862	0.9724	0.9584	0.9445	0.9304	0.9162
	1	0.9849	0.9711	0.9572	0.9433	0.9292	0.915
	2	0.9134	0.9006	0.8878	0.875	0.8621	0.849
	3	0.9849	0.9712	0.9574	0.9436	0.9297	0.9155
Uniform	0	0.9862	0.9724	0.9584	0.9445	0.9304	0.9162
	1	1.9342	1.907	1.8797	1.8524	1.8247	1.7968
	2	1.9888	1.9609	1.9329	1.9049	1.8766	1.848
	3	2.2338	2.2026	2.1712	2.1397	2.1079	2.0757
Inverse Distance	0	0.9862	0.9724	0.9584	0.9445	0.9304	0.9162
	1	3.5457	3.496	3.4461	3.3961	3.3455	3.2944
	2	3.5512	3.5014	3.4514	3.4013	3.3507	3.2995

Table 3. STPACF Value (Space Time Partial Autocorrelation Function)

Weight	Time lag (s) Spatial lag (t)	STPACF Value (Space Time Partial Autocorrelation Function)					
		0	1	2	3	4	5
	0	0.9998	-0.0139	-0.000053	-0.000205	-0.000368	0.9998

Cross Correlation	1	-0.0103	0.0208	-0.0108	0.000369	-0.000038	-0.0103
	2	-0.002	0.0038	-0.0018	-0.000025	-0.000008	-0.002
	3	-0.000479	0.000928	-0.000459	-0.000003	-0.000004	-0.000479
Binary	0	0.9998	-0.0139	-0.000053	-0.000205	-0.000368	0.9998
	1	-0.0718	0.1437	-0.0727	0.0014793	-0.000902	-0.0718
	2	-0.1452	0.2895	-0.1462	0.002556	-0.00007	-0.1452
	3	-0.0696	0.1392	-0.07	0.0012061	-0.000057	-0.0696
Uniform	0	0.9998	-0.0139	-0.000053	-0.000205	-0.000368	0.9998
	1	-0.3573	0.712	-0.3573	0.005163	-0.00106	-0.3573
	2	-0.2775	0.5551	-0.2804	0.0054562	-0.000251	-0.2775
	3	-0.2789	0.5553	-0.2751	0.002163	-0.000206	-0.2789
Inverse Distance	0	0.9998	-0.0139	-0.000053	-0.000205	-0.000368	0.9998
	1	-0.9226	1.8396	-0.921	0.0125647	-0.001547	-0.9226
	2	-0.9179	1.8301	-0.9157	0.012185	-0.001496	-0.9179

The value of STACF in Table 2, uses a cross correlation matrix of binary, uniform, and inverse distance decreases significantly (tail off) on all spatial lags so it can be concluded that the data obtained is stationary data. STPACF value in Table 3 cut off at certain time lags and spatial lags. The following is a list of candidate models from the four weight matrices of the location.

Table 4. Candidates for *Generalized Space-Time Autoregressive (GSTAR)* Model
 for Farmer Exchange Rate data in 32 Provinces in Indonesia

Weight Matrix	Candidate Model
Normalization Cross Correlation	G S T A R (1 ; 1) GSTAR(2;1,1)
Binary	G S T A R (1 ; 1) GSTAR(2;1,1)
Uniform	G S T A R (1 ; 1) GSTAR(2;1,1)
Inverse Distance	G S T A R (1 ; 1) GSTAR(2;1,1)

Based on Table 4, it can be concluded that the model candidates for Farmer Exchange Rate data include GSTAR (1; 1) and GSTAR (2; 1.1).

4. Conclusion

In this paper we have analyzed that the application of spatial weight matrix of GSTAR Model can be conclude as follow:

- The Role of Matrix Weight The location at the identification stage of the model is to see how much correlation each neighbor has to a location. The Location Weight Matrix also plays a role in checking stationary and identifying candidates for the Generalized Space-Time Autoregressive (GSTAR) model.
- Model candidates for Farmer Exchange Rate data include GSTAR (1; 1) and GSTAR (2; 1.1).

Acknowledgements

Acknowledgments are conveyed to the Rector, Director of Directorate of Research, Community Involvement and Innovation, and the Dean of Faculty of Mathematics and Natural Sciences, Universitas Padjadjaran.

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