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Preface: 4th International Conference on Applied Sciences, Mathematics, and Informatics (ICASMI) 2022

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Preface: 4th International Conference on Applied Sciences, Mathematics, and Informatics (ICASMI) 2022

It was an honor for the Institute for Research and Community Services of Universitas Lampung to host the 4th International Conference on Applied Sciences, Mathematics, and Informatics (ICASMI) 2022. On September 8-9, 2022, due to the COVID-19 pandemic, the entire event was held online utilizing Zoom. The event was additionally supported by The Indonesian Mathematical Society (IndoMS) of Southern Sumatra, Himpunan Kimia Indonesia (HKI) Lampung, Physical Society of Indonesia (PSI) Lampung, and Perhimpunan Biologi Indonesia Lampung.

The pandemic has forced us to work from home. However, we believe that scientific communication should remain connected and up-to-date. This conference has been devoted to encouraging synergy in natural sciences and technology through interdisciplinary and multidisciplinary research. Therefore, to provide us with both academic and practical knowledge, we invited speakers who were specialists in their fields of study. They originated from several countries, including Pakistan, Malaysia, Thailand, Russia, and Indonesia. Thus, the 4th ICASMI 2022 Conference provided an opportunity to investigate a wide range of topics related to our conference theme, "The Role of Natural Sciences, Mathematics, and Informatics in the Development of Advanced Materials Based on Natural Resources."

The 4th ICASMI 2022 conference was anticipated to be both stimulating and informative, with the goal of fostering relationships and exchange of theoretical and practical ideas and knowledge among those interested in collaborative interdisciplinary and multidisciplinary research in the fields of physics, informatics, chemistry, mathematics, biology, innovative instruction for mathematics and natural sciences development, and applications of mathematics and natural sciences in agriculture, medicine, and other fields. This conference comprised invited sessions and panel discussions with notable speakers on a wide range of academic topics. Throughout the interactive sessions, both speakers and attendees were able to connect online with one another.

This edition of AIP Conference Proceedings has 177 articles representing a selection of the contributions given at the 4th ICASMI 2022. The papers address a variety of issues connected to the theme of the conference. We consider it an honour to deliver the most up-to-date scientific knowledge and developments in mathematics and the natural sciences. In addition, we feel these proceedings will serve as a significant resource for researchers around the world.

The meeting represents the culmination of countless persons' efforts. As a result, we would like to express our appreciation to the members of the organizing committee for their daily efforts in assuring the success of the conference and to the reviewers for their diligent work in evaluating the submissions. In addition, we are grateful to the invited keynote speakers for sharing their insights and knowledge with us. The conference would not be possible without the authors' outstanding contributions. We would like to thank all authors for their participation and contributions to the 4th ICASMI 2022.

We look forward to seeing you at the 5th ICASMI 2024.

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Generalized space-time autoregressive (GSTAR) modeling with seemingly unrelated regression (SUR) for forecasting inflation data in five cities on the island of Sumatra

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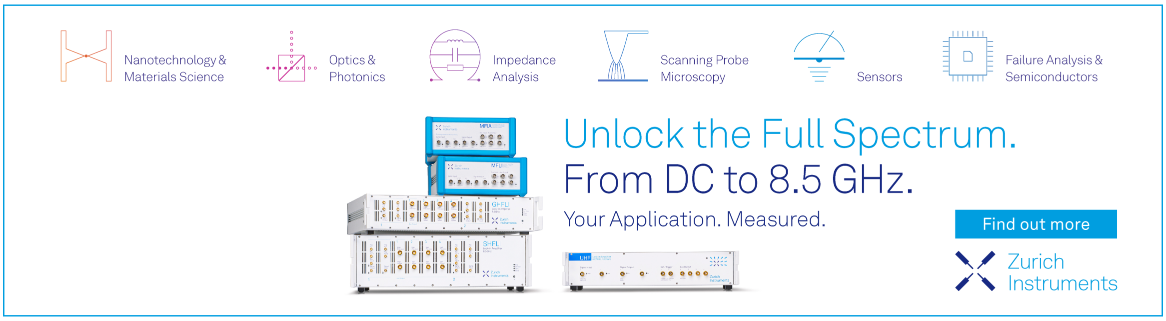

Generalized Space-Time Autoregressive (GSTAR) Modeling with Seemingly Unrelated Regression (SUR) for Forecasting Inflation Data in Five Cities on the Island of Sumatra

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Abstract. The Covid-19 pandemic and Russian invasion of Ukraine made food and energy prices in the world soar. This price spike has triggered inflation in various countries, such as Indonesia. Currently, the most developed forecasting method is the time series. The development of a multivariate time series, apart from looking at the time element, also involves an element of location. One model that involves time and location is the Generalized Space Time Autoregressive (GSTAR) model. The GSTAR model is a development of the Space Time Autoregressive (STAR) model which assumes that the location element is heterogeneous. The purpose of this study was to obtain the GSTAR model using Seemingly Unrelated Regression (SUR) on inflation data in five cities on the island of Sumatra. The methods used in this study are, 1) perform descriptive analysis, 2) perform stationarity test, 3) identify the GSTAR model, 4) calculate the location weight matrix, and 5) calculate parameter estimates for the GSTAR model using the SUR method. In this study, it is found that the inflation model for five cities on the island of Sumatra at time t is correlated with inflation data at the previous time and is influenced by inflation data from other cities.

INTRODUCTION

Currently, the main thing for countries in the world is inflation. Inflation is a tendency to increase the price of goods and services that takes place continuously and will result in a decrease in the value of the currency [1]. Inflation is the root of economic dynamics that risks hampering the pace of economic recovery due to the impact of Covid-19. In addition, the Russian invasion of Ukraine also made food and energy prices in the world soar. This price spike is what triggers inflation in various countries [2].

Time series is the most developed forecasting method today. The development of a multivariate time series, apart from looking at the time element, also involves an element of location. Data that has a relationship between time series and location is called space-time data [3]. The model that can be used for space-time data is Space Time Autoregressive (STAR) [4]. In the STAR model, the location is assumed to be homogeneous, which causes this model to have a weakness in parameter flexibility, so if the location characteristics are heterogeneous, the STAR model is not good to use. In 1973, Cliff and Ord introduced a method that can overcome the weaknesses of the STAR model, this model is called Generalized Space Time Autoregressive (GSTAR). According to [5], the locations in the GSTAR model are assumed to have heterogeneous characteristics, with differences between locations represented in a weighting matrix. Research that has been carried out with the GSTAR model includes, Siagian, et al. [6], Handayani, et al. [7], Mario, et al. [8], Eni, et al. [9], Hasbi & Rahman [10], Zewdie, et al. [11], Yundari, et al. [12], Siswanto, et al. [13], Suhartono, et al. [14], Prastuti & Ratih [15], Islamiyah, et al. [16], Yundari & Martha [17], Agustina, et al. [18], Permatasari, et al. [19], Aufa, et al. [20], Jusman, et al. [21], Masdin, et al. [22], Habibie, et al. [23], Amri [24], Aryani, et al. [25], and Fransiska, et al. [26].

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Stationarity

In conducting time series analysis, the assumption that must be met is that the data is in a stationary state. Stationarity is the absence of a drastic change in the data. Data fluctuations are at a constant mean value and do not depend on the time and variance of these fluctuations [7]. In multivariate time series, to see whether data is stationary or not, we can use a plot, namely the Matrix Autocorrelation Function (MACF) and Matrix Partial Autocorrelation Function (MPACF). If there is a slow decline in the MACF plot, this indicates that the data is not stationary on average, so differencing is needed. Likewise, for non-stationary data in variance, the data needs to be transformed so that the data becomes stationary [27].

The sample correlation matrix is very useful in identifying orders in the Moving Average (MA) model. However, it will be difficult to identify the model if a matrix and graph have larger dimensions and vectors, making it difficult to identify the model. In [27], Wei introduced a simple method of summarizing sample correlation, using the symbols $(+)$, $(-)$, and $(.)$ for the correlation matrix (i,j). These symbols can be interpreted as follows:

1. The symbol $(+)$ indicates that the value of $\hat{\rho}_{i,j}(k)$ is greater than 2 times the standard error of $\hat{\rho}_{i,j}(k)$ and shows a positive correlation between components (i,j).
2. The symbol $(-)$ indicates that the value of $\hat{\rho}_{i,j}(k)$ is less than -2 times the standard error of $\hat{\rho}_{i,j}(k)$ and indicates a negative correlation between the components (i,j).
3. The symbol $(.)$ indicates that the value of $\hat{\rho}_{i,j}(k)$ is between ± 2 times the standard error of $\hat{\rho}_{i,j}(k)$ and indicates that there is no correlation between components (i,j).

The standard error of the value of $\hat{\rho}_{i,j}(k)$ can be obtained using the following equation:

$$S_{\hat{\rho}_{i,j}(k)} = \sqrt{\frac{1}{N}(1 + 2\hat{\rho}_{i,j}(1) + 2\hat{\rho}_{i,j}(2) + \cdots + 2\hat{\rho}_{i,j}(k-1))}, \tag{1}$$

where $S_{\hat{\rho}_{i,j}(k)}$ is the standard error of the value of $\hat{\rho}_{i,j}(k)$, $\hat{\rho}_{i,j}(k)$ is the correlation of the (i,j) sample, and N is the number of observations.

For the identification of AR (p) model in univariate time series, we can use PACF. Wei [27] explains MPACF at the k^{th} lag which is denoted by $\boldsymbol{\mathcal{P}}(k)$, where $\boldsymbol{\mathcal{P}}(k)$ is the last matrix coefficient when the data is entered into a time series vector calculation process of order p. $\boldsymbol{\mathcal{P}}(k)$ is the equation for $\boldsymbol{\phi}_{k,k}$, in multivariate linear regression. The equation for the partial autocorrelation matrix is as follows:

$$\mathcal{P}(k) = \{ \Gamma'(1)[\Gamma(1)]^{-1},\ k = 1 \quad \{\Gamma'(k) - c'(k)[A(k)]^{-1}b(k)\}\{\Gamma'(0) - b'(k)[A(k)]^{-1}b(k)^{-1}\}, k > 1 \tag{2}$$

Vector Autoregressive (VAR)

To show the relationship between several time series variables can use the time series vector model [27]. The classic method used to model time series data for the closest location that tends to have a relationship is the VAR model. The VAR model only contains autoregressive parameters of order p [28]. The VAR (3) model is written as follows:

$$z(t) = \Phi_1 z(t-1) + e(t). \tag{3}$$

In matrix form, equation (3) for time series data with two variables can be written as follows:

$$[z_1(t)\ z_2(t)] = [\Phi_{11}\ \Phi_{12}\ \Phi_{21}\ \Phi_{22}][z_1(t-1)\ z_2(t-1)] + [e_1(t)\ e_2(t)]. \tag{4}$$

The process of the autoregressive vector model (p) can be written with the following equation [15]:

$$z(t) = \Phi_1 z(t-1) + \cdots + \Phi_p z(t-p) + e(t) \tag{5}$$

where:

$z(t)$ = observation vector at time t and location n of size $(n \times 1)$,
Φ_p= p-order autoregressive vector parameter matrix of size $(n \times n)$,
$e(t)$ = white noise error vector, where $e(t) \sim MN(0, \Sigma)$ of size $(n \times 1)$.

Generalized Space-Time Autoregressive (GSTAR)

The GSTAR model is an extension of the STAR model, this model allows autoregressive parameters to vary at each location: $\Phi_{ks}^{(i)}, i = 1, 2, \dots, N$. If it is known that an $\{z(t): t = 0, \pm 1, \pm 2, \dots, \pm T\}$ series is a multivariate time series with N variables, then the GSTAR model of autoregressive order and spatial order $(\lambda_1, \lambda_2, \dots, \lambda_p)$, GSTAR $(p_{\lambda_1,\lambda_2,\dots,\lambda_p})$, in matrix notation can be written as follows [5]:

$$z(t) = \sum_{k=1}^{p} \left[\Phi_{k0} z(t-k) + \sum_{s=1}^{\lambda_p} \Phi_{ks} W^{(s)} z(t-k)\right] + e(t) \quad (6)$$

where:

$z(t)$ = observation vector at time t and location n of size $(N \times 1)$,
Φ_{k0} = diagonal matrix of autoregressive parameters of k-time order and 0-order space,
Φ_{ks} = diagonal matrix of autoregressive parameters of k-time order and s-order space,
$W^{(s)}$ = weight matrix $(N \times N)$ for spatial lag $s(s = 0, 1, \dots, \lambda_p)$,
e_t = white noise error vector of size $(N \times 1)$ with independent, identical, normally distributed with mean 0 and variance matrix covariance $\sigma^2 I_N$.

The Location Weight Matrix

In GSTAR modeling, the problem that often occurs lies in the selection or determination of location weights. The most commonly used weights are weights based on the inverse Euclidean distance or a straight line between locations. According to [29], the inverse equation of the Euclidean distance between locations is:

$$c(1 + d_{i,j})^{-a} \quad (7)$$

where $d_{i,j}$ is the location distance from i to j and c, a is any positive constant.

Furthermore, the determination of the inverse weight of the distance is done by normalizing the inverse value and the Euclidean distance between locations. In the inverse weight of the location distance, there is an assumption that if the location is close, it will have a strong relationship, so that in general the inverse weight of the location distance for each location can be expressed as follows:

$$W_{ij} = \frac{c(1+d_{i,j})^{-a}}{\sum_{j \neq i}^{n} c(1+d_{i,j})^{-a}} \quad (8)$$

where $i \neq j$ and satisfies $\sum_{j \neq i} W_{ij}^{(l)} = 1$.

Parameter Estimation

According to [5], parameter estimation for the GSTAR model can be performed using the OLS method, namely by minimizing the sum of squares errors, or minimizing $e'e = (Y - X\beta)'(Y - X\beta)$. Thus, the estimator of β using the OLS method is as follows:

$$\hat{\beta} = (X'X)^{-1}X'Y \quad (9)$$

In most cases, the OLS estimator in the GSTAR model is inefficient because the residual of GSTAR correlates with locations. To overcome this, we can use the Generalized Least Squares (GLS) method, where this method is an estimation method that can solve the problem of correlation between residuals at different locations. This method is usually applied to the Seemingly Unrelated Regression (SUR) model. The SUR model consists of several equations and the relationship between variables is not a two-way relationship, and there is a correlation between equations, so it can be said that the residuals also correlate with equations. According to [30], the equation of the SUR model with the dependent variable M is:

$$Z_i = X_i \beta_i + e_i, i = 1, 2, \dots, M \quad (10)$$

where:

Z_i = vector $(N \times 1)$ from dependent observation row variable,
X_i = observation matrix $(N \times k)$ from independent variables,
β_i = parameter vector $(k \times 1)$,
e_i = residual vector $(N \times 1)$.

The previous equation (10) if written in matrix form will be as follows:

$$[Z_1\ Z_2\ \ \vdots\ Z_M\ ] = [X_1\ 0\ \ 0\ X_2\ \ \ \dots\ \dots\ \ 0\ 0\ \ \vdots\ 0\ \vdots\ 0\ \ \ddots\ \dots\ \vdots\ X_M\ ][\beta_1\ \beta_2\ \ \vdots\ \beta_M\ ] + [e_1\ e_2\ \ \vdots\ e_M\ ] \tag{11}$$

This equation is a SUR model with the assumption that $E[e|X_1, X_2, \dots, X_M] = 0$ and $E[ee'|X_1, X_2, \dots, X_M] = \Omega$, where Ω is the variance-covariance matrix, i.e. $\Omega = \Sigma \otimes I$.

Akaike's Information Criterion (AIC)

Selection of the best model can be done using AIC. AIC was first introduced by Akaike to identify the model of a data set. The VAR model with the smallest AIC value will be the order for the GSTAR model. The following is the calculation of the AIC value [27]:

$$AIC(i) = ln\ (|S(p)| + \frac{2pb^2}{N}) \tag{12}$$

where b = the number of parameters expected in the model, N = the number of observations, $S(p)$ = sum of squares error, and p = VAR model order.

METHOD

In this study, inflation data was used for five cities on the island of Sumatra, including Padang City, Jambi City, Bengkulu City, Palembang City, and Bandar Lampung City with a time period from January 2013 to May 2022. This research data is secondary data sourced from the Badan Pusat Statistik Indonesia [1] with 113 data. There are five variables used in this study, 1) $z_1(t)$: Inflation in Padang City, 2) $z_2(t)$: Inflation in Jambi City, 3) $z_3(t)$: Inflation in Palembang City, 4) $z_4(t)$: Inflation in Bengkulu City, and 5) $z_5(t)$: Inflation in Bandar Lampung City.

The analysis in this study was carried out with the help of SAS 9.4 software. The analytical steps used in the study consist of:

1. Perform descriptive analysis on data.
2. Perform stationarity test.
3. Identify the GSTAR model.
4. Calculate the inverse distance location weight matrix.
5. Calculating the estimated autoregressive parameters for the GSTAR model using the SUR method.

RESULT AND DISCUSSION

Descriptive Analysis

In the analysis of the GSTAR model, the first step that must be done is to do a descriptive analysis. The descriptive analysis of inflation data in five cities on the island of Sumatra is summarized in Table 1.

TABLE 1. Descriptive Statistics of Inflation Data in Five Cities on the Island of Sumatra

Location	N	Mean	Standard Deviation	Total	Min.	Max.
Padang City (z_1)	113	0.3655	0.7659	41.31	-2.07	3.44
Jambi City (z_2)	113	0.3400	0.7788	38.42	-1.50	3.25
Palembang City (z_3)	113	0.3185	0.5638	36.00	-1.15	2.92
Bengkulu City (z_4)	113	0.3833	0.7589	43.32	-1.80	3.40
Bandar Lampung City (z_5)	113	0.3430	0.5634	38.76	-0.76	2.75

From the analysis results obtained in Table 1, inflation data from 2013 to 2022 for five cities with a total of 113 data in each city, has the highest average city inflation of 0.3833, namely Bengkulu City, with the lowest inflation value was -1.80 and the highest inflation value was 3.40. The city with the lowest average value is Palembang City with an average inflation rate of 0.3185, where the lowest inflation value is -1.15 and the highest inflation value is 2.92.

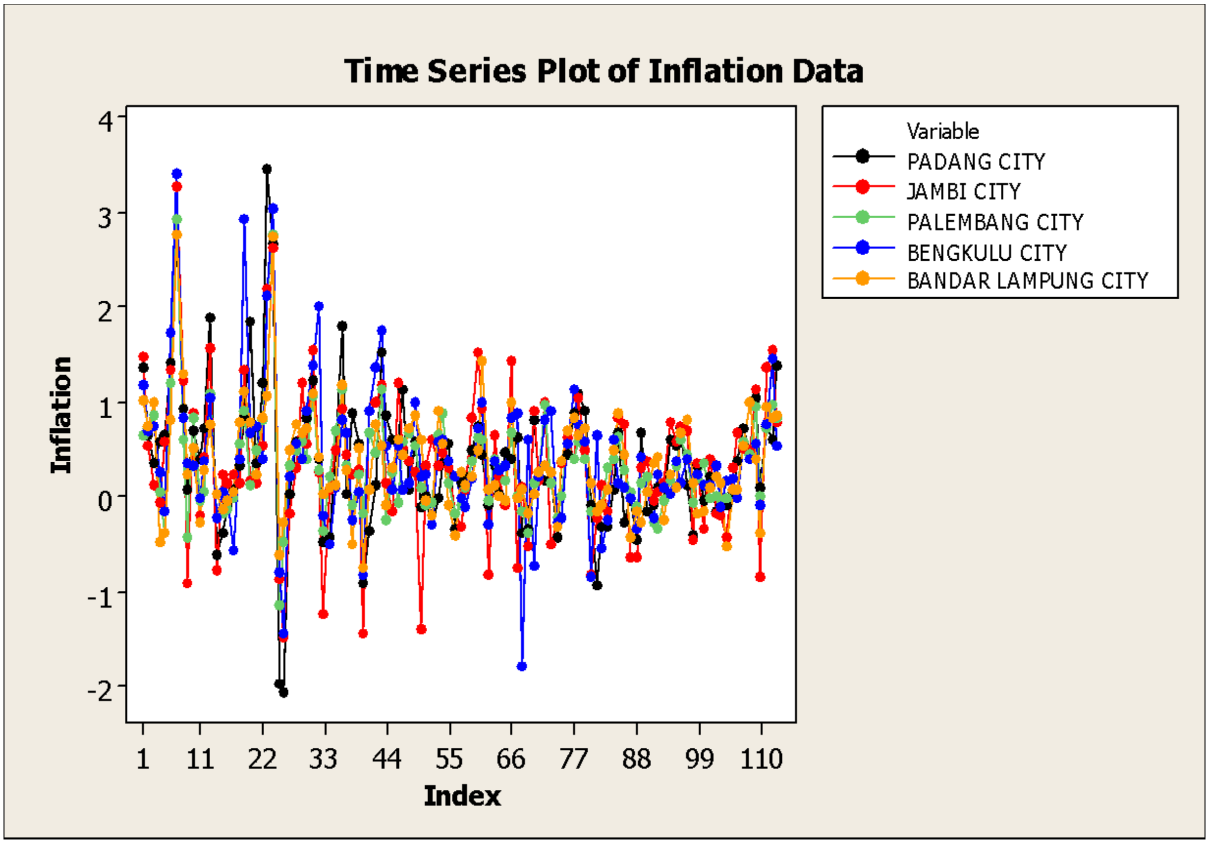

FIGURE 1. Time series plot of inflation data in five cities on the island of Sumatra.

From Figure 1, the plot shows that in general the inflation data pattern in five cities on the island of Sumatra is relatively the same. This can allow the tendency of a relationship between one location to another.

TABLE 2. Correlation Value of Inflation Data in Five Cities on The Island of Sumatra

Location	z_1	z_2	z_3	z_4	z_5
z_1	1.00000	0.74743	0.77715	0.69152	0.67164
$p-value$		<.0001	<.0001	<.0001	<.0001
z_2	0.74743	1.00000	0.80191	0.68452	0.71470
$p-value$	<.0001		<.0001	<.0001	<.0001
z_3	0.77715	0.80191	1.00000	0.76991	0.82073
$p-value$	<.0001	<.0001		<.0001	<.0001
z_4	0.69152	0.68452	0.76991	1.00000	0.72066
$p-value$	<.0001	<.0001	<.0001		<.0001
z_5	0.67164	0.71470	0.82073	0.72066	1.00000
$p-value$	<.0001	<.0001	<.0001	<.0001	

Based on Table 2, the correlation coefficient between locations is close to 1 and is positive. The high correlation coefficient value indicates that the inflation data for the five cities have a great relationship with each other. In addition, at the 5% significance level, there is a significant correlation between inflation data in five cities on the island of Sumatra. So based on this, it can indicate the tendency of a relationship between locations with one another.

Stationarity Test

The stationarity of inflation data in five cities on the island of Sumatra is presented in Table 3. If the MACF plot consists of several (+) and (-) signs, or almost all signs are symbolized (.), then the data is stationary.

TABLE 3. MACF for Inflation Data in Five Cities on The Island of Sumatra

Variable/Lag	0	1	2	3	4	5	6	7	8	9	10
Padang	+++++	+++++	.....	.....	.....	.....	.....	.....	.....	.....	.....
Jambi	+++++	+.+++	.-...	.--..	...--	.....	.++..	....+	.....	.--.-	..---
Palembang	+++++	+.+++	---..	--...	.....	.....	.+.+.	.....	.....	..-..	.....
Bengkulu	+++++	+..++	---..	.....	.....	.++..	.....	.....	.....	.....	.....
Bandar_Lampung	+++++	...++	.--..	.-...	.....	.++..	.....	.....	.-...	.....	.....

TABLE 4. MPACF for Inflation Data in Five Cities on the Island of Sumatra

Variable/Lag	1	2	3	4	5	6	7	8	9	10
Padang	+....	.....	.....	...+.	.....	.....	.....	.....	.....	.....
Jambi	+...-	.....	.....	.....	.....	.....	.....	.....	.....	.....
Palembang	+....	.....	.....	.....	.....	.....	.....	.....	.....	.....
Bengkulu	.....	.....	.....	.....	.....	.....	.....	.....	.....	.....
Bandar_Lampung	.....	.+...	.....	.-.+.	.....	+....	.....	.....	.....	.....

From Tables 3 and 4, it can be seen that some values have a positive (+) or negative (-) correlation for a certain lag, while the rest of the correlation values are indicated by a dot (.) which means that the three variables have no correlation simultaneously. So it can be said that inflation data in five cities on the island of Sumatra is stationary with respect to the mean.

In addition to looking at the MACF table, the stationarity test can be done with the ADF test. The calculation of the ADF test has been presented in Table 5.

TABLE 5. Augmented Dickey-Fuller Test (ADF)

Variable	Rho	Pr < Rho	Tau	Pr < Tau
Padang	-88.26	<.0001	-6.62	<.0001
Jambi	-97.40	<.0001	-6.97	<.0001
Palembang	-89.10	<.0001	-6.65	<.0001
Bengkulu	-80.54	<.0001	-6.33	<.0001
Bandar_Lampung	-67.47	<.0001	-5.74	<.0001

After carrying out the tests that have been summarized in Table 5, the p-value for the five cities is smaller than $\alpha = 0.05$, this indicates that there is no unit root or we can say that the data is stationary.

GSTAR Model Identification

In identifying the GSTAR model, the smallest AIC value is the optimum selection used to determine the order of the VAR model, because a good AIC can produce a model that provides a small error rate. The results of the summary of AIC values are presented in Table 6.

TABLE 6. AIC Value

Minimum Information Criterion Based on AICC						
Lag	**MA 0**	**MA 1**	**MA 2**	**MA 3**	**MA 4**	**MA 5**
AR 0	-7.815405	-7.863205	-7.813132	-7.533028	-7.451599	-6.930816
AR 1	**-8.05232**	-7.733256	-7.640532	-7.39165	-7.158535	-6.77218
AR 2	-7.730848	-7.771529	-7.319179	-6.98813	-6.69639	-6.154622
AR 3	-7.391419	-7.604268	-7.107069	-6.757507	-6.455219	-5.662819
AR 4	-7.189354	-7.401359	-6.867002	-6.307056	-5.83862	-4.924875
AR 5	-6.719942	-6.95903	-6.328881	-5.663432	-4.807453	-3.733593

Based on the AIC value obtained in Table 6, the smallest AIC value lies in AR (1) and MA (0) with a value of -8.05232, so the best model used is VAR (1). Based on the time order of the selected VAR model, the time order used for the formation of the GSTAR model is $p = 1$, with the spatial order being order 1. So that the GSTAR model formed is GSTAR (1_1).

The Location Weight Matrix

The location weight matrix used in this study is the inverse distance location weight matrix, with the inverse equation of the Euclidean distance between locations is, namely $c(1 + d_{i,j})^{-a}$. In this study, the value of c, a used is 1, so the inverse of the Euclidean distance between locations becomes $(1 + d_{i,j})^{-1}$. Location distances between cities are presented in Table 7.

TABLE 7. Distance of Locations between Cities

Location	Distance (km)
Padang – Jambi $(d_{1,2} = d_{2,1})$	592
Padang – Palembang $(d_{1,3} = d_{3,1})$	859
Padang – Bengkulu $(d_{1,4} = d_{4,1})$	704
Padang – Bandar Lampung $(d_{1,5} = d_{5,1})$	1120
Jambi – Palembang $(d_{2,3} = d_{3,2})$	277
Jambi – Bengkulu $(d_{2,4} = d_{4,2})$	453
Jambi – Bandar-Lampung $(d_{2,5} = d_{5,2})$	587
Palembang – Bengkulu $(d_{3,4} = d_{4,3})$	502
Palembang – Bandar Lampung $(d_{3,5} = d_{5,3})$	316
Bengkulu – Bandar Lampung $(d_{4,5} = d_{5,4})$	602

By using the inverse distance location weight equation, the weighted matrix formed is as follows.

$$W = [0\ 0.33\ 0.23\ 0.27\ 0.17\ 0.18\ 0\ 0.39\ 0.24\ 0.19\ 0.12\ 0.36\ 0\ 0.20\ 0.32\ 0.20\ 0.30\ 0.27\ 0\ 0.23\ 0.12\ 0.23\ 0.43\ 0.22\ 0].$$

GSTAR Model Parameter Estimation

The results obtained for parameter estimation in the GSTAR (1_1) model using the inverse distance weight using the SUR method are presented in Table 8.

TABLE 8. Estimating GSTAR (1_1) Parameters with Inverse Distance Weight

Parameter	Estimate	Std Err	t Value	Pr > |t|
$\phi_{10}^{(1)}$	0.119879	0.0957	1.25	0.2132
$\phi_{10}^{(2)}$	-0.01875	0.0982	-0.19	0.8489
$\phi_{10}^{(3)}$	0.202675	0.0982	2.06	0.0414
$\phi_{10}^{(4)}$	-0.08971	0.0930	-0.96	0.3370
$\phi_{10}^{(5)}$	0.089377	0.0913	0.98	0.3300
$\phi_{11}^{(1)}$	0.399054	0.1351	2.95	0.0039
$\phi_{11}^{(2)}$	0.42315	0.1353	3.13	0.0023
$\phi_{11}^{(3)}$	0.188238	0.1019	1.85	0.0676
$\phi_{11}^{(4)}$	0.712873	0.1313	5.43	<.0001
$\phi_{11}^{(5)}$	0.416651	0.0996	4.18	<.0001

After obtaining parameter estimates using the SUR method in Table 8, with a significance level of $\alpha = 0.05$ there are several parameters that are not significant, namely the parameters $\phi_{10}^{(1)}$, $\phi_{10}^{(2)}$, $\phi_{10}^{(4)}$, $\phi_{10}^{(5)}$, and $\phi_{11}^{(3)}$. Therefore, it is necessary to select the backward method, which is to gradually eliminate insignificant parameters.

The results of parameter estimation of the GSTAR model with inverse distance weights using the backward method are presented in Table 9.

TABLE 9. Estimating GSTAR (1_1) Parameters with Backward Method

Parameter	Estimate	Std Err	t Value	Pr > |t|
$\phi_{10}^{(4)}$	-0.25517	0.0955	-2.67	0.0088
$\phi_{11}^{(1)}$	-0.34822	0.1089	-3.20	0.0018
$\phi_{11}^{(2)}$	-0.46053	0.1271	-3.62	0.0004
$\phi_{11}^{(3)}$	-0.33357	0.0819	-4.07	<.0001
$\phi_{11}^{(4)}$	1.091254	0.1304	8.37	<.0001

Based on the parameter estimates obtained in Table 9, we can see that the significant parameters to be used in the model are $\phi_{10}^{(4)}$, $\phi_{11}^{(1)}$, $\phi_{11}^{(2)}$, $\phi_{11}^{(3)}$, and $\phi_{11}^{(4)}$, so that a matrix for the GSTAR (1_1) model can be made with the inverse distance weight using the SUR method as follows.

$$\left(z_1(t)\hat{z}_2(t)\hat{z}_3(t)\hat{z}_4(t)\hat{z}_5(t)\right) = (0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0.25517\ 0\ 0\ 0\ 0\ 0\ 0\ )\left(z_1(t-1)z_2(t-1)z_3(t-1)z_4(t-1)z_5(t-1)\right)(-0.34822\ 0\ 0\ 0\ 0\ 0\ -0.46053\ 0\ 0\ 0\ 0\ 0\ -0.33357\ 0\ 0\ 0\ 0\ 0\ 1.091254\ 0\ 0\ 0\ 0\ 0\ 0)$$

$$(0\ 0.33\ 0.23\ 0.27\ 0.17\ 0.18\ 0\ 0.39\ 0.24\ 0.19\ 0.12\ 0.36\ 0\ 0.20\ 0.32\ 0.20\ 0.30\ 0.27\ 0\ 0.23\ 0.12\ 0.23\ 0.43\ \ 0.22\ 0)$$

$$(z_1(t-1)\ z_2(t-1)\ z_3(t-1)\ z_4(t-1)\ z_5(t-1)\ )$$

Based on the matrix above, the GSTAR (1_1) model is obtained for inflation data for each location, namely as follows.

1. GSTAR (1_1) model Padang City
   $\hat{z}_1(t) = -0.1149133\ z_2(t-1) - 0.08009106\ z_3(t-1) - 0.09401994\ z_4(t-1) - 0.05919774\ z_5(t-1)$
2. GSTAR (1_1) model Jambi City
   $\hat{z}_2(t) = -0.0828954\ z_1(t-1) - 0.17960670\ z_3(t-1) - 0.11052720\ z_4(t-1) - 0.08750070\ z_5(t-1)$
3. GSTAR (1_1) model Palembang City
   $\hat{z}_3(t) = -0.0400284\ z_1(t-1) - 0.1200852\ z_2(t-1) - 0.066714\ z_4(t-1) - 0.1067424\ z_5(t-1)$
4. GSTAR (1_1) model Bengkulu City
   $\hat{z}_4(t) = 0.2182508\ z_1(t-1) + 0.3273762\ z_2(t-1) + 0.29463858\ \ z_3(t-1) - 0.25517\ z_4(t-1) + 0.25098842\ z_5(t-1)$

CONCLUSION

Based on the results obtained in the previous section, it can be seen that the inflation model for five cities on the island of Sumatra at time t is correlated with inflation data from the previous time and is influenced by inflation data from other cities. For more details, it is explained as follows:

1. Padang City inflation at time t is influenced by Jambi City inflation, Palembang City inflation, Bengkulu City inflation, and Bandar Lampung City inflation in the previous month $(t-1)$.
2. Jambi City inflation at time t is influenced by Padang City inflation, Palembang City inflation, Bengkulu City inflation, and Bandar Lampung City inflation in the previous month $(t-1)$.
3. Palembang City inflation at time t is influenced by Padang City inflation, Jambi City inflation, Bengkulu City inflation, and Bandar Lampung City inflation in the previous month $(t-1)$.

Bengkulu City inflation at time t is influenced by Padang City inflation, Jambi City inflation, Palembang City inflation, Bengkulu City inflation, and Bandar Lampung City inflation in the previous month $(t-1)$.

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