Received: 11 Dec 2025 | Revised: 05 May 2026 | Accepted: 06 May 2026 | Available online: 04 Jun 2026
https://doi.org/10.13057/ijas.v9i1.112470

E-ISSN: 2621-086X
https://jurnal.uns.ac.id/ijas

Indonesian Journal of Applied Statistics Vol. 9, No.1, pp. 16-29, 2026

Forecasting Clove Price in South, Central, and North Sulawesi Using Generalized Space Time Autoregressive and Vector Autoregressive

Elly Pusporani*, M. Fariz Fadillah Mardianto, Nike Meliana Rahmawati, Anggita Nariswari, Firqa Aqila Hizbullah
Statistics Study Program, Universitas Airlangga, Surabaya, Indonesia
*Corresponding author: elly.pusporani@fst.unair.ac.id

Abstract

Cloves are a strategic plantation commodity in Indonesia with important economic and cultural value, and their price volatility directly affects farmers' welfare, supply chain stability, and regional economic planning. Although previous studies have shown that the generalized space time autoregressive (GSTAR) model is more flexible than the space time autoregressive (STAR) model for heterogeneous locations, empirical studies comparing GSTAR and vector autoregressive (VAR) models for clove price forecasting across geographically interconnected provinces remain limited. This study addresses that gap by comparing the forecasting performance of GSTAR and VAR for monthly clove prices in North Sulawesi, Central Sulawesi, and South Sulawesi. The novelty of this study lies in the application of GSTAR with three spatial weighting schemes uniform, inverse distance, and cross-correlation normalization and its comparison with VAR in the context of clove price forecasting. Monthly data from January 2015 to December 2024 obtained from the Central Statistics Agency were analyzed using an 80:20 training-testing split. Stationarity testing showed that all series became stationary after first differencing, and lag selection based on the Akaike information criterion identified lag 1 as optimal for both models. The results indicate that the GSTAR(1)I(1) model with cross-correlation normalization weights provides the best forecasting performance, with an average MAPE of 3.18% and RMSE of 5,729.84, outperforming the VARI(1,1) model, which produced an average MAPE of 10.57% and RMSE of 15,214.11. These findings confirm that incorporating spatial dependence significantly improves forecasting accuracy and demonstrates that GSTAR is a more effective model for geographically interconnected commodity markets.

Keywords: Love price, forecast, GSTAR, SDGs 8, decent work and economic growth, VAR.

How to Cite:
E. Pusporani, M. F. F. Mardianto, N. M. Rahmawati, A. Nariswari, and F. A. Hizbullah, "Forecasting clove price in South, Central, and North sulawesi using generalized space time autoregressive and vector autoregressive," *Indonesian Journal of Applied Statistics,* vol. 9, no. 1, pp. 16-29, 2026, doi: 10.13057/ijas.v9i1.112470.

1. INTRODUCTION

Cloves are one of Indonesia's strategic plantation commodities that not only support the economy, but also contain historical and cultural meaning. Cloves are famous to the international realm and have been used for hundreds of years which have benefits to avoid bad breath and bad breath. Until now, this commodity has become a leading commodity that has a strategic role in both the clove cigarette industry, food, beverages, and pharmaceuticals. Cloves themselves have a distinctive aroma, this is strengthened by the minister's decree that designated Cloves as the identity flora of North Maluku Province based on the decree of the Minister of Home Affairs No. 48 of 1989. Based on data obtained from Indonesia's Central Statistics Agency (BPS), the exchange rate of farmers in the plantation subsector will reach 149.10 in 2024 [1]. This shows that commodities in the plantation sector are very influential for the welfare of the community, including cloves. Fluctuations in clove prices are often a major concern for farmers, traders, and policymakers because price changes can have a direct impact on people's incomes and welfare. Therefore, efforts to understand the pattern of clove price movements to clove price forecasting are very important in supporting more appropriate decision-making to support the economic stability of the local community, especially the area with the largest clove producer in Indonesia.

The region with the largest clove producer in Indonesia is more in eastern Indonesia such as the islands of Sulawesi and Maluku. The provinces of North Sulawesi, Central Sulawesi, and South Sulawesi are the largest clove producing centers in Indonesia. Each province has different production characteristics, trade patterns, and market dynamics that cause price variations between regions. This condition makes price forecasting an urgent need to minimize market uncertainty. Price forecasting information is very helpful for farmers in determining the right selling time and helps local governments in anticipating price fluctuations through more responsive policies. The price forecast in question is a prediction of future prices within a certain period of time, so that the results obtained are in the form of future price outputs [2]. In the context of the time series analysis approach, forecasting is the use of models to predict future values based on previously observed values [3]. In this study, the data obtained comes from several different regions that are connected to each other which can be caused by market interaction, distribution of goods, and competition between regions so that conventional analysis is not able to capture data patterns. Therefore, an appropriate modeling method is needed for clove price forecasting that is able to accommodate spatial and time dependences at the same time.

Modeling in time series analysis that can capture spatial and temporal dependency patterns at the same time is space time autoregressive (STAR), this model generates constant parameters for each location weight [4]. Previous research by [5] has developed a STAR model for heterogeneous locations, i.e. using the generalized space time autoregressive (GSTAR) method. This model is more flexible than the STAR model because the autoregressive (AR) parameters vary between locations shown in the form of a weighting matrix [6]. Through this approach, it can include first-order spatial lag as well as first-order temporal lag. The GSTAR model can also explain the patterns of change and interaction between locations that occur in a spatial-temporal system. In general, first-order spatial lag indicates that observations at one location are influenced by observations at other locations, while first-order temporal lag shows temporal relationships that describe the relationship between the time period that is being observed currently being influenced by observations in the previous period. This makes GSTAR have characteristics and advantages in reading more complex data structures. Meanwhile, the VAR model is used to describe the relationships between variables that are not only influenced by internal factors in terms of time, but involve causal relationships between two or more variables in a time series [7]. Both methods have their own advantages and have the potential to provide accurate forecasting results if applied correctly.

Based on this description, this study aims to compare the performance of the GSTAR and VAR models in estimating clove prices in North Sulawesi, Central Sulawesi, and South Sulawesi Provinces. Through this analysis, it is hoped that the best model will be obtained that is able to provide more accurate and useful prediction results for farmers, market participants, and policy makers as well as make an academic contribution to the development of plantation commodity forecasting methods in areas that have strong geographical and market linkages. Furthermore, this research also supports the Sustainable Development Goals (SDGs) program, namely the 8th point, Decent Work and Economic Growth which aims to improve an inclusive and sustainable economy.

2. METHODS

2.1. Generalized Space Time Autoregressive (GSTAR)

The generalized space time autoregressive (GSTAR) model is a further development of the space time autoregressive (STAR) model, which is basically a specific form of the vector autoregressive (VAR) model. The main difference between the GSTAR and STAR models lies in the assumption of their parameters. The STAR model assumes that the locations used in the study have the same properties, so

https://doi.org/10.13057/ijas.v9i1.112470
E-ISSN: 2621-086X

the model can only be used in uniform locations. On the other hand, the GSTAR model assumes that the study sites are heterogeneous and have different parameters for each site [8]. GSTAR model with autoregressive order p and spatial order $\lambda_1, \lambda_2, \dots, \lambda_k$ it is generally stated as follows.

$$Z_t = \sum_{k=1}^{p} \sum_{l=0}^{\lambda k} \boldsymbol{\Phi}_{kl} \boldsymbol{W}^{(l)} Z_{t-k} + e_t \tag{1}$$

with Z_t is $(N \times 1)$ observation vector at time t, λ_k denotes the spatial lag order associated with the k temporal lag, $\boldsymbol{\Phi}_{kl}$ is a diagonal coefficient matrix, $\boldsymbol{W}^{(l)}$ is the spatial weighting matrix for the l spatial lag, and $e_t$is an error vector with mean zero and covariance $\sigma^2 I$ [9]. The diagonal coefficient matrix is defined as $\boldsymbol{\Phi}_{kl} = diag\left(\Phi_{kl}{}^{(1)}, \Phi_{kl}{}^{(2)}, \dots, \Phi_{kl}{}^{(N)}\right)$, which allows each location to have its own autoregressive coefficient. The spatial relationships among location are represented through the spatial weighting matrices. Here is a GSTAR model equation for time order and spatial order 1 involving 3 different locations.

$$Z_t = \boldsymbol{\Phi}_{10} Z_{t-1} + \boldsymbol{\Phi}_{11} \boldsymbol{W}^{(1)} Z_{t-1} + e_t \tag{2}$$

And in the form of a matrix, equation (2) can be written as follows.

$$\begin{bmatrix} Z_{1t} \\ Z_{2t} \\ Z_{3t} \end{bmatrix} = \begin{bmatrix} \Phi_{10}^1 & 0 & 0 \\ 0 & \Phi_{10}^2 & 0 \\ 0 & 0 & \Phi_{10}^3 \end{bmatrix} \begin{bmatrix} Z_{1,t-1} \\ Z_{2,t-1} \\ Z_{3,t-1} \end{bmatrix} + \begin{bmatrix} \Phi_{11}^1 & 0 & 0 \\ 0 & \Phi_{11}^2 & 0 \\ 0 & 0 & \Phi_{11}^3 \end{bmatrix} \begin{bmatrix} 0 & W_{12} & W_{13} \\ W_{21} & 0 & W_{23} \\ W_{31} & W_{32} & 0 \end{bmatrix} \begin{bmatrix} Z_{1,t-1} \\ Z_{2,t-1} \\ Z_{3,t-1} \end{bmatrix} + \begin{bmatrix} e_{1,t} \\ e_{2,t} \\ e_{3,t} \end{bmatrix} \tag{3}$$

2.2. Pearson Correlation Test

Correlation tests are used to determine the pattern and tightness of relationships between two or more variables. Pearson correlation is a statistical test that aims to test the hypothesis of two variables on an interval scale or ratio by looking at the relationship between the two variables [10]. This method was developed by Karl Pearson and can be calculated with the following formula.

$$r_{xy} = \frac{n \sum X_i Y_i - \sum X_i \sum Y_i}{\sqrt{n \sum X_i^2 - (\sum X_i)^2} \sqrt{n \sum Y_i^2 - (\sum Y_i)^2}} \tag{4}$$

with n is the sum of the sample, X is an independent variable and Y is a dependent variable, while r_{xy} as a correlation coefficient. The interpretation of the correlation coefficient is as shown in Table 1.

Table 1. Correlation coefficient levels

Correlation Coefficients	Category
0.81 – 1	Very Powerful
0.61 – 0.80	Strong
0.41 – 0.60	Enough
0.21 – 0.40	Weak
0.00 – 0.20	Very weak

2.3. Stationarity Test

Stationary data is time-series data that has means, variances, and covariances that are not dependent on observation. Data stationarity testing can be performed using the augmented Dickey Fuller (ADF) test. The ADF test uses the concept of calculation to assess whether there is a root unit in the time series data [11]. In calculating ADF test statistics, the following formula is used.

$$\Delta Z_t = \beta_1 + \delta Z_{t-1} + e_t \tag{5}$$

where, $\delta = \rho - 1$ with H_0 is a non-stationary data hypothesis and H_1 is a stationary data hypothesis. It can also be done with statistical tests $\tau = \frac{\hat{\delta}}{SE(\hat{\delta})}$ with a certain real degree or $p - value < 5\%$. If the statistical test exceeds the critical value of the ADF, then H_0 is failed to reject and concluded Z_t has a root

https://doi.org/10.13057/ijas.v9i1.112470
E-ISSN: 2621-086X

unit (not stationary). Conversely, if the statistical test value is less than the critical ADF value then H_0 rejected and concluded Z_t does not have a root or stationary unit [12].

2.4. Spatial Weights on GSTAR

The application of generalized space time autoregressive (GSTAR) modelling has several spatial weight selection methods as follows.

1. Uniform Weight
   Uniform spatial weight assumes that the locations used in the study are homogeneous. The formula for determining the value of the weight is
   $$\boldsymbol{W_{ij}} = \frac{1}{n_i} \tag{6}$$
   With n_i is the number of locations nearby and W_{ij} is the weight of the location of the i and j.
2. Inverse Distance Weight
   Inverse distance spatial weight is used to measure the degree of interconnectedness between locations in a study, a weight given based on the actual distance between locations. Inverse distance weights provide high weight values for shorter distances and provide low weights for longer distances [13]. Here is the formula for the inverse weighting of the distance
   $$\boldsymbol{W_{ij}} = \frac{\frac{1}{d_{ij}}}{\sum_{j=1}^{s_i} \frac{1}{d_{ij}}}, \qquad i \neq j \tag{7}$$
   With d_{ij} is the actual distance between the i and j locations.
3. Cross Correlation Normalization Weight
   This method uses the results of cross-normalization between locations at the corresponding lag. In general, the cross-correlation between the i and j locations in the k lag is defined as follows.
   $$\rho_{ij}(k) = \frac{\gamma_{ij}(k)}{\sigma_i \sigma_j} \tag{8}$$
   with $\gamma_{ij}(k)$ is a cross covariance between the incident at the i and j locations. The estimate of this cross-correlation in the sample can be calculated using the following formula.
   $$r_{ij}(k) = \frac{\sum_{t=k+1}^{T} (Y_i(t) - \bar{Y}_i)\left(Y_j(t-k) - \bar{Y}_j\right)}{\sqrt{\sum_{t=1}^{T} (Y_i(t) - \bar{Y}_i)^2 \sum_{t=1}^{T} \left(Y_j(t) - \bar{Y}_j\right)^2}} \tag{9}$$
   Then it is normalized, so that the required weight is obtained with the following formula.
   $$\boldsymbol{W_{ij}} = \frac{r_{ij}^k}{\sum_{j \neq i} |r_{ij}^k|}, \quad i \neq j \tag{10}$$

2.5. Residual White Noise

Residual is considered white noise if it has a fixed variance, no correlation between residuals, homogeneous, and follows a normal distribution. White noise testing is carried out by representing the residual obtained from the modeling process. The null hypothesis of white noise testing using Ljung-Box is $\rho_1 = \rho_2 = \cdots = \rho_k$ (residual white noise) with the alternative hypothesis at least one $\rho_k \neq 0$ with $k = 1,2, \dots, K$ (residual white noise). The test statistics is as follow:
$$Q = n(n+2) \sum_{k=1}^{K} \frac{\hat{\rho} k^2}{n-k} \tag{11}$$
with Q is the Ljung-Box test statistic, n is the sum of observational data, and $\hat{\rho} k^2$ is the ACF residual lag k. H_0 rejected if $Q > \chi^2_{\alpha;K-p-q}$ or $p - value < \alpha$. If the residual distribution is obtained on the plot close to a straight line, then the residual follows the multivariate normal distribution. In addition to using plots, to see whether or not the residual is normally distributed, formal tests can be carried out using the Kolmogorov-Smirnov, Skewness, and Kurtosis tests [14].

https://doi.org/10.13057/ijas.v9i1.112470
E-ISSN: 2621-086X

2.6. Forecasting Accuracy

After obtaining the model, the accuracy or accuracy of data prediction from the models that have been carried out is measured. In this measurement, it can be done by looking at the MAPE (mean absolute percentage error) value. The MAPE equation below is as follows [15].

$$MAPE = \frac{\sum_{i=1}^{n} \left| \frac{y_i - \hat{y}}{y_i} \right| \times 100}{n} \tag{12}$$

with n is the sample size used with y_i is the value of the original data and $\hat{y}$ is the value of the forecast results. The MAPE value has its own criteria, where the smaller the MAPE value produced will show that the better the accuracy value. The MAPE value criteria are shown in Table 2 [16].

Table 2. MAPE value categories

MAPE	Accuracy Rate
$< 10\%$	Highly accurate forecasting
$10\% < MAPE \leq 20\%$	Accurate forecasting
$20\% < MAPE \leq 50\%$	Forecasting is quite accurate
$> 50\%$	Inaccurate assessment

2.7. Vector Autoregressive (VAR)

The vector autoregressive (VAR) model is a multivariate time series model used to describe the dynamics of relationships between endogenous variables. In VAR order p, The value of a time series vector in a period t depends on the lag values of the vector. In general, the VAR(p) model is written as follows.

$$Z_t = \boldsymbol{\Phi_1} Z_{t-1} + \cdots + \boldsymbol{\Phi_p} Z_{t-p} + a_t \tag{13}$$

where Z_t is a variable vector of $m \times 1$, $\boldsymbol{\Phi_i}$ is the matrix of the coefficient $m \times m$, and a_t is an error vector that satisfies the multivariate white noise property with covariances Σ_a positive-definite [17].

One of the main conditions in the VAR model is stationarity, which is met when all the roots of the polynomial characteristic $det\left(I_m z^p - \boldsymbol{\Phi_1} z^{p-1} - \cdots - \boldsymbol{\Phi_p}\right) = 0$, is outside the unit circle. This condition ensures that the process is stable, so that the averages and variances do not change over time. If these conditions are met, the VAR solution becomes stable and valid for analysis.

Parameter estimation in the VAR model is generally done using ordinary least squares (OLS) in each equation separately. This method is valid because all equations in VAR have the same set of regressors, namely lag variables of all series in the system. In addition, the error in the period t is not correlated with these lag variables, so it does not cause bias in the estimation. With these conditions met, OLS produces a consistent and efficient estimator within the VAR model framework.

2.8. Data Sources, Variables, and Model Implementation Steps

The data used in this study is secondary data obtained from the Central Statistics Agency [18]. The research data used is clove price data in three provinces in Indonesia, namely North Sulawesi, Central Sulawesi, and South Sulawesi in Rupiah. The data is in the form of a monthly time series from January 2015 to December 2024 with a total of 120 observations. This period was selected because clove price data for 2025 were not yet available. Therefore, the analysis in this study were developed based on the most recent data available, so that the results reflect historical patterns up to the end of 2024. Of the total data, 80% was used as training data (January 2015 – December 2022 as many as 96 data) and 20% as data testing (January 2023 – December 2024 as many as 24 data). The research variables consist of time variables as predictive variables and three response variables in the form of commodity prices in each province, as explained in Table 3.

https://doi.org/10.13057/ijas.v9i1.112470
E-ISSN: 2621-086X

Table 3. Research variables

Variable	Description	Unit
$Z_{t,1}$	Clove Prices in North Sulawesi	Rupiah per kg
$Z_{t,2}$	Clove Prices in Central Sulawesi	Rupiah per kg
$Z_{t,3}$	Clove Prices in South Sulawesi	Rupiah per kg

The following are the analysis steps using the GSTAR and VAR method:

1. Make a time series graph of clove price data in North Sulawesi, Central Sulawesi, and South Sulawesi on a monthly basis and conduct descriptive statistical analysis.
2. Conduct a correlation test between response variables to determine the relationship between clove prices in North Sulawesi, Central Sulawesi, and South Sulawesi.
3. Test the stationary data on three response variables with the augmented Dickey-Fuller (ADF) test.
4. Determining the time order in the GSTAR model using VAR modeling with a minimum AIC value to select the order of the VAR model to be used as the time order in the GSTAR model [19].
5. Determining the location weight using three methods, namely uniform weight, inverse distance weight, and cross-correlation normalization weight [20].
6. Estimating the GSTAR model using the seemingly unrelated regression (SUR) method for each location weight.
7. Conducting diagnostic tests on residual GSTAR models.
8. Calculate the MAPE and MSE values of the GSTAR model for each location weight based on training data.
9. Make forecast evaluation using each GSTAR model and compare the forecast evaluation results with testing data.
10. Calculate MAPE and MSE values on forecast evaluation results based on testing data.
11. Choose the best GSTAR model with minimum MAPE and MSE values.
12. Choosing a VAR model based on stationarity and order lag tests.
13. Performing diagnostic tests on residual VAR models.
14. Calculating the MAPE value on the results of VAR forecast evaluation based on testing data.
15. Compare the GSTAR model with the VAR model to see which method is the best to analyze the price of cloves in North Sulawesi, Central Sulawesi, and South Sulawesi on a monthly basis.

3. RESULTS AND DISCUSSION

3.1. Descriptive Statistics

The first step to conducting an analysis is to know the characteristics of the data to be used. One way to find out these characteristics is to make a plot of time series related to clove prices in the provinces of North Sulawesi, Central Sulawesi, and South Sulawesi.

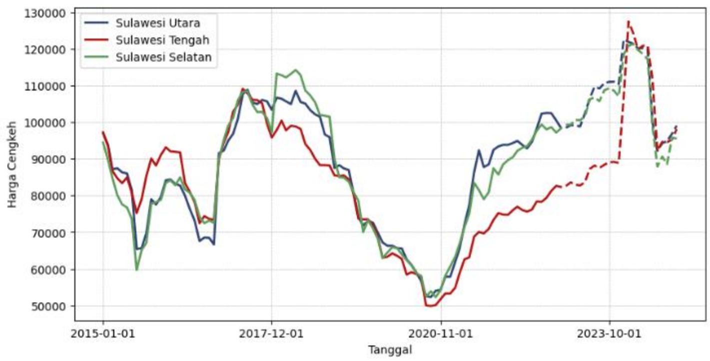

Figure 1. Time series plot of clove price data in North Sulawesi, Central Sulawesi, and South Sulawesi

https://doi.org/10.13057/ijas.v9i1.112470
E-ISSN: 2621-086X

Figure 1 shows the movement of clove prices in North Sulawesi, Central Sulawesi, and South Sulawesi during the 2015–2024 period. North Sulawesi consistently has the highest prices, while South Sulawesi is at the lowest level. The three provinces showed a similar pattern of fluctuations, with prices falling in 2016–2017, rising in 2018, and downward trend again in 2020–2021 before increasing sharply until early 2023. After reaching its peak, prices are moving downward again until 2024. These movements are likely influenced by production conditions, harvest seasons, and market dynamics, which are the basis of the analysis in the GSTAR model.

Table 4. Descriptive analysis

	North Sulawesi	Central Sulawesi	South Sulawesi
Maximum	122532	127462	121341
Minimum	52326	49884	52307
Mean	89120,82	83671,08	88403,80

In Table 4, it is known that the average price of cloves in North Sulawesi, Central Sulawesi, and South Sulawesi respectively is IDR 89,120.82; IDR 83,671.08; and IDR 88,403.80. Although not much different, Central Sulawesi was recorded to have the lowest average price, which is generally related to a larger production volume in a certain period so as to suppress market prices.

If viewed from the maximum value, the three provinces experienced a peak in prices in early 2024. North Sulawesi recorded the highest price of IDR 122,532 in January 2024, Central Sulawesi reached IDR 127,462 in February 2024, and South Sulawesi reached IDR 121,341 in March 2024. The price spike at the beginning of the year is usually influenced by a decrease in supply because it has not yet entered the harvest season, while industrial demand remains stable or increases after the year-end holidays. This imbalance between supply and demand causes prices to soar quite high.

In contrast, the minimum prices of the three provinces occurred almost in the same period, namely 2020. North Sulawesi touched a low price of IDR 52,326 in September 2020, Central Sulawesi IDR 49,884 in September 2020, and South Sulawesi IDR 52,307 in October 2020. The sharp decline in the year is most likely related to the festive harvest season, which led to an abundant supply of cloves in the market. This condition was exacerbated by the COVID-19 pandemic, which led to a decline in industrial activity and a weakening of market absorption, causing prices to plummet to the lowest point.

3.2. Correlation Test

After descriptive statistical analysis was carried out, a correlation test was carried out between observation locations. The correlation test in this study uses the Pearson correlation test because the data used is on an interval scale.

Table 5. Pearson correlation test

		North Sulawesi	Central Sulawesi	South Sulawesi
North Sulawesi	Pearson's Correlation	1	0.8229	0.9692
	P-value	0	8.34×10^{-25}	5.25×10^{-59}
Central Sulawesi	Pearson's Correlation	0.8229	1	0.8420
	P-value	8.34×10^{-25}	0	6.14×10^{-27}
South Sulawesi	Pearson's Correlation	0.9692	0.8420	1
	P-value	5.25×10^{-59}	6.14×10^{-27}	0

Based on Table 5, the p-value of all locations is obtained with a value of less than the real level (0.05). The highest correlation coefficient (r) is found between North Sulawesi and South Sulawesi Market with a correlation of 0.9692. Meanwhile, the lowest correlation was found between North Sulawesi and Central Sulawesi, which was 0.8229. However, all correlations are significant. From this statement, it can be shown that the average price of cloves in the three locations has a close and real relationship.

https://doi.org/10.13057/ijas.v9i1.112470
E-ISSN: 2621-086X

3.3. Stationary Test

Building a time-series data model requires stationary data, which is why stationary testing is essential. If the data being tested is not stationary, differencing steps need to be taken until the data becomes stationary, then it can proceed to the next stage of analysis.

Table 6. Augmented Dickey-Fuller test

	North Sulawesi	Central Sulawesi	South Sulawesi
P-value before differencing	0.3719	0.7238	0.4122
P-value after differencing	1.7×10^{-06}	3.44×10^{-05}	2.94×10^{-12}

Based on Table 6, the p-value of the test was obtained using the Augmented Dickey-Fuller Test (ADF test) for each location with a value greater than the real level (0.05). Therefore, it can be concluded that the data is not stationary, so it is necessary to do differential 1 and re-test ADF. In the ADF test after differentiating 1, a p-value was obtained that was less than the real level (0.05). Therefore, it can be concluded that the data used is stationary.

3.4. GSTAR Modelling

Model Identification (Order Determination)

Determining the order of time in the GSTAR model is done using the order from the VAR model (p). The process of identifying the order of the VAR model can be carried out by determining the optimal lag length, which is characterized by the smallest AIC value of the various lags tested.

Table 7. AIC value of VAR model

Lag	0	1*	2	3	4	5
AIC	54.2	47.73	47.74	47.86	47.89	48.03

Based on Table 7, it was found that the smallest AIC value was at the 1st lag. So it can be concluded that the autoregressive order of the GSTAR model is 1. In general, the determination of the spatial order of the GSTAR model is limited to spatial order 1. This is due to the difficulty of interpretation at higher orders [21]. Spatial order 1 indicates that the three locations are still classified as one region, namely Sulawesi Island. Based on this statement, the GSTAR model obtained is GSTAR $(1)I(1)$.

Spatial Weight Matrix Calculation

In space-time modeling, location utilization is one of the important factors in consideration for the forecast evaluation process. This study used three types of location weights, namely uniform weight, inverse distance location weight, and cross correlation normalization location weight. For the uniform weight matrix to set the same value for each location, in this study there are 3 different locations that are analyzed so that each location has 2 neighbouring locations. The weight of the uniform location is expressed in the form of a matrix W, with $W_{ij} = {}^{1}/_{n_i}$. The results obtained from the uniform location weight are stated as follows.

$$\boldsymbol{W}(\mathbf{1}) = \begin{bmatrix} 0 & 0.5 & 0.5 \\ 0.5 & 0 & 0.5 \\ 0.5 & 0.5 & 0 \end{bmatrix}$$

Next is to determine the inverse distance weight matrix that can be determined based on the actual location distance.

Table 8. Distance between locations

Symbol	Location	Distance (km)
$r_{1,2}$	North Sulawesi – Central Sulawesi	932
$r_{1,3}$	North Sulawesi – South Sulawesi	1682
$r_{2,3}$	Central Sulawesi – South Sulawesi	755

https://doi.org/10.13057/ijas.v9i1.112470
E-ISSN: 2621-086X

Based on the three actual distances in Table 8, the results of the calculation of the inverse weight matrix of the distance are as follows.

$$\boldsymbol{W}(\mathbf{1}) = \begin{bmatrix} 0 & 0.3565 & 0.6435 \\ 0.5524 & 0 & 0.4476 \\ 0.3098 & 0.6902 & 0 \end{bmatrix}$$

Next, the calculation of the cross-correlation normalization matrix is obtained through equation (10).

$$\boldsymbol{W}(\mathbf{1}) = \begin{bmatrix} 0 & 0.4601 & 0.5399 \\ 0.4939 & 0 & 0.5061 \\ 0.5338 & 0.4662 & 0 \end{bmatrix}$$

All the weight that will be used has been qualified, namely the main diagonal of the matrix is 0 and the sum of each column is 1.

Parameter Estimation

The estimation of each autoregressive parameter of GSTAR model can be done using the least square method, which is by minimizing the number of residual squares. What is necessary in forecast evaluation is the extent to which the model can predict the data, so that the significance of the parameters is not an issue [22]. The following is a comparison of the GSTAR model on clove prices in North Sulawesi, Central Sulawesi, and South Sulawesi using a weighting matrix, namely uniform weights, inverse distance location weights, and cross-correlation normalization location weights.$(1)I(1)$. It should be noted that the cross-correlation normalization weights were derived from the training data used in model estimation.

GSTAR(1)I(1) model with uniform location weight

$$\begin{bmatrix} Z_{1,t} \\ Z_{2,t} \\ Z_{3,t} \end{bmatrix} = \begin{bmatrix} 0.9979 & 0 & 0 \\ 0 & 0.9965 & 0 \\ 0 & 0 & 0.9986 \end{bmatrix} \begin{bmatrix} Z_{1,t-1} \\ Z_{3,t-1} \\ Z_{3,t-1} \end{bmatrix} + \begin{bmatrix} 0.0911 & 0 & 0 \\ 0 & 0.1377 & 0 \\ 0 & 0 & -0.9965 \end{bmatrix} \begin{bmatrix} Z_{1,t} - Z_{1,t-1} \\ Z_{2,t} - Z_{2,t-1} \\ Z_{3,t} - Z_{3,t-1} \end{bmatrix}$$
$$+ \begin{bmatrix} 0.2595 & 0 & 0 \\ 0 & 0.1366 & 0 \\ 0 & 0 & 0.4528 \end{bmatrix} \begin{bmatrix} 0 & 0.5 & 0.5 \\ 0.5 & 0 & 0.5 \\ 0.5 & 0.5 & 0 \end{bmatrix} \begin{bmatrix} Z_{1,t} - Z_{1,t-1} \\ Z_{2,t} - Z_{2,t-1} \\ Z_{3,t} - Z_{3,t-1} \end{bmatrix}$$

GSTAR$(1)I(1)$ model with inverse distance weight

$$\begin{bmatrix} Z_{1,t} \\ Z_{2,t} \\ Z_{3,t} \end{bmatrix} = \begin{bmatrix} 0.9978 & 0 & 0 \\ 0 & 0.9966 & 0 \\ 0 & 0 & 0.9988 \end{bmatrix} \begin{bmatrix} Z_{1,t-1} \\ Z_{3,t-1} \\ Z_{3,t-1} \end{bmatrix} + \begin{bmatrix} 0.0761 & 0 & 0 \\ 0 & 0.1344 & 0 \\ 0 & 0 & -0.0841 \end{bmatrix} \begin{bmatrix} Z_{1,t} - Z_{1,t-1} \\ Z_{2,t} - Z_{2,t-1} \\ Z_{3,t} - Z_{3,t-1} \end{bmatrix}$$
$$+ \begin{bmatrix} 0.2401 & 0 & 0 \\ 0 & 0.1233 & 0 \\ 0 & 0 & 0.4269 \end{bmatrix} \begin{bmatrix} 0 & 0.3565 & 0.6435 \\ 0.5524 & 0 & 0.4476 \\ 0.3098 & 0.6902 & 0 \end{bmatrix} \begin{bmatrix} Z_{1,t} - Z_{1,t-1} \\ Z_{2,t} - Z_{2,t-1} \\ Z_{3,t} - Z_{3,t-1} \end{bmatrix}$$

GSTAR$(1)I(1)$ model with cross-correlation normalization

$$\begin{bmatrix} Z_{1,t} \\ Z_{2,t} \\ Z_{3,t} \end{bmatrix} = \begin{bmatrix} 0.9978 & 0 & 0 \\ 0 & 0.9965 & 0 \\ 0 & 0 & 0.9986 \end{bmatrix} \begin{bmatrix} Z_{1,t-1} \\ Z_{3,t-1} \\ Z_{3,t-1} \end{bmatrix} + \begin{bmatrix} 0.1016 & 0 & 0 \\ 0 & 0.1271 & 0 \\ 0 & 0 & -0.1063 \end{bmatrix} \begin{bmatrix} Z_{1,t} - Z_{1,t-1} \\ Z_{2,t} - Z_{2,t-1} \\ Z_{3,t} - Z_{3,t-1} \end{bmatrix}$$
$$+ \begin{bmatrix} 0.2404 & 0 & 0 \\ 0 & 0.1425 & 0 \\ 0 & 0 & 0.4418 \end{bmatrix} \begin{bmatrix} 0 & 0.4601 & 0.5399 \\ 0.4939 & 0 & 0.5061 \\ 0.5338 & 0.4662 & 0 \end{bmatrix} \begin{bmatrix} Z_{1,t} - Z_{1,t-1} \\ Z_{2,t} - Z_{2,t-1} \\ Z_{3,t} - Z_{3,t-1} \end{bmatrix}$$

Residual Evaluation

Model goodness of fit testing was conducted using the Ljung Box Pearce (LB) test, which was performed univariately, meanwhile residual normality testing was conducted using Kolmogov Smirnov (KS) test. If the GSTAR model is white noise (residuals are independently distributed) and normally distributed, then the model is considered suitable to use.

https://doi.org/10.13057/ijas.v9i1.112470
E-ISSN: 2621-086X

Table 9 shows that the testing for all locations is the same, namely failed to reject H_0 with p-value > 0.05, which means that the residuals of the GSTAR(1)I(1) model at the three locations are independently and normally distributed. Therefore, the GSTAR(1)I(1) model is suitable for use with uniform spatial weight, inverse distance spatial weight, or cross-correlation normalization spatial weight.

Table 9. Ljung Box Pearce and Kolmogorov Smirnov test of GSTAR model

Spatial Weight	Variable	LB P-value	KS P-value	Residual Assumption
Uniform	North Sulawesi	0.7690	0.1286	White Noise and Normally Distributed
	Central Sulawesi	0.8579	0.1151	White Noise and Normally Distributed
	South Sulawesi	0.8041	0.0842	White Noise and Normally Distributed
Inverse Distance	North Sulawesi	0.8360	0.1454	White Noise and Normally Distributed
	Central Sulawesi	0.8240	0.1006	White Noise and Normally Distributed
	South Sulawesi	0.8366	0.0721	White Noise and Normally Distributed
Cross Correlation Normalization	North Sulawesi	0.7634	0.1298	White Noise and Normally Distributed
	Central Sulawesi	0.8476	0.1121	White Noise and Normally Distributed
	South Sulawesi	0.7934	0.0902	White Noise and Normally Distributed

Best GSTAR Model Selection

Model accuracy can be examined by comparing the size of the model error, namely by looking at the mean absolute percentage error (MAPE), root mean squared error (RMSE), and symmetric mean absolute percentage error (sMAPE) value in the testing data. The model with the smallest value is considered the best model.

Table 10. MAPE value on testing data of GSTAR model

Spatial Weight		North Sulawesi	Central Sulawesi	South Sulawesi	Mean
Uniform	MAPE	2.7228%	3.6537%	3.2540%	3.2102%
	RMSE	5,295.07	6,636.43	5,334.54	5,755.35
	sMAPE	2.6898%	3.7080%	3.2285%	3.2088%
Inverse Distance	MAPE	2.6402%	3.6657%	3.3954%	3.2338%
	RMSE	5,216.28	6,672.81	5,501.98	5,797.02
	sMAPE	2.6066%	3.7186%	3.3689%	3.2314%
Cross Correlation Normalization	MAPE	2.6853%	3.6421%	3.2108%	3.1794%
	RMSE	5,259.4	6,634.3	5,295.82	5,729.84
	sMAPE	2.6521%	3.6970%	3.1850%	3.1780%

From Table 10, it is known that testing data with a cross-correlation normalization spatial weight matrix has the smallest MAPE, RMSE, and sMAPE, namely 3.1794%, 5,729.84, and 3.1780%. Thus, the GSTAR(1)I(1) with the cross-correlation normalization spatial weight matrix is selected as the best model.

The advantage of cross-correlation normalization weighting stems from its ability to represent the actual interdependence of price movements between regions. Unlike uniform weighting, which assumes equal influence between provinces, or inverse distance weighting, which emphasizes geographical proximity, the cross-correlation approach incorporates the empirical strength of the joint movement of clove prices. Given that North, Central, and South Sulawesi show very high simultaneous price correlations, this method is more effective in capturing spillover effects and actual market linkages. The resulting weights are more stable, proportional, and aligned with the economic structure of the commodity market, resulting in a more accurate representation of spatial dependence with the lowest forecast evaluation error among all other weights tested.

https://doi.org/10.13057/ijas.v9i1.112470
E-ISSN: 2621-086X

Forecast Evaluation Using the Best GSTAR Model

The following are the results of clove price forecast evaluation in North Sulawesi, Central Sulawesi, and South Sulawesi using the GSTAR(1)I(1) model with cross-correlation normalization spatial weight.

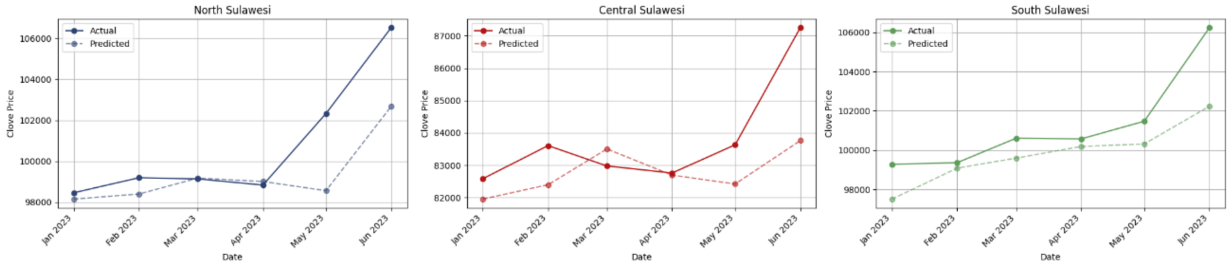

Figure 2. Comparison chart of actual and predicted clove prices in North Sulawesi, Central Sulawesi, and South Sulawesi with GSTAR for first 6 months

From Figure 2, it can be seen that the values between the actual data and the predicted data are relatively close to each other. This is because the best model, namely the GSTAR(1)I(1) model with cross-correlation normalization spatial weight, produces MAPE values that fall into the category of highly accurate forecast evaluation.

3.5. VAR Modelling

Before modelling, the data should be tested for cointegration using Johansen Cointegration Test. If there is a cointegration, vector error correction model (VECM) should be used instead of VAR.

Table 11. Johansen cointegration test

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	Critical Value (95%)	Max-Eigen Statistic	Critical Value (95%)
None	0.1142	15.2688	29.7961	11.3956	21.1314
At most 1	0.0265	3.8732	15.4943	2.5225	14.2639
At most 2	0.0143	1.3507	3.8415	1.3507	3.8415

As shown in Table 11, for the hypothesis of no cointegration, the trace statistic of 15.2688 and the maximum eigenvalue statistic of 11.3956 are both below their respective 95% critical values of 29.7961 and 21.1314, so the null hypothesis cannot be rejected. Similarly, the hypotheses of at most 1 and at most 2 cointegrating equations are also not rejected at the 95% significance level, since all test statistics remain below their critical values. The eigenvalues are all very close to zero, which further supports the absence of a long-run equilibrium relationship between rice prices in North Sulawesi, Central Sulawesi, and South Sulawesi. Since no cointegration relationship is found, the use of the VECM is not justified.

Next, Box-Cox transformation was applied to stabilize variance and normalize the distribution of each variable, reducing heteroscedasticity and improving the performance of the VAR model. The transformation follows the formula $(y^\lambda - 1)/\lambda$ for $\lambda \neq 0$, where the optimal λ is estimated via maximum likelihood estimation. The followings are the optimal λ value for each variable.

Table 12. Box-Cox transformation

Variable	λ Value
North Sulawesi	1.68
Central Sulawesi	1.26
South Sulawesi	0.89

As shown in Table 12, North Sulawesi (λ = 1.68) required moderate power transformations, while Central Sulawesi (λ = 1.26) and South Sulawesi (λ = 0.89) was already near-normal, requiring minimal adjustment.

https://doi.org/10.13057/ijas.v9i1.112470
E-ISSN: 2621-086X

Then, using the previously mentioned lag order and stationary test, the model obtained is VARI(1,1). Next, to assess whether the VARI(1,1) model meets the necessary assumptions for valid inference, diagnostic tests are conducted on the residuals. The Ljung-Box and Kolmogorov-Smirnov test as follows.

Table 13. Ljung Box Pearce and Kolmogorov Smirnov test of VAR model

Variable	LB P-value	KS P-value	Residual Assumption
North Sulawesi	0.9757	0.1274	White Noise and Normally Distributed
Central Sulawesi	0.8112	0.1615	White Noise and Normally Distributed
South Sulawesi	0.9418	0.0553	White Noise and Normally Distributed

Table 13 shows that the testing result is failed to reject H_0 with p-value > 0.05, so the model is independently distributed and the residuals are normally distributed. Therefore, the VARI(1,1) model is considered adequate for forecast evaluation purposes. The forecast diagnostic of the model is as follows.

Table 14. MAPE value on testing data of VAR model

Variable	MAPE	RMSE
North Sulawesi	8.3454%	12,164.54
Central Sulawesi	14.6227%	21,948.71
South Sulawesi	8.7505%	11,529.07
Mean	10.5729%	15,214.11

Table 14 presents the forecast accuracy of the VARI(1,1) model on the testing data. The model achieves varying performance across regions, with North Sulawesi showing the best accuracy at 8.35% MAPE, followed by South Sulawesi at 8.75% MAPE, while Central Sulawesi exhibits the highest error at 14.62% MAPE. On the other hand, South Sulawesi has the lowest RMSE at 11,529.07, followed by North Sulawesi and Central Sulawesi at 12,164.54 and 21,948.71 respectively. Overall, the VARI(1,1) model achieves a mean MAPE of 10.57%, indicating reasonably accurate forecasts.

3.6. Model Comparison

After establishing the individual performance characteristics of the GSTAR$(1)I(1)$ and VARI(1,1) models, a comparative analysis is essential to determine the best model for clove prices forecast evaluation in Sulawesi. Although both models use the same lag structure and are fitted to first-differenced stationary data, their difference lies in the incorporation of a spatial weight matrix by the GSTAR model, which accounts for interdependencies between geographically adjacent regions. This spatial component allows GSTAR to capture price transmission effects and regional spillovers that may cannot be represented by a standard VAR model, which treats variables as independent entities.

The results show a substantial performance gap between the two approaches. The GSTAR$(1)I(1)$ model with cross correlation normalization spatial weight achieved an average MAPE of 3.18% and average RMSE of 5,729.84, demonstrating highly accurate forecast evaluation across the three regions. In contrast, the VARI(1,1) model obtained an average MAPE of 10.57% and average RMSE of 15,214.11, representing more than triple the forecast evaluation error of GSTAR. This difference means there is an improvement in forecast evaluation accuracy when spatial dependence is incorporated into the modelling, and that ignoring these spatial relationships results in a substantial loss of forecast evaluation power.

4. CONCLUSION

This study concludes that incorporating spatial dependence is essential for accurately predicting clove prices in various interconnected regions. Although the GSTAR$(1)I(1)$ and VARI(1,1) models satisfy diagnostic assumptions and provide adequate predictive performance, the GSTAR model consistently outperforms the VAR model. Among the three spatial weighting schemes, the GSTAR$(1)I(1)$ model, which

https://doi.org/10.13057/ijas.v9i1.112470
E-ISSN: 2621-086X

uses cross-correlation normalization weighting, produces the highest accuracy with an average MAPE of 3.18% and average RMSE of 5,729.84, which is considered highly accurate. In comparison, the VARI(1,1) model produced a much higher forecast evaluation error of 10.57%% and average RMSE of 15,214.11. These results indicate that spatial spillover effects and regional price transmission play an important role in clove price dynamics, making GSTAR a more appropriate modeling framework for geographically connected commodity markets. The main contribution of this study is to identify the most accurate model for evaluating clove price forecasting in a spatial context. Practically, these findings may serve as a basis for local governments and policymakers in formulating price stabilization strategies and designing more responsive policies toward fluctuations in clove prices. For farmers, the results are also useful in anticipating price changes and determining the most appropriate selling time. However, this study is limited by data availability, as clove price data for 2025 were not yet available at the time the research was conducted. Therefore, the findings reflect historical patterns over the 2015–2024 period. Future studies are recommended to use more recent data and expand the spatial coverage of the analysis so that the results can be more comprehensive.

The author would like to express his gratitude to the lecturers of the Statistics Study Program at Airlangga University who have guided and assisted the author during the research and preparation of this research journal. The author would also like to express his gratitude to the Central Statistics Agency for providing the dataset that the author used to conduct this research.

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https://doi.org/10.13057/ijas.v9i1.112470
E-ISSN: 2621-086X