THE ROLE OF GENERALIZED SPACE TIME AUTOREGRESSIVE (GSTAR) MODELLING IN UNDERSTANDING ECONOMIC INDICATORS: FARMER VALUE FOOD CROPS SUBSECTOR

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ABSTRACT

Indonesia, as an agrarian nation, relies heavily on agriculture for rural livelihoods. The Farmer Terms of Trade (FTT) is a key indicator of farmer welfare. However, agriculture is often seen as ineffective in boosting income and reducing poverty. Despite this, the sector remains crucial for national development, especially the crops sub-sector, which sustains the country's food supply. The Generalized Space Time Autoregressive (GSTAR) model is employed to explore data relationships across proximate locations, focusing on geographical or observational locational factors. This analysis incorporates three spatial weights in the GSTAR model: (1) queen contiguity- weights, (2) uniform location weights, and (3) inverse distance spatial weights. Our findings indicate that the GSTAR model (1_1)I(1) with uniform spatial weight emerges as the optimal model. This model not only satisfies the white noise and normality assumptions but also demonstrates superior performance metrics, including a Mean Squared Error (MSE) of 2.34, Root Mean Squared Error (RMSE) of 1.53, and Mean Absolute Percentage Error (MAPE) of 1.10%. These figures notably surpass those obtained with the GSTAR models employing queen contiguity-based weights and inverse distance spatial weights, thereby highlighting its efficacy in capturing the dynamics within the crops sub-sector.

Keywords: Farmer Terms of Trade, GSTAR, Spatial weight.

INTRODUCTION

Indonesia is known as an agrarian country because most of the country's population works in agriculture or farming. Based on BPS data, the number of people working in the agricultural sector in the first quarter of 2024 reached 28.64% of Indonesia's total working population of 142.18 million people (AgroNews.id, 2024). Known as an agricultural country, Indonesia has several advantages, including agriculture being a key sector in supporting the country's economy. It allows for easier access to fulfilling food needs without relying on imports, helps ensure food security, improves welfare to reduce poverty, and helps prevent food crises.

Indonesia's national development is closely tied to various factors, including the agricultural sector. This sector, along with the welfare of farmers, plays a pivotal role in fostering economic growth and remains a central focus in national progress. The high demand for food in Indonesia makes the agricultural sector a major contributor to the success of national development. The food crops sub-sector, in particular, plays a vital role as it provides the staple foods consumed by the Indonesian population.

In particular, the welfare of food farmers needs to be a concern, because it is related to the future of rice farming or other food in sustainable production as the staple food of the Indonesian people. Farmer Terms of Trade (FTT) is one of the indicators that can be used as a reference in determining the direction of agricultural policy. According to (Badan Pusat Statistik, 2023), FTT represents the ratio between the price index received by farmers and the price index paid by them, expressed as a percentage. This metric is essential for assessing farmer welfare, as it varies across regions and fluctuates over time. An increase in FTT indicates improved farmer welfare, while a decrease signals the opposite. The FTT encompasses various commodities, including food crops, horticulture, smallholder plantation crops, livestock, and fisheries. Specifically, the FTT in the food crop subsector measures the value of rice and secondary crops.

According to the 2018 Inter-Census Agricultural Survey (SUTAS2018), the number of farmers in Central Java Province is 2.88 million, in West Java Province 3.2 million, and in East Java Province 6.29 million. (Badan Pusat Statistik, 2019) reports that East Java, Central Java, and West Java are the provinces with the largest areas of paddy fields in Indonesia. East Java Province accounts for 16% (1.214.909 hectares), Central Java 14% (1.049.661 hectares), and West Java 12% (928.218 hectares) of the total paddy field area in the country. Additionally, these three provinces also have the highest harvest areas for rice, corn, soybean, and potato crops in Indonesia, making them the main contributors to national food production. The large number of farmers, extensive agricultural land, and high productivity levels highlight the strategic importance of these provinces in ensuring food security and supporting the agricultural economy. Their significant role in both cultivation and harvest makes them essential regions for studying agricultural development, policies, and sustainability efforts in Indonesia.

East Java, Central Java, and West Java are the leading provinces in Indonesia in terms of agricultural production, particularly for rice, corn, soybean, and potatoes. East Java has the largest rice harvest area, covering approximately 1,754,380 hectares, followed by Central Java with 1,666,931 hectares, and West Java with 1,586,889 hectares. Similarly, East Java dominates corn production, yielding 6,131,163 tons, while Central Java and West Java produce 3,212,391 tons and 959,933 tons, respectively. In soybean production, East Java also leads with 344,998 tons, whereas Central Java and West Java produce 129,794 tons and 98,938 tons, respectively. For potatoes, Central Java records the largest harvested area at 17,212 hectares, followed by East Java with 15,710 hectares, and West Java with 9,226 hectares. These figures highlight the significant contribution of these provinces to Indonesia’s agricultural sector.

Forecasting the value of the food crops subsector is an important effort to assess the future potential of the agricultural sector. Currently, numerous studies focus on time series analysis, and some suggest that certain data not only relates to previous time periods but also to location. A statistical modeling method that incorporates geographical or observational location factors, used to determine whether data is related to or influenced by neighboring locations, is the Generalized Space-Time Autoregressive (GSTAR) model (Nahdliyah, 2018) .

Time series data from several neighboring locations sometimes have an interrelated relationship. The GSTAR method is an extension of STAR method developed by Cliff and Ord which is inflexible when applied to locations that have heterogeneous characteristics applied to locations that have heterogeneous characteristics (Gusnadi et al., 2015). In the STAR model, the resulting parameter values only apply to homogeneous locations and are less suitable if applied to heterogeneous locations. The GSTAR model is an advanced extension of the STAR model (Wei, 2019). The fundamental difference between the two is the parameter assumption. In the STAR model, the parameters are location-independent, so the STAR model is only suitable for homogeneous locations. Whereas in the GSTAR model, the model parameters change for each location(Talungke et al., 2015).

To illustrate the existence of a spatial relationship, a location weighting matrix is used. In modeling the Farmer Terms of Trade (FTT) data for the food crops subsector, three types of location weights are applied to determine which provides the most optimal results in GSTAR modeling. The location weights used in this research include the queen contiguity weight, uniform location weight, and inverse distance location weight. These weights will help identify which method yields the best performance in capturing spatial dependencies within the data.

Based on the background described, the author conducted research using the Generalized Space Time Autoregressive (GSTAR) Model to forecast the Farmer Terms of Trade (FTT) with spatial weighting variations. The case study focuses on FTT data for the food crops subsector in East Java, Central Java, and West Java, covering the period from January 2010 to December 2022. The results of this study are expected to provide accurate forecasts using the GSTAR model with FTT data from the food crops subsector, which can serve as a reference for determining future FTT in this sector.

METHOD

The data used in this study are secondary data obtained from the website of the *Badan Pusat Statistik* (BPS) of East Java Province, Central Java Province, and West Java Province (*Badan Pusat Statistik*, 2023).

Table 1. Definition of Variables and data sources used

Variable	Definition	Data sources
Z_1	Farmer value food crops subsector of East Java Province for the period January 2010 - December 2022	BPS of East Java Province
Z_2	Farmer value food crops subsector of Central Java Province for the period January 2010 - December 2022	BPS of Central Java Province
Z_3	Farmer value food crops subsector of West Java Province for the period January 2010 - December 2022	BPS of West Java Province

This research phase begins with a literature study, identifying topics relevant to current conditions and linking them to various scientific articles and news sources. Next, data for the analysis is collected and input, specifically data on the Farmer Terms of Trade (FTT) for the food crops subsector in East Java, Central Java, and West Java Provinces, obtained from the official websites of the Central Bureau of Statistics for each province. After the data is gathered, a descriptive analysis is conducted to provide an overview of the FTT for the food crops subsector in the three provinces from January 2010 to December 2022. The next step involves detecting spatial influence by calculating the correlation values. The correlation value (r) ranges from -1 to 1. The value of r can be written -1 ≤ r ≤ 1 with the following formula:

$$r = \frac{n\sum_{j=1}^{n}\sum_{i=1}^{n} Z_i Z_j - \sum_{i=1}^{n} Z_i \sum_{j=1}^{n} Z_j}{\sqrt{n\sum_{i=1}^{n} Z_i^2 - \left(\sum_{i=1}^{n} Z_i\right)^2}\sqrt{n\sum_{j=1}^{n} Z_j^2 - \left(\sum_{j=1}^{n} Z_j\right)^2}} \quad (1)$$

The next step involves conducting a spatial heterogeneity test using the Gini index in East Java, Central Java, and West Java, which serves as a prerequisite for using the GSTAR model. Generally, the Gini index method is used to assess the level of income distribution within the population, where a Gini index of 0 indicates perfect equality and a Gini index of 1 indicates complete inequality (Aryani et al., 2020).

$$G = 1 + \frac{1}{n} - \frac{2}{n^2 \bar{Z}_i} \sum_{i=1}^{N} Z_i \tag{2}$$

Following this, a stationarity check of the data is performed. This can be done by examining the autocorrelation function (ACF) plots of each variable or by conducting the Augmented Dickey-Fuller (ADF) test (Aktivani, 2021). In this study, the ADF test is employed to ensure a more objective assessment of data stationarity.

$\mathrm{H}_0 :\ \delta = 1$ (Data is not stationary or data contains unit root in the model)
$\mathrm{H}_1 : \delta < 1$ (Stationary data or data does not contain a unit root in the model)

If the results indicate non-stationary data, a differencing process will be applied. After differencing, a re-evaluation of the data's stationarity is conducted. The first differencing $(d = 1)$ of Z_t can be written as follows:

$$\nabla Z = Z_t - Z_{t-1} \tag{3}$$

Next, the order of the GSTAR model is selected by identifying the model with the lowest Akaike Information Criterion (AIC) value. The AIC value is a value used as a measure of model quality. Determination of the best order for the GSTAR model can be seen based on the smallest AIC value at various lags (Andriyani et al., 2018). The AIC value can be determined by the following formula:

$$\ln AIC = \frac{2k}{n} + \ln\left(\sum_{i=1}^{n} \frac{\hat{e}_i^2}{n}\right) \tag{4}$$

Determination of location weights is one of the problems in GSTAR modeling because the selection of location weights must be appropriate to apply to the time series data being analyzed, utilizing three types of location weights in this study: queen contiguity for contiguity-based weighting, uniform location weighting, and inverse distance weighting for distance-based weighting. Queen contiguity weighting is a location weighting with the concept of contiguity where areas that intersect or the corners meet are given a value of $W_{ij} = 1$, while for other areas that do not intersect or the corners do not meet are given a value of $W_{ij} = 0$ (Gezi Fajri et al., 2023).

$$W_{ij} = \frac{c_{ij}}{c_i} \tag{5}$$

Uniform location weights are weights that provide the same weight value for each location. Therefore, uniform location weights are often used for data with the same (homogeneous) distance between locations (Arini et al., 2023).

$$W_{ij} = \frac{1}{n_i} \tag{6}$$

The inverse distance location weight refers to the actual distance between locations. The distance used is taken from the distance between the center points of each location. If it is assumed that a close distance has a strong relationship between locations, then in general the inverse distance weight for each location is obtained by the following formula (Pani & Yanti, 2020):

$$W_{ij} = \frac{d_{ij}}{\sum_{j=1}^{N} d_{ij}} \quad , \qquad j \neq i \tag{7}$$

The next step involves estimating the parameters using the least squares method, which minimizes the sum of squared residuals.

$$Z_i(t) = \sum_{s=1}^{p} \Phi_{s0} Z_i(t-1) + \sum_{s=1}^{p} \sum_{k=1}^{\lambda s} \Phi_{sk}\, W^k Z_{ij}(t-1) + e_i \tag{8}$$

Suppose there is a GSTAR(1_1)I(1) model with the number of locations N = 3. This means that the GSTAR model has an autoregressive order of 1 and a spatial order of 1, with first-order differencing applied. Thus, the following matrix notation is formed.

$$\begin{bmatrix} Z_1(t) \\ Z_2(t) \\ Z_3(t) \end{bmatrix} = \begin{bmatrix} \phi_{10}^1 & 0 & 0 \\ 0 & \phi_{10}^2 & 0 \\ 0 & 0 & \phi_{10}^3 \end{bmatrix} \begin{bmatrix} Z_1(t-1) \\ Z_2(t-1) \\ Z_3(t-1) \end{bmatrix} + \begin{bmatrix} \phi_{11}^1 & 0 & 0 \\ 0 & \phi_{11}^2 & 0 \\ 0 & 0 & \phi_{11}^3 \end{bmatrix} \begin{bmatrix} 0 & W_{12} & W_{13} \\ W_{21} & 0 & W_{23} \\ W_{31} & W_{32} & 0 \end{bmatrix} \begin{bmatrix} Z_1(t-1) \\ Z_2(t-1) \\ Z_3(t-1) \end{bmatrix} + \begin{bmatrix} e_1(t) \\ e_2(t) \\ e_3(t) \end{bmatrix} \tag{9}$$

If the model equation is translated into,

$$\begin{bmatrix} Z_1(t) \\ Z_2(t) \\ Z_3(t) \end{bmatrix} = \begin{bmatrix} \phi_{10}^1\, Z_1(t-1) \\ \phi_{10}^2\, Z_2(t-1) \\ \phi_{10}^3\, Z_3(t-1) \end{bmatrix} + \begin{bmatrix} \phi_{11}^1\, [W_{12}Z_2(t-1) + W_{13}Z_3(t-1)] \\ \phi_{11}^2\, [W_{21}Z_1(t-1) + W_{23}Z_3(t-1)] \\ \phi_{11}^3\, [W_{31}Z_1(t-1) + W_{32}Z_2(t-1)] \end{bmatrix} + \begin{bmatrix} e_1(t) \\ e_2(t) \\ e_3(t) \end{bmatrix} \tag{10}$$

Once the parameter estimates for the GSTAR model are determined, the model's adequacy is tested using the white noise test to assess the correlation of residuals across lags. If the white noise test is satisfied, the model is considered valid for use; conversely, if it fails, the model is deemed unsuitable for forecasting future data (Handayani et al., 2018).

$$Q = n(n+2)\sum_{k=1}^{K}\frac{\rho_k^2}{n-k} \tag{11}$$

White noise residuals are independent, identical and normally distributed lines with mean 0 and variance σ^2. The residual correlation test is used to determine whether there is a residual correlation between lags. To fulfill the white noise assumption, the Ljung Box Pierce test is used.

$\mathrm{H}_0 : \rho_1 = \rho_2 = \ldots = \rho_k = 0$ (residuals are white noise)
$\mathrm{H}_1 : \rho_k \neq 0, k = 1,2, \ldots, k$ (residuals are not white noise)

Following the model adequacy check, the best model is selected based on the lowest values of Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). MSE is a method to evaluate forecasting methods. MSE is used to measure the accuracy of the model's estimated value expressed in terms of the mean square of the error and can also be used to compare the forecast accuracy between different forecasting methods (Kurnia Informatika et al., 2022).

$$MSE = \frac{\sum e_i^2}{n} = \frac{\sum\left(Z_t - \hat{Z}_t\right)^2}{n} \tag{12}$$

RMSE is a measure of the difference between the predicted value of the model or estimation and the true value of the observation. Each residual is squared, then summed and added to the number of observations (Ayu Pramesti Susilo et al., 2020).

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n}\sum\nolimits_{i=1}^{n}\left(Z_t - \hat{Z}_t\right)^2} \tag{13}$$

MAPE is a metric used to assess the accuracy of model estimations, represented as the average absolute percentage error. A smaller MAPE value indicates a more accurate forecast (Nabillah & Ranggadara, 2020).

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Z_t - \widehat{Z}_t}{Z_t}\right| \times 100\% \tag{14}$$

Table 2. MAPE Value Range

Range of MAPE	Meaning
MAPE ≤10%	Excellent forecasting
10% < MAPE ≤ 20%	Good forecasting
20% < MAPE ≤ 50%	Acceptable forecasting
MAPE >50%	Poor forecasting

Souce: (Lewis, 1982)

From Table 2, it can be observed that the MAPE value is considered acceptable as long as it does not exceed 50%. When the MAPE value exceeds 50%, the forecasting model is deemed unreliable and should no longer be used (Azman, 2019).

Once this series of processes is completed, forecasting is conducted using the best model on the Farmer Terms of Trade (FTT) data for the food crops subsector in East Java, Central Java, and West Java for the period from January to December 2023.

RESULTS AND DISCUSSION

Descriptive Analysis

Descriptive analysis is employed to summarize the characteristics and information within the data. In this study, a descriptive analysis was conducted on the farmer value food crops subsector in East Java, Central Java, and West Java from January 2010 to December 2022. The analysis utilizes a total of 156 monthly data points for each province.

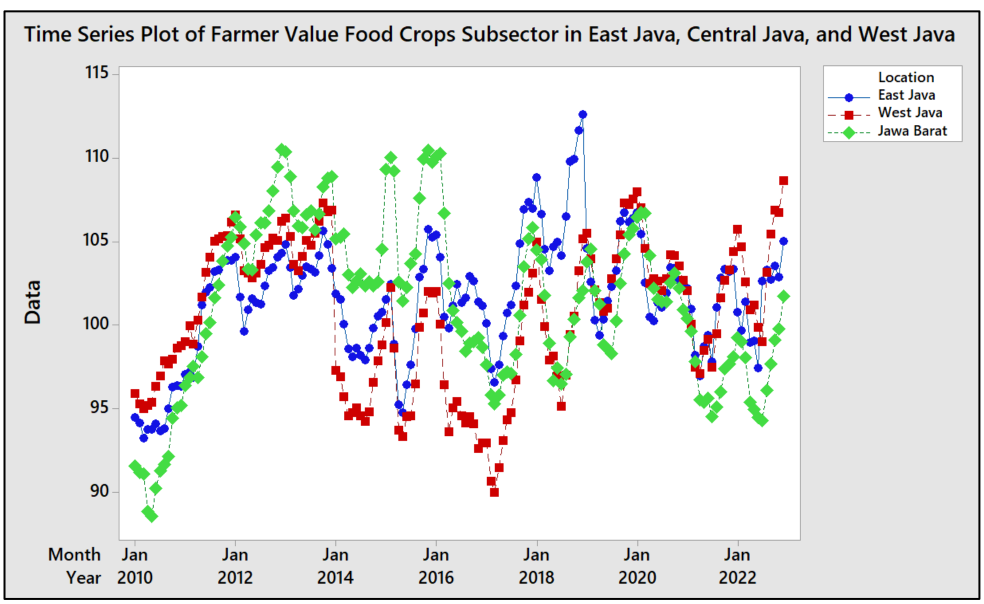

Figure 1. Farmer value food crops subsector in three provinces

Figure 1 presents a graph of the farmer value food crops subsector across the three provinces. The blue curve represents East Java Province, the red curve indicates Central Java Province, and the green curve illustrates West Java Province.

The movement of the farmer value food crops subsector in the three provinces from January 2010 to December 2022 exhibits distinct patterns. East Java shows a more pronounced trend with significant increases over time compared to Central Java and West Java. In contrast, Central Java experiences a more notable decline in value than both West Java and East Java. West Java's farmer value food crops subsector remains relatively stable, showing neither significant decreases nor increases.

The graph in Figure 1 reveals that geographical proximity does not necessarily dictate similar patterns in the farmer value food crops subsector. For example, East Java and Central Java are geographically closer to each other than East Java and West Java. However, the data pattern for East Java’s farmer value food crops subsector bears greater resemblance to that of West Java than to Central Java.

Correlation of Data

The correlation coefficient is used to assess the strength of the relationship between the farmer value of the food crops subsector in East Java, Central Java, and West Java. The table below presents the correlation coefficients among the provinces.

Table 3. Correlation coefficient of farmer value of the food crops subsector

	East Java	Central Java	West Java
East Java	1	0.5909	0.5532
Central Java		1	0.4937
West Java			1

Table 3 explains that the correlation coefficient between the farmer value of the food crops subsector in East Java and Central Java is 0.5909, indicating the strongest relationship among the provinces. In comparison, the correlation between East Java and West Java is lower, at 0.5532. The weakest correlation is observed between Central Java and West Java, with a coefficient of 0.4937.

These correlation test results suggest that the data meet the assumptions of the GSTAR model, indicating that each observation location is interconnected.

Location Heterogeneity

The main difference between the GSTAR model and the STAR model lies in the location characteristics, the STAR model has homogeneous location characteristics, while the GSTAR model has heterogeneous location characteristics.

Table 4. Spatial heterogeneity test with gini index

Province	Gini Index
East Java	1.000712
Central Java	1.000712
West Java	1.000712

Table 4 shows the results of the location heterogeneity test for the three provinces, indicating that each location has a Gini index value greater than 1. This confirms that the data satisfies the assumptions of the GSTAR model, as each observation site exhibits heterogeneous characteristics (Aryani et al., 2020).

GSTAR Analysis

In conducting GSTAR modeling, there are several steps that must be taken, namely data stationarity test, GSTAR model identification, GSTAR model location weight calculation, GSTAR model parameter estimation, model feasibility test, model error test, and forecasting using the best model.

1) Data Stationarity

In a time series model, it is essential for the data to be stationary; thus, testing for stationarity is necessary. If the test indicates that the data is not stationary in terms of the mean, a differencing process can be applied until the data becomes stationary, allowing for subsequent analysis.

Table 5. ADF test of farmer value of the food crops subsector

Province	*p-value*
East Java	0.0232
Central Java	0.3964
West Java	0.0938

Based on the ADF test results presented in Table 5, it is observed that the data for East Java, Central Java, and West Java is not stationary, as indicated by a p-value greater than 0.05. When the data is found to be non-stationary, the differencing process should be conducted. After applying the differencing, the ADF test can be performed again. The results of the ADF test after differencing the data are shown below (A. B. Salsabila et al., 2024).

Table 6. ADF test of farmer value of the food crops subsector after differencing process

Province	*p-value*
East Java	0.01
Central Java	0.01
West Java	0.01

Table 6 shows that following the differencing process, the ADF test results indicate that the stationarity test for the Farmer Value of the food crops subsector data at each research location is now stationary, with p-values less than 0.05. This confirms that the data is suitable for further analysis.

2) GSTAR Model Identification

In determining the time order (autoregressive) in the GSTAR model, it can be done by using the VAR (p) model order. The order of the VAR model is identified based on the optimal lag length, which is determined by selecting the lag with the smallest AIC value (Agnesya Risnandar & Anneke Iswani Achmad, 2023).

Table 7. Value of AIC

Lag	1	2	3	4	5	6
AIC	1.22287	1.301505	1.331411	1.314416	1.361939	1.374925
Lag	7	8	9	10	11	12
AIC	1.467037	1.50135	1.499903	1.513783	1.524961	1.500069

Table 7 shows that the smallest AIC value occurs at lag 1, indicating that the autoregressive order of the GSTAR model is 1. The spatial order of the GSTAR model is limited to order 1, as higher orders are more challenging to interpret (Muzdhalifah et al., 2023). Spatial order 1 implies that the three locations East Java, Central Java, and West Java are within the same region, namely Java Island (S. Salsabila, 2022). Based on this, the resulting GSTAR model is GSTAR(1_1)I(1).

3) GSTAR Model Location Weight Calculation

a. Queen Contiguity Weight

The Queen Contiguity location weight matrix is a concept of intersection where areas that intersect or meet at an angle are given a value of $w_{ij} = 1$, while other areas are given a value of $w_{ij} = 0$. Queen contiguity location weights using 3 research locations, namely East Java, Central Java, and West Java Provinces obtained the following matrix.

$$W^1(1) = \begin{array}{c} \\ A \\ B \\ C \end{array} \begin{array}{c} \begin{array}{ccc} A & B & C \end{array} \\ \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix} \end{array}$$

A - B (East Java Province - Central Java Province) is assigned a value of 1 because the locations/regions intersect or their boundaries meet, which also applies to the B - A, B - C, and C - B regions. In contrast, A - C (East Java Province - West Java Province) is assigned a value of 0, as these locations/regions do not intersect or their boundaries do not meet, which also applies to the C - A region.

The resulting matrix is then standardized by rows. Standardization ensures that the matrix weights are proportional, especially in cases where the number of neighboring regions varies. This produces a standardized matrix, as shown below.

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

b. Uniform Weight

The uniform location weight matrix assigns the same value to each location. In this study, three locations are considered: East Java, Central Java, and West Java Provinces. Each location has two neighboring locations.

$$W^1(1) = \begin{bmatrix} 0 & \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & 0 & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} & 0 \end{bmatrix} = \begin{bmatrix} 0 & 0.5 & 0.5 \\ 0.5 & 0 & 0.5 \\ 0.5 & 0.5 & 0 \end{bmatrix}$$

The following matrix shows the uniform location weights for these provinces. The values of $\frac{1}{2}$ in the matrix are derived from the equation $W_{\text{ij}} = \frac{1}{n_i}$, where n_i a represents the number of neighboring locations. In this study, with three locations (East Java, Central Java, and West Java), $n_i = 2$ meaning that each location has two adjacent locations.

c. Inverse Distance Weight

An inverse distance spatial weight matrix that can be determined based on the actual distance. r1 represents the distance between location 1 (East Java) and location 2 (Central Java). r2 represents the distance between location 1 (East Java) and location 3 (West Java). Meanwhile, r3 represents the distance between location 2 (Central Java) and location 3 (West Java). So the values of r1, r2, and r3 are 350 km (distance from Surabaya – Semarang), 707 km (distance from Surabaya – Bandung), and 368 km (distance from Semarang – Bandung). The distance data is obtained from google maps by looking at the true distance.

$$W^1(1) = \begin{bmatrix} 0 & \frac{350}{350+707} & \frac{707}{350+707} \\ \frac{350}{350+368} & 0 & \frac{368}{350+368} \\ \frac{368}{707+368} & \frac{707}{707+368} & 0 \end{bmatrix}$$
$$= \begin{bmatrix} 0 & 0.4874652 & 0.3423256 \\ 0.3311258 & 0 & 0.6576744 \\ 0.6688742 & 0.5125348 & 0 \end{bmatrix}$$

4) Parameter Estimation of GSTAR Model (1_1)I(1)

Parameter estimation of the GSTAR (1_1)I(1) model with queen contiguity weights, uniform weights and inverse distance weights on the farmer value food crops subsector data at three locations using the OLS method produces several significant parameters. The results are presented in Table 8.

Table 8. Parameter estimation of GSTAR model $(1_1)I(1)$

Queen Contiguity Weight		Uniform Weight		Inverse Distance Weight	
Parameter	**Estimation**	**Parameter**	**Estimation**	**Parameter**	**Estimation**
ϕ_{10}^{1}	1.006151	ϕ_{10}^{1}	1.034774	ϕ_{10}^{1}	1.038603
ϕ_{10}^{2}	1.006418	ϕ_{10}^{2}	1.006418	ϕ_{10}^{2}	1.008302
ϕ_{10}^{3}	0.919814	ϕ_{10}^{3}	0.889136	ϕ_{10}^{3}	0.896623
ϕ_{11}^{1}	-0.011357	ϕ_{11}^{1}	-0.034481	ϕ_{11}^{1}	-0.038283
ϕ_{11}^{2}	-0.002834	ϕ_{11}^{2}	-0.005668	ϕ_{11}^{2}	-0.007536
ϕ_{11}^{3}	0.162937	ϕ_{11}^{3}	0.111838	ϕ_{11}^{3}	0.104497

Based on the calculation of AIC scores in Table 7, the optimal autoregressive order of the GSTAR model is 1, and the order for differencing also has a value of 1. The next step is to determine the spatial order. A spatial order of 1 is obtained because the three research locations are all on the Java Island. This the model can be written as GSTAR $(1_1)I(1)$. From the results of the analysis of queen contiguity-based, uniform, and inverse distance weights parameter estimation, the GSTAR $(1_1)I(1)$ model was obtained for each observation location.

The equation in matrix form can be expanded for each location as follows. The GSTAR $(1_1)I(1)$ model uses the queen contiguity weights:

East Java : $Z_1(t) = 1.006151Z_1(t-1) - 0.011357Z_2(t-1) - 0Z_3(t-1)$
Central Java : $Z_2(t) = 1.006418Z_2(t-1) - 0.001417Z_1(t-1) - 0.001417Z_3(t-1)$
West Java : $Z_3(t) = 0.919814Z_3(t-1) + 0Z_1(t-1) + 0.162937Z_2(t-1)$

Model GSTAR $(1_1)I(1)$ using uniform weights:
East Java : $Z_1(t) = 1.034774Z_1(t-1) - 0.017240Z_2(t-1) - 0.017240Z_3(t-1)$
Central Java : $Z_2(t) = 1.006418Z_2(t-1) - 0.002834Z_1(t-1) - 0.002834Z_3(t-1)$
West Java : $Z_3(t) = 0.889136Z_3(t-1) + 0.055919Z_1(t-1) + 0.055919Z_2(t-1)$

Model GSTAR $(1_1)I(1)$ using inverse distance weights:
East Java : $Z_1(t) = 1.038603Z_1(t-1) - 0.018661Z_2(t-1) - 0.013105\,Z_3(t-1)$
Central Java : $Z_2(t) = 1.008302\,Z_2(t-1) - 0.002495Z_1(t-1) - 0.004956Z_3(t-1)$
West Java : $Z_3(t) = 0.896623\,5Z_3(t-1) + 0.069895Z_1(t-1) + 0.053558Z_2(t-1)$

5) Model Fit Test

Then the assumptions that must be met are that the residues are white noise or there is no autocorrelation in the residues. The results of the residual check can be seen in Table 9.

Table 9. Ljung box pierce test results with Q value

Spatial weight	*Q*	Sign	$\chi^2_{(\alpha,K-p)}$
Queen Contiguity	136.685	<	185.052332
Uniform	137.607	<	185.052332
Inverse distance	135.477	<	185.052332

The Ljung-Box Pierce diagnostic test results as shown on table 9 indicate that the GSTAR (1_1)I(1) model is is feasible, both by using queen contiguity location weights, uniform location weights and by using inverse distance location weights.

6) Model Validation

The model obtained is GSTAR (11)I(1) with inverse distance weighting. Model validation test is used to see whether the model used has good forecasting accuracy seen from the MSE, RMSE and MAPE values.

Table 10. Model validation test

Error Metric	Queen Contiguity	Uniform	Inverse Distance
MSE	2.37	2.34	2.35
RMSE	1.54	1.53	1.53
MAPE	1.10%	1.10%	1.10%

Table 9 shows the comparison of MSE, RMSE and MAPE, values from farmer value food crops subsector of the GSTAR (1_1)I(1) model with queen contiguity-based spatial weights, uniform spatial weights and inverse distance spatial weights. Based on Table 11, we can conclude that the GSTAR (1_1)I(1) model with uniform spatial weights is considered better than the GSTAR (1_1)I(1) model with queen contiguity-based spatial weights and inverse distance spatial weights. This is because the MSE, RMSE and MAPE of uniform spatial weights are smaller, with the values 2.34, 1.53 and 1.10% respectively.

7) Forecasting Farmer value food crops subsector

Based on the analysis using the GSTAR method, the GSTAR (1_1)I(1) model is obtained with inverse distance weighting. The model obtained is used to predict farmer value food crops subsector at the three provinces in 2023.

Table 10. Forecasting value farmer value food crops subsector

Month (2023)	East Java	Central Java	West Java
January	105.05	108.75	102.41
February	105.06	108.86	103.01
March	105.06	108.97	103.55
April	105.05	109.08	104.04
May	105.03	109.19	104.48
June	104.99	109.29	104.88
July	104.95	109.40	105.23
August	104.90	109.51	105.55
September	104.84	109.61	105.84
October	104.77	109.72	106.10
November	104.70	109.83	106.33
January	104.61	109.93	106.54

The forecasting procedure using the GSTAR (1_1)I(1) model involves several key steps. First, the model is specified with an autoregressive order of 1, a spatial order of 1, and first-order differencing. The parameters are estimated using historical data, incorporating spatial dependencies based on the queen contiguity weight matrix. The model's assumptions, including white noise residuals, normality, and stationarity, are then validated. Forecasts are generated iteratively using the previous period's observed values and spatial relationships, as shown in the equations for East Java, Central Java, and West Java. The forecast accuracy is evaluated using metrics such as MAPE, MSE, and RMSE, ensuring the model provides reliable short-term predictions. These results help in decision-making for regional planning and agricultural policy, as they account for both temporal and spatial dependencies.

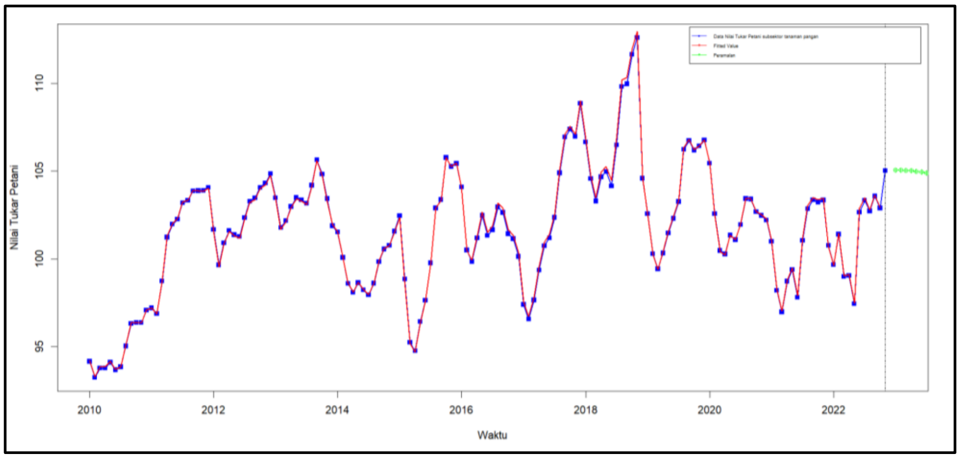

Figure 2. Forecasting chart of farmer value food crops subsector of East Java Province

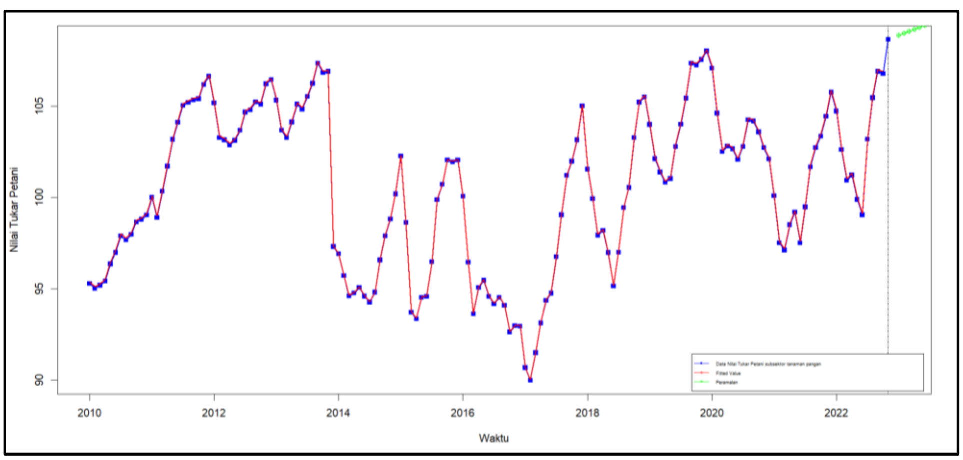

Figure 3. Forecasting chart of farmer value food crops subsector of Central Java Province

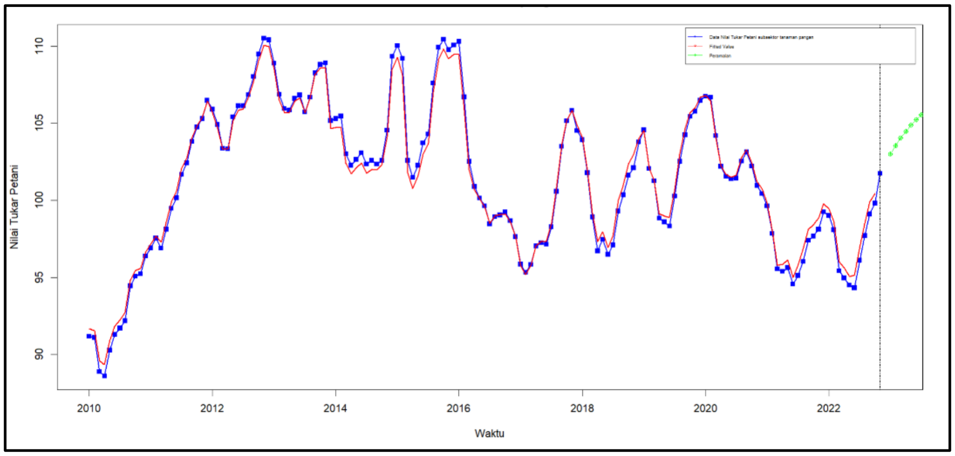

Figure 4. Forecasting chart of farmer value food crops subsector of West Java Province

Sequentially, Figures 2, 3, and 4 present comparative graphs of the data analysis results for the Farmer Exchange Rate of the food crops subsector in East Java, Central Java, and West Java Provinces from January 2010 to December 2022. In these graphs, the blue line represents the actual farmer value food crops subsector data, the red line shows the fitted value data, and the green line represents the forecasted Farmer Exchange Rate. Overall, the fitted value line in each province closely aligns with the actual farmer value food crops subsector. This is because the fitted value is generated using elements of the actual data in the forecasting process.

The forecasted trends for 2023, indicated by the green line, reveal significant regional variations in FER dynamics. In East Java, the forecast suggests a gradual decline in the FER, with a 0.42% decrease, from 105.05 in January to 104.61 in December. Conversely, Central Java and West Java exhibit positive growth trends. The FER in Central Java is projected to increase by 1.08%, from 108.75 in January to 109.93 in December, while West Java demonstrates the most substantial growth, rising by 4.03%, from 102.41 in January to 106.54 in December.

CONCLUSION

After comparing GSTAR models using queen contiguity location weights, uniform location weights and inverse distance location weights, the results show that the GSTAR (1_1)I(1) model with uniform location weights is the best model. This is because the model fulfills the white noise assumption and normality assumption and has an MSE value obtained of 2.34824, RMSE value of 1.53239, MAPE value of 1.10155% which is smaller than the GSTAR (1_1)I(1) model with queen contiguity location weight and inverse distance location weight. The superior performance of the uniform location weights model suggests that this approach captures the spatial dependencies between regions more effectively, leading to better forecast accuracy. Therefore, the GSTAR (1_1)I(1) model with uniform location weights is recommended for future forecasting in the context of agricultural productivity in East Java, Central Java, and West Java. This model provides reliable forecasts that can inform regional policy and decision-making, contributing to more effective planning and resource allocation in the agricultural sector. Furthermore, this approach can be applied to other regions or sectors where spatial and temporal dependencies play a significant role in predicting future trends.

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