Enhancing Rice Price Forecasts with Generalized Space-Time Autoregressive (GSTAR) Models and Spatial Weighting Variations

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Abstract

Rising rice demand in Indonesia, driven by population growth, causes price fluctuations that impact household spending. Accurate forecasting is crucial for price stability and government planning. This study employs the Generalized Space-Time Autoregressive (GSTAR) model with spatial weight variations to forecast rice prices across six provinces in Java. The results indicate that the GSTAR (71)I(1) model, utilizing radial distance weights (RDW), was identified as the optimal model. It satisfies the white noise assumption and achieves superior performance metrics, with a mean squared error (MSE) that is considerably lower than those obtained from other spatial weight models tested in this study. The mean absolute error (MAE) also demonstrates a strong accuracy, and the mean absolute percentage error (MAPE) is exceptionally small, suggesting minimal deviation from actual values when compared to other models. These values are notably lower compared to those of other spatial weight models tested in this study.

Keywords	***DOI***	***JEL code***
GSTAR, Spatial Weighted Variance, rice price	*https://doi.org/10.54694/stat.2024.66*	*C01, C21, C49*

INTRODUCTION

Population growth and rising per capita rice consumption in Indonesia have led to a substantial increase in the demand for rice (Ruvananda and Taufiq, 2022). As a staple food, fluctuations in rice prices significantly impact the stability of the food system. To prevent shortages or surpluses that could negatively

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affect consumers and farmers, a balance between rice supply and demand is essential. Rice price volatility is driven by a range of factors, including rising demand, decreased production, government policies, and extreme weather conditions, which may disrupt production and limit supply (Sujarwo, 2023). The public strongly favors stable rice prices, as price increases directly affect the household spending. Consequently, government management of rice reserves plays a crucial role in maintaining price stability.

In 2022, the Director General of Food Crops at the Ministry of Agriculture reported that Java Island remains Indonesia‘s largest rice producer, with a harvest area covering 5.5 million hectares, representing 52.2% of the national harvest area. Within Java, East Java Province has the largest share, with a harvest area of 1.7 million hectares, or 31.1% of the island‘s total (Annur, 2023). As both the leading rice-producing region and the most densely populated area, Java Island continues to experience rising rice demand. Additionally, rice prices in several provinces on Java Island tend to be higher than in other provinces, influenced by various regional factors. Forecasting rice prices using time series data is essential to address the issue of price fluctuations effectively. The Generalized Space-Time Autoregressive (GSTAR) model is particularly suitable for this purpose, as conventional time series models like ARIMA do not account for spatial effects. According to LeSage and Kelley Pace (2009) traditional time series models, such as ARIMA, analyze data from past periods at a single location, overlooking spatial relationships between locations.

The GSTAR model does not require the parameter values to be the same for all locations, which means it is assumed that the location characteristics are not the same (heterogeneous). Therefore, the GSTAR model is more realistic as more models are found with different parameters for different locations. This model has two types of parameters: time series parameters and spatial parameters (Wardhani et al., 2020). The GSTAR model, as a spatio-temporal approach, captures the interaction between location and time, making it better suited for forecasting rice prices across multiple regions (Wea et al., 2024). Besides GSTAR, there are several other models that also take into account spatial relationships, such as the Spatial Autoregressive Model (SAR), Spatial Error Model (SEM), and Space-Time Autoregressive Integrated Moving Average (STARIMA) (Zhao et al., 2018). However, GSTAR excels in handling dynamic spatial relationships, especially when involving time and space data with complex variations.

The GSTAR model was developed from the Space-Time Autoregressive (STAR) model introduced by Cliff and Ord. The STAR model incorporates elements of time and space, but assumes homogeneous autoregressive parameters across all locations (Gustiasih et al., 2018). Borovkova, Lopuhaa, and Ruchjana addressed this issue of homogeneity in 2012 by applying an alternative spatio-temporal method (Ruchjana et al., 2012). GSTAR, as a spatio-temporal analysis method, is applied to data observed over both time and space, utilizing a spatial weight matrix to represent spatial relationships. Related studies include Kharisma (2022), who applied the GSTAR model to forecast rice prices; Pani and Yanti (2020), who used the GSTAR method for Dengue Fever (DBD) cases; and Aryani et al. (2020), who applied the GSTAR model to farmer exchange rate data in three provinces on Sumatra Island, using cross-correlation normalization and inverse distance as spatial weighting schemes. Despite these applications, the effect of different spatial weighting schemes on the GSTAR model has not been extensively explored. Thus, this study aims to investigate the impact of varying weighting schemes in the GSTAR model.

1 DATA AND METHODOLOGY

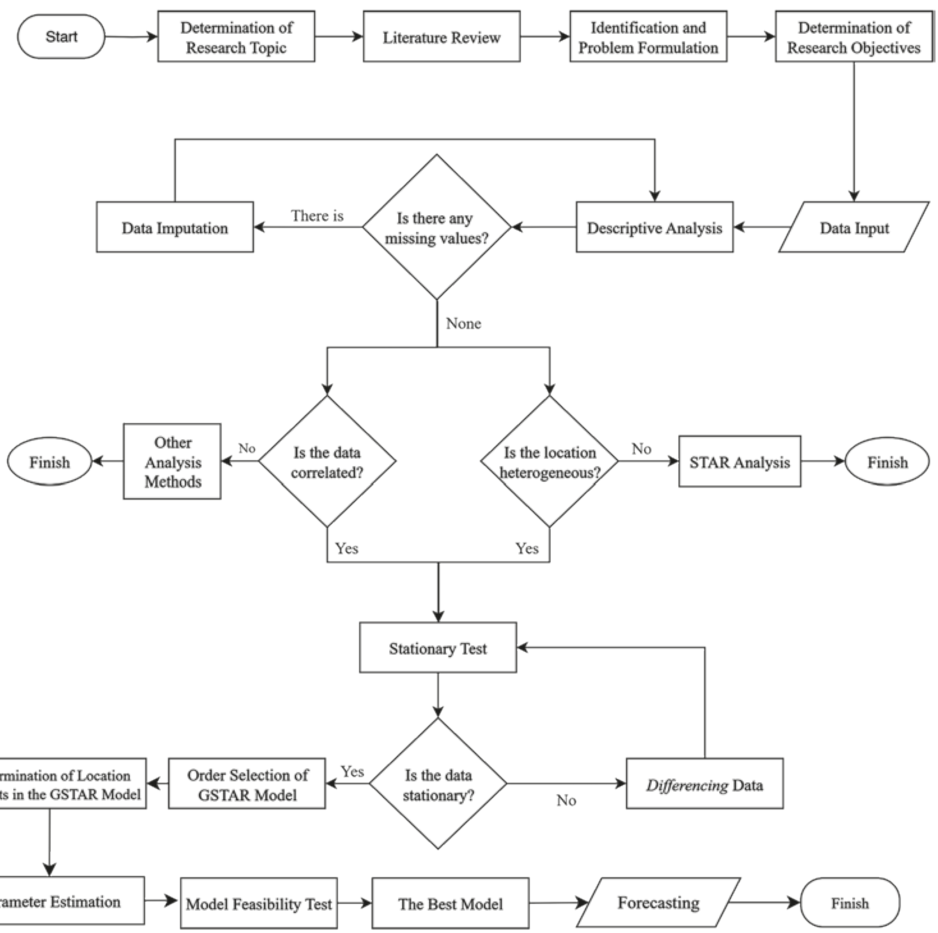
1.1 Data and research variables

This study utilizes secondary data obtained from the National Strategic Food Price Information Center (PIHPS Nasional) via the website: <*https://www.bi.go.id/hargapangan*>. The study examines rice price data from six Java Island provinces: DKI Jakarta, Banten, West Java, Central Java, East Java, and Yogyakarta (DIY). The sample includes daily rice prices from all markets in these regions from January 2020 to May 2023. To ensure consistency, all rice types are averaged without distinguishing between variations such as white, brown, or long-grain rice.

1.2 Research methodology

The stages of this research are illustrated in Figure 1. The initial stage involves descriptive analysis to provide an overview of rice prices across six provinces and to identify any missing values. If missing values are detected, they are imputed using the Kalman Filter method. Following imputation, a correlation test and a location heterogeneity test are performed as prerequisites for applying the GSTAR model. If any of these assumptions are not satisfied, further analysis is conducted; for instance, the STAR model is applied if the location heterogeneity assumption is violated. In the GSTAR analysis, data stationarity is assessed using the Augmented Dickey-Fuller (ADF) test. If the data is non-stationary, differencing is applied, followed by retesting with the ADF test until stationarity is achieved. The optimal order of the GSTAR model is then selected based on the smallest Akaike Information Criterion (AIC) value. Subsequently, spatial weights are calculated using different schemes, including contiguity (Queen Contiguity) and distance-based weights, such as uniform weights, inverse distance, critical cut-off (CCO) neighborhood, k-nearest neighbor, exponential distance, radial distance, and power distance weights (Djuraidah and Anisa, 2023; Pebesma and Bivand, 2023).

Figure 1 Research flowchart



Source: Data processing results

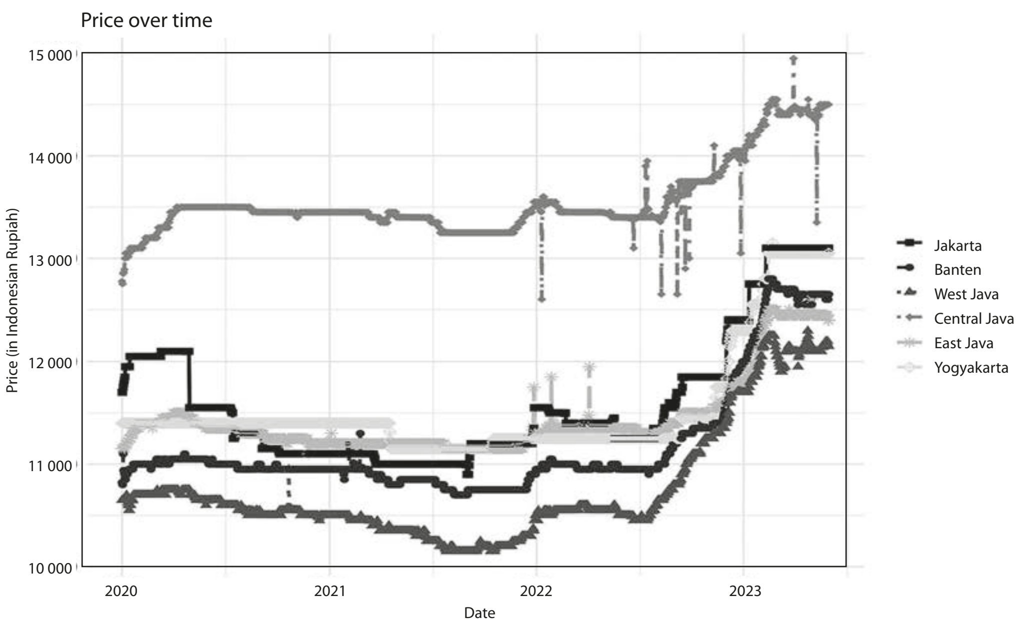
Parameter estimation is performed using the Ordinary Least Squares (OLS) by minimizing the sum of squared residuals. Model validation involves a white-noise test to check residual autocorrelation across lags. If the residuals meet the white-noise assumption, the model is considered valid for forecasting; otherwise, it is rejected (Handayani et al., 2018). The normality of residuals is assessed using the Kolmogorov-Smirnov test. The best model is selected based on mimizing of the Mean Squared Error (MSE), the Mean Absolute Error (MAE), and the Mean Absolute Percentage Error (MAPE), and is subsequently used to forecast rice prices in the six provinces of Java.

2 RESULTS AND DISCUSSION

2.1 Pre-analysis processing

Before conducting the analysis using the GSTAR method, several preliminary steps are required. First, a descriptive analysis is performed to provide an overview of rice prices in the provinces of DKI Jakarta, Banten, West Java, Central Java, East Java, and Yogyakarta (DIY). This analysis is based on daily rice price data from January 2020 to May 2023, comprising a total of 1 247 observations per province. The results of this analysis are presented in Figure 2.

Figure 2 Rice prices in six provinces on Java island over time



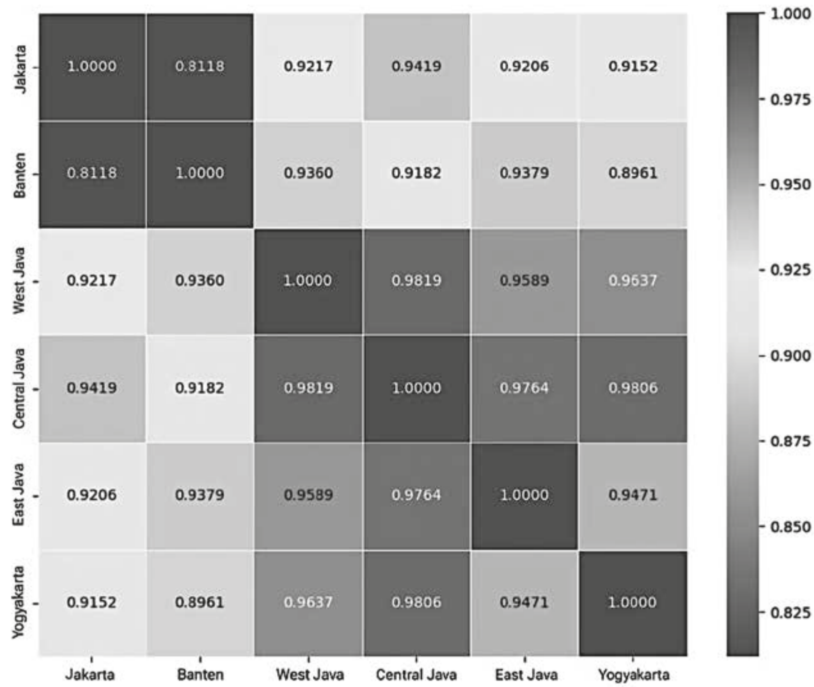
Source: Data processing results

In Figure 2, six lines are shown, each representing the rice price data from one of the six provinces. Some of the lines are broken, indicating missing values in the data. The descriptive analysis reveals that there are 404 missing values for DKI Jakarta and Banten, 397 missing values for West Java, Central Java, and East Java, and 406 missing values for Yogyakarta (DIY). To address these missing values, data imputation is performed using the Kalman Filter method. The Kalman filter is used for missing price imputation due to its ability to estimate missing values by considering inter-temporal relationships, spatial weights, and uncertainty caused by noise. This method can iteratively update estimates based on the relationship between previous observations and information from neighboring location points. This makes this imputation method suitable for filling in missing values by considering the dynamic patterns present in the data. In addition, if data is missing in consecutive time periods, methods such as interpolation or simple regression may produce biased estimates. The Kalman Filter works with prediction and correction and thus can provide more accurate estimates even when data is missing in large amounts or over long periods of time (Hadeed et al., 2020; Saputra et al., 2021). It is thus superior to simple imputation methods such as averaging, linear interpolation, or KNN, especially in handling unevenly distributed incomplete data (Durbin and Koopman, 2012).

After the data imputation process, two checks were performed: (1) analyzing the relationships between variables and (2) examining location heterogeneity. These analyses help in understanding spatial and temporal dependencies in rice price movements across different regions. GSTAR modeling relies on the assumption that price movements at different locations are correlated, capturing the interconnectedness of spatial and temporal patterns. This interconnectedness is essential for predicting future rice price trends (Pasaribu et al., 2021). In GSTAR analysis, understanding the correlation in non-stationary data can help in identifying the initial relationship patterns before transforming the data into a stationary series. If correlations are calculated only after differencing, key spatial relationships might be altered. Thus, examining the raw data structure before transformation is important in maintaining the integrity of spatial dependencies.

To illustrate spatial dependencies, a correlation heatmap (Figure 3) is used to visualize the strength of relationships between rice prices across six Java provinces. The strongest correlation (0.9) is observed between West Java and Central Java, likely due to similar economic conditions, consumption patterns, and interconnected supply chains that lead to synchronized price movements. In contrast, the weakest correlation (0.8) is found between DKI Jakarta and Banten, possibly due to differences in demand, supply chains, and market structures (Pusat Pengkajian Pedagangan Dalam Negeri, 2020).

Figure 3 Spatial correlation heatmap



Source: Data processing results

The primary distinction between the GSTAR and STAR models lies in the characteristics of the locations. In the STAR model, location characteristics are assumed to be homogeneous, whereas in the GSTAR model, they are heterogeneous (Mulyaningsih et al., 2015). Understanding location heterogeneity is essential in modeling spatial dependencies in rice price movements across different regions. To analyze the variation in price distributions across locations, the Gini Index is used as a measure of heterogeneity (Fadila et al., 2023). The Gini Index allows for comparisons of price variations over time and between provinces (Aryani et al., 2020). The results indicate that the Gini Index values for each province exceed 1, suggesting that the rice price distribution varies significantly across DKI Jakarta, Banten, West Java, Central Java, East Java, and Yogyakarta. These findings highlight the diverse economic and supply chain factors influencing rice prices in different regions.

2.2 GSTAR analysis

The GSTAR model is a generalization of the STAR model, offering greater flexibility as it does not require identical parameters across locations (Dhoriva et al., 2012). The GSTAR model allows autoregressive parameters to vary by location, making it well-suited for heterogeneous locations, where each has distinct characteristics. In contrast, the STAR model assumes homogeneity, with the same autoregressive parameters across all locations. Mathematically, the notation for the GSTAR model is similar to that of the STAR model, with the distinction being that autoregressive parameters can differ across locations. The GSTAR model with autoregressive order p and spatial $\lambda_1, \lambda_2, \ldots, \lambda_p$ is denoted as GSTAR ($p; \lambda_1, \lambda_2, \ldots, \lambda_p$) (Artianti, 2017):

$$Z_N(t)=\sum_{s=1}^{p}\left[\Phi_{s0}+\sum_{k=1}^{\lambda_s}\Phi_{sk}W^{k}\right]Z_N(t\text{-}s)+\varepsilon(t)\ , \tag{1}$$

$Z_N(t)$: vector of observations at time t location N with dimensions ($N \times 1$), Φ_{s0}: diagonal matrix of the autoregressive parameters, $s = 1,2, \ldots, p$ where $\Phi_{s0} = diag(\Phi^1_{s0}, \ldots, \Phi^N_{s0})$, Φ_{sk}: diagonal matrix of spatial regression parameters $k = 1,2, \ldots, \lambda_s$ where $\Phi_{sk} = diag(\Phi^1_{sk}, \ldots, \Phi^N_{sk})$, W^k: spatial weighting matrix or a space with dimensions ($N \times N$) where the weight values are selected to meet the criteria $w^k_{jj}=0$ and $\sum_{i\neq j} w^k_{ji}=1; i=1,2,\ldots, N$, $\boldsymbol{\varepsilon(t)}$: noise vector with dimensions ($n \times 1$) which follows the normal distribution with mean 0 and a variance-covariance matrix $\sigma^2 1_N$.

The GSTAR analysis process involves four stages: (1) ensuring data stationarity, (2) identifying the GSTAR model order, (3) calculating location weights, and (4) estimating the GSTAR model parameters. Each stage is explained as follows. To ensure that the data exhibits stable trends over time, a stationarity check was conducted using time series transformation techniques. If non-stationary patterns were detected, differencing was applied to remove trends and seasonal components (Hossain et al., 2019; Primandari and Kartikasari, 2020). This transformation was performed iteratively until the data showed stable characteristics. The initial analysis indicated that the rice price data across all research locations exhibited non-stationary behavior. Therefore, a differencing process was applied. After applying differencing, the transformed data showed stable patterns suitable for further analysis.

2.2.1 GSTAR model identification

The GSTAR model consists of two types of orders: spatial order and time order. The spatial order in the GSTAR model is typically limited to order 1, as higher spatial orders are often difficult to interpret (Dhoriva et al., 2012). The time order (autoregressive component) can be determined using the VAR(p) model, with the optimal time lag selected based on the smallest Akaike Information Criterion (AIC) value. The AIC value is calculated using Formula (2):

$$logAIC = \frac{2k}{n} + log\left(\sum_{i=1}^{n}\frac{\hat{e}_i^2}{n}\right), \tag{2}$$

k: number of estimated parameters, n: number of observations, $\hat{e}_i$: the i-th residual ($i = 1, 2, ..., n$). The AIC values of the VAR model are presented in Table 2.

Table 1 AIC Values of the VAR model depends on the optimal lag length

Lag	1	2	3	4	5	6	7	8	9	10	11	12
AIC	40.6	40.4	40.3	40.3	40.2	40.2	40.1	40.1	40.2	40.2	40.2	40.3

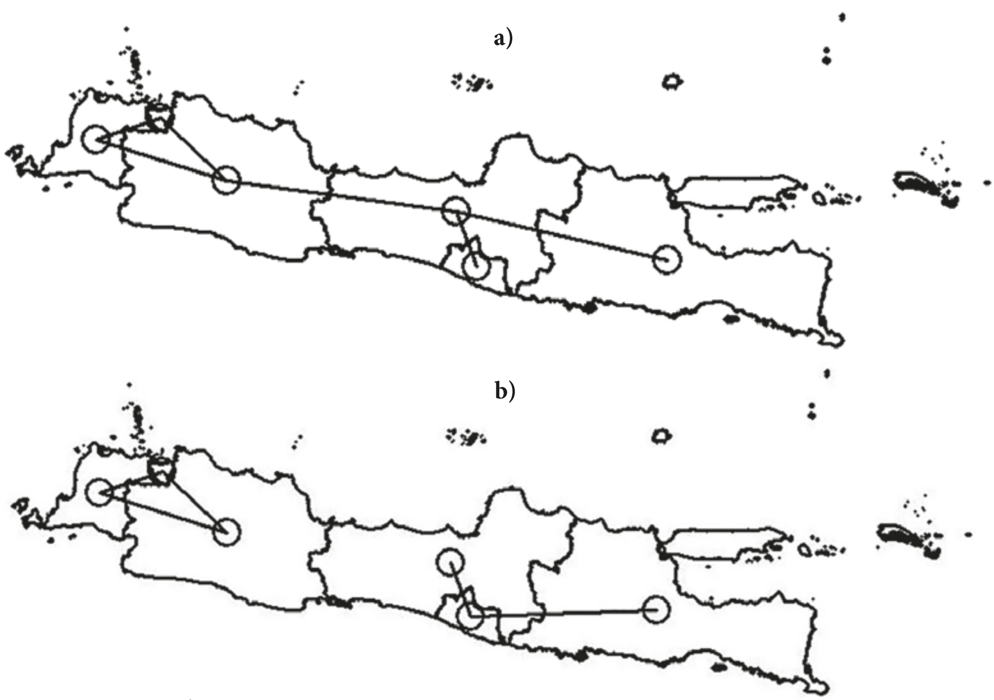
Source: Data processing results

Based on Table 2, it is concluded that the autoregressive order of the GSTAR model in this study is 7, with a spatial order of 1. Spatial order 1 indicates that the six research locations are in one geographical area. Therefore, the GSTAR model formed is GSTAR (7_1)I(1).

2.2.2 GSTAR model location weights computation

This study applies the GSTAR analysis using two types of location weights: contiguity-based and distance-based. Queen Contiguity represents the contiguity-based weight, while various distance-based weights are also considered. Figure 4 illustrates the neighbor formation for each weighting type (Fitriani and Efendi, 2019)

Figure 4 Illustration of neighbor formation with (a) Queen contiguity and (b) RDW weights



Source: Data processing results

2.2.3 Parameter estimation of the GSTAR (7_1)I(1) model

Autoregressive parameter estimation of the GSTAR model is computed using the Ordinary Least Square (OLS) method. sFor example, in the GSTAR(1,1) model, based on Formula (2), the GSTAR model formed can be written as in Formula (3):

$$Z_i(t)=\sum_{s=1}^{p}\Phi_{s0} Z_i(t\text{-}1)+\sum_{s=1}^{p}\sum_{k=1}^{\lambda s}\Phi_{sk} W^k Z_{ij}(t\text{-}1)+e_i\,, \tag{3}$$

$Z_i(t)$: observation at time t with dimensions $N \times 1$, Φ_{s0}: diagonal matrix of autoregressive parameters, Φ_{sk}: diagonal matrix of spatial parameters $k = 1, 2, ..., \lambda_s$, W^k: weight matrix with dimensions ($N \times N$), e_i: vector of residuals with dimensions ($N \times 1$) (Putri et al., 2018). Using the GSTAR(7_1)I(1) model, a model estimation was conducted for each location weight used in this study. There are twelve GSTAR(7_1)I(1) model estimations based on the number of location weights.

2.3 Forecasting analysis pre-processing

After the best GSTAR model is selected for forecasting analysis, it is important to evaluate the model fit. A well-fitted model should produce residuals that do not exhibit systematic correlations over time. Residuals from the GSTAR(7_1)I(1) model were analyzed to check for patterns. A visual inspection of the residuals indicated no significant autocorrelation, suggesting that the model is well-fitted for forecasting. To determine the best location weights for forecasting, model error measurements were calculated. Since forecasting results may deviate from actual values, error metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) were computed for each location weight. The following section presents a comparison of these error measures.

Table 2 Comparison of the MSE, MAE, and MAPE values from the GSTAR(71)I(1) model

Location weights	MSE	MAE	MAPE (%)
Uniform	1 575.70	10.8	0.09
Inverse distance	1 577.90	10.7	0.09
Queen contiguity	1 581.80	10.7	0.09
CCO with a distance of 0.55 from the Min-Max distance	1 583.50	10.6	0.09
CCO with a distance of 0.60 from the Min-Max distance	1 580.60	10.8	0.09
CCO with a distance of 0.65 from the Min-Max distance	1 581.20	10.7	0.09
CCO with a distance of 0.70 from the Min-Max distance	1 581.20	10.7	0.09
CCO with a distance of 0.75 from the Min-Max distance	1 581.40	10.6	0.09
K-Nearest Neighbors (KNN)	1 580.60	10.8	0.09
Exponential Distance Weights (EDW)	1 579.00	10.7	0.09
Radial Distance Weights (RDW)	1 583.50	10.6	0.09
Power Distance Weights (PDW)	1 580.80	10.7	0.09

Source: Own data processing

Based on Table 2, the results of the MSE, MAE, and MAPE error calculations on the GSTAR(7_1)I(1) model for all location weights show values that are not much different. However, the RDW location weight and the CCO location weight with a distance of 0.6 from the min-max distance have the smallest

MSE, MAE, and MAPE values, 1 583.6, 10.6, and 0.09%, respectively. Therefore, these two weights are considered better than the other weights, and will be considered for use in the forecasting process. However, based on the principle of parsimony, which states that the simpler a statistical model is, but still informative enough to explain the dependent variable, the better the model, the GSTAR(7_1)I(1) model with RDW weights was chosen. This is because the CCO weight is only the result of trial and error iterations. The equation in matrix form can be expressed for each location. For example, the equation for GSTAR (7_1)I(1) Model with RDW location weights in Jakarta Province is expressed as Formula (4):

$$\begin{aligned} Z_1(t) = {} & 0.15Z_1(t-1) + 0.06Z_2(t-1) + 0.06Z_3(t-1) + 0.18Z_1(t-2) + 0.02Z_2(t-2) + 0.02Z_3(t-2) \\ & + 0.003Z_6(t-2) + 0.18Z_1(t-3) + 0.01Z_2(t-3) + 0.01Z_3(t-3) + 0.11Z_1(t-4) - 0.01Z_2(t-4) \\ & - 0.01Z_3(t-4) + 0.09Z_1(t-5) + 0.01Z_2(t-5) + 0.01Z_3(t-5) + 0.04Z_1(t-6) - 0.13Z_2(t-6) \\ & - 0.13Z_3(t-6) + 0.21Z_1(t-7) + 0.05Z_2(t-7) + 0.05Z_3(t-7) + e_1(t). \end{aligned} \tag{4}$$

2.4 Rice price forecasting

Based on the analysis using the GSTAR model, the best-fitting model for rice price data across the six provinces of Java Island is GSTAR(7_1)I(1) with Radial Distance Weights. This model was selected because it meets the white noise assumption and has the lowest MSE, MAE, and MAPE values. The GSTAR(7_1) I(1) model with Radial Distance Weights is used to forecast rice prices in these six provinces for the period of June–July 2023. Table 3 below presents the descriptive statistics of the data used in this study. These statistics provide an overview of the distribution, central tendency, and variability of the data being analyzed, and help in understanding the basic characteristics of the variables under study.

Table 3 Error measurement of forecasting results for the June–July 2023 period

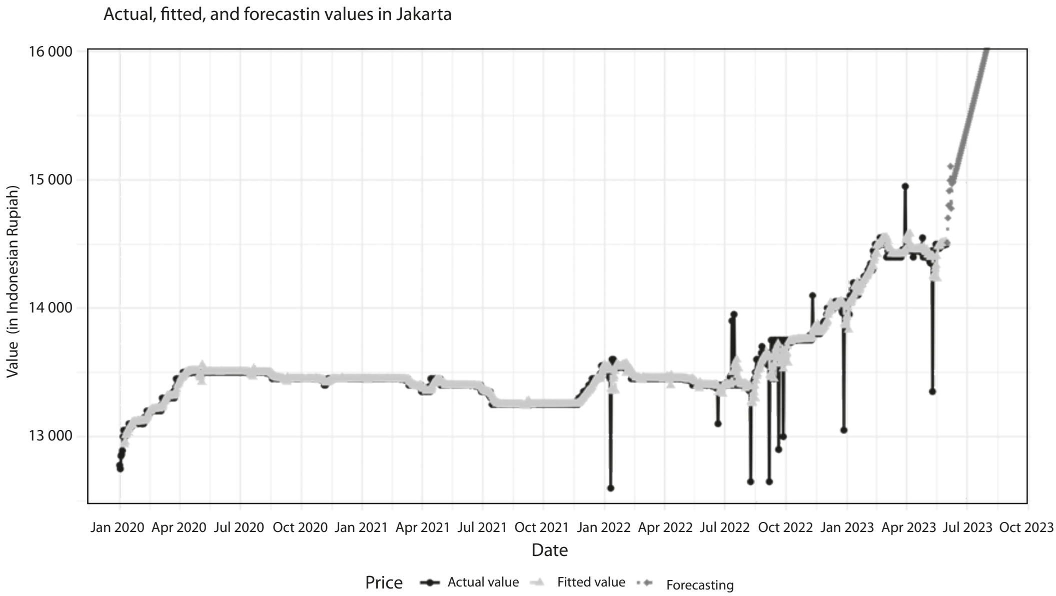
Location	Min	1st Q.	Median	Mean	3rd Q.	Max
Jakarta	14 512	15 109	15 411	15 410	15 718	16 031
Banten	14 496	15 114	15 397	15 400	15 704	16 017
West Java	14 335	14 985	15 283	15 271	15 588	15 898
Central Java	14 477	15 078	15 367	15 378	15 673	15 986
East Java	14 427	15 039	15 299	15 309	15 604	15 915
Yogyakarta	14 399	15 024	15 304	15 304	15 610	15 921

Source: Own data processing

The forecast results for rice prices during this period are presented in Figure 5, with DKI Jakarta Province shown as an illustrative example.

Figure 5 shows that the fitted values for each province closely align with the actual rice price data. This close alignment occurs because the fitted values are derived from actual data elements. However, the forecasted rice prices differ significantly from the actual data, as the forecasts do not incorporate actual data elements, in the form of price fluctuations in the market, production declines, government policies, weather factors, etc. The forecasting results indicate an increase in rice prices across all provinces during June to July 2023. The peak rice prices on July 31, 2023, were as follows: Jakarta (16 031.5), Banten (16 016.7), West Java (15 898.5), Central Java (15 985.7), East Java (15 914.8), and Yogyakarta (15 920.7).

Figure 5 Forecasting results in Jakarta province



Source: Data processing results

To evaluate the extent to which a forecasting model is able to produce predictions that are close to actual values, a measurement of the error of the forecasting results is carried out. This measurement is very important in the development, validation, and application of forecasting models.

Table 4 Error measurement of forecasting results for the June–July 2023 period

Location	MSE	MAE	MAPE (%)
Jakarta	1 032 283.8	944.8	6.42
Banten	5 046 380.0	2 246.1	16.74
West Java	8 436 767.5	2 903.6	23.00
Central Java	7 954 037.7	2 824.3	22.05
East Java	10 545 785.3	3 253.9	26.43
Yogyakarta	5 316 154.7	2 294.0	17.29

Source: Own data processing

Based on Figure 5, upward trend in the forecasting results for the June to July 2023 period suggests price pressure, likely due to seasonal factors, increased demand, or supply disruptions. These rice price forecasts are expected to be valuable for the government in anticipating future price fluctuations and supporting planning for price stabilization policies, market interventions, or establishing adequate food reserves to mitigate harmful price spikes for consumers.

CONCLUSION

The spatio-temporal model integrates the interdependence of both time and location, capturing dynamic changes not only across temporal but also spatial dimensions. In this study, various types of spatial weighting schemes were developed to optimize the model, categorized by distance or adjacency criteria. The weight matrices employed include: uniform weighting, Inverse Distance Weighting (IDW), Queen Contiguity, Critical Cutoff, k-Nearest Neighbors (k-NN), Exponential Distance Weights, Radial Distance Weights, and Power Distance Weights.

The preprocessing phase involved ensuring data consistency and handling missing values. Subsequently, various spatial weighting schemes were tested. The GSTAR model parameters were estimated using maximum likelihood estimation, and the models were evaluated using criteria such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). Through this process, the GSTAR(7,1)I(1) model with Radial Distance Weights emerged as the optimal model. This model was selected based on its superior performance metrics, achieving a Mean Squared Error (MSE) of 1 583.5, Mean Absolute Error (MAE) of 10.646, and Mean Absolute Percentage Error (MAPE) of 0.09%, demonstrating lower error values compared to other weighting schemes.

The forecasting results show a general upward trend in rice prices during the forecast period. The radial distance weighted (RDW) GSTAR model successfully identifies spatial and temporal patterns that reflect the dynamics of rice prices in different provinces. The forecasting provides useful insights for planning food inflation mitigation policies. Although rice prices are expected to rise, the pattern of price movements in each province shows variations depending on local factors, highlighting the importance of understanding spatial dynamics in food price forecasting. As a recommendation for further application, this methodology can be adapted for forecasting other staple food prices, such as beef, eggs, shallots, and cooking oil. Future research should explore the influence of spatial location in combination with varying temporal scales to enhance the robustness and applicability of spatio-temporal models across broader datasets.

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