CAUCHY – Jurnal Matematika Murni dan Aplikasi
Volume 10 (2) (2025), Pages 1372-1387
p-ISSN: 2086-0382; e-ISSN: 2477-3344

Spatial-Temporal Modeling of Regional Sales Using Generalized Space Time Autoregressive (GSTAR): Spillover Effect Analysis

Firstyan Deviena Citra Rahayu* and Ardana Putri Farahdiansari

Program Studi Teknik Industri, Fakultas Sains dan Teknik, Universitas Bojonegoro, Jalan Lettu Suyitno No.2, Jawa Timur 62111, Indonesia

Abstract

This study forecasts healthcare product sales across the provinces of Java Island using the Generalized Space-Time Autoregressive (GSTAR) model. The dataset comprises 48 monthly observations from January 2020 to December 2023 for DKI Jakarta, West Java, Central Java, and East Java. The methodological steps include stationarity testing using the Augmented Dickey–Fuller (ADF) test, model identification based on the Akaike Information Criterion (AIC), spatial weight matrix construction using inverse distance weighting, parameter estimation through Ordinary Least Squares (OLS), and performance evaluation using Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE). The GSTAR(1,1) model is identified as the optimal specification with an AIC value of 1769.47, successfully capturing strong spatial dependencies, including a substantial spillover effect from West Java to DKI Jakarta (0.76). The model exhibits excellent predictive accuracy, with MAPE values of 1.92% (DKI Jakarta), 3.30% (West Java), 7.97% (Central Java), and 4.93% (East Java), resulting in an overall average of 4.53%, classified as highly accurate. The Ljung–Box test further confirms model adequacy, with all residuals meeting independence criteria. Overall, the findings demonstrate that incorporating both spatial and temporal dependencies through GSTAR provides an effective framework for regional sales forecasting and strategic planning across Java Island.

Keywords: Forecasting; GSTAR; spatio-temporal; sales; spillover effect.

1 Introduction

Relevant data from the past will be used as a reference to predict a value, either quantitatively or qualitatively, in the future [1]. In supply chain management and business strategy, forecasting is crucial, particularly in the context of regional economics, such as on the island of Java, which is the center of national economic activity [2].

Time series forecasting is a method that has developed recently due to the rapid changes in market trends. This time series forecasting method involves collecting data sequentially over time [3]. Data patterns with many variables can also utilize this time series forecasting [3]. Unlike univariate time series, which only discuss time, multivariate time series also discuss space, a concept known as the spatiotemporal model.

*Corresponding author. E-mail: fdeviena@gmail.com

Submitted: October 6, 2025 Reviewed: November 5, 2025 Accepted: November 28, 2025
DOI: https://doi.org/10.18860/cauchy.v10i2.36799

The spillover effect phenomenon in inter-regional economic activity requires an analytical approach that can capture spatial and temporal dependencies simultaneously [4], [5]. Forecasting methods such as ARIMA and Exponential Smoothing are conventional methods that focus solely on the temporal aspect, without considering the spatial aspect. Therefore, this will be a limitation if the data to be analyzed has a spatial relationship within a specific period [6].

The model was first introduced by Pfeifer and Deutsch, who presented it as a space-time model [7], [8]. The STAR model is a method that incorporates aspects of time and location, characterized by uniform location characteristics. The STAR model includes multivariate time series. However, the STAR model produces constant parameter values for all locations, making it more suitable for homogeneous areas and less appropriate for locations with high heterogeneity [9].

The Generalized Space-Time Auto Regressive (STAR) model is a refinement of the STAR model that is enhanced through a flexible model for determining its parameters [7], [10]. The advantage of the GSTAR model lies in its ability to accommodate both spatial heterogeneity and temporal dependency within a single analytical framework [11]. This occurs because GSTAR assumes heterogeneous location characteristics, so that the Autoregressive parameters have different values between locations [12]. The effectiveness of this model has been proven in various fields, including weather prediction, epidemiological analysis, and regional economic modeling [7].

Previous research has shown the effectiveness of the GSTAR model in research on various aspects of the regional economy [8]. For example, to predict inflation in Java Island, research uses a uniform location weighting matrix and produces the best GSTAR model (1:1) [10]. In forecasting farmer exchange rates in three provinces in Sumatra Island, researchers tried normalized cross-correlation location weights and inverse distance, and obtained the best GSTAR(1;1)-I(1) model with normalized cross-correlation weights. In addition, research that models inflation values in Sulawesi Island with an inverse distance weighting matrix also produces a GSTAR(1;1)-I(1) [12].

In this study, referring to several methodological aspects, the GSTAR parameter (1,1) is the best model. The temporal lag parameter (1) means that a province's sales in period t are a function of its own sales in period $t-1$. Conversely, the spatial lag parameter (1) explains that sales in the province are also influenced by sales from neighboring provinces in the same time period only.

Matrix structure measuring (4×4) represents the interaction of the four provinces in Java Island that have gone through a stationarization process [10]. The Ordinary Least Squares (OLS) method is used to estimate the parameters, aiming to ensure that unbiased estimates are obtained [2]. The interpretation of the temporal parameters is divided into diagonal elements (internal temporal lag effects) and non-diagonal elements (cross-influences between provinces). The spatial parameters measure the geographic spillover effects that have been weighted based on the economic proximity between provinces [4].

Based on the background, this research focuses on several areas in Java Island, such as DKI Jakarta, West Java, Central Java, and East Java, to analyze the spillover effect using GSTAR modeling [2], [4]. This research is highly needed to develop effective business strategies and product distribution policies in the Java Island region, which has heterogeneous characteristics [2], [13].

2 Methods

This section outlines the methodological framework employed in this study. First, we present the GSTAR model formulation and its mathematical structure. Next, we describe the construction of the spatial weight matrix using the Inverse Distance Weighting (IDW) approach. Finally, we detail the research data, including the temporal coverage, geographic scope, and train-test split used for model validation. The estimation procedure employs Ordinary Least Squares (OLS), and model performance is evaluated using Mean Absolute Percentage Error (MAPE) and Root

Mean Square Error (RMSE).

2.1 GSTAR Modeling

The Generalized Space Time Autoregressive (GSTAR) model is a refinement of the Space Time Autoregressive (STAR) model, allowing autoregressive parameters to vary for each location [7], [8]. This model has been proven effective in various applications, including weather prediction, epidemiological analysis, and regional economic modeling [10].

In the current study, the GSTAR model was implemented using the Python programming language. The Google Colab platform was utilized as the development environment, providing valuable support for debugging and resolving coding errors throughout the implementation process. The Generalized Space Time Autoregressive (GSTAR) model of order (p, λ) is written as:

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

where p denotes the temporal order (time lag), λ represents the spatial lag, and $Z_t(s)$ is the vector of observations at time t and location s. The term $\phi_{kl}(s)$ refers to the autoregressive coefficient associated with temporal lag k and spatial lag l at location s, while $W^{(l)}$ is the spatial weight matrix corresponding to spatial lag l. The error term $e_t(s)$ is assumed to follow a white-noise process.

2.2 Spatial Weight Matrix

The spatial weight matrix is constructed using the Inverse Distance Weighting (IDW) approach, which implements relationships between locations based on their geographic proximity [8], [14]. The weight between two distinct locations i and j is defined as:

$$w_{ij} = \frac{1}{d_{ij}^{\alpha}}, \qquad i \neq j \tag{2}$$

The selection of the appropriate weight matrix significantly affects the performance of the GSTAR model [15]. Each element w_{ij} is calculated as the inverse of the geographical distance between provinces i and j, raised to the exponent parameter α [10]. In this study, α is set to 1. Thus, locations that are closer have larger spatial weights, whereas locations farther apart receive lower weights. Diagonal elements (w_{ii}) are set to zero to prevent self-influence in spatial analysis.

This study employs uniform location weights and normalized cross-correlation for conceptual comparison, as both approaches have been shown to be effective in spatio-temporal analysis [10], [15]. However, the final GSTAR(1,1) model estimation exclusively uses the normalized Inverse Distance Weighted (IDW) spatial weight matrix, as this structure more accurately reflects the geographic proximity relationships between provinces.

2.3 Research Data

The dataset used in this study consists of 48 monthly observations of healthcare product sales recorded from January 2020 to December 2023. For model development and validation, the data are divided into two subsets:

- **Training data:** January 2020–September 2023 ($n = 45$)
- **Testing data:** October 2023–December 2023 ($n = 3$)

The analysis focuses on four locations, each represented as a separate time-series variable, as summarized in Table 1.

Table 1: Table of Variables

Variable (t)	Description
y_{1t}	Jakarta
y_{2t}	West Java
y_{3t}	Central Java
y_{4t}	East Java

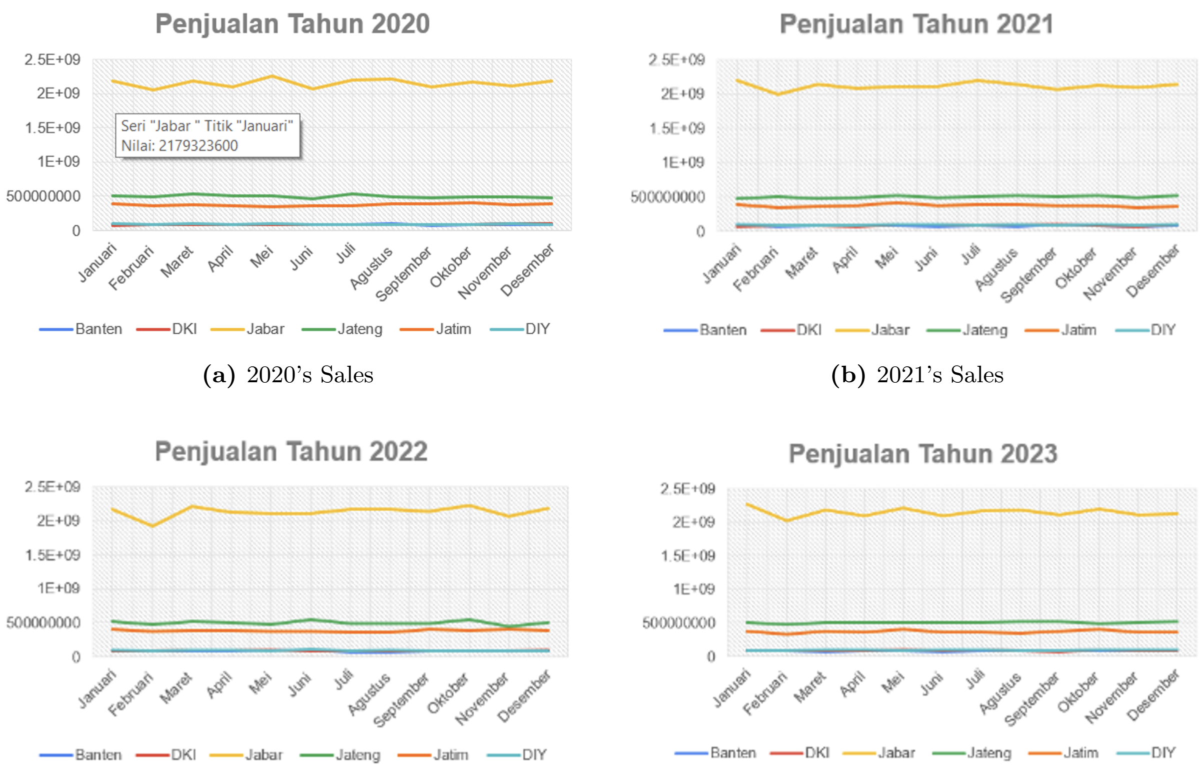
3 Results and Discussion

This section presents the empirical findings from the GSTAR(1,1) model applied to healthcare product sales across four provinces in Java Island. We begin with descriptive statistics and data visualization followed by stationarity testing using the Augmented Dickey-Fuller (ADF) test. This section describes the construction of the spatial weight matrix based on inverse distance weighting. Section presents the estimated GSTAR(1,1) parameters, including temporal and spatial coefficients and evaluates model adequacy through the Ljung-Box test and accuracy metrics (MAPE and RMSE) also presents the forecasting results for the validation period (October–December 2023).

Table 2: Table of Descriptive Analysis

Province	Min	Max	Variance	Mean
Jakarta	65,401,500	102,589,400	7.090×10^{13}	87,164,425.00
West Java	1,927,182,400	2,265,512,400	4,158,793,799,363,500.00	2,136,798,193.75
Central Java	453,103,100	2,265,512,400	387,471,255,958,954	500,908,635.40
East Java	332,857,900	412,491,900	334,260,335,226,315	374,515,968.80

Table 2 shows significant variations between provinces, with West Java having the highest sales value, followed by East Java, DKI Jakarta, and Central Java.



(a) 2020's Sales (b) 2021's Sales

(c) 2022's Sales (d) 2023's Sales

Figure 1: Annual Sales Data Visualization (2020–2023)

3.1 Stationarity Test

Stationarity testing is a fundamental step in time series analysis because many modeling techniques require the underlying data to be stationary. In this study, the Augmented Dickey–Fuller (ADF) test is applied at the level form to assess the stationarity of sales data from each province. The ADF test is based on the following equation:

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta Y_{t-i} + \varepsilon_t, \tag{3}$$

where ΔY_t denotes the first difference of the series, t is the time index, and ε_t is the error term.

Table 3: Stationarity Test Results (Level)

Province	ADF Statistic	P-value	Status
Jakarta	-8.34721	0.000873	Stationary
West Java	-10.880	0.000000	Stationary
Central Java	-2.190	0.209000	Non-stationary
East Java	-5.890	0.000002	Stationary

A series is considered non-stationary if the p-value exceeds 0.1. In such cases, differencing is applied to achieve stationarity. The differencing process is defined by:

$$\Delta Y_t = Y_t - Y_{t-1}. \tag{4}$$

After applying first differencing to the non-stationary series, the updated ADF results are summarized below.

Table 4: Stationarity Test Results After Differencing

Province	ADF Statistic	P-value	Status
Jakarta	-5.300	0.000000	Stationary
West Java	-3.360	0.012000	Stationary
Central Java	-8.690	0.000000	Stationary
East Java	-4.900	0.000034	Stationary

3.2 Identification of the VAR Model

The Vector Autoregressive (VAR) model serves as a preliminary step for determining the optimal order of the GSTAR model. In this study, the VAR(p) model is formulated as:

$$\text{VAR}(p): \quad Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + \varepsilon_t, \tag{5}$$

where Y_t is the multivariate time series vector and ε_t denotes the error term.

Building upon the VAR structure, the GSTAR model incorporates spatial dependencies through a spatial weight matrix W. The general GSTAR(p, λ) specification is given by:

$$\text{GSTAR}(p, \lambda): \quad Y_t = \Phi_{10} Y_{t-1} + \Phi_{11} W Y_{t-1} + \cdots + \varepsilon_t. \tag{6}$$

Based on the AIC values in Table 4.3, the optimal model is the GSTAR model with lag 4, which yields the lowest AIC score. This model is applied to the differenced sales data and is expressed as:

$$Y_{s,t} = C_s + \sum_{i=1}^{4} \phi_{s,i} Y_{s,t-i} + \sum_{i=1}^{4} \theta_{s,i} (W Y_{t-i})_s + \varepsilon_{s,t}, \tag{7}$$

where C_s is the constant for location s, $\phi_{s,i}$ represents the temporal autoregressive parameters, $\theta_{s,i}$ denotes the spatial lag parameters, and $(WY_{t-i})_s$ is the spatially weighted lagged observation at location s.

Table 5: VAR and GSTAR Model Identification Based on AIC

Model	Lag (p)	AIC
VAR	1	1784.83
GSTAR	1	1769.47
VAR	2	1765.05
GSTAR	2	1734.85
VAR	3	1751.71
GSTAR	3	1707.22
VAR	4	1733.71
GSTAR	4	1678.16

3.3 Spatial Weight Construction

To model spatial interactions among provinces, this study constructs spatial weight matrices based on geographic proximity. The following map illustrates the locations of the four variables used in the analysis.

Figure 2: Variable Locations

3.3.1 Spatial Weight Construction Using Distance Matrix (km)

The first step in constructing spatial weights is to measure the physical distances between provinces. Table 1 presents the pairwise distance matrix in kilometers, which serves as the basis for subsequent weight normalization.

Table 6: Distance Matrix (km)

	Jakarta	West Java	Central Java	East Java
Jakarta	0	115.07	378.58	613.34
West Java	115.07	0	279.61	514.46
Central Java	378.58	279.61	0	235.36
East Java	613.34	514.46	235.36	0

3.3.2 Euclidean Distance Matrix

In addition to physical distance, this study also evaluates spatial relationships using the Euclidean distance formula. The resulting matrix, shown in Table 2, provides an alternative representation of spatial separation between provinces.

Table 7: Euclidean Distance Matrix

	Jakarta	**West Java**	**Central Java**	**East Java**
Jakarta	0	1.0491	3.4262	5.5537
West Java	1.0491	0	2.5330	4.6630
Central Java	3.4262	2.5330	0	2.1330
East Java	5.5537	4.6630	2.1330	0

This study initially applies uniform location weights and normalized cross-correlation for comparison. The uniform weight matrix used is:

$$W = \begin{bmatrix} 0 & 0.671071 & 0.203430 & 0.125500 \\ 0.612486 & 0 & 0.251092 & 0.136423 \\ 0.252642 & 0.341661 & 0 & 0.405697 \\ 0.208595 & 0.248439 & 0.542965 & 0 \end{bmatrix}$$

For the final GSTAR(1,1) model estimation, the spatial structure is determined using the normalized Inverse Distance Weighted (IDW) matrix. After normalization, the weight matrix becomes:

$$W = \begin{bmatrix} 0.0000 & 0.670 & 0.203 & 0.125 \\ 0.611 & 0.0000 & 0.251 & 0.136 \\ 0.252 & 0.341 & 0.0000 & 0.405 \\ 0.208 & 0.248 & 0.542 & 0.0000 \end{bmatrix}$$

3.4 Estimation of the GSTAR(1,1) Model

The GSTAR(1,1) model used in this study is expressed as:

$$Z_t = \Phi_{10} Z_{t-1} + \Phi_{11} W Z_{t-1} + \varepsilon_t, \tag{8}$$

where:

- Z_t : sales vector (4×1),
- Φ_{10} : temporal autoregressive matrix (4×4),
- Φ_{11} : spatial autoregressive matrix (4×4),
- W : normalized spatial weight matrix.

3.4.1 Temporal Parameters (Φ_{10})

The estimated temporal autoregressive parameter matrix is:

$$\Phi_{10} = \begin{bmatrix} -0.032 & 0.000 & 0.000 & 0.000 \\ 0.000 & -0.340 & 0.000 & 0.000 \\ 0.000 & 0.000 & 0.980 & 0.000 \\ 0.000 & 0.000 & 0.000 & -0.210 \end{bmatrix}$$

3.4.2 Spatial Parameters (Φ_{11})

The estimated spatial autoregressive parameter matrix is:

$$\Phi_{11} = \begin{bmatrix} -0.040 & 0.000 & 0.000 & 0.000 \\ 0.000 & 0.530 & 0.000 & 0.000 \\ 0.000 & 0.000 & -0.080 & 0.000 \\ 0.000 & 0.000 & 0.000 & -0.270 \end{bmatrix}$$

3.5 Model Parameter Interpretation

a. Temporal Parameters (Own Effects)

- $\phi_{11} = -0.032$: DKI Jakarta shows mean-reversion behavior with a decay rate of 3.2%.
- $\phi_{22} = -0.34$: West Java shows strong mean-reversion behavior with a decay rate of 34%.
- $\phi_{33} = 0.98$: Central Java demonstrates very strong positive persistence at 98%.
- $\phi_{44} = -0.21$: East Java shows mean-reversion behavior with a decay rate of 21%.

The temporal parameters reveal distinct sales dynamics across provinces. Central Java ($\phi_{33} = 0.98$) exhibits the strongest persistence, indicating that 98% of the previous period's sales movement is carried forward to the current period, suggesting highly stable and predictable sales patterns.

In contrast, DKI Jakarta ($\phi_{11} = -0.032$), West Java ($\phi_{22} = -0.34$), and East Java ($\phi_{44} = -0.21$) show negative coefficients, indicating mean-reversion. This means sales tend to move back toward long-run equilibrium levels. East Java exhibits the strongest mean-reversion (21% decay), implying that its sales fluctuations are short-lived and quickly stabilize. DKI Jakarta shows mild self-correction (3.2%), signaling relatively stable but slightly mean-reverting patterns.

b. Spatial Parameters (Spillover Effects)

- DKI Jakarta: $\theta = -0.04$
- West Java: $\theta = 0.53$
- Central Java: $\theta = -0.08$
- East Java: $\theta = -0.27$

The spatial parameters indicate heterogeneous spillover effects across provinces. West Java exhibits the strongest positive spillover ($\theta = 0.53$), meaning that sales in neighboring provinces substantially influence sales in West Java. This reflects strong economic integration and cross-territorial consumer mobility.

DKI Jakarta shows a weak negative spatial effect ($\theta = -0.04$), suggesting minimal influence from surrounding provinces. Central Java also exhibits a slight negative spillover ($\theta = -0.08$), potentially indicating competitive interaction or partial market segmentation.

East Java shows a pronounced negative spatial effect ($\theta = -0.27$), meaning that increases in neighboring provinces' sales are associated with decreases in East Java's sales. This may indicate competitive market dynamics or regional substitution effects.

Overall, the spatial analysis highlights varied inter-provincial relationships. West Java benefits from positive integration with neighboring regions, whereas Jakarta, Central Java, and East Java display varying degrees of negative spatial dependence, reflecting competition, independent market structures, or substitution-driven dynamics.

3.5.1 Spillover Effect Analysis

The direct spillover effect from region j to region i is defined as:

$$SE_{\text{direct}}(j \to i) = \phi_{11}^{(i)} \times W_{ij}. \tag{8}$$

For Jakarta

$$\begin{aligned} SE_{\text{direct}}(\text{West Java} \to \text{Jakarta}) &= \phi_{11}^{(1)} \times W_{12} = -0.04 \times 0.670 = -0.0268 \\ SE_{\text{direct}}(\text{Central Java} \to \text{Jakarta}) &= \phi_{11}^{(1)} \times W_{13} = -0.04 \times 0.203 = -0.0081 \\ SE_{\text{direct}}(\text{East Java} \to \text{Jakarta}) &= \phi_{11}^{(1)} \times W_{14} = -0.04 \times 0.125 = -0.0050 \end{aligned}$$

For West Java

$$SE_{\text{direct}}(\text{Jakarta} \to \text{West Java}) = \phi_{22}^{(1)} \times W_{21} = 0.53 \times 0.611 = 0.3238$$
$$SE_{\text{direct}}(\text{Central Java} \to \text{West Java}) = \phi_{22}^{(1)} \times W_{23} = 0.53 \times 0.251 = 0.1330$$
$$SE_{\text{direct}}(\text{East Java} \to \text{West Java}) = \phi_{22}^{(1)} \times W_{24} = 0.53 \times 0.136 = 0.0721$$

For Central Java

$$SE_{\text{direct}}(\text{Jakarta} \to \text{Central Java}) = \phi_{33}^{(1)} \times W_{31} = -0.08 \times 0.252 = -0.0202$$
$$SE_{\text{direct}}(\text{West Java} \to \text{Central Java}) = \phi_{33}^{(1)} \times W_{32} = -0.08 \times 0.341 = -0.0273$$
$$SE_{\text{direct}}(\text{East Java} \to \text{Central Java}) = \phi_{33}^{(1)} \times W_{34} = -0.08 \times 0.405 = -0.0324$$

For East Java

$$SE_{\text{direct}}(\text{Jakarta} \to \text{East Java}) = \phi_{44}^{(1)} \times W_{41} = -0.27 \times 0.208 = -0.0562$$
$$SE_{\text{direct}}(\text{West Java} \to \text{East Java}) = \phi_{44}^{(1)} \times W_{42} = -0.27 \times 0.248 = -0.0670$$
$$SE_{\text{direct}}(\text{Central Java} \to \text{East Java}) = \phi_{44}^{(1)} \times W_{43} = -0.27 \times 0.542 = -0.1463$$

Full Spillover Matrix (4×4)

$$SE = \begin{bmatrix} 0.0000 & -0.0268 & -0.0081 & -0.0050 \\ 0.3238 & 0.0000 & 0.1330 & 0.0721 \\ -0.0202 & -0.0273 & 0.0000 & -0.0324 \\ -0.0562 & -0.0670 & -0.1463 & 0.0000 \end{bmatrix}$$

3.5.2 Sum of Spillover Received (Row Sum)

Table 8: Sum of Spillover Effect

	Jakarta	West Java	Central Java	East Java	**Spillover In**
Jakarta	0	-0.0268	-0.0081	-0.0050	-0.0399
West Java	0.3238	0	0.1330	0.0721	0.5289
Central Java	-0.0202	-0.0273	0	-0.0324	-0.0799
East Java	-0.0562	-0.0670	-0.1463	0	-0.2695
Spillover Out	0.6700	-0.1211	0.1875	0.0347	0

The spillover analysis reveals distinct inter-provincial interaction patterns. West Java receives the strongest total inbound spillover (*Spillover In* = 0.5289), primarily from Jakarta (0.3238), Central Java (0.1330), and East Java (0.0721). This indicates that West Java is the province most strongly affected by regional economic activity.

DKI Jakarta exhibits moderate outbound spillover (*Spillover Out* = 0.6700), with its largest influence directed toward West Java. However, Jakarta's inbound spillover is minimal (−0.0399), suggesting that although Jakarta affects surrounding regions, its own sales dynamics operate relatively independently.

Central Java shows overall negative spillover dynamics (*Spillover In* = −0.0799, *Spillover Out* = 0.1875), indicating that increases in neighboring provinces' sales tend to have a dampening effect. The strongest negative influence comes from East Java (−0.0324), suggesting possible substitution or competitive effects.

East Java records the most negative spillover profile (*Spillover In* = −0.2695), with substantial negative spillovers from Central Java (−0.1463) and West Java (−0.0670). This suggests that East Java's market is more competitive or segmented, where increases in neighboring provinces' sales are associated with decreases in East Java's sales.

The following table compares actual and forecast values for each province, computed using Equation (6).

Table 9: Comparison of Actual and Forecast Values

	Last Period	Next Period	Change	% Change
Jakarta	Rp 95,087,300	Rp 8.89×10^8	-7.824×10^6	-6.51
West Java	Rp 2.125×10^9	Rp 2.074×10^9	-5.065×10^7	-2.40
Central Java	Rp 519,685,100	Rp 5.389×10^8	1.922×10^7	+3.70
East Java	Rp 358,534,900	Rp 4.051×10^8	4.658×10^7	+13.0

The comparison of actual and forecast values against the GSTAR spillover structure highlights several discrepancies between predicted changes and spatial roles. DKI Jakarta, despite being a major net transmitter (*Spillover Out* = 0.6700), shows a forecast decline of −6.51%, which cannot be fully explained by its spillover position. West Java, which receives the highest inbound spillover (0.5289), experiences only a modest decline (−2.40%), suggesting that its sales stability is more influenced by external regional dynamics than by internal factors.

Central Java, with a moderate increase (+3.70%), behaves as a mild net transmitter (*Spillover Out* = 0.1875), which is consistent with its limited but positive outward influence. The most notable discrepancy arises in East Java, which shows the highest forecasted growth (+13.0%) despite having strongly negative inbound spillover (−0.2695). This indicates that East Java's growth is driven primarily by internal factors or strong local demand rather than positive spillover from neighboring provinces.

Overall, these findings demonstrate that forecasted sales patterns do not always align with spatial dependency structures. Regional performance is influenced by a combination of internal momentum, inter-provincial interactions, and province-specific characteristics, underscoring the complexity of spatial sales dynamics.

3.6 Model Accuracy Evaluation

The Ljung–Box Q-test is used to examine whether autocorrelation (serial correlation) remains in the residuals of the model. A p-value greater than 0.05 indicates that the residuals behave randomly (white noise), meaning the model has successfully captured the essential temporal and spatial patterns in the data. Conversely, a p-value less than 0.05 indicates significant autocorrelation, suggesting that the model may require improvement because some patterns remain unexplained.

Model accuracy is evaluated using the Ljung–Box statistic, defined as:

$$Q(k) = n(n+2) \sum_{j=1}^{k} \frac{p_j^2}{(n-j)} \tag{9}$$

Table 10: Ljung–Box Test Results

	Significance Level (α)	Q-Statistic	P-Value	Decision
Jakarta	0.05	18.9011	0.4140	Pass
West Java	0.05	6.7866	0.7454	Pass
Central Java	0.05	3.3704	0.9713	Pass
East Java	0.05	10.4033	0.4058	Pass

All provinces meet the Ljung–Box requirement at a significance level of $\alpha = 0.05$. West Java (p = 0.7454), Central Java (p = 0.9713), and East Java (p = 0.4058) show p-values far above the threshold, indicating no significant residual autocorrelation up to lag 4. Central Java, with the smallest Q-statistic (3.3704) and the highest p-value (0.9713), demonstrates residual behavior closest to ideal white noise.

Overall, the Ljung–Box test confirms that the GSTAR(1,1) model is adequately specified for all provinces. The absence of significant autocorrelation suggests that the model successfully captures the temporal and spatial structures in the sales data. This supports the model's suitability for forecasting and analyzing regional sales dynamics across Java Island. However, DKI Jakarta's p-value (0.4140), while still acceptable, is relatively close to the threshold and should be monitored for potential sensitivity to data fluctuations.

Model accuracy is further evaluated using the Root Mean Squared Error (RMSE):

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum(Y_{\text{actual}} - Y_{\text{forecast}})^2} \tag{10}$$

and the Mean Absolute Percentage Error (MAPE):

$$\text{MAPE} = \frac{100}{n}\sum\left|\frac{Y_{\text{actual}} - Y_{\text{forecast}}}{Y_{\text{actual}}}\right| \tag{11}$$

Table 11: MAPE Accuracy Scale

MAPE Scale	Accuracy Level
$\leq 10\%$	Highly Accurate
$10\% < \text{MAPE} \leq 20\%$	Good Prediction
$20\% < \text{MAPE} \leq 50\%$	Reasonable Prediction
$> 50\%$	Weak Prediction

3.7 Forecasting

Below is a table of actual and forecast values for DKI Jakarta Province, covering the sampling period from October 2023 to December 2023.

Table 12: Table of Actual and Forecast DKI Jakarta Province (3 Sampling)

	AKTUAL	FORECAST
23-Oct	96989400	94819504
23-Nov	79054100	78450876
DES 23	83712500	81407470

Below is a table of actual and forecast values for West Java Province, covering the sampling period from October 2023 to December 2023.

Table 13: Table of Actual and Forecast West Java Province (3 Sampling)

	AKTUAL	FORECAST
23-Oct	2197918600	2,240,723,000
23-Nov	2115868100	2,184,845,000
DES 23	2125594300	2,225,233,000

Below is a table of actual and forecast values for Central Java Province, covering the sampling period from October 2023 to December 2023.

Table 14: Table of Actual and Forecast Central Java Province (3 Sampling)

	AKTUAL	FORECAST
23-Oct	495973700	528,147,000
23-Nov	499128800	543,617,700
DES 23	519685100	563,906,100

Below is a table of actual and forecast values for East Java Province, covering the sampling period from October 2023 to December 2023.

Table 15: Table of Actual and Forecast East Java Province (3 Sampling)

	AKTUAL	FORECAST
23-Oct	400574700	360,375,200
23-Nov	358098600	342,577,200
DES 23	358534900	356,981,100

After calculating the actual and forecast values for each province using samples from October 2023 to December 2023, the accuracy of the results was calculated using RMSE and MAPE, with the results below.

Table 16: Comparison Table of MAPE and RMSE Values

	MAPE (%)	RMSE	KET
DKI	1.92	1860599.1547	Very Accurate Prediction
JABAR	3.30	74202243.5020	Very Accurate Prediction
JATENG	7.97	40701691.7059	Very Accurate Prediction
JATIM	4.93	24895299.9146	Very Accurate Prediction

3.8 Discussion

The empirical results show substantial heterogeneity in healthcare product sales across the four provinces of Java Island. West Java has the largest market, with the highest mean and variance of sales, indicating both strong demand and pronounced volatility. Central Java and East Java occupy intermediate positions with moderate average sales and variability, whereas DKI Jakarta records the lowest mean and smallest variance, reflecting a relatively small but stable market. These differences confirm that regional sales dynamics are not homogeneous and support the use of a spatial–temporal framework rather than a purely univariate or purely temporal approach.

From a time-series perspective, the Augmented Dickey–Fuller (ADF) test results indicate that most series are stationary at level, except for Central Java, which requires first differencing. After differencing, all provinces satisfy the stationarity requirement, ensuring that VAR and GSTAR estimations are statistically valid. Model identification based on the Akaike Information Criterion (AIC) shows that GSTAR models systematically outperform VAR models at all lag orders, confirming the added explanatory power of spatial information. Although GSTAR with lag 4 yields the lowest AIC, the final specification adopted is GSTAR(1,1), which provides a more balanced trade-off between goodness of fit, parameter parsimony, and interpretability. This choice is also consistent with economic intuition that immediate past values and first-order spatial interactions dominate regional sales dynamics.

The spatial weight matrix, constructed using the Inverse Distance Weighting (IDW) approach and row-normalized, effectively captures inter-provincial linkages. The final matrix reveals strong mutual connectivity between DKI Jakarta and West Java, reflecting the economic integration of the Greater Jakarta region. Central Java distributes its spatial weights mainly between West Java and East Java, while East Java allocates more than half of its weight to Central Java. This structure is consistent with the geographic layout of Java Island and the observed pattern of inter-regional trade and distribution networks.

The estimated GSTAR(1,1) parameters decompose sales dynamics into temporal persistence and spatial spillover effects. Temporally, Central Java exhibits very strong positive persistence, with an own-lag coefficient close to one, implying that shocks to sales are carried forward almost fully into the next period. In contrast, DKI Jakarta, West Java, and East Java show negative temporal coefficients, indicating mean-reversion: deviations from long-run equilibrium tend to be corrected over time. East Java displays the strongest mean-reversion, so its sales return to equilibrium relatively quickly, whereas DKI Jakarta shows only mild self-correction, consistent with a relatively stable but slowly adjusting market.

Spatially, the coefficients indicate heterogeneous spillover behavior. West Java has the largest positive spatial parameter, meaning it is highly responsive to changes in neighboring provinces. DKI Jakarta has a weak negative spatial effect, suggesting that its dynamics are driven mainly by internal factors rather than regional conditions. Central Java also shows a small negative spatial coefficient, pointing to partial substitution or competitive interaction with its neighbors. East Java has the most pronounced negative spatial effect, implying that increases in surrounding provinces' sales tend to be associated with reductions in its own sales, consistent with competitive or market-segmentation mechanisms rather than complementary growth.

The spillover matrix quantifies these cross-provincial linkages more explicitly. West Java receives the strongest total inbound spillover, mainly from DKI Jakarta, Central Java, and East Java, making it the most sensitive province to regional shocks. DKI Jakarta exerts a substantial positive effect on West Java but receives only a small net inbound effect, indicating that Jakarta functions primarily as a transmitter rather than a receiver in the regional system. Central Java and East Java are characterized by predominantly negative inbound spillovers, especially the strong negative influence from Central Java to East Java. This pattern suggests that some provinces compete for overlapping markets or distribution channels, so gains in one province may coincide with losses in another.

The comparison of actual and forecast values for the validation period (October–December 2023) reveals heterogeneous adjustment paths. DKI Jakarta and West Java are projected to experience modest sales declines, consistent with mean-reverting temporal behavior and, in the case of West Java, sensitivity to regional conditions. In contrast, Central Java shows moderate growth, while East Java records the largest forecasted increase (around 13%). Notably, East Java's growth occurs despite negative inbound spillovers, indicating that its expansion is driven primarily by internal momentum or local demand factors rather than positive regional spillover effects.

Model adequacy is supported by the Ljung–Box Q-test, which shows no significant residual autocorrelation for any province, indicating that the GSTAR(1,1) model successfully captures the main temporal and spatial structures in the data. Forecast accuracy evaluated using RMSE and MAPE confirms that all provinces achieve MAPE values below 10%, placing them in the "highly accurate" category. The average MAPE of about 4–5% demonstrates that the GSTAR(1,1) specification is not only statistically sound but also practically useful for short-term sales forecasting and planning.

These findings have several managerial and policy implications. West Java emerges as a strategic leverage point: because it combines a large market with high spillover sensitivity, interventions in logistics, marketing, or distribution that target West Java are likely to generate broader regional effects. DKI Jakarta should be treated as an influential but relatively autonomous metropolitan market whose dynamics are only weakly shaped by neighboring provinces. Central Java, with its strong persistence, can serve as a stable anchor in a regional portfolio, providing predictable demand. East Java, with strong mean-reversion, negative spillovers, and high projected growth, requires province-specific strategies that emphasize internal demand drivers rather than reliance on favorable regional spillovers. Overall, the GSTAR(1,1) framework proves effective for disentangling temporal, spatial, and spillover effects in regional sales data and for supporting geographically differentiated business and policy decisions.

4 Conclusion

This study analyzes regional sales dynamics on Java Island using the GSTAR(1,1) model. The results show clear heterogeneity across provinces. West Java is the most responsive region, receiving the largest inbound spillover (Spillover In = 0.5289), mainly from Jakarta (0.3238), Central Java (0.1330), and East Java (0.0721). DKI Jakarta acts primarily as a transmitter, exerting moderate outbound influence (Spillover Out = 0.2474) while remaining relatively independent (Spillover In = -0.0399). Central Java behaves as a stable, self-sustaining market with very strong temporal persistence ($\phi = 0.98$) and small net spillovers (In = -0.0799, Out = -0.0214). East Java shows the most competitive profile, with strongly negative inbound spillovers (Spillover In = -0.2695) but the highest forecasted growth (about 13%), driven by internal momentum and supported by strong mean-reversion ($\phi = -0.21$).

The GSTAR(1,1) model achieves high predictive accuracy, with an average MAPE of 4.53%: Jakarta (1.92%), West Java (3.30%), Central Java (7.97%), and East Java (4.93%), all within the "highly accurate" (MAPE $\leq$ 10%) category. Heterogeneous temporal parameters (-0.21 to 0.98) and spatial parameters (-0.27 to 0.53) confirm location-specific responses to shocks. Ljung–Box tests indicate no significant residual autocorrelation up to lag 4 for all provinces, supporting the adequacy of the GSTAR(1,1) specification for capturing both temporal and spatial structures.

From a managerial and policy perspective, West Java should be treated as the main leverage point for regional interventions, functioning as the primary responsive hub. Central Java can serve as a secondary, stable hub due to its high persistence, Jakarta as an independent metropolitan market, and East Java as a volatile but self-correcting growth pole. Supply chain and inventory strategies should reflect these roles: higher safety stock in West Java, moderate in Central Java, more flexible strategies in East Java, and leaner stock in Jakarta. Market entry and expansion can be sequenced through West Java for regional reach, followed by tailored strategies for Jakarta, Central Java, and East Java. The Jakarta–West Java link (0.3238) remains important but indicates moderate rather than critical dependence, allowing for regional coordination without excessive systemic vulnerability.

CRediT Authorship Contribution Statement

Firstyan Deviena Citra Rahayu: Conceptualization, Methodology, Data Curation, Formal Analysis, Writing–Original Draft Preparation, Visualization. **Ardana Putri Farahdiansari:** Software, Validation, Writing–Review & Editing, Supervision, Project Administration.

Declaration of Generative AI and AI-assisted Technologies

Generative AI and AI-assisted tools were used only to improve grammar and language clarity (Grammarly). The author reviewed and approved all final content.

Declaration of Competing Interest

The authors declare no competing interests. The research was conducted independently without any financial, professional, or personal relationships that could influence the results or interpretation of the study.

Funding and Acknowledgments

This research received financial support from the author's parent. The author would like to express sincere gratitude to the supervising lecturer for guidance and support throughout the research process.

Data Available

The code used in this research, developed using the Google Colab platform and Python, can be accessed online.[1] All datasets, calculation files, and the plagiarism report are available in the

[1] https://colab.research.google.com/drive/1NYXyOo2zpK5OlXguOYSvotBhnscM4xQv?usp=sharing

following Google Drive directory.[2]

References

[1] B. Efron, "Prediction, estimation, and attribution," *Journal of the American Statistical Association*, vol. 115, no. 530, pp. 636–655, Apr. 2020. DOI: 10.1080/01621459.2020.1762613.

[2] M. Y. Dwi Ervinda and I. G. A. Ariutama, "Economic interdependence of indonesia in global value chain: An analysis of multiregional input-output," *JEJAK*, vol. 15, no. 1, pp. 151–164, Jun. 2022. DOI: 10.15294/jejak.v15i1.34747.

[3] D. Harlianto, S. Mardiyati, and D. Lestari, "The comparison between recurrent neural network and grey model to predict indonesia tuberculosis morbidity rate," in *Journal of Physics: Conference Series*, vol. 1722, Jan. 2021, p. 012 093. DOI: 10.1088/1742-6596/1722/1/012093.

[4] I. Febriyana and L. S. Badriah, "Spatial analysis and spillover effects on economic growth in central java," *Economic Development Analysis Journal*, vol. 14, no. 1, pp. 124–139, Mar. 2025. DOI: 10.15294/edaj.v14i1.19732.

[5] A. Kusuma Nur Ichsan, Y. Rahmawati, and F. N. Anggraeni, "Spatial spillover effect of east java economic growth," *East Java Economic Journal*, vol. 6, no. 1, pp. 1–24, Mar. 2022. DOI: 10.53572/ejavec.v6i1.73.

[6] A. Aswi, Sukarna, S. Cramb, and K. Mengersen, "Effects of climatic factors on dengue incidence: A comparison of bayesian spatio-temporal models," in *Journal of Physics: Conference Series*, vol. 1863, Mar. 2021, p. 012 050. DOI: 10.1088/1742-6596/1863/1/012050.

[7] P. R. Arum, A. R. Indriani, and M. A. Haris, "Forecasting the consumer price index with generalized space-time autoregressive seemingly unrelated regression (gstar-sur): Compromise region and time," *BAREKENG: Jurnal Ilmu Matematika dan Terapan*, vol. 17, no. 2, pp. 1183–1192, Jun. 2023. DOI: 10.30598/barekengvol17iss2pp1183-1192.

[8] N. M. Huda, N. Imro'ah, N. F. Arini, D. S. Utami, and T. Umairah, "Looking at gdp from a statistical perspective: Spatio-temporal gstar(1;1) model," *JTAM (Jurnal Teori dan Aplikasi Matematika)*, vol. 7, no. 4, p. 976, 2023. DOI: 10.31764/jtam.v7i4.16236.

[9] M. Marcén and M. Morales, "The effect of culture on home-ownership," *Journal of Regional Science*, vol. 60, no. 1, pp. 56–87, Jan. 2020. DOI: 10.1111/jors.12433.

[10] H. Pratiwi, N. Imro'ah, N. M. Huda, and M. Y. Ayyash, "Comparison of weight matrix in hotspot modeling in west kalimantan using the gstar method," *Jurnal Matematika UNAND*, vol. 14, no. 1, pp. 31–45, 2025. DOI: 10.25077/jmua.14.1.31-45.2025.

[11] X. Ye and P. Rogerson, "The impacts of the modifiable areal unit problem (maup) on omission error," *Geographical Analysis*, vol. 54, no. 1, pp. 32–57, Jan. 2022. DOI: 10.1111/gean.12269.

[12] A. Zaki, Irwan, and Lutfiah, "Application of the generalized space time autoregressive (gstar) method in forecasting the consumer price index in five cities of south sulawesi province," *Barekeng*, vol. 19, no. 1, pp. 375–384, 2025. DOI: 10.30598/barekengvol19iss1pp375-384.

[13] E. E. Aktas and P. V. Iyidogan, "Nonlinear effects of income inequality on economic growth: A comparative analysis of selected countries," *Economic Journal of Emerging Markets*, pp. 72–84, Apr. 2022. DOI: 10.20885/ejem.vol14.iss1.art6.

[2] https://drive.google.com/drive/folders/1-rNLGaqp2xr66_GzkmOBKNVw1UKY23xr?usp=sharing

[14] S. Maadani, G. R. Mohtashami Borzadaran, and A. H. Rezaei Roknabadi, "Varentropy of order statistics and some stochastic comparisons," *Communications in Statistics - Theory and Methods*, vol. 51, no. 18, pp. 6447–6460, Sep. 2022. DOI: 10.1080/03610926.2020.1861299.

[15] G. Fajri, S. Syafriandi, N. Amalita, and Z. Martha, "Comparison of queen contiguity and customized weighting matrices on spatial regression to identify factors impacting poverty in east java," *UNP Journal of Statistics and Data Science*, vol. 1, no. 3, pp. 203–210, May 2023. DOI: 10.24036/ujsds/vol1-iss3/67.