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BEEF PRICE FORECASTING BASED ON TEMPORAL, SPATIAL AND SPACE-TIME PARAMETER INDICES

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ABSTRACT

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Beef is among the most sought-after commodities in Indonesia, resulting in significant price fluctuations, particularly during religious holidays. These price variations affect inflation and necessitate adjustments in government policies concerning beef distribution and imports. Therefore, it is essential to analyze and predict beef prices using empirical data from regions with the highest beef production and consumption levels. This study aims to examine beef price data through the lenses of temporal, spatial, and space-time dependencies within Java. The methodologies employed in this research include ARIMA, Semivariogram, Kriging, and GSTAR models applied to weekly beef price data from Java. ARIMA is used to analyze and forecast time series data based on past values and past forecast errors. The Semivariogram measures spatial dependence by quantifying how price similarities change with distance. Kriging is a geostatistical interpolation method that predicts price values at unobserved locations based on spatial correlation. GSTAR extends ARIMA by incorporating spatial and temporal dependencies to model interactions across different locations over time. The data used in this study consists of weekly beef price records from major markets across Java, obtained from National Food Agency of Indonesia, from August 2022 to May 2024. The findings of this study reveal that beef price fluctuations in Java are primarily influenced by temporal factors, particularly major religious holidays, rather than by location or a combination of location and time. However, there are spatial variations in beef prices across different observation locations. The best predictive model for forecasting beef prices is the ARIMA model. These results provide valuable insights into the patterns of beef prices based on temporal, spatial, and space-time parameters, offering a robust framework for understanding and anticipating price dynamics in the region.

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1. INTRODUCTION

Beef is a highly demanded food commodity in Indonesia, valued not only for its nutritional content but also as a staple in various regional cuisines consumed daily and during specific occasions [1]. According to data from the Indonesian Central Statistics Agency (BPS) and the Ministry of Agriculture, the average annual beef consumption has reached 2.93 kilograms per capita over the past five years [2]. Java stands out as both the most significant consumer (3.75/capita-year) and producer of beef (54.95%), mainly due to its considerable demographic concentration (155.76 million people) [2], [3].

However, the demand for beef in Java, which reaches 583.36 thousand tonnes annually, is often unmet by current production levels, which only reach 260.38 thousand tonnes annually [3]. This shortfall is attributed to insufficient beef producers, who are also geographically concentrated in specific areas. These supply constraints contribute to significant price volatility across different regions. Consequently, such fluctuations impact inflation rates and influence government policies regarding beef imports [4]. For instance, inflation and the decision to increase beef import quotas can have long-term ramifications on the business sustainability of domestic producers [5], [6].

Ensuring the sustainability of beef suppliers is crucial for maintaining a stable beef supply chain. To mitigate the negative impacts of these supply-demand imbalances caused by various factors such as climate change, energy markets [7], global beef prices [8], and foot-and-mouth disease [9], it is essential to develop a method for analyzing beef price behavior in Indonesia. There is a pressing need for a robust model that can analyze and forecast beef prices across various regions in Indonesia. Such modeling efforts would equip producers with the insights needed to optimize supply and assist government policymakers in implementing proactive measures to stabilize beef prices, thereby protecting consumers from harmful price fluctuations. This approach emphasizes the importance of a comprehensive and collaborative effort to sustain the beef industry in Indonesia.

Since beef prices are continuous data influenced by temporal dynamics, time series analysis is a highly suitable method for their examination and modeling. One of the time series models that can capture trend patterns is ARIMA. In addition, ARIMA can handle non-stationary data through differencing and transformation processes [10]. Some research presents results that ARIMA is better at forecasting commodity price problems such as chicken meat and egg [11], beef [12], [13], rice and shallot [14], gold [15], [16] than other time series methods such as GARCH. In this research, the ARIMA model is compared and combined with different temporal and spatial methods simultaneously.

Moreover, considering that the beef price data are sourced from various cities across Java, it is imperative to incorporate Kriging and Space-Time Series Analysis. These sophisticated analytical techniques facilitate the development of a robust model that comprehensively captures the underlying patterns in the data and provides accurate forecasts. By leveraging these methodologies, the model effectively accounts for spatial and temporal variations in beef prices, yielding valuable insights and accurate short-run price forecasts for policymakers and industry stakeholders.

Research concludes that Beef price volatility is low and persistent in the long run [17]. Various studies have employed different methodologies and datasets to examine and predict beef prices. One study utilized a multivariate time series model based on monthly data on beef prices and inventories at a single location [18]. Another study analyzed 208 weekly data points from seven locations, highlighting regional variation [19].

Several forecasting techniques have been employed in the literature, including exponential smoothing [20], nonlinear autoregressive models [21], vector autoregression (VAR) [22], double exponential smoothing, and Holt-Winters seasonal smoothing [23], MTM LSTM and MLP model [24]. Research has shown a significant time dependency in price fluctuations across different locations, indicating that beef prices are influenced by temporal factors [25]. Furthermore, studies have identified a spatial dependence of beef prices, demonstrating that regional factors also play a crucial role in price dynamics [26]. These findings suggest a multifaceted approach is necessary to understand and fully predict beef price behavior.

This study employs sophisticated temporal, spatial, and space-time analytical techniques to model and predict beef prices using weekly data from urban centers across Java. Time series as data and methodologies have been extensively employed across diverse disciplines to address a wide array of challenges, including those in finance [27], insurance [28], climatology [29], and disaster management [30]. Spatial analysis, on the other hand, is a critical tool utilized by experts in fields such as mining [31], disease mapping [32], and hydrology [33] to resolve complex spatially-dependent problems. Additionally, Generalized Space-Time Autoregressive (GSTAR) models, as referenced in the study by [34], have been effectively applied to various issues related to climate [35], disaster management [36], oil production [37], and epidemiology [38], [39] and economy [40].

In this research, the temporal modeling leverages the Box-Jenkins methodology used to derive the most effective time series model, capturing the underlying temporal dependencies. Concurrently, spatial analysis and kriging are utilized to explore the geographic distribution and spatial correlation of the data. The space-time analysis integrates both temporal and spatial dimensions to evaluate their combined effect on beef prices using the three stages of the procedure by Pfeifer & Deutsch [41]. The primary aim is to ascertain the predominant factor influencing beef price fluctuations—temporal variations, spatial disparities, or the interplay. This investigation seeks to provide a comprehensive understanding of the relative contributions of temporal and spatial factors to beef price dynamics, thereby informing more accurate predictive models and effective policy interventions.

This paper is thoughtfully organized into several sections. The Introduction sets the stage by providing essential background information, outlining the motivation behind the study, and establishing clear objectives. In the Research Methodology section, we thoroughly describe the data sources, the preprocessing steps taken, and the statistical models utilized, which include ARIMA, GSTAR, Semivariogram, and Kriging. The results and discussion section provides an insightful analysis of the findings, highlighting beef prices' temporal, spatial, and space-time dependencies while also comparing the effectiveness of the predictive models. Finally, the Conclusion encapsulates the key insights gained from the research, reflects on the implications of the results, and offers constructive suggestions for future research endeavors.

2. RESEARCH METHODS

This study utilizes secondary data, specifically daily retail beef prices for all cities and districts on the island of Java, excluding Kepulauan Seribu. The data from the National Food Agency of Indonesia spans August 2022 to May 2024 (*panelharga.badanpangan.go.id/harga-eceran*). The daily beef price data was aggregated to a weekly frequency using arithmetic means for analytical purposes. The research design adopted for this study is depicted in **Figure 1**. The data prediction results in temporal analysis, and data interpolation results in spatial and space-time analysis, which are compared based on the smallest RMSE value to determine which model best represents the data.

Based on the aim of this research, a comprehensive analysis of beef prices concerning temporal, spatial, and space-time parameters is conducted. This analysis is achieved by examining the Root Mean Square Error (RMSE) values of predicted or interpolated beef prices across ten specific locations: South Jakarta City, Indramayu Regency, Sukabumi Regency, South Tangerang City, Cilacap Regency, Jepara Regency, Sleman Regency, Pamekasan Regency, Trenggalek Regency, and Situbondo Regency. The results are then compared with the RMSE of the actual data. In addition, location-specific RMSE identification is performed to determine the region's most accurate beef price forecasting or interpolation model. To consistently compare the three methods, 10 cities were selected to validate the results. Therefore, cross-validation was not performed for all cities. The models used in the analysis are based on time, spatial, and space-time parameters, which are ARIMA, semivariogram and kriging, and GSTAR-Kriging, respectively. This research uses Maximum Likelihood and Weighted Least Squared Fit for parameter estimation in ARIMA and GSTAR models. Meanwhile, ordinary kriging is used for estimation and interpolation.

2.1 ARIMA Model

Time series modeling generally employs three primary models: the Autoregressive (AR) model, the Moving Average (MA) model, and the homogeneous non-stationary Autoregressive Integrated Moving Average (ARIMA) model. To address non-stationary time series data, an appropriate d-th differencing process is applied, transforming the data into a stationary form, which is then modeled using the Autoregressive Integrated Moving Average (ARIMA (p,d,q)) model [42], [43]. This modeling approach can be expressed as follows in **Equation (1)**.

$$\phi_p(B)(1-B)^d Y_t = \theta_q(B)e_t \tag{1}$$

with $\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p$ and $\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q$.

An essential step in analyzing time series data is to ensure that the data satisfies the properties of stationarity. To this end, it is necessary to conduct the Augmented Dickey-Fuller (ADF) test, which assesses whether the data meets the stationarity requirements. The ADF test formula is presented in **Equation (2)**.

$$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + a_1 \Delta Y_{t-1} + a_2 \Delta Y_{t-2} + \ldots + a_p \Delta Y_{t-p} + \varepsilon_t \tag{2}$$

with ε_t representing a *white noise* process that follows a normal distribution $N(0, \sigma^2)$ and $\Delta Y_{t-1} = Y_{t-1} - Y_{t-2}$. The hypotheses for ADF test are follows:

$H_0: \delta = 0$, indicating that the data is non-stationary.

$H_1: \delta < 0$, indicating that the data is stationary.

At a given significance level α, H_0 is rejected if the ADF test statistic is less than the critical value form *Dickey-Fuller* or if the *p-value* < α. The ADF test statistic used is:

$$t = \frac{\hat{\delta}}{SE(\hat{\delta})} \tag{3}$$

where $\hat{\delta}$ is the estimated coefficient of Y_{t-1} and $SE(\hat{\delta})$ is standard error for $\hat{\delta}$.

2.2 GSTAR Model

Process $\{Y_i(t)\}$ follows GSTAR $(p; \lambda_1, \lambda_2, \ldots, \lambda_p)$ model if can be expressed as **Equation (4)**:

$$Y_i(t) = \sum_{k=1}^{p} \sum_{l=0}^{\lambda_p} \Phi_{kl} W^{(l)} Y_i(t-k) + \varepsilon_i(t) \ ; \ t = 1,2,\ldots,T \ ; \ i,j = 1,2,\ldots,N \tag{4}$$

with $\Phi_{kl} = diag\left(\phi_{kl}^{(1)}, \phi_{kl}^{(2)}, \ldots, \phi_{kl}^{(p)}\right)$ and $W^{(l)}$ is the weight matrix defined based on the correlation between the location to one location and another [42]. The weight matrix used in this study is as follows:

a. Uniform Weight gives the same weight for each location. Therefore, this weight is often used on homogenous data or has the exact distance between locations. This formulation calculates the values of the uniform location. The uniform weight is defined as:

$$w_{ij} = 1/n_i \tag{5}$$

where n_i is the number of the locations which are located near to location *i* [37].

b. Inverse Distance Weight is based on the actual distance between locations. The weight calculations obtained from the normalization of the actual inverse distance results. The first step is calculating the actual distance between locations. The Inverse Distance Weights is defined as:

$$w_{ij} = \frac{1}{d_{ij}} \Big/ \sum_{j=1}^{N} \frac{1}{d_{ij}} \tag{6}$$

where d_{ij} is distance bewteen location *i* and *j* [45].

2.3 Semivariogram and Kriging

A semivariogram is a fundamental tool in spatial statistics and geostatistics used to describe the spatial correlation or continuity of a random field or stochastic process. It provides a measure of how the similarity between observations changes with distance. A comprehensive explanation of the theory behind semivariograms and kriging can be found in [46]. The semivariogram is defined as half the expected squared difference between the values at two locations as a function of the distance between those locations. Mathematically, the semivariogram γ(h) is defined as follows in Equation (7).

$$\gamma(h) = \frac{1}{2} E[(Z(x) - Z(x+h)^2)] \tag{7}$$

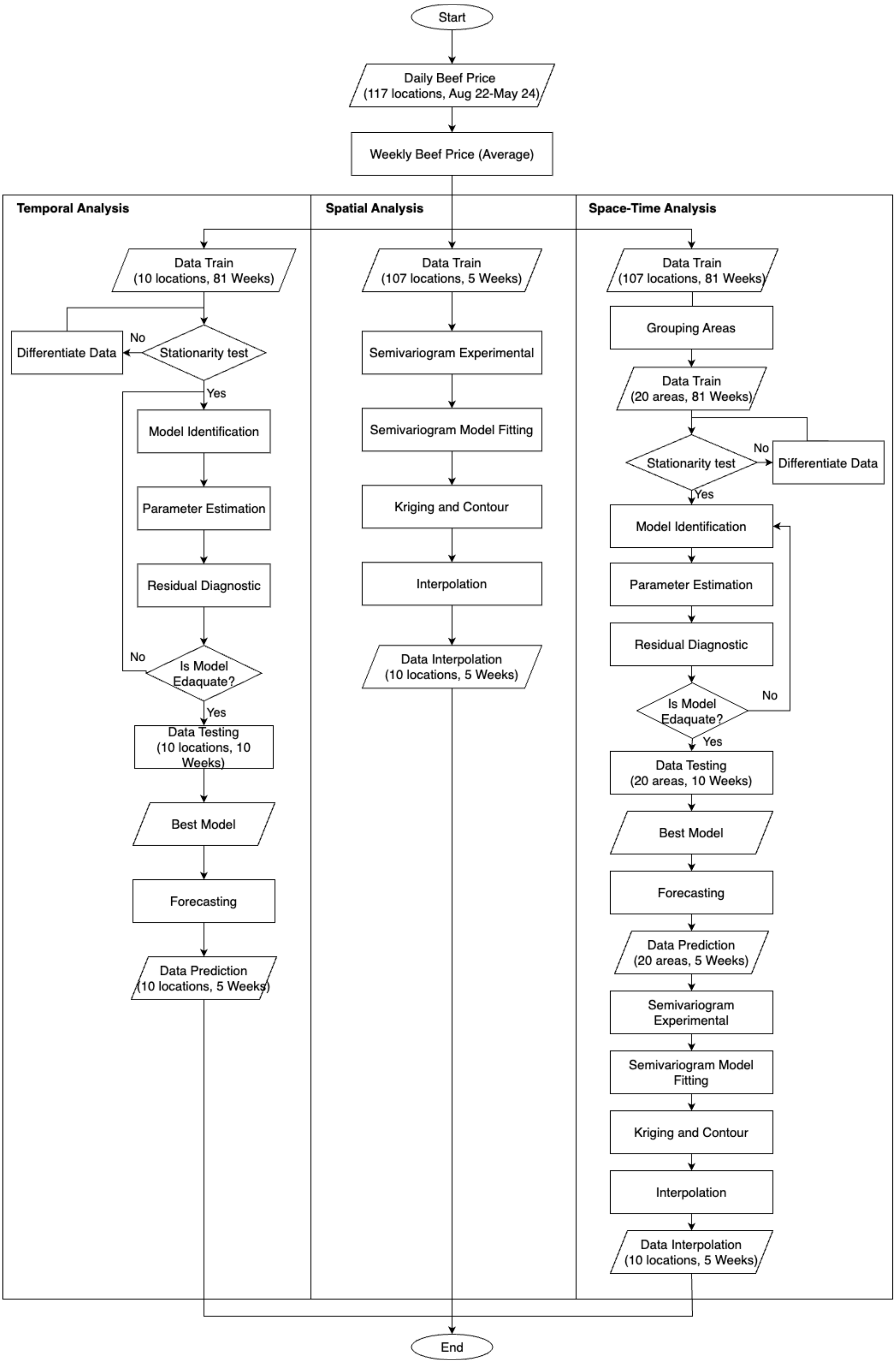

Figure 1. **Research Design**

The semivariogram can be estimated from data using the following empirical formula in **Equation (8)**.

$$\hat{\gamma}(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [(Z(x) - Z(x+h)]^2 \tag{8}$$

The semivariogram typically has three main components:

a. Nugget: The value of the semivariogram at $h = 0$. It represents measurement error or microscale variation.

b. Sill: The value at which the semivariogram levels off, indicating the variance of the process.

c. Range: The distance at which the semivariogram reaches the sill, beyond which observations are no longer correlated.

The semivariogram can be modeled using various functions, such as the spherical, exponential, and Gaussian models, to facilitate kriging and other geostatistical analysis. These models help fit the empirical semivariogram to estimate the spatial structure and make predictions at unsampled locations. The kriging formulation is defined in **Equation (9)**.

$$\hat{Z}(S_0) = \sum_{i=1}^{n} \lambda_i Z(S_i) \tag{9}$$

where S_0 unobserved location, S_i observed locations, λ_i weighted Kriging for location *i-th*, and $Z(S_i)$ value of random variable of location *i-th*.

Meanwhile, Kriging is a geostatistical interpolation technique that provides the best linear unbiased prediction of the value of a random field at an unobserved location, given observations at nearby locations. It leverages the spatial correlation structure described by the semivariogram to make these predictions. Kriging not only predicts values but also estimates the prediction uncertainty. The main advantage of kriging over other interpolation methods is its ability to provide an optimal and unbiased prediction and estimate the prediction error, making it a powerful tool in spatial data analysis. Additionally, contour mapping is utilized in both the spatial analysis and the GSTAR-Kriging analysis. This contour mapping aids in visualizing the spatial distribution of beef prices, enabling the identification of regional patterns and trends.

3. RESULTS AND DISCUSSION

The data analysis process yielded comprehensive and multifaceted results through a rigorous approach encompassing descriptive, temporal, spatial, and space-time analyses. Each analytical step is meticulously detailed in this subsection, providing an advanced and in-depth understanding of the dynamics and patterns in the weekly beef price data. These analyses collectively offer robust insights and contribute significantly to the study's overall findings.

3.1 Descriptive Analysis

In this paper, three types of analysis of weekly beef price data are conducted: time series, spatial, and space-time analysis. For the temporal analysis, ARIMA modeling is applied to each location using data from week 1 to week 81 (from 31 July 2022 to 17 February 2024) as training data, week 82 to week 91 (from 18 February 2024 to 27 April 2024) as test data for model selection, and week 92 to week 96 (from 28 April 2024 to 1 June 2024) as prediction data.

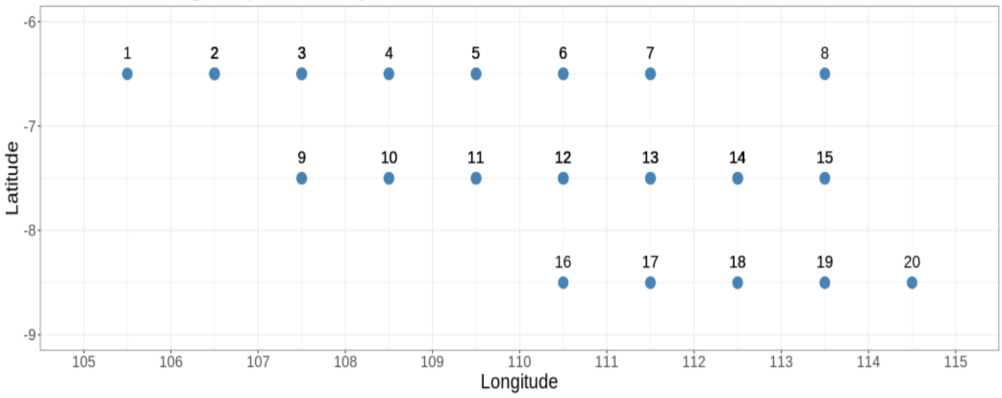

Figure 2. Area Distribution Map

For space-time analysis, data from 107 locations are utilized, divided into 20 regions with grid sizes around 111 km x 111 km, as seen in **Table 1**. This division aims to capture regional variations and spatial dependencies in beef prices. The regional divisions are illustrated in **Figure 2**.

Table 1. Area Distribution

Area	Cities/ Regencies	Area	Cities
1	Serang Regency	11	Wonosobo Regency, Banyumas Regency, Pekalongan Regency, Banjarnegara Regency, Tegal Regency, Kebumen Regency, Purbalingga Regency
2	East Jakarta City, Tangerang Regency, Cilegon City, Bekasi City, Bekasi Regency, Depok City, West Jakarta City, Tangerang City, Lebak Regency, Bogor Regency, Serang City, Sukabumi City, Bogor City, Pandeglang Regency, North Jakarta Utara City, Central Jakarta City	12	Grobogan Regency, Boyolali Regency, Sukoharjo Regency, Kulon Progo Regency, Karanganyar Regency, Klaten Regency, Salatiga City, Surakarta City, Semarang Regency, Magelang Regency, Temanggung Regency, Yogyakarta City, Bantul Regency, Magelang City, Purworejo Regency, Wonogiri Regency
3	Bandung Barat Regency, Sumedang Regency, Cianjur Regency, Cimahi City, Purwakarta Regency, Karawang Regency, Subang Regency, Bandung City	13	Bojonegoro Regency, Ngawi Regency, Madiun Regency, Madiun City, Sragen Regency, Nganjuk Regency, Magetan Regency, Ponorogo Regency
4	Cirebon City, Kuningan Regency, Majalengka Regency	14	Kediri Regency, Lamongan Regency, Kediri City, Pasuruan City, Surabaya City, Bangkalan Regency, Pasuruan Regency, Malang City, Jombang Regency, Sidoarjo Regency, Mojokerto City, Mojokerto Regency, Gresik Regency, Batu City
5	Pekalongan City, Tegal City, Pemalang Regency, Brebes Regency, Batang Regency	15	Sampang Regency, Probolinggo Regency, Probolinggo City, Bondowoso Regency
6	Demak Regency, Kendal Regency, Semarang City, Kudus Regency	16	Gunung Kidul Regency
7	Rembang Regency, Pati Regency, Tuban Regency, Blora Regency	17	Pacitan Regency, Tulungagung Regency
8	Sumenep Regency	18	Blitar City, Malang Regency, Blitar Regency
9	Bandung Regency, Cirebon Regency, Garut Regency	19	Jember Regency, Lumajang Regency
10	Tasikmalaya City, Tasikmalaya Regency, Ciamis Regency, Banjar City	20	Banyuwangi Regency

The spatial analysis calculates experimental semivariograms, followed by model fitting and interpolating for 10 specific locations from weeks 92 to 96 (from 28 April 2024 to 1 June 2024). A total of 10 locations were selected based on the proportion of training and testing data [47], where in this study, the training data comprised 91%, and the testing data comprised 9% of the total 117 cities. Due to the limited dataset, we maximized the training data and minimized the testing data to evaluate the model performance more accurately.

These 10 locations were chosen from each province while considering the total number of towns per province. Consequently, East Java is represented by three cities out of 38, Central Java by two cities out of 35, and West Java by two cities out of 26. Meanwhile, Jakarta, Banten, and Yogyakarta are each represented by a single city. While Table 2 presents the statistical centredness measures of the data for each city, Figure 3 illustrates the time series plot of beef price actual data from 10 cities. One of the research objectives is to compare the model with actual data. Since ARIMA and GSTAR cannot be incompatible in predicting the long term [48], 5 weeks are taken to test the data. So, we have short-run forecasting results.

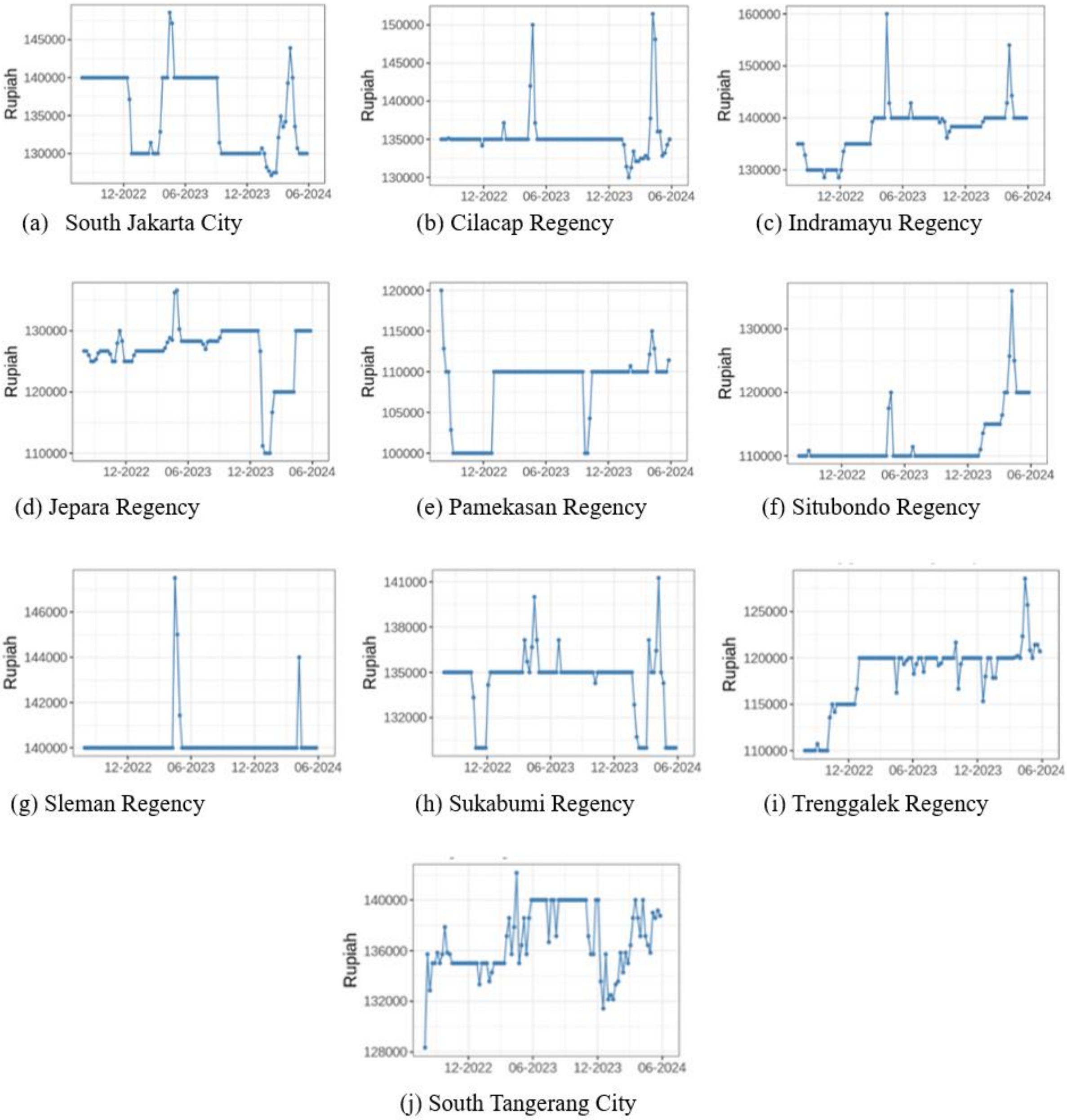

Figure 3. Beef Price Plot

It is clear that for each location in Figure 3, variances of the data are non-stationary. The data tend to be homogeneous in many intervals, while volatility occurs at certain times. Specifically, for Sleman Regency, most of the data tend to be homogeneous. Table 2 shows that the minimum beef price is in the range of 100.000-140.000, with Sleman Regency is the location with the highest minimum price, while the maximum beef price is in the range of 120.000-160.000, with Indramayu Regency is the location with the highest maximum price. In addition, it can also be seen that the Sleman Regency has the highest average price and tends to be more evenly distributed than other locations. It can also be observed that the eastern region of Java has the lowest average prices due to its proximity to beef production centers.

3.2 Temporal Analysis

The initial phase of the temporal analysis focuses on verifying that the time series data adheres to the necessary stationarity conditions, as detailed in **Table 3**. The table provides a comprehensive summary of this analysis, presenting both the test statistics and their corresponding p-values, along with interpretative remarks on the stationarity status of the series. This meticulous approach ensures that the subsequent phases of the temporal analysis are grounded on a solid foundation, allowing for more reliable and insightful modeling and inference.

Table 2. Statistical Centredness Measures

Location	South Tangerang	South Jakarta	Indramayu Regency	Sukabumi Regency	Cilacap Regency
Minimum	128333	127126	128571	130000	130000
Maximum	142143	148571	160000	141250	151448
Median	135833	136026	139284	135000	135000
Mean	136751	135307	137699	134409	135262
Std.	2632	5311	4805	2131	2961
Location	**Jepara Regency**	**Sleman Regency**	**Pamekasan Regency**	**Trenggalek Regency**	**Situbondo Regency**
Minimum	110000	140000	100000	110000	110000
Maximum	136600	147500	120000	128571	136000
Median	127500	140000	110000	120000	110000
Mean	126531	140187	108147	118315	112109
Std.	4729	1004	4356	3752	4483

Table 3 presents the results of the stationarity test for the training data of 10 selected cities. The results indicate that only the Sleman Regency location meets the stationarity requirement, with a p-value of less than $\alpha = 0.05$. For this reason, differencing is necessary for locations that do not yet exhibit stationarity. Differencing is a technique employed to transform a non-stationary time series into a stationary one by subtracting the previous observation from the current observation.

Table 3. Stationarity Test for Temporal Analysis Data Train

Location	South Tangerang City	South Jakarta City	Indramayu Regency	Sukabumi Regency	Cilacap Regency
ADF	-1.1744	-2.2087	-1.6790	-2.8304	-3.1422
p-value	0.9052	0.4903	0.7101	0.2358	0.1081
Location	**Jepara Regency**	**Sleman Regency**	**Pamekasan Regency**	**Trenggalek Regency**	**Situbondo Regency**
ADF	-1.4159	-3.5561	-2.4346	-1.9733	-2.2255
p-value	0.8149	0.0425	0.3978	0.5850	0.4834

After applying this differencing, all locations meet the data stationarity requirements, as indicated by the results in **Table 4**. Once the observation data fulfills the stationarity condition, the next step involves the selection of the best-fitting model.

Table 4. Stationarity Test for Temporal Analysis Data Train

Location	South Tangerang City	South Jakarta City	Indramayu Regency	Sukabumi Regency	Cilacap Regency
ADF	-4.9728	-3.7667	-5.4245	-4.3414	-5.8037
p-value	0.0100	0.0247	0.0100	0.0100	0.0100
Location	**Jepara Regency**	**Sleman Regency**	**Pamekasan Regency**	**Trenggalek Regency**	**Situbondo Regency**
ADF	-5.0924	-3.5561	-5.0703	-4.5503	-5.1522
p-value	0.0100	0.0425	0.0100	0.0100	0.0100

Table 5 presents the optimal ARIMA model for each observation location, which is determined based on the smallest Root Mean Squared Error (RMSE) value. The RMSE metric quantifies the model's predictive accuracy against actual data, with lower values indicating better performance.

Table 5. ARIMA Model

Location	Model Selection	Parameter Estimation	RMSE	AIC
South Tangerang City	ARIMA(2,1,0)	$\phi_1 = -0.4951$; $\phi_2 = -0.4356$	3425.1	195.2
South Jakarta City	ARIMA(0,1,2)	$\theta_1 = 0.2992$; $\theta_2 = -0.2460$	8984.7	214.4
Indramayu Regency	ARIMA(1,1,0)	$\phi_1 = -0.3609$	4717.3	199.6
Sukabumi Regency	ARIMA(0,1,1)	$\theta_1 = 0.1638$	5642.7	203.1
Cilacap Regency	ARIMA(1,1,0)	$\phi_1 = -0.0574$	7617.5	207.2
Jepara Regency	ARIMA(1,1,0)	$\phi_1 = 0.2569$	4078.8	196.6
Sleman Regency	ARIMA(1,0,0)	*Intercept = 140,168* ; $\phi_1 = -0.5160$	1220.5	174.5
Pamekasan Regency	ARIMA(1,1,0)	$\phi_1 = 0.2003$	2040.5	182.8
Trenggalek Regency	ARIMA(1,1,0)	$\phi_1 = -0.2437$	3341.4	192.7
Situbondo Regency	ARIMA(1,1,0)	$\phi_1 = -0.0152$	8560.6	211.5

The best ARIMA models identified in Table 5 were subsequently tested for residual normality, with the results of the error diagnostic tests presented in Table 6. The diagnostics reveal that, while the residuals from all observation locations are independent, they do not satisfy the normality assumption. In the ARIMA model, while the normality of residuals is often considered necessary, research indicates that violations of normality do not necessarily lead to adverse effects if the assumptions of independence and homoscedasticity are satisfied [49]. Therefore, the primary focus should be ensuring that the residuals meet the assumptions of autonomy and homoscedasticity rather than normality. Despite this, the residuals meet the homoskedasticity condition, indicating that the variance of the residuals is constant over time. Therefore, no ARCH or GARCH approach is needed to treat these beef price data.

Table 6. Error Diagnostic Test for ARIMA Model

Location	South Tangerang City	South Jakarta City	Indramayu Regency	Sukabumi Regency	Cilacap Regency
Normality	No	No	No	No	No
Independent	Yes	Yes	Yes	Yes	Yes
Homoskedastic	Yes	Yes	Yes	Yes	Yes
Location	**Jepara Regency**	**Sleman Regency**	**Pamekasan Regency**	**Trenggalek Regency**	**Situbondo Regency**
Normality	No	No	No	No	No
Independent	Yes	Yes	Yes	Yes	Yes
Homoskedastic	Yes	Yes	Yes	Yes	Yes

The ARIMA models obtained were subsequently utilized to forecast beef prices for the next 5 weeks. Table 7 presents the forecasted beef prices and the Root Mean Squared Error (RMSE) values, comparing the predictions with actual test data. The results indicate varying levels of predictive accuracy across different observation locations. In particular, four observation locations (Indramayu Regency, Sukabumi Regency, Jepara Regency, and Situbondo Regency) exhibit zero RMSE values, implying a perfect match between the predicted values and the actual test data. This indicates that the ARIMA models for these locations accurately capture the price trends.

Table 7. Data Prediction for Temporal Analysis

Location	Weekly Data Prediction (Rupiah)					RMSE
	92	93	94	95	96	
South Tangerang City	138697	138905	138825	138774	138834	1298.6
South Jakarta City	130034	130040	130040	130040	130040	300.5
Indramayu Regency	140000	140000	140000	140000	140000	0.0
Sukabumi Regency	129999	129999	129999	129999	129999	0.5
Cilacap Regency	134959	134961	134961	134961	134961	1357.6
Jepara Regency	130000	130000	130000	130000	130000	0.0
Sleman Regency	140081	140123	140145	140156	140161	136.3
Pamekasan Regency	111714	111772	111783	111786	111786	1586.0
Trenggalek Regency	120888	120846	120856	120854	120854	528.4
Situbondo Regency	120000	120000	120000	120000	120000	0.0

Conversely, the observation locations in South Jakarta City, Sleman Regency, and Trenggalek Regency report RMSE values ranging between 100 and 500, suggesting moderate predictive accuracy. Meanwhile, South Tangerang City, Cilacap Regency, and Pamekasan Regency locations have higher RMSE values, ranging between 1200 and 1500. The ARIMA model demonstrates substantial predictive capability, particularly in locations with zero RMSE values.

3.3 Spatial Analysis

The spatial analysis commenced with fitting a semivariogram model to evaluate the influence of directional dependence, determining whether the spatial variability exhibited anisotropy or isotropy. The semivariogram model fitting is critical in understanding spatial correlations and the degree of spatial continuity across different directions. The results of this fitting process are comprehensively presented in Table 8. If the nugget, sill, and range between isotropy and anisotropy models are similar in value, then choose isotropy because it is simpler according to the principle of parsimony if isotropy and anisotropy models have different nuggets, sill, and ranges, the angle between locations affects the model, so an anisotropy model is selected.

Table 8. Semivariogram Fitting Model for Spatial Analysis

Week	Isotropy/Anisotropy	Model	Nugget	Psill	Range	Model Selection
92	Isotropy	Gaussian	0.0005	0.0064	2.5887	Isotropy
	Anisotropy	Gaussian	0.0005	0.0065	2.6359	
93	Isotropy	Gaussian	0.0008	0.0045	2.3502	Anisotropy
	Anisotropy	Spherical	0.0000	0.0083	7.8643	
94	Isotropy	Spherical	0.0000	0.0073	4.8172	Isotropy
	Anisotropy	Spherical	0.0000	0.0073	4.8557	
95	Isotropy	Spherical	0.0000	0.0068	4.2549	Isotropy
	Anisotropy	Spherical	0.0000	0.0069	4.2914	
96	Isotropy	Gaussian	0.0010	0.0059	2.1804	Anisotropy
	Anisotropy	Spherical	0.0000	0.0069	4.6437	

From Table 8, it is evident that isotropy models were applied for weeks 92, 94, and 95, whereas anisotropy models were chosen for weeks 93 and 96. Predominantly, the semivariogram adheres to the Spherical model, except for week 92, which follows the Gaussian model.

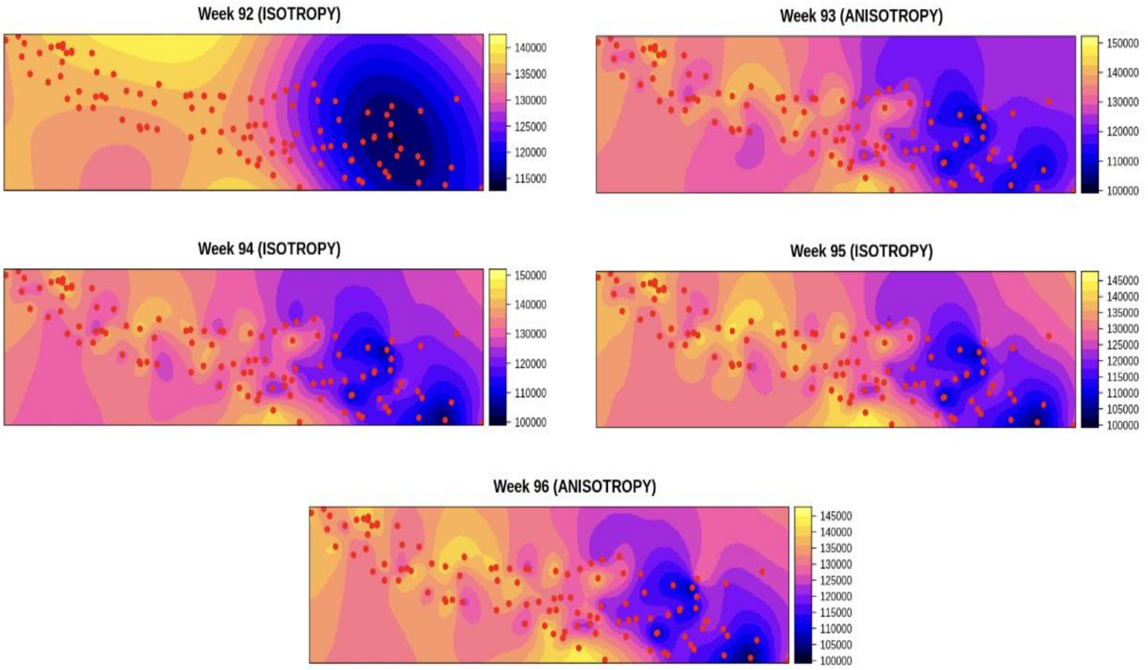

Figure 4. Kriging and Contour for Spatial Analysis

After obtaining the semivariogram model, the next step is to utilize the model to interpolate the data and predict beef prices at locations around the observation. The interpolated kriging contours are shown in Figure 4, which clearly illustrates that beef prices consistently decrease towards the east of Java and increase towards the west. Table 9 presents the interpolation results for 10 locations predicted from week 92 to week 96. The analysis indicates that the smallest RMSE values are observed in South Tangerang City and Indramayu Regency, while the largest RMSE value is found in Pamekasan Regency. The data also reveals that the lowest predicted beef prices during this period are in Situbondo Regency, while the highest prices are expected in Indramayu Regency, South Jakarta City, and South Tangerang City. Overall, beef price forecasting using spatial analysis resulted in higher RMSE values than those obtained from temporal time series analysis.

Table 9. Data Interpolation for Spatial Analysis

Location	Weekly Data Prediction (Rupiah)					RMSE
	92	93	94	95	96	
South Tangerang City	136985	138455	137917	137932	137055	1135.6
South Jakarta City	137018	138850	138497	137774	136219	7609.5
Indramayu Regency	138885	138128	137981	137319	137772	2048.2
Sukabumi Regency	135710	135729	132039	131716	131639	3878.5
Cilacap Regency	134948	130797	130667	129979	130655	3134.9
Jepara Regency	130169	123868	125550	125618	125513	4399.2
Sleman Regency	133789	130736	130891	131091	131343	8505.4
Pamekasan Regency	117530	120064	120374	121061	120185	9639.9
Trenggalek Regency	123516	125164	127542	128205	127366	5681.6
Situbondo Regency	119484	114820	116246	116406	116196	3703.3

3.4 Space-Time Analysis

The initial step of the space-time analysis involves testing the stationarity of the data train using the Augmented Dickey-Fuller (ADF) test. The results of the ADF test are presented in Table 10.

Table 10. Stationarity Test for Space-Time Analysis Data Train

Area	1	2	3	4	5
ADF	-1.73	-2.30	-3.12	-1.82	-2.75
p-value	0.69	0.45	0.12	0.65	0.27
Area	**6**	**7**	**8**	**9**	**10**
ADF	-2.77	-2.05	-2.10	-2.43	-2.33
p-value	0.26	0.56	0.53	0.40	0.44
Area	**11**	**12**	**13**	**14**	**15**
ADF	-2.27	-2.90	-2.19	-1.78	-3.07
p-value	0.46	0.22	0.50	0.66	0.14
Area	**16**	**17**	**18**	**19**	**20**
ADF	-2.42	-1.75	-2.56	-1.89	-0.65
p-value	0.40	0.68	0.35	0.62	0.97

We can conclude from **Table 10** that 20 area locations do not meet the stationarity requirements, as indicated by *p*-values more than 0.05. Therefore, the data train was different to achieve stationarity, resulting in the GSTARI model. The outcomes of this differencing process are depicted in **Table 11**.

Table 11. Stationarity Test for Space-Time Analysis Data Train After Differencing

Area	1	2	3	4	5
ADF	-4.32	-5.51	-5.21	-4.02	-4.99
p-value	0.01	0.01	0.01	0.01	0.01
Area	**6**	**7**	**8**	**9**	**10**
ADF	-4.68	-3.86	-4.80	-5.10	-5.34
p-value	0.01	0.02	0.01	0.01	0.01
Area	**11**	**12**	**13**	**14**	**15**
ADF	-4.23	-5.22	-4.07	-4.32	-4.58
p-value	0.01	0.01	0.01	0.01	0.01
Area	**16**	**17**	**18**	**19**	**20**
ADF	-5.01	-4.42	-4.36	-4.94	-3.87
p-value	0.01	0.01	0.01	0.01	0.02

Once the training data meets the stationarity requirements, the next step is determining the GSTARI model's weight matrix. In **Figure 5**, we present the STPACF value for GSTARI Model Selection.

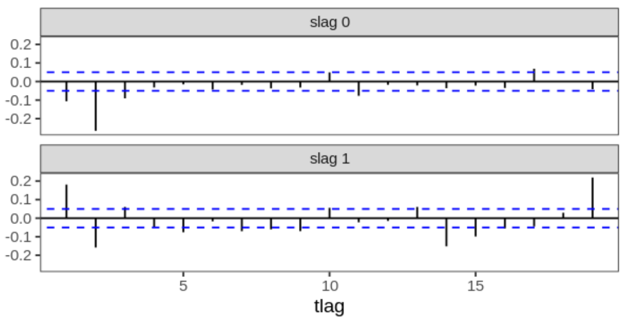

Figure 5. STPACF for GSTARI Model Selection

As outlined in the methods section, this analysis involves selecting two types of weight matrices: the uniform weight matrix and the inverse distance weight matrix. The results of applying these weighting schemes are presented below:

a. Uniform Weight Matrix

The constructed uniform weight matrix assigns a weight value of 0.0053 to each observation location. This weight matrix is a 20 x 20 matrix, corresponding to the total number of observation locations. This matrix is shown in Figure 6.

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\end{array}\right]
$$

Figure 6. Uniform Weight Matrix

b. Inverse Distance Weight Matrix

The constructed weight matrix exhibits different weight values for each observation location, with the highest weight being 0.12 and the lowest being 0.01. Higher weight values signify that the corresponding observation locations are relatively distant from each other. This matrix is shown in Figure 7.

The selection of the GSTARI model is verified from the RMSE and MAPE values using the two weighting matrices previously described, namely the uniform weighting matrix and the inverse distance weighting matrix. The results of the verification are presented in Table 12.

$$
\left[\begin{array}{cccccccccccccccccccc}
0{,}00 & 0{,}01 & 0{,}02 & 0{,}03 & 0{,}04 & 0{,}05 & 0{,}06 & 0{,}08 & 0{,}02 & 0{,}03 & 0{,}04 & 0{,}05 & 0{,}06 & 0{,}07 & 0{,}08 & 0{,}05 & 0{,}06 & 0{,}07 & 0{,}08 & 0{,}09 \\
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0{,}05 & 0{,}03 & 0{,}02 & 0{,}00 & 0{,}02 & 0{,}03 & 0{,}05 & 0{,}09 & 0{,}02 & 0{,}02 & 0{,}02 & 0{,}04 & 0{,}05 & 0{,}07 & 0{,}09 & 0{,}05 & 0{,}06 & 0{,}08 & 0{,}09 & 0{,}11 \\
0{,}08 & 0{,}06 & 0{,}04 & 0{,}02 & 0{,}00 & 0{,}02 & 0{,}04 & 0{,}08 & 0{,}04 & 0{,}03 & 0{,}02 & 0{,}03 & 0{,}04 & 0{,}06 & 0{,}08 & 0{,}04 & 0{,}06 & 0{,}07 & 0{,}09 & 0{,}11 \\
0{,}10 & 0{,}08 & 0{,}06 & 0{,}04 & 0{,}02 & 0{,}00 & 0{,}02 & 0{,}06 & 0{,}06 & 0{,}05 & 0{,}03 & 0{,}02 & 0{,}03 & 0{,}05 & 0{,}06 & 0{,}04 & 0{,}05 & 0{,}06 & 0{,}07 & 0{,}09 \\
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\end{array}\right]
$$

Figure 7. Inverse Distance Weight Matrix

We can conclude from Table 12, the GSTARI model using a uniform weight matrix tends to have a small RMSE value compared to the inverse distance weight matrix for training data. However, the GSTARI model using the inverse distance weight matrix for test data is much smaller. The GSTARI(1;1;1) model has the smallest RMSE value, using uniform and inverse distance weighting matrices.

Table 12. GSTAR Model

	Model	Uniform Weight		Inverse Distance Weight	
		GSTARI (2;1,1;1)	GSTARI (1;1;1)	GSTARI (2;1,1;1)	GSTARI (1;1;1)
Data Train	RMSE	1446.2	1531.4	1456.5	1544.7
	MAPE	0.5084	0.5170	0.5083	0.5174
Data Test	RMSE	4375.3	4398.4	4364.3	4315.1
	MAPE	2.2104	2.2369	2.2140	2.1847

Therefore, the GSTARI(1;1;1) model with an inverse distance weight matrix is selected to predict beef prices. The model is shown in **Equation (10)**.

$$Y_i(t) = \phi_{10} Y_i(t-1) + \phi_{11} \sum_{j=1}^{N} W^{(1)} Y_j(t-1) + \varepsilon_i(t) \tag{10}$$

where

$$Y_i(t) = Z_i(t) - Z_i(t-1)$$

$\boldsymbol{Z_i(t)}$: beef price in location $i-$th at time $t-$th.

$\boldsymbol{\Phi_{10}}$: diag(0.085, -0.099, 0.375, -0.506, -0.251, -0.112, -0.467, -0.370, 0.047, 0.193, -0.011, 0.050, -0.150, -0.205, -0.175, -0.494, -0.082, -0.147, -0.120, -0.582).

$\boldsymbol{\Phi_{11}}$: diag(-0.226, 0.124, -1.012, 2.095, 0.952, 0.914, 0.455, -0.115, -0.119, -0.924, 0.046, 0.031, 0.306, 0.241, 0.289, 0.868, -0.124, 0.018, -0.097, -0.295).

$W^{(1)}$: inverse distance weight matrix.

$\varepsilon_i(t)$: error in location i-th at time t-th.

Next, the residual normality test is conducted. The results of the residual normality test are presented in **Table 13**. It is clear from **Table 13** that the GSTARI(1;1;1) model is mutually independent and satisfies homoscedasticity, though it does not conform to normality.

Table 13. Error Diagnostic Test for GSTARI (1;1;1) Using Inverse Distance Weight Matrix

Normality	Independent	Homoscedastic
No	Yes	Yes

After determining the time model, the next step is to forecast the next 5 weeks and select the semivariogram model from the forecast data. The outcomes of this selection are displayed in **Table 14**.

Table 14. Semivariogram Fitting Model for Space-Time Analysis

Week	Isotropy/ Anisotropy	Model	Nugget	Psill	Range	Model Selection
92	Isotropy	Spherical	0.0000	0.0060	5.0387	Isotropy
	Anisotropy	Spherical	0.0000	0.0061	5.0903	
93	Isotropy	Spherical	0.0000	0.0059	4.9321	Isotropy
	Anisotropy	Spherical	0.0000	0.0060	4.9846	
94	Isotropy	Spherical	0.0000	0.0059	4.8147	Isotropy
	Anisotropy	Spherical	0.0000	0.0059	4.8652	
95	Isotropy	Spherical	0.0000	0.0058	4.7777	Isotropy
	Anisotropy	Spherical	0.0000	0.0059	4.8275	
96	Isotropy	Gaussian	0.0006	0.0047	1.9760	Isotropy
	Anisotropy	Gaussian	0.0002	0.0052	1.7419	

Table 14 reveals that all models from weeks 92 to 96 are isotropy. The semivariogram model predominantly follows the Spherical model, except week 96, which follows the Gaussian model. After obtaining the semivariogram model, we interpolate the data and predict the beef price at the location around the observation by constructing kriging contours, as shown in **Figure 8.**

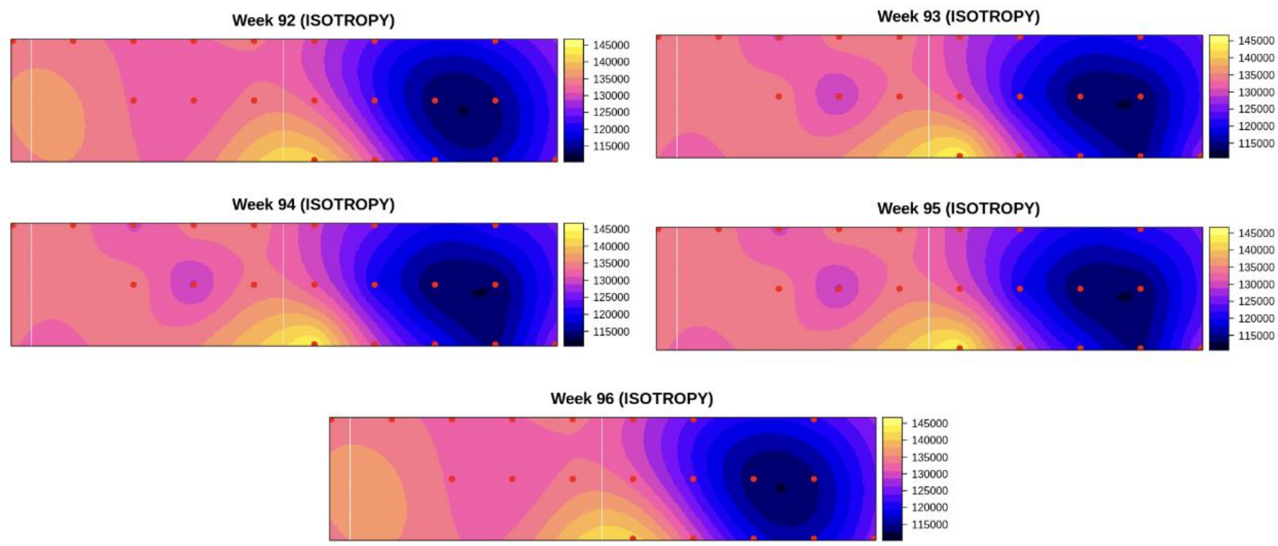

Figure 8. Kriging and Contour for Space-Time Analysis

Based on **Figure 8**, a similar conclusion is drawn from the contour kriging results of the spatial analysis. Next, **Table 15** presents the interpolation results for 10 locations predicted from week 92 to week 96. The smallest RMSE values are observed in the Jepara Regency and Cilacap Regency, whereas the most significant RMSE values are found in the Indramayu Regency and Sleman Regency.

Table 15. Data Interpolation for Space-Time Analysis

Location	Weekly Data Prediction (Rupiah)					RMSE
	92	93	94	95	96	
South Tangerang City	133319	133279	133247	133230	133109	5185.7
South Jakarta City	133099	133047	133004	132965	133048	2903.0
Indramayu Regency	133529	133753	133657	133731	132810	6513.5
Sukabumi Regency	133193	133122	133081	133038	133590	3211.1
Cilacap Regency	132888	132823	132805	132771	132997	1807.0
Jepara Regency	128461	128492	128491	128499	128798	1457.3
Sleman Regency	134259	134237	134255	134254	134493	5701.2
Pamekasan Regency	115511	115458	115468	115451	115671	5249.0
Trenggalek Regency	123137	123120	123111	123099	123417	2364.9
Situbondo Regency	116869	117045	117165	117251	117861	2787.5

Additionally, the table indicates that the lowest beef price predictions from week 92 to week 96 are in Pamekasan Regency and Situbondo Regency, while the highest price predictions are in Sleman Regency, Indramayu Regency, South Tangerang City, South Jakarta City, and Sukabumi Regency. Meanwhile, **Figure 9** shows the price maps for 10 locations from week 92 to week 96.

Week 92

Week 93

Week 94

Week 95

Week 96

Figure 9. Price Maps For 10 Locations for Week 92-96

3.5 Comparison Analysis

Based on the results and analysis, beef price is influenced by temporal and spatial or space-time. These findings align with previous research [50], [26], which indicates that spatial dependencies influence beef prices. However, of the three analyses (temporal, spatial, and space-time), temporal time series analysis yields the smallest average of RMSE value, as shown in Table 16. his indicates that overall changes in beef prices on the island of Java are predominantly influenced by temporal factors, especially in the periods leading up to major religious holidays [51], despite significant spatial variations at individual observation points.

Table 16. RMSE Comparison for Temporal, Spatial, and Space-Time Analysis

RMSE		
Temporal	**Spatial**	**Space-Time**
520.79	4973.61	3718.02

Clearly, the RMSE in the temporal model is significantly lower than in the other two models. This is because the temporal variance of the beef price values at each location is smaller than the spatial variance of the beef price values at the same time.

4. CONCLUSIONS

Based on the analysis and discussion of beef price data, a beef price prediction model is obtained from week 92 to week 96 based on temporal, spatial, and space-time analysis. First, for temporal analysis, the best ARIMA model for each observation location has the smallest RMSE value of zero, and the largest is 1,504. 9. Second, for spatial analysis, the best semivariogram model with the lowest RMSE value is 1,135.6 and the highest is 9,639. Last, for space-time analysis, the GSTARI(1;1;1) model for each observation point with the lowest RMSE value is 1,457.3 and the highest is 6,513.5.

Based on these results, the temporal analysis has the smallest range of RMSE values across observation points [52]. Overall, the temporal analysis model achieves the lowest RMSE value of 504.7, followed by the space-time analysis with an RMSE value of 3,717.5 and the spatial analysis with an RMSE value of 4,973.6. This implies that beef price fluctuations are mainly driven by temporal factors, especially during religious holidays, rather than by spatial factors or a combination of both. Nevertheless, there are significant price variations at each observation location. Based on the results obtained, this research's limitation is that the model used only produces short-term forecasts for the Java Island region. The area division in the GSTAR model is only 20 areas. The selection of the best model among temporal, spatial, and space-time models is based on RMSE only. Further research can be done taking into account the limitations of this research.

The findings of this study can serve as a consideration for the government as policymakers to take preventive measures in addressing beef shortages, particularly during religious holidays so that extreme price fluctuations can be controlled. Additionally, these results provide supplementary information for policy decisions regarding beef supply, especially in Java. For future research, exploring the impact of external factors such as inflation, local income, and beef import/export prices is essential, which may also contribute to beef price variations in Java.

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