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Generalized Space Time Autoregressive (GSTAR) Modeling in Predicting the Price of Bird's Eye Chili in East Java, West Java, and Central Java

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ABSTRACT

Bird's eye chili (Capsicum frutescens L.) is a major agricultural commodity in Indonesia that contributes to the economy through high market demand and its impact on inflation. In 2022, production reached 1,544,441 tons, with East Java, Central Java, and West Java being the top producing provinces. However, price fluctuations due to production and market mismatches are a concern for farmers and policy makers. The objective of this study was to model the price dynamics of bird's eye chili in the provinces of East Java, Central Java, and West Java, given their substantial contribution to national production. To address this, the Generalized Space Time Autoregressive (GSTAR) method was applied to model the price of bird's eye chili from February to November 2023 using data from the National Food Agency with 8:2 ratio between training and testing data. By utilizing different weighting schemes-uniform weight, inverse distance, and cross-correlation normalization, the GSTAR$(2_1)I(1)$ with uniform location weights performed best, showing high predictive accuracy with MAPE values of 2.021% for training data and 2.045% for test data. The model is recommended to stabilize the price of bird's eye chili, with further validation recommended to improve reliability.

Keywords: GSTAR; Bird's Eye Chili Price; End Hunger; Prediction; Java Island

INTRODUCTION

Bird's eye chili or *Capsicum frutescens L.* is one of the commodities that has high potential in improving the country's economy [1]. Bird's eye chili is known by various other names, including African pepper, chili pepper, goat's pod, Mexican chili, red pepper, Tabasco pepper, Zanzibar pepper, and Cayenne pepper. Its small, highly pungent fruits easily detach from the calyx [2]. This commodity has a great opportunity to be developed, because bird's eye chili plays a role of 80% to meet the daily needs of the community and 20% to meet the needs of the food industry [3]. Bird's eye chili is an essential vegetable commodity with substantial economic importance. Additionally, bird's eye chili are irreplaceable by other products, so any mismatch between production and market

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demand inevitably leads to price fluctuations. These unpredictable price changes make cayenne pepper farmers anxious about potential losses, as they cannot foresee market trends [4]. Bird's eye chili is classified as a type of plant that has a short life and is widely cultivated for commercial benefits [5]. Some of the reasons behind the high development of bird's eye chili commodities are a) easy to adapt to the surrounding environment, such as lowlands and highlands; b) has a large and diverse target market, such as traditional, modern, to large industrial markets; c) has a significant influence on the inflation of the country; d) one of the commodities that has a major impact on farmers' income; e) commodities that have good import and export values, so as to improve the trade balance [6]. The optimal planting season for bird's eye chili offers farmers a great opportunity, and the system provides essential support, assisting them in improving their farming techniques and managing the unpredictability of the chili market [7].

A significant number of bird's eye chili producers are located in Asian countries like India, Myanmar, Bangladesh, Pakistan, Thailand, Vietnam, China, and Indonesia. Indonesia ranks as the fifth-largest chili producer globally, following India, China, Turkey, and Bangladesh [8]. In 2022, Indonesia's bird's eye chili production increased to 1,544,441 tons. The three provinces that ranked highest in bird's eye chili production were East Java, Central Java, and West Java. Bird's eye chili production in East Java reached 646,740 tons, in Central Java as much as 242,303 tons, while West Java reached 149,053 tons [9]. East Java has fertile soil and a very favorable climate in producing bird's eye chili, so it is not surprising that this province ranks first in bird's eye chili production. There are five regencies/cities that produce the most bird's eye chili, namely Blitar, Sampang, Kediri, Malang, and Banyuwangi [10]. While in West Java province, there are five regencies/cities that produce the highest bird's eye chili, including Bekasi, Bandung, Subang, West Bandung, and Purwakarta [11].

In recent years, Indonesia has experienced increases and decreases in bird's eye chili prices. According to Aminullah and Purba [12], the problem of fluctuating bird's eye chili prices needs further attention, as also emphasized by Zulkifli Hasan. One of the causes of fluctuating prices is that farmers do not have adequate processing and preservation technology in bird's eye chili production [13]. To overcome the uncertain price of bird's eye chili, appropriate analytical methods are needed to predict the price of bird's eye chili in order to help the government to formulate policies that are right on target. This is also in line with efforts to achieve the *second Sustainable Development Goals* (SDG's), namely *End Hunger, Achive Food Security, and Improved Nutrition and Promote Sustainable Agriculture*.

Debby et al. [14] estimated the price of red chili pepper using Generalized Space Time Autoregressive (GSTAR) in Jakarta. The variable of this study is the daily prices of the red chili pepper in seven central markets Jakarta. The alternative model of the result is GSTAR(1,1) and GSTAR(2,1,2). The parameter estimation showed that those models is significant and stationary. The price of red chili peppers can be effectively modeled using GSTAR (1,1), as indicated by a lower RMSE of 3920,527. In comparison, the estimated price of red chili peppers using GSTAR (2,1,2) results in a higher RMSE of 4664,829 [14].

In a previous literature study, Kharisma [15] predicted rice prices using the GSTAR method in the provinces of East Java, Central Java, and East Java. The variable used in this study is the price of rice in the three provinces in the period August 2017-January 2022. Based on this study, the results of the comparison of GSTAR models using uniform location weighting and distance *inverse* location were obtained, it was obtained that the

GSTAR $(8_1)I(1)$ model with uniform location weighting became the best model. In addition, the model also meets the *white noise* assumption test and has the most optimal MSE and MAPE values when compared to the weight of the distance inverse *location*. Where the MSE and MAPE values for models with uniform weights are 45.223% and 1.597%. Based on these predictions, it can be concluded that rice price predictions tend to go up and down every day. However, the difference in price fluctuations is relatively small, only up or down tens of rupiah [15].

Based on the presentation of previous literature studies, this research has the latest in using the GSTAR method. The latest form is in the form of weights used to model GSTAR. In this study, the GSTAR method was used with uniform location weights, distance *inverse,* and cross-correlation normalization. By comparing the three weights, it will produce a more accurate prediction. Therefore, it can help the Indonesian government to stabilize the price of bird's eye chili so that the price of this commodity does not rise too high and fall too low.

METHODS

This study used secondary data as the main data source. This research data was bird's eye chili commodity prices data in three provinces in Indonesia, namely East Java, Central Java, and West Java in Rupiah with a daily period from February to November 2023 obtained from "Badan Pangan Indonesia" with the official website https://panelharga.badanpangan.go.id./

The data in this study was divided into two parts, namely in-sample data and out-sample data. In-sample data was used to train the data and form a GSTAR model, while out-sample data is used to evaluate the GSTAR model formed by looking at its accuracy through MAPE. Data was divided into 8:2 ratio, which was 80% of the data used for in-sample and 20% of the data used for out-sample. The division of in-sample and out-sample data includes:

1. In-sample data: February 01, 2023 - September 16, 2023 (228 observations)
2. Out-sample data: September 17, 2023 - November 12, 2023 (57 observations)

There are 11 steps that must be completed in the GSTAR method. The following is an explanation of each step and the conditions that must be met:

1. Plot a time series graph of bird's eye chili prices data in three locations (East Java, Central Java, and West Java) on a daily basis and conduct descriptive statistical analysis.
2. Perform a correlation test between response variables to determine the correlation of bird's eye chili prices in three locations. The hypothesis used in the correlation test is as follows:
   H_0 : There is no correlation between response variables
   H_1 : There is a correlation between response variables
3. Examine data stationarity on three response variables with the Augmented Dickey-Fuller (ADF) test. The hypothesis used in the ADF test is as follows:
   H_0 : Data on three response variables are not stationary
   H_1 : Data on three response variables are stationary
4. Determine the time order in the GSTAR model through VAR modeling with the minimum AIC value, the selected VAR model order will be used as the time order in the GSTAR model.
5. Calculate location weights using three methods: uniform weight, inverse distance

weight, and normalized cross-correlation weight.
6. Estimate the GSTAR model with the Seemingly Unrelated Regression (SUR) method on each location weight.
7. Perform diagnostic tests on the residuals of the GSTAR model.
8. Calculate the MAPE and MSE of the GSTAR model for each location weight obtained from the in-sample data.
9. Forecast each GSTAR model and compare the prediction results with the out-sample data.
10. Calculate MAPE and MSE on the prediction results with out-sample data.
11. Find the best GSTAR model with the minimum MAPE and MSE values.

RESULT AND DISCUSSION

Descriptive Analysis

The first step to conducting the analysis is to know the characteristics of the data to be used. One way to find out these characteristics is to make a time series plot related to the price of bird's eye chili in the provinces of East Java, Central Java, and West Java.

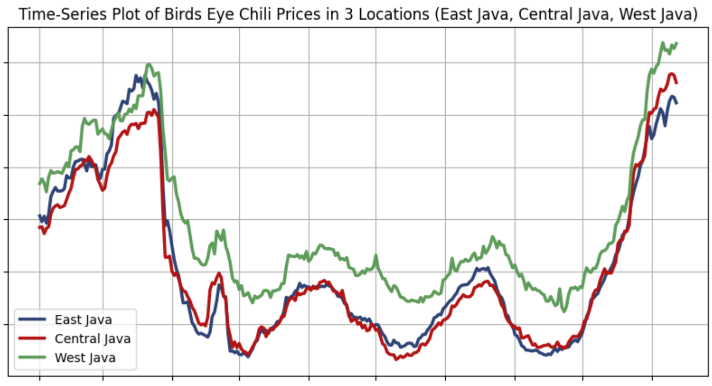

Figure 1. Time Series Plot of Bird's eye chili Price Data in East Java, Central Java, and West Java from February to November 2023

Based on Figure 1, it can be seen that the data pattern of bird's eye chili prices in the three provinces is similar. However, in West Java, the price of this commodity tends to be higher compared to the provinces of East Java and Central Java. In mid-March, the price of bird's eye chili rose simultaneously in all three provinces but declined gently in mid-April. The decline in prices in April was due to the increasing production of bird's eye chili because it had entered the harvest season and the arrival of the month of Ramadan, where commodity prices tend to fall during the celebration of holidays [16]. From October to November, the price of bird's eye chili jumped dramatically. The increase in the price of bird's eye chili is due to a very long drought, so the stock of bird's eye chili is decreasing and thinning, so the price is increasing [17].

Correlation Test

After analyzing the descriptive data, the correlation between observation locations will be tested. This test uses the Pearson correlation test with a p-value for each observation location.

Table 1. Correlation between locations

		East Java	Central Java	West Java
East Java	**Pearson Correlation**	1	0.9856	0.9693
	p- value	0	0.0000	0.0000
Central Java	**Pearson Correlation**	0.9856	1	0.9825
	p- value	0.0000	0	0.0000
West Java	**Pearson Correlation**	0.9693	0.9825	1
	p- value	0.0000	0.0000	0

Based on Table 1, it can be concluded that the p-value of the three locations has a value less than the real level (0.05). In addition, East Java province with Central Java has the highest correlation coefficient of 0.9856 and East Java province with West Java has the lowest correlation coefficient of 0.9693. With a correlation coefficient close to 1 and a significant p-value, it can be concluded that the three locations have a strong relationship.

Stationarity Test

In modeling time series data, the data used must be stationary, so data stationarity testing is required. If the tested data is not stationary, then a differencing process must be carried out until the data is stationary and can be continued to the next analysis process.

Table 2. Augmented Dickey-Fuller Test after Differencing 1

	East Java	Central Java	West Java
p-value before differencing	0.7385	0.5236	0.8076
p-value after differencing	0.0001	0.0001	0.0001

Based on Table 2, the p-value from testing using the Augmented Dickey-Fuller (ADF) test for each location is greater than the real level (0.05). Therefore, it can be concluded that the data is not yet stationary, so it is necessary to do differencing 1 and do the ADF test again. In the ADF test after differencing 1, the p-value is less than the real level (0.05). Therefore, it can be concluded that the data used is stationary.

GSTAR Model Identification

To determine the time order of the GSTAR model is to use the order of the VAR (p) model. In identifying the order of the VAR model, it can be determined by the optimal lag length with the smallest AIC value between lags.

Table 3. AIC value of the VAR model

Lag	0	1	2	3	4	5	6	7	8	9	10
AIC	42.617	42.092	**42.002**	42.011	42.029	42.024	42.038	42.019	42.068	42.061	42.129

Based on Table 3, it is known that the smallest AIC value is at the 2nd lag which is 42.002. Therefore, it can be concluded that the autoregressive order of the GSTAR model is 2. Quoted from [8], the selection of spatial order for the GSTAR model is limited to spatial order 1, because a higher order will have an impact on its interpretation which is more difficult. Based on spatial order 1, it can be interpreted that the three provinces are in one region, namely Java Island. Therefore, the GSTAR model is obtained $(2_1)I(1)$.

GSTAR Model Location Weight Calculation

Based on Table 3, it is known that the smallest AIC value is at the 2nd lag which is 42.002. Therefore, it can be concluded that the autoregressive order of the GSTAR model is 2. Quoted from [8], the selection of spatial order for the GSTAR model is limited to spatial order 1, because a higher order will have an impact on its interpretation which is more difficult. Based on spatial order 1, it can be interpreted that the three provinces are in one region, namely Java Island. Therefore, the GSTAR model is obtained $(2_1)I(1)$.GSTAR Model Location Weight Calculation

In modeling space-time, the use of location is one of the considerations for predicting the price of bird's eye chili. This study uses three types of location weights, namely uniform location weights, inverse distance location weights, and cross-correlation weights between locations. By using three locations, namely East Java, Central Java, and West Java.

The calculation of uniform location weights has the same value for each location. With the equation for uniform location weight matrix W, with $W_{ij} = \frac{1}{n_i}$. Therefore, the results of uniform location weights are obtained as follows,

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

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

Based on the uniform location weight matrix above, it can be concluded that the value of the location weights has met the requirements, namely with the main diagonal being 0 and the matrix components in each column totaling 1.

The calculation of the inverse distance location weight can be determined based on the actual location distance. For the location distance between the three locations is as follows,

Table 4. Distance between locations

Coat of arms	Location	Distance (km)
r_1	East Java - Central Java (Surabaya - Semarang)	351.61
r_2	East Java - West Java (Surabaya - Bandung)	770
r_3	Central Java - West Java (Semarang - Bandung)	354.53

With the actual distance between the three locations in Table 4, the calculation of the inverse distance location weight matrix is obtained as follows,

$$W^1(1) = \begin{bmatrix} 0 & 0.3135 & 0.6865 \\ 0.4979 & 0 & 0.5021 \\ 0.3152 & 0.6847 & 0 \end{bmatrix}$$

Based on the distance inverse location weight matrix above, it can be concluded that the value of the location weight has met the requirements, namely with the main diagonal being 0 and the matrix components in each column totaling 1.

The calculation of normalized cross-correlation weights between locations can be determined. Therefore, the cross-correlation weight matrix between locations is obtained as follows,

$$W^1(1) = \begin{bmatrix} 0 & 0.369 & 0.631 \\ 0.467 & 0 & 0.532 \\ 0.368 & 0.632 & 0 \end{bmatrix}$$

Parameter Estimation of GSTAR Model $(\mathbf{2_1})\boldsymbol{I}(\mathbf{1})$

Estimation of each autoregressive parameter of the GSTAR model can be done using the least square method, which minimizes the residual sum of squares. The most important part of forecasting is the ability of the model to forecast the data. Therefore, it does not matter if the parameter significance test is not performed [18]. So that all parameters can be used for the next stage of analysis.

The GSTAR model equation for spatial order $(p; \lambda_1, \lambda_2, \dots, \lambda_p)$ can be formulated as follows [19];

$$Z_t = \sum_{s=1}^{p} \left[\Phi_{s0} + \sum_{k=1}^{\lambda_s} \Phi_{sk}\, w^k \right] Z_{(t-s)} + \varepsilon_{(t)} \tag{1}$$

The GSTAR model equation $(2_1)I(1)$ on bird's eye chili price data at three locations, namely in East Java, Central Java, and West Java Provinces can be formed using a uniform weight matrix, a distance inverse location weight matrix, and a cross-correlation normalized weight matrix as follows.

GSTAR $(2_1)I(1)$ model with uniform location weights in East Java

$$\begin{aligned} Z_1(t) = {} & 0.112(Z_1(t-1) - Z_1(t-2)) + 0.315(Z_2(t-1) - Z_2(t-2)) + 0.315(Z_3(t-1) \\ & - Z_3(t-2)) - 0.0266(Z_1(t-2) - Z_1(t-3)) - 0.067(Z_2(t-2) \\ & - Z_2(t-3)) - 0.067(Z_3(t-2) - Z_3(t-3)) + Z_1(t-1) + a_1(t) \end{aligned}$$

GSTAR $(2_1)I(1)$ model with uniform location weights in Central Java

$$\begin{aligned} Z_2(t) = {} & 0.288(Z_1(t-1) - Z_1(t-2)) + 0.214(Z_2(t-1) - Z_2(t-2)) + 0.288(Z_3(t-1) \\ & - Z_3(t-2)) - 0.027(Z_1(t-2) - Z_1(t-3)) - 0.085(Z_2(t-2) \\ & - Z_2(t-3)) - 0.027(Z_3(t-2) - Z_3(t-3)) + Z_2(t-1) + a_2(t) \end{aligned}$$

GSTAR $(2_1)I(1)$ model with uniform location weights in West Java

$$\begin{aligned} Z_3(t) = {} & 0.208(Z_1(t-1) - Z_1(t-2)) + 0.208(Z_2(t-1) - Z_2(t-2)) \\ & - 0.1132(Z_3(t-1) - Z_3(t-2)) + 0.159(Z_1(t-2) - Z_1(t-3)) \\ & + 0.159(Z_2(t-2) - Z_2(t-3)) - 0.1724(Z_3(t-2) - Z_3(t-3)) \\ & + Z_3(t-1) + a_3(t) \end{aligned}$$

GSTAR $(2_1)I(1)$ model with inverse distance location weights in East Java

$$\begin{aligned} Z_1(t) = {} & 0.1889(Z_1(t-1) - Z_1(t-2)) + 0.161(Z_2(t-1) - Z_2(t-2)) \\ & + 0.353(Z_3(t-1) - Z_3(t-2)) - 0.0468(Z_1(t-2) - Z_1(t-3)) \\ & - 0.045(Z_2(t-2) - Z_2(t-3)) - 0.099(Z_3(t-2) - Z_3(t-3)) \\ & + Z_1(t-1) + a_1(t) \end{aligned}$$

GSTAR $(2_1)I(1)$ model with inverse distance location weights in Central Java

$$\begin{aligned} Z_2(t) = {} & 0.308(Z_1(t-1) - Z_1(t-2)) + 0.1516(Z_2(t-1) - Z_2(t-2)) \\ & + 0.310(Z_3(t-1) - Z_3(t-2)) - 0.039(Z_1(t-2) - Z_1(t-3)) \\ & - 0.0582(Z_2(t-2) - Z_2(t-3)) - 0.040(Z_3(t-2) - Z_3(t-3)) \\ & + Z_2(t-1) + a_2(t) \end{aligned}$$

GSTAR $(2_1)I(1)$ model with inverse distance location weights in West Java

$$\begin{aligned} Z_3(t) = {} & 0.127(Z_1(t-1) - Z_1(t-2)) + 0.276(Z_2(t-1) - Z_2(t-2)) \\ & - 0.0971(Z_3(t-1) - Z_3(t-2)) + 0.094(Z_1(t-2) - Z_1(t-3)) \\ & + 0.162(Z_2(t-2) - Z_2(t-3)) + 0.1704(Z_3(t-2) - Z_3(t-3)) \\ & + Z_3(t-1) + a_3(t) \end{aligned}$$

GSTAR $(2_1)I(1)$ model with normalized cross-correlation weights in East Java

$$\begin{aligned} Z_1(t) = {} & 0.1521(Z_1(t-1) - Z_1(t-2)) + 0.21(Z_2(t-1) - Z_2(t-2)) + 0.359(Z_3(t-1) \\ & - Z_3(t-2)) + 0.0428(Z_1(t-2) - Z_1(t-3)) - 0.053(Z_2(t-2) \\ & - Z_2(t-3)) - 0.091(Z_3(t-2) - Z_3(t-3)) + Z_1(t-1) + a_1(t) \end{aligned}$$

GSTAR $(2_1)I(1)$ model with normalized cross-correlation weights in Central Java

$$\begin{aligned} Z_2(t) = {} & 0.281(Z_1(t-1) - Z_1(t-2)) + 0.1764(Z_2(t-1) - Z_2(t-2)) \\ & + 0.321(Z_3(t-1) - Z_3(t-2)) - 0.031(Z_1(t-2) - Z_1(t-3)) \\ & - 0.069(Z_2(t-2) - Z_2(t-3)) - 0.036(Z_3(t-2) - Z_3(t-3)) \\ & + Z_2(t-1) + a_2(t) \end{aligned}$$

GSTAR $(2_1)I(1)$ model with normalized cross-correlation weights in West Java

$$\begin{aligned} Z_3(t) = {} & 0.149(Z_1(t-1) - Z_1(t-2)) + 0.255(Z_2(t-1) - Z_2(t-2)) \\ & - 0.0964(Z_3(t-1) - Z_3(t-2)) + 0.112(Z_1(t-2) - Z_1(t-3)) \\ & + 0.193(Z_2(t-2) - Z_2(t-3)) - 0.1721(Z_3(t-2) - Z_3(t-3)) \\ & + Z_3(t-1) + a_3(t) \end{aligned}$$

White Noise Test on Residual of GSTAR Model

After determining the model of each location weight, the next step is to test the feasibility of the model. If the residuals are white noise, then the model is suitable for use. In conducting this test, the Ljung Box Pearce test is used for each weight with the following results,

Tabel 5. Ljung Box Pearce Test on Location Weight Matrix

Weight	Variables	P-Value	Residual Assumptions
Uniform Location Weight	Multivariate	0.355	White Noise
	East Java	0.137	White Noise
	Central Java	0.586	White Noise
	West Java	0.795	White Noise
Distance Inverse Location Weight	Multivariate	0.150	White Noise
	East Java	0.167	White Noise
	Central Java	0.428	White Noise
	West Java	0.763	White Noise
Location Weight Normalized Cross Correlation	Multivariate	0.210	White Noise
	East Java	0.148	White Noise
	Central Java	0.466	White Noise
	West Java	0.758	White Noise

Based on Table 5, the residuals of multivariate variables in the three location weights have fulfilled the assumption that the residuals are white noise because p-value > α = 0.05.

Selection of the Best GSTAR Model

Evaluating the accuracy of the model can be done by comparing the error rate of the model, which can be seen from the MAPE value on the training and testing data. The model that has the smallest MAPE value on both data sets is considered the best model.

Table 6. MAPE value of training data

Weight	MAPE In-Sample			Average MAPE
	East Java	Central Java	West Java	
Uniform	**2.099%**	**2.196%**	**1.767%**	**2.021%**
Inverse Distance	2.161%	2.196%	1.784%	2.047%
Cross Correlation Normalization	2.151%	2.21%	1.776%	2.046%

Table 7. MAPE value of testing data

Weight	MAPE Out-Sample			Average MAPE
	East Java	Central Java	West Java	
Uniform	**2.157%**	**1.867%**	**2.111%**	**2.045%**
Inverse Distance	2.219%	1.895%	2.081%	2.065%
Cross Correlation Normalization	2.215%	1.901%	2.081%	2.066%

In Tables 6 and 7, it can be seen that based on training and testing data with a uniform location weight matrix, inverse distance, and normalized cross correlation, the smallest MAPE value is obtained, namely on a uniform location weight matrix with the GSTAR $(2_1)I(1)$ model. The location weights produced a MAPE value of 2.021% in the training data and 2.045% in the testing data.

The Best GSTAR Model

The following are the results of forecasting chili price data in East Java, Central Java, and West Java provinces based on the best model, namely $(2_1)I(1)$ using uniform location weights.

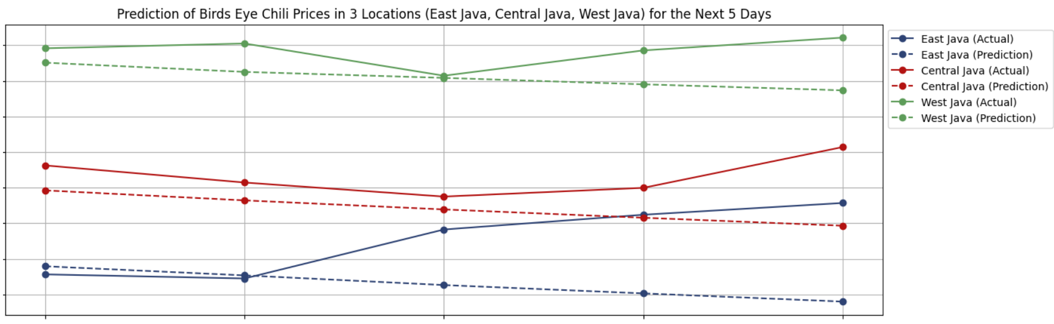

Figure 2. Comparison of Actual Data with Predicted Data using the Best GSTAR Model

Based on Figure 2, it can be observed that the values between the actual data and the prediction results are relatively close to each other. This similarity is due to the best model, namely the GSTAR $(2_1)I(1)$ model with uniform location weights, which produces a MAPE value that falls into the category of highly accurate forecasting. The level of MAPE is quite high when compared to the results of studies [20, 21, 22] which have MAPE values ranging from 5%–15%. However, the MAPE value in this study can be increased as in research [23] which has an average MAPE value of 1.25%.

CONCLUSIONS

Based on the previous analysis and discussion, it can be concluded that the GSTAR method on bird's eye chili price data at three locations, namely in East Java, Central Java, and West Java Provinces can be formed using a uniform weight matrix, a distance inverse location weight matrix, and a cross-correlation normalized weight matrix. The best model for forecasting the price of bird's eye chili in East Java, Central Java, and West Java Provinces is GSTAR $(2_1)I(1)$ after differencing one time, using uniform location weights. The GSTAR equation of best model is expressed as follows

GSTAR $(2_1)I(1)$ model with uniform location weights in East Java

$$\begin{aligned} Z_1(t) = {} & 0.112(Z_1(t-1) - Z_1(t-2)) + 0.315(Z_2(t-1) - Z_2(t-2)) + 0.315(Z_3(t-1) \\ & - Z_3(t-2)) - 0.0266(Z_1(t-2) - Z_1(t-3)) - 0.067(Z_2(t-2) \\ & - Z_2(t-3)) - 0.067(Z_3(t-2) - Z_3(t-3)) + Z_1(t-1) + a_1(t) \end{aligned}$$

GSTAR $(2_1)I(1)$ model with uniform location weights in Central Java

$$\begin{aligned} Z_2(t) = {} & 0.288(Z_1(t-1) - Z_1(t-2)) + 0.214(Z_2(t-1) - Z_2(t-2)) + 0.288(Z_3(t-1) \\ & - Z_3(t-2)) - 0.027(Z_1(t-2) - Z_1(t-3)) - 0.085(Z_2(t-2) \\ & - Z_2(t-3)) - 0.027(Z_3(t-2) - Z_3(t-3)) + Z_2(t-1) + a_2(t) \end{aligned}$$

GSTAR $(2_1)I(1)$ model with uniform location weights in West Java

$$\begin{aligned} Z_3(t) = {} & 0.208(Z_1(t-1) - Z_1(t-2)) + 0.208(Z_2(t-1) - Z_2(t-2)) \\ & - 0.1132(Z_3(t-1) - Z_3(t-2)) + 0.159(Z_1(t-2) - Z_1(t-3)) \\ & + 0.159(Z_2(t-2) - Z_2(t-3)) - 0.1724(Z_3(t-2) - Z_3(t-3)) \\ & + Z_3(t-1) + a_3(t) \end{aligned}$$

The performance of this model can be seen from its compliance with the white noise assumption, indicated by the MAPE value of 2.021% in the training data and 2.045% in the testing data. The prediction results obtained are not very different from the actual data, as they produce MAPE values that fall into the category of highly accurate prediction results. To enhance the GSTAR $(2_1)I(1)$ model's performance for forecasting bird's eye chili prices, further validation using new data is recommended to ensure robustness.

Incorporating external factors like weather and supply chain disruptions may improve accuracy, and comparing the model with alternatives like ARIMAX or machine learning models could identify better fits.

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