Shallot Price Forecasting in Three Locations in Indonesia Using Generalized Space-Time Autoregressive Model

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Abstract

Shallots are one of the commodities that have an important role for the economy in Indonesia. Many shallot farmers, especially in production center areas, depend for their economy on shallot farming. The price of shallots in Indonesia during 2010-2022 fluctuated quite a bit. This is because the demand for shallots tends to increase over time, while shallot production is seasonal, and the distribution is uneven. The fluctuation of shallot prices and the huge costs of shallot farming result in risk and uncertainty for farmers. The forecasting method used is Generalized Space-Time Autoregressive (GSTAR). The results of the best model for predicting shallot prices in three locations in Indonesia, namely Cirebon, Tegal, and Madiun based on RMSE values, namely the GSTAR (31)-I(1) model use inverse distance normalization weights. Forecasting results for the highest shallot prices in Cirebon, Tegal and Madiun occur in the first week of August 2022. Meanwhile the lowest shallot prices in Cirebon and Madiun occur in the fifth week of August 2022, however the lowest shallot prices in Tegal occur in the fourth week of August 2022. Shallot price movement patterns in Cirebon, Tegal, and Madiun for the next 14 periods will continue to fluctuate but tends to show a downward trend. This was caused by several regions entering the harvest season, resulting in a spike in yields at the same time. As a result, the yield of shallots in the three locations was abundant and caused the price of shallots to decrease.

Keywords: Forecasting; GSTAR; Shallot prices

1. Introduction

Red onion (*Allium Cepa L.*) is a strategic horticultural commodity and has high economic value [1]. Household consumption of shallots during the 2002-2021 period relatively fluctuated but tended to increase every year. The demand for shallots tends to increase at any time, while the production of shallots is seasonal and the uneven distribution causes fluctuations in the price of shallots. During the off season, the government will adopt an import policy to overcome the shortage of shallots and maintain shallot price stability. However, the inappropriate timing and amount of imports caused an increase in the supply of red goods, so that the price of shallots fell and if not followed by a decrease in farming costs, it will be a cause of loss to farmers. These losses will make farmers not intensive in increasing onion productivity, so that in the following season productivity will decrease [2].

Many shallot farmers, especially in production center areas, depend for their economy on shallot farming. However, the fluctuating price of these onions and the enormous farming costs result in risks and uncertainties for farmers [3]. Farmers in production centers generally have the same planting season, so there is usually a spike in yields at the same time. As a result of the abundant harvest, the price of shallots will drop in every region. This can be indicated that there is a relationship between locations on the price of shallots in Indonesia.

Therefore a forecasting method is needed, namely GSTAR which combines elements of time and location dependencies and there are assumptions that the parameters are allowed to differ for each location, so that the GSTAR model can be used to predict the price of shallots in several locations in Indonesia, namely West Java which is represented by Cirebon, Central Java represented by Tegal, and East Java represented by Madiun. So that, it is hoped that this research can produce predictions that can be used as information and as a basis for the efforts of shallot farmers to plan and prepare the right time for planting shallots in order to get a good selling price. A good selling proce is a price where there is at least no loss or even profit from production costs. For example, the previous studies of [4] with tittle Generalized Space-Time Autoregressive (GSTAR) Model on Farmers' Exchange Rate Data (Case Study: Farmers' Exchange Rate Data of East Java Province, Central Java Province, and West Java Province Period January 2013-January 2021, the previous studies of [5] with tittle Comparison of VARIMA and Generalized Space Time ARIMA in Modeling Chili Prices, the previous studies of [6] with tittle Modeling Rice Prices on Sumatra Island Using the

Generalized Space Time ARIMA Model, the previous studies of [6] Analysis of National Shallot Price Forecasting Using the ARIMA Model, the previous studies of [7] with tittle Shallot Prices Forecasting in Malang Regency, the previous studies of [8] with tittle Shallot Prices Forecasting and Factors Affecting in North Sumatra, the previous studies of [9] with tittle Shallot Prices Forecasting and Fluctuations in Malang Regency, the previous studies of [10] with tittle Application of the ARCH-GARCH Model in Analyzing Red Onion Price Volatility, the previous studies of [11] with title Least Squares Estimation of Generalized Space Time Auto Regressive (GSTAR) Model and Its Properties, the previous studies of [12] with tittle Spatial Weight Determination of GSTAR (1;1) Model by Using Kernel Function, the previous studies of [13] with tittle Shallot Price Forecasting Models: Comparison among Various Techniques, the previous studies of [14] with tittle Estimated Price of Shallots Commodities National based on Parametric and Nonparametric approaches, the previous studies of [15] with tittle Forecasting The Price of Shallots and Red Chilies Using The ARIMAX Model, the previous studies of [16] with tittle Comparison between VAR, GSTAR, FFNN-VAR, and FFNN-GSTAR models for forecasting oil production, the previous studies [17] with tittle GSTAR: Generalized Storage-Aware Routing for Mobility First in The Future Mobile Internet, the previous studies of [18] with tittle GSTAR Computer Models and Their Applications, Part II: Applications, the previous studies of [19] with tittle Modelling of Energy Productivity Prediction Systems of Shallots Classification Growth Phase System Using Convolutional Neural Networks, the previous studies of [20] with tittle VAR and GSTAR-Based Feature Selection in Support Vector Regression for Multivariate Spatio-Temporal Forecasting.

2. Method

2.1 Method of Collecting Data

The data used in this study is secondary data regarding shallot prices in Cirebon, Tegal and Madiun which were obtained through the website of the National Strategic Food Price Information Center (PIHPS) from the first week of January 2019 to the fourth week of July 2022.

2.2 Research Variable

In this study the variable used is shallot price data in Cirebon, Tegal and Madiun with the data period from the first week of January 2019 to the fourth week of July 2022 with a total of 185 data. The data used was obtained from the National PIHPS website which was then compiled with the following data structure.

Table 1. Research Variable

Year	**Month**	**Sunday**	$\mathbf{Z_{1,t}}$	$\mathbf{Z_{2,t}}$	$\mathbf{Z_{3,t}}$
2019	January	1	$Z_{1,1}$	$Z_{2,1}$	$Z_{3,1}$
		2	$Z_{1,2}$	$Z_{2,2}$	$Z_{3,2}$
		3	$Z_{1,3}$	$Z_{2,3}$	$Z_{3,3}$
		4	$Z_{1,4}$	$Z_{2,4}$	$Z_{3,4}$
	:	:	:	:	:
	December	1	$Z_{1,48}$	$Z_{2,48}$	$Z_{3,48}$
		2	$Z_{1,49}$	$Z_{2,49}$	$Z_{3,49}$
		3	$Z_{1,50}$	$Z_{2,50}$	$Z_{3,50}$
		4	$Z_{1,51}$	$Z_{2,51}$	$Z_{3,51}$
:	:	:	:	:	:
2022	January	1	$Z_{1,157}$	$Z_{2,157}$	$Z_{3,157}$
		2	$Z_{1,158}$	$Z_{2,158}$	$Z_{3,158}$
		3	$Z_{1,159}$	$Z_{2,159}$	$Z_{3,159}$
		4	$Z_{1,160}$	$Z_{2,160}$	$Z_{3,160}$
	:	:	:	:	:
	July	1	$Z_{1,183}$	$Z_{2, 183}$	$Z_{3, 183}$
		2	$Z_{1,184}$	$Z_{2,184}$	$Z_{3,184}$
		3	$Z_{1,185}$	$Z_{2,185}$	$Z_{3,185}$
		4	$Z_{1,186}$	$Z_{2,186}$	$Z_{3,186}$

Information:

$Z_{1,t}$: Shallot Price in Cirebon

$Z_{2,t}$: Shallot Price in Tegal

$Z_{3,t}$: Shallot Price in Madiun

2.3 Analysis Step

The steps of analysis in this study include the following.

1. Describe the characteristics of shallot price data in Cirebon, Tegal, and Madiun.
2. Dividing the data into two parts, namely in-sample data totaling 148 data to form forecast models and out-sample data to validate forecasting model totaling 37 data.
3. Perform GSTAR modeling for each location, namely Cirebon, Tegal, and Madiun with the following steps.
   a. Identification stage with the following steps.
      1) Identifying shallot price data patterns at three locations using time series plots
      2) Checking the stationarity of the data in the mean through the MCCF plot, where if the data is not stationary in the mean then differencing is done.
      3) Determines the spatial order is 1
      4) Identify the time order based on the smallest MPCCF and AIC plots from stationary data.
   b. Estimation stage with the following steps.
      1) Determining the value of spatial weights using distance inverse normalization weights and partial normalization of cross-correlation.
      2) Estimating model parameters using the Generalized Least Square method.
      3) Perform GSTAR model parameter significance test.
      4) Get the GSTAR model for each location, namely Cirebon, Tegal, and Madiun.
   c. Conducting diagnostic model testing including white noise testingand normally distributed test.
   d. Selecting the best GSTAR model using the RMSE goodness-of-fit criteria.
4. Forecasting shallot prices in Cirebon, Tegal, and Madiun.
5. Interpret the results of the analysis.
6. Draw conclusions and suggestions.

3. Results and Discussion

Forecasting the price of shallots in Cirebon, Tegal and Madiun uses data from the first week of January 2019 to the fourth week of July 2022 with analysis including data characteristics, the best GSTAR model, and forecast results with the best GSTAR model as follows.

3.1 Shallot Price Characteristics in Cirebon, Tegal, and Madiun

The location mapping used in this study, Cirebon, Tegal, and Madiun is shown in Figure 1.

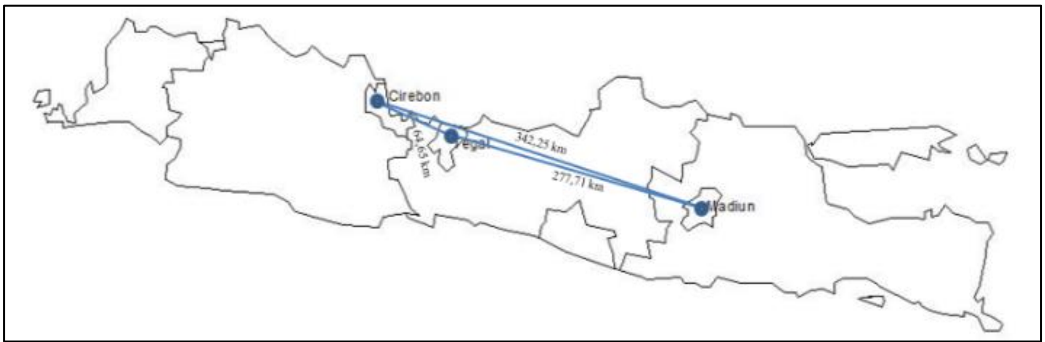

Figure 1. Map of Research Locations in Three Shallot Price Locations in Indonesia

Figure 1 shows the location of the three locations along with the distance between them. The distance between Cirebon and Tegal is 64.65 km, while the distance between Cirebon and Madiun is 342.5 km, and the distance between Tegal and Madiun is 277.71 km.

Characteristics of shallot prices in Cirebon, Tegal and Madiun using descriptive statistics are shown in Table 2.

Table 2. Shallot Price Characteristics in Cirebon, Tegal, and Madiun

Location	*Means*	Standard Deviation	Min	Max
Cirebon	30,276	8,845	15,950	69,000
Tegal	29,958	8,939	15,000	70,500
Madiun	30,252	8,972	16,500	75,500

Table 2 shows that the highest average price of shallots from the three locations is Cirebon, which is IDR 30,276/kg, with the highest price, IDR 69,000/kg and the lowest price, IDR 15,950/kg. Based on the standard deviation value, it can be seen that the highest level of shallot price variation is in Madiun, which is IDR 8,972/kg.

The results of the descriptive statistical analysis of shallot prices by month for each location are shown in Table 3.

Table 3. Average Monthly Shallot Prices in Cirebon, Tegal and Madiun 2019-2022

Month	Cirebon	Tegal	Madiun
January	24,330	24,371	26,497
February	25,934	24,691	28,078
March	31,164	28,672	31,131
April	35,314	33,286	33,613
May	36,357	36,458	35,213
June	**39,473**	**39,116**	38,131
July	36,228	38,061	**38,444**
August	25,807	26,408	26,456
September	22,756	22.134	21,867
October	25,996	26,200	24,204
November	26,779	28,421	26,363
December	28,372	27,005	27,843

Table 3 shows that the highest average shallot price in Cirebon is June 2019-2022 amounting to IDR 39,473/kg, while the highest average shallot price in Tegal is June 2019-2022 amounting to IDR 39,116//kg. as well as the highest average price of shallots in Madiun, namely July 2019-2022 of IDR 38,444/kg.

The movement of shallot price data in Cirebon, Tegal and Madiun from the first week of January 2019 to the fourth week of July 2022 is explained in the form of a time series plot shown in Figure 2.

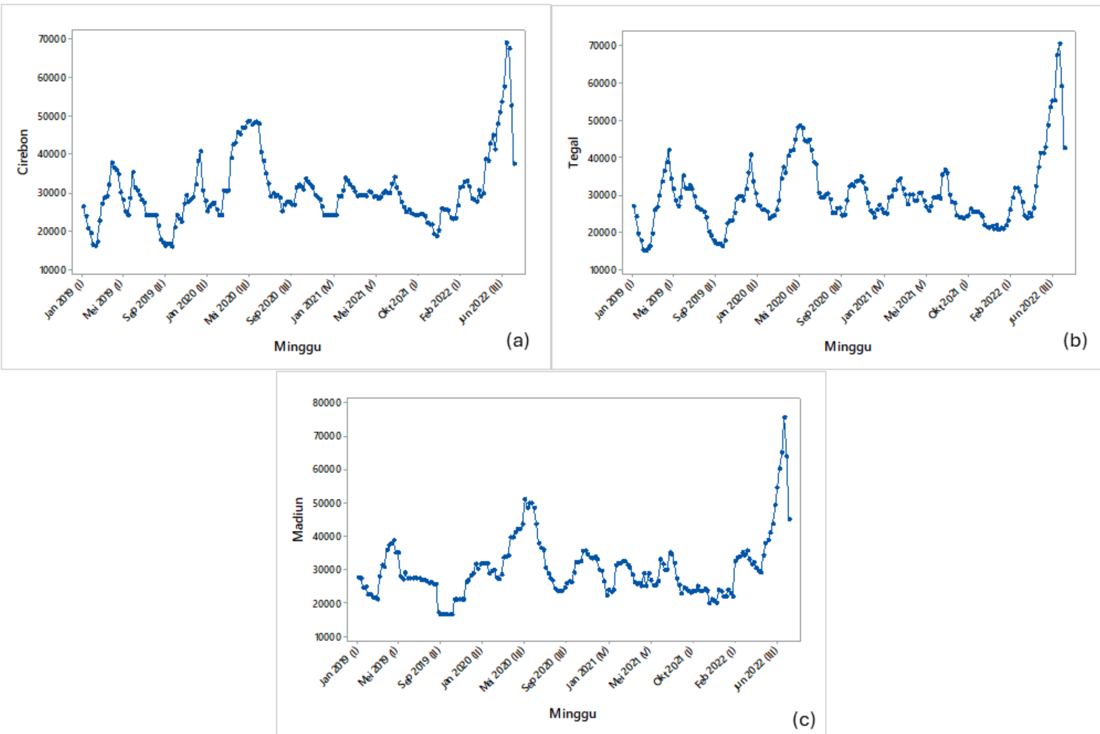

Figure 2. Time Series Plot of Shallot Prices in Cirebon (a), Tegal (b), and Madiun (c)

Figure 2 shows that the highest shallot price in Cirebon was in the first week of July 2022, while the lowest shallot price in Cirebon was in the fifth week of September 2019. The highest shallot price in Tegal was in the second week of July 2022, while the The lowest shallot price is in Tegal in the second week of February 2019. The highest shallot price in Madiun is in the second week of July 2022, while the lowest shallot price is in the second week of September to the second week of October 2019.

The movement pattern of high and low shallot prices in three locations indicates that there is the same pattern every week, namely when the price of shallots in one location rises, the price of shallots in other locations also tends to rise, and vice versa. Shallot prices in three locations are related at the same time, this can be proven based on the correlation values between locations in Table 4.

Table 4. Shallot Price Correlation Value Between Locations

	Cirebon	**Tegal**
Tegal	0.959	
p-values	0.00	
Madiun	0.910	0.920
p-values	0.00	0.00

Table 4 shows that the three locations, Cirebon, Tegal, and Madiun, are correlated with each other. This can be seen from the very high correlation values between Cirebon and Tegal, Cirebon and Madiun, and Tegal and Madiun, respectively 0.959, 0.910 and 0.920, and reinforced by the three p-value values of 0.00 which are smaller than α (0.05). This can be interpreted if the price of shallots in a location is high, then the price of shallots in Tegal will also be high, and vice versa. This also happened between Cirebon and Madiun locations and Tegal and Madiun.

Next, the price of shallots at the three locations is visualized using the boxplot in Figure 3.

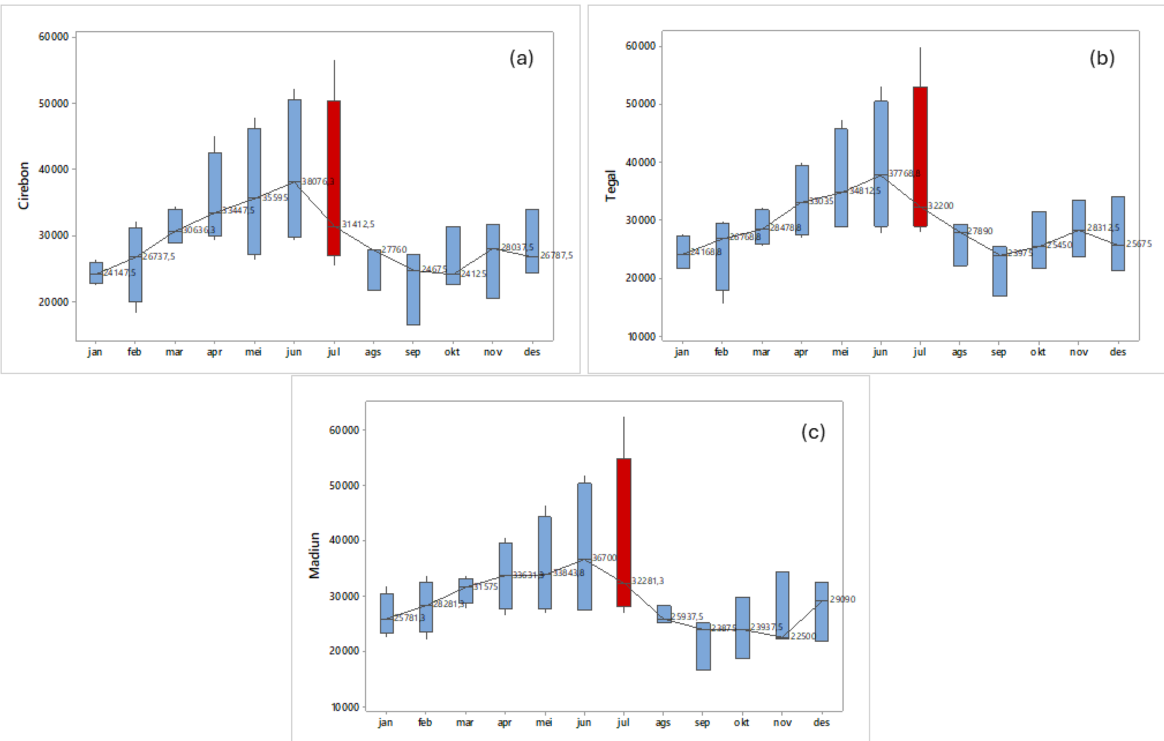

Figure 3. Box Plot Shallot Prices in Cirebon (a), Tegal (b), and Madiun (continued) (c)

Figure 3 shows the price of shallots in Cirebon, Tegal and Madiun by month for 3.5 years. The high disparity or difference in shallot prices is visually shown in the longest boxplot. Shallot prices in three locations showed the highest disparity in July. The boxplot of shallot prices in Cirebon in July has a median value of IDR 31,412.50, which means that 50 percent of the data is above and below IDR 31,412.50. The variance in the data above the median is greater than the variance in the data below the median, so the boxplot of shallot prices in Cirebon in July is said to be asymmetric. The boxplot of shallot prices in Tegal in July has a median value of Rp. 32,200.00, which means that 50 percent of the data is above and below Rp. 32,200.00. The variance in the data above the median is greater than the variance in the data below the median, so the boxplot of shallot prices in Tegal in July is said to be asymmetric. The boxplot of shallot prices in Madiun in July has a median value of IDR 32,281.30, which means that 50 percent of the data is above and below IDR 32,281.30. The variance in the data above the median is greater than the variance in the data below the median, so the boxplot for shallot prices in Madiun in July is said to be asymmetric.

3.2 GSTAR Model Shallot Prices in Cirebon, Tegal and Madiun

The analysis phase in GSTAR modeling consists of stationarity identification, model identification, parameter estimation, model significance, model diagnostic check and selection of the best model.

1. Stationarity Identification

Variable/Lag	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Cirebon	+++	+++	+++	+++	+++	+++	+++	+++	..+	...	...	...	...	...	...	...	...	...
Tegal	+++	+++	+++	+++	+++	+++	..+	...	...	...	.-.	.--	.--	.--	..-	...	...	...
Madiun	+++	+++	+++	+++	+++	+++	+++	..+	...	...	...	...	...	...	...	...	...	...
Variable/Lag	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**
Cirebon	...	...	...	...	...	...	...	...	...	...	...	-..	-..	-..	-..	--.	--.	---
Tegal	...	...	...	...	...	...	...	...	...	...	...	...	-..	-..	-..	-..	--.	--.
Madiun	...	...	...	...	...	...	-..	-..	---	---	---	---	---	---	---	---	---	---

Figure 4. MCCF Plot of Shallot Prices in Cirebon, Tegal, and Madiun

Figure 4 shows that positive and negative symbols appear in almost all lags, which means that the shallot price data in Cirebon, Tegal and Madiun are not stationary. Data that is not stationary needs to be overcome by differencing the order d=1. The results of the MCCF plot after the differencing process is shown in Figure 5.

Variable/Lag	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Cirebon	+++	..+	..+	...	...	...	...	...	...	...	.-.	--.	..-	..-	...	...	...	...
Tegal	+++	..+	...	...	...	...	.-.	.-.	..-	..-	.-.	-..	..-	..-	...	...	...	...
Madiun	.+.	...	...	...	-..	.-.	---	...	...	...	...	...	...	...	...	...	+..	...
Variable/Lag	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**
Cirebon	...	...	...	...	...	...	...	...	...	...	...	-..	...	...	...	...	...	...
Tegal	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
Madiun	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...

Figure 5. MCCF Plot of Shallot Prices in Cirebon, Tegal, and Madiun Differencing Results (d=1)

Figure 5 shows that the positive and negative symbols that appear after differencing are fewer and only at certain lags, which means that the shallot price data in Cirebon, Tegal and Madiun are stationary. Next, identify the GSTAR model using stationary shallot price data.

2. GSTAR Model Identification

Identification of the model order is done by looking at the MPCCF plot of data that is already stationary and also by looking at the smallest AIC value. MPCCF plots and AIC values can be seen in Figure 7 and Table 5.

Variable/Lag	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Cirebon	.++	-.+	.+.	...	...	...	...	...	.+.	...	...	-..	...	...	...	...	...	...
Tegal	..+	..+	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	.-.
Madiun	...	...	...	...	-..	...	...	+..	...	...	...	...	...	.-.	...	...	+..	...
Variable/Lag	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**
Cirebon	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
Tegal	...	.-.	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
Madiun	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...

Figure 6. MPCCF Plot of Diffferencing Shallot Prices (d=1)

Figure 6 shows that the MPCCF is cut off or truncated at lags 1, 2 and 3. This can be seen from the three positive or negative sign locations that appear in lags 1, 2, and 3. Meanwhile the smallest AIC value is also located at lag AR 3. Therefore, based on the MPCCF plot and the smallest AIC value, the GSTAR model formed is GSTAR(31)-I(1).

Table 5. Model AIC ValueGSTAR(31)-I(1)

lag	**MA 0**
AR 0	45,996
AR 1	45,715
AR 2	45,689
AR 3	45,685*
AR 4	45,744
AR 5	45,799
AR 6	45,936

3. Parameter Estimation and Parameter Significance Testing of the GSTAR Model

The GSTAR model is a model for time series data that takes into account spatial and location factors. This location factor is indicated by the weighting given to each variable. The weights used are uniform weight, distance inverse, and cross-correlation normalization.

a. GSTAR Model Parameter Estimation with Distance Inverse Normalized Weights

GSTAR modeling with inverse distance normalization weights assumes that the price of shallots at a location is affected by the distance it has from other locations. The distance between two distant locations tends to have less weight than the distance between two close locations.

The inverse distance normalization weight matrix formed between each location by normalizing the inverse value of the distance between locations is as follows.

$$\begin{array}{cc} & \begin{array}{ccc} \textit{Cirebon} & \textit{Tegal} & \textit{Madiun} \end{array} \\ \mathbf{W}_{ij} = & \begin{bmatrix} 0 & 0.8423 & 0.1576 \\ 0.8115 & 0 & 0.1885 \\ 0.4462 & 0.5538 & 0 \end{bmatrix} \begin{array}{c} \textit{Cirebon} \\ \textit{Tegal} \\ \textit{Madiun} \end{array} \end{array}$$

Model parameter estimation results GSTAR (31)-I(1) with distance inverse weights has18 parameters, but when viewed from the p-value of each parameter it is known that not all parameters have a significant effect on the model. Therefore, the insignificant variables were removed one by one until all parameters were significant $\alpha = 0,05$. Significant variables are shown in Table 6.

Table 6. Model Parameter Estimation GSTAR (31)-I(1) with Distance Inverse Normalized Weights

Location	**Parameter**	**Estimation**	***Standard Error***	***T-values***	***P-values***	**Variable**
Cirebon	ϕ_{10}^{1}	0.269	0.079	3.43	0.0008	$(Z_{1,t-1})$
Tegal	ϕ_{21}^{1}	0.509	0.079	6.37	<0.0001	$(V_{2,t-1})$
	ϕ_{20}^{3}	-0.242	0.075	-3.23	0.0015	$(Z_{2,t-3})$
	ϕ_{21}^{3}	0.309	0.086	3.60	0.0004	$(V_{2,t-3})$
Madiun	ϕ_{31}^{1}	0.359	0.083	4.33	<0.0001	$(V_{3,t-1})$
	ϕ_{31}^{2}	0.276	0.080	3.45	0.0007	$(V_{3,t-2})$

Table 6 shows that based on the significant parameters, a mathematical equation model can be formed in the form of a matrix for the model GSTAR (31)-I(1)by using distance inverse normalized weights.

$$\begin{bmatrix} Z^*_{1,t} \\ Z^*_{2,t} \\ Z^*_{3,t} \end{bmatrix} = \begin{bmatrix} 0.269 & 0 & 0 \\ 0.413 & 0 & 0.096 \\ 0.160 & 0.199 & 0 \end{bmatrix} \begin{bmatrix} Z^*_{1,t-1} \\ Z^*_{2,t-1} \\ Z^*_{3,t-1} \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0.123 & 0.153 & 0 \end{bmatrix} \begin{bmatrix} Z^*_{1,t-2} \\ Z^*_{2,t-2} \\ Z^*_{3,t-2} \end{bmatrix}$$
$$+ \begin{bmatrix} 0 & 0 & 0 \\ 0.251 & -0.242 & 0.058 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} Z^*_{1,t-3} \\ Z^*_{2,t-3} \\ Z^*_{3,t-3} \end{bmatrix} + \begin{bmatrix} e_{1,t} \\ e_{2,t} \\ e_{3,t} \end{bmatrix}$$

Variable $z^*_{i,t}$ is the result of differencing 1 of $z_{i,t}$ which is the original data, so

$$\begin{aligned} Z^*_{i,t} &= (1-B)Z_{i,t} \\ &= Z_{i,t} - Z_{i,t-1} \end{aligned}$$

The equation model in matrix form is then translated into variables $z^*_{i,t}$ substituted into the equation. So that the form of the GSTAR model is obtained which is used to predict shallot prices in the three locations, namely Cirebon, Tegal, and Madiun.

1) Model GSTAR (31)-I(1) in Cirebon

$$\hat{Z}_{1,t} = 1.269Z_{1,t-1} - 0.269Z_{1,t-2} + e_{1,t}$$

2) Model GSTAR (31)-I(1) in Tegal

$$\begin{aligned} \hat{Z}_{2,t} = {} & Z_{2,t-1} + 0.413Z_{1,t-1} - 0.413Z_{1,t-2} + 0.096Z_{3,t-1} - 0.096Z_{3,t-2} \\ & +0.251Z_{1,t-3} - 0.251Z_{1,t-4} - 0.242Z_{2,t-3} + 0.242Z_{2,t-4} + 0.058Z_{3,t-3} \\ & -0.058Z_{3,t-4} + e_{2,t} \end{aligned}$$

3) Model GSTAR (31)-I(1) in Madiun

$$\begin{aligned} \hat{Z}_{3,t} = {} & Z_{3,t-1} + 0.160Z_{1,t-1} - 0.037Z_{1,t-2} - 0.123Z_{1,t-3} + 0.199Z_{2,t-1} \\ & -0.046Z_{2,t-2} - 0.153Z_{2,t-3} + e_{3,t} \end{aligned}$$

Model results GSTAR (31)-I(1) using distance inverse normalized weightsfor each location shows that the price of shallots in Cirebon is affected by the price of shallots in Cirebon itself in 1 week and 2 weeks before. The price of shallots in Tegal is influenced by the price of shallots in Tegal itself and the price of shallots in Cirebon and Madiun in the 1 to 4 weeks beforehand. The price of shallots in Madiun is influenced by the price of shallots in Madiun itself and the price of shallots in Cirebon and Tegal in the 1 to 3 weeks beforehand.

b. GSTAR Model Parameter Estimation with Cross Correlation Partial Normalized Weights

GSTAR modeling with partial normalized cross-correlation weights assumes that the relationship between shallot prices between locations is influenced by the correlation between shallot prices in one location and another. The lags used in this analysis are lags 1, 2, and 3 adjusted for the time order of the GSTAR model. The partial cross-correlation weight matrix based on the MPCCF plot and the partial cross-correlation values used in this analysis is as follows.

$$\begin{array}{cc} & \begin{array}{ccc} \textit{Cirebon} & \textit{Tegal} & \textit{Madiun} \end{array} \\ \mathbf{W}_{ij}(1) = & \begin{bmatrix} 0 & 0.681 & 0.319 \\ 0.020 & 0 & 0.980 \\ 0.216 & 0.784 & 0 \end{bmatrix} \begin{array}{c} \textit{Cirebon} \\ \textit{Tegal} \\ \textit{Madiun} \end{array} \end{array}$$

$$\mathbf{W}_{ij}(2) = \begin{bmatrix} 0 & 0.248 & 0.752 \\ -0.262 & 0 & 0.738 \\ 0.919 & 0.081 & 0 \end{bmatrix} \begin{array}{c} \textit{Cirebon} \\ \textit{Tegal} \\ \textit{Madiun} \end{array}$$

$$\mathbf{W}_{ij}(3) = \begin{bmatrix} 0 & 0.835 & 0.165 \\ -0.211 & 0 & 0.789 \\ -0.394 & 0.606 & 0 \end{bmatrix} \begin{array}{c} \textit{Cirebon} \\ \textit{Tegal} \\ \textit{Madiun} \end{array}$$

Model parameter estimation results GSTAR (31)-I(1) with partial normalized cross-correlation weights has18 parameters, but when viewed from the p-value of each parameter it is known that not all parameters have a significant effect on the model. Therefore, the insignificant variables were removed one by one until all parameters were significant $\alpha = 0,05$. Significant variables are shown in Table 7.

Table 7. Model Parameter EstimationGSTAR(31)-I(1) with Cross Correlation Partial Normalized Weights

Location	**Parameter**	**Estimation**	***Standard Error***	***T-values***	***P-values***	**Variable**
Cirebon	ϕ_{11}^{1}	0.299	0.101	2.95	0.0037	$(V_{1,t-1})$
	ϕ_{10}^{2}	-0.183	0.072	-2.56	0.0116	$(Z_{1,t-2})$
	ϕ_{11}^{2}	0.211	0.079	2.64	0.0091	$(V_{1,t-2})$
	ϕ_{10}^{3}	-0.129	0.064	-2.02	0.0455	$(Z_{1,t-3})$
Tegal	ϕ_{20}^{1}	0.322	0.075	4.32	<0.0001	$(Z_{2,t-1})$
Madiun	ϕ_{31}^{1}	0.324	0.083	3.87	0.0002	$(V_{3,t-1})$
	ϕ_{31}^{3}	0.249	0.080	3.11	0.0023	$(V_{3,t-2})$

Table 7 shows that based on the significant parameters, a mathematical equation model can be formed in the form of a matrix for the modelGSTAR(31)-I(1)by using the partial normalized weight of cross-correlation.

$$\begin{bmatrix} Z_{1,t}^{*} \\ Z_{2,t}^{*} \\ Z_{3,t}^{*} \end{bmatrix} = \begin{bmatrix} 0 & 0.204 & 0.095 \\ 0 & 0.322 & 0 \\ 0.069 & 0.254 & 0 \end{bmatrix} \begin{bmatrix} Z_{1,t-1}^{*} \\ Z_{2,t-1}^{*} \\ Z_{3,t-1}^{*} \end{bmatrix} + \begin{bmatrix} -0.183 & 0.052 & 0.159 \\ 0 & 0 & 0 \\ 0.054 & 0.195 & 0 \end{bmatrix} \begin{bmatrix} Z_{1,t-2}^{*} \\ Z_{2,t-2}^{*} \\ Z_{3,t-2}^{*} \end{bmatrix} + \begin{bmatrix} -0.129 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} Z_{1,t-3}^{*} \\ Z_{2,t-3}^{*} \\ Z_{3,t-3}^{*} \end{bmatrix} + \begin{bmatrix} e_{1,t} \\ e_{2,t} \\ e_{3,t} \end{bmatrix}$$

Variable $Z^*_{i,t}$ is the result of differencing 1 of $Z_{i,t}$ which is the original data, so

$$\begin{aligned} Z^*_{i,t} &= (1-B)Z_{i,t} \\ &= Z_{i,t} - Z_{i,t-1} \end{aligned}$$

The equation model in matrix form is then translated into variables $Z^*_{i,t}$ substituted into the equation. So that the form of the GSTAR model is obtained which is used to predict shallot prices in the three locations, namely Cirebon, Tegal, and Madiun.

1) Model GSTAR (31)-I(1) in Cirebon

$$\begin{aligned} \hat{Z}_{1,t} &= Z_{1,t-1} + 0.204Z_{2,t-1} - 0.152Z_{2,t-2} + 0.095Z_{3,t-1} + 0.064Z_{3,t-2} \\ &-0.183Z_{1,t-2} + 0.054Z_{1,t-3} - 0.052Z_{2,t-3} - 0.159Z_{3,t-3} + 0.129Z_{1,t-4} + e_{1,t} \end{aligned}$$

2) Model GSTAR (31)-I(1) in Tegal

$$\hat{Z}_{2,t} = 1.322Z_{2,t-1} - 0.322Z_{2,t-2} + e_{2,t}$$

3) Model GSTAR (31)-I(1) in Madiun

$$\begin{aligned} \hat{Z}_{3,t} &= Z_{3,t-1} + 0.069Z_{1,t-1} - 0.015Z_{1,t-2} + 0.254Z_{2,t-1} - 0.059Z_{2,t-2} \\ &-0.054Z_{1,t-3} - 0.195Z_{2,t-3} + e_{3,t} \end{aligned}$$

The results of the GSTAR (31)-I(1) model using the normalized cross-correlation weights for each location show that the shallot price in Cirebon is affected by the shallot price in Cirebon itself and the shallot price in Tegal and Madiun from 1 week to 4 weeks before. The price of shallots in Tegal is influenced by the price of shallots in Tegal itself in the 1 week and 2 weeks before. The price of shallots in Madiun is influenced by the price of shallots in Madiun itself and the price of shallots in Cirebon and Tegal in the 1 to 3 weeks beforehand.

4. Diagnostic Check for Residual White Noise and Normal Distribution

Residual diagnostic examination consists of white noise examination and normal distribution of residual diagnostic examination.

a. Check Residual White Noise Diagnostic

Examination of white noise residuals is carried out to find out whether the model residuals are identical and independent. Residual checks that are identical can be seen using the ARCH-LM test shown in Table 8.

Table 8. ARCH-LM Test Statistics GSTAR(31)-I(1)

Model	**Location**	**F**	**$F_{0,05(3,139)}$**	***P-values***	**Decision**
GSTAR(31)-I(1)	Cirebon	0.01	2.67	0.9260	Failed to Reject H0
Distance Inverse	Tegal	0.63		0.4302	Failed to Reject H0
Normalized Weights	Madiun	0.80		0.3728	Failed to Reject H0
GSTAR(31)-I(1) Cross	Cirebon	0.00		0.9708	Failed to Reject H0
Correlation Partial	Tegal	0.67		0.4154	Failed to Reject H0
Normalized Weights	Madiun	0.34		0.5588	Failed to Reject H0

Table 8 shows that at the Cirebon, Tegal, and Madiun locations from GSTAR(31)-I(1) using inverse distance normalized weights and normalized cross-correlation weights respectively have an F value of less than $F_{0,05(3,139)}$ of 2.67, and reinforced by a p-value of more than α of 0.05 means that the residual model at the Cirebon, Tegal, and Madiun locations is identical or the residual variance is homogeneous. Furthermore, an independent examination was carried out using the Durbin Watson test shown in Table 9.

Table 9. Durbin Watson Test Statistics GSTAR(31)-I(1)

Model	**Location**	***D***	***d_L***	***d_U***	**Decision**
	Cirebon	2,177	1.68	1.76	Failed to Reject H0
	Tegal	2,139			Failed to Reject H0

GSTAR(31)-I(1) Distance Inverse Normalized Weights	Madiun	2.07		Failed to Reject H0
GSTAR(31)-I(1) Cross Correlation Partial Normalized Weights	Cirebon	2,091		Failed to Reject H0
	Tegal	2,209		Failed to Reject H0
	Madiun	2,064		Failed to Reject H0

Table 9 shows that at the Cirebon, Tegal, and Madiun locations from GSTAR(31)-I(1) using distance inverse weights and normalized cross-correlation weights respectively, the d_U value is 1.76 and 4-d_U value is 2.24 means that the residual model at the Cirebon, Tegal, and Madiun locations is independent or there is no autocorrelation.

b. Normal Distribution Residual Diagnostic Check

Examination of the residual normal distribution univariately using the Jarque-Bera Normality test shown in Table

Table 10. Statistical Test for Jarque-Bera Normality GSTAR(31)-I(1)

Model	**Location**	χ^2	$\chi^2_{(0,05;2)}$	***P-values***	**Decision**
GSTAR (31)-I(1) Distance Inverse Weights	Cirebon	126.92	5.99	<0.0001	Reject H0
	Tegal	41.99		<0.0001	Reject H0
	Madiun	1.64		0.4413	Failed to Reject H0
GSTAR (31)-I(1) Cross Correlation Normalized Weights	Cirebon	106.98		<0.0001	Reject H0
	Tegal	36,12		<0.0001	Reject H0
	Madiun	2.52		0.2830	Failed to Reject H0

Table 10 shows that at the Cirebon and Tegal locations the GSTAR (31)-I(1) model using the inverse distance normalization weights and the normalized cross-correlation weights respectively has a value of more than 5.99 meaning that the residual model at the Cirebon and Tegal locations is not normally distributed. Meanwhile, at the Madiun location, the GSTAR (31)-I(1) moswl used distance inverse normalization weights and normalized cross-correlation weights respectively had a value of less than 5.99, meaning that the residual model at the Madiun location was normally distributed. It is suspected that there are residual outliers from the three locations as shown in Figure 7.

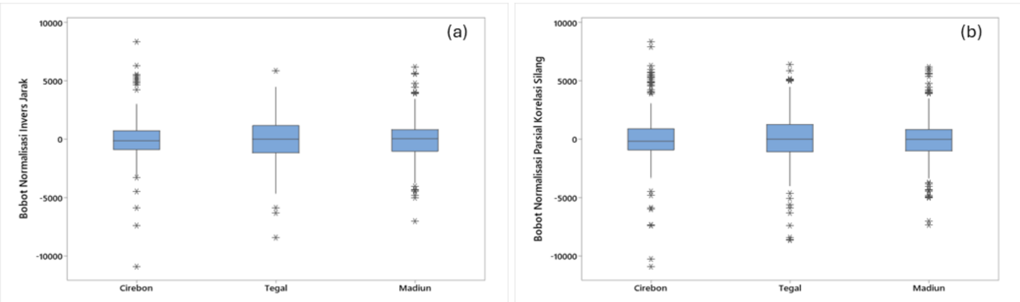

Figure 7. Box Plot Residual Shallot Prices in Cirebon, Tegal, and Madiun Using Weights Normalized Inverse Distance (a), and Partial Normalized Cross Correlation (b)

Figure 7 shows that there are outlier residuals in the GSTAR(31)-I(1) model using distance inverse normalized weights and partial normalized cross-correlation weights at each location which causes the data to not be normally distributed. However, in this case no handling of outlier data was carried out

3.3 Selection of the Best Shallot Price Forecasting Model in Cirebon, Tegal, and Madiun

Selection of the best forecasting model by calculating the RMSE value of *out samples* the three locations using two weights are shown in Table 11.

Table 11. RMSE Best Model Criteria

Model	**RMSE**			**RMSE Total**
	Cirebon	**Tegal**	**Madiun**	
GSTAR(31)-I(1) Distance Inverse Normalized Weights	**4533,66***	**3857.98***	**4279.06***	**4232.74***

GSTAR(31)-I(1) Cross Correlation Partial Normalized Weights	4659,47	4056.51	4430.51	4389.20

Table 11 shows the results of a comparison of the RMSE values of the models at the three locations using three weights. The best model was chosen based on the smallest RMSE value at each location and the smallest total RMSE value (with asterisk). The best model for the Cirebon, Tegal, and Madiun locations is GSTAR(31)-I(1) with inverse distance normalized weights. The best RMSE should have a small value, so the RMSE value is large, because the presence of outliers in the data can have a large influence on the RMSE. Outliers are values that are far from the general pattern or majority of the data, and their presence can increase the error of the prediction model.

Shallot price forecast results at three locations for data insample and an outsample with the GSTAR(31)-I(1) model using distance inverse normalized weights along with actual data on shallot prices at three locations is shown in Figure 8.

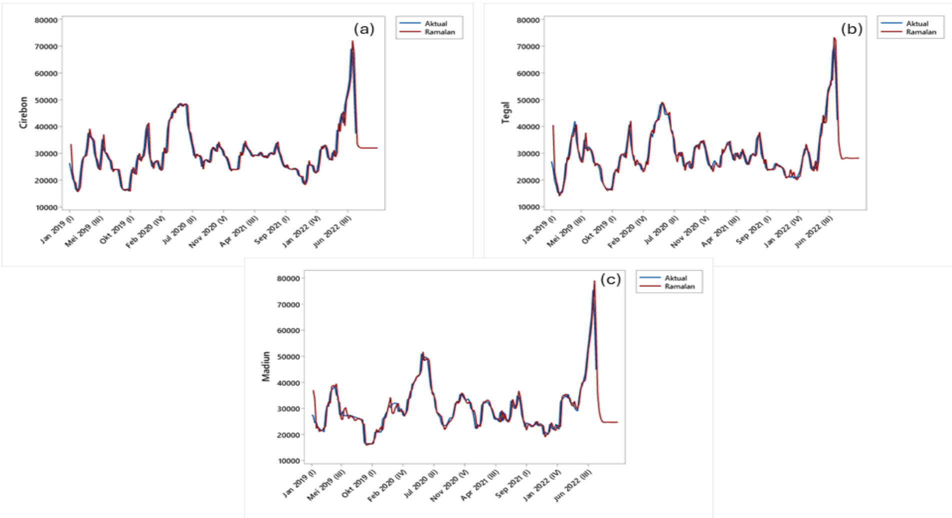

Figure 8. Time Series Plot of Actual Data and Forecast Results of Shallot Prices in Cirebon (a), Tegal (b), and Madiun (c)

Figure 8 shows that the blue line is actual data on the price of shallots, while the red line is the forecast result using the GSTAR (31)-I(1) model with inverse distance normalized weights for Cirebon, Tegal and Madiun locations. The forecast results for the insample and outsample data from the model move relatively fluctuate and approach the actual data on shallot prices.

3.4 Shallot Price Forecasting in Cirebon, Tegal, and Madiun

The best shallot price forecasting model obtained for the three locations is GSTAR(31)-I(1) with distance inverse normalized weights. This model is used for forecasting shallot prices in three locations for 14 periods starting from the first week of August 2022 to the fifth week of October 2022 as shown in Table 12.

Table 12. Shallot Price Forecasting 14 Periods

Period	Cirebon	Tegal	Madiun	Period	Cirebon	Tegal	Madiun
August (I)	33465*	34012*	35712*	September (III)	31980	28174	24780
August (II)	32380	29790	29008	September (IV)	31980	28128	24748
August (III)	32088	27839	26199	October (I)	31980	28156	24728
August (IV)	32009	27951	24984	October (II)	31980	28171	24727
August (V)	31988	28162	24660	October (III)	31980	28181	24734
September (I)	31982	28358	24706	October (IV)	31980	28173	24739
September (II)	31981	28243	24774	October (V)	31980	28170	24738

Table 12 shows that the highest shallot prices in Cirebon, Tegal and Madiun occurred in the first week of August 2022, IDR 33,465/kg, IDR 34,012/kg and IDR 35,712/kg respectively. The lowest shallot price in Cirebon occurred in the third week of September to the 2nd week of October 2022, IDR 31,980/kg, while the lowest shallot price in Tegal occurred in the third week of August 2022, IDR 27,839/kg and the lowest shallot price in Madiun occurs in the fifth week of August 2022, which is IDR 24,660/kg.

The pattern of shallot price movements in Cirebon, Tegal and Madiun over the next 14 periods will continue to fluctuate but tends to show a downward trend. This was caused by several regions entering the harvest season, resulting in a spike in yields at the same time. As a result, the yield of shallots in the three locations was abundant and caused the price of shallots to decrease.

4. Conclusions

A well-written conclusion gives you several opportunities to show the reader how well you understand the research problem. This includes providing the final word on the issues raised in your paper. Just as the introduction makes a first impression on your reader, the conclusion provides an opportunity to leave a lasting impression. For example, highlight key points in your analysis or findings. Summarizing your ideas and communicating the overall implications of your research. The conclusion provides an opportunity to succinctly answer the "so what?" question by placing the study in the context of previous research on the topic you've studied. Demonstrating the significance of your ideas. Do not be shy. The conclusion gives you an opportunity to elaborate on the significance of your findings. Introducing possible new or expanded ways of thinking about the research problem. This does not refer to introducing new information, but to offer new insight and creative approaches for framing/contextualizing the research problem based on the results of your study. Do not write the conclusion point by point.

Acknowledgment

Based on the results of the analysis that has been carried out, the movement of shallot prices in Cirebon, Tegal and Madiun over 14 periods tended to show a downward trend. This was caused by several regions entering the harvest period, resulting in a surge in yields at the same time which resulted in a decrease in the price of shallots. Shallot farmers should be able to plan different planting times between regions so that there is no bumper harvest which causes the price of shallots to continue to decline in the next period, so that farmers have different harvest times and do not sell their crops simultaneously between regions so that don't get the low price.

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