

Volatility, Seasonality, and Tomato Price Forecasting in Kupang City: Implications for Regional Price Stabilisation

Louis Marlina^{1*}, Irnad², Reflish²

¹Master of Agribusiness Study Program, Faculty of Agriculture, University of Bengkulu

²Department of Agricultural Socio-Economics, Faculty of Agriculture, University of Bengkulu.

*Corresponding Author

Louis Marlina

Email:

lmarlina@gmail.com

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Abstract: Tomatoes are a strategic horticultural commodity whose price instability has a direct impact on farmers' incomes, consumer purchasing power, and regional inflation, especially in cities in eastern Indonesia that depend on supply from outside the region. This study aims to characterize the dynamics, volatility, and seasonal patterns of tomato prices in Kupang City, compare the accuracy of forecasting *exponential smoothing models*, *moving averages*, and linear trends, and compile price forecasts for 2024. The data used are monthly retail prices for the period January 2019 to December 2023 (n = 60) sourced from the Central Statistics Agency of East Nusa Tenggara Province. All accuracy measures were calculated strictly on the basis of one-step forward forecasting using *mean absolute deviation*, *mean squared error*, *root mean squared error*, and *mean absolute percentage error*. The results showed an overall coefficient of variation of 26.41 percent, with the highest price of IDR 24,792 per kilogram occurring in January 2023 and the lowest price of IDR 7,083 per kilogram in October 2019. The most dominant feature of this series is the very strong annual seasonal cycle, where the seasonal index moves from 68.9 in September to 128.2 in April with a range of fifty-nine index points. The *Dickey-Fuller augmented* test rejects the unit root hypothesis so that data differentiation is not necessary. The slope coefficient of the linear trend is positive but not statistically significant and only explains 0.56 percent of price diversity. Among the three methods defined, *exponential smoothing* with a smoothing constant of 0.95 is the most accurate model with a *mean absolute percentage error* of 16.79 percent, followed by a two-period *moving average* of 19.63 percent and a linear trend of 23.71 percent. The inclusion of seasonal indices into the *exponential smoothing* model substantially reduced the error to 12.12 percent. The recommended forecast for 2024 ranges from IDR 9,698 per kilogram in September to IDR 18,041 per kilogram in April. These findings show that seasonality, not trends, should be the basis for analysis and policy for tomato price management in Kupang City.

Keywords: forecasting accuracy, *exponential smoothing*, tomato price, seasonal index, Kupang City, *moving average*.

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Introduction

Tomatoes (*Lycopersicon esculentum* Miller) are one of the horticultural commodities with high economic value that occupy an important position in Indonesian household consumption patterns. This commodity is multipurpose because it is not only consumed as fresh vegetables and fruits, but also used as raw materials for the food processing industry, cosmetic ingredients, and medicinal mixtures. The breadth of use makes the demand for tomatoes relatively stable throughout the year, while the supply is highly dependent on the growing season and agroclimatic conditions in the production center. The imbalance between demand stability and supply instability is the main source of tomato price volatility at the consumer level.

Theoretically, the price volatility of fresh horticultural products is a consequence of a combination of three structural conditions. Tomek and Kaiser (2014) explained that the supply of agricultural products is inelastic in the short term due to the biological gap between planting decisions and harvest realization, demand is also inelastic because this commodity is a complement to consumption that is difficult to substitute, while the very limited shelf life makes the formation of buffer stocks almost impossible. Gilbert and Morgan (2010) added that food price volatility is clustered, that is, periods of high volatility tend to be followed by periods of high volatility, so price shocks do not stand alone but continue in several consecutive periods. In the Indonesian context, the volatility pattern of major food commodities has been empirically proven by Sumaryanto (2009), while Nugrahapsari and Arsanti (2018) and Miftahuljanah et al. (2020) show that the volatility of horticultural commodities is relatively high, especially at the producer and wholesale levels.

Kupang City in East Nusa Tenggara Province has characteristics that strengthen this vulnerability. As the provincial capital with a limited horticultural production base and the geographical location of the archipelago, the fulfillment of tomato needs in this city depends on supply from surrounding districts and from outside the province, so prices at the retail level are very sensitive to disturbances in sea distribution, weather conditions, and transportation costs. Supriadi and Sejati (2018) emphasized that inter-island trade dynamics are the main determinants of price stability of horticultural commodities in areas that are not production centers. Timisela et al. (2020) show in the case of Ambon City that changes in selling prices at each distribution institution will accumulate and push prices at the final consumer level to be higher, a mechanism that structurally also applies to other island cities in eastern Indonesia.

Tomato price instability has two-way consequences. For consumers, price spikes suppress purchasing power and

encourage inflation in the foodstuffs group. For farmers, the price drop during the harvest season weakens the motivation to return to planting tomatoes, potentially reducing planting area and production in the following season. This cycle, if repeated, will widen the amplitude of price volatility in the coming years. The availability of anticipatory price information is therefore a real necessity, both for farmers in compiling planting calendars, for traders in managing stock procurement, and for local governments in setting the right time for market intervention.

Time series forecasting is the most practical instrument to answer this need. Makridakis et al. (1998) emphasized that the advantage of a forecasting model is not determined by the complexity of its specifications, but by the suitability between the model structure and the characteristics of the forecasted data. This principle is confirmed in various studies in Indonesia. Sukiyono and Janah (2019) found that the selection of a model for forecasting the price of horticultural commodities at the retail level should be based on the comparison of measurable error criteria and not on initial assumptions about the advantages of a method, and Sukiyono et al. (2018) reached a similar conclusion on cocoa price forecasting. In tomato commodities, Haba (2021) applied *the moving average* method to predict tomato production, while Yuniarti (2019) showed the application of *single exponential smoothing* in sales forecasting. Tsaur (2012) showed that the development of more complex time series models can improve accuracy, but such improvements are only meaningful if the data structure demands it.

Previous studies have left three gaps that are the basis of this study. First, the price of tomatoes in Kupang City has never been the object of a forecasting study, even though the characteristics of an archipelago city with a supply that depends on distribution between regions make it a different case from the production center on the island of Java. Second, most previous studies have concluded the direction of price movements based on the sign of the trend line slope coefficient without first testing the statistical significance of the coefficient, so that the conclusion about the upward or downward trend risks being erroneous when the value of the determination coefficient is very low. Third, the seasonal component, which in horticultural commodities is the source of the greatest diversity, is often overlooked, even though Hyndman and Athanasopoulos (2018) emphasized that ignoring the seasonal component in a series with a strong seasonal pattern will result in systematic and avoidable forecasting errors.

Based on this description, this study is designed to achieve three objectives. The first objective is to characterize the dynamics, volatility levels, and seasonal patterns of tomato prices in Kupang City during the period 2019 to 2023, including testing stationarity and

intertemporal dependency structures. The second objective is to compare the accuracy of *the exponential smoothing* model, *moving average*, and linear trend analysis as established in the research framework, with the naïve model comparators, all of which are evaluated on an equivalent one-step forward forecasting basis and accompanied by testing the statistical significance of the trend coefficient. The third objective is to compile the 2024 tomato price forecast along with its prediction intervals and formulate policy implications that can be operationalized by stakeholders at the regional level.

Research Methods

Location, Type, and Data Source

This research was carried out in Kupang City, East Nusa Tenggara Province, using a quantitative descriptive approach. The data analyzed was secondary data in the form of retail prices of vegetable tomatoes in rupiah per kilogram with a monthly frequency, covering the period from January 2019 to December 2023 so that 60 observations were obtained. Data was sourced from the Central Statistics Agency of East Nusa Tenggara Province (2024). The five-year span was chosen because it covers five full seasonal cycles so that the annual pattern can be adequately estimated, as well as covering the period before, during, and after the Covid-19 pandemic. Data processing was carried out using Microsoft Excel for the calculation of forecasting models and statistical software for inferential testing.

Time Series Characterization

The first stage of analysis is to describe the behaviour of the price series. The level of volatility is measured using the variation coefficient, which is the ratio of the standard deviation to the average expressed in percent, calculated both for the entire period and for each year. Mawarni et al. (2023) emphasized that the variation coefficient is the right measure to assess the price stability of a commodity because it is unit-free and can be compared between periods and between commodities.

Seasonal patterns are identified through seasonal indices calculated as the ratio of the price of a particular month to the average price of the year in question, then averaged over the entire year of observation and normalized so that the average index is equal to one hundred. Index values above one hundred indicate months with prices above the annual average, while values below one hundred indicate the opposite. The stationarity of the series was tested using *the Dickey-Fuller augmented test* as developed by Dickey and Fuller (1979), while the intertemporal dependency structure was examined through the autocorrelation function and the Ljung-Box test as described by Box et al. (2015). The stationarity test was performed first because it determined whether data differentiation was required before

modelling, while the examination of the autocorrelation function determined the type of structure that was theoretically most suitable for forecasting.

Forecasting Models

Three forecasting models were applied according to the research framework, with the addition of one naïve model as a basic comparator and one extension model that included a seasonal component. All models were evaluated on a one-step forward forecasting basis, meaning that the forecast value for period t was only formed from information until period t was subtracted by one.

Moving Average (MA)

The *moving average* method predicts the price of the next period as a simple average of the last number of observations, with the aim of smoothing out short-term fluctuations and highlighting long-term movements. The equation is:

$$MA_t = (P_{t-1} + P_{t-2} + \dots + P_{t-n}) / n$$

with MA_t is the forecast value in period t , P is the actual price in previous periods, and n is the length of the moving average window. The calculation window ends at period t minus one and does not include the observation of period t itself. The inclusion of period observations into the window will transform the model from a forecasting tool to a smoothing tool in the sample, so that the error value generated can no longer be compared with other forecasting models (Hyndman & Athanasopoulos, 2018). In this study, three window lengths were tested, namely two, three, and four periods, as Haba (2021) also applied to tomato production predictions.

Single Exponential Smoothing (SES)

Exponential smoothing is a forecasting technique that provides an exponential weighing of past data, so that the most recent observations acquire the greatest weight (Brown, 1963; Gardner, 2006; Yuniarti, 2019). The recursive form is:

$$F_t = \alpha P_{t-1} + (1 - \alpha) F_{t-1}$$

where F_t is the forecast value of period t , P_{t-1} is the actual price of the previous period, F_{t-1} is the forecast value of the previous period, and α is the smoothing constant that is between zero and one. The initial value of the forecast is set the same as the first observation. The smoothing constant is not set arbitrarily, but is searched by tracing the grid in the range of 0.01 to 1.00 with an interval of 0.01 and a value that minimizes *mean squared error* is selected.

Linear Trend Analysis

Linear trend analysis assumes that price changes over time are constant or constant. The formulation of the model

is similar to that of the regression model, but the explanatory variable used is time (Yulianto, 2012):

$$Y_t = a + b t + e_t$$

where Y_t is the trend value of a given period, a is the model constant, b is the directional coefficient that shows the rate of price change per month, t is the time of one to sixty, and e_t is the error. The parameter is suspected by the usual smallest squared method. In contrast to the common practice found in the previous literature, this study does not stop at reporting the values of the direction coefficient and the determination coefficient, but rather tests the hypothesis of zero that b equals zero using the test t with a free degree of n minus two. Trend line extrapolation can only be statistically accounted for if the zero hypothesis is rejected.

Comparison Models and Extension Models

The naïve model sets the forecast of the next period as the same as the last observation. This model is included because Hyndman and Koehler (2006) assert that the claim of superiority of a forecasting model is only meaningful if the model is able to outperform the simplest comparator. In addition, a naïve seasonal model that sets the forecast is the same as the price in the same month of the previous year is also tested.

As an extension, a seasonally corrected *exponential smoothing model* is applied through a decomposition procedure. The price series is first cleaned of seasonal influences by dividing the actual price by dividing the actual price by the seasonal index of the month in question, then the *exponential smoothing model* is applied to the series of adjusted results, and the forecast value is returned to the original scale by multiplying it back by the forecasted monthly seasonal index. This procedure is a simple form of the decomposition approach on which the Holt-Winters model is based (Holt, 2004; Winters, 1960) and is systematically described by Hyndman and Athanasopoulos (2018). This expansion model is included to test how much the seasonal component contributes to improving forecasting accuracy.

Forecasting Accuracy Criteria

The accuracy of the model was evaluated using four criteria. *Mean absolute deviation* (MAD) measures the average absolute value of the difference between the actual price and the forecast price in rupiah units. *Mean squared error* (MSE) measures the mean squared of the difference so that it provides a greater penalty for large errors. *Root mean squared error* (RMSE) is the root of MSE and is expressed

in rupiah units. *Mean absolute percentage error* (MAPE) measures the average percentage of error relative to the actual value so that it is unit-free. The four criteria are formulated as:

$$MAD = \frac{1}{n} \sum |A_i - F_i|$$

$$MSE = \frac{1}{n} \sum (A_i - F_i)^2$$

$$RMSE = \sqrt{MSE}$$

$$MAPE = \frac{\sum \frac{|A_i - F_i|}{A_i} \times 100}{N}$$

with A_i is the actual value, F_i is the predicted value, and n is the number of observations compared. The interpretation of the MAPE value refers to the criteria formulated by Lewis (1982) as presented in Table 1.

Table 1. Interpretation Criteria for MAPE Values

Yes	MAPE Range	Interpretation of Forecasting Accuracy
1	< 10%	Excellent forecasting capabilities
2	10% – 20%	Good forecasting ability
3	20% – 50%	Decent or adequate forecasting ability
4	> 50%	Forecasting capabilities are not feasible

Source: Lewis (1982)

Results and Discussion

Tomato Price Dynamics and Volatility

The development of vegetable tomato prices in Kupang City during the period January 2019 to December 2023 is presented in Table 2. Throughout this period, prices moved in a very wide range, namely from the lowest point of IDR 7,083 per kilogram in October 2019 to the highest point of IDR 24,792 per kilogram in January 2023. This range of IDR 17,709 per kilogram is equivalent to 120.8 percent of the overall average price of the entire period recorded at IDR 14,661.53 per kilogram. This means that the difference between the highest and lowest prices is greater than the average value of the price itself, an amplitude that confirms the character of tomatoes as a highly volatile commodity.

Table 2. Tomato Vegetable Prices in Kupang City, January 2019 – December 2023 (IDR/kg)

Yes	Moon	2019	2020	2021	2022	2023
1	January	16.979	16.458	15.938	13.542	24.792
2	February	18.542	21.220	16.667	15.000	18.958
3	March	16.667	16.711	16.667	16.458	20.625
4	April	20.000	15.982	16.667	20.625	20.417
5	May	15.885	13.382	22.708	18.125	15.000
6	June	12.083	15.833	18.646	15.625	14.167
7	July	14.896	12.708	13.854	15.208	12.083
8	August	9.896	11.125	10.417	14.167	11.250
9	September	7.604	8.667	10.625	11.667	12.292
10	October	7.083	9.167	13.958	11.250	10.625
11	November	8.750	10.708	14.417	13.125	12.500
12	December	10.833	14.583	14.823	20.417	10.625
Average		13.268	13.879	15.449	15.434	15.278

Source: Central Statistics Agency of East Nusa Tenggara Province (2024)

It is necessary to propose one factual correction to the data reading. The highest price during the observation period did not occur in May 2021 of IDR 22,708 per kilogram, but in January 2023 of IDR 24,792 per kilogram. The value of IDR 22,708 is indeed the highest price in 2021, but it is not the highest price in the entire range of 2019 to 2023. This correction is important because the determination of extreme points is a reference for the identification of critical periods in the formulation of price stabilization policies.

Descriptive statistics and annual volatility measures are presented in Table 3. The overall coefficient of variation for the period was recorded at 26.41 percent. On an annual basis, the highest volatility occurred in 2019 at 33.51 percent, then gradually decreased to 26.24 percent in 2020, 21.59 percent in 2021, and reached a low of 19.78 percent in 2022, before increasing sharply again to 31.00 percent in 2023. This pattern differs from simply a monotonous decline or increase; what occurs is a stabilization phase during the first four years that is then interrupted by shocks in the last year.

Table 3. Descriptive Statistics and Volatility of Tomato Prices per Year

Year	Average (IDR/kg)	Raw deviation (IDR/kg)	Coefficient of variation (%)	Minimum (IDR/kg)	Maximum (IDR/kg)	Range (IDR/kg)
2019	13.268	4.446	33,51	7.083	20.000	12.917
2020	13.879	3.642	26,24	8.667	21.220	12.553
2021	15.449	3.336	21,59	10.417	22.708	12.291
2022	15.434	3.053	19,78	11.250	20.625	9.375
2023	15.278	4.736	31,00	10.625	24.792	14.167
2019–2023	14.662	3.873	26,41	7.083	24.792	17.709

Source: Processed secondary data (2024)

The surge in volatility in 2023 deserves special attention. In that year, prices moved from IDR24,792 per kilogram in January to only IDR10,625 per kilogram in October, which is a decrease of 57.1 percent in nine months. The annual price range of IDR14,167 per kilogram is the widest throughout the observation period. This condition is consistent with the thesis of Gilbert and Morgan (2010) regarding volatility grouping, namely that the absence of stock buffers makes direct supply and demand shocks translate into large-scale price movements. For tomato farmers in the Kupang City supplier area, this magnitude of amplitude means that farmer revenues can differ more than twice simply because of the difference in harvest time in the same year.

Seasonal Price Patterns

The seasonal price index of tomatoes in Kupang City is presented in Table 4 and visualized in Figure 1. The pattern formed is very strong and is the most dominant feature of this series. The highest seasonal price occurs in April with an index of 128.2, followed by February with 124.4, January with 119.9, and March with 119.1. On the other hand, the lowest seasonal price occurs in September with an index of 68.9, followed by October with 70.4 and August with 77.5. The range between the peak and the valley reaches 59.3 index points, which means that solely due to seasonal factors, tomato prices in April tend to be about 86 percent higher than in September.

Table 4. Seasonal Index of Tomato Prices in Kupang City (average = 100)

Moon	Table of Contents	Categories	Moon	Table of Contents	Categories
January	119,9	Above average	July	94,2	Below average
February	124,4	Above average	August	77,5	Below average
March	119,1	Above average	September	68,9	Below average
April	128,2	Above average	October	70,4	Below average
May	115,7	Above average	November	80,7	Below average
June	104,0	Above average	December	96,9	Below average

Source: Processed secondary data (2024)

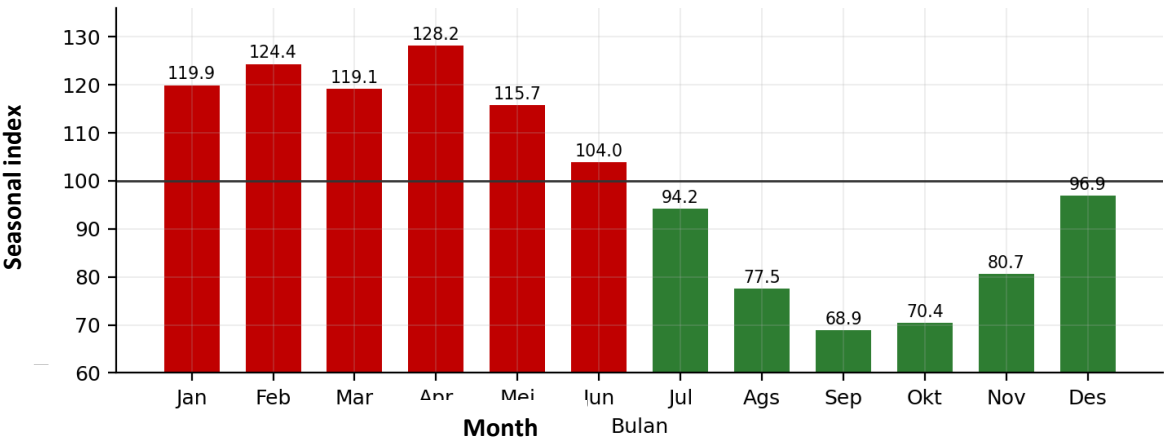


Figure 1. Seasonal Index of Tomato Prices in Kupang City, 2019–2023

Source: Processed secondary data (2024)

This pattern can be explained through the agroclimatic calendar of East Nusa Tenggara which has a relatively short rainy season from December to March and a long dry season from April to November. High prices from January to April reflect a period when local production is depressed by high rainfall which increases disease attacks

and deterioration, while inter-island shipments are also disrupted by sea wave conditions. Conversely, the price valley from August to October coincides with the harvest period from the supplier area so that the supply is abundant at a time when local market absorption is limited. This finding strengthens the explanation of Timisela et al. (2020)

that the limited market absorption capacity in the archipelago cities makes oversupply directly suppress prices at the retail level without a buffer mechanism.

The magnitude of this seasonal amplitude has two implications. Analytically, the seasonal component is clearly the largest source of diversity in the tomato price series in Kupang City, so any forecasting model that ignores it will bear systematic errors that can actually be avoided. In policy, the existence of a stable seasonal pattern is actually good news, because the seasonal price component can be anticipated well in advance, in contrast to the unpredictable random shock component.

Statistical Characteristics of Price Series

The results of the *Dickey-Fuller augmented test* produced a statistical value of -3.776 with a probability value of 0.0032 , so that the hypothesis of zero the existence of the root unit was rejected at a real level of one percent with a critical value of -3.548 . The tomato price series in Kupang City is thus stationary at the level level. This finding contains a correction to the assumption that tomato price data is initially not stationary and needs to be changed through differentiation before it can be modeled. Differentiation is not necessary, and in sequences that are already stationary, the differentiation action actually risks causing excessive differentiation that adds to the variety of errors without benefit (Box et al., 2015). As an additional examination, the same test on the first differentiated result sequence yielded a statistic of -6.919 with a probability of less than 0.001 , which did reject the root of the unit but did not provide new information given that the original series was stationary.

The autocorrelation function shows a very informative structure. The coefficient at the first lag of 0.69 and the second lag of 0.34 indicates strong short-term persistence. More importantly, the coefficient turns negative and reaches a low of -0.45 at the sixth and seventh lags, then returns positive and reaches 0.37 at the twelfth lag. This swinging pattern with a twelve-month period is a standard sign of the existence of an annual seasonal cycle. The Ljung-Box test at twelve lags yielded a statistical value of 108.47 with a probability of less than 0.001 , so the zero hypothesis that the series is white noise is very convincingly rejected.

The combination of the three findings provides clear theoretical guidance. The tomato price series is stationary, has a strong short-term persistence, and contains a firm annual seasonal cycle. The model that gives the dominant weight to the last observation will capture the persistence component, but without the inclusion of the seasonal component the model will systematically miss the peak and valley months. This conjecture will be verified in the following sections.

Forecasting with Single Exponential Smoothing

A grid search of the top of the smoothing constant shows that the *mean squared error* decreases monotonically as the α value increases, with the minimum value being at the upper limit of the parameter range. Since α equal to one will reduce the model to be identical to the naïve model and eliminate the smoothing property, an interior solution of α is chosen equal to 0.95 . This high α value is a direct consequence of the first lag autocorrelation structure of 0.69 ; in sequences with such high persistence, the latest observations are the most valuable source of information.

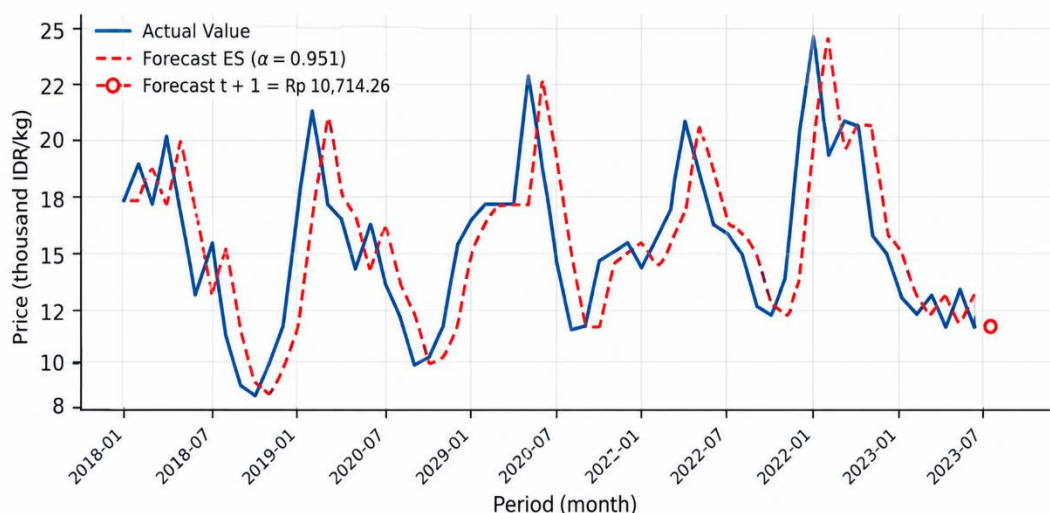


Figure 2. Results of Tomato Price Forecasting by Single Exponential Smoothing Method ($\alpha = 0.95$)

Source: Processed secondary data (2024)

Figure 2 shows that the forecast line follows the actual price movement with a gap of one period. This model produces a MAD of IDR 2,429.97, MSE of IDR 8,929,591, RMSE of IDR 2,988.24, and a MAPE of 16.79 percent. The forecast value for one period after the end of the data, namely January 2024, is IDR 10,714.26 per kilogram. Referring to Lewis' (1982) criteria, the MAPE value in the range of 10 to 20 percent places this model in the category of good forecasting ability, but has not yet reached the very good category.

The predictive value also corrects the results of the previous calculation which stated the figure of IDR 2,187,419 per kilogram. This figure cannot be the result of exponential smoothing because it is about 149 times the historical average price, and mathematically the *predicted value of single exponential smoothing* is always within the observed data range. This kind of error is most likely due to addition rather than weighting on the worksheet, and shows the importance of checking the fairness of the result before interpretation is carried out.

The main weakness of this model is evident in Figure 2. Because the forecast for the horizon of more than one period is flat, it is not able to anticipate a price increase at the beginning of the year or a sharp decline in the third quarter. The forecast value of IDR 10,714.26 for January 2024 is a clear example: January is seasonally a high-value month with an index of 119.9, so the flat forecast formed from low December prices will almost certainly miss the bottom. This is the form of systematic error referred to in the previous section.

Forecasting with Moving Averages

The moving average *model* was tested on three window lengths with results consistent with the series autocorrelation structure, i.e. the accuracy decreases as the window length increases. The *two-period moving average* produces a MAPE of 19.63 percent, a three-period of 22.25 percent, and a four-period of 24.72 percent. The forecast value for January 2024 from the two-period model is IDR 11,562.50 per kilogram, which is the average price of November and December 2023.

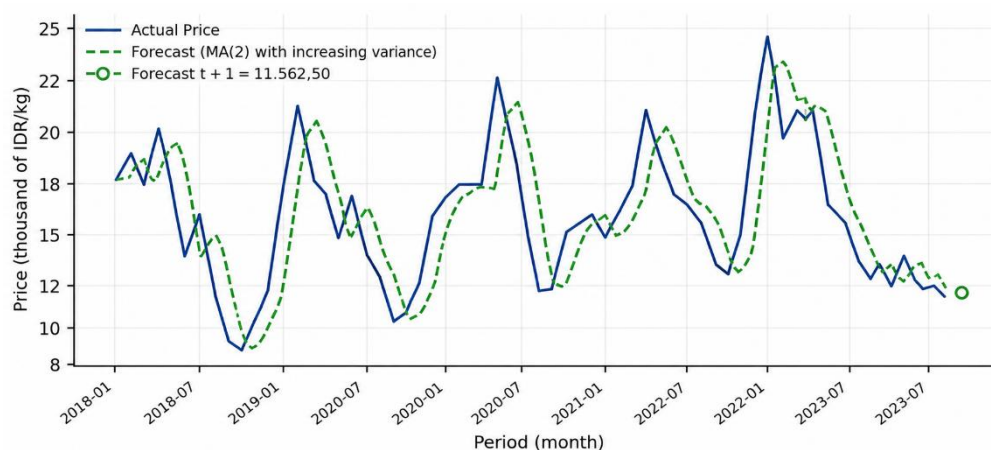


Figure 3. Results of Tomato Price Forecasting with the *Two-Period* Moving Average Method

Source: Processed secondary data (2024)

This forecast value also corrects the previous result which stated a figure of IDR 10,625 per kilogram. The figure of IDR 10,625 is actually the actual price for December 2023, which is the last observation in the series, and not the result of calculating the moving average. Using the last observation as a forecast is basically the application of a naïve model, not a *moving average*. This difference is not just a naming issue, because the two models have different error characteristics and produce different predictive values.

The decrease in accuracy as the window lengthens can be understood directly. Flattening out the back three or four months means forcing the model to give the same weight to the third lag information whose autocorrelation is

only 0.04 with the first lag information with an autocorrelation of 0.69. As a result, the forecast becomes too slow in responding to changes in price levels. In a series with strong seasonal patterns, window elongation also means mixing high-priced months with low-priced months, so that the forecast is drawn towards the middle value and loses the ability to distinguish peaks from valleys. Haba (2021) gained a consistent experience in the application of *moving averages* for tomato production predictions, i.e. the best accuracy is achieved in short windows.

Linear Trend Analysis

The estimation of the linear trend model results in the following equation.

$$Y_t = 14,157.29 + 16,532 t$$

The directional coefficient of 16.532 literally indicates a price increase of IDR 16.53 per kilogram every month. However, the standard error of the coefficient is 29.036, so the t-test statistic is only 0.569 with a probability value of 0.571. The null hypothesis that the directional coefficient is equal to zero cannot be rejected, even at the real level of ten percent. The value of the determination

coefficient of 0.0056 confirms the same thing: only 0.56 percent of the diversity of tomato prices is able to be explained by the time variable, while the remaining 99.44 percent is unexplained. The value of the standard error of the estimate of IDR 3,895.00 is even slightly larger than the standard deviation of the data itself of IDR 3,872.70, which means that the trend model does not provide any improvement compared to simply using the average value as a guesser.

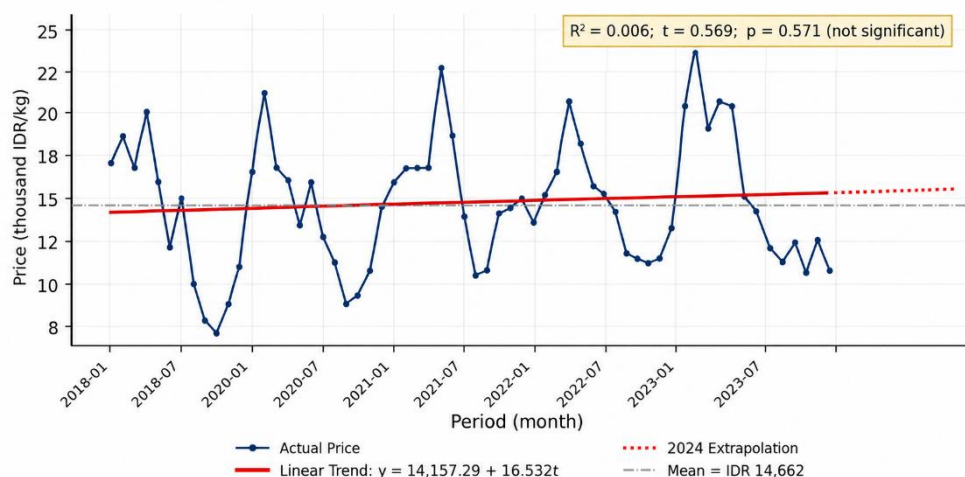


Figure 4. Linear Trend Line of Tomato Prices in Kupang City and Its Extrapolation

Source: Processed secondary data (2024)

This finding corrects the statement that the development of tomato prices in Kupang City tends to continue to increase every month due to increasing demand. Statistically, the upward trend cannot be proven. What actually happened was not an upward trend, but a return to an average of around IDR 14,661.53 per kilogram accompanied by large-scale seasonal oscillations, as confirmed by the results of the unit root test. Conceptually, the stationary series is indeed inconsistent with the existence of a long-term deterministic trend, so the two test results corroborate each other.

The practical consequence is that extrapolating the trend line to produce a monthly forecast for 2024 is statistically unjustifiable. The extrapolation results are indeed calculable and appear neat because they increase linearly by IDR 16 to IDR 17 every month, but the neatness

is a mathematical artifact of the straight-line equation and not a reflection of market behavior. Furthermore, the extrapolation projects a practically constant price in the range of IDR 15,166 to IDR 15,348 throughout the year, even though historical data shows that the price difference between the peak and valley months in the same year routinely exceeds IDR 9,000 per kilogram. The trend model is thus not only insignificant, but also conveys a misleading picture of price stability. As a forecasting model, the linear trend produces a MAPE of 23.71 percent, which places it in the feasible category according to Lewis (1982).

Comparison of Accuracy Between Models

A comprehensive comparison of all the models tested is presented in Table 5. All values are calculated on a one-step forward forecasting basis so that they can be compared equally.

Table 5. Comparison of Tomato Price Forecasting Model Accuracy

Yes	Forecasting models	MAD (IDR)	MSE	RMSE (IDR)	MAPE (%)	Categories Lewis
1	Seasonally corrected ES ($\alpha = 0.30$)	1.785,86	5.869.752	2.422,76	12,12	Good
2	Naif (<i>random walk</i>)	2.411,19	8.841.911	2.973,54	16,62	Good
3	<i>Exponential smoothing</i> ($\alpha = 0.95$)	2.429,97	8.929.591	2.988,24	16,79	Good
4	<i>Exponential smoothing</i> ($\alpha = 0.80$)	2.511,13	9.417.252	3.068,75	17,57	Good
5	Naïve Seasons (Y_{t-12})	2.702,67	13.142.745	3.625,29	17,82	Good
6	<i>Exponential smoothing</i> ($\alpha = 0.50$)	2.684,44	11.547.098	3.398,10	19,46	Good
7	<i>Moving average</i> ($n = 2$)	2.756,89	11.891.531	3.448,41	19,63	Good
8	<i>Moving average</i> ($n = 3$)	3.051,11	14.938.117	3.864,99	22,25	Worthy
9	Linear Train	3.130,42	14.665.655	3.829,58	23,71	Worthy
10	<i>Exponential smoothing</i> ($\alpha = 0.20$)	3.195,51	14.878.265	3.857,24	24,14	Worthy
11	<i>Moving average</i> ($n = 4$)	3.348,31	17.588.312	4.193,84	24,72	Worthy

Source: Secondary data processed (2024). Bold indicates the best model. All values are calculated on the basis of a one-step forward forecast.

Table 5 yields four analytical conclusions. First, among the three methods established in the study framework, the order of accuracy was *exponential smoothing* as the best with a MAPE of 16.79 percent, followed by a two-period *moving average* of 19.63 percent, and linear trend analysis as the worst at 23.71 percent. This sequence corresponds exactly to the theoretical conjecture constructed from the series autocorrelation structure, namely that the model that gives dominant weight to the most recent observations will outperform the model that flattens the long history, and both will outperform the model that assumes a long-term deterministic trajectory on a series that is actually stationary.

Second, in the *exponential smoothing* family, the accuracy increases monotonous as the α value increases from 0.20 to 0.95, while in the *moving average* family, the accuracy decreases monotonically as the window length increases from two to four periods. The consistency of these two patterns strengthens the interpretation that short-term information is the most valuable component for tomato price forecasting in Kupang City.

Third, none of the models without a seasonal component were able to achieve a MAPE below ten percent, and the best model among them only achieved the 16.62 percent achieved by the naïve model. The proximity between the naïve and *exponential smoothing* models with high α suggests that in the very short term tomato prices

behave close to random paths, a condition that in the framework of Fama (1970) is consistent with weak form market efficiency. However, in contrast to the case of commodities that do not have seasonal patterns, here the behavior of approaching random paths on a one-month period coincides with a very strong seasonal regularity on an annual basis. Hyndman and Koehler (2006) assert that the inclusion of naïve comparators aims precisely to reveal this kind of condition.

Fourth, and most importantly, the *exponential smoothing* model corrected for the seasonal index ranked at the top with a MAPE of 12.12 percent. Compared to regular *exponential smoothing*, the inclusion of seasonal components lowered the MAPE by 4.67 percentage points or equivalent to an accuracy improvement of 27.8 percent, and lowered the MSE from 8,929,591 to 5,869,752 or a decrease of about 34.3 percent. This magnitude of improvement was obtained without adding a single new explanatory variable, but solely by utilizing seasonal information already contained in the same data. Interestingly, the naïve seasonal model that used the price of the same month the previous year actually performed worse with a MAPE of 17.82 percent, which suggests that the seasonal component needs to be estimated as a cross-year average and not enough to be taken from a single year containing idiosyncratic shocks.

Selected Models and Forecasts for 2024

Based on these accuracy comparisons, the seasonally corrected *exponential smoothing model* with a smoothing constant of 0.30 was determined as the selected model. The performance of this model against the historical data is

presented in Figure 5. It can be seen that the forecast lines were able to follow the peak at the beginning of the year and the valley in the third quarter consistently in all five years of observation, something that the three basic models could not do.

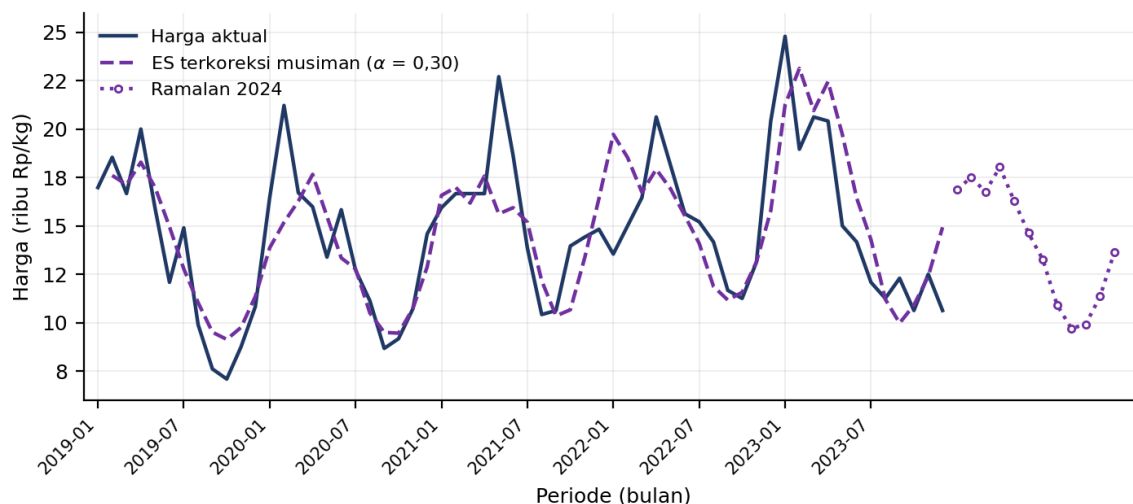


Figure 5. Seasonally Corrected *Exponential Smoothing* Model Performance and Forecast for 2024

Source: Processed secondary data (2024)

The forecast of tomato prices in Kupang City for 2024 is presented in Table 6 in three scenarios. The first scenario is a linear trend extrapolation that is included solely as a comparison, with the firm note that the trend coefficient is not significant so the figure is not recommended as a basis

for decision-making. The second scenario is a flat forecast from the usual *exponential smoothing* model. The third scenario is a forecast from the selected model, and this is the recommended scenario for planning purposes.

Table 6. Tomato Price Forecast in Kupang City in 2024 (IDR/kg)

Yes	Moon	Trend extrapolation (insignificant)	Exponential smoothing (flat forecast)	Seasonally corrected ES (recommended)	Seasonal indices
1	January	15.166	10.714	16.879	119,9
2	February	15.182	10.714	17.500	124,4
3	March	15.199	10.714	16.761	119,1
4	April	15.215	10.714	18.041	128,2
5	May	15.232	10.714	16.288	115,7
6	June	15.248	10.714	14.629	104,0
7	July	15.265	10.714	13.259	94,2
8	August	15.281	10.714	10.908	77,5
9	September	15.298	10.714	9.698	68,9
10	October	15.315	10.714	9.913	70,4
11	November	15.331	10.714	11.350	80,7
12	December	15.348	10.714	13.635	96,9

Source: Processed secondary data (2024)

The recommended scenario projects the highest price in April 2024 at IDR 18,041 per kilogram and the lowest price in September 2024 at IDR 9,698 per kilogram, with a difference of IDR 8,343 per kilogram or around 86 percent. This range is much more informative than the flat forecast scenario that sets a single figure of IDR 10,714 throughout the year, or the trend extrapolation scenario that projects an almost constant price in the range of IDR 15,200. The comparison of the three columns in Table 6 clearly shows that model selection is not just a technical issue, but rather determines a completely different market picture: the trend model suggests a stable market, the *flat flattening exponential* model suggests a cheap market throughout the year, while the selected model suggests a market that moves in a wide cycle that can be anticipated.

As is typical of horticultural commodity forecasting, all of these figures are point forecasts that include considerable uncertainty. The standard deviation of the selected model of error of IDR 2,443.50 results in an 80 percent prediction interval for January 2024 of IDR 13,747 to IDR 20,010 per kilogram and a 95 percent prediction interval of IDR 12,089 to IDR 21,668 per kilogram. The width of this interval is an honest reflection of the uncertainty inherent in commodities that cannot be stored for a long time, and at the same time a warning that the point forecast value should be treated as a map of the direction of seasonal movements, not as a price figure.

Conclusion

Tomato prices in Kupang City during the period 2019 to 2023 moved at an average of IDR 14,661.53 per kilogram with an overall coefficient of variation of 26.41 percent. The highest price of IDR 24,792 per kilogram occurred in January 2023 and the lowest price of IDR 7,083 per kilogram occurred in October 2019. The price series proved to be stationary at the level level so data differentiation was not necessary, with the first lag autocorrelation of 0.69 and a twelve-month swinging autocorrelation pattern signaling a firm annual seasonal cycle. The seasonal index moved from 68.9 in September to 128.2 in April, so the seasonal component is the largest source of diversity in this series.

Among the three methods determined, *single exponential smoothing* with a smoothing constant of 0.95 was the most accurate model with a MAPE of 16.79 percent, followed by a two-period *moving average* of 19.63 percent, and linear trend analysis of 23.71 percent. The linear trend direction coefficient had a positive value of 16.532 but was not statistically significant with a t-value of 0.569 and a probability of 0.571 and a determination coefficient of only 0.0056, so the tendency to increase in prices cannot be inferred and extrapolation is not recommended as the basis for the decision. The inclusion of seasonal indices in the

exponential smoothing model lowered the MAPE to 12.12 percent, which is an accuracy improvement of 27.8 percent without the addition of any explanatory variables, so this model is recommended. The forecast for 2024 from the selected model ranges from IDR 9,698 per kilogram in September to IDR 18,041 per kilogram in April.

Policy Implications and Suggestions

For the Kupang City Government and the Regional Inflation Control Team, the findings on the seasonal amplitude of 59 index points provide a basis for changing the price stabilization approach from a reactive to an anticipatory and scheduled one. Since price pressures are concentrated in the January-April window with a peak in April, intervention preparations should begin in November of the previous year and not after price increases have occurred. The most relevant forms of intervention include scheduling market operations in the first quarter, strengthening inter-regional trade cooperation with supplier districts in mainland Timor and Flores, and intensive monitoring of the smooth running of marine distribution channels during the rainy season and high tide seasons. In contrast, in the period from August to October when the seasonal index is in the range of 68.9 to 77.5, the policy focus should shift completely from consumer protection to farmer income protection. In those months, the problem faced is not too expensive prices, but prices that are too cheap so that they do not cover the cost of farming. Supriadi and Sejati (2018) emphasized that the smooth inter-island trade is the main determinant of price stability in areas that are not production centers, so strengthening sea logistics connectivity should be a medium-term priority for cities like Kupang.

For the Agriculture Office and farmer groups in the supplier area, the seasonal index can be directly translated into a planting calendar guide that has real economic value. The 86 percent price difference between April and September means that a shift in harvest time for just a few weeks can substantially change farm revenues. Given that the highest prices occur from January to April while production in that period is depressed by high rainfall, there are opportunities for farmers who can afford to produce during the rainy season. This opportunity needs to be facilitated through the provision of varieties that are more resistant to wilt and fruit rot, the application of cultivation in shade or simple plastic houses, improved land drainage, and counseling on pest and disease management during the rainy season. On the other hand, plantings that are entirely geared towards harvesting from August to October will face the lowest price of the year, so setting a planting schedule in groups so that harvests do not accumulate in the same month is a collective step that should be facilitated by extension workers.

Because the root of the tomato price problem lies in the very limited shelf life as Tomek and Kaiser (2014) emphasized, the development of post-harvest processing is the most promising structural intervention. Simple processing such as tomato paste, sauce, dried tomatoes, or refrigerated storage on the scale of farmer groups allows some of the harvest in low-priced months to be transferred to a form that can be stored and sold in high-priced months. The seasonal price difference of more than IDR 8,000 per kilogram provides a wide enough margin to finance these processing activities, so the feasibility of the business is worth further study. The necessary support includes equipment assistance, quality assistance and food safety, as well as facilitation of licensing and market access for processed products.

For traders, culinary business actors, and household consumers, the most important implication is to limit expectations while providing practical direction. Because tomato prices behave close to random paths within a month, efforts to build a procurement strategy based on long-horizon point forecasts will not provide significant advantages. What is actually reliable is the regularity of the seasons. A rational strategy, therefore, is to increase purchases and processing from August to October when seasonal prices are well below average, as well as manage stocks more tightly and consider ingredient substitution in January to April. For culinary business actors, selling prices should be based on the average annual cost of raw materials, not on the current month's price, so that menu price adjustments do not need to be made too often.

For the Central Statistics Agency and data provider agencies, this study shows that monthly price data has real limitations for the purpose of monitoring food inflation. With only sixty observations, the power of the statistical test is limited and price fluctuations that take place in a matter of weeks are not recorded at all. The provision of weekly price series disaggregated by market level, namely producer, wholesale, and retail levels, will significantly improve the quality of analysis and allow the application of conditional volatility models and price transmission analysis as carried out by Miftahuljanah et al. (2020) and Nugrahapsari and Arsanti (2018). This kind of disaggregated data also allows the identification of which market levels play a role in price formation, information that greatly determines the accuracy of intervention targets.

For further research development, three directions can be recommended. First, given the contribution of seasonal components that have proven to be dominant, the application of models that explicitly capture seasonality such as Holt-Winters (Holt, 2004; Winters, 1960), SARIMA, or the fuzzy time series approach as developed by Tsaur (2012) has the potential to provide further accuracy improvements. Second, the inclusion of explanatory

variables such as rainfall, production volume of supplier areas, inter-island transportation costs, and substitution commodity prices will transform the model from a mere extrapolation to an explanatory model that can be used for policy simulation. Third, and most fundamentally, future research needs to consistently apply forecast-based evaluations one step forward, conduct significance testing of trend coefficients before drawing conclusions about the direction of price movements, and check the fairness of the calculation results before interpretation. This study shows that negligence in these things can result in erroneous conclusions about the same commodity and the same data.

Limitations of the Research

This study has a number of limitations that need to be presented openly. The data used are limited to aggregate retail prices so that it is not possible to trace price formation at the producer and wholesale levels. The number of observations of sixty months only covers five seasonal cycles, so the seasonal index is estimated from five observations per month and is still sensitive to certain year shocks. The power of the *Dickey-Fuller augmented* test on this sample size is also relatively limited, so the results need to be interpreted with caution. The accuracy evaluation is carried out on a one-step forward forecasting basis in the full sample and has not used the separation of training data and test data sequentially, so the accuracy of the data that is really not visible still needs to be verified. In addition, all models used are univariate so they are not able to explain the factors that cause price movements. These limitations also open up opportunities for further research.

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