OPEN ACCESS

World Journal of Economics, Business and Management
ISSN (Online): 3049-2181 | Vol. 2, No. 12, Dec, 2025
Website: https://wasrpublication.com/index.php/wjebm

FORECAST OF THE PRICE OF FRESH FRUIT BUNCHES OF OIL PALM IN BENGKULU PROVINCE FOR THE PERIOD 2021–2024

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Received: 10/08/2025 | Accepted: 07/11/2025 | Published: 21/12/2025

Abstract: Fresh fruit bunch (FFB) prices are a principal source of income vulnerability for independent smallholders. This study maps FFB price volatility in Bengkulu Province, evaluates the accuracy of the three-period weighted moving average (WMA) method, and assesses the stability of that accuracy under normal and shock conditions. Monthly data on FFB prices from January 2021 to May 2024 (41 observations) were obtained from the Ministry of Trade's SP2KP system and Statistics Indonesia of Bengkulu Province. Accuracy was measured using MAD, MSE, RMSE, MAPE, and MPE, benchmarked against a naïve model via Theil's inequality coefficient, and validated by a hold-out test. The results show a mean price of IDR. 2,312.76/kg with a coefficient of variation of 19.46%; volatility peaked in 2022 (CV 34.49%), the deepest monthly decline being 52.63% in July 2022. The best weight combination, 9:1:1, yielded a MAPE of 9.56% and RMSE of IDR 346.16, outperforming equal weights (13.70%) and the conventional 3:2:1 scheme (11.86%). Nevertheless, all specifications produced Theil U values exceeding unity, failing to surpass the naive benchmark. Accuracy was also unstable across subperiods, at 7.13% during recovery but 34.39% during the shock. WMA is therefore defensible as a smoothing and short-run reference-price instrument but inadequate as an early-warning system.

Keywords: *FFB price, forecasting, oil palm, price volatility, weighted moving average*.

Cite This Article:

Nurfauzan, A. Y., Sukiyono, K., Mulyasari, G., (2025). FORECAST OF THE PRICE OF FRESH FRUIT BUNCHES OF OIL PALM IN BENGKULU PROVINCE FOR THE PERIOD 2021–2024. *World Journal of Economics, Business and Management*, *2*(12), 57-68.

Introduction

Oil palm is a plantation commodity that contributes the largest contribution to Indonesia's foreign exchange income and at the same time becomes the livelihood of millions of rural households. The rapid expansion of oil palm area over the past two decades, especially on the islands of Sumatra and Kalimantan, has changed the structure of the rural economy through job creation, increased smallholder income, and the growth of derivative economic activities around production centers (Syahza, 2011). Bengkulu Province is one of the regions that has undergone this transformation, with a dominant proportion of smallholder plantations and a high dependence of smallholder household income on the sale of fresh fruit bunches (FFB).

In contrast to food commodities whose prices are formed mainly by the interaction of domestic demand and supply, FFB prices are derived prices from the price of crude palm oil (CPO) in the international market. Changes in world CPO prices, rupiah exchange rates, and trade policies of producing countries and importing countries will be transmitted to the level of palm oil mills (PKS), then forwarded to the smallholder level with a magnitude and speed that is not always symmetrical (Wahyuni et al., 2021). The government has made efforts to protect smallholders through the Regulation of the Minister of Agriculture Number 01/Permentan/KB.120/1/2018 which regulates guidelines for the purchase price of FFB produced by smallholders. However, the determination mechanism is only binding for smallholders who partner with plantation companies, while the majority of independent smallholders sell FFB through collectors at prices that are generally

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below the price set by the plantation office (Tety et al., 2013).

The layered price-formation structure puts independent smallholders in the most vulnerable position when price shocks occur. Sukiyono et al. (2017) showed that the volatility of FFB prices in Bengkulu Province is directly correlated with the vulnerability of smallholder households, especially in households with a narrow cultivation area and limited diversification of income sources. A similar pattern is also found in horticultural commodities in the same province, where price transmission between market levels is imperfect so that price shocks at the upstream level are not fully enjoyed by farmers when prices rise, but are almost entirely borne by farmers when prices fall (Sukiyono & Asriani, 2020). Implicitly, price information that can be anticipated in advance has real economic value for smallholders, especially in harvest decision-making, fertilizer purchases, and household cash flow arrangements.

The need for predictable price information has become even more urgent after a series of policy shocks in 2022. The policy of banning the export of CPO and its derivatives from April 28 to May 23, 2022 caused mill storage tanks to be fully filled, farmer FFB uptake stalled, and prices at the farmer level plummeted drastically in a matter of weeks. These shocks were exogenous to the fundamental conditions of production at the plantation level, but their impact on smallholder incomes was enormous and lasted for several months after the ban was lifted. The event provided an important empirical context to test the extent to which simple forecasting methods are still reliable when price series undergo structural changes.

In the time series forecasting literature, the moving average and weighted moving average (WMA) methods are the most widely used smoothing approaches due to their computational simplicity, minimal data requirements, and ease of interpretation for non-technical users (Makridakis et al., 1998; Hyndman & Athanasopoulos, 2018). A number of studies in Indonesia have reported satisfactory performance for this method, including in forecasting the price of green cayenne pepper (Putri & Wardhani, 2020), the consumer price index (Nurfadilah et al., 2022), the price of staples (Ustadatin et al., 2023), and the production of oil palm fruit (Irawan et al., 2021). In palm oil commodities, other smoothing methods such as exponential smoothing have also been applied with fairly accurate results (Setiawan et al., 2020).

However, most of these studies have the same three methodological limitations. First, the accuracy of the model is generally only reported as a single aggregate number without checking whether the accuracy is stable throughout the observation period; whereas in price series containing structural changes, the aggregate value can hide the failure of the model in the segment that is most important for decision-making. Second, the forecasting results are rarely compared with the simplest benchmark model, i.e. the naïve model, so it cannot be assessed whether the complexity of the weighting really provides predictive added value (Hyndman & Koehler, 2006). Third, accuracy evaluation is generally carried out in a sample manner without a hold-out test, so it is prone to giving an overly optimistic picture of performance. Studies that specifically evaluate FFB price forecasting at the provincial level, especially in Bengkulu Province, and that explicitly test the resilience of the method to policy shocks are still very limited.

Based on this description, this study aims to map the pattern and level of volatility of palm oil FFB prices in Bengkulu Province for the period January 2021 to May 2024; test the accuracy of the three-period weighted moving average method in forecasting monthly FFB prices and determine the best combination of weights; and evaluating the stability of the accuracy of the method through comparison with naïve models, inter-subperiod analysis, and hold-out tests. The contribution of this study lies in providing empirical evidence regarding the limits of the ability of simple forecasting methods in commodity price series that experience policy shocks, as well as in the formulation of price risk management policy implications for oil palm smallholders in the regions.

Research Methods

Data Types and Sources

This study uses a descriptive quantitative approach with secondary data in the form of a time series of the average monthly price of palm oil FFB at the mill level in Bengkulu Province. The observation period covers January 2021 to May 2024 so that 41 monthly observations expressed in rupiah per kilogram (IDR /kg) are obtained. Data was collected from the Market and Basic Needs Monitoring System (SP2KP) of the Ministry of Trade of the Republic of Indonesia and is complemented by a publication by the Central Statistics Agency of Bengkulu Province. The length of the series of 41 observations is considered adequate for the application of the low-order refining method, although it is not sufficient for the full identification of seasonal components; this limitation is explicitly stated in the discussion section.

Weighted Moving Average Method

Moving average is a forecasting method that works by taking a group of last observation values, calculating the average, and using the average as a forecast for the next period (Makridakis et al., 1998). The weighted moving average is a development that assigns different weights to each observation, with the largest weights given to the period closest to the forecasted period, making the model more responsive to recent changes. The general form of a WMA with three weights is formulated as follows:

$$Ft = (c1Xt-1 + c2Xt-2 + c3Xt-3) / (c1 + c2 + c3) \quad (1)$$

where Ft is the predicted value of the period t, Xt−1, Xt−2, and Xt−3 are the actual prices of the previous three periods, and c1, c2, and c3 are the qualifying weights of c1 ≥ c2 ≥ c3. If c1 = c2 = c3, equation (1) simplifies to a simple moving average of order three. Since the initial three observations do not have a complete history, the predicted values are calculated only for the periods t = 4 to t = 41 so that 38 pairs of actual values and predictive values are obtained that are used in all accuracy calculations.

The determination of weights in this study was not carried out ad hoc, but through a grid search of all combinations of integers c1, c2, and c3 in the range of 1 to 9 that met the weight order requirements, so that 165 combinations were obtained. The best combination was selected based on the smallest MAPE value, with RMSE and MAD as supporting criteria. This procedure avoids the subjectivity of weight selection commonly found in similar studies and at the same time allows the mapping of accuracy sensitivity to the weighting structure.

Forecasting Accuracy Measures

Forecast error in period t is defined as et = Xt − Ft, which is the difference between the actual price and the forecast price. The accuracy of the forecast is measured using five indicators, namely mean absolute deviation (MAD), mean squared error (MSE), root mean squared error (RMSE), mean absolute percentage error (MAPE), and mean percentage error (MPE), which are each formulated as the arithmetic average of absolute error, square error, mean square error root, absolute error percentage, and directional error percentage, throughout n evaluation periods. The emphasis on arithmetic averages needs to be emphasized because the use of the median instead of the average will result in numbers that are not comparable to the standard definitions of the three measures and tend to obscure the influence of extreme errors that are important in volatile price series (Sungkawa & Megasari, 2011).

MAD and RMSE are expressed in original units so that they are easy to interpret economically as the amount of error in rupiah per kilogram, while MAPE is relative so that it can be compared between periods and between commodities. RMSE is more sensitive to large errors than MAD because it squares the errors, so the striking difference between the two indicates the existence of extreme errors (Hyndman & Koehler, 2006). MPE is used to detect directional bias, which is the tendency of the model to systematically forecast too high (negative value) or too low (positive value). The interpretation of MAPE refers to the criteria of Lewis (1982), namely that the forecasting ability is very good if the MAPE is less than 10%, good if it is in the range of 10% to 20%, feasible if it is in the range of 20% to 50%, and inaccurate if it exceeds 50%.

Comparison with Naïve and Validation Models

To assess whether the weighting structure actually provides predictive added value, the WMA results were compared with a naïve or random walk model, i.e. Ft = Xt−1, which places the previous month's price as a forecast of the current month. Comparisons were made through the first type Theil inequality coefficient, which is calculated as the ratio of the model's RMSE to the RMSE of the naïve model (Theil, 1966). A value of less than one indicates a model more accurate than a naïve model, a value equal to one indicates equivalent accuracy, and a value of more than one indicates a model that is less accurate than a naïve model. The use of naïve comparators is standard practice in forecasting evaluation because without such comparators a low MAPE value can simply reflect a stable sequence, not the model's superiority (Hyndman & Athanasopoulos, 2018).

Accuracy stability was tested through two additional procedures. First, the evaluation period was divided into three subperiods based on the policy context, namely the shock subperiod (April 2021–April 2022), the shock subperiod (May 2022–December 2022) which includes the implementation and subsequent impact of the CPO export ban, and the recovery subperiod (January 2023–May 2024). The accuracy measure was calculated separately for each subperiod. Second, a hold-out test was carried out by holding the last five observations (January–May 2024) as test data, while the previous period was treated as model-forming data, then a one-step-ahead forecast was generated in a rolling one-step-ahead manner. All calculations were carried out using statistical data processing software.

Results and Discussion

Development and Volatility of FFB Prices

During the period from January 2021 to May 2024, the average price of palm oil FFB in Bengkulu Province reached IDR 2,312.76/kg with a standard deviation of IDR 450.07/kg, so the coefficient of variation reached 19.46%. This figure is relatively high for a monthly price series and indicates that smallholder income faces substantial uncertainty in terms of price alone, regardless of fluctuations in plantation productivity. The lowest price was recorded at IDR 1,440/kg in August 2022, while the highest price reached IDR 3,420/kg in June 2022. The range between the lowest and highest values is IDR 1,980/kg, or equivalent to 85.63% of the average value, and more importantly, the two extreme values occurred only two months apart. Full descriptive statistics are presented in Table 1.

Table 1. Descriptive statistics on palm oil FFB prices in Bengkulu Province, January 2021–May 2024

Period	Number of observations	Average (IDR /kg)	Raw deviation (IDR/kg)	Coefficient of variation (%)	Range (IDR/kg)
2021	12	2.226,75	183,63	8,25	1.900–2.551
2022	12	2.300,00	793,27	34,49	1.440–3.420
2023	12	2.341,00	225,36	9,63	1.980–2.650
2024 (January–May)	5	2.482,00	43,24	1,74	2.450–2.550
Overall	**41**	**2.312,76**	**450,07**	**19,46**	**1.440–3.420**

Source: Results of SP2KP data processing of the Ministry of Trade and BPS of Bengkulu Province (2024).

The year-by-year breakdown in Table 1 shows that price volatility was not evenly distributed throughout the observation period, but was concentrated in 2022. The variance coefficient in that year reached 34.49%, or more than four times the variation coefficient in 2021 which was only 8.25% and more than three times in 2023 which was 9.63%. In the first five months of 2024, prices were even very stable with a variation coefficient of only 1.74%. These findings show that the FFB price series in Bengkulu Province does not come from a homogeneous data generation process, but rather contains at least one sharp structural change. The methodological implications are important: any measure of forecast accuracy calculated in aggregate for the entire period will be a mixture of two very different market regimes.

Analysis of the monthly rate of change strengthens this conclusion. The average monthly price change was 1.19% with a standard deviation of 11.85%, which means that the standard deviation of change was almost ten times the average value. The deepest negative change occurred in July 2022 at 52.63%, when the price plummeted from IDR 3,420/kg in June 2022 to IDR 1,620/kg. On the other hand, the largest positive change was recorded in January 2023 at 20.83%. The complete pattern of price developments is shown in Figure 1.

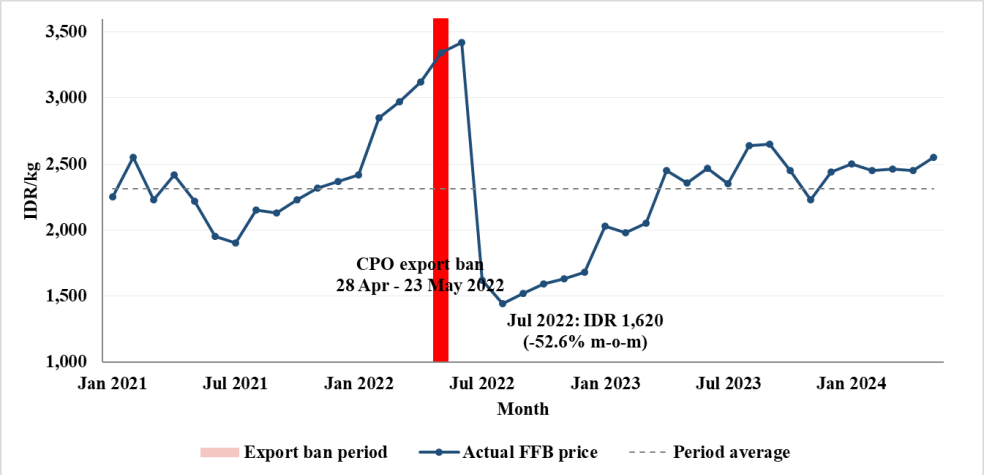


Figure 1: Development of palm oil FFB prices in Bengkulu Province, January 2021–May 2024

Figure 1 shows four phases that can be clearly distinguished. The first phase, throughout 2021, was characterized by relatively flat price movements in the range of IDR.1,900–IDR 2,551/kg with a tendency to strengthen in the second half of the year. The second phase, from January to June 2022, was a period of sharp increase of 41.32% in six months driven by soaring world vegetable oil prices. The third phase was the price collapse in July 2022 which continued to the lowest point in August 2022, followed by a period of low prices that lasted until December 2022. The fourth phase, from January 2023, is a period of gradual recovery towards the range of IDR 2,400–IDR 2,650/kg which then remains relatively stable throughout 2024.

The price collapse in the third phase is closely related to the policy of banning the export of CPO and its derivative products imposed by the government from April 28 to May 23, 2022. The policy is aimed at securing supply and stabilizing cooking oil prices in the domestic market, but has

unintended consequences on the upstream side. The cessation of exports causes the CPO storage tanks owned by PKS to be fully filled, so that factories limit or stop the purchase of FFB and prioritize supply from partner smallholders. Independent smallholders, who are not protected by the pricing mechanism as stipulated in the Regulation of the Minister of Agriculture Number 01/Permentan/KB.120/1/2018, bear the heaviest impact in the form of a decrease in selling prices that far exceeds the decrease in the reference price of the plantation office. It should be noted that the full impact of the shock was only recorded in July 2022 data, which is about two months after the ban was lifted, which reflects a time lag in the transmission of shocks from the policy level to the farmer's price level. The existence of this deadline conceptually opens up opportunities for policy information-based forecasting, but at the same time it is a serious problem for forecasting methods that rely solely on price history itself.

Results of Forecasting and Selection of Weight Combinations

A thorough search of 165 weight combinations resulted in a consistent accuracy rating across all precision measures used. The best weight combination was 9:1:1, which is a scheme that places nine-tenths of the weight at the last month's price, with MAPE of 9.56%, RMSE of IDR 346.16/kg, and MAD of IDR 196.02/kg. The worst combination was the same weight (1:1:1) which is equivalent to a simple moving average of order three, with a MAPE of 13.70%, RMSE of IDR 426.60/kg, and MAD of IDR 273.28/kg. A summary of the performance of some of the selected weight combinations is presented in Table 2.

Table 2. Comparison of forecasting accuracy by three-period WMA weight combination (n = 38)

Weight combination (c_1:c_2:c_3)	MAD (IDR/kg)	MSE (IDR²)	RMSE (IDR/kg)	MAPE (%)	MPE (%)	Thil U
9:1:1 (best)	196,02	119.829,8	346,16	9,56	−1.28	1,022
8:1:1	198,40	120.885,5	347,69	9,70	−1.32	1,026
7:1:1	201,40	122.310,8	349,73	9,86	−1.37	1,032
9:2:1	202,23	124.096,9	352,27	9,92	−1.39	1,040
8:2:1	205,41	125.769,8	354,64	10,09	−1.43	1,047
3:2:1 (conventional)	238,29	150.033,4	387,34	11,86	−1.89	1,144
1:1:1 (equal weight)	273,28	181.990,6	426,60	13,70	−2.33	1,259
Naïve model ($Ft = Xt_{-1}$)	**180,11**	**114.738,4**	**338,73**	**8,69**	**−0.89**	**1,000**

Source: Data processing results (2024). Theil U is calculated as the ratio of the model's RMSE to the naïve model's RMSE.

Table 2 provides three interrelated findings. First, accuracy increased monotonous as weights became more concentrated in the last period. Switching from equal weights to 3:2:1 weights lowered MAPE by 1.84 percentage points, and moving further to 9:1:1 weights lowered MAPE by an additional 2.30 percentage points. Economically, this improvement was equivalent to a decrease in average forecast errors from IDR 273.28/kg to IDR 196.02/kg, or around IDR 77/kg. For smallholders with a production of 10 tonnes of FFB per month, the difference is equivalent to IDR 770,000 per month in the accuracy of revenue estimates, an amount that cannot be ignored in household cash flow planning.

Second, only four weight combinations out of 165 combinations tested were able to break the MAPE threshold of less than 10%, which according to Lewis (1982) criteria is categorized as excellent forecasting ability. All of these combinations placed the dominant weights in the t−1 period with a ratio of at least seven to one. The conventional weight combination of 3:2:1 commonly used in various applied studies was only in the good category with a MAPE of 11.86%, while the same weight was also in the same category as the MAPE of 13.70%. These findings correct the implicit assumption often found in the applied literature that conventional weighting schemes are an adequate option without the need for testing.

Third, and most methodologically important, all of the WMA specifications tested had a Theil U value greater than one. The naïve model produced a MAPE of 8.69%, an RMSE of IDR 338.73/kg, and a MAD of IDR 180.11/kg, which means that it is more accurate than all WMA combinations including the best combinations. The Theil U value for the 9:1:1 combination of 1.022 indicates that the model error is still 2.2% greater than the naïve model error, while for the same weight the value is 1.259 or 25.9% greater. This convergence pattern is logical: the greater the

weight given in the last period, the closer the WMA resembles the naïve model, and the smaller the accuracy difference. In other words, the source of the accuracy improvement in weight tracing is not the sophistication of the weighting mechanism, but rather the reduction in refinement that this sequence does not require.

The finding that the naïve model outperforms the actual refinement method is consistent with the statistical nature of commodity price sequences that approach random walks, as has long been known in the time-series econometric literature (Box et al., 1994). In such a sequence, the best forecast for the next period is the last value observed, and every attempt to equalize historical values adds a deadline (lag) that results in systematic errors when prices move in the same direction. This can be seen from the negative MPE values of all models, which indicate the tendency of the model to forecast too high in periods of price decline and too low in periods of price increases. Most applied studies in Indonesia do not report this kind of comparison (Putri & Wardhani, 2020; Nurfadilah et al., 2022; Ustadatin et al., 2023), so the claims of superiority of the refining method in the literature need to be interpreted with caution. A visual comparison between the actual data and the predicted results of the three weighting schemes is presented in Figure 2.

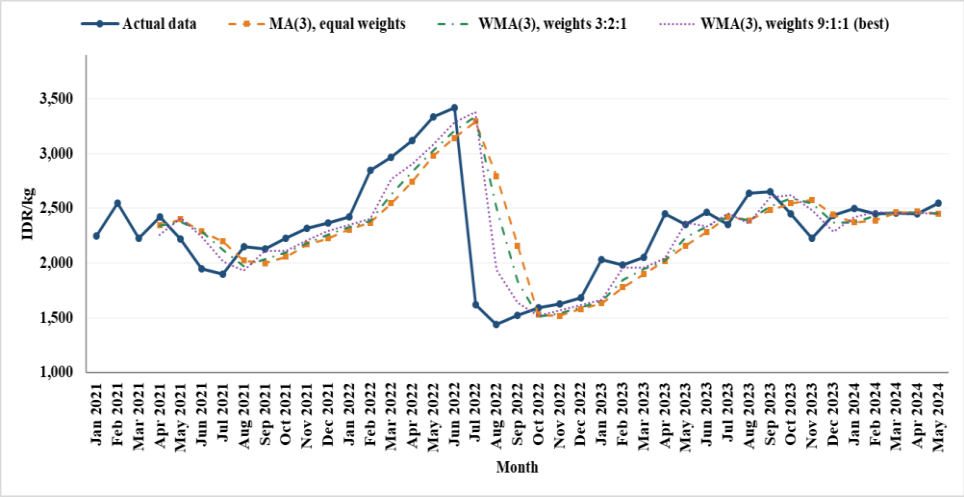


Figure 2: Comparison of actual data and forecast results by weight combination, April 2021–May 2024

Figure 2 shows that in periods of sloping price movements, the entire forecast curve is almost perfectly aligned with the actual curve. A striking difference appears only in two segments, namely the sharp rise segment of February–June 2022 and the collapse segment of July–August 2022. In both segments, the forecast curve systematically lags behind the actual curve, and the delay is most severe in the equal-weight scheme and the mildest in the 9:1:1 scheme. This pattern provides visual confirmation of the conclusions drawn from the accuracy measures in Table 2.

Accuracy Stability Between Subperiods

The aggregate MAPE values of 9.56% to 13.70% reported in the previous section conceal a large disparity between the segments of the observation period. A breakdown of accuracy measures by the three policy subperiods, as presented in Table 3, reveals that almost all forecasting errors were concentrated in the eight-month shock period.

Table 3. Accuracy of three-period MA forecasting by policy sub-period

Subperiod	Number of observations	MAD (IDR/kg)	RMSE (IDR/kg)	MAPE (%)
Shocks (Apr 2021–Apr 2022)	13	231,03	264,38	9,55
Shocks (May 2022–Dec 2022)	8	572,50	811,95	34,39
Recovery (Jan 2023–May 2024)	17	164,78	207,62	7,13
Overall	**38**	**273,28**	**426,60**	**13,70**

Source: Data processing results (2024).

Table 3 shows that in the recovery subperiod, the third-order moving average method worked very well with a MAPE of only 7.13% and an average error of IDR 164.78/kg, which is in the category of excellent forecasting ability according to the criteria of Lewis (1982). In the pre-shock subperiod, the accuracy was still very good with a MAPE of 9.55%. On the other hand, in the shock subperiod, the MAPE jumped to 34.39%, or almost five times the value in the recovery subperiod, with an average error of IDR 572.50/kg and an average RMSE of IDR 811.95/kg. The large difference between RMSE and MAD in this subperiod, which was IDR 239.45/kg, confirmed the existence of extreme errors that dominated the aggregate accuracy measure.

The disproportionate contribution of the shock subperiod becomes clearer when calculated directly. The eight observations in the shock subperiod represent only 21.05% of the total evaluation observations, but account for 76.26% of the total squared error. Consequently, the aggregate MAPE value of 13.70% is not essentially a representative measure of performance for any specific market condition: it is too pessimistic to describe the performance of the model in a calm market and far too optimistic to describe its performance in the event of shocks. The distribution of absolute error percentages by period is shown in Figure 3.

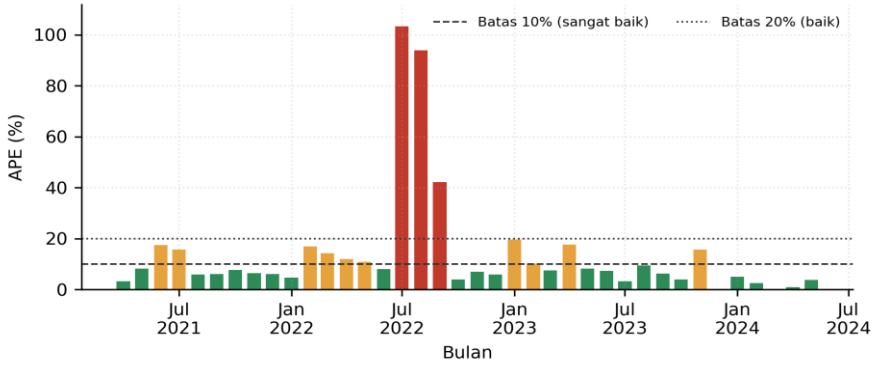


Figure 3. Absolute error percentage (APE) distribution of forecasting by month, April 2021–May 2024

Figure 3 confirms that large errors are not randomly dispersed over the observation period, but rather clustered over a specific time span. Most months with APEs below 10% are below 10%, while months with APEs above 20% are almost entirely in the range of May to December 2022. This kind of grouping of errors is a classic indication that the forecasting model is being applied to a series that is undergoing structural changes, rather than simply experiencing a random increase in noise. These findings explain why accuracy evaluations that rely on only one aggregate number can mislead users of forecast results, especially when they are used as a basis for decisions at times when markets are volatile.

Hold-out Validation and Ex-Ante Forecast

The hold-out test was carried out by holding the last five observations as test data and producing a one-step forward forecast on a rolling basis. The results are presented in Table 4. In the period from January to May 2024, the third-order moving average method produced a MAPE of only 2.45% with a MAD of IDR 61.33/kg and an RMSE of IDR 76.68/kg. The largest error occurred in January 2024 at 5.07%, while the smallest error occurred in March 2024 which was only 0.14%.

Table 4. Results of the hold-out test of one step ahead forecast, January–May 2024

Moon	Actual price (IDR/kg)	Forecast price (IDR/kg)	Error (IDR/kg)	APE (%)
January 2024	2.500	2.373,33	+126,67	5,07
February 2024	2.450	2.390,00	+60,00	2,45
March 2024	2.460	2.463,33	−3.33	0,14
April 2024	2.450	2.470,00	−20,00	0,82
May 2024	2.550	2.453,33	+96,67	3,79
Average	**2.482,00**	**2.429,99**	**MAD 61.33**	**2,45**

Source: Data processing results (2024). A positive sign indicates the actual price is higher than forecast.

The forecast value for May 2024 of IDR 2,453.33/kg compared to the actual price of IDR 2,550/kg resulted in an error of IDR 96.67/kg or 3.79%. The MPE value in the test period of +2.07% indicates a tendency for the model to forecast slightly lower than the actual price, which is reasonable considering that prices are in a slow strengthening trend throughout early 2024. Based on the last three observations, the ex-ante forecast for June 2024 using the same weight is IDR 2,486.67/kg, while using the best weight combination of 9:1:1 is IDR 2,532.73/kg. The difference of IDR 46.06/kg between the two figures concretely illustrates the practical consequences of the selection of the weighting structure.

It should be emphasized that the MAPE of 2.45% in the hold-out test should not be interpreted as evidence of the method's general superiority. The figure was obtained in a period with a coefficient of price variation of only 1.74%, i.e. unusually calm market conditions. In such a calm period, any reasonable forecasting method, including naïve models and even the use of simple average values, would yield high accuracy. The result of this hold-out is therefore more apt to be read as confirmation of the study's main conclusion, which is that the accuracy of the smoothing method is essentially a reflection of the calm of the market it is facing, rather than a reflection of the intrinsic ability of the method to anticipate price changes.

Discussion

The above series of findings leads to a coherent conclusion regarding the position of the weighted moving average method in the management of FFB price information. This method has three distinct advantages, namely the simplicity of computation that allows its application to spreadsheet software available in almost all district offices, the need for minimal data in the form of the last three observations, and the transparency of calculations that make it easier to explain to stakeholders at the farmer level. This advantage is consistent with the reason for the popularity of the smoothing method in applied forecasting practices as stated by Makridakis et al. (1998) and Hyndman and Athanasopoulos (2018).

However, the study also shows that these advantages are accompanied by structural limitations, not just technical limitations that can be overcome by parameter adjustments. The moving average method works by extrapolating weighted averages from the past, so that by definition it cannot anticipate changes whose source lies outside the price series itself. The July 2022 shock stemmed from a trade policy decision announced at the end of April 2022, i.e. information that was publicly available more than two months before its impact was recorded in the price data, but was in no way contained in the price history of the previous three months. In this framework, the failure of the model in the shock subperiod is not a failure of specifications, but rather a logical consequence of the narrowness of the information set used.

The consequences of such failures are not evenly distributed among the perpetrators. Sukiyono et al. (2017) showed that the vulnerability of smallholder households in Bengkulu Province to FFB price volatility is inversely proportional to the household's capacity to postpone sales and access alternative sources of income. Small-scale independent smallholders, who are precisely the largest group, have the most limited delay capacity because FFB must be processed immediately within 24 to 48 hours of harvest to avoid an increase in free fatty acid levels. The absence of a reliable early warning system therefore impacts the groups that have the least risk buffer. A similar asymmetry pattern has been documented in the price transmission of other commodities in the same province, where the benefits from price increases are not fully passed on to farmers while the losses from price reductions are almost entirely borne by farmers (Sukiyono & Asriani, 2020).

Thus, the results of this study are not intended to reject the use of the weighted moving average method, but to place it in a function that is in accordance with its capabilities. This method is appropriate to be used as a price series refining instrument for the purpose of determining weekly or monthly reference prices, as a short-term noise filter in price publications by the plantation office, and as a tool for planning farmers' cash flows under calm market conditions. On the other hand, this method is not appropriate to be used as the sole basis for strategic decisions such as replanting scheduling, taking investment credits, or determining the amount of regional reserve funds, because these decisions require the most information about the possibility of shocks, i.e. precisely in the conditions when this method is most unreliable.

This study has a number of limitations that need to be stated openly. First, the length of the series of 41 monthly observations does not allow for adequate identification of seasonal components, even though FFB production has a clear seasonal pattern related to the rainfall cycle. Second, the data used are the provincial average prices so that they do not capture price disparities between districts or price differences between partner and independent smallholders, even though it is precisely the difference that is most relevant for vulnerability analysis. Third, this study does not compare WMA with model classes that are theoretically more adequate for volatile series, such as ARIMA, an intervention model with policy puppet variables, or the ARCH/GARCH model which explicitly models conditional variety. Further research is suggested to expand the range of data, disaggregating prices by district and smallholder partnership status, and comparing the performance of several model classes by including external explanatory

variables in the form of international CPO prices, rupiah exchange rates, and trade policy puppet variables.

Policy Implications and Suggestions

The finding that forecast accuracy collapsed sharply just when smallholders needed price information the most had fundamental policy implications for the Bengkulu Provincial Government, especially the Plantation Office. The current price information system is fully retrospective, reporting prices that have occurred without any indication of the direction of future price movements or the level of confidence in these indications. This study suggests that the weekly publication of FFB prices that has been routinely carried out is complemented by short-term projections and confidence intervals, and last but not least, accompanied by information about the current market regime. A simple distinction between calm market conditions and volatile market conditions, which can be determined operationally through the monitoring of the price variation coefficient over the past three months, is enough to tell farmers when the projected figures are worth holding and when they should be treated with extreme caution. The publication of projections without information from the regime risks creating a false sense of security in the most dangerous period.

The second implication relates to the need to build an early warning system that does not rely solely on price history. Since the July 2022 shock stemmed from a policy decision that had been announced more than two months earlier, a monitoring system that integrates indicators outside the price series will have much better anticipation power than any refining method. Indicators recommended to be monitored regularly include the occupancy rate of CPO storage tanks at factories operating in Bengkulu Province, monthly export volume and value, CPO price movements at KPBN auctions and international benchmark exchanges, rupiah exchange rates, as well as any trade policy announcements regarding export bans, export levies, and domestic supply obligations. The Plantation Service together with the Central Statistics Agency and growers' associations can compile a simple price pressure index that combines these indicators, then link them to a tiered level of vigilance that triggers certain actions when a certain threshold is exceeded. This kind of approach does not require complex econometric models, but it does require institutional commitment to collect and share data on a regular basis.

The third implication concerns protection for independent smallholders who are beyond the reach of the pricing mechanism. Regulation of the Minister of Agriculture No. 01/Permentan/KB.120/1/2018 provides price protection only to smallholders who partner with plantation companies, while the majority of smallholders in Bengkulu Province sell FFB through collectors at prices that during the shock period are very far below the set price. Local governments need to encourage the expansion of the scope of protection through the governor's regulation on the FFB trading system that regulates the obligation to announce the purchase price by each palm oil mill, the setting of the maximum limit of the quality deduction that can be imposed, and the provision of complaint channels that are easily accessible to smallholders. The experience of several provinces that already have governor's regulations on FFB trading system shows that the existence of these regulations is able to withstand the depth of price declines at the level of independent smallholders at the time of the shock, although it does not completely eliminate it. Strengthening smallholder institutions through cooperatives and farmer groups also needs to be directed at increasing the bargaining position in collective sales, not just on the distribution of production facilities.

The fourth implication is related to risk management at the household level of smallholders. The standard deviation of monthly price changes of 11.85% indicates that smallholders routinely face large revenue uncertainty even under normal market conditions, and at times of price decline shocks can reach more than half of the previous month's value in one month. Extension programs need to be directed so that smallholders do not develop household spending plans or installment payment schedules by relying on the highest prices ever experienced, but rather by referring to long-term average prices and setting aside the difference as reserve funds at times of high prices. Since FFB cannot be stored so that postponement of sales is not an available option, risk buffers must be built on the side of household finances and diversification of sources of income, for example through intercropping on unyielding crops, livestock businesses, or non-agricultural economic activities. Microfinance institutions in palm oil hub areas can be encouraged to develop term savings schemes whose deposits are linked to the current FFB price level.

The fifth implication is aimed at the central government in formulating trade policies that have an impact on upstream prices. The series of events in 2022 shows that policies aimed at stabilizing prices at the consumer level can incur enormous costs at the producer level if implemented suddenly and without a buffer mechanism. Any export restriction policy should be accompanied by an impact assessment on smallholders' FFB absorption capacity, accompanied by an adequate adjustment deadline for business actors, and equipped with compensation instruments that can be disbursed quickly for affected smallholders. Funds collected from export levies through the Oil Palm Plantation Fund Management Agency can be considered as a source of financing for price stabilization schemes at the smallholder level, with disbursement triggers set transparently based on measurable price indicators. In the end, the study's main conclusion, that price history-based forecasting will never be able to anticipate policy shocks, should be read as an argument for

the importance of policy predictability itself: when policy is predictable, prices become more predictable.

Conclusion

The price of palm oil FFB in Bengkulu Province during January 2021 to May 2024 averaged IDR 2,312.76/kg with a coefficient of variation of 19.46%, and the volatility was concentrated in 2022 with a coefficient of variation of 34.49%. The deepest monthly price decline occurred in July 2022 by 52.63%, which is related to the continued impact of the CPO export ban policy for the period of April 28 to May 23, 2022. The price series is therefore not homogeneous, but consists of a calm market regime and a shock regime with very different statistical characteristics.

The application of the three-period weighted moving average method with a thorough search of 165 weight combinations yielded the best combination of 9:1:1 with a MAPE of 9.56%, RMSE of IDR 346.16/kg, and a MAD of IDR 196.02/kg, which according to Lewis' criteria is classified as very good. The combination of conventional weights of 3:2:1 results in a MAPE of 11.86% and the same weight results in a MAPE of 13.70%, so the choice of weight structure is proven to have a real effect on accuracy. However, all specifications produce a Theil U value greater than one, which means that none of them has been able to outperform the naïve model with a MAPE of 8.69%. The forecast for May 2024 of IDR 2,453.33/kg compared to the actual price of IDR 2,550/kg resulted in an error of 3.79%, while the hold-out test from January to May 2024 resulted in a MAPE of 2.45%.

The accuracy of the method proved to be very volatile between subperiods, namely 9.55% in the shock subperiod and 7.13% in the recovery subperiod, but jumped to 34.39% in the shock subperiod which only included 21.05% of observations but accounted for 76.26% of the total squared error. Thus, it can be concluded that the weighted moving average method is suitable for use as a short-term benchmark refining and pricing instrument in calm market conditions, but it is inadequate as an early warning system against shocks stemming from trade policy. Strengthening the price information system in the regions therefore needs to be directed at the integration of indicators outside the price series, not at the refinement of the specification of the refinement model alone.

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APPENDIX

Appendix 1. Actual price data and the results of the three-period moving average forecast, January 2021–May 2024 (IDR/kg)

t	Month	Actual	MA Prediction(3)	Error	APE (%)
1	Jan 2021	2.250	–	–	–
2	Feb 2021	2.551	–	–	–
3	Mar 2021	2.230	–	–	–
4	Apr 2021	2.420	2.343,67	+76,33	3,15
5	May 2021	2.220	2.400,33	−180.33	8,12
6	June 2021	1.950	2.290,00	−340.00	17,44
7	Jul 2021	1.900	2.196,67	−296.67	15,61
8	Aug 2021	2.150	2.023,33	+126,67	5,89
9	Sep 2021	2.130	2.000,00	+130,00	6,10
10	Oct 2021	2.230	2.060,00	+170,00	7,62
11	Nov 2021	2.320	2.170,00	+150,00	6,47
12	From 2021	2.370	2.226,67	+143,33	6,05
13	Jan 2022	2.420	2.306,67	+113,33	4,68

t	Month	Actual	MA Prediction(3)	Error	APE (%)
14	Feb 2022	2.850	2.370,00	+480,00	16,84
15	Mar 2022	2.970	2.546,67	+423,33	14,25
16	Apr 2022	3.120	2.746,67	+373,33	11,97
17	May 2022	3.340	2.980,00	+360,00	10,78
18	June 2022	3.420	3.143,33	+276,67	8,09
19	Jul 2022	1.620	3.293,33	−1,673.33	103,29
20	Aug 2022	1.440	2.793,33	−1,353.33	93,98
21	Sep 2022	1.520	2.160,00	−640,00	42,11
22	Oct 2022	1.590	1.526,67	+63,33	3,98
23	Nov 2022	1.630	1.516,67	+113,33	6,95
24	From 2022	1.680	1.580,00	+100,00	5,95
25	Jan 2023	2.030	1.633,33	+396,67	19,54
26	Feb 2023	1.980	1.780,00	+200,00	10,10
27	Mar 2023	2.050	1.896,67	+153,33	7,48
28	Apr 2023	2.450	2.020,00	+430,00	17,55
29	May 2023	2.355	2.160,00	+195,00	8,28
30	June 2023	2.467	2.285,00	+182,00	7,38
31	Jul 2023	2.350	2.424,00	−74,00	3,15
32	Aug 2023	2.640	2.390,67	+249,33	9,44
33	Sep 2023	2.650	2.485,67	+164,33	6,20
34	Oct 2023	2.450	2.546,67	−96.67	3,95
35	Nov 2023	2.230	2.580,00	−350,00	15,70
36	From 2023	2.440	2.443,33	−3.33	0,14
37	Jan 2024	2.500	2.373,33	+126,67	5,07
38	Feb 2024	2.450	2.390,00	+60,00	2,45
39	Mar 2024	2.460	2.463,33	−3.33	0,14
40	Apr 2024	2.450	2.470,00	−20,00	0,82
41	May 2024	2.550	2.453,33	+96,67	3,79

Source: Data processing results (2024). Forecasts are not calculated for the initial three periods because the data history is incomplete.