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Stepping up Food Price Prediction using Prophet Model

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Abstract

Price fluctuations of strategic food commodities in metropolitan regions like DKI Jakarta present a critical economic challenge, heavily driven by supply chain constraints and localized demand surges during religious festivities. This study addresses the limitation of traditional forecasting models in capturing such non-linear anomalies by implementing the Prophet empirical framework to predict daily food prices across various essential commodities. Utilizing the Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology, the prediction models were rigorously trained and evaluated using Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) metrics. The empirical results demonstrate that the optimized Prophet model delivers exceptional predictive accuracy for stable commodities, yielding highly accurate scores for garlic (MAPE 5.58%), beef (4.86%), chicken meat (5.73%), chicken eggs (4.55%), sugar (7.01%), and rice (8.61%). Conversely, volatile commodities like curly red chili peppers yielded a moderately accurate performance (MAPE 31.53%). These findings indicate that the structural decomposition approach of the Prophet model offers a highly robust decision-support tool for metropolitan inflation monitoring and market intervention policies.

Keywords:
Food, Prediction, Prophet, MAPE, RMSE

1. Introduction

Food price prediction has become a critical research area due to its direct impact on economic stability, food security, and agricultural sustainability. Agricultural commodity markets remain highly volatile because they are influenced by weather conditions, supply chain disruptions, inflation, and geopolitical instability. Chen and Sin emphasize that farmers often struggle with price instability and limited market knowledge, which reduces profitability and discourages participation in agriculture. To address this, they explore machine learning models such as ARIMA, LSTM, SVR, Prophet, and XGBoost for forecasting agricultural prices, highlighting the need for data-driven decision support systems in farming ecosystems. However, no single model consistently performs best across all conditions, indicating persistent challenges in model generalization for agricultural forecasting tasks. [1]

Recent research increasingly adopts hybrid and ensemble approaches to improve prediction accuracy in volatile financial and agricultural markets. A.M. et al. propose an ARIMA-Prophet ensemble model that combines ARIMA's strength in short-term linear forecasting with Prophet's ability to handle seasonality and trend fluctuations. Their work demonstrates that hybridization improves robustness in stock price prediction systems, especially under uncertain market behavior. Other studies similarly confirm that single statistical models are often insufficient for capturing nonlinear and abrupt price changes in

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real-world datasets. Despite these improvements, hybrid systems still face challenges related to increased computational complexity and deployment scalability in practical applications. [2]

Prophet-based models have gained significant attention because of their flexibility in handling seasonality, missing data, and trend shifts in time series forecasting. Bhattacharyya and Jha apply Prophet to agricultural commodity price forecasting and show that it effectively captures long-term trends in agricultural datasets. Omonayajo et al. extend this application to Ethereum gas price prediction, demonstrating that Prophet performs well across financial and blockchain environments. However, these studies also indicate that Prophet alone struggles with sudden spikes and highly nonlinear fluctuations that frequently occur in commodity markets. This limitation highlights the need for improved or hybrid forecasting strategies to enhance robustness in real-world conditions. [3][7].

Hybrid architectures combining Prophet with deep learning models such as LSTM have shown significant improvements in forecasting accuracy. Periketi et al. propose a fusion of LSTM and Prophet for Bitcoin price prediction and demonstrate better trend capture and reduced forecasting error compared to standalone models. Meng and Dou introduce a Prophet-LSTM-BP ensemble for carbon trading price prediction and show that combining multiple learning paradigms improves both stability and accuracy. These findings confirm that integrating statistical and neural approaches helps balance interpretability and nonlinear learning capability. However, such hybrid models increase system complexity and require careful parameter tuning, which can limit interpretability and increase computational cost. [4][5].

In parallel, ARIMA remains a widely used benchmark model in time-series forecasting due to its simplicity and effectiveness in stationary data environments. Jin et al. compare ARIMA and Prophet for Google stock price prediction and find that ARIMA performs better in short-term forecasting during stable periods. Prasetyono and Anggraini also apply ARIMA to socioeconomic forecasting and confirm its reliability in structured linear time series. However, ARIMA struggles to capture nonlinear relationships and seasonal variations, which limits its performance in complex commodity markets. These limitations motivate researchers to integrate ARIMA with more adaptive models such as Prophet and neural networks to improve forecasting performance. [8][11].

Optimization techniques and model tuning strategies play a crucial role in improving forecasting accuracy in modern time-series systems. Prastyo and Utama highlight that hyperparameter optimization significantly enhances decomposable time-series models like Prophet by improving adaptability to dataset-specific patterns. Fang demonstrates that optimized neural network models can significantly reduce prediction errors in food commodity forecasting, while Shehu et al. show that deep learning-based commodity forecasting models optimized through neural architectures achieve superior accuracy in volatile markets. These studies confirm that model performance is highly dependent on parameter selection, training strategy, and optimization techniques. However, excessive tuning can also lead to overfitting and reduced generalization performance in unseen data. [10][15][17].

Recent research in food price prediction also emphasizes system-level design and multi-indicator integration to improve forecasting robustness. Arisandi et al. design a structured food price prediction system using the Iconix method, showing that system engineering approaches improve practical implementation of forecasting models. Khan et al. and Şenel et al. demonstrate that integrating macroeconomic indicators and multi-feature frameworks significantly improves predictive accuracy in food price modeling. These studies highlight that forecasting performance depends not only on algorithms but also on feature engineering, data quality, and system design. However, challenges such as data scarcity, feature selection complexity, and dynamic market behavior remain unresolved in real-world applications. [22][23][24].

Across domains such as agriculture, stock markets, cryptocurrencies, and carbon trading, Prophet-based models consistently show strong performance in capturing trends and seasonal behavior. Taylor and Letham introduce Prophet as a scalable forecasting framework designed for business time series, and subsequent studies validate its applicability across diverse datasets. Zheng and Ji further argue that traditional time-series models are increasingly competing with generative AI approaches, showing that forecasting remains an evolving and highly competitive research field. This ongoing competition between statistical, machine learning, and hybrid methods highlights the need for continuous improvement in forecasting systems. In this context, enhancing Prophet-based food price prediction models becomes essential to improve accuracy, stability, and real-world usability in agricultural decision-making systems. [13][14][16].

2. Related Works

Researchers previously explored machine learning methods for agricultural commodity price prediction to support farmers and policymakers in managing market uncertainty. Chen and Sin investigated multiple models, including ARIMA, LSTM, SVR, Prophet, and XGBoost, to identify suitable forecasting approaches for agricultural applications. They found that machine learning models improved prediction accuracy compared to traditional approaches. However, their study also showed that no single model consistently performed best across different datasets and conditions. This limitation indicated the need for more robust and adaptive forecasting frameworks for agricultural markets. [1]

Several studies focused on Prophet and ARIMA as baseline models for time-series forecasting in economic and agricultural domains. Bhattacharyya and Jha applied Prophet to agricultural commodity prices and reported strong performance in capturing trend and seasonality patterns. Jin et al. compared ARIMA and Prophet for stock price prediction and found ARIMA more effective for short-term forecasting under stable conditions. However, Prophet performed better in handling trend shifts and seasonal variations. These studies confirmed that both models had complementary strengths but also highlighted their individual limitations when used independently. [3][8]

Hybrid modeling approaches emerged as a solution to overcome weaknesses of single forecasting models. A.M. et al. proposed an ARIMA-Prophet ensemble model for stock price prediction and improved forecasting accuracy by combining short-term and long-term modeling capabilities. They showed that ensemble learning enhanced prediction stability under volatile market conditions. However, the model increased system complexity and required careful integration of outputs. This created challenges in scalability and real-world deployment for time-sensitive forecasting systems. [2]

Deep learning integration with Prophet also gained attention in financial and cryptocurrency forecasting studies. Periketi et al. developed a Prophet-LSTM fusion model for Bitcoin price prediction and achieved improved accuracy compared to standalone models. The hybrid approach effectively captured both sequential dependencies and seasonal trends. However, the model required large datasets and significant computational resources. This limited its applicability in environments with limited data availability or computing power. [4]

In carbon trading and energy markets, researchers further extended hybrid forecasting frameworks using multiple learning models. Meng and Dou proposed a Prophet-LSTM-BP ensemble model for carbon trading price prediction. They demonstrated higher stability and accuracy compared to individual Prophet and LSTM models. The model successfully handled nonlinear and volatile price movements. However, the increased number of components made model interpretation more difficult and reduced transparency in decision-making. [5]

Other studies enhanced Prophet-based models using hybrid optimization and decomposition techniques for improved accuracy. Huang et al. integrated Prophet with

ICEEMDAN and error correction methods for metal price prediction. They reported significant improvement in forecasting precision. Omonayajo et al. applied Prophet to Ethereum gas price prediction and showed its ability to handle long-term forecasting trends. However, both studies highlighted that Prophet alone still struggled with abrupt fluctuations and noise in real-world time-series data. These limitations motivated further hybridization and optimization strategies. [6][7]

Traditional statistical models such as ARIMA continued to serve as benchmark approaches in forecasting studies. Prasetyono and Anggraini applied ARIMA for poverty prediction and confirmed its effectiveness in stationary datasets. ARIMA performed well in linear and structured time-series environments. However, it failed to capture nonlinear patterns and structural breaks in volatile datasets. This limitation reduced its effectiveness in modern financial and agricultural forecasting tasks. [11]

Recent research emphasized system-level improvements and advanced predictive frameworks for food price forecasting. Arisandi et al. designed a food price prediction system using the Iconix method and structured system engineering principles. Khan et al. used multiple machine learning models to analyze food price index interdependencies and achieved improved prediction accuracy with feature-rich datasets. Şenel et al. further demonstrated that hybrid feature engineering and machine learning models significantly improved forecasting performance in volatile markets. However, these studies also identified challenges related to data scarcity, feature selection, and model generalization across different regions. [22][23][24]

3. Proposed Method

This section describes the methodological framework employed to execute time series forecasting and assess the Prophet model's efficacy in projecting future price points. The adopted strategy is specifically tailored to mitigate challenges posed by non-linear trends and cyclical seasonal variations inherent in the dataset. To facilitate scientific rigor and replicability, the following procedures are detailed in a systematic sequence, covering data preprocessing through to model evaluation. The research process begins with data collection, then the next step is data preprocessing to ensure consistencies and data quality. This includes handling missing values, data formatting, and preparing the dataset according to the requirements of the Prophet model. The preprocessed data are then used to develop the forecasting model using Prophet, which decomposes time series data into trend, seasonal, and irregular components.

Furthermore, the forecasting results are evaluated using Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) to assess the accuracy and reliability of the model. These evaluation metrics are selected to provide a comprehensive measurement of prediction errors, both in absolute and percentage terms. The final stage involves analyzing the forecasting results to determine the effectiveness of the model in capturing underlying data patterns and supporting data-driven decision-making. Forecasting integrates historical data analysis with predictive techniques to reduce future ambiguity. This process is fundamental for creating evidence-based frameworks that support effective planning and sustainable organizational growth [5]. Error evaluation in forecasting is conducted to measure the accuracy level of the forecasting results that have been produced, so that errors can be identified and forecasting methods can be adjusted if necessary. Forecasting errors can be calculated in several ways, including: [12].

1. **Root Mean Square Error (RMSE):** Determines the forecast precision by measuring the deviation of predicted values from the ground truth. Equation (1) presents the mathematical formulation of the Root Mean Square Error (RMSE).

$$RMSE = \sqrt{\frac{1}{n}} \sum_{i=1}^{n} (\hat{y}_i - y_i) \quad (1)$$

2. **Mean Absolute Percentage Error (MAPE):** The performance metric used to assess the average percentage error is MAPE, with its interpretation scales shown in Table 1.

Table 1. MAPE Forecasting Criteria

MAPE	MAPE Forecasting Criteria
<10%	The accuracy of the forecast is very accurate.
10-20%	The accuracy of the forecast is accurate.
20-50%	The accuracy of the forecast is quite accurate.
>50%	The accuracy of the forecast is less accurate

The evaluation criteria for forecasting accuracy, categorized by Mean Absolute Percentage Error (MAPE) thresholds, are summarized in Table 1. A lower MAPE value signifies superior model performance, indicating a minimal deviation between predicted and actual observations. The mathematical formulation for calculating MAPE is defined in Equation (2).

$$MAPE = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right| x\ 100 \quad (2)$$

The Prophet forecasting framework employs a decomposable time-series model consisting of three main model components: trend, seasonality, and holidays. The general formulation is expressed in Equation (3):

$$\mathrm{y(t)} = \mathrm{g(t)} + \mathrm{s(t)} + \mathrm{h(t)} + €\mathrm{(t)} \quad (3)$$

Where $y(t)$ represents the predicted food price at time *t*, *g(t)* is the trend function modeling non-periodic changes, *s(t)* represents periodic changes or seasonality, *h(t)* denotes the effects of holidays or localized events, and $€(\mathrm{t})$ represents the idiosyncratic error term which is assumed to be normally distributed.The trend component *g(t)* can be modeled using a piecewise linear growth or a logistic growth function. For commodities exhibiting saturating growth dynamics, the logistic growth function is formulated as follows:

$$g(t) = \frac{C(t)}{1+\exp(-k(t-m))} \quad (4)$$

Where *C(t)* is the dynamic carrying capacity, *k* represents the growth rate, and *m* is the offset parameter. To handle abrupt shifts in food trends caused by economic shocks, Prophet automatically incorporates change points where the growth rate *k* is allowed to adjust. The seasonality component *s(t)* captures cyclical fluctuations (e.g., weekly and annual price changes) using a Fourier series to approximate arbitrary periodic patterns. The formulation is given by:

$$s(t) = \sum_{i=1}^{n} \left(a_n cos\left(\frac{2\pi nt}{P}\right) + b_n sin\left(\frac{2\pi nt}{P}\right) \right) \quad (5)$$

Where *P* is the regular period of the time series (e.g., *P* = 365.25 days for yearly seasonality), and a_n, b_n are the parameters estimated during model training to fit the historical cyclical patterns. The holiday component *h(t)* accounts for predictable, irregular shocks in food prices that occur during major religious and national festivities (e.g., Eid al-Fitr, Christmas). It is formulated as a matrix of indicator variables:

$$h(t) = Z(t)\kappa = \sum_{i=1}^{L} \kappa_i \cdot 1_{(t \in D_i)} \quad (6)$$

Where *Z(t)* is a vector of holiday indicator functions that output 1 if time *t* falls within holiday window $\boldsymbol{D_i}$ and 0 otherwise, and κ represents the parameter vector determining the corresponding price impact of each holiday event. Time series data consist of observations recorded sequentially, typically at equidistant intervals, which serve as the fundamental framework for forecasting. By decomposing these data, researchers can isolate critical components such as trends, seasonality, cyclical patterns, and stochastic noise (irregular variations), all of which are pivotal for evidence-based, future-oriented decision-making [12].

4. Experimental Setup

This study gathered dataset from the Strategic Food Price Information Center (PIHPS). It comprises daily price records spanning from January 2020 to June 2025, totaling 2,008 observations per commodity. Ten essential food commodities were selected for analysis: rice, chicken meat, beef, chicken eggs, garlic, shallots, curly red chili peppers, red cayenne peppers, packaged cooking oil, and granulated sugar. The data, originally stored in Excel format (.xlsx), contains two primary attributes: the observation date (temporal) and the commodity price (numerical) [13].

To ensure data quality and consistency, a series of preprocessing steps were executed before the modeling phase. This process includes handling missing values using forward fill and backward fill methods, removing duplicate and invalid data, and transforming the dataset into a format compatible with the Prophet model, where *ds* columns represent the timestamp and *y* represents the observed value. In addition, data aggregation into monthly intervals was performed to reduce noise and improve seasonal pattern detection.

The experimental framework for this study was implemented using Python programming language, leveraging the Prophet library as the primary forecasting engine. For model training and validation, the data were partitioned into an 80:20 ratio, where the first 80% of chronological observations were used to fit the model and the subsequent 20% served as the test set to evaluate out-of-sample performance. To achieve optimal results, hyperparameter tuning was focused on the *changepoint_prior_scale* and *seasonality_prior_scale* to strike a balance between trend flexibility and overfit prevention. The final model performance was quantified using Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE).

5. Result and Analysis

The results of this study are obtained from the implementation of ten food commodities in DKI Jakarta using Prophet Model. The model was evaluated using Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE). The evaluation results are presented in Tables 2 and 3.

Table 2. MAPE and RSME evaluation result without tuning

No	Commodity	MAPE(%)	RMSE	Description
1	Garlic	11.11	6471.55	Accurate
2	Shallot	15.01	7498.43	Accurate
3	Beef	3.80	5931.01	Highly Accurate
4	Chicken Meat	6.71	3090.57	Highly Accurate

5	Red Cayenne Pepper	18.96	15265.61	Accurate
6	Curly Red Chili	31.84	17343.81	Fairly Accurate
7	Chicken Egg	10.79	3400.52	Accurate
8	Granulated Sugar	4.02	894.65	Highly Accurate
9	Rice	8.23	1374.44	Highly Accurate
10	Packaged Cooking Oil	8.67	2180.53	Highly Accurate
Average		**11.91%**	**6.345,11**	**Accurate**

Table 2 shows the evaluation results of the Prophet model without parameter tuning. The MAPE values range from 3.80% to 31.84%, while the RMSE values vary across commodities. Several commodities such as beef, granulated sugar, rice, and chicken meat produce MAPE values below 10%, while others such as shallots, red cayenne peppers, and garlic produce MAPE values between 10% and 20%. Curly red chili peppers show the highest MAPE value of 31.84%. The average MAPE value obtained is 11.91%, with an average RMSE of 6,345.11.

Table 3. MAPE and RSME evaluation result tuning

No	Commodity	MAPE (%)	RMSE	Description
1	Garlic	5.58	4106.16	Accurate
2	Shallot	15.94	7458.71	Accurate
3	Beef	4.86	7318.62	Highly Accurate
4	Chicken Meat	5.73	2592.23	Highly Accurate
5	Red Cayenne Pepper	18.49	15321.4	Accurate
6	Curly Red Chili	31.53	17184.75	Fairly Accurate
7	Chicken Egg	4.55	1515.47	Accurate
8	Granulated Sugar	7.01	1775.12	Highly Accurate
9	Rice	8.61	1433.1	Highly Accurate
10	Packaged Cooking Oil	16.48	3913.08	Highly Accurate
Average		**11.88%**	**6.2611,86**	**Accurate**

The empirical results show that Prophet model performance varies significantly depending on whether hyperparameter tuning is applied. Without tuning, the model achieved an average MAPE of 11.91% and RMSE of 6,345.11. In this baseline setting, volatile commodities produced higher errors, with Garlic and Shallots reaching 11.11% and 15.01% MAPE, while Curly Red Chili showed the highest error at 31.84%. In contrast, stable commodities such as Beef, Sugar, and Rice remained below 10% MAPE, indicating better predictive stability. After tuning the changepoint_prior_scale and seasonality_prior_scale, the model performance improved. The average RMSE decreased to 6,261.86, while MAPE slightly improved to 11.88%. More importantly, volatile commodities showed clear error reduction. Garlic dropped from 11.11% to 5.58% MAPE, indicating a significant gain in forecasting accuracy. These results show that hyperparameter tuning improves Prophet's ability to adapt to abrupt market changes while preserving stable trend learning.

A comparative evaluation across the ten commodities shows a clear link between market stability and forecasting accuracy. Stable, centrally managed commodities such as Rice, Beef, and Granulated Sugar consistently achieved low error rates, with MAPE values below 10%. These products follow predictable trends and seasonal demand patterns, which the

Prophet model captures effectively. In contrast, highly volatile commodities like Curly Red Chili showed much higher error, reaching 31.53% MAPE. Their prices fluctuate due to irregular shocks such as weather disruptions and supply chain issues. Since Prophet relies on historical trend and seasonality patterns, it struggles to fully capture these unpredictable external factors, leading to higher prediction errors.

Fig. 1. Garlic Visualization Chart

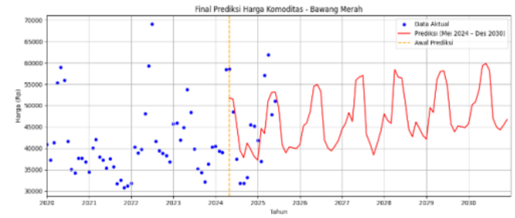

Fig. 2. Red Onion Visualization Chart

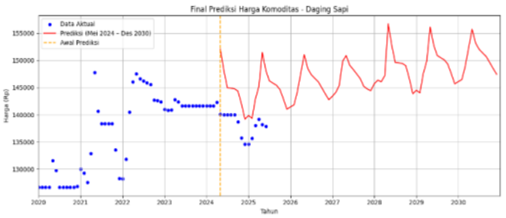

Fig. 3. Beef Visualization Chart

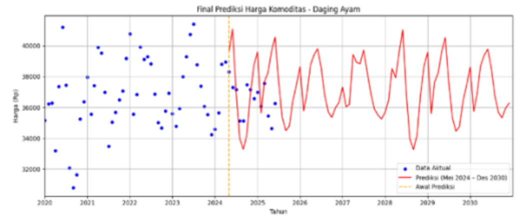

Fig. 4. Chicken Visualization Chart

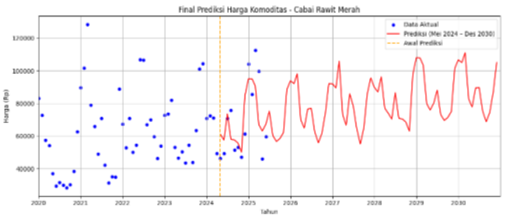

Fig. 5. Red Chili Pepper Visualization Chart

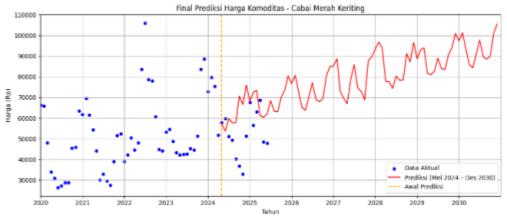

Fig. 6. Curly Red Chilli Visualization Chart

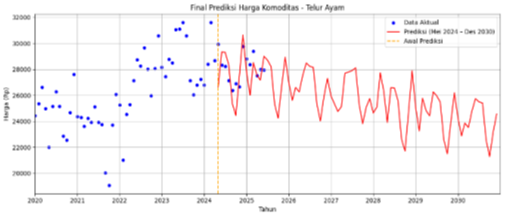

Fig. 7. Egg Visualization Chart

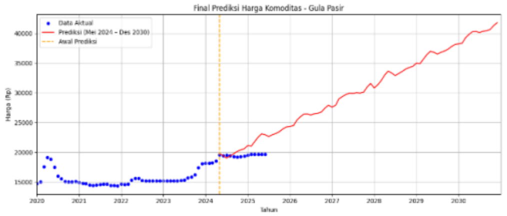

Fig. 8. Sugar Visualization Chart

6. Conclusion

This study demonstrates the empirical efficacy of implementing the Prophet forecasting framework to monitor and predict food price volatility within the metropolitan landscape of DKI Jakarta. The comprehensive evaluation across ten essential food commodities reveals that the model delivers highly dependable predictive intelligence. Stable-demand items backed by solid supply chains achieved optimal forecasting parameters, marked by highly accurate MAPE scores for rice (8.61%), beef (4.86%), garlic (5.58%), chicken meat (5.73%), chicken eggs (4.55%), and granulated sugar (7.01%). However, the framework encounters predictive performance limitations when deployed on short-term perishable crops with high supply uncertainty, exemplified by the 31.53% MAPE recorded for curly red chili.

The core finding validates that Prophet's structural decomposition framework provides a scalable, computationally efficient, and practical forecasting approach for regional food price monitoring. The model separates trend, seasonality, and residual components, which allows it to capture long-term movement patterns while maintaining robustness under routine seasonal fluctuations. This decomposition improves interpretability for policymakers because each component can be directly analyzed to understand price behavior. As a result, Prophet functions effectively as an early-warning tool to identify potential price escalations in essential commodities before they fully materialize in the market.

For future work, the forecasting accuracy can be improved by incorporating exogenous variables that influence price volatility beyond historical price patterns. Environmental factors such as rainfall anomalies, temperature variations in production zones, and harvest-cycle disruptions can strengthen the model's ability to respond to supply-side shocks. These enhancements can address the limitations of purely time-series-based decomposition models, particularly under non-periodic and irregular shocks. Ultimately, such hybrid extensions can bridge the performance gap between stable commodities and highly volatile agricultural products.

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