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Rice Price Prediction In East Java Based on Weather Using Long Short-Term Memory (LSTM)

Davina Mufidah[1], Noviyanti Santoso[2], Moch. Abdillah Nafis[3]
Statistika Bisnis, Institut Teknologi Sepuluh Nopember
davina03.dm@gmail.com[1]

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ABSTRACT

Rice is the primary staple food commodity in Indonesia, crucial for food security and economic stability, with price fluctuations significantly affecting public purchasing power. Data from Statistics Indonesia (BPS) in May 2025 indicated a 0.15% decline in medium-quality rice prices in East Java; however, price disparities between regions remain high, necessitating accurate prediction models. East Java, as one of the major production hubs contributing 20% to the national paddy production, is vulnerable to climate change phenomena such as El Niño and La Niña, which impact harvests and prices. Rice price fluctuations are influenced by various complex factors, including non-linear weather conditions such as rainfall, temperature, and humidity. This study focuses on forecasting the price of medium-quality rice, the most widely consumed variety in Indonesia. The multivariate Long Short-Term Memory (LSTM) model is proposed due to its capability in handling long-term dependencies and non-linear patterns within time-series data. This study analyzes the performance of LSTM using historical rice price data and integrates weather factors to enhance prediction accuracy. Daily data from January 1, 2020, to December 31, 2025, was utilized, sourced from the National Strategic Food Price Information Center (PIHPS) and BMKG East Java, covering variables such as medium rice price, rainfall, wind speed, humidity, sunshine duration, and temperature. The results indicate that the LSTM model with a configuration of 45 timesteps, a dropout rate of 0.3, a batch size of 16, 150 neurons, and 150 epochs yielded the most optimal performance, achieving a Train MAPE of 0.73% and a Test MAPE of 1.40%. These findings empirically demonstrate that a historical memory of approximately 1.5 months plays a crucial role in prediction accuracy, perfectly aligning with the short-to-medium-term supply chain dynamics. Based on the out-of-sample forecasting results for January to March 2026, the model predicts a sharp price correction in early January, followed by a gradual increase that stabilizes in the range of Rp14,380–Rp14,400 per kilogram. This projection visualizes a new equilibrium, confirming that historical climate damage establishes a permanent baseline price shift, while the high forecast accuracy (MAPE 0.25%) provides a highly reliable basis for government policy formulation.

I. INTRODUCTION

Rice is the primary staple food commodity in Indonesia, playing a strategic role in national food security and economic stability. As the main staple for the majority of the population, fluctuations in rice prices directly affect public purchasing power and welfare [1]. East Java, as one of the provinces with the largest rice production centers in Indonesia contributing approximately 20% of the total national rice production, faces unique challenges regarding price instability. Despite being a major granary, data indicates significant price disparities between districts, influenced by distribution costs and supply availability. This instability is a serious problem that requires an accurate predictive approach to support the government and stakeholders in formulating appropriate policies related to stabilization and distribution.

Price fluctuations are complex phenomena influenced by various factors, with weather conditions playing a fundamental role in determining productivity and harvest yields. East Java is vulnerable to climate change, including floods and droughts caused by El Nino and La Nina phenomena, which directly affect harvest yields and local market prices [2]. Factors such as rainfall, temperature, and humidity have a significant impact on plant growth. The complexity of the relationship between these variables, particularly non-linear and dynamic weather factors, emphasizes the need for prediction methods capable of capturing long-term dependencies.

Previous researchers have examined the impact of climate change on rice production and price volatility, [3] found that climate change, particularly temperature changes, negatively affects rice production in Indonesia in both the short and long term, while positively influencing price fluctuations where larger temperature increases result in higher price volatility. Other research by [4] also highlights the impact of ENSO phenomena on food commodity prices, further emphasizing the importance of considering climate factors in rice price analysis.

To address these challenges, the Long Short-Term Memory (LSTM) method is proposed as a potential approach for predicting rice prices due to its ability to consider various influencing variables. LSTM is a type of Recurrent Neural Network (RNN) architecture designed specifically to handle time-series data with the ability to learn long-term dependencies and overcome the vanishing gradient problem often found in conventional RNN models [5]. Previous studies have applied LSTM to forecast agricultural raw material prices with promising results, such as predicting red chili prices [6] and cooking oil prices [7].

Recent studies have specifically developed machine learning-based rice price prediction models. [8] developed an LSTM model incorporating weather data as input variables, achieving a very high prediction accuracy. Similarly, research by [9] applying the LSTM algorithm to predict rice prices in Central Java showed fairly good model performance. Furthermore, [10] highlighted that determining time steps or window size is a crucial parameter determining how much past data is used for prediction, where a balance of past information volume is key to prediction accuracy.

Despite several studies using LSTM for commodity price prediction, limitations remain in previous research. Most studies only use historical price data as a single variable in prediction without considering external factors affecting prices [11]. Therefore, this study aims to complement previous models by developing an LSTM-based model specifically focused on predicting medium rice prices in East Java by integrating weather data. This research aims to model rice price predictions to identify non-linear relationship patterns and the influence of weather variables, as well as to determine optimal hyperparameters.

The results of this research are expected to provide significant benefits for the government and agricultural industry players in formulating appropriate price stabilization policies, stock management, and rice import strategies, thereby increasing national food security and public welfare. For future researchers, this study provides a foundation and framework for the further development of agricultural commodity prediction models or method comparison studies in the same context, utilizing a multivariate time series approach to capture the complexity of relationships between variables.

Traditional forecasting methods, such as ARIMA or SARIMAX, have been widely used in Indonesian agricultural studies [4]. However, these baseline models often struggle to capture long-term non-linear dependencies caused by erratic climate changes. Unlike previous univariate studies that solely rely on historical prices [11], this research introduces a novelty by developing a multivariate Long Short-Term Memory (LSTM) model specifically tailored for East Java. By systematically integrating complex weather variables such as rainfall, temperature, humidity, wind speed, and sunshine duration this study empirically examines how extreme climate phenomena e.g., El Niño and La Niña induce sudden price shocks, providing a more robust framework for regional food security [3].

II. METHOD

This study utilizes daily secondary data from the National Strategic Food Price Information Center (PIHPS) and BMKG East Java from January 1, 2020, to December 31, 2025. Following data pre-processing which included median imputation for missing values e.g., 7.48% missing data in rainfall the dataset yielded a total of 1,565 valid observations. Prior to modeling, a correlation matrix was generated to observe the relationships between weather variables and to evaluate potential multicollinearity.

Rice price is defined as the monetary exchange value of medium quality rice paid by consumers at the retail level in traditional or modern markets. Weather variables include rainfall, defined as the amount of rain falling in a specific area; wind speed, which is the rate of horizontal air movement; humidity, referring to the amount of water vapor in the air; sunshine duration, measuring the duration of bright sunshine reaching the earth's surface; and temperature, which is the measure of the degree of heat or cold of the air. The complete list of research variables is presented in Table 1.

TABLE I
RESEARCH VARIABLES

Variable	Symbol	Scale	Unit
Medium Rice Price	Y	Ratio	Rupiah
Rainfall	X_1	Ratio	mm
Average Wind Speed	X_2	Ratio	m/s
Average Humidity	X_3	Ratio	Percent
Sunshine Duration	X_4	Ratio	Hours
Wind Speeds	X_5	Ratio	℃

To prevent data leakage, a strict chronological time-series split was employed. The data is divided into two parts:

training data 80% consisting of 1,252 observations from January 1, 2020, to October 18, 2024, and testing data 20% consisting of 313 observations from October 19, 2024, to December 31, 2025. Furthermore, all variables both the target and weather features underwent Z-score standardization to ensure uniform scaling, stabilize the learning process, and prevent gradient explosion. The analysis method used is Long Short-Term Memory (LSTM), a Recurrent Neural Network (RNN) architecture designed to model time-series data with long-term dependencies, as it can capture non-linear patterns, seasonal trends, and the influence of weather variables on rice prices.

The modeling process involved systematic hyperparameter tuning using a grid search approach across multiple parameters to find the optimal configuration such as timesteps 14, 30, 45, 60, 90 days, dropout rate 0.1, 0.2, 0.3, batch size 16, 32, 64, number of neurons 50, 100, 150, epochs 150, and 1 hidden layers. The model utilizes the Mean Squared Error (MSE) loss function and the ADAM optimizer. To provide a comprehensive assessment, the performance of the formed LSTM models is evaluated using Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). However, the best model is primarily selected based on the smallest Test MAPE, as it provides a relative percentage error that is highly interpretable for evaluating economic price volatility. Finally, forecasting is conducted for the out-of-sample period using the best model.

III. RESULTS AND DISCUSSION

This chapter presents the analysis and discussion of rice price modeling in East Java from January 2020 to December 2025 using daily data frequency. The study utilizes the multivariate Long Short-Term Memory (LSTM) method to capture the complex relationships between historical prices and weather variables. The modeling process involves a systematic hyperparameter tuning using a grid search approach. To provide a comprehensive assessment, each LSTM model configuration is evaluated based on its prediction accuracy using Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). Ultimately, the configuration that yields the lowest Test MAPE is determined as the best model for forecasting rice prices.

A. *Pre-Processing Data*

Data pre-processing involved detecting missing values in the East Java rice price dataset for the period of January 2020 to December 2024. As shown in Table 2, missing values were found in several variables, with Rainfall having the highest percentage of missing data 7.48%.

TABEL 2
MISSING VALUE

Variable	Total Data	*Missing Value*	
		Missing Count	Percentage
Temperature	1565	2	0.13%
Humidity	1565	2	0.13%
Rainfall	1565	117	7.48%
Sunshine Duration	1565	9	0.58%
Wind Speeds	1565	0	100%

These missing values were handled using median imputation to maintain dataset completeness and consistency. Subsequently, all variables were standardized using Z-score normalization to align data scales, facilitating the model's processing. The data was then split into 80% training data and 20% testing data.

B. *Data Characteristics*

The characteristics of variables suspected to influence rice prices were analyzed using time series plots. Figure 1 shows that rice prices in East Java rose sharply, from around Rp8,500 in early 2020 to over Rp14,500 in the 2024–2025 period. The sharpest spike began in early 2024 due to supply shortages caused by El Niño and massive harvest delays.

The time series plot also indicates a clear upward trend over the observed period, suggesting a persistent increase rather than short-term volatility. Seasonal patterns appear to be present, with recurring fluctuations that may correspond to planting and harvest cycles. However, the magnitude of price increases in 2024 significantly exceeds previous seasonal variations, indicating the presence of structural shocks rather than normal cyclical movements. Additionally, price volatility becomes more pronounced toward the end of the observation period, reflecting increasing market uncertainty and supply-side instability. Overall, the series exhibits non-stationary behavior, characterized by a strong trend component and changing variance over time.

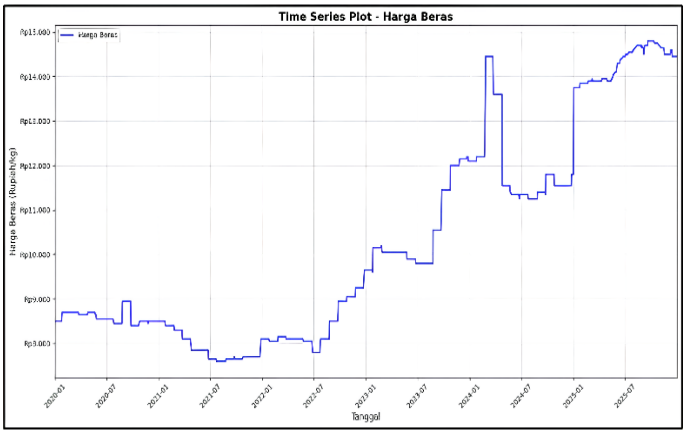


Figure 1. Time Series Plot of Rice Price

Further analysis compares rice prices with weather variables. Figure 2 shows that the drastic price increase in early 2024 coincided with high and unstable temperatures, reflecting extreme climate conditions like El Niño. By 2025, prices remained high despite temperature fluctuations, indicating a new price equilibrium.

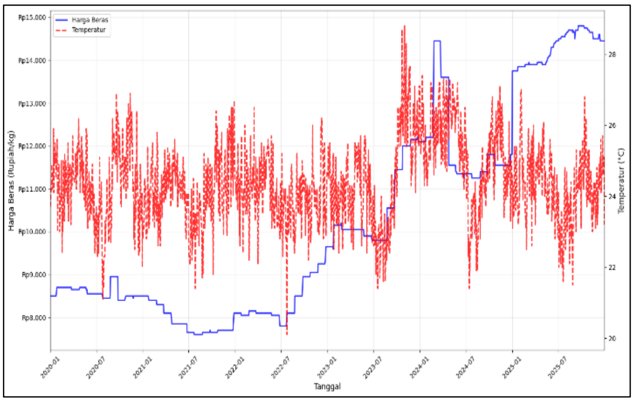


Figure 2. Time Series Plot Rice Price vs Temperature

The time series plot reveals that while temperature and prices were relatively stable prior to 2023, increased temperature variability starting in mid-2023 coincided with prolonged dry conditions and a sharp price escalation in early 2024. This suggests a supply-side shock driven by climate stress. However, the relationship is non-linear and asymmetric; moderate temperature fluctuations in 2025 did not result in equivalent price declines, indicating that market adjustments prevented prices from returning to previous levels. Consequently, temperature acts primarily as a triggering variable during extreme events rather than a constant driver, reinforcing the necessity of a non-linear modeling approach like LSTM to capture these complex dynamics.

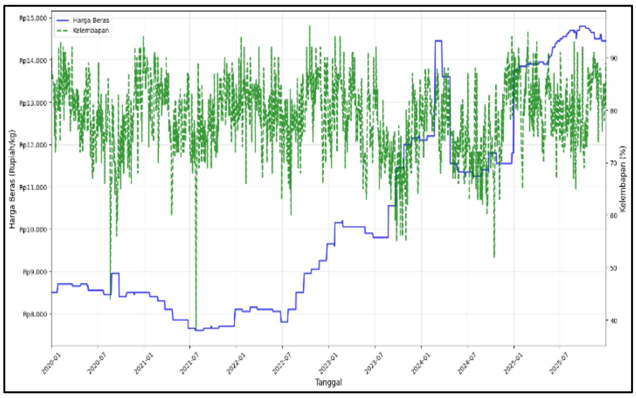


Figure 3. Time Series Plot Rice Price vs Humidity

Figure 3 illustrates the dynamic relationship between humidity and rice prices. High humidity levels 80–90% during 2020–2021 coincided with stable lower prices, indicating favorable growing conditions that supported agricultural productivity. Conversely, the price surge in 2024 correlated with a significant decline in humidity 60–70%, increasing the risk of crop failure due to drought stress. Interestingly, despite humidity levels recovering in 2025, rice prices did not decrease proportionally but remained stable at a high level, suggesting an asymmetric market response where past climate shocks established a new, higher price equilibrium. This pattern confirms that humidity functions as a critical risk variable, further justifying the need for a nonlinear modeling framework such as LSTM.

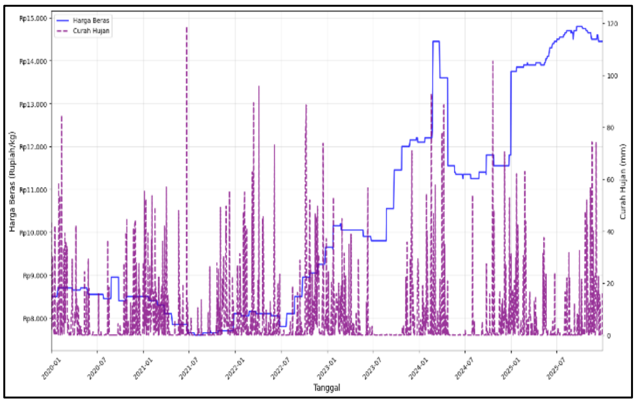


Figure 4. Time Series Plot Rice Price vs Rainfall

Figure 4 demonstrates that while regular rainfall patterns in 2020–2021 supported stable rice prices, extreme rainfall spikes reaching 100–120 mm and unstable weather in 2024 disrupted planting and distribution, driving prices upward. This variability reflects abnormal climate dynamics where excessive rain likely caused flooding and delayed harvesting. The plot shows a nonlinear relationship where optimal rainfall supports stability, while extreme deviations such as droughts and floods can trigger market instability. Furthermore, price adjustments appear asymmetric, as rainfall normalization in 2025 did not result in immediate price correction, indicating structural supply constraints. Similarly, Figure 5 and Figure 6 show that fluctuations in sunshine duration and extreme wind speeds reaching 3.0–4.0 m/s in 2024 contributed to production instability, leading to the permanent price increase observed in 2025.

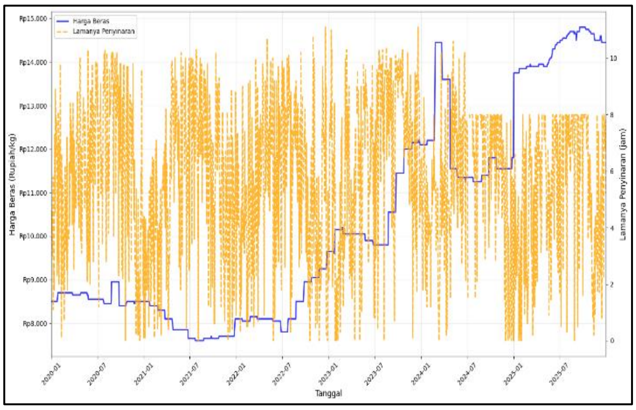


Figure 5. Time Series Plot Rice Price vs Sunshine Duration

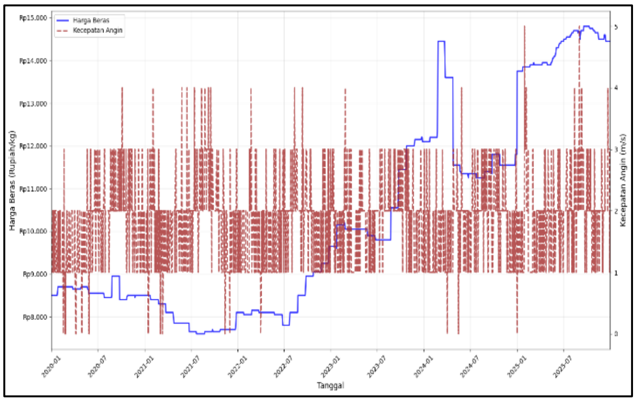
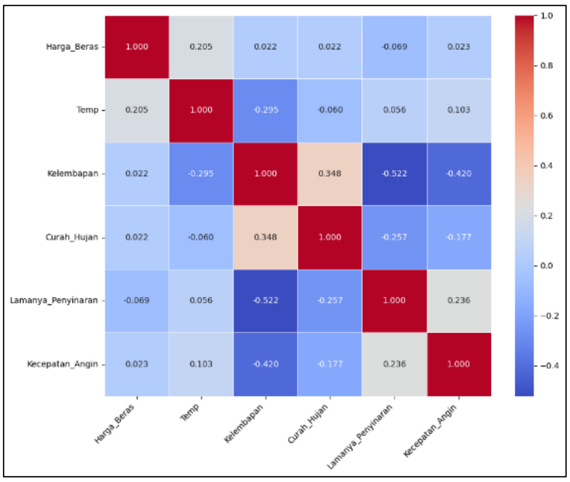


Figure 6. Time Series Plot Rice Price vs Wind Speeds

Figure 5 indicates that stable sunshine duration during 2020–2022 supported steady prices, whereas erratic patterns starting in late 2023 fluctuating between excessive exposure and sharp declines coincided with the 2024 price surge, signaling climate-induced stress. Similarly, Figure 6 reveals that while wind speeds were initially mild below 2.5 m/s, spikes reaching 3.0–4.0 m/s in 2024 likely increased crop damage and disrupted logistics, amplifying production instability. Crucially, the normalization of these variables in 2025 did not trigger an immediate price correction, suggesting that climate shocks create persistent economic effects. This confirms the nonlinear relationship between weather and prices, validating the selection of LSTM to capture these complex temporal dependencies.



	Harga_Beras	Temp	Kelembapan	Curah_Hujan	Lamanya_Penyinaran	Kecepatan_Angin
Harga_Beras	1.000	0.205	0.022	0.022	-0.069	0.023
Temp	0.205	1.000	-0.295	-0.060	0.056	0.103
Kelembapan	0.022	-0.295	1.000	0.348	-0.522	-0.420
Curah_Hujan	0.022	-0.060	0.348	1.000	-0.257	-0.177
Lamanya_Penyinaran	-0.069	0.056	-0.522	-0.257	1.000	0.236
Kecepatan_Angin	0.023	0.103	-0.420	-0.177	0.236	1.000

Figure 7. Correlation Matrix of Variables

To support the integration of weather variables, a Pearson correlation analysis was conducted. As shown in Figure 7, the direct linear correlations between rice prices and individual weather variables are relatively weak e.g., temperature at 0.205, humidity at 0.022. This weak linear relationship empirically justifies the necessity of utilizing a complex, non-linear model like LSTM. While simple correlation fails to detect direct impacts, the LSTM architecture particularly with a 45-day historical memory successfully captures the delayed, hidden, and non-linear effects of weather anomalies on sudden price shocks.

C. *Rice Price Modeling in East Java Using Long Short-Term Memory (LSTM)*

The modeling process involved hyperparameter tuning dropout rate, batch size, neurons, epochs and testing various timesteps 14, 30, 45, 60, 90 days to determine the optimal historical memory length. Table 3 presents the performance comparison.

TABEL 3
COMPARISON OF LSTM MODEL PERFORMANCE

Timesteps	*Dropout Rate*	*Batch Size*	*Neurons*	*Test* MAPE	*Test* MAE	*Test* RMSE
14	0.2	16	100	2.12%	0.13	0.28
30	0.3	16	150	1.66%	0.13	0.26
45	**0.3**	**16**	**150**	**1.40%**	**0.15**	**0.30**
60	0.3	16	150	2.14%	0.15	0.31
90	0.3	16	150	2.17%	0.13	0.29

Based on the systematic grid search, the model with 45 timesteps was selected as the optimal configuration, yielding the lowest Test MAPE of 1.40% alongside a Train MAPE of 0.73%. Although the model with 30 timesteps produced marginally lower absolute errors (Test MAE of 0.13 and Test RMSE of 0.26 compared to 0.15 and 0.30 for 45 timesteps), MAPE is prioritized as the primary evaluation metric in this study. In the context of economic and agricultural forecasting, MAPE provides a highly interpretable relative percentage error that is crucial for analyzing price volatility on a scale-independent basis. Furthermore, the selection of 45 timesteps approximately 1.5 months of historical memory is empirically justified: it perfectly aligns with the short-to-medium-term supply chain dynamics of rice distribution from grain drying post-harvest to retail market delivery. The training loss curve converged smoothly near zero without bouncing back, indicating that the dropout mechanism, rate 0.3 successfully mitigated potential overfitting despite the highly accurate performance.

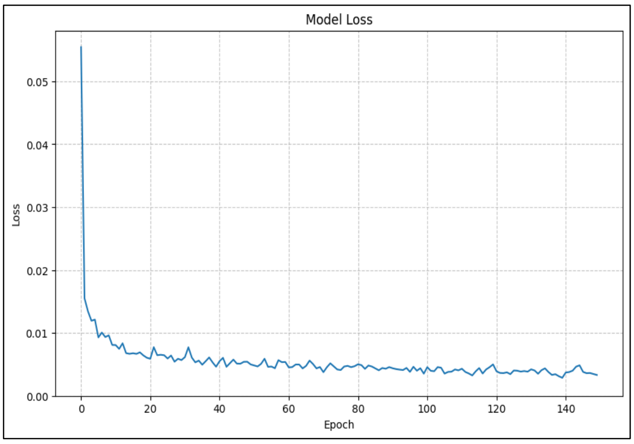


Figure 7. Model Loss of the Best Model

Figure 8 displays the forecasting results on testing data. The predicted price (yellow line) closely follows the actual price (green line), including the sharp rise in 2024-2025. This confirms that integrating weather variables allows the model to precisely respond to drastic trend changes.

The empirical results strongly capture the model's sensitivity to extreme weather changes. The dramatic price shock in early 2024 reaching over Rp14,450/kg was directly correlated with the prolonged El Niño phenomenon. The model successfully learned that drastic drops in humidity to 60% and extreme rainfall fluctuations act as leading indicators of harvest failures, subsequently inducing massive supply-side constraints and sudden price spikes.

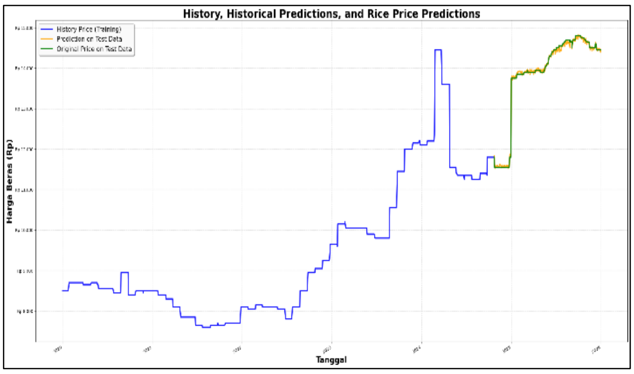


Figure 8. Best Model Forecasting Results on Testing Data

D. *Rice Price Forecasting Using the Best LSTM Model*

The best LSTM model was used to forecast rice prices. Figure 9 compares actual prices and predicted prices from 2020 to early 2026. The model captures the historical stability in 2020-2022 and the significant escalation in 2023-2025. For the out-of-sample period Jan-Mar 2026, the projection moves relatively flat around Rp14,450, suggesting a new equilibrium, although this static baseline may not fully capture potential La Niña-induced anomalies in early 2026.

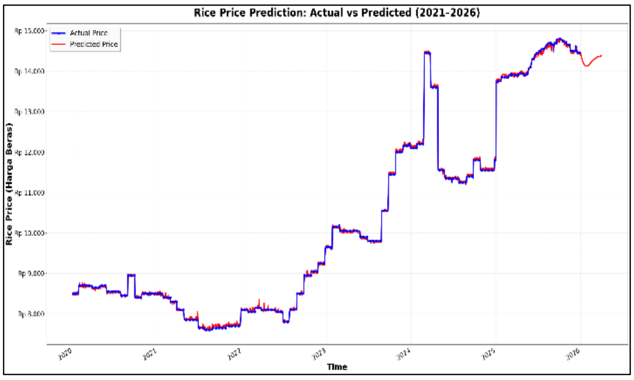


Figure 9. Comparison of Actual and Predicted Prices 2020-2026

Figure 10 details the out-of-sample forecasting period for January to March 2026. The model predicts a sharp price correction down to approximately Rp14,150/kg in early January. Economically, this drop aligns with the seasonal availability of year-end stocks and the onset of the main harvest season (*panen raya*). However, the subsequent gradual increase, which is projected to stabilize between Rp14,380 and Rp14,400/kg by the end of March, reflects the planting cycle (*musim tanam*) where market supply typically tightens. This pattern visualizes a new equilibrium, confirming that historical climate damage has established a permanent baseline price shift. Finally, the exceptionally high model accuracy, demonstrated by a forecast MAPE of 0.25%, confirms that this projection provides a highly reliable basis for government policy formulation.

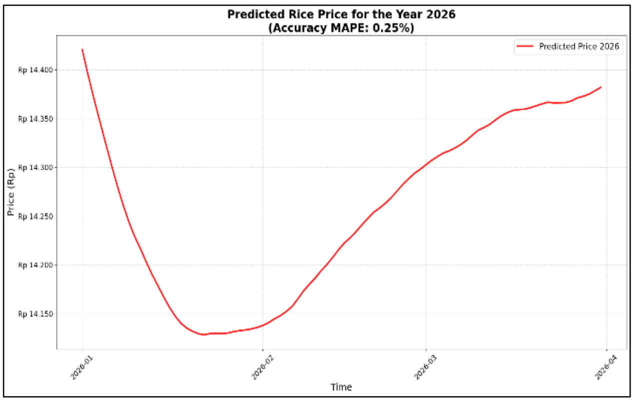


Figure 10. Rice Price Forecast in East Java 2026

IV. CONCLUSION

Based on the modeling results and performance evaluation, the multivariate Long Short-Term Memory (LSTM) model with a configuration of 45 timesteps, 0.3 dropout rate, a batch size of 16, 150 neurons, and 150 epochs proved to be the most optimal for forecasting rice prices in East Java. Although other configurations yielded marginally lower absolute errors, the 45-timestep model was selected for its superior Test MAPE of 1.40% and its empirical alignment with agricultural supply chain dynamics. Furthermore, the out-of-sample forecast estimates that rice prices from January to March 2026 will experience a brief adjustment at the beginning of the year before gradually stabilizing in the range of Rp14,380–Rp14,400 per kilogram. This projection indicates the formation of a permanent new price equilibrium following the previous year's surge. Supported by an exceptionally high forecast accuracy (MAPE 0.25%), these findings provide a highly reliable basis for the government in formulating regional price stabilization policies.

While this study demonstrates the robust capability of LSTM in modeling weather-induced price shocks with an accuracy of approximately 1%, there is still room for methodological advancements. To build upon these findings, future studies are recommended to validate the model's statistical significance by benchmarking it against traditional econometric baselines such as ARIMA or SARIMAX. In addition, comparing its performance with other advanced architectures like Bidirectional LSTM (Bi-LSTM) and Gated Recurrent Unit (GRU), as well as assessing the computational training time, would provide a more holistic evaluation of the model's efficiency.

Beyond methodological enhancements, future research should also expand the analytical scope by including macroeconomic variables such as government rice stock reserves, import policies, and fertilizer price fluctuations to represent market conditions more comprehensively. Conducting analyses on a more detailed spatial scale, up to the district or city level, is also crucial to capture localized weather patterns and market dynamics. Ultimately, integrating this predictive model into an interactive Early Warning System application is highly encouraged. Such a system would practically assist the government and agricultural industry players in strategizing stock management, market operations, and distribution mitigations against future climate uncertainties.

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