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Long-Memory Modeling of Farmers' Terms of Trade in Indonesia: A Comparative Analysis of SARIMA and SARFIMA Approaches

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Abstract: Indonesia, as an agrarian country, relies heavily on agriculture for economic growth and food security, with farmers' welfare assessed through the Farmers' Terms of Trade (FTT). This study compares the forecasting performance of Seasonal ARIMA (SARIMA) and Seasonal ARFIMA (SARFIMA) models using monthly FTT data from 2009 to 2024. The results indicate that SARIMA$(0,1,1)(0,1,1)_{12}$ outperforms SARFIMA$(1,0.2688,0)(0,1,1)_{12}$ in short-term forecasting, achieving a MAPE of 5.29% versus 5.97%, despite the presence of long-memory characteristics in the data. Forecasts based on SARIMA suggest a gradual increase in FTT throughout 2025, peaking in December with temporary seasonal declines. These findings highlight the methodological advantage of SARIMA for short-term FTT prediction and provide quantitative evidence to inform targeted agricultural policies, including price stabilization, subsidy allocation, and marketing strategies that enhance farmers' welfare and support national food security.

Keywords: Farmers' Terms of Trade, SARIMA, SARFIMA, Forecasting, Long Memory

Introduction

Indonesia is recognized as an agrarian country with a tropical climate that fosters soil fertility and supports agricultural activities [1]. The agricultural sector plays a vital role in the national economy, particularly in employment absorption and food security. According to data from Statistics Indonesia (BPS), as of August 2024, the agriculture, forestry, and fisheries sector accounted for 28.1% of the total national workforce, making it the largest employment sector in Indonesia. The heavy dependence of society on this sector underscores the importance of strengthening and sustaining agricultural development to maintain national food availability [2, 3].

Farmers' welfare serves as a key indicator of the success of agricultural development, one of which is measured through the Farmers' Terms of Trade (FTT) the ratio between the price index received by farmers and the price index paid by farmers [4]. The Ministry of Agriculture emphasizes that FTT is a strategic indicator used to assess the performance of the agricultural sector and serves as the basis for formulating national development policies. This aligns with the vision of the Prabowo Subianto and Gibran Rakabuming Raka administration for the 2024–2029 period, particularly the Asta Cita No. 2, which emphasizes food self-sufficiency through agrarian reform and increased production across various agricultural subsectors. Therefore, forecasting FTT is essential to predict the future dynamics of farmers' welfare. Forecasting is both an art and a science that utilizes historical data to predict future events through various mathematical models [5, 6].

Based on BPS data (2009–2024), the movement of FTT exhibits seasonal and fluctuating patterns, reflecting planting and harvesting cycles. Previous studies by

Setyaningrum, Zukhronah, & Handajani [3] confirm that FTT data follow a seasonal structure, leading to the widespread application of the Seasonal Autoregressive Integrated Moving Average (SARIMA) model [7]. While SARIMA effectively captures seasonality, it assumes integer differencing and short-memory dependence. However, empirical examination of the autocorrelation function (ACF) reveals a slowly decaying pattern, indicating potential long-memory characteristics that may not be fully explained by seasonal components alone. To accommodate both seasonal and persistent dependence, the Seasonal Autoregressive Fractionally Integrated Moving Average (SARFIMA) model extends SARIMA by allowing fractional differencing [8]. Previous research shows mixed findings regarding its superiority. Qi et al. [9] reported that SARFIMA produced lower AIC and RMSE values than SARIMA in modeling seasonal infectious disease data, suggesting improved performance in the presence of long memory. In contrast, Yuanti [10] found that SARIMA performed better for short-term electricity consumption data, indicating that model effectiveness depends strongly on data characteristics.

Despite these developments, systematic evidence on whether fractional integration meaningfully improves forecasting accuracy for agricultural economic indicators such as Indonesia's FTT remains limited, particularly when supported by formal long-memory testing and out-of-sample validation. Accordingly, this study compares the forecasting performance of SARIMA and SARFIMA models using Indonesia's monthly FTT data for the 2009–2024 period by integrating long-memory diagnostics and out-of-sample forecasting evaluation. The results provide empirical insight into whether a parsimonious seasonal model or a fractional alternative is more appropriate for modeling agricultural economic time series and offer practical implications for policy planning toward the Indonesia Emas 2045 vision.

Materials and Methods

Materials

This study employs secondary data obtained from the official website of Statistics Indonesia (BPS). The dataset consists of the national-level monthly Farmers' Terms of Trade (FTT) index published under the Agricultural Price Statistics section of BPS (https://www.bps.go.id), covering the period from January 2009 to December 2024 with a total of 192 monthly observations. The geographical scope of the data is national (Indonesia), and the research variable analyzed is the Farmers' Terms of Trade (FTT), defined as an index measuring the ratio between the price index received by farmers (It) and the price index paid by farmers (Ib). In this study, FTT is treated as a univariate time series variable and serves as the primary object of modeling and forecasting. All data processing, modeling, and forecasting procedures were conducted using RStudio version 4.5.1.

Methods

The method used involves comparing and forecasting FTT using two models, namely the Seasonal Autoregressive Integrated Moving Average (SARIMA) and the Seasonal Autoregressive Fractionally Integrated Moving Average (SARFIMA). The SARIMA model is applied to analyze time series data that exhibit seasonal patterns [11, 12]. In general, the SARIMA model can be expressed as follows [13]:

$$\phi_p(B)\Phi_P(B^S)(1-B)^d(1-B^S)^D Z_t = \theta_q(B)\Theta_Q(B^S)a_t \quad (1)$$

Notation:
p, d, q : orders of non-seasonal AR, differencing, and MA components.
P, D, Q : orders of seasonal AR, differencing, and MA components.
Z_t : value of the series at time *t*.
$(1-B)^d$: non-seasonal differencing operator.
$(1-B^S)^D$: seasonal differencing operator.
a_t : random error (white noise).
S : seasonal period.
B : backward shift operator.
$\phi_p(B) = 1 - \phi_1 B - \cdots - \phi_p B^p$ is the non-seasonal autoregressive polynomial of order *p*.
$\Phi_P(B^S) = 1 - \Phi_1 B^S - \cdots - \Phi_P B^{PS}$ is the seasonal autoregressive polynomial of order *P*.
$\theta_q(B) = 1 - \theta_1 B - \cdots - \theta_q B^q$ is the non-seasonal moving average polynomial of order *q*.
$\Theta_Q(B^S) = 1 - \Theta_1 B^S - \cdots - \Theta_Q B^{QS}$ is the seasonal moving average polynomial of order *Q*.

Meanwhile, the SARFIMA model is applied when the data not only exhibit seasonal patterns but also possess long-memory properties [14, 15]. This model is an extension of SARIMA, introduced by Granger and Joyeux [16], with the main difference lying in the differencing parameter (d), which can take fractional values $0 < d < 0.5$, allowing the model to simultaneously capture both seasonality and long-memory behavior [17]. In general, the form of SARFIMA is similar to SARIMA, and parameter estimation for both models is conducted using the Maximum Likelihood Estimation (MLE) approach [18,19].

Long-memory characteristics in the data can be identified through the autocorrelation function (ACF) patterns and the Hurst exponent (H) [20, 21]. If the ACF decays slowly with a hyperbolic pattern, it indicates the presence of long-memory properties in the data [22, 23]. Additionally, the Hurst exponent, calculated using the Rescaled Range (R/S) statistical method [24] is also used. If $(0.5 < H < 1)$, the data exhibit long-memory behavior [25]. Besides identifying long-memory properties, the Hurst exponent can also be used to estimate the fractional differencing parameter (d) in the SARFIMA model. According to Beran [26], the Hurst exponent (H) can be used to estimate the fractional order (d) in the SARFIMA model as follows:

$$\hat{d} = H - 0.5 \quad (2)$$

This implies that when the value of (d) falls within $(0 < d < 0.5)$, it indicates a stationary long-memory process with positive autocorrelation that decays slowly [27, 28]. Model evaluation is conducted using the Mean Absolute Percentage Error (MAPE) to measure forecasting accuracy by comparing the absolute differences between actual and predicted values in percentage terms [23, 29]. The MAPE formula is expressed as follows:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \times 100 \quad (3)$$

Where y_t represents the actual value of the time series at period (t), $\hat{y}_t$ denotes the forecasted value at period (t), and (n) is the total number of data points used in the calculation. The research procedures are summarized as follows:

1. Collect monthly FTT data (January 2009–December 2024) from the official BPS website.

2. Perform descriptive statistics and exploratory analysis using time series and decomposition plots.
3. Split the data into training (80%) and testing (20%) sets.
4. Examine stationarity in variance (Box-Cox transformation if needed) and mean (ADF test).
5. Conducting SARIMA modeling
   a. Apply non-seasonal and seasonal differencing if required.
   b. Identify tentative model orders (p, d, q) and (P, D, Q) using ACF and PACF plots.
   c. Estimate parameters using MLE and test their significance.
   d. Conduct diagnostic tests (Ljung-Box for white noise and Kolmogorov-Smirnov for normality).
   e. Select the best model based on AIC.
   f. Generate forecasts on testing data and compute MAPE.
6. Conducting SARFIMA modeling
   a. Identify long-memory properties using ACF patterns and the Hurst exponent (R/S method).
   b. Estimate fractional differencing parameter (d) and apply seasonal differencing if necessary.
   c. Identify model orders using ACF and PACF plots.
   d. Estimate parameters and perform diagnostic tests.
   e. Select the best SARFIMA model based on AIC.
   f. Forecast testing data and compute MAPE.
7. Compare SARIMA and SARFIMA forecasting performance using MAPE.
8. Produce a 12-step-ahead forecast using the best-performing model and interpret the results.

Results and Discussions

Descriptive Statistics and Exploration of Farmers' Terms of Trade (FTT) in Indonesia

Table 1. Descriptive Statistics FTT in Indonesia

N	Minimum	Q1	Median	Mean	Q3	Maximum
192	98.3	101.7	103	104.6	105.3	122.8

FTT in Indonesia ranges from 98.3 to 122.8, with a median of 103 and a mean of 104.6. Most values are above 100, indicating a relatively favorable condition for farmers and a tendency toward improved farmers' welfare, although it remains influenced by price fluctuations and seasonal factors. The dominance of values above 100 suggests that, on average, the price index received by farmers exceeds the price index paid, reflecting positive purchasing power conditions during most observation periods. The time series pattern of the FTT data is presented as shown in Figure 1.

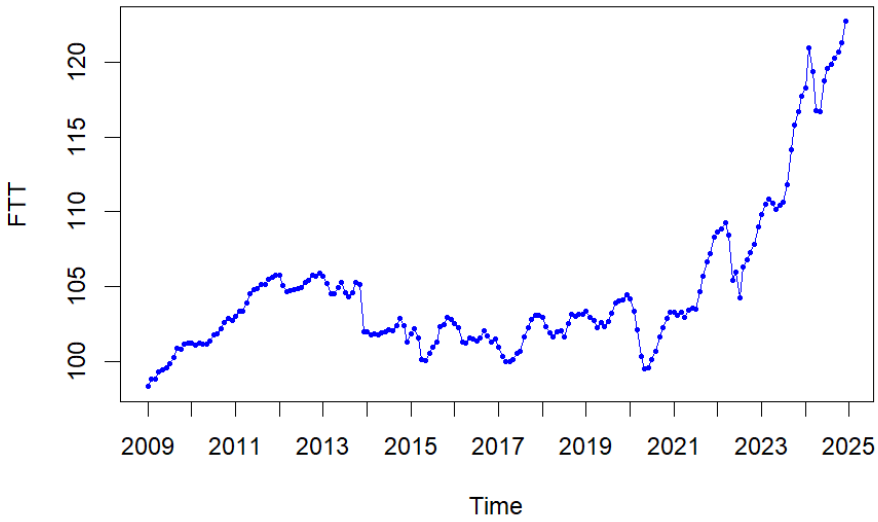


Figure 1. Time Series Pattern of FTT in Indonesia

Figure 1 illustrates fluctuations with a long-term increasing trend. During the 2009–2013 period, FTT increased alongside stable food prices and supportive agricultural policies. However, from 2014 to 2020, FTT remained relatively stagnant around 100–105, with annual fluctuations indicating seasonal patterns, influenced by a global economic slowdown that pressured agricultural commodity prices. Since 2021, FTT has risen sharply, particularly from 2022 to 2024, driven by post-pandemic economic recovery, rising global commodity prices, and programs to strengthen the agricultural sector. Overall, this pattern reflects farmers' welfare dynamics that were initially stable and then sharply increased in recent years. The upward structural movement in the later period suggests that long-term economic adjustments and policy interventions may have played a more dominant role than short-term cyclical shocks. However, seasonal patterns are not clearly visible, necessitating time series decomposition to identify seasonal components, as shown in Figure 2.

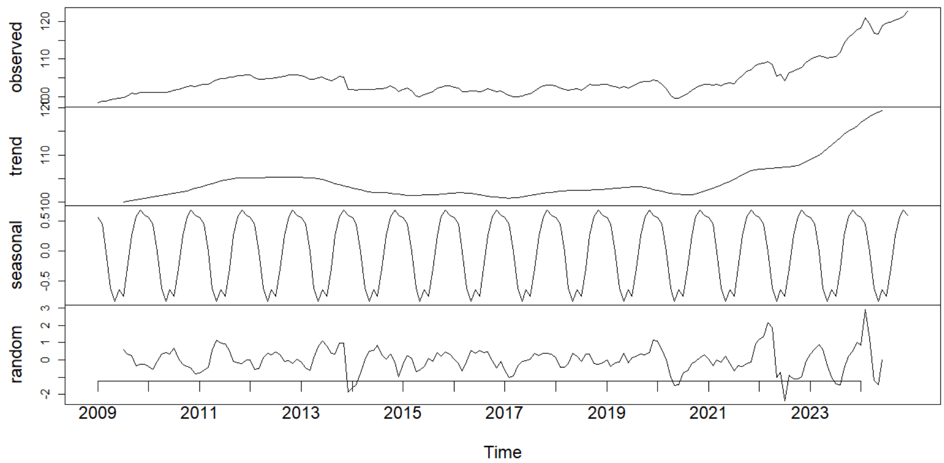
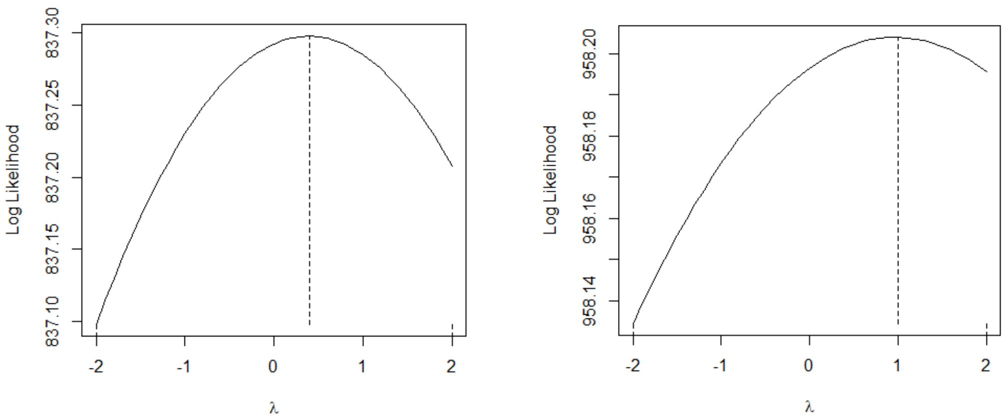


Figure 2. FTT Decomposition Plot

Figure 2 shows the results of the FTT time series decomposition, consisting of trend, seasonal, and random components. The decomposition results reveal a seasonal component, confirming an annual seasonal pattern with relatively small fluctuations. The relatively small amplitude of the seasonal component compared to the dominant trend indicates that long-term structural movements may contribute more substantially to FTT dynamics than short-run seasonal shocks. This finding has important implications for model selection. When the seasonal variation is relatively stable and limited in magnitude, seasonal differencing within a SARIMA framework may already be sufficient to capture the systematic pattern of the data without requiring additional complexity. These findings form the basis for selecting the SARIMA and SARFIMA models. For the analysis, the data were split into 80% training data and 20% testing data to evaluate the models' forecasting capabilities.

Data Stationarity Test

The initial step in time series modeling is to test the stationarity of the data. A dataset is considered stationary if its mean and variance remain constant over time. Data is said to be stationary in variance if the estimated transformation parameter (λ) equals 1 ($\lambda = 1$), indicating that the data variance is stable. Conversely, if $\lambda \neq 1$, the data is not stationary in variance, and a Box-Cox transformation is required. The results of the Box–Cox transformation are presented as shown in Figure 3.



(a) (b)

Figure 3. Box-Cox Plots: (a) Before Transformation and (b) After Transformation

Based on Figure 3, the transformation parameter obtained at the initial stage was 0.4. This indicates that the data is not yet stationary in variance, necessitating one transformation. After applying the transformation, the data can be considered stationary in variance as it results in a parameter value of $\lambda = 1$. The need for transformation suggests the presence of heteroscedasticity in the original series, meaning that variability changes over time. Stabilizing the variance is essential to ensure reliable parameter estimation in subsequent ARIMA-based modeling.

Next, the stationarity of the transformed FTT data was tested using the Augmented Dickey-Fuller (ADF) test. The test results showed a p-value of 0.3236, which is greater than 0.05. With a significance level of $\alpha = 5\%$ and the decision criterion to reject H_0 if $p - value < \alpha(0.05)$, the test fails to reject H_0. This means the data is not yet stationary in mean. Therefore, differencing is required to make the data stationary. The failure to achieve stationarity in mean indicates the presence of a unit root, reflecting persistent stochastic trends in the FTT series. Consequently, differencing is necessary to remove the non-stationary component before proceeding to model identification. Ensuring both variance and mean stationarity is crucial for avoiding spurious regression results and improving forecasting reliability.

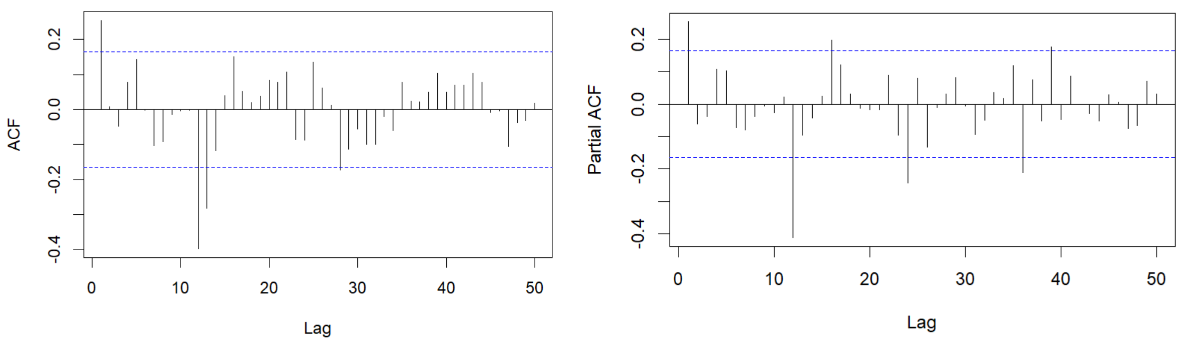
Forecasting FTT Using the SARIMA Model

Differencing Process

Based on the ADF test, the transformed data were not yet stationary in mean. Therefore, a non-seasonal differencing of order 1 was applied, and the results were retested using the ADF test. The test yielded a p-value of $0.01 < 0.05$. With a significance level of $\alpha = 5\%$ and the decision criterion to reject H_0 if $p - value < \alpha(0.05)$, the result indicates rejection of H_0. This means that the differenced data is stationary in mean. After applying non-seasonal differencing, the ACF plot showed significant spikes at lag 12, indicating the presence of an annual seasonal component. Consequently, a seasonal differencing of order 1 was applied to clarify the seasonal pattern. The presence of a significant autocorrelation at lag 12 confirms the existence of yearly seasonality, which is consistent with agricultural production cycles and periodic price adjustments in Indonesia.

SARIMA Model Identification

The seasonally differenced data were then analyzed using ACF and PACF plots to identify potential SARIMA models, as shown in Figure 4.



(a) (b)

Figure 4. Plots of ACF (a) and PACF (b) After Seasonal Differencing

Based on Figure 4, the ACF analysis shows significant peaks at lag 1 and lag 12, indicating non-seasonal MA(1) and seasonal MA(1) components. Meanwhile, the PACF shows significant peaks at lag 1, as well as lags 12, 24, and 36, suggesting non-seasonal AR(1) and seasonal AR components up to order 3. Based on these component combinations, 21 tentative SARIMA models with a seasonal period of 12 months were proposed. The identification process reflects a systematic approach in balancing model flexibility and parsimony, ensuring that both short-term dynamics and seasonal structures are adequately represented.

Parameter Estimation and Significance Test

After identifying tentative SARIMA models, the next step was to estimate parameters and test their significance. The criterion for testing was to reject H_0 if $|Z| > 1.96$, where H_0 indicates that a model parameter is not significant. From the 21 tentative SARIMA models (p,d,q)(P,D,Q)$_{12}$, only eight models met the significance criteria for all parameters. The elimination of non-significant parameters helps avoid overfitting and enhances the robustness of the forecasting model.

Model Diagnostic Test

After selecting SARIMA models with significant parameters, diagnostic tests were conducted to ensure model adequacy. This included a white noise test, consisting of residual independence and normality tests. Residual independence was tested using the L-jung Box test with a significance level of $\alpha = 5\%$, where H_0 states that the residuals are white noise and is rejected if $p - value < \alpha$.

Residual normality was tested using the Kolmogorov–Smirnov test with a significance level of $\alpha = 5\%$ where H_0 states that the residuals follow a normal distribution and is rejected if $p - value < \alpha$. The diagnostic test results for the SARIMA models with significant parameters are presented in Table 2.

Table 2. SARIMA Model Diagnostic Tests

No	SARIMA Model	*P-value*		Description
		L-jung Box	KS	
1	**SARIMA(0,1,1)(0,1,1)$_{12}$**	0.894	0.148	Random and Normal
2	**SARIMA(0,1,1)(1,1,0)$_{12}$**	0.424	0.174	Random and Normal
3	**SARIMA(0,1,1)(2,1,0)$_{12}$**	0.616	0.155	Random and Normal
4	**SARIMA(0,1,1)(3,1,0)$_{12}$**	0.770	0.124	Random and Normal
5	**SARIMA(1,1,0)(0,1,1)$_{12}$**	0.686	0.181	Random and Normal
6	**SARIMA(1,1,0)(1,1,0)$_{12}$**	0.255	0.252	Random and Normal
7	**SARIMA(1,1,0)(2,1,0)$_{12}$**	0.434	0.120	Random and Normal
8	**SARIMA(1,1,0)(3,1,0)$_{12}$**	0.527	0.144	Random and Normal

Based on Table 2, all selected models satisfied the independence and normality assumptions, indicating that the residuals are free from autocorrelation and approximately normally distributed. These results confirm that the selected models adequately capture the underlying data structure, leaving no systematic pattern unexplained in the residuals.

Selection of the Best Model

The best SARIMA model was selected by comparing the Akaike Information Criterion (AIC) values of all candidate models. The model with the lowest AIC was considered the most appropriate for representing the FTT data. Based on the comparison, the SARIMA(0,1,1)(0,1,1)$_{12}$ model had the lowest AIC of -571.5254 and was therefore selected as the best model for forecasting. The relatively low AIC value indicates an optimal trade-off between goodness-of-fit and model complexity. The corresponding SARIMA model equation is expressed as:

$$(1 - B)(1 - B^{12})Z_t = (1 + 0.267B)(1 - 0.761B^{12})a_t \quad (4)$$

Evaluation of SARIMA Forecasting Results

After the identification, parameter estimation, and model selection steps, SARIMA(0,1,1)(0,1,1)$_{12}$ was confirmed as the best model. Using this model, forecasts were generated for the test data and compared with actual values using the Mean Absolute Percentage Error (MAPE). The MAPE value obtained was 5.29%, indicating a very low forecast error. Therefore, this SARIMA model is considered highly effective in predicting FTT. The strong predictive performance suggests that seasonal differencing combined with simple ARMA components is sufficient to capture the main dynamics of the FTT series. This further supports the use of parsimonious seasonal models for short-term agricultural economic forecasting.

Forecasting FTT Using the SARFIMA Model

Identification of Long-Memory Properties

Long-memory characteristics are identified by examining the ACF plot of the transformed data and calculating the Hurst exponent (H). The results of the ACF plot are presented as shown in Figure 5.

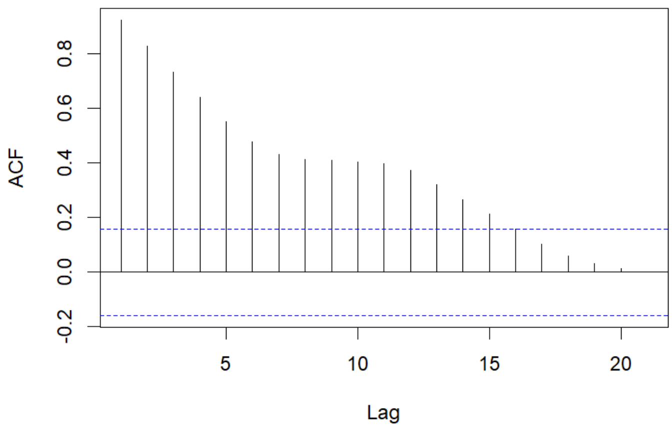


Figure 5. ACF Plot of FTT Data in Indonesia

Figure 5 shows a slowly decaying autocorrelation, indicating the presence of long-term dependence. The Hurst exponent obtained was 0.7688 $(0.5 < H < 1)$, further confirming that the FTT data exhibit long-memory properties. This suggests a strong correlation between past and future values, meaning current changes can influence subsequent periods. Therefore, the use of fractional differencing is appropriate to make the data stationary without losing long-term information. Although the H value indicates persistent behavior, the magnitude (H = 0.7688) suggests moderate rather than extremely strong long-range dependence, implying that the degree of persistence should be empirically evaluated in terms of its forecasting contribution.

Estimation of Differencing Parameter

Rescaled Range Statistics (R/S) or the Hurst exponent (H) can be used to estimate the fractional differencing parameter (d). Using the Hurst value obtained through the

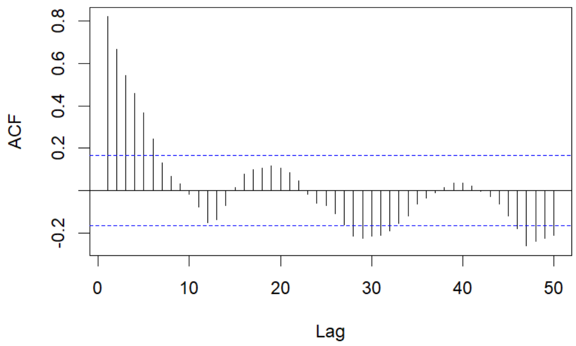
Simple R/S Hurst Estimation method (H = 0.7688), the estimated d value is 0.2688. This falls within the range $0 < d < 0.5$, indicating that the FTT data represent a stationary long-memory process with slowly decaying positive autocorrelation. The estimated value of d = 0.2688 reflects moderate persistence, meaning shocks to the system dissipate gradually but remain mean-reverting, which theoretically justifies the SARFIMA framework.

Differencing Process

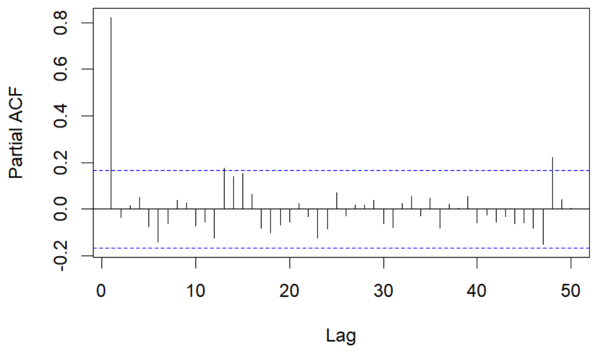
In the SARFIMA model, differencing was applied to the transformed data using $d = 0.2688$. After differencing, the data were retested with the ADF test to ensure stationarity in the mean before further modeling. The test resulted in a p-value of $0.0356 < 0.05$. ith a significance level of $\alpha = 5\%$ and the decision criterion to reject H_0 if $p - value < \alpha$, the null hypothesis was rejected, indicating that the differenced data is stationary in mean. After non-seasonal differencing, the ACF plot showed a slowly decaying positive pattern, characteristic of long-memory data in the SARFIMA model. For consistency with the SARIMA model, seasonal differencing of order 1 with a 12-month period was also applied. Applying the same seasonal structure as in the SARIMA model allows for a fair comparative evaluation between the two approaches.

SARFIMA Model Identification

The seasonally differenced data were then reanalyzed using the ACF and PACF plots to identify the SARFIMA model, as shown in Figure 6.



(a)



(b)

Figure 6. Plots of ACF (a) and PACF (b) After Seasonal Differencing Plots of ACF (a) and PACF (b) After Seasonal Differencing

Based on Figure 6, the ACF pattern shows a slowly decaying positive trend, indicating the presence of long-memory properties. Theoretically, this corresponds to a model with an infinite-order MA component; however, following the principle of parsimony, the non-seasonal and seasonal AR components were limited to order 3 to keep the model simple yet representative. Meanwhile, the PACF shows a significant peak at lag 1 for the non-seasonal component and no significant pattern for the seasonal component, indicating a non-seasonal AR(1) and a seasonal AR(0) component. Based on this combination of components, 21 tentative SARFIMA models with a 12-month seasonal period were proposed. This restriction reflects a practical compromise between theoretical long-memory representation and empirical model tractability.

Parameter Estimation and Significance Test

After proposing tentative SARFIMA models, parameter estimation and significance testing were conducted. The test criterion was to reject H_0 if $|Z| > 1.96$, where H_0 states that a parameter is not significant. From the 21 SARFIMA models (p,d,q)(P,D,Q)$_{12}$, only six models met the significance criteria for all parameters. The relatively small number of fully significant SARFIMA models compared to SARIMA candidates suggests that incorporating fractional differencing increases model complexity without necessarily improving parameter stability.

Model Diagnostic Test

Diagnostic tests were conducted on SARFIMA models with significant parameters to ensure model adequacy. The tests included white noise testing, comprising residual independence and normality checks. Residual independence was tested using the L-jung Box test at a significance level of $\alpha = 5\%$ where H_0 assumes residuals are white noise, rejected if $p - value < \alpha$.

Next, residual normality was tested using the Kolmogorov–Smirnov test with a significance level of $\alpha = 5\%$, where the decision criterion is to reject H_0 if $p - value < \alpha$, and H_0 states that the residuals are normally distributed. The diagnostic test results for the SARFIMA model with significant parameters are presented in Table 3.

Table 3. SARFIMA Model Diagnostic Tests

No	SARFIMA Model	*P-value*		Description
		L-jung Box	KS	
1	SARFIMA(0,d,1)(0,1,1)$_{12}$	2.2e-16	0.585	Not Random and Normal
2	SARFIMA(0,d,1)(0,1,2)$_{12}$	2.2e-16	0.398	Not Random and Normal
3	SARFIMA(0,d,2)(0,1,2)$_{12}$	1.354e-14	0.502	Not Random and Normal
4	SARFIMA(0,d,3)(0,1,1)$_{12}$	1.364e-09	0.585	Not Random and Normal
5	SARFIMA(0,d,3)(0,1,2)$_{12}$	5.951e-05	0.492	Not Random and Normal
6	**SARFIMA(1,d,0)(0,1,1)$_{12}$**	0.451	0.180	Random and Normal

Based on Table 3, the residual assumption tests indicate that only one selected model met both the independence and normality criteria, namely SARFIMA(1,d,0)(0,1,1)$_{12}$. This outcome indicates that most SARFIMA specifications fail to fully capture the residual structure, highlighting the sensitivity of fractional models to parameter selection.

Selection of the Best Model

Based on the diagnostic tests, the only model meeting all assumptions was SARFIMA(1,0.2688,0)(0,1,1)$_{12,}$ with an AIC value of -969.1227 which was therefore selected as the best model. The corresponding SARFIMA model equation is expressed as:

$$(1 - 0.916B)(1 - B)^{0.2688}(1 - B^{12})Z_t = (1 + 0.769B^{12})a_t \tag{5}$$

Evaluation of SARFIMA Forecasting Results

Following identification, parameter estimation, and model selection, SARFIMA(1,0.2688,0)$(0,1,1)_{12}$ was confirmed as the best model. Using this model, forecasts were generated for the test data and compared with actual values using the Mean Absolute Percentage Error (MAPE). The MAPE value obtained was 5.97%, indicating a very low forecast error. Therefore, the SARFIMA model is also considered highly effective in predicting FTT. However, when compared with the SARIMA model, the SARFIMA model does not provide superior predictive accuracy. This suggests that while long-memory characteristics are statistically present, their practical contribution to short-term forecasting improvement is limited in this case.

Comparison of SARIMA and SARFIMA Model Performance

Through the SARIMA and SARFIMA modeling processes, the best models for each approach were obtained: SARIMA(0,1,1)$(0,1,1)_{12}$ and SARFIMA(1,0.2688,0)$(0,1,1)_{12}$. A comparison of the evaluation results for these two models is presented in Table 4.

Table 4. Comparison of the Evaluation Results of Models

Model	MAPE Value
SARIMA(0,1,1)$(0,1,1)_{12}$	5.29%
SARFIMA(1,0.2688,0)$(0,1,1)_{12}$	5.97%

Based on Table 4, both models demonstrate very good forecasting ability with low MAPE values. However, the SARIMA model has a lower MAPE compared to the SARFIMA model, indicating that the FTT data are better modeled using SARIMA. Therefore, incorporating the long-memory component in the SARFIMA model does not improve forecasting accuracy, making the SARIMA approach more suitable.

Although long-memory characteristics were statistically identified, the degree of persistence appears to be moderate rather than strong [16]. As a result, the seasonal ARMA structure in the SARIMA model is sufficient to capture the dominant dynamics of the FTT series without requiring fractional integration. Nevertheless, the SARFIMA model still performs well, with an MAPE difference of only 0.68% from SARIMA, suggesting that it can also model the data with reasonable accuracy.

The relatively small difference in MAPE values indicates that both models are capable of providing reliable short-term forecasts. However, following the principle of parsimony, when two models yield comparable predictive accuracy, the simpler model is generally preferred. In this case, SARIMA offers slightly better accuracy with lower structural complexity. These results align with the findings of Yuanti [10], who showed that for short-term electricity consumption data in East Java, the SARIMA model outperformed SARFIMA. This indicates that, depending on the data context, SARIMA can provide better performance than SARFIMA.

More broadly, this finding contributes empirical evidence that the presence of long-memory properties does not automatically justify the use of fractional models in short-term forecasting applications. The effectiveness of SARFIMA depends heavily on the strength of persistence and the forecasting horizon considered. In the context of Indonesia's FTT, the seasonal dynamics appear to dominate long-range dependence effects.

Best Forecasting Results

Based on the model comparison, SARIMA(0,1,1)(0,1,1)$_{12}$, which has the lowest MAPE, was selected as the best model. This model was then used to forecast FTT for the next 12 periods. The forecasting results are presented as shown in Figure 7.

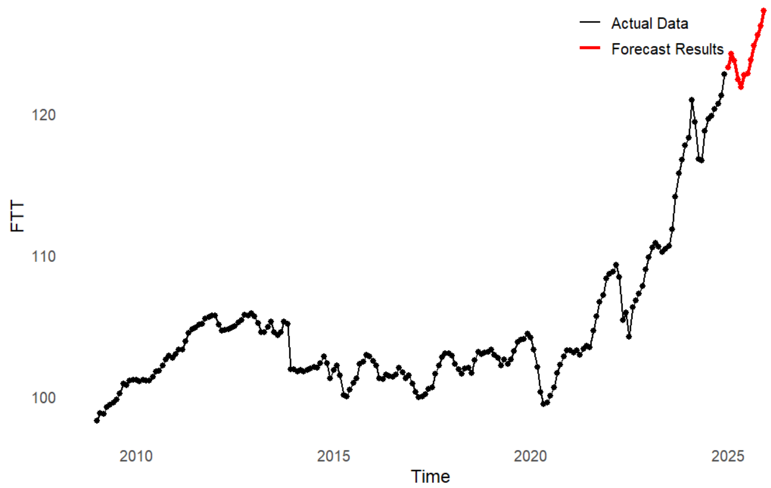


Figure 7. Pattern of Actual Data and Forecasted FTT

Figure 7 shows the historical FTT data along with the forecasted values for the period January–December 2025. The forecast indicates a gradual increase in FTT, reaching a peak of 127.2920 in December 2025, although a temporary decline is projected for March–May with the lowest value at 121.8456, likely due to seasonal fluctuations or temporary price changes. This pattern aligns with BPS [30], which notes that FTT movements are strongly influenced by fluctuations in agricultural commodity prices and seasonal patterns. Overall, the trend since 2020 shows improvements in farmers' welfare, and the 2025 projection reinforces the indication of increased purchasing power.

From a policy perspective, these forecasting results provide quantitative support for short-term planning related to price stabilization, input subsidy allocation, and agricultural market interventions. Accurate forecasts of FTT can help policymakers anticipate seasonal declines and implement timely mitigation strategies. Furthermore, integrating time series forecasting into agricultural policy design contributes to evidence-based decision-making, which is essential for achieving long-term development goals, including food security and farmers' welfare in line with the Indonesia Emas 2045 vision.

Conclusion

This study compared SARIMA and SARFIMA models for forecasting Farmers' Terms of Trade (FTT) and found that SARIMA(0,1,1)(0,1,1)$_{12}$ provides superior short-term forecasting performance. Although long-memory characteristics were statistically identified, incorporating fractional integration through SARFIMA did not improve predictive accuracy. This suggests that, in the context of short-term FTT forecasting, seasonal dynamics are more influential than long-range dependence effects. The projections indicate a generally increasing trend in FTT throughout 2025 with temporary seasonal fluctuations. These forecasts may serve as quantitative support for short-term agricultural planning. In particular, they can assist the government in formulating more targeted agricultural policies, including price stabilization measures, subsidy allocation, and marketing strategies for agricultural products. Such evidence-based planning contributes to the 2024–2029 food self-sufficiency agenda and the Indonesia Emas 2045 vision by supporting improvements in farmers' welfare and national food security. However, this study is limited to a univariate time series framework and does not incorporate exogenous determinants such as commodity prices, climate variability, or macroeconomic factors. Future research may explore multivariate models, hybrid approaches, or machine learning techniques to enhance forecasting robustness and capture broader structural dynamics.

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