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Arima Model for Forecasting Coffee Productivity in West Sumatra, Indonesia

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Vonny Indah Mutiara[1], Dwi Nur'aini Putri[1], Rusda Khairati[1]

[1]Department of socioeconomics, Faculty of Agriculture, Universitas Andalas

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Corresponding Author:
Vonny Indah Mutiara
mutiaravonny@agr.unand.ac.id

ABSTRACT

As the 10th highest coffee-producing region in Indonesia, West Sumatra played a significant role in the country's coffee sector. Coffee productivity in West Sumatra had been fluctuating; therefore, accurate productivity forecasting was essential for effective coffee farm management, resource allocation, and market stability. This study aimed to identify the best forecasting model for predicting coffee productivity in West Sumatra from 2024 to 2028. The research method used was the descriptive analysis method, applying a time series forecasting approach. The data used in this study were historical records of coffee productivity in West Sumatra for the past 24 years. The data were annual figures from 2000 to 2023. The results showed that ARIMA (1,3,0) was the most suitable, with a Mean Absolute Percentage Error (MAPE) below 50%. This indicated a declining trend in coffee productivity over the forecast period. The projected productivity values (tons per hectare) were 1.000 in 2024, 0.6266 in 2025, 0.6125 in 2026, 0.0538 in 2027, and -0.1709 in 2028. The pattern of minor variations suggested that the ARIMA (1,3,0) model reflected an unstable and downward trend in coffee productivity.

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1. Introduction

Coffee is a plantation commodity with significant potential for growth in Indonesia. West Sumatra ranked as the tenth highest coffee-producing region in Indonesia, with a total production of 23,800 tons in 2023. Despite the recent decline in coffee exports, the high demand for coffee consumption has shown a positive trend globally (Cotter et al., 2021; Ibnu & Rosanti, 2022). According to the International Coffee Organization (2024), world coffee consumption was expected to grow by 2.2% to 177.0 million bags. The world coffee consumption outlook for the coffee year 2023/2024 was broadly framed by the assumption that the global economy would continue to grow above 3.0% (ICO, 2024). In addition to strong global demand, coffee consumption in Indonesia also increased (Sunarharum et al., 2021), with 33% of coffee production distributed to the domestic market (Asosiasi Ekspor Kopi Indonesia, 2024).

Indonesia is a major coffee producer, ranking second in the Asia & Pacific region behind Vietnam. Between 2020 and 2022, the total area under coffee cultivation increased by 41,400 hectares. However, Indonesia's average yield of 8.9 bags per hectare for the coffee years 2017–2021 remained below the world average of 15.6 bags over the same period (International Coffee Organization, 2024). Although Indonesia had a large coffee cultivation area, the average yield/productivity was still below the global average. Over the past 10 years (2010–2020), coffee production in Indonesia, when compared to land availability, was still low. The crop area decreased from 1.27 million ha to 1.25 million ha, representing an average decline of 0.14% per year. As one of Indonesia's key export commodities, coffee exports also fell during the last decade, from 432,781 tons to 375,671 tons, an average decrease of 1.41% per year. This indicated declining farmer interest in maintaining coffee plants (BRIN, 2024).

Moreover, frequent rain and strong winds during the flowering stage disrupted coffee tree growth, impacting the main harvest season between April and May. This resulted in a 1.1% decrease in coffee output compared to the previous year (International Coffee Organization, 2024). Heavy rain driven by the La Niña weather phenomenon during and after the flowering period has been shown to have a significant negative impact on coffee production (Merga & Alemayehu, 2019; Koh et al., 2020).

Considering that Indonesia's coffee sector faces challenges such as declining growth, reduced coffee exports, and fluctuating production levels due to climate change (Bilen et al., 2022; Ferreira et al., 2019), there is a need to develop a reliable coffee productivity forecasting model (Nayak et al., 2022; Phung et al., 2024). Research on coffee productivity forecasting has gained significant attention in Indonesia (Nasirudin et al., 2022; Syifahati et al., 2023; Prasetia et al., 2024;Guntoro et al., 2024). Although several studies have been conducted on coffee agribusiness development in West Sumatra (Awalina et al., 2022; Azzahra et al., 2024; Paloma et al., 2023; Yusmarni et al., 2020), none has focused on forecasting coffee productivity in the region, particularly using the ARIMA model. Therefore, to develop an effective coffee productivity forecast for West Sumatra, it was important to conduct this research. Accurate coffee productivity forecasting was necessary to provide better insights into future production trends, improve farm management strategies, and ensure market stability.

2. Methods

This research used a descriptive analysis method with time series analysis through the ARIMA (Autoregressive Integrated Moving Average) model for forecasting. The data collected in this study were obtained from the website of the Central Bureau of Statistics of West Sumatra (https://sumbar.bps.go.id/id/statistics-table/2/NzE0IzI=/produksi-tanaman-perkebunan-kopi-arabika-dan-kopi-robusca.html). The study used historical data on coffee productivity in West Sumatra for the past 24 years, consisting of annual data from 2000 to 2023. The variable analyzed was coffee productivity in West Sumatra. The analytical tools used included Microsoft Excel 2010 and R Studio.

The ARIMA (Autoregressive Integrated Moving Average) model was a forecasting model that determined the correlation or statistical relationship between the predicted variables and their historical values. The ARIMA model performed accurate short-term forecasting to estimate projections for subsequent periods (Gujarati, 2008). The ARIMA (p, d, q) model is a combination of the $AR\ (p)$ and $MA\ (q)$ models, incorporating differencing to achieve stationarity. According to Brockwell & Davis (2016) the general form of the model was as follows:

$$\Phi_p(B)\nabla^d X_t = \Theta_q(B)\varepsilon_t$$
$$\Phi_p(B)(1-B)^d X_t = \Theta_q(B)\varepsilon_t$$

Where:
$\Phi_p =$ Coefficients of the AR model of order p
$\Theta_q =$ Coefficients of the MA model of order q
$\nabla^d =$ differencing operator of order d

The ARIMA methodology, often referred to informally as the Box-Jenkins (BJ) methodology, emphasized analyzing the stochastic characteristics of economic time series independently rather than relying on single- or simultaneous-equation models ((Gujarati, 2008). This approach, based on the principle of letting the data speak for itself, contrasted with regression models, which explained Y_t using k regressors $X_1, X_2, \dots, X_k$.

The forecasting steps with the ARIMA model were as follows: (1) The data were split into a 20-year training set and a 4-year testing set. (2) A time series plot was created using R Studio to visualize patterns in coffee production in West Sumatra from the time series data. (3) The data were checked for stationarity. The Levene's Test, accompanied by a Box-Cox transformation graph, was used to assess stationarity with respect to variance. The Augmented Dickey-Fuller (ADF) test was used to check stationarity with respect to the mean. If differencing resulted in negative values, the variance was stabilized before differencing. A stationary time series relative to the mean fluctuated around a constant mean, meaning the data did not exhibit trends or seasonality (Montgomery, 2007). (4) A preliminary ARIMA model was identified based on Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. (5) Parameters for all possible ARIMA models were estimated from the data. (6) The best model was selected based on significance tests and performance criteria. (7) The residual assumptions were checked. (8) The model was validated. (9) The final forecast was performed.

3. Results and Discussion

3.1. Results

Over the years, coffee productivity in West Sumatra has shown fluctuations, reflecting variations in both production and planted area. West Sumatra Province consists of 19 Regencies/Municipalities. The regencies with the high coffee production are Solok Regency with 5,482.60 tons, South Solok Regency with 2,659.36 tons, and South Pesisir Regency with 2,562.36 tons. The development of coffee productivity in West Sumatera from 2000 to 2023 is shown in Figure 1. The highest recorded coffee productivity occurred in 2002, reaching 1.80 tons per hectare. Similarly, another high productivity year was in 2006, with a recorded value of 1.35 tons per hectare, indicating another period of efficient production despite a relatively small planted area.

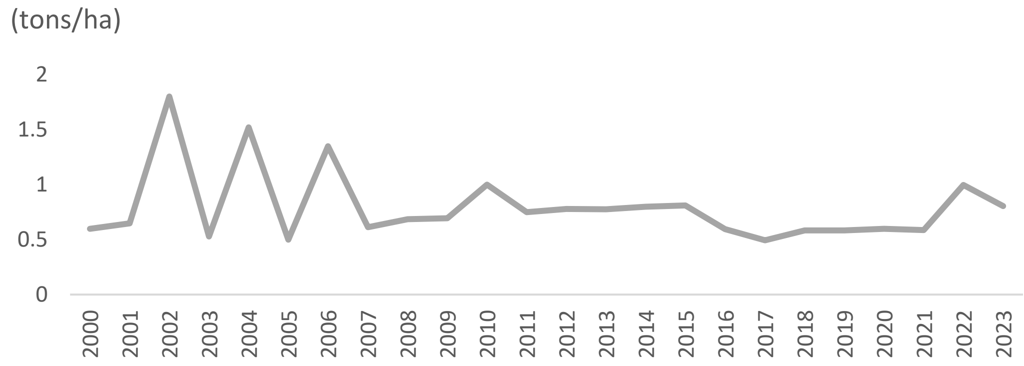

Figure 1 Coffee productivity in West Sumatra from 2000 to 2023
Source: Central Bureau of Statistics West Sumatra (BPS), 2024

Conversely, the lowest coffee productivity was observed in 2017, with a value of 0.49 tons per hectare. This decline could be attributed to unfavourable environmental conditions, aging coffee plants, or a reduction in farm maintenance and input applications. The period between 2015 and 2018 exhibited consistently low coffee productivity, with values remaining below 0.6 tons per hectare. This trend indicates a prolonged challenge in coffee cultivation during these years. Furthermore, this condition is closely related to the land area owned by farmers, as larger cultivated areas can contribute to higher total production. The planted area has also fluctuated throughout this period (Figure 2).

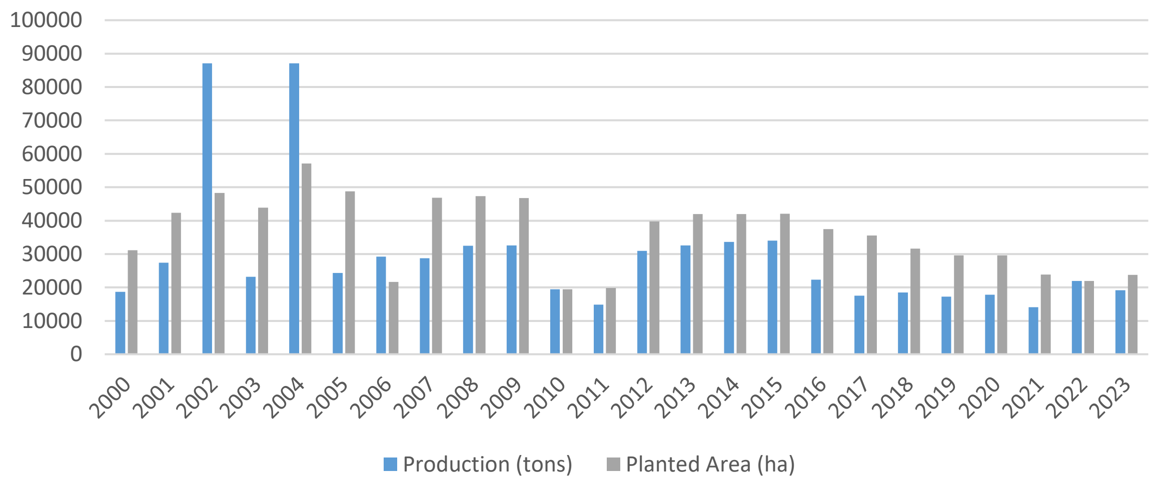

Figure 2 Coffee production and planted area in West Sumatra from 2000 to 2023
Source: Central Bureau of Statistics West Sumatera (BPS), 2024)

Over the past five years (2019–2023), coffee productivity in West Sumatera has shown a gradual improvement, with values ranging from 0.58 to 0.99 tons per hectare**.** Despite this positive trend, the average productivity remains relatively low compared to the global standard. This aligns with the national context, where Indonesia's average coffee yield from 2017 to 2021 was 8.9 bags per hectare, equivalent to approximately 0.534 tons per hectare. This number is significantly below the world average of 15.6 bags per hectare (or 0.936 tons per hectare) (ICO, 2024).

3.1.1. Forecasting steps with ARIMA Model (Time Series Analysis)

3.1.1.1. Split the Data

Data splitting was carried out with an 80:20 division technique for training and testing data. The data used in this research is 24 years data, to test the model's reliability, the data were split into two parts: one for building the model (20 years) and another for validation (4 years). The data used for training is the coffee productivity data from 2000-2019 and testing data from 2020-2023. The training data is used to build the model of forecasting, and testing data to see the error between the forecasted training data and actual data (Figure 3).

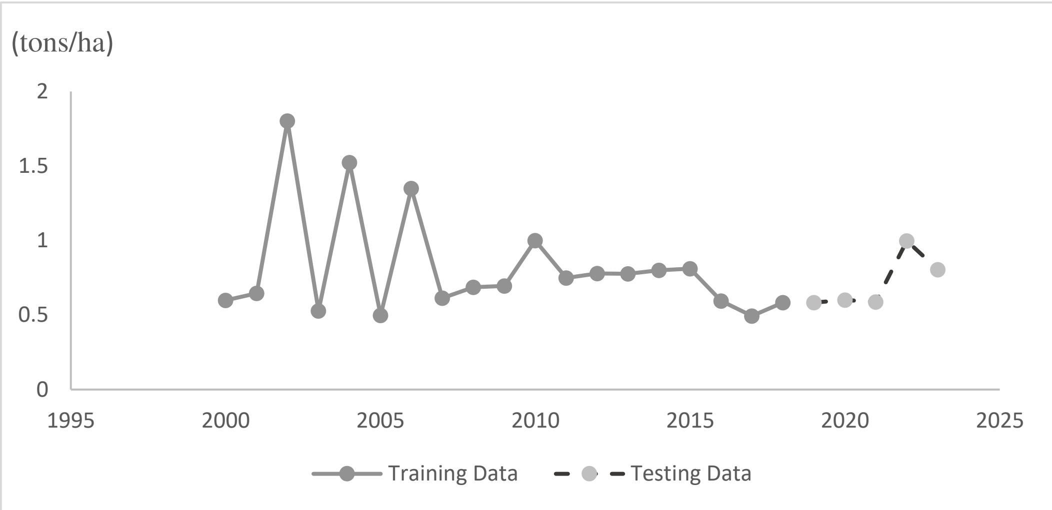

Figure 3 Splitting data of coffee productivity in West Sumatra, year 2000 - 2023

3.1.1.2. Time Series Plot

Figure 4 illustrates the plot fluctuations in coffee productivity in West Sumatra from the early 2000 to 2019, measured in tons per hectare. The data exhibits significant volatility, with notable peaks around 2003, 2005, and 2007, followed by periods of decline and relative stabilization in the later years. These fluctuations indicate potential external influences such as climatic variability, shifts in agricultural practices, economic conditions, or policy interventions affecting coffee production. From an ARIMA modelling perspective, the presence of sharp fluctuations suggests that the time series may be non-stationary, meaning the statistical properties, such as mean and variance, are not constant over time.

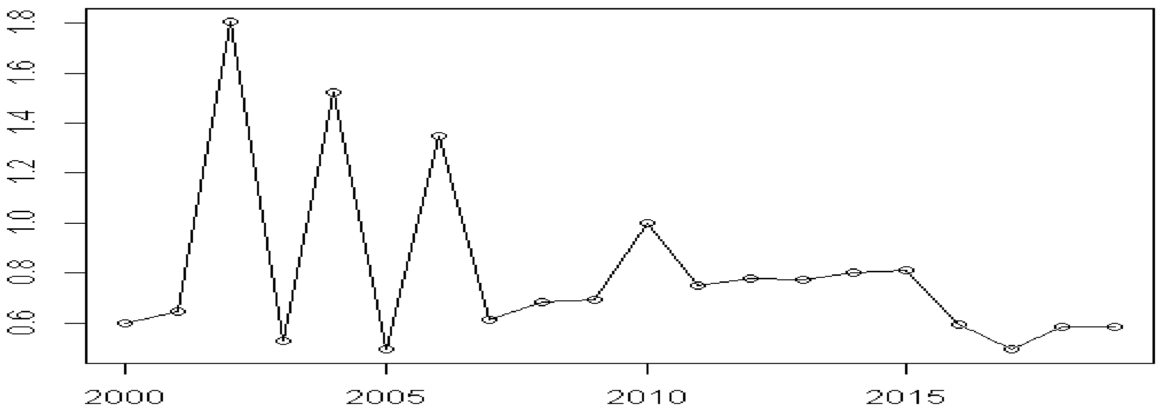

Figure 4 Plot data training of coffee productivity in West Sumatra, year 2000 - 2019

3.1.1.3. Stationary Test

Levene's Test was conducted to assess the stationarity of variance or homogeneity of variance in the dataset. The test result indicates a test statistic of 4.5098 with a p-value of 0.04782. Since the p-value is less than the conventional significance level of 0.05, the null hypothesis of equal variance is rejected, suggesting that the variance in coffee productivity is not homogeneous over time. Figure 5 shows the Box-Cox transformation after conducting the Levene test. To test the stationary data against mean, the test carried out with ADF (Augmented Dickey-Fuller) test to the transformed data, and the result shows that p-value higher than 0.005 which means the time series still appears not stationary, meaning that further transformation may be required to make the data stationary.

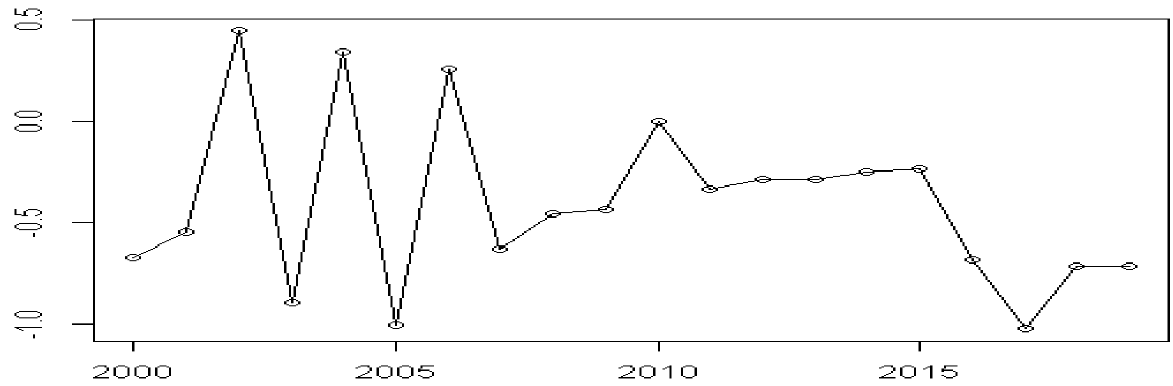

Figure 5 Box-Cox transformed of coffee productivity data

3.1.1.4. Identify Preliminary ARIMA Model Based on Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) Plots

Figure 6 shows that in the ACF plot, there is a significant spike at lag 1 and then quickly tapers off, which indicates a possible autoregressive (MA) component, suggesting the possibility of moving average order q = 1. Besides that, the ACF shows diminishing significance at higher lags, particularly at lag 2, making a higher-order MA model plausible (q = 2 and 3). The PACF shows a significant cuts off after lag 1, indicating the presence of an autoregressive (AR) component (p = 1).

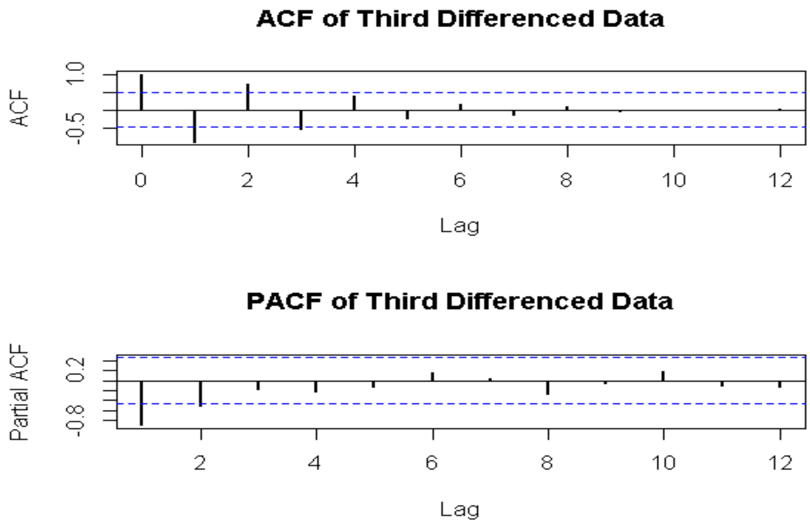

Figure 6 Plot ACF and PACF of data after transformation

Therefore, possible ARIMA models might include ARIMA (1, 3, 0), ARIMA (1, 3, 1), ARIMA (1, 3, 2), and ARIMA (1, 3, 3) considering the third differencing to account for stationarity (d= 3). In time-sequence analysis, the most important part is identifying and forming a model based on existing data. In the identification of the model, the principle of parsimony applies, which involves as few parameters as possible.

3.1.1.5. ARIMA Model Parameter Estimation

Parameter estimation was conducted using the Maximum Likelihood Estimator (MLE). Test the significance of the ARIMA model parameters and select the model where all parameters are significant. According to Cryer & Chan (2008), a model can be deemed appropriate based on the significance of its parameters, which can be determined through a parameter significance test. Table 1 shows significant test result of ARIMA models.

Table 1 Significant Test Result of ARIMA models

No	Model	p-value	Siginificant
1	**ARIMA (1,3,0)**	**< 0.05**	**Significant**
2	ARIMA (1,3,1)	≥ 0.05	Not Significant
3	ARIMA (1,3,2)	≥ 0.05	Not Significant
4	ARIMA (1,3,3)	≥ 0.05	Not Significant

The model that meet the significant test is ARIMA (1,3,0). Further models comparison, Akaike Information Criterion and Bayesian Information Criterion, are no need to do.

3.1.1.6. Select The ARIMA Best Model

The evaluation of various ARIMA models indicates that ARIMA (1,3,0) is the most suitable choice for this dataset. It has the p-value lower than 0.05, which means the data models has already significant. Based on these criteria, ARIMA (1,3,0) is recommended as the best model for forecasting in this analysis, effectively capturing the underlying patterns in the data while maintaining a reasonable complexity

3.1.1.7. Residual Diagnostic for the Best Model

The Ljung-Box test was conducted to determine whether the residuals resemble "white noise," meaning they are random and show no patterns. ARIMA (1,3,0), the p-value from the test is 0.346, which is higher the standard 0.05 threshold. This low p-value leads us to fail reject the null hypothesis that the residuals are white noise. In other words, the residuals white noise. This suggests that ARIMA (1,3,0) captures the data's underlying structure effectively.

3.1.1.8. Validate The Selection Model

The ARIMA were tested with different configurations to predict coffee productivity trends, and the MAPE (Mean Absolute Percentage Error) were used to evaluate accuracy. For this reason, utilizing 24 years of data for model training helps in capturing significant patterns while still providing enough years for testing the model's predictive capabilities. MAPE (Mean Absolute Percentage Error) is a measure of the accuracy of forecasting results. The smaller the error of the forecast value, the better the model used in forecasting the time streak.

Testing over the 4-years period ensures the generalization of the model beyond the training data. Ultimately, model comparison based on MAPE 41.22279% confirms if the ARIMA configuration offers the resonable forecast accuracy as shown in Table 2 where the MAPE between 20-50% the ARIMA model is sufficient.

Table 2 Criteria for the accuracy of forecasting results with MAPE

Score	Criteria
<10%	Very accurate
10-20%	Good
20-50%	**Sufficient**
>50%	Inaccurate

3.1.1.9. Perform Final Forecast

The final step was create the best forecast of coffee productivity for year 2024 to 2028 based on the best ARIMA model. A five-year forecast is selected as it aligns with the periodic cycle of government policy updates, which typically occur every five years. This is to ensure that the forecast provides relevant insights to support evidence-based decision-making and long-term planning.

Table 3 Coffee productivity forecasting in West Sumatera, year 2024 - 2028

Year	Productivity (Tons/ha)
2024	1
2025	0.62660644
2026	0.61254612
2027	0.05384929
2028	-0.17089135

Table 3 presents the forecasted coffee productivity for the year 2024 to 2028 using the ARIMA (1,3,0) model. This model provides a more conservative outlook, capturing slight fluctuations over time. In 2024, productivity is forecasted at 1, which gradually declines to 0.62 in 2025 and continue decline until the productivity shows -0.17 tons/ha. This pattern of minor variations suggests that the ARIMA (1,3,0) model reflects unstable and downward trend in productivity.

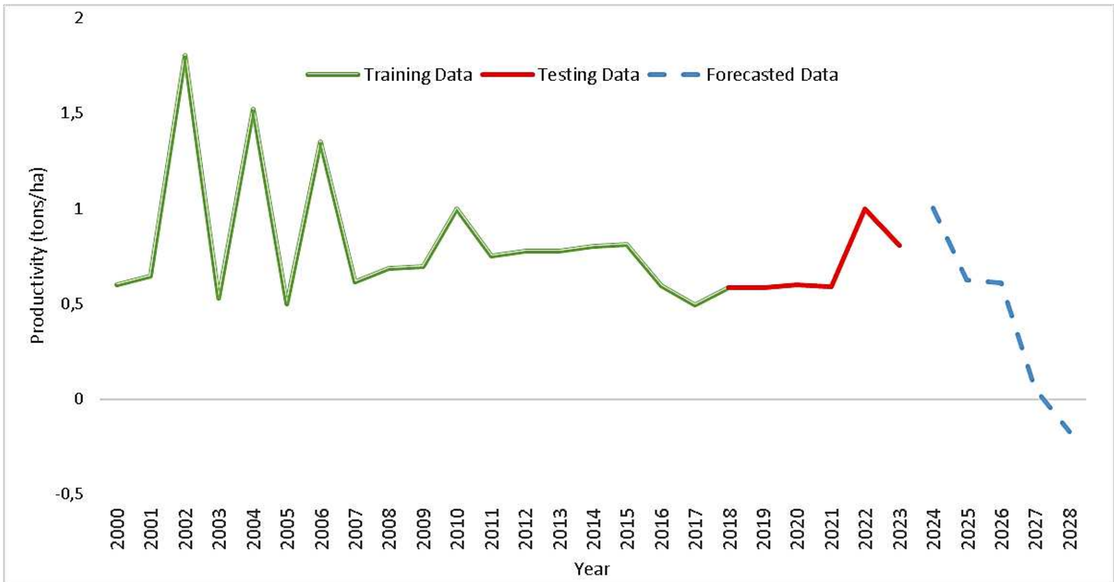

Figure 7 Result of forecasting coffee productivity from the best model for year 2024-2028

Figure 7 presents the forecasting results for coffee productivity from 2024 to 2028, based on historical data from 2000 to 2023. The graph displays two key data series: the actual productivity values from 2000 to 2023 and the projected values for the period 2024-2028. The actual line represents the actual productivity values, showing significant drop, showing the productivity for the years 2024-2028 will decrease significantly. The figure projecting productivity with drastic decreases, implying an expectation of unstable conditions in the coffee productivity sector in West Sumatera for the forecast period. While these forecasts provide a reasonable outlook, it is important to note that forecasted results may differ from actual data. This discrepancy was observed when testing the ARIMA (1,3,0) model by training on 20 years of data and validating it with 4 years of data.

3.2. Discussion

This study applies the ARIMA (1,3,0) model, which provides a conservative outlook with mayor decrease over the forecast period from 2024 to 2028. This result similar to Nayak et al., (2022) study on forecasting for coffee productivity in Hassan district of Karnataka, showed downward trend in year 2021 to 2025. Their study showed a downward trend in productivity over a 25-year period (1995-96 to 2019-20). While Phung et al., (2024) study using ARIMA model on forecasting coffee production in Vietnam, found that the fluctuation in coffee export production annually is unstable and tends to increase. On the other hand, a study by Ferreira et al., (2019) on coffee productivity in Brazil forecasted up to the year 2040 using the ARIMA model (1,1,0). They utilized non-stationary ARIMA models optimized for their data, acknowledging the fluctuating yet relatively stable trends in coffee productivity. ARIMA (1,1,0) model projects that coffee production in Brazil could reach nearly four million tons, with productivity averaging around 2500 kg/ha, or 2.5 tons/ha. In comparison, our study on coffee productivity in West Sumatra forecasts an average productivity of only 0.425 tons/ha for the period 2024 to 2028, using the ARIMA (1,3,0) model. This difference highlights the contrast in productivity levels between the two regions, with Brazil achieving significantly higher yields, likely due to technological advancements emphasized in the Brazilian forecast.

Another comparison, a study by Nasirudin et al., (2022) on forecasting coffee production in East Java from January 2020 to December 2021 using the Seasonal Autoregressive Integrated Moving Average (SARIMA) model. Their findings showed that coffee production in East Java followed similar seasonal trends in 2020-2021, though there was a slight decline in overall production. In comparison, our study showed time period from around 2024 to 2028 projects coffee productivity trends downward. This longer-term forecast appears to focus more on general trend stability rather than short-term seasonal variations. It is more applicable for evaluating trends in productivity rather than specific seasonal variations. Our finding related to Syifahati et al., (2023) study, where they found that by using Double exponential Smoothing (DES) and Triple Exponential Smoothing (TES) to forecast Indonesia coffee production is not able to meet demand of coffee consumption every year.

The study result shows a projected declining in coffee productivity. This might be due to several structural constraints. Arabica coffee, which thrives at elevations between 1,000 to 1,600 meters above sea level, is particularly sensitive to climatic fluctuations. Meanwhile, Robusta coffee, which is more resilient to varying environmental conditions, also faces productivity challenges due to soil degradation and the limited adoption of rejuvenation techniques, such as replanting high-yielding clones and improving fertilization methods The increasing variability in rainfall patterns and rising temperatures contribute to stress conditions for Arabica plantations, thereby reducing yields. In addition, good agricultural practices (GAP) for Arabica coffee, including soil management, shade optimization, and pest control, remain under-implemented in many areas, limiting productivity improvements (Ministry of Agriculture, 2019).

Indonesia's coffee sector also faces challenges from climate change. ENSO (El Niño-Southern Oscillation) and IOD (Indian Ocean Dipole) events have been shown to cause production declines of 6–22% during La Niña years (Sarvina et al., 2021). Overall, rising temperatures and erratic rainfall have shrunk suitable Arabica-growing areas in Indonesia by more than half and intensified pest pressures (Ramadhillah & Masjud, 2024), both of which severely undermine long-term productivity. In Indonesia, high rainfall not only disrupts cherry development through cracking and fermentation but also delays harvest and degrades quality, leading to both yield and income losses (SumatraCoffee, 2022). Structural and agronomic factors compound these environmental risks. Aging coffee trees, inadequate shade cover, and poor agronomic practices (e.g., limited rejuvenation, soil mismanagement) restrict productivity gains (Ministry of Agriculture, 2019). Therefore, there is a need for multi-dimensional intervention. Rainforest Alliance initiatives promoting agroforestry and climate adaptation training are essential for enhancing resilience (SumatraCoffee, 2022).

4. Conclusion

The analysis using the ARIMA model to forecast coffee productivity in West Sumatra from 2000 to 2023 has led to several key findings. The ARIMA (1,3,0) model was determined to be the most suitable for forecasting, as it passed the significance test and exhibited white noise residuals, with a MAPE value of 41.22%, indicating a reasonable level of accuracy. The forecast results suggest a continuous decline in productivity, with values decreasing from 1 ton per hectare in 2024 to 0.6266 tons per hectare in 2025, followed by 0.6125 tons per hectare in 2026. A more dramatic drop is projected in 2027, reaching 0.0538 tons per hectare, and by 2028, the forecasted productivity turns negative at -0.1709 tons per hectare, signaling severe production challenges. These findings emphasize the urgent need for government intervention to support agricultural development through investments in modern farming technologies and precision agriculture that can help mitigate the negative trend and sustain coffee productivity. Future research should explore factors affecting coffee productivity, particularly the impact of climate change and technological advancements, to provide deeper insights for policymakers.

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