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Forecasting Annual Coffee Production in Lampung Province, Indonesia: Comparing Linear Regression and Smoothing Methods

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ABSTRACT

Reliable production forecasts are useful for planning when the supply of agricultural raw materials varies from year to year. This study compared several methods for forecasting annual coffee production in Lampung Province, Indonesia, using production data for 2015–2024 from BPS-Statistics Indonesia, Lampung Province. The methods were linear regression, a three-period moving average, a three-period weighted moving average, simple exponential smoothing (α = 0.3, 0.6, and 0.9), and trend-adjusted exponential smoothing (α = 0.7; β = 0.5 or 0.7). Forecast accuracy was evaluated using mean absolute deviation (MAD), mean squared error (MSE), and mean absolute percentage error (MAPE) in POM-QM for Windows version 3. Linear regression produced the lowest errors (MAD = 7,007.457 tons; MSE = 93,557,210; MAPE = 5.8%) and the equation y = 1,290x + 110,039. The model projected production of 124,229 tons in 2025 and 130,679 tons in 2030. Among the methods examined, linear regression performed best for the available annual series. The projections should be used as planning estimates rather than fixed production targets.

IMPACT STATEMENT

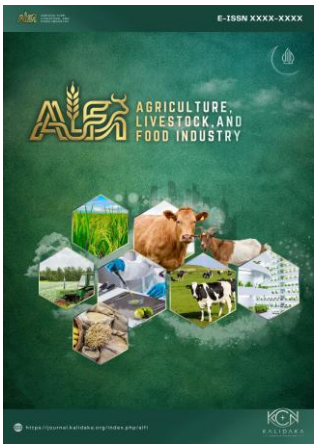
The results provide a simple reference for provincial agencies, coffee processors, and other stakeholders that need an estimate of future raw-material availability. For the 2015–2024 Lampung series, linear regression produced lower errors than the moving-average and exponential-smoothing settings examined in the study. The resulting projections may support discussions of processing capacity, procurement, storage, and supply planning. Because the analysis is based on a short annual series, the forecasts should be updated when new production data become available and considered together with climate, agronomic, and market information.

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1. Introduction

Coffee production is linked to processing, distribution, and market activities, so changes in raw-material availability can affect the wider coffee value chain. Recent studies describe coffee supply chains as complex systems that depend on coordination among producers, processors, traders, and other stakeholders [1]. Digital tools can improve information flows and decision support [2], but planning still depends on a reasonable estimate of future production. For producing regions, annual production forecasts can therefore help inform procurement, processing capacity, inventory, and policy planning.

Lampung Province is an important Robusta-producing area in Indonesia. Studies of Robusta production show that yield can be affected by fertilizer management and environmental conditions [3], while climate-suitability analysis indicates that production areas in Indonesia, including Lampung, may face changes in climatic suitability [4]. Research in Lampung also shows that production risk is related to farm and institutional conditions, including contract farming [5]. These findings help explain why provincial coffee production can vary from year to year.

Evidence from other coffee-producing regions shows similar sensitivity. Climate variability can affect coffee through temperature, rainfall, water stress, pests, and diseases [6]. Global assessments project changes in the suitability of areas for Arabica and Robusta [7], [10], [11], and studies in Indonesia also report spatial differences in future suitability [8], [9]. Robusta is not immune to warming; temperature sensitivity has been observed even for this relatively heat-tolerant species [12]. Historical production data are therefore useful for forecasting trends, but they do not explain the causes of production changes.

Studies using farm-level and process-based data show that coffee-yield forecasts can be strengthened by including climate, remote-sensing, and crop-process information [13]–[16]. Other research demonstrates that shade and agroforestry structure [17]–[19], plant physiology and climate–yield relationships [20], [21], and water and disease dynamics [22]–[24] affect production. These studies help explain why annual output can vary even when a long-run trend appears stable; however, they require variables that are not available in the annual provincial series used here.

For short annual series, simple statistical methods remain useful because they can be applied and updated with limited data. Studies of climate adaptation and land suitability show the value of richer explanatory information when it is available [25], [26], and seasonal climate forecasts can influence agricultural decisions [27]. Forecasting research also shows that no method is consistently best across all series and horizons [28]. Model rankings may change with the accuracy measure used [29], [30]. For that reason, comparing several methods with more than one error metric is appropriate for this dataset.

Accordingly, this study compares linear regression, moving average, weighted moving average, simple exponential smoothing, and trend-adjusted exponential smoothing for annual coffee production in Lampung from 2015 to 2024. The objective is to identify the method with the lowest MAD, MSE, and MAPE values and to use that method to obtain baseline projections for 2025–2030. The study provides a straightforward comparison based on official annual data and is intended to support planning while recognizing the limits of a short univariate series.

2. Literature Review and Analytical Framework

2.1. Coffee-production variability and the role of exogenous drivers

Coffee output is influenced by several interacting factors. Reviews identify temperature, rainfall, water stress, pests, diseases, and changes in suitable growing areas as important sources of variability [6]. Global studies project geographic shifts in suitability for Arabica and Robusta [7], [10], [11], while Indonesian studies show that the size and location of suitable areas may change over time [8], [9]. Evidence of Robusta temperature sensitivity [12] also indicates that a historical time trend cannot represent all processes that determine future output.

Farm-level studies add further evidence. Long-term fertilizer management affects Robusta production [3], and contract-farming arrangements are associated with production risk in Lampung [5]. Shade and agroforestry structure influence coffee yield and ecosystem conditions [17]–[19], while physiological responses, climate–yield relationships, soil water, and foliar disease also affect production [20]–[24]. These factors help explain year-to-year variation that a univariate model cannot explicitly represent.

2.2. Baseline forecasting for short annual series

Simple models are often used as forecasting benchmarks because added complexity does not guarantee better predictions [28]. The M4 Competition showed large differences in performance across series and

horizons, with simple and combined statistical approaches remaining competitive [32]. Similar concerns have been raised when machine-learning methods are compared with statistical baselines, particularly for small samples [33]. This is important here because the dataset contains only ten annual observations.

Linear regression, moving averages, and exponential smoothing use historical information in different ways. A linear time trend estimates a constant average change; a moving average uses the recent local level; a weighted moving average gives different importance to recent observations; and exponential smoothing updates forecasts recursively, with larger weights on newer data [28]. Trend-adjusted exponential smoothing adds a changing trend component. These methods remain common benchmarks in comparative forecasting studies [38], including agricultural applications that compare classical and neural models [40].

2.3. Forecast evaluation and model selection

Forecast accuracy should be evaluated with care because each metric emphasizes a different type of error. Hyndman and Koehler discuss limitations of several commonly used measures [29], and Koutsandreas et al. show that model rankings can change when different measures are used [30]. Temporal evaluation also requires attention to data leakage and the separation of training and evaluation periods [31]. Evidence from forecasting competitions confirms that evaluation choices can affect model comparisons [32].

MAD, MSE, and MAPE were used in this study. MAD reports the average absolute error in the original unit of production; MSE gives greater weight to larger errors; and MAPE expresses the error relative to the actual value. MAPE can be problematic when actual values are zero or close to zero [29], [35], although that problem does not occur in this series. Using more than one metric reduces dependence on a single loss function, since the preferred point forecast can vary with the accuracy measure [34] and model-selection criteria may disagree [39].

More complex approaches, including recurrent neural networks and hybrid exponential-smoothing/neural models, have produced strong results in larger forecasting problems [36], [37]. Their use is not examined here because the available series contains only ten annual observations and no additional covariates. A meaningful comparison with such models would require a longer series and an explicit out-of-sample validation design.

3. Methods

3.1. Research design and data universe

This study used a quantitative comparative time-series forecasting design based on ten annual observations of coffee production in Lampung Province from 2015 to 2024. The unit of analysis was annual provincial production in tons. The study compared several univariate forecasting methods applied to the same series; no human participants or experimental intervention were involved.

3.2. Data source and variable definition

The production series was obtained from BPS-Statistics Indonesia, Lampung Province. Annual coffee production (tons) was the forecast variable, and the chronological time index served as the predictor in the linear-regression model. Climate, land area, fertilizer, labor, prices, pests, and other external variables were not included. The models therefore estimate continuation of the observed statistical pattern rather than causal effects.

3.3. Forecasting specifications

Five forecasting families were compared: (1) linear regression; (2) a three-period moving average (MA-3); (3) a three-period weighted moving average (WMA-3); (4) simple exponential smoothing with $\alpha = 0.3$, 0.6, and 0.9; and (5) trend-adjusted exponential smoothing with $\alpha = 0.7$ and $\beta = 0.5$ or $\beta = 0.7$. Together, these methods provide benchmarks for linear trend, recent-average, weighted-recent-history, and level-plus-trend representations of the series [28], [38].

For the linear-regression model, the fitted value for period t is represented as:

$$\hat{y}_t = a + bt \tag{1}$$

where $\hat{y}_t$ is the fitted coffee-production value, a is the intercept, b is the estimated average annual change, and t is the chronological time index. The linear-regression equation obtained from the analysis was y = 1,290x + 110,039.

For the three-period moving average, the one-step-ahead forecast is the arithmetic mean of the three most recent actual observations:

$$F_{t+1} = (A_t + A_{t-1} + A_{t-2}) / 3 \quad (2)$$

where A denotes actual production and F denotes the forecast. For WMA-3, the corresponding expression is:

$$F_{t+1} = w_1A_t + w_2A_{t-1} + w_3A_{t-2}, \quad \Sigma w_i = 1 \quad (3)$$

The WMA-3 output contained the forecast and error statistics, but the numerical weights were not documented. Because the weighting scheme cannot be reproduced from the available information, the WMA-3 results are presented without inferring or assigning new weights.

Simple exponential smoothing updates the forecast recursively:

$$F_{t+1} = \alpha A_t + (1 - \alpha)F_t \quad (4)$$

where α is the smoothing constant. The tested values were α = 0.3, 0.6, and 0.9. Trend-adjusted exponential smoothing represents an evolving level and trend. In standard notation, the level and trend can be expressed as $L_t = \alpha A_t + (1 - \alpha)(L_{t-1} + T_{t-1})$ and $T_t = \beta(L_t - L_{t-1}) + (1 - \beta)T_{t-1}$, with future forecasts derived from the updated level and trend [28]. The tested combinations were α = 0.7 with β = 0.5 and β = 0.7. The analysis used these stated POM-QM outputs and no additional parameter tuning was undertaken.

3.4. Forecast-accuracy criteria

Model performance was compared using MAD, MSE, and MAPE. Multiple metrics were retained because forecast rankings can depend on the error measure and the decision loss it approximates [29]–[31], [34], [39]. The measures are defined as follows:

$$MAD = (1/n) \Sigma |A_t - F_t| \quad (5)$$

$$MSE = (1/n) \Sigma (A_t - F_t)^2 \quad (6)$$

$$MAPE = (100/n) \Sigma |(A_t - F_t) / A_t| \quad (7)$$

where A_t is actual production in period t, F_t is the fitted or forecast value for the same period, and n is the number of evaluated errors. The MAPE equation uses the conventional mean absolute percentage error and yields the reported 5.8% value for linear regression. All actual production values are positive, so the zero-denominator problem does not arise [29], [35].

3.5. Analytical procedure and software

Annual production data for 2015–2024 were entered into POM-QM for Windows version 3. Each forecasting method was applied to the same series, and the resulting MAD, MSE, MAPE, and 2025 forecast were compared. The method with the lowest errors across the three criteria was selected for the 2025–2030 projection. For linear regression, the fitted equation was then used to extend the annual forecast through 2030. No additional predictors or parameter settings were introduced.

3.6. Reproducibility and validity considerations

All methods were evaluated on the same annual series and with the same three accuracy measures. However, no independent holdout period or rolling-origin validation was used. The reported errors should therefore be interpreted as in-sample comparative performance, not as verified out-of-sample accuracy [31]. With a longer series, future work should evaluate the models on temporally separated observations.

3.7. Ethical considerations

The study used aggregated secondary statistics and did not involve human participants, animals, personal data, or intervention; therefore, ethical approval and informed consent were not applicable.

4. Results and Discussion

4.1. Results

4.1.1 Observed coffee-production pattern, 2015–2024

Annual coffee production in Lampung fluctuated substantially during 2015–2024 (Table 1). Production increased from 108,964 tons in 2015 to 128,074 tons in 2016 (17.5%). From 2017 to 2022, production ranged from 107,183 to 118,139 tons. It then fell to 105,807 tons in 2023 before rising to 141,918 tons in 2024, an increase of 34.1% from the previous year. The 2024 value is notably higher than most earlier observations, whereas the regression model summarizes the ten-year series with a single linear trend.

Table 1. Annual coffee production in Lampung Province, 2015–2024.

Year	Production (tons)	Year	Production (tons)
2015	108,964	2020	117,311
2016	128,074	2021	116,281
2017	107,183	2022	118,139
2018	110,570	2023	105,807
2019	117,092	2024	141,918

4.1.2. Comparative forecasting performance

Table 2 summarizes the error measures and 2025 forecasts reported by POM-QM. Linear regression produced the smallest MAD, MSE, and MAPE among all evaluated specifications: MAD = 7,007.457 tons, MSE = 93,557,210, and MAPE = 5.8%. The next-lowest MAPE was obtained by MA-3 (6.2%), followed by WMA-3 (6.5%). Simple exponential smoothing produced progressively larger reported errors as α increased from 0.3 to 0.9. Both trend-adjusted exponential-smoothing specifications had larger errors than the other tested methods, with the α = 0.7, β = 0.7 configuration producing the largest MSE and MAPE in the comparison.

Table 2. Reported forecasting performance across the evaluated methods.

Method	Parameter	MAD	MSE	MAPE (%)	Forecast 2025 (tons)
Linear regression	—	7,007.457	93,557,210	5.8	124,229
Moving average (3)	—	7,737.523	142,844,000	6.2	121,954
Weighted moving average (3)	weights not reported	8,152.056	163,860,100	6.5	127,238
Exponential smoothing	α = 0.3	9,050.769	158,047,800	7.3	121,643
Exponential smoothing	α = 0.6	9,720.6	190,250,800	7.9	129,328
Exponential smoothing	α = 0.9	10,765.8	238,042,600	8.8	138,428
Trend exp. smoothing	α = 0.7; β = 0.5	11,322.3	264,576,200	9.2	141,704
Trend exp. smoothing	α = 0.7; β = 0.7	12,220.2	295,943,600	10.0	146,454

The regression equation was y = 1,290x + 110,039, indicating an estimated linear increase of approximately 1,290 tons for each one-period increase in the time index. The lower error values support selecting linear regression as the best-performing method in this comparison. This ranking applies to the observed series and tested settings and does not guarantee superior performance on future data.

4.1.3. Baseline projection for 2025–2030

Applying the selected model produced a 2025 forecast of 124,229 tons. The projection rises by 1,290 tons each year, reaching 130,679 tons in 2030 (Table 3). Because the model uses a constant time-trend coefficient, the projected path is linear and does not represent possible year-to-year shocks or climate-related variability. Figure 1 shows the observed series and the projected values.

Table 3. Linear-regression forecast of coffee production in Lampung Province, 2025–2030.

Year	Forecast production (tons)
2025	124,229
2026	125,519
2027	126,809
2028	128,099
2029	129,389
2030	130,679

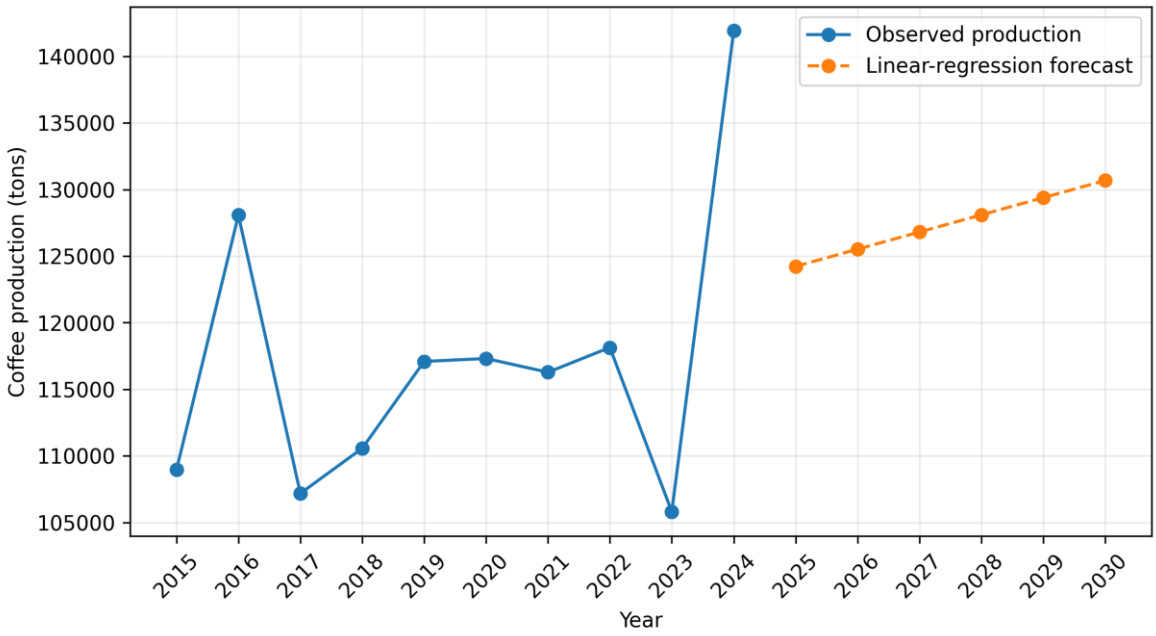


Figure 1. Observed annual coffee production (2015–2024) and linear-regression projection (2025–2030).

4.2. Discussion

4.2.1. Performance of linear regression relative to the other methods

For the 2015–2024 Lampung series, linear regression produced the lowest MAD, MSE, and MAPE among the tested settings. This result is consistent with evidence that simple models can perform well when they capture the main pattern in a series [28], [32]. Linear regression uses all ten observations to estimate a common level and trend, whereas moving-average and smoothing methods respond more strongly to recent observations. In this series, production rose sharply from 105,807 tons in 2023 to 141,918 tons in 2024. The exponential-smoothing results reflect that sensitivity: as α increased from 0.3 to 0.9, both the 2025 forecast and the reported errors increased.

Even so, the linear trend should not be interpreted as a causal model of coffee production. Climate variability, temperature, agronomic management, and spatial suitability can influence coffee output [3], [6]–[12]. Studies that include agroclimatic, remote-sensing, and process-based variables show that these factors can improve the representation of production dynamics [13]–[16]. The advantage of the regression model is its simplicity and ease of interpretation; it does not capture the underlying biological or environmental mechanisms.

Linear regression ranked first under all three error measures, so its selection is not dependent on a single metric. However, each measure emphasizes error differently [29], [30], [34], [39]. MSE penalizes large errors more strongly, MAD remains in tons, and MAPE expresses relative error but has known limitations [29], [35]. Considering the three metrics together provides a more balanced basis for comparison than relying only on the 5.8% MAPE.

4.2.2. Practical interpretation for coffee-sector planning

The 2025–2030 projections can be used as baseline quantities for provincial and industry planning. Coffee supply chains require coordination among several actors [1], and better information can support decisions across the chain [2]. The forecast may therefore be useful when discussing processing capacity, raw-material procurement, storage, logistics, and downstream development. Because the model is estimated from a short annual series, it should be updated whenever new production data become available.

Planning should also consider information that is not included in the model. Climate-suitability studies show that coffee-growing conditions can shift over time [4], [7]–[11], while farm and production-system studies identify effects of fertilizer management, shade, water relations, disease, and institutional arrangements [3], [5], [17]–[24]. Combining the statistical forecast with current agronomic assessments, climate outlooks, market conditions, and field information would provide a fuller basis for decisions. Evidence from seasonal climate forecasting also shows that climate information can influence agricultural decisions [27].

Model complexity should also match the amount of data available. Machine-learning and hybrid methods can perform well in larger datasets [36], [37], and agricultural studies have compared neural and classical

methods [40]. With only ten annual observations, however, a high-capacity model would be difficult to evaluate reliably. A longer series and explicit out-of-sample testing would be needed before concluding that a more complex method improves forecasting performance.

4.2.3. Limitations

Several limitations should be considered. First, the dataset contains only ten annual observations (2015–2024), so the estimated trend and long-horizon projections are sensitive to individual years. Second, the MAD, MSE, and MAPE values were calculated on the available historical series without an independent holdout or rolling-origin evaluation; the ranking therefore reflects in-sample performance rather than verified future accuracy [31]. Third, no prediction intervals were available, so the 2025–2030 forecasts do not quantify uncertainty. Fourth, the models do not include climate, planted area, crop age, fertilizer, labor, pests, prices, or other explanatory factors known to influence coffee production [3], [24]. Finally, the comparison is limited to the five forecasting families analyzed here; ARIMA/SARIMA, other state-space models, machine learning, hybrid methods, and forecast combinations were not evaluated.

5. Conclusion

This study compared linear regression, MA-3, WMA-3, simple exponential smoothing, and trend-adjusted exponential smoothing using annual coffee-production data for Lampung Province from 2015 to 2024. Linear regression produced the lowest errors (MAD = 7,007.457 tons, MSE = 93,557,210, and MAPE = 5.8%) and was selected for the baseline projection. The equation y = 1,290x + 110,039 yielded forecasts of 124,229 tons in 2025 and 130,679 tons in 2030. The results show that a simple linear trend can provide a useful benchmark for this short annual series, but its future accuracy has not been tested out of sample. Future studies should use longer series, prediction intervals, external variables, and temporally ordered validation.

Author contribution statement

Sri Hidayati: Conceptualization; Methodology; Formal analysis; Data curation; Writing—original draft; Writing—review and editing.

Disclosure statement

The author declares no conflict of interest with respect to the research, authorship, or publication of this article.

AI-assisted technologies disclosure

AI-assisted tools were used for language editing, manuscript organization, and reference formatting. They were not used to generate or modify the study data, forecast values, or reported error metrics. The author reviewed the final manuscript and remains responsible for its accuracy, interpretation, and integrity.

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Data availability statement

The annual coffee-production series used in this study was obtained from BPS-Statistics Indonesia, Lampung Province. The study did not generate primary data.

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