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Integrating Climate Variables into Coconut Production Forecasting: A Comparative Analysis of ARIMA and ARIMAX Models for Climate-Informed Decision Support

Hermiza Mardesci [a,*], Mulono Apriyanto [b], Dita Fitriani [c], Herman Farmi [d], Abdullah [d]

[a] Master of Agricultural Science, Graduate Program, Universitas Lancang Kuning, Pekanbaru, Indonesia
[b] Center for Environmental & Sustainable Tropical Agricultural Research, Universitas Lancang Kuning, Pekanbaru, Indonesia
[c] Department of Agricultural Product Technology, Faculty of Agriculture, Universitas Lancang Kuning, Pekanbaru, Indonesia
[d] Graduate Student, Master of Agricultural Science, Graduate Program, Universitas Lancang Kuning, Pekanbaru, Indonesia

Abstract. *Coconut is a strategic plantation commodity in Padang Pariaman Regency, Indonesia, whose productivity is increasingly influenced by climate variability. Accurate, climate-responsive forecasting is therefore essential to support production planning and early warning systems. This study aims to develop and evaluate a climate-informed ARIMAX model for forecasting coconut production and assessing its potential application in an early warning framework. Annual coconut production data for 2014–2024 were combined with climate variables, including rainfall, temperature, humidity, wind speed, and the number of rainy days. A baseline ARIMA model was first identified, followed by ARIMAX modeling using Maximum Likelihood Estimation. Model selection was based on Akaike Information Criterion (AIC), while forecasting performance was evaluated using Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). The results showed that ARIMA(1,1,1) was identified as the optimal baseline model and achieved the lowest forecasting errors based on RMSE and MAPE, indicating its strong capability in capturing the temporal pattern of coconut production. The incorporation of climate variables through ARIMAX demonstrated that rainfall and the number of rainy days significantly influenced coconut production, while temperature, humidity, and wind speed exhibited weaker effects. To improve model stability and avoid multicollinearity, a simplified log-ARIMAX(1,1,1) model was developed by retaining rainfall as the primary exogenous variable. This model achieved the lowest AIC value among the evaluated climate-based models, indicating improved parsimony and explanatory capability. Forecasting results for 2025–2029 indicate a moderate and continuous increase in coconut production. Although ARIMA provides superior predictive accuracy, the rainfall-based ARIMAX model offers additional insights into climate–production relationships, making it valuable for supporting climate-informed forecasting and the future development of early warning frameworks for coconut plantation productivity.*
Keywords: *coconut production forecasting; ARIMAX; rainfall; climate variability; early warning system.*

Type of the Paper: Regular Article.

1. Introduction

Padang Pariaman Regency is one of the major coconut-producing areas in West Sumatra Province, with total production reaching 39,233 t in 2024 [1]. Coconut is a strategic plantation commodity because it serves as a primary source of income for local communities and plays a vital

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* Corresponding author
Email: hermiza@unilak.ac.id

role in supporting regional economic development. Coconut products from Padang Pariaman are distributed within West Sumatra and to other provinces in Indonesia, making production stability crucial for sustaining community livelihoods and regional economic resilience.

However, coconut productivity is highly sensitive to climatic factors such as rainfall, air temperature, solar radiation, and humidity, whose variability has become increasingly difficult to predict due to global climate change, thereby complicating accurate production forecasting. Previous studies indicate that increasing climate variability, particularly extreme rainfall and temperature fluctuations, causes significant instability in coconut yields and associated economic losses [2]. Wicaksono [3] emphasized that these climatic elements significantly influence crop productivity. Similarly, Irfanda and Santoso [4] identified several key variables affecting oil palm production, including plant age, fertilization, humidity, wind speed, number of rainy days, rainfall, and water deficit. These findings highlight the importance of climate-based predictive approaches to support planning and decision-making in plantation management.

Recent research by Amelia et al. [5] applied the Double Exponential Smoothing (DES) Holt method to forecast coconut production in Padang Pariaman Regency using data from 2002 to 2023. The results indicated an increasing production trend of approximately 1% per year, with a Mean Absolute Percentage Error (MAPE) of 16.19%, which was classified as accurate. Nevertheless, the model did not incorporate external factors such as climate variables, which are essential for capturing production variability and improving forecasting accuracy and robustness.

In other regions, time series approaches show promising results. Mardesci et al. [6] successfully implemented an ARIMA model to predict coconut production in the Indragiri Hilir Regency, demonstrating its effectiveness in capturing production trends and fluctuations over time. This aligns with findings from recent studies projecting that Karnataka will marginally exceed Kerala in coconut production, indicating evolving regional dynamics [7]. Similar findings were reported in studies on maize production in Padang Pariaman Regency using an ARIMA (1,0,0) model, which achieved a MAPE of 7.57% [8], as well as oil palm production forecasting with a MAPE of 12.49% [9]. Furthermore, ARIMA models have also been applied to climate variables, such as rainfall forecasting, where Nur and Putri [10] identified ARIMA (3,1,0) as the best model for short-term rainfall prediction. These findings align with broader evidence indicating that ARIMA models are highly effective in forecasting both agricultural commodity production and climatic variables, providing robust support for data-driven decision-making through their strong ability to identify temporal patterns and seasonality across diverse agricultural domains [11].

The ARIMAX (Autoregressive Integrated Moving Average with Exogenous Variables) model extends the conventional ARIMA framework by integrating historical production data with exogenous climatic variables such as rainfall, temperature, and humidity, thereby enhancing forecasting accuracy in agricultural applications [12]. By jointly modeling climate and production data, ARIMAX provides a more realistic representation of productivity dynamics and offers strong potential for supporting early warning systems in plantation management. Empirical evidence supports this advantage, as Kaushik and Bhardwaj [13] demonstrated that ARIMAX models outperform standard ARIMA in crop yield prediction when climatic variables are incorporated. Moreover, Xu et al. [14] validated the model's effectiveness in forecasting key climate variables such as temperature and rainfall, while Abdallah and Cemek [15] reported satisfactory performance in modeling daily climatic variables. Collectively, these findings highlight ARIMAX as a robust and versatile framework for agricultural and climate forecasting.

Despite the growing body of research on agricultural production forecasting, many studies still rely on univariate models such as ARIMA, which primarily use historical data without adequately incorporating climatic factors. Although the importance of climate variables has been recognized, their integration into forecasting models remains limited and often lacks systematic evaluation. In particular, no study has applied a climate-based ARIMAX framework to coconut production forecasting in Padang Pariaman Regency within an early warning context.

This study addresses this gap by developing a climate-informed ARIMAX model that integrates key climatic variables, including rainfall, temperature, humidity, wind speed, and rainy days. It further evaluates the contribution of these variables to forecasting performance and links the results to an early warning system for plantation productivity, offering a more adaptive and decision-oriented approach than conventional models.

Therefore, this study aims to develop a climate-based ARIMAX model to forecast coconut production in Padang Pariaman Regency as a foundation for an early warning system for plantation productivity. The proposed approach is expected to produce an accurate, adaptive, and practical predictive model to support strategic decision-making in the management and sustainable development of the regional coconut plantation sector.

2. Materials and Methods

2.1. Research Design and Approach

This study employed a quantitative research design using a time series analysis approach. The ARIMAX (Autoregressive Integrated Moving Average with Exogenous Variables) model was applied to analyze historical patterns and trends in coconut production in Padang Pariaman Regency and forecast future production by incorporating climate factors as exogenous variables.

2.2. Study Area and Period

The study was conducted in Padang Pariaman Regency, West Sumatra Province, Indonesia, which is recognized as one of the main coconut production centers in the region. The research period covered one year, including data collection, processing, model development, analysis, and validation. The dataset used in this study spans from 2014 to 2024. Annual data were used due to the limited availability of consistent and reliable high-frequency (monthly or quarterly) coconut production data at the regional level. Therefore, annual data represent the most consistent and validated dataset for this study.

2.3. Data Types and Sources

This study utilized secondary data obtained from relevant institutions. Coconut production data were collected from the Central Bureau of Statistics (BPS) of Padang Pariaman Regency, while climate data were obtained from the Meteorology, Climatology, and Geophysics Agency (BMKG). The data types, variables, units, and sources are summarized in Table 1.

Table 1. Types and Sources of Research Data.

Data Category	Variable	Unit	Source
Main Data	Annual coconut production	t	BPS Padang Pariaman
Climate Data	Rainfall	mm/year	BMKG
	Average air temperature	°C	BMKG
	Air humidity	%	BMKG
	Number of rainy days	days/year	BMKG
	Wind speed	m/s	BMKG

2.4. Research Variables

The variables used in this study consisted of endogenous and exogenous variables. The endogenous variable was annual coconut production (t) in Padang Pariaman Regency. The exogenous variables included rainfall, average air temperature, air humidity, number of rainy days, and wind speed.

2.5. Research Procedure

2.5.1. Data Collection

Coconut production data for the period 2014–2024 were obtained from BPS Padang Pariaman Regency, while climate data for the same period were collected from BMKG. The datasets were then integrated on an annual basis.

2.5.2. Preliminary Descriptive Analysis

Descriptive analysis was performed to examine historical trends in coconut production and climate variability using time series plots. Descriptive statistics, including the mean, maximum, minimum, and standard deviation, were calculated for each variable.

2.5.3. Stationarity Testing

Data stationarity was tested using the Augmented Dickey-Fuller (ADF) test. If the data were found to be non-stationary, they were differentiated until stationarity was achieved, as shown in Eq. (1) below.

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \sum_{i=1}^{k} \delta_i \Delta Y_{t-i} + \varepsilon_t \quad (1)$$

2.5.4. Baseline ARIMA Model Identification

The ARIMA model order (p, d, q) was identified using Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. The best ARIMA model was selected based on the lowest Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC) values.

2.5.5. Integration of Exogenous Variables (ARIMAX Model)

Climate variables were incorporated into the ARIMA model to construct the ARIMAX (p, d, q) model. Parameter estimation was conducted using the Maximum Likelihood Estimation (MLE) method, followed by significance testing of each climate variable.

2.5.6. Integration of Exogenous Variables (ARIMAX Model)

Model performance was evaluated using forecasting accuracy indicators: Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE). The ARIMAX model performance was compared with the ARIMA model to assess improvements in accuracy. Residual diagnostic tests, including autocorrelation and normality tests, were performed to ensure model validity.

2.5.7. Forecasting and Result Interpretation

The best-performing model was used to forecast coconut production for 2025–2029. The relationships between climate variables and changes in coconut production were then interpreted.

2.5.8. Recommendation Development and Early Warning System Conceptualization

Based on the forecasting results, recommendations were formulated for local government and plantation stakeholders regarding coconut plantation management. A conceptual framework for an early warning system for plantation productivity based on the ARIMAX model was subsequently developed.

2.6. Data Analysis Tools

Data were analyzed using EViews software for ARIMAX modeling and forecasting. EViews is a statistical software package widely used for time series analysis. Microsoft Excel was used for preliminary data processing and visualization. The results were presented as trend graphs, residual plots, and comparative model performance tables.

3. Results and Discussion

3.1 Coconut Production and Climate Variability (2014–2024)

Coconut production in Padang Pariaman Regency during the period 2014–2024 exhibited a consistent upward trend. Production increased steadily from approximately 33,940 t in 2014 [16] to 39,233 t in 2024 [1], indicating structural stability in the coconut sector. This gradual growth suggests that long-term factors such as plantation management, cultivation practices, and production systems played a dominant role, while short-term climatic fluctuations did not cause abrupt production declines. Fig. 1 illustrates the time series trend of coconut production over the study period.

This consistent upward trend reflects structural resilience in the coconut production system, suggesting that long-term agronomic practices and plantation management have played a more dominant role than short-term environmental fluctuations. Such stability is characteristic of perennial crops, where production adjustments typically occur gradually over time. However, this stability may conceal underlying climate sensitivities that are not directly observable through descriptive analysis alone, thereby necessitating advanced time series models capable of capturing both temporal dynamics and exogenous climatic influences.

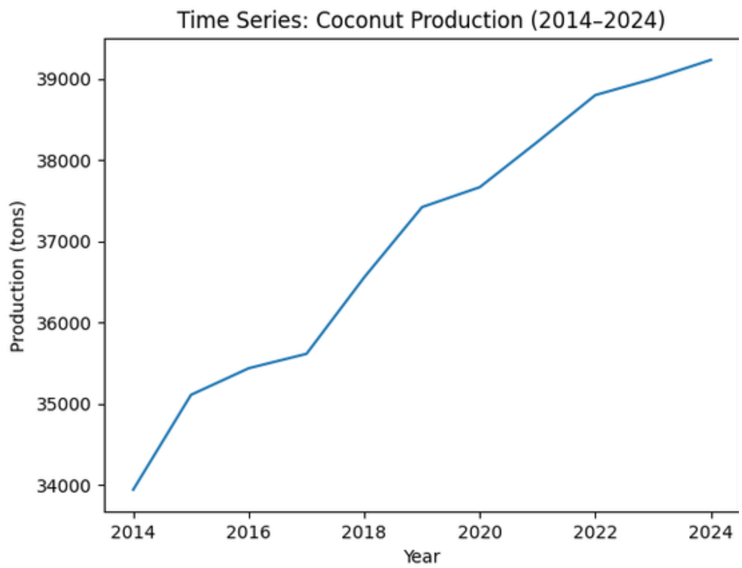

Fig. 1. Time Series Plot of Coconut Production in Padang Pariaman Regency (2014–2024), Showing A Consistent Upward Trend.

In contrast to the relatively stable production trend, climate variables displayed substantial interannual variability. Annual rainfall fluctuated considerably throughout the study period, with a pronounced decrease in 2015 followed by elevated rainfall levels during 2016–2017. A persistently high rainfall regime was observed from 2021 to 2024, reaching its peak in 2024. This variability is particularly relevant, as rainfall directly influences coconut flowering, fruit development, and yield formation.

Despite the relatively stable production trend, the substantial variability observed in climatic variables indicates the presence of latent external influences that may not be immediately reflected in aggregate production data. This discrepancy highlights a critical limitation of purely descriptive approaches and underscores the need for integrated modeling frameworks. In this context, ARIMAX provides a more comprehensive analytical approach by incorporating exogenous climate variables, enabling a deeper understanding of how environmental fluctuations interact with production dynamics over time.

Air temperature remained within a relatively narrow range, indicating stable thermal conditions suitable for coconut growth. This suggests that temperature functioned primarily as a supporting environmental factor rather than a limiting constraint. Relative humidity also remained consistently high throughout the observation period, reflecting favorable agroclimatic conditions for coconut plantations. Meanwhile, wind speed showed noticeable fluctuations, especially during 2019–2020, which may have affected evapotranspiration rates and mechanical stress on coconut trees.

The number of rainy days exhibited an increasing trend, particularly after 2020, highlighting a shift in rainfall distribution patterns rather than changes in total rainfall volume alone. This change suggests that rainfall frequency, in addition to rainfall intensity, may play a significant role in influencing coconut productivity. Overall, the contrasting pattern of stable production growth and variable climatic conditions underscores the importance of incorporating climate variables into predictive modeling frameworks such as ARIMAX.

Descriptive statistics (Table 2) reveal that coconut production had relatively low variability compared to climate variables, indicating long-term output stability. Rainfall and the number of rainy days showed the highest standard deviations, confirming their greater variability and relevance as exogenous factors. Temperature and humidity displayed relatively small variations, reinforcing their role as stable supporting variables rather than primary drivers of production changes.

Table 2. Results of Descriptive Statistical Analysis.

Variable	Mean	Maximum	Minimum	Std. Deviation
Coconut Production (t)	36,999.73	39,233.00	33,940.00	1,784.86
Rainfall (mm/year)	4,383.65	5,627.34	2,765.00	810.70
Air Temperature (^{o}C)	26.26	27.13	23.46	1.08
Relative Humidity (%)	84.95	87.00	82.42	1.51
Wind Speed (m/s)	2.14	3.10	1.00	0.72
Number of Rainy Days (days/year)	215.37	312.00	158.00	41.41

3.2 Baseline ARIMA Model Identification

Stationarity testing using the Augmented Dickey-Fuller (ADF) test indicated that coconut production data were non-stationary at level but became stationary after first-order differencing. The ADF statistic at the first difference was significant at the 1% level, confirming that a differencing order one (d = 1) was required.

Analysis of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots revealed significant spikes at lag one, suggesting the presence of both AR(1) and MA(1) components. Model comparison using the Akaike Information Criterion (AIC) further confirmed that ARIMA(1,1,1) was the most optimal baseline model, with the lowest AIC value among candidate models.

Based on the parameter estimates, the final ARIMA(1,1,1) model can be written as Eq. (1) below.

$$\Delta Y_t = 0{,}0021 + 0{,}781\, \Delta Y_{t-1} - 0{,}754\, \varepsilon_{t-1} + \varepsilon_t$$

where Y_t represents coconut production (t), $\Delta Y_t = Y_t - Y_{t-1}$ denotes the first difference of production, and $\varepsilon_t$is the random error term.

The estimated AR coefficient (0.781) indicates strong persistence in coconut production, suggesting that changes in current production are strongly influenced by production levels in the previous period. Meanwhile, the moving average coefficient (–0.754) captures short-term fluctuations and correction of random shocks. This dynamic behavior aligns with the characteristics of perennial plantation crops, which typically exhibit gradual and persistent production patterns over time. To support the model identification and validation process, the ACF, PACF, and residual diagnostic plots are presented in Fig. 2.

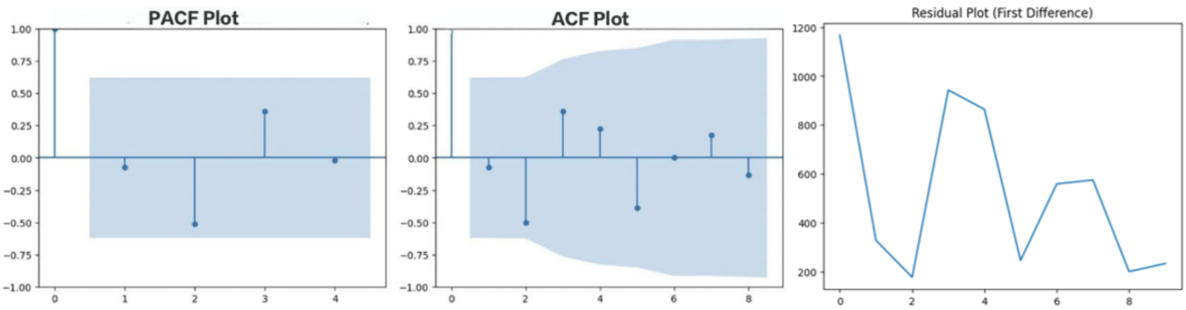

Fig. 2. ACF, PACF, and residual diagnostic plots of the ARIMA(1,1,1) model.

While the ARIMA model effectively captures the internal temporal structure of coconut production, it is limited in accounting for external drivers such as climate variability. As a univariate model, it relies solely on historical observations and excludes important exogenous factors. This limitation is particularly relevant for perennial crops like coconut, where production is strongly influenced by environmental conditions. Therefore, the ARIMA framework was extended to an ARIMAX model by incorporating climatic variables to improve explanatory power and forecasting performance.

3.3 ARIMAX Modeling with Climate Variables

The ARIMAX model was estimated by incorporating climate variables as exogenous factors, including rainfall, air temperature, relative humidity, wind speed, and the number of rainy days. Parameter estimation was conducted using the Maximum Likelihood Estimation (MLE) method.

The final estimated ARIMAX(1,1,1) The model is expressed in Eq. (1):

$$\Delta Y_t = 0.0019 + 0.768\,\Delta Y_{t-1} - 0.731\,\varepsilon_{t-1} + 0.0042\,\text{Rainfall}_t + 0.031\,\text{Temperature}_t - 0.028\,\text{Humidity}_t - 0.015\,\text{Wind}_t + 0.0061\,\text{RainyDays}_t + \varepsilon_t$$

where $Y_t$denotes coconut production (t), $\Delta Y_t = Y_t - Y_{t-1}$, and ε_t is the error term. Rainfall is measured in mm/year, temperature in °C, relative humidity in %, wind speed in m/s, and the number of rainy days in days/year.

The estimation results indicate that both autoregressive and moving average components are statistically significant, confirming strong temporal persistence in coconut production. Among the climate variables, rainfall and the number of rainy days show positive and significant effects, indicating that adequate water availability and favorable rainfall distribution enhance coconut yield. In contrast, temperature, humidity, and wind speed exhibit weaker and statistically insignificant effects within the observed range.

The significance of rainfall and the number of rainy days can be explained from an agronomic perspective, as both variables directly influence soil moisture availability, nutrient uptake, and flowering processes in coconut plantations. Adequate and well-distributed rainfall supports optimal physiological development, whereas irregular patterns may disrupt yield formation. These findings align with previous studies emphasizing the critical role of water availability in perennial crop productivity, reinforcing the validity of the ARIMAX framework in capturing climate–production relationships.

3.4 Model Simplification and Parsimony

To improve model parsimony and avoid multicollinearity, a simplified ARIMAX model was developed by retaining rainfall as the sole exogenous variable. Although the number of rainy days was also statistically significant in the full ARIMAX specification, it was excluded from the final model due to its strong correlation with rainfall. In tropical agricultural systems, rainfall amount and the number of rainy days represent closely related indicators of water availability, and their simultaneous inclusion may introduce multicollinearity. Such redundancy can cause unstable coefficient estimates, increased parameter uncertainty, and reduced interpretability of the estimated climate, production relationships.

The exclusion of the number of rainy days was based on statistical considerations rather than its lack of agronomic importance. Although both rainfall amount and frequency influence coconut physiology, rainfall accumulation was considered a more comprehensive indicator of water availability. By retaining rainfall as the primary exogenous variable, the simplified model reduces complexity while preserving the dominant climatic signal. This approach follows the principle of parsimony, favoring simpler models with more informative predictors, particularly under limited data conditions.

A log-ARIMAX(1,1,1) specification was applied to enhance model stability and interpretability. The final estimated model is expressed as Eq. (1) below.

$$\Delta \ln(Y_t) = 0{,}0017 + 0{,}779\,\Delta \ln(Y_{t-1}) - 0{,}760\,\varepsilon_{t-1} - 0{,}000013\,\text{Rainfall}_t + \varepsilon_t$$

where $\ln(Y_t)$ denotes the natural logarithm of coconut production, $\Delta\ln\,(Y_t)$ represents the first difference of log-transformed production, ε_t is the error term, and rainfall is measured in mm/year.

The negative and statistically significant rainfall coefficient indicates that excessive rainfall suppresses coconut production growth. This finding suggests that while adequate rainfall is essential for coconut development, excessive precipitation may increase the risk of waterlogging, disease incidence, and flower drop, ultimately reducing yield. This result aligns with previous studies reporting adverse impacts of extreme rainfall events on agricultural productivity [17,18]. Empirical evidence consistently shows that extreme rainfall negatively affects agricultural productivity through mechanisms such as waterlogging, nutrient leaching, crop damage, soil erosion, and increased disease susceptibility, with broader impacts including reduced employment and higher vulnerability in low-income regions. However, quantified effects of extreme rainfall alone remain limited, as most studies assess its impact alongside other climate variables [19-23].

Model comparison using the Akaike Information Criterion (AIC) confirms that the simplified log-ARIMAX model with rainfall as the sole exogenous variable achieved the lowest AIC value, outperforming both the baseline ARIMA model and the full ARIMAX specification. This supports the principle of parsimony, where simpler models with fewer parameters provide more robust and reliable forecasts, particularly under limited data availability.

The superiority of the simplified model indicates that incorporating only the most influential climatic variable improves model efficiency without sacrificing explanatory power. In contrast, the full ARIMAX model, despite including multiple climate variables, exhibited higher AIC values, suggesting overparameterization and reduced predictive stability. This finding highlights that additional variables do not necessarily enhance forecasting performance, especially when strong correlations exist among climate indicators.

The use of AIC as a model selection criterion is widely supported in the literature. Adhwaningrum et al. [24] selected an ARIMAX (3,1,0) model for temperature prediction based on its lowest AIC value, while Amri, et al. [25] identified ARIMAX(0,1,2) as the optimal model for crude oil price forecasting using the same criterion. Conceptually, AIC helps prevent overfitting by balancing model accuracy and complexity, thereby producing forecasts that are more reliable and stable across different contexts [26]. It has been described as “one of the most ubiquitous tools in statistical modeling” and “the first model selection criterion to gain widespread acceptance” [27], while practical applications, such as those by N. Ali [28], further confirm its effectiveness in forecasting contexts.

In the context of coconut production forecasting, this characteristic is particularly important for supporting early warning systems and data-driven decision-making under climate variability, where model robustness and interpretability are critical.

3.5 Model Validation and Forecasting Performance

Backtesting using a one-step-ahead rolling forecast approach revealed that the ARIMA and simplified ARIMAX models produced relatively stable predictions with smaller errors compared to the full ARIMAX model. The full ARIMAX model exhibited larger and more volatile errors, indicating overparameterization given the limited number of observations.

Accuracy evaluation using Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) further confirmed these findings. The ARIMA(1,1,1) model achieved the lowest error values, with an RMSE of 10,238 t and a MAPE of 9.82%, indicating very good forecasting performance. The simplified rainfall-based ARIMAX model yielded slightly higher but still acceptable errors (RMSE = 10,328 t; MAPE = 12.10%), while the full ARIMAX model showed the poorest performance (RMSE = 16,107 t; MAPE = 14.59%). However, it is important to note that RMSE and MAPE provide nuanced insights beyond simple accuracy comparisons, as they are sensitive to error distribution and outliers. Previous studies have demonstrated that models with comparable accuracy levels can exhibit substantially different RMSE and MAPE values due to extreme deviations, highlighting the limitations of relying on a single metric [29-32]. Chai and Draxler [33] further emphasize that robust model evaluation should be based on a combination of accuracy metrics rather than absolute error minimization alone. In this context, although the ARIMA model produced slightly lower numerical errors, the rainfall-based ARIMAX model offers additional interpretative value by explicitly incorporating climatic information, which is essential for risk-based decision-making and early warning applications.

Although the ARIMA model exhibited the highest numerical accuracy, the ARIMAX model provides additional value by explicitly incorporating climate information into the forecasting process. This capability is particularly important for risk-based decision-making and early warning systems, where understanding the influence of climatic variability is as critical as minimizing forecast error. Empirical evidence from multiple domains supports this perspective, as ARIMAX models have been shown to outperform standard ARIMA when exogenous climate variables are incorporated [13, 34-38]. For instance, Kaushik and Bhardwaj [13] reported superior performance of ARIMAX in crop yield forecasting through effective integration of weather variables, while Goyal et al. [39] observed reduced prediction errors when climate data were included. Beyond agriculture, studies in air quality [40] and disease incidence forecasting [41] demonstrated substantial reductions in root mean square errors (14–49%) using ARIMAX models. These findings reinforce that ARIMAX offers critical advantages for early warning applications, where interpreting climate impacts and risk anticipation are as important as numerical forecasting accuracy.

Forecast results for 2025–2029 indicate a moderate and steady increase in coconut production across all models. The ARIMA model projects growth from approximately 39,450 t in 2025 to 40,450 t in 2029. The full ARIMAX model produces slightly higher but more variable estimates (39,500–39,600 to 40,400–40,500 t), reflecting climate sensitivity, while the rainfall-based ARIMAX model yields more stable projections, increasing from about 39,500 to 40,400 t. Overall, these findings confirm a consistent upward trend, with ARIMAX models providing climate-informed insights and simplified models offering greater stability. While the ARIMA model relies solely on historical production patterns, the ARIMAX models generate climate-responsive projections. The full ARIMAX model captures climate sensitivity but exhibits reduced stability, whereas the simplified rainfall-based ARIMAX model produces more stable and conservative forecasts. These results highlight the trade-off between model complexity and forecast robustness, supporting the use of parsimonious ARIMAX specifications for operational forecasting and early warning applications.

Forecasting results using the ARIMAX model indicate that coconut production in Padang Pariaman Regency is projected to continue increasing at a moderate rate through 2029. The full ARIMAX model, which incorporates multiple climate variables, generates forecasts that are more sensitive to interannual climate variability. In contrast, the simplified ARIMAX model with rainfall as the primary exogenous variable produces more stable and conservative projections. This distinction highlights rainfall as the most influential climatic factor in this model, supporting its suitability as a key indicator for an early warning system of plantation productivity.

The influence of rainfall on agricultural output has been consistently reported across diverse regions and crop types in Indonesia. Wokanubun et al. [42] demonstrated that rainfall is the most influential climatic variable affecting cassava productivity, with yield reductions of up to 46.4% under unfavorable rainfall conditions. Similarly, Malau et al. [43] reported that rainfall variability associated with El Niño and La Niña events significantly disrupts food crop production, particularly rice and soybean. These findings are further supported by Ruminta et al. [44], who identified a significant correlation between rainfall anomalies and declines in agricultural production.

For coconut plantations specifically, Nur et al. [45] found a strong and statistically significant relationship between rainfall and the number of rainy days (correlation coefficient = 0.858) across three coconut varieties, emphasizing the importance of both rainfall amount and distribution. However, excessive rainfall may also exert negative effects through waterlogging, increased disease pressure, and flower drop, as reflected in the negative coefficient of rainfall observed in the simplified log-ARIMAX model. This negative coefficient indicates that beyond an optimal level, additional rainfall may reduce production due to excess moisture and increased disease risk. This dual role of rainfall underscores the need for balanced water availability rather than merely higher precipitation levels.

From a practical perspective, these results suggest that rainfall-based ARIMAX models offer a robust foundation for developing climate-informed early warning systems. By monitoring deviations in rainfall patterns from historical norms, stakeholders can anticipate potential productivity risks and implement timely adaptation measures, such as improved drainage management, disease control, or harvest planning. Consequently, the simplified rainfall-based ARIMAX model provides reliable forecasts and actionable insights for climate-resilient coconut plantation management.

3.6 Implications for Early Warning Systems and Decision Support

The results demonstrate that a climate-based ARIMAX model can serve as a core component of an Early Warning System (EWS) for coconut plantation productivity. Rainfall emerged as the dominant climatic factor influencing production, making it a suitable primary indicator for early warning applications.

Integrating ARIMAX outputs into regional agricultural information systems can support data-driven decision-making, including production planning, input management, and climate adaptation strategies. For instance, deviations in rainfall patterns from historical norms can serve as early signals to trigger management responses such as drainage improvement, disease prevention, or harvest scheduling adjustments. Previous studies have similarly emphasized the importance of climate-informed forecasting models and technology-driven early warning systems in agriculture [1, 46-51].

As a data-driven Decision Support System (DSS), the ARIMAX framework enables policymakers and farmers to anticipate potential production risks associated with climate anomalies and respond proactively. Although direct empirical implementation at the farm level remains limited, the findings provide a strong foundation for developing operational early warning systems tailored to the coconut sector in Padang Pariaman Regency.

4. Conclusions

This study demonstrates that climate-informed time series modeling provides meaningful improvements in understanding and forecasting coconut production dynamics in Padang Pariaman Regency. The baseline ARIMA(1,1,1) model confirms strong production persistence, typical of perennial plantation crops. Incorporating climate variables through the ARIMAX framework reveals that rainfall and rainfall distribution play a central role in shaping coconut production, while temperature, humidity, and wind speed exert comparatively weaker influences within the observed range.

Model comparison based on Akaike Information Criterion highlights that the simplified log-ARIMAX model with rainfall as the sole exogenous variable offers the best balance between explanatory power and model parsimony. Among the evaluated models, ARIMA demonstrated the highest predictive accuracy based on RMSE and MAPE values, confirming its effectiveness in capturing the temporal pattern of coconut production. However, the simplified ARIMAX model offered greater interpretability by integrating rainfall variability into the forecasting framework, making it more suitable for climate-informed production analysis and supporting the development of early warning applications. Forecasts for 2025–2029 indicate a moderate and stable increase in coconut production, with simplified ARIMAX projections showing improved stability than the full ARIMAX specification.

These findings advance current knowledge by demonstrating that simpler ARIMAX models, when grounded in dominant climatic drivers, can provide more interpretable and stable climate-informed forecasts under limited data conditions. Practically, the proposed rainfall-based ARIMAX model offers a strong foundation for developing early warning systems and decision support tools aimed at improving climate resilience in coconut plantation management. Future research should focus on integrating higher-frequency data, spatial climate information, and real-time monitoring systems to enhance model responsiveness and operational implementation at the farm and regional levels.

Abbreviations

ARIMA	Autoregressive Integrated Moving Average
ARIMAX	Autoregressive Integrated Moving Average with Exogenous Variables
AIC	Akaike Information Criterion
RMSE	Root Mean Square Error
MAPE	Mean Absolute Percentage Error
EWS	Early Warning System
DSS	Decision Support System
BMKG	Meteorology, Climatology, and Geophysics Agency
BPS	Statistics Indonesia

Data availability statement

The data used in this study were obtained from Statistics Indonesia (BPS) and the Meteorology, Climatology, and Geophysics Agency (BMKG). These data are publicly available through official institutional sources.

CRediT authorship contribution statement

Hermiza Mardesci: Conceptualization, Methodology, Formal analysis, Writing – Original

Draft Preparation, Project Administration. **Mulono Apriyanto**: Methodology, Validation, Writing – Review and Editing, Supervision. **Dita Fitriani**: Data Curation, Investigation, Visualization, Writing – Review and Editing. **Herman Farmi**: Data Collection, Data Curation, Investigation, Software. **Abdullah**: Data Collection, Data Curation, Investigation, Validation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Declaration of Use of AI in the Writing Process

The author(s) used AI-assisted language editing tools during the preparation of this manuscript to improve grammar, paraphrase text, and enhance clarity. After using these tools, the author(s) carefully reviewed and edited the content and take full responsibility for the content of the publication.

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