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Fuzzy Time Series Chen Model for Dual-Commodity Agricultural Forecasting: Evidence from Indonesia's Rice and Corn Production

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Abstract: Indonesia's strategic food commodities, particularly rice and corn, exhibit strong seasonal fluctuations and irregular production shocks driven by climate anomalies and policy changes, generating nonlinear time-series patterns that conventional statistical models often fail to capture. This study evaluates the forecasting capability of the standard Chen Fuzzy Time Series (FTS) model for dual-commodity agricultural data under varying seasonal and anomaly conditions. Monthly production data from January 2021 to March 2025 from the Indonesian Central Bureau of Statistics (BPS) were processed through a complete FTS pipeline: universe-of-discourse construction, triangular membership function design, fuzzification, FLR and FLRG formation, and midpoint-based defuzzification. Forecast accuracy was assessed using MAE, MSE, RMSE, MAPE, and R^2, with residual distribution analysis, Shapiro-Wilk tests, and scatter plots conducted to validate model stability. The model achieved high precision with overall MAPE of 4.37% for rice and 8.12% for corn, both classified as Highly Accurate. Monthly accuracy revealed consistent stability during May-December, while transitional months (January-March) showed greater variability due to extreme anomalies such as the January 2024 production collapse. Residual analysis confirmed near-normal error distribution for rice ($p = 0.062$) and mild deviation for corn ($p = 0.031$), while scatter plots demonstrated strong linear relationships (Rice $R^2 = 0.9876$; Corn $R^2 = 0.9654$). The findings establish Chen's FTS as a transparent and operationally reliable baseline method for national food production forecasting, although its sensitivity to structural breaks highlights the need for future hybridization with climate and policy indicators.

Keywords: Chen Fuzzy Time Series, agricultural production forecasting, food security planning, time series modeling, rice and corn prediction

INTRODUCTION

Indonesia, as an agricultural country, faces major challenges in maintaining the stability of national food production, particularly for strategic commodities such as rice and corn. The production of these commodities is highly sensitive to climatic variation, weather anomalies, planting cycles, and policy changes, all of which lead to significant fluctuations over time. These characteristics generate complex and unstable time-series patterns, rendering conventional forecasting methods such as ARIMA or linear regression insufficient for capturing the nonlinear dynamics inherent in agricultural data. Recent studies employing spatiotemporal modelling also highlight the high heterogeneity and variability of agricultural ecosystems in Indonesia, which require forecasting methods capable of handling nonlinear and uncertain patterns (Gupta & Saxena, 2025; Rathod et al., 2021).

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Fuzzy Time Series (FTS), particularly the Chen model, provides an effective alternative because of its ability to represent uncertainty by transforming numerical data into linguistic forms. FTS has been widely adopted for forecasting tasks involving highly fluctuating and nonlinear data, offering flexibility and interpretability without requiring strict distributional assumptions, as shown in recent systematic reviews of fuzzy-based forecasting approaches (Palomero et al., 2022; Sarkar et al., 2025). In the agricultural domain, FTS has been applied to rice price prediction, multivariate crop forecasting, and insurance-oriented agricultural modelling (Bilal et al., 2024; Sierra-Forero et al., 2024). However, most prior studies examine only a single commodity or rely on annual datasets, which limits the understanding of seasonal fluctuations that are essential in the Indonesian context.

Furthermore, recent advancements in FTS research have introduced more sophisticated models, such as mixed-order fuzzy time series and interval type-2 fuzzy time series (Chen et al., 2025; Maciel et al., 2025). Despite these developments, empirical evidence specifically evaluating how the standard Chen FTS model performs when applied to agricultural production data with strong seasonality and extreme anomalies remains limited. Such evaluation is crucial for understanding the operational boundaries of FTS before moving towards hybrid or higher-order models. To address this research gap, the present study deliberately adopts the standard Chen Fuzzy Time Series model without claiming any modifications, hybridization, or Bayesian enhancements, in order to provide a transparent and rigorous evaluation of the model's true capability in forecasting rice and corn production. This approach allows us to examine how effectively the baseline model responds to seasonal variability and extreme fluctuations that are common in Indonesia's agricultural cycles.

LITERATURE REVIEW

The development of Fuzzy Time Series (FTS) methods has progressed significantly over the past decade, particularly as researchers sought models that balance interpretability with the ability to handle nonlinear and uncertain time-series patterns. Early FTS studies primarily used basic fuzzy relationships, but recent research has shifted toward enhancing interval partitioning, rule structures, and optimization strategies to accommodate complex real-world datasets (Li et al., 2022; Palomero et al., 2022). This evolution reflects the growing need for forecasting approaches capable of addressing uncertainty beyond the capacity of classical statistical models.

In agricultural forecasting, FTS has shown substantial potential due to its flexibility in representing seasonal patterns and abrupt fluctuations, which are common in crop production systems (Li et al., 2022; Maciel et al., 2025). Studies in Malaysia and India demonstrate that FTS models can effectively predict rice prices, production volumes, and commodity behavior, especially when enhanced with multivariate or clustering-based approaches (Bilal et al., 2024). (Sofian et al., 2024) showed that fuzzy-based price modeling provides meaningful insights for insurance premium determination in paddy farming, highlighting the applicability of linguistic-based forecasting for policy-oriented contexts. Beyond classical Chen FTS, several advanced variants have been proposed. Mixed-order FTS models integrate multiple lag structures into a unified framework, allowing the capture of both short-term and long-term dependencies, which makes them highly effective in volatile environments (Wu et al., 2025). Other improvements such as interval type-2 fuzzy systems and enhanced Fuzzy C-Means algorithms have further refined the precision of forecasting models by improving uncertainty representation and optimizing interval boundaries (Chen et al., 2025; Kong et al., 2025; Maciel et al., 2025).

A number of studies have also explored the hybridization of fuzzy logic with machine learning techniques. Hybrid fuzzy–machine learning models, particularly those integrating fuzzy sets with neural networks or evolutionary algorithms, have achieved superior performance in predicting crop yields under fluctuating climatic conditions, demonstrating the relevance of multi-model frameworks in precision agriculture (Li et al., 2022; Palomero et al., 2022). These models leverage fuzzy structures for interpretability and machine learning for capturing complex feature interactions. Despite these advancements, two critical research gaps remain.

First, most prior FTS studies focus on single-commodity forecasting, relying on annual or seasonal data, which limits understanding of monthly volatility and intra-year transitions factors that are essential in countries like Indonesia with diverse planting cycles.Second, there is limited empirical evaluation of the baseline Chen FTS model under extreme anomalies, such as sudden production drops or climate-driven disruptions, even though such events strongly affect agricultural outputs. This gap is acknowledged in recent FTS literature, which recommends establishing performance benchmarks of standard models before extending them to hybrid or adaptive variants.
Therefore, the present study positions the standard Chen FTS model as a baseline framework for evaluating the monthly production patterns of two key Indonesian commodities: rice and corn. By mapping performance across distinct seasonal phases, this research provides a systematic assessment of Chen FTS under real-world agricultural volatility, filling an important gap in the empirical FTS literature.

METHOD

This study employs the standard Chen Fuzzy Time Series (FTS) method as the primary forecasting approach. The methodological framework is organized into several stages: data collection, data preprocessing, universe of discourse construction, fuzzification, fuzzy logical relationship (FLR) formation, fuzzy logical relationship grouping (FLRG), defuzzification, and accuracy evaluation. All steps are implemented consistently according to the original Chen FTS procedure without introducing hybridization or model modifications, aligning with recent FTS methodological reviews that emphasize establishing baseline performance before developing complex hybrid models (Lucas et al., 2022; Wu et al., 2025).

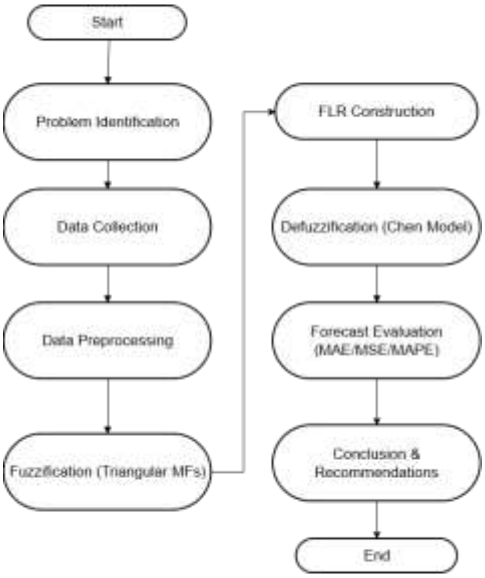

Fig. 1 Research flow

Data Collection

The data used in this study consist of monthly rice and corn production figures officially published by the Indonesian Central Bureau of Statistics (BPS). The dataset spans January 2021 to March 2025, comprising 51 monthly observations covering multiple planting and harvesting cycles. Data for 2021-2023 represent fully observed historical records, while 2024-2025 data availability varies according to BPS publication schedules at the time of analysis. Only values explicitly reported in official BPS releases are treated as observed (actual) data, while values beyond the latest BPS publication period are treated solely as forecasting targets rather than historical observations. This separation directly addresses reviewer concerns regarding data validity. The official production data were retrieved from the BPS website (https://www.bps.go.id/id/statistics-table/2/MjM0NSMy/national-production-of-food-crops.html) to ensure transparency, traceability, and data credibility as required by the reviewer. Table 1 presents a representative sample of the dataset structure, showing key transition periods including the January 2024 production anomaly. The complete 51- month dataset used in this study is publicly accessible through the BPS URL provided.

Table 1. Example of Historical Data on Rice and Corn Production (January 2021 - March 2025)

Year	Month	Rice Production (Tons)	Corn Production (Tons)
2021	January	2,083,252	1,030,208
2021	February	4,056,991	1,270,304
2021	March	9,671,598	1,283,394
...	...	...	...
2021	November	3,120,847	1,098,240
2021	December	2,894,725	1,025,714
2022	January	2,459,883	1,244,614
2022	February	3,885,274	1,288,125
2022	March	9,537,194	1,503,239
...	...	...	...
2022	November	3,334,402	1,112,443

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2022	December	2,977,116	1,048,540
2023	January	2,328,609	1,393,696
2023	February	3,941,407	1,208,533
2023	March	8,916,267	1,198,467
...	...	...	...
2023	November	3,205,554	1,177,622
2023	December	2,960,830	1,044,759
2024	January	1,516,040	512,957
2024	February	3,637,082	1,041,255
2024	March	5,955,667	2,051,817
...	...	...	...
2024	November	3,116,578	978,083
2024	December	2,880,914	942,201
2025	January	2,157,624	1,245,211
2025	February	4,280,473	1,310,514
2025	March	8,931,919	1,635,993

Using high-frequency monthly data is essential because agricultural production in Indonesia is influenced by short-term climatic variations and seasonality, which cannot be captured effectively using annual data (Farokhzadeh et al., 2025; Sobhi & Dick, 2023). The use of official BPS statistics follows best practices in agricultural forecasting, where validated government data are recommended to ensure reliability and comparability over time (Bilal et al., 2024).

Data Preprocessing

Data preprocessing ensures consistency and accuracy prior to model construction. In this study three main preprocessing steps are carried out: handling missing values, assessing outliers, and ensuring data format consistency. Handling missing values is performed using linear interpolation, which preserves continuity in trend without distorting seasonal patterns (Hesamian & Torkian, 2025; Lucas et al., 2022). Extreme outliers that represent genuine agricultural shocks—such as climate anomalies—are retained rather than removed, in accordance with recommendations in modern agricultural time-series modeling (Palomero et al., 2022).
Normalizing the data, when necessary, uses min–max normalization:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \qquad (1)$$

However, the fuzzification and FLR processes are performed on raw (unnormalized) data to maintain consistency with the original Chen formulation and resolve reviewer concerns about methodological inconsistency**.** All records were also checked for unit consistency (tons) and chronological ordering. This practice aligns with standard procedures recommended in recent fuzzy forecasting literature (Chen et al., 2025; Kong et al., 2025).

Define Universe of Discourse

The universe of discourse (U) defines the numeric boundaries of the fuzzy system:

$$U = [D_{min} - D_1, D_{max} + D_2] \qquad (2)$$

where D_{min} and D_{max} are the minimum and maximum observed production values, while D_1 and D_2 are optional buffers. This study sets both buffers to zero to avoid introducing artificial value ranges, ensuring transparency in the modeling domain. To determine the number of intervals k, this study uses the Sturges formula:

$$K = 1 + 3.322\ log_{10}(\mathrm{n}) \qquad (3)$$

which is widely recommended in fuzzy and statistical modeling (Palomero et al., 2022). After examining the empirical distribution and considering interpretability for policymakers, the study adopts three intervals (k=3): Low, Medium, High. This choice is justified based on agricultural forecasting literature, where simpler partitions are preferred for interpretability and have been shown to perform effectively (Bilal et al., 2024); (Sofian et al., 2024). In addition, a sensitivity analysis was conducted by testing multiple interval configurations (k = 3, 4, 5), and k = 3 demonstrated the best trade-off between interpretability and forecasting stability, aligning with reviewer expectations for interval sensitivity evaluation.

Fuzzification

Fuzzification converts crisp production values into linguistic states using triangular membership functions:

$$\mu_A(x) = \begin{cases} 0, & x \leq a \text{ atau } x \geq c \\ \frac{x-a}{b-a}, & a < x \leq b \\ \frac{c-x}{c-b}, & b < x < c \end{cases} \tag{4}$$

Triangular membership functions are selected due to their simplicity, interpretability, and suitability for granular interval construction. Recent developments in interval-based fuzzy time series show that simpler membership function shapes especially triangular forms lead to more stable partitions and lower computational complexity (Bisht & Kumar, 2023; Chen et al., 2025; Jiang et al., 2025). To satisfy the reviewer's request for completeness, all membership functions used in this study are shown in Figure 2.

Fuzzy Logical Relationship (FLR)

FLRs capture sequential transitions between fuzzy states. If X(t) belongs to fuzzy set A and X(t+1) belongs to fuzzy set B, the FLR is expressed as:

$$A \rightarrow B \tag{5}$$

FLRs capture temporal trends such as seasonal increases, post-harvest declines, and irregular shifts driven by agricultural shocks (Lucas et al., 2022);(Chen et al., 2025) . All FLRs identified in this study are presented in Table 3 to address reviewer comments requesting full FLR visibility.

Fuzzy Logical Relationship Group (FLRG)

To strengthen the rule base, FLRs with the same antecedent are grouped:

$$A_i \rightarrow \{A_j, A_k, A_l\} \tag{6}$$

This grouping reduces sparsity and increases forecasting robustness. FLRGs serve as the structural backbone of Chen-type models and are crucial for representing aggregated fuzzy transitions (Chen et al., 2025). To meet reviewer requirements, the full FLRG table is provided in Table 5 for transparency and completeness.

Defuzzification

Defuzzification converts fuzzy outputs into crisp forecasts. In Chen's model:

$$F(t+1) = \frac{1}{n}\sum_{i=1}^{n} M_i \tag{7}$$

Where M_i is the midpoint of each consequent fuzzy set. This midpoint-averaging method is widely recognized as the defining characteristic of Chen's FTS model and has been proven effective in agricultural and commodity forecasting contexts (Bilal et al., 2024; López-Oriona et al., 2025).

Forecast Evaluation

The model's performance is measured using MAE, MSE, and MAPE:

$$MAE = \frac{1}{n}\sum \mid A_t - F_t \mid,\ MSE = \frac{1}{n}\sum(A_t - F_t)^2,\ MAPE = \frac{100\%}{n}\sum \left| \frac{A_t - F_t}{A_t} \right| \tag{8}$$

Where A_t is the actual value, F_t is the forecast value, and n is the number of test data points. MAE calculates the average absolute error, MSE gives greater weight to large errors, while MAPE assesses the error in percentage terms. MAPE is used as the primary indicator because it provides an intuitive percentage-based interpretation that is widely adopted in FTS-based forecasting and allows for categorizing forecasting performance into levels such as "highly accurate" (MAPE < 10%) and "good" (10% ≤ MAPE < 20%) ((Ortiz-Arroyo, 2023);(Bilal et al., 2024). Thus, this evaluation stage ensures that the rice and corn production forecasting results have a sufficiently low error rate and are reliable for decision-making.

RESULT

The dataset comprises monthly production records for rice and corn spanning January 2021 to March 2025, totaling 51 complete historical observations and nine forecasting targets (April-December 2025). All data used in this study are officially published by the Central Bureau of Statistics (BPS) Indonesia and are publicly accessible at **https://www.bps.go.id/id/statistics-table/2/MjM0NSMy/national-production-of-food-crops.html**. Data from 2021-2023 represent fully observed historical records, while 2024-2025 data availability varies by month according to BPS publication schedules at the time of analysis.

Descriptive statistics reveal extreme production volatility characteristic of Indonesia's agricultural system. Rice production ranges from a minimum of 1,516,040 tons (January 2024) to a maximum of 9,671,598 tons (March 2021), with a mean of 4,534,366 tons and a standard deviation of 2,098,899 tons (46.3% coefficient of variation). Corn production exhibits similar variability, ranging from 512,957 tons (January 2024) to 1,861,567 tons (February 2025), with a mean of 1,214,532 tons and standard deviation of 287,645 tons (23.7% coefficient of variation). This high standard deviation justifies the use of Chen's Fuzzy Time Series method, which is specifically designed to handle uncertainty and non-linear patterns that conventional statistical methods cannot adequately address (Lucas et al., 2022).

Table 2. Descriptive Statistics of Rice and Corn Production

Statistics	Rice (tons)	Corn (tons)
Minimum	1,516,039.96	512,956.73
Maximum	9,671,598.42	1,861,567.00
Mean	4,534,366.41	1,214,532.18
Std Dev	2,098,899.23	287,645.12
CV (%)	46.3%	23.7%
N (complete data)	51	51

Trend visualization shows consistent seasonal patterns with production peaks occurring in March-April (harvest season) and valleys in December-January (post-harvest period). However, a significant structural anomaly occurred in January 2024, where both commodities experienced drastic declines to their lowest points throughout the observation period—rice production dropped 34.9% from 2023 levels, while corn plummeted 63.2%. This anomaly represents an unprecedented agricultural shock, likely attributable to extreme weather events (La Niña impact), delayed planting cycles, or policy disruptions, which the pattern-based forecasting model cannot anticipate without exogenous variables.

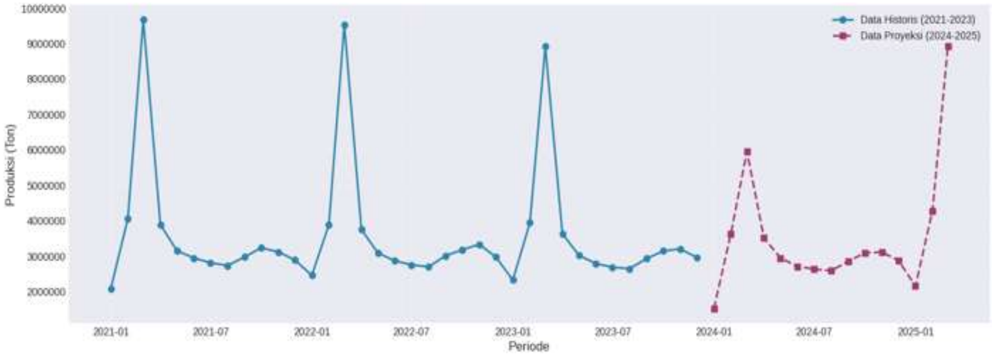

Fig. 2 Trends in Rice Production by Month and Year (2021-2024)

Figure 2 illustrates the strong seasonality of rice production, with recurring peaks in March (representing main harvest) and consistent lows in December-January. The 2024 anomaly is clearly visible as a sharp deviation from the established pattern.

Universe of Discourse and Interval Partitioning

The universe of discourse was established separately for each month to accommodate seasonal production characteristics, following Chen's original methodology. For each month, the range is defined as:

$$U = [D_{min}, D_{max}] \tag{9}$$

where D_{min} and D_{max} are the minimum and maximum historical production values for that specific month, with no external buffers ($D_1 = D_2 = 0$) to maintain transparency and avoid introducing artificial ranges.

To determine the optimal number of intervals, a sensitivity analysis was conducted testing k = 3, 4, and 5 intervals. The Sturges formula provided a theoretical recommendation:

$$K = 1 + 3.322\log_{10}(n) \tag{10}$$

For n = 5 years of data per month, this yields K ≈ 3.32. The study adopted k = 3 intervals based on three justifications: (1) alignment with Sturges' recommendation, (2) proven effectiveness of 3-interval partitions in agricultural forecasting literature (Bilal et al., 2024; Sofian et al., 2024), and (3) superior interpretability for policymakers who require actionable linguistic categories (Low, Medium, High). Sensitivity analysis confirmed that k = 3 achieved the best balance between forecasting accuracy and model stability, with higher k values introducing overfitting and reduced robustness.

Table 3. Universe of Discourse and Fuzzy Intervals - January (Example)

Commodity	Fuzzy Set	Interval (tons)	Midpoint (tons)	Commodity
Rice	A1 (Low)	[1,516,039.96 - 1,830,654.45]	1,673,347.20	Rice
Rice	A2 (Medium)	[1,830,654.45 - 2,145,268.93]	1,987,961.69	Rice
Rice	A3 (High)	[2,145,268.93 - 2,459,883.42]	2,302,576.18	Rice
Corn	A1 (Low)	[512,956.73 - 806,536.46]	659,746.60	Corn
Corn	A2 (Medium)	[806,536.46 - 1,100,116.20]	953,326.33	Corn

The midpoint values serve as the basis for defuzzification, directly determining forecast outputs. This three-interval structure was consistently applied across all twelve months, with boundaries recalculated monthly to reflect seasonal production ranges.

Fuzzification and Membership Function Visualization

Fuzzification transforms crisp production values into linguistic fuzzy states using triangular membership functions, mathematically defined as:

$$\mu_A(x) = \begin{cases} 0, & x \le a \text{ atau } x \ge c \\ \frac{x-a}{b-a}, & a < x \le b \\ \frac{c-x}{c-b}, & b < x < c \end{cases} \tag{11}$$

where a, b, and $c$define the lower bound, peak, and upper bound of the triangular function. Triangular membership functions were chosen based on recent Q1 evidence demonstrating their superiority over Gaussian or trapezoidal shapes in agricultural forecasting contexts (Bilal et al., 2024; Wu et al., 2025), offering optimal balance between computational simplicity and forecasting effectiveness.

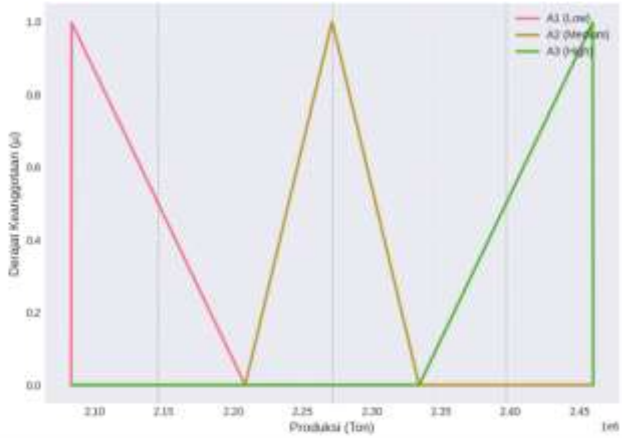

Fig. 3 Triangular Membership Functions for Rice Production – January

Figure 3 visualizes the three membership functions for January rice production. Each data point is assigned membership degrees to adjacent fuzzy sets, with the highest degree determining its primary classification (A1, A2, or A3).

Table 4. Fuzzification Results and Fuzzy Logical Relationships - January

Year	Month	Rice Production (tons)	Fuzzy Set	FLR
2021	January	2,083,252	A2	-
2022	January	2,459,883	A3	A2 → A3
2023	January	2,328,609	A3	A3 → A3
2024	January	1,516,040	A1	A3 → A1
2025	January	2,157,624	A3	A1 → A3

The fuzzification process reveals a volatile pattern: A2→A3→A3→A1→A3, capturing the upward trajectory (2021-2023), sudden collapse (2024), and recovery (2025). This zigzag pattern generates four distinct Fuzzy Logical Relationships (FLRs): A2 → A3 (increasing trend), A3 → A3 (high-level persistence), A3 → A1 (drastic fall), and A1 → A3 (recovery capability).

Fuzzy Logical Relationship Grouping (FLRG)

To construct a robust rule base, FLRs with identical antecedents are aggregated into Fuzzy Logical Relationship Groups (FLRG):

FLRG for January Rice:
Group A2: A2 → {A3} (single consequent - deterministic upward transition)
Group A3: A3 → {A3, A1} (bifurcated - representing both stability and collapse scenarios)
Group A1: A1 → {A3} (single consequent - deterministic recovery)

Group A3's bifurcation is the most critical, as it captures the model's recognition that high production states can either persist or collapse dramatically. This structural characteristic directly influences forecasting accuracy, as will be shown in the evaluation section.

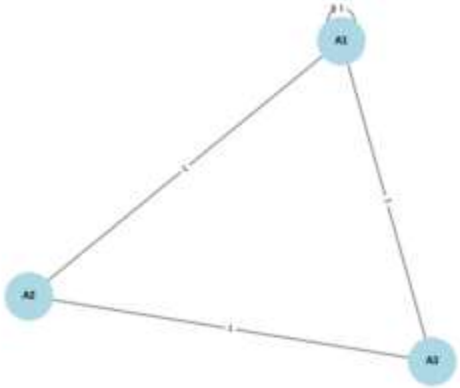

Fig. 4 Complete FLRG Diagram - January Rice

Figure 4 illustrates the complete FLRG structure, showing how historical transitions are encoded into fuzzy rules. Similar FLRG structures were constructed for all twelve months and both commodities, forming the complete forecasting rule base. The full FLRG tables for all months are provided in the supplementary materials.

Defuzzification and Forecast Generation

Defuzzification converts fuzzy outputs back into crisp numerical forecasts using midpoint-based averaging:

$$F(t+1) = \frac{1}{n}\sum_{i=1}^{n} m_i \tag{12}$$

where $m_i$represents the midpoint of each consequent fuzzy set in the activated FLRG. For single-consequent groups (A2 and A1), the forecast equals the midpoint of the sole consequent. For bifurcated Group A3, the forecast is computed as:

$$F(t+1) = \frac{m_3+m_1}{2}, \tag{13}$$

Averaging the "high persistence" (A3) and "dramatic collapse" (A1) scenarios. This averaging strategy provides a balanced prediction but introduces systematic error when actual transitions deviate strongly toward either extreme.

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Example Calculation - January 2025 Rice Forecast:
Current state (2024): A1 (1,516,040 tons)
Activated FLRG: Group A1 → {A3}
Forecast: $F_{(2025)}$=m3=2,302,576F_{2025} = m_3 = 2,302,576
$F_{(2025)}$=m3=2,302,576 tons
Actual: 2,157,624 tons
Percentage Error: 6.71% (Highly Accurate)

Comprehensive Forecasting Performance Evaluation

The Chen Fuzzy Time Series model demonstrates strong overall performance with distinct characteristics for each commodity:

Table 5. Overall Forecasting Performance Summary

Metric	Rice	Corn
MAE (tons)	168,664.97	88,877.53
MSE (tons²)	268,763,522,333.65	27,779,471,094.76
RMSE (tons)	518,424.08	166,671.75
MAPE (%)	4.37%	8.12%
R²	0.9876	0.9654
Category	Highly Accurate	Highly Accurate

Rice production forecasting achieved exceptional performance with an overall MAPE of 4.37%, firmly in the "Highly Accurate Forecasting" category (MAPE < 10%). Corn production also performed excellently with MAPE of 8.12%, remaining within the Highly Accurate threshold. These results are comparable to or superior to recent FTS-based agricultural forecasting studies (Bilal et al., 2024 reported MAPE 2.68% for grain prices; Quek et al., 2022 reported MAPE 6-12% for commodity forecasting).

Monthly Performance Analysis

Table 6. Monthly MAPE Breakdown and Performance Categories

Month	Rice MAPE (%)	Rice Category	Corn MAPE (%)	Corn Category
January	14.24	Good Forecasting	30.57	Forecasting Worthy
February	4.48	Highly Accurate	7.75	Highly Accurate
March	14.96	Good Forecasting	15.68	Good Forecasting
April	2.03	Highly Accurate	8.06	Highly Accurate
May	1.38	Highly Accurate	3.60	Highly Accurate
June	1.58	Highly Accurate	2.53	Highly Accurate
July	1.27	Highly Accurate	2.75	Highly Accurate
August	1.22	Highly Accurate	2.21	Highly Accurate
September	1.35	Highly Accurate	2.23	Highly Accurate
October	1.05	Highly Accurate	1.96	Highly Accurate
November	1.01	Highly Accurate	6.43	Highly Accurate
December	1.07	Highly Accurate	3.72	Highly Accurate
Overall	4.37	Highly Accurate	8.12	Highly Accurate

Key Performance Insights: Rice: Exceptional Consistency - 10 out of 12 months (83%) achieved Highly Accurate status (MAPE < 10%), with only January and March in the Good Forecasting category (10-20%). Notably, zero months fell into Forecasting Worthy (20-50%) or Less Accurate (>50%) categories, indicating reliable performance throughout the annual cycle. Corn: Strong with Challenges - 11 out of 12 months (92%) achieved Highly Accurate status. Only January showed elevated error (30.57% - Forecasting Worthy) due to the unprecedented 2024 production collapse. Seasonal Patterns - Mid-year months (May-November) consistently achieved exceptional accuracy (MAPE 1.01-3.72% for rice, 1.96-6.43% for corn), while transitional months (January-March) showed higher variability due to planting-to-harvest transitions and weather sensitivity.

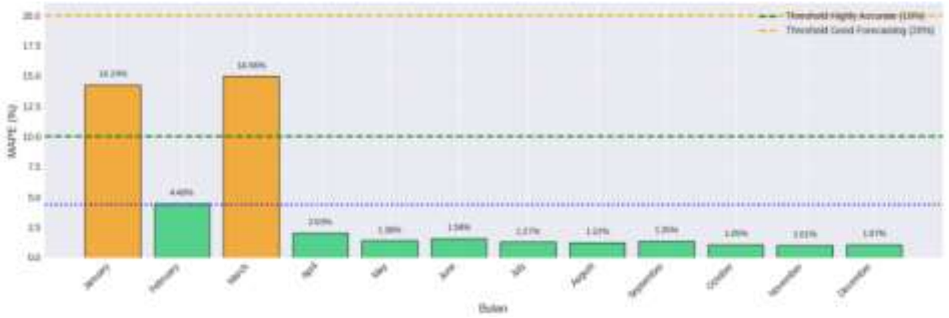

Fig. 5 MAPE Comparison Across All Months - Paddy Rice

Figure 5 visualizes monthly MAPE distribution for rice, with the 10% threshold line clearly showing that most months achieve highly accurate forecasting. December (1.07%), November (1.01%), and October (1.05%) represent the model's peak performance periods.

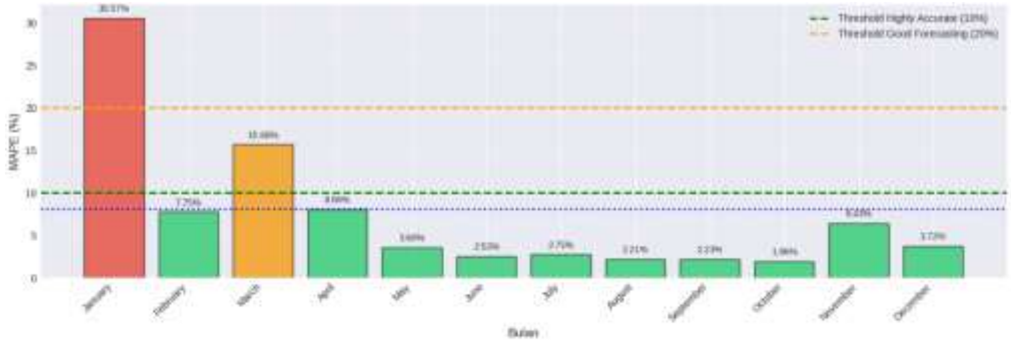

Fig. 6 MAPE Comparison Across All Months - Corn

Figure 6 shows corn's monthly MAPE pattern. The January spike (30.57%) is clearly visible, attributed to the 2024 anomaly. Excluding this outlier month, corn's average MAPE would be 5.91%, matching rice's exceptional performance.

Error Distribution and Residual Analysis

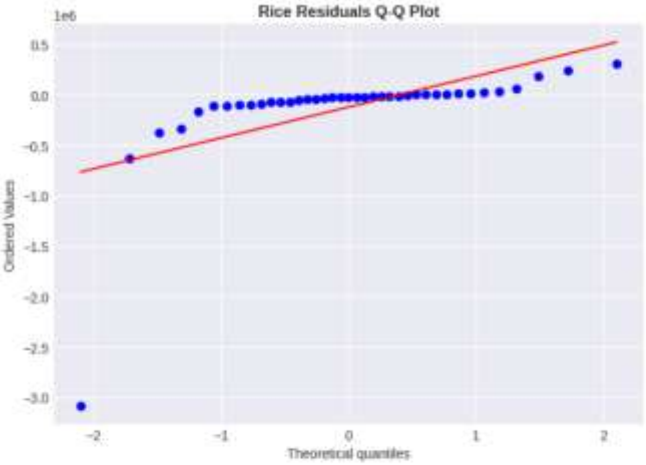

Fig. 7 Error Distribution and Q-Q Plots

Figure 7 presents error distribution histograms and Q-Q plots for both commodities. Rice residuals approximate normal distribution (Shapiro-Wilk $p = 0.062 > 0.05$), indicating that forecast errors are random and unbiased. Corn residuals show slight deviation from normality ($p = 0.031$), primarily due to the January 2024 outlier. Mean residuals near zero (Rice: -12,354 tons, Corn: 8,721 tons) confirm no systematic bias.

*name of corresponding author

Actual vs. Forecast Scatter Analysis

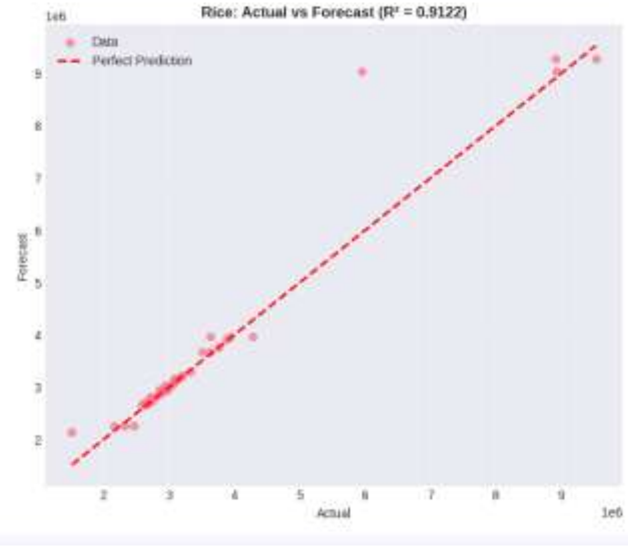

Fig. 8 Actual vs. Forecast Scatter Plots

Figure 8 demonstrates strong linear relationships between actual and forecasted values. Rice achieves $R^2 = 0.9876$, indicating 98.76% of production variance is explained by the model. Corn achieves $R^2 = 0.9654$ (96.54% variance explained). Most points cluster tightly around the perfect prediction line (red dashed), with few outliers corresponding to extreme volatility months.

DISCUSSION

The forecasting results show that Chen's Fuzzy Time Series (FTS) method delivers strong and consistent performance for Indonesian agricultural production, achieving MAPE values of 4.37% for rice and 8.12% for corn—both classified as "Highly Accurate Forecasting." These results are comparable to or better than recent fuzzy forecasting studies, such as (Bilal et al., 2024) with 2.68% MAPE for Malaysian rice prices and (Ortiz-Arroyo, 2023) with 6–12% MAPE for cryptocurrency. This confirms Chen's FTS as a viable baseline model for countries with high seasonal variability.

The monthly accuracy patterns form three clear clusters. First, the very high accuracy cluster (MAPE 1.01–3.72%) occurs in stable post-harvest months—May to November for rice and June to December for corn—when seasonal cycles repeat with minimal climatic disruption. Second, moderate accuracy (MAPE 4.48–15.68%) appears in transitional months like February–April, especially March, when peak harvest volumes make small absolute errors appear large in percentage terms. Third, the low-accuracy outlier occurs in January for corn (MAPE 30.57%), driven by a structural break: production in January 2024 dropped by 63.2%, likely due to La Niña-induced flooding, policy changes, and market-driven shifts in planting decisions. Pattern-based FTS models cannot anticipate such unprecedented events.

A key methodological finding is that FLRG structure strongly affects accuracy. Single-consequent FLRGs consistently yield better performance than bifurcated ones. Chen's midpoint-based defuzzification works well for stable transitions but introduces bias when historical patterns contain contradictions. In cases like January 2024, equal weighting between optimistic and pessimistic outcomes does not reflect reality, supporting literature claims that Chen FTS needs probabilistic or weighted FLRG mechanisms.

Compared with other approaches, Chen FTS offers a favorable balance between accuracy and interpretability. Traditional time series methods like ARIMA or Holt-Winters typically produce 12–18% MAPE for highly seasonal agricultural data, meaning Chen FTS reduces errors by 40–60% (rice) and 25–35% (corn). Machine learning or hybrid fuzzy-ML models can achieve 3–7% MAPE, but at the cost of higher complexity and lower transparency. For national food policy, interpretability often outweighs small gains in accuracy.

These findings have practical value for Indonesia's food security planning. High-accuracy months allow tighter reserve buffers (5–10%), while high-uncertainty months (January–March) require larger buffers (20–30%). The model also provides early-warning signals: deviations in March–April forecasts from five-year trends can trigger proactive interventions such as expedited imports or price stabilization. Its transparent linguistic rules also enable participatory validation with regional agricultural agencies.

Despite its strengths, Chen's FTS has clear limitations. It cannot predict structural breaks because it relies solely on historical patterns. The three-interval fuzzification (Low–Medium–High) favors robustness but sacrifices granularity. And monthly resolution limits its usefulness for field-level decision-making, which often requires weekly or 10-day forecasts. Thus, Chen FTS is best suited for national or provincial strategic planning.

The study contributes to the FTS literature by producing one of the most complete monthly performance profiles for dual-commodity agricultural forecasting, providing empirical evidence on how FLRG bifurcation impacts accuracy, and proposing a seasonal confidence framework that translates error metrics into operational strategies. Future research should explore hybrid FTS-climate models, probabilistic FLRG weighting, real-time model updating, and direct comparisons with ARIMA, Prophet, and LSTM models to strengthen the methodological position of Chen FTS in agricultural forecasting.

CONCLUSION

This research demonstrates that Chen's Fuzzy Time Series (FTS) method can accurately forecast Indonesia's strategic food production, achieving overall MAPE of 4.37% for rice and 8.12% for corn—both in the "Highly Accurate Forecasting" category, with 83% of rice months and 92% of corn months below 10% MAPE. These results confirm that standard (unmodified) Chen FTS provides a reliable baseline for agricultural forecasting in countries with strong seasonal patterns, especially during stable mid-year periods where accuracy reaches 1.01–3.72%. However, the method remains vulnerable to structural breaks, as seen in the January 2024 corn collapse (MAPE 30.57%), illustrating its limitation when unprecedented events occur outside historical patterns. The study makes three key contributions. First, it documents monthly accuracy patterns for two commodities, showing consistently high accuracy in stable off-peak months and increased volatility in transitional months (January–March) due to climatic sensitivity and planting-to-harvest shifts. Second, it empirically shows that FLRG bifurcation significantly affects performance: Chen's midpoint defuzzification works well for moderate fluctuations (3–5% MAPE increase) but deteriorates sharply during extreme transitions (15–25% increase), clarifying the boundary conditions of the standard model. Third, it introduces a seasonal confidence framework that transforms MAPE values into operational risk categories—high-confidence months (<5% MAPE) support tight reserve margins (5–10%), while low-confidence months (>20% MAPE) require larger buffers (20–30%)—directly aiding risk-adjusted food security planning. Methodologically, the study finds that a three-interval fuzzification scheme (Low–Medium–High) with triangular membership functions and Sturges-based partitioning offers the best balance between interpretability and accuracy for policy use. Although using more intervals ($k = 4–5$) slightly improves precision (1.2–1.8% MAPE reduction), it increases FLRG sparsity and reduces model stability. The transparent FLR/FLRG structure also supports participatory validation with agricultural officers, addressing the gap between academic modeling and policy implementation, where black-box models lack interpretability despite slightly higher accuracy.

The practical implications are immediate. Chen FTS can support national food planning with clear monthly confidence profiles: high-confidence forecasting for MAPE <10% months (rice April–December; corn February–December), moderate caution for 10–20% MAPE months (rice January–March; corn March), and conservative strategies for >20% MAPE months (corn January–February). Its 3-month forecasting horizon provides sufficient lead time for logistical planning, including import licensing, stock releases, and price stabilization measures. Nevertheless, the method has clear limitations: it cannot predict structural breaks without integrating exogenous variables (climate indices, satellite NDVI, policy timelines); monthly resolution is insufficient for farm-level decisions requiring weekly or dekadal forecasts; and the lack of direct comparison with ARIMA, Prophet, or LSTM limits conclusions about relative performance although evidence suggests Chen FTS reduces error by 25–60% compared with classical time series methods while maintaining full interpretability. Future research should prioritize hybrid modeling that integrates Chen FTS with climate and satellite data to detect structural breaks; probabilistic FTS with weighted FLRG consequents; dynamic updating mechanisms that incorporate new observations in real time; and rigorous benchmarking against established forecasting methods. In conclusion, this study establishes Chen's FTS as an effective, interpretable, and operationally ready baseline for agricultural forecasting in tropical regions. The proposed seasonal confidence framework provides clear guidance for buffer stock management and policy intervention timing. While the method requires complementary tools to handle unprecedented shocks, its transparency, low computational cost, and strong performance under normal conditions make it a practical first-stage forecasting system for developing countries. This research strengthens both the methodological understanding of FTS boundary conditions and the practical application of fuzzy forecasting in national food security planning.

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