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Forecasting Farmer Exchange Rate (FER) in Southeast Sulawesi Province Using Cheng's Fuzzy Time Series Method

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Abstract

Introduction/Main Objectives: This study aims to forecast the Farmer Exchange Rate (FER) in Southeast Sulawesi Province for 2024 as a basis for short-term economic assessment and policy-related analysis. **Background Problems:** FER is a key indicator of farmers' purchasing power and agricultural welfare; however, its monthly dynamics are characterized by fluctuations and uncertainty, making conventional forecasting methods less effective in capturing its behavior. **Novelty:** This study contributes by implementing the the Fuzzy Time Series (FTS) Cheng approach for FER forecasting in Southeast Sulawesi, emphasizing its suitability for handling vagueness and nonlinear patterns inherent in agricultural economic indicators. **Research Methods:** The analysis utilizes monthly secondary FER data obtained from BPS-Statistics of Southeast Sulawesi Province, covering the period from January 2014 to December 2023. Forecast accuracy is evaluated using the Mean Absolute Percentage Error (MAPE). **Finding/Results:** The forecasting results indicate that the FER values for January, February, and March 2024 are each estimated at 105.93. The model achieved a MAPE of 0.3027%, corresponding to an accuracy level of 99.6973%, which places the forecasting performance in the "excellent" category.

1. Introduction

Forecasting is an approach used to estimate something that will happen in the next few periods based on historical data [1]. There are two types of forecasting methods, namely qualitative and quantitative. Qualitative methods are predictions based on the opinions of experts as a basis for decision making, and the data cannot be expressed clearly in numerical form. Meanwhile, quantitative methods are predictions that can be arranged in the form of numbers based on historical data commonly referred to as time series data [2].

Time series data is a type of data that is collected according to a time series within a certain period of time. The time used can be days, weeks, months, years, and so on. Time series data is very useful for decision makers to estimate or predict future events. This is because the pattern of changes in time series data in a period in the past is likely to be repeated in the future. Time series forecasting can predict future values and decide on certain policies that are influenced by the results of forecasting.

Southeast Sulawesi is one of the provinces in Indonesia where most of the population lives in rural areas and generally still depends on the agricultural sector for their livelihood. The agricultural sector plays an important role in the national economy. This is evident in terms of Production, Agricultural, Forestry, and Fisheries Business Fields which make the most dominant contribution to the GDP of Southeast Sulawesi Province, which is 21.99% in the economic growth of Southeast Sulawesi Province in the second quarter of 2023. Therefore, it can be said that the agricultural sector is one of the sectors to increase economic growth in Southeast Sulawesi Province.

Based on what has been explained, the development of the agricultural sector must be the main thing. Farmers are often disadvantaged with relatively small incomes, while production costs are higher than the costs received [3]. As a form of agricultural development efforts for the welfare of farmers in an area, a benchmark is needed. The benchmark in question is the Farmer Exchange Rate (FER). FER is a comparison between the price index received by farmers (*It*) and the price index paid by farmers (*Ib*) expressed as a percentage, namely the price of consumption and production needs [4]. The meaning of FER is: FER < 100 means the farmer is experiencing a surplus. FER $= 100$ means the farmer is breaking even. FER > 100 means the farmer is experiencing a deficit.

As an indicator of welfare, FER plays an important role in supporting the evaluation of agricultural sector development because it can illustrate the balance between farmers' income and expenditure. Recent research indicates that FER remains relevant for assessing farmer welfare across various commodities and regions in Indonesia, and serves as a basis for formulating agricultural policies aimed at improving farmer well-being [5]. However, the value of FER is fluctuating and influenced by changes in agricultural product prices and production costs, necessitating forecasting efforts to gain insight into farmers' conditions in the future [6]. Forecasting FER is crucial to enable the government and stakeholders to anticipate changes in farmer welfare and develop more targeted and data-driven policies [7].

Data obtained from BPS shows that the growth of FER in Southeast Sulawesi Province has fluctuated from time to time, where the state of FER in Southeast Sulawesi Province from January 2014 to December 2023 has increased or decreased. FER that tends to be low can affect the level of welfare and productivity of the agricultural sector to decrease, so that in the long run it results in a decrease in production rate and an increase in consumption rate [8]. In fact, it is expected that FER from time to time should always increase. Therefore, the right method is needed to forecast FER in Southeast Sulawesi Province.

FER data is available on a monthly basis so it includes the time series data type. One of the methods that can be used to forecast time series data is the Fuzzy Time Series. Fuzzy Time Series (FTS) is a data forecasting method that uses fuzzy sets as the basis for forecasting modeling. FTS is a method introduced by Song and Chissom (1993) which is a concept used to predict problems where actual data is formed in linguistic values [9]. This method is capable of handling data fluctuations, uncertainty and subjectivity in data, compared to classical statistics. FTS has the advantage that it does not require a large amount of historical data and does not require assumptions in forecasting [10]. There are several FTS methods that have been developed, one of which is the Fuzzy Time Series Cheng method [11]. FTS Cheng is a development and improvement of the method proposed by Chen in 1996. This method was proposed by Cheng, Cheng has a different way of determining intervals, namely seen from the frequency obtained. Then in the formation of the fuzzy set for each relationship is inserted and given weights based on the same sequence and loops [12].

Research on the Fuzzy Time Series method has previously been conducted by [13], namely comparing Cheng's Fuzzy Time Series method with the Box-Jenkins method in predicting the Composite Stock Price Index (JCI), then the forecasting accuracy value is calculated using MAE, MSE, MAPE. The result is Cheng's Fuzzy Time Series method is more accurate [13]. Furthermore, research conducted by [2] is to compare the Fuzzy Time Series Cheng and Fuzzy Time Series Markov Chain methods in forecasting the Farmer Exchange Rate (FER) in Indonesia, then the forecasting accuracy value is calculated using MAE, MSE, MAPE. The result is that Cheng's Fuzzy Time Series method is more accurate. [14] compared the Fuzzy Time Series Cheng and Lee methods for forecasting clean water supply and reported that the FTS Cheng method achieved a MAPE value below 3%, indicating very high forecasting accuracy. Additionally, Tursina [15] also used FTS Cheng to predict the Consumer Price Index with a MAPE of 0.23%.Based on these backgrounds and problems, the researcher is interested in conducting research on Farmer Exchange Rate Forecasting (FER) in Southeast Sulawesi Province using the Fuzzy Time Series Cheng Method, then to determine the level of accuracy using the Mean Absolute Percentage Error (MAPE) value. The purpose of this study is to find out the results of forecasting the Farmer Exchange Rate (FER) in Southeast Sulawesi Province using the Fuzzy Time Series Cheng method.

2. Material and Methods

2.1. Type of Research

The type of research used is applied research. Applied research was chosen because the results of this study are not only intended to increase knowledge, but can also be directly used as a basis for formulating policies related to farmer management and welfare improvement. Thus, the Farmer Exchange Rate (FER) forecasting conducted is expected to assist local governments in making more accurate decisions to improve the welfare of farmers in Southeast Sulawesi Province.

2.2. Data Source

The data used in this study is secondary data obtained from [4] The data is monthly data on the Farmer Exchange Rate (FER) in Southeast Sulawesi Province from January 2014 to December 2023. The data used amounted to 120. Then the data was divided into two, namely 80% of the training data (January 2014 – December 2021) and 20% of the test data (January 2022 – December 2023). This data split ratio was chosen because empirical studies show that optimal results are achieved when using 20-30% of the data for testing and the remaining 70-80% for training. Prediction using data splitting is done by dividing the historical data used according to the ratio of training data and testing data, which is then processed sequentially following the steps in the FTS Cheng method to obtain prediction results and MAPE as a comparison to evaluate how well the model that has been created performs [16].

2.3. Data Analysis

The selection of Cheng's Fuzzy Time Series method in this study is supported by recent empirical research showing that this method often produces lower forecasting error rates compared to classical time series models when applied to economic and agricultural data. Therefore, Cheng's FTS method is considered suitable for use in forecasting FER, which has fluctuating and uncertain characteristics [17]. The steps of data analysis in this study are as follows:

1) Describe FER data through line charts to find out data patterns.
2) Model Fuzzy Time Series Cheng using FER data, with the following steps:
   a. Universe Set

$$U = [D_{min} - D_1, D_{max} + D_2], \tag{1}$$

where D_{min} is the lowest data, while D_{max} is the highest data with D_1 and D_2 are arbitrary positive real numbers determined by the researcher. D_1 is a real number determined by the researcher to widen the lower limit of the interval and D_2 is a real number determined by the researcher to widen the upper limit of the interval [18].

   b. The length of the interval.
   - Determine the number of intervals using the Sturges equation,

$$n = 1 + 3{,}322 \times \log(N), \tag{2}$$

where n is the number of intervals, and N is the amount of data used. From these results, a number of linguistic values will be formed to represent a fuzzy set at intervals formed from the universe set (U).

$$U = \{u_1, u_2, \dots, u_n\} \tag{3}$$

where,
U : Universe set
u_i : the number of intevals in U, for $i = 1, 2, \dots, n$.

   - The value of the range or range,

$$R = (D_{max} + D_2) - (D_{min} - D_1) \tag{4}$$

- The length of the interval,

$$l = \frac{R}{n}, \tag{5}$$

- The middle value

$$m_i = \frac{(lower\ limit + upper\ limit)}{2} \tag{6}$$

Where i is a fuzzy set.
So each interval can be calculated by,

$$u_1 = [D_{min} - D_1\ ;\ D_{min} - D_1 + l]$$

$$u_2 = [D_{min} - D_1 + l\ ;\ D_{min} - D_1 + 2l]$$

$$u_3 = [D_{min} - D_1 + 2l\ ;\ D_{min} - D_1 + 3l]$$

$$\vdots$$

$$u_n = [D_{min} - D_1 + (n-1)l\ ;\ D_{min} - D_1 + nl] \tag{7}$$

c. The Fuzzy Set and fuzzification.

Roughly speaking, a fuzzy set can be defined as a class of numbers with vague boundaries. If the universe of discourse (U) is the set of universes $U = \{u_1, u_2, \dots, u_n\}$, then a fuzzy set A_i of U with membership degree is generally expressed as follows.

$$A_i = \frac{\mu_{A_i}(u_1)}{u_1} + \frac{\mu_{A_i}(u_2)}{u_2} + \frac{\mu_{A_i}(u_3)}{u_3} + \cdots + \frac{\mu_{A_i}(u_n)}{u_n} \tag{8}$$

Where $\mu_{A_i}(u_j)$ is the degree of membership from u_j to A_i where $\mu_{A_i}(u_j) \in [0,1]$ and $1 \le j \le n$. The membership degree value of $\mu_{A_i}(u_j)$ is defined as follows.

$$\mu_{A_i}(u_j) = \begin{cases} 1 & ; i = j \\ 0{,}5 & ; j = i-1 \ or\ j = i+1 \\ 0 & ; i \neq j \end{cases} \tag{9}$$

This can be illustrated with the following rules:

Rule 1: If the actual data X_t belongs to u_j, then the membership degree for u_j is 1, and u_{j+1} is 0.5 and if not u_j and u_{j+1}, then it is zero.

Rule 2: If the actual data X_t belongs to u_i, $1 \le i \le n$ then the membership degree for u_j is 1, for u_{j-1} and u_{j+1} is 0.5 and if not u_j, u_{j-1} and u_{j+1} then it is zero.

Rule 3: If the actual data X_t belongs to u_j, then the membership degree for u_j, and for u_{j-1} is 0.5 and if it is not u_j and u_{j-1} then it is zero.

Suppose $A_1, A_2, \dots, A_n$ is a fuzzy set that has a linguistic value of a linguistic variable, the fuzzy set an $A_1, A_2, \dots, A_n$ in the set universe U is defined as follows:

$$A_1 = \left\{\frac{1}{u_1} + \frac{0{,}5}{u_2} + \frac{0}{u_3} + \cdots + \frac{0}{u_n}\right\}$$

$$A_2 = \left\{\frac{0{,}5}{u_1} + \frac{1}{u_2} + \frac{0{,}5}{u_3} + \cdots + \frac{0}{u_n}\right\}$$

$$A_3 = \left\{\frac{0}{u_1} + \frac{0,5}{u_2} + \frac{1}{u_3} + \cdots + \frac{0}{u_n}\right\}$$

$$\vdots$$

$$A_n = \left\{\frac{0}{u_1} + \frac{0}{u_2} + \cdots + \frac{0,5}{u_{n-1}} + \frac{1}{u_n}\right\} \quad (10)$$

Where u_j $(i = 1, 2, \dots, n)$ is an element of the universe set (U) and the number given the symbol "-" expresses the degree of membership $\mu_{A_i}(u_j)$ to A_i $(i = 1, 2, \dots, n)$ whose value is 0, 0.5 or 1 [8].

d. Fuzzy Logical Relations (FLR) and Fuzzy Logical Relations Group (FLRG)

Establish fuzzy logical relationships based on historical data. In fuzzified data, two consecutive fuzzy sets $A_i(t-1)$ and $A_j(t)$ can be expressed as FLR $A_i \rightarrow A_j$. The relationship is identified based on the results of fuzzification of time series data. If the time series variable $F(t-1)$ is fuzzified as A_i dan $F(t)$ is fuzzified as A_j, then A_i and A_j can be denoted as $A_i \rightarrow A_j$, where A_i is the current state and A_j is the next state. Suppose if FLR $A_1 \rightarrow A_1$, $A_1 \rightarrow A_1$, $A_1 \rightarrow A_3$ then the FLRG formed is $A_1 \rightarrow A_1, A_2, A_3$.

e. Weighting matrix from the FLRG

Determine the weights of FLR relations into FLRG by including all relations and assigning weights based on the same order and recurrence. FLRs that have the same current state (A_i) are combined into a group in the form of a weighting matrix. Then transfer the weights into a weighting matrix whose equation is written as follows:

$$W = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \vdots & \vdots & w_{ij} & \vdots \\ w_{n1} & w_{n2} & \cdots & w_{nn} \end{bmatrix} \quad (11)$$

where W is the weight matrix and W_{ij} is the weight matrix at the i-th row and j-th column with $i = 1, 2, \dots, ; j = 1, 2, \dots, n$.

f. Standardized weighting matrix

Next, transfer the FLRG weights into the form of a standardized weight matrix (W^*) which has the following equation.

$$W^* = \begin{bmatrix} {w_{11}}^* & {w_{12}}^* & \cdots & {w_{1n}}^* \\ {w_{21}}^* & {w_{22}}^* & \cdots & {w_{2n}}^* \\ \vdots & \vdots & {w_{ij}}^* & \vdots \\ {w_{n1}}^* & {w_{n2}}^* & \cdots & {w_{nn}}^* \end{bmatrix} \quad (12)$$

Where W^* is a standardized weight matrix with the following formula.

$$W_{ij}{}^* = \frac{W_{ij}}{\sum_{i=1}^{n} W_{ij}} \quad (13)$$

g. Defuzzification

To generate forecasting values, the standardized weight matrix W^* is multiplied by m_i. So the forecasting calculation becomes as follows.

$$F_i = w_{i1}^*(m_1) + w_{i2}{}^*(m_2) + \cdots + w_{in}{}^*(m_n) \quad (14)$$

Where F_i is the forecasting result, with 〚$w_{in}{}^*$ is equation 13. If the fuzzification result of the i-th period is A_i, and A_i has no FLR in FLRG or can be written with the condition $A_i \rightarrow \emptyset$, where the maximum value of the membership degree is at u_i, then the forecasting value (F_i) is the middle value of u_i, or defined by m_i [19].

h. MAPE

MAPE is an error measurement that calculates the size of the percentage deviation between actual data and forecasting data. If the lower the error rate on the forecast data, the more accurate the level of the forecast results [20]. The MAPE calculation is shown in the following equation:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|X_t - F_t|}{X_t} \times 100\% \qquad , t = 1, 2, \ldots, n \tag{15}$$

Where X_t is the actual data in the t-th period, F_t is the value of the forecasting results on the data, and n is the amount of actual data. The accuracy criteria using the MAPE value can be seen in Table 1 [21].

Table 1. MAPE accuracy criteria

MAPE Value	Accuracy Criteria
MAPE ≤ 10%	Very good
10% < MAPE ≤ 20%	Good
20% < MAPE ≤ 50%	Fair
MAPE > 50%	Poor

3) Making conclusions

To clarify the research procedure, Figure 1 outlines the forecasting process using Cheng's Fuzzy Time Series method in a structured manner. The flowchart illustrates each step, starting from data input to model evaluation and forecasting results. This representation provides a clear overview of the methodological framework applied to forecast the Farmer Exchange Rate (FER).

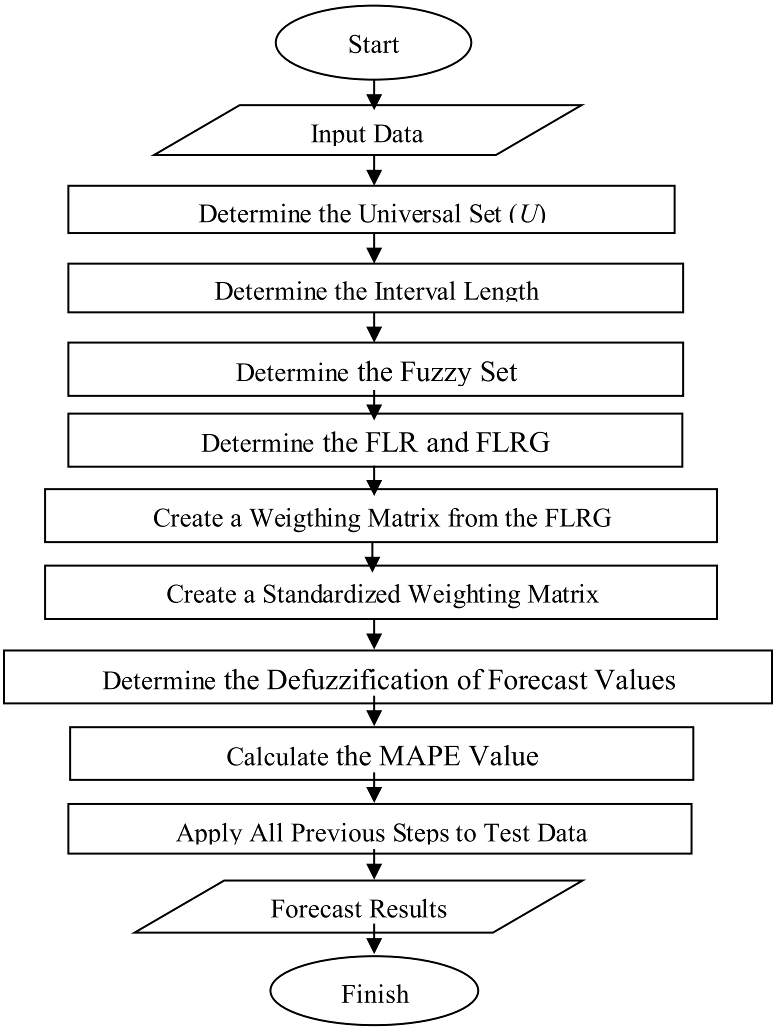

Figure 1. Flowchart of the Cheng's Fuzzy Time Series Method for Forecasting the FER

3. Results and Discussion

3.1. Characteristics of the Farmer Exchange Rate (FER) in Southeast Sulawesi Province

The data used in this study is the monthly time series data of the Farmer Exchange Rate (FER) in Southeast Sulawesi Province from January 2014 to December 2023. The graph of the FER can be seen in Figure 2. The FER pattern shows fluctuations over time, as evidenced by the increase and decrease in value during each period. For example, from November to December 2014, there was a decrease in value from 101.23 to 99.63, while in the same period in 2015, there was an increase from 100.64 to 101.01, followed by another decrease in 2016.

Figure 2. FER chart in Southeast Sulawesi January 2014 - December 2023

This fluctuation occurs because FER is influenced by changes in agricultural commodity prices, which determine farmers' income, as well as changes in production costs and household consumption, which determine the level of expenditure. When production and consumption costs increase faster than the selling price of agricultural products, FER will decrease, weakening farmers' purchasing power. Conversely, when income from harvests is greater than expenditure, FER increases and farmers gain an economic surplus. This fluctuating condition indicates that the welfare of farmers in Southeast Sulawesi Province is highly vulnerable to price and production cost dynamics, necessitating a forecasting method capable of representing this uncertainty to support informed decision-making.

3.2. Cheng's Fuzzy Time Series Prediction

In forecasting using the fuzzy time series cheng, the first step that must be done is to determine the values of *D1* and *D2*, where the values of *D1* and *D2* are positive numbers determined by the researcher himself. So that to obtain optimal *D1* and *D2* values, experiments were carried out on the training data on several *D1* and *D2* values, where in this study the *D1* and *D2* values were equalized, namely 0, 0.005, 0.05, and 0.1, respectively. So that the MAPE value for four variations of D_1 and D_2 value can be seen in Table 2.

Table 2. MAPE values for a number of variations of D_1 and D_2

D_1	D_2	MAPE
0	0	0.6619%
0.005	0.005	0.6618%
0.05	0.05	0.6494%
0.1	0.1	0.6463%

From the table, it can be seen that the D_1 and D_2 values that produce the smallest MAPE value are 0.1, which is 0.6463%. So, the next step is to do FER forecasting in Southeast Sulawesi Province using the D_1 and D_2 values of 0.1 each in the test data. The steps of applying Cheng's Fuzzy Time Series method using test data in this study are as follows. So, the next step is to carry out FER forecasting in

Southeast Sulawesi Province using D_1 and D_2values of 0.1 each on the test data. The steps to apply the Fuzzy Time Series Cheng method using test data in this study are as follows:

1) Formation of the U Universe

The first step in the fuzzy time series method is to form a universe of discourse. The following is the calculation process in the set of universes.

$$U = [D_{min} - D_1;\ D_{max} + D_2]$$

$$= [98.97 - 0.1;\ 106.47 + 0.1]$$

$$= [98.87;\ 106.57]$$

Where *Dmin* is the lowest data of 98.87 and *Dmax* is the highest data of 106.57. In this study, a D_1 value of 0.1 and a D_2 of 0.1 were taken.

2) Forming Interval Length

In this step, the formation of the length of the interval goes through several stages, first by calculating the number of intervals, determining the value of the range or distance, then determining the size of the interval, and calculating the midpoint value. The following is the process of calculating the interval length.

a. Calculating the number of intervals

In determining the number of intervals, the method used by the researcher uses the Sturges formula, as follows.

$$n = 1 + 3.322\ Log\ N$$

$$= 1 + 3.322\ Log\ 24$$

$$= 5.5851 \approx 6$$

So the number of intervals used is 6 intervals.

b. Specifying a range value

$$R = (D_{maks} + D_2) - (D_{min} + D_1)$$

$$= 106.57 - 98.87$$

$$= 7.7$$

c. Determining the length of the interval

$$l = \frac{R}{n}$$

$$= \frac{7.7}{6}$$

$$= 1.2833$$

From these results, the partitions of the set of the universe are obtained according to the length of the interval.

$$u_1 = [98.87;\ 100.15]$$

$$u_2 = [100.15; 101.44]$$

$$u_3 = [101.4;\ 102.72]$$

$u_4 = [102.72;\ 104.00]$

$u_5 = [104.00;\ 105.29]$

$u_6 = [105.29;\ 106.57]$

Next, a table of interval classes, middle or midpoint values obtained from the upper and lower limit values, and the data frequency can be seen in Table 3.

Table 3. Frequency at each interval of the set of universes

u_i	Lower Limit	Upper Limit	Middle Value	Frequency
u_1	98.87	100.15	99.51	11
u_2	100.15	101.44	100.80	8
u_3	101.44	102.72	102.08	1
u_4	102.72	104.00	103.36	1
u_5	104.00	105.29	104.65	1
u_6	105.29	106.57	105.93	2

Then the next step is to calculate the average frequency value for each interval. The average frequency for each interval is the result of division between the number of frequencies and the number of intervals, namely 4, so the interval value must be smaller than the average frequency. Based on Table 3, it can be seen that there are two intervals that have a frequency value greater than the average frequency, namely the u_1 and u_2 intervals. So it is necessary to divide the interval again on the two intervals whose division results can be seen in Table 4.

Table 4. Frequency at each interval of the universal set after division

u_i	Lower Limit	Upper Limit	Middle Value	Frequency
u_1	98.87	99.19	99.03	2
u_2	99.19	99.51	99.35	3
u_3	99.51	99.83	99.67	2
u_4	99.83	100.15	99.99	4
u_5	100.15	100.58	100.37	3
u_6	100.58	101.01	100.80	3
u_7	101.01	101.44	101.22	2
u_8	101.44	102.72	102.08	1
u_9	102.72	104.00	103.36	1
u_{10}	104.00	105.29	104.65	1
u_{11}	105.29	106.57	105.93	2

d. Fuzzification Process

The fuzzification process or converting numerical data into linguistic data. The process assumes $A_1, A_2, \dots, A_n$ or a fuzzy collection of linguistic values of linguistic variables. The number of A_n is as many as the number of interval classes that have been obtained, namely 11 class intervals formed. From each interval class, fuzzy set A_i will be defined, with $1 \leq i \leq 11$. Then the linguistic variables will be formed as follows.

$$A_1 = \left\{ {}^{1}/_{u_1} + {}^{0.5}/_{u_2} + {}^{0}/_{u_3} + {}^{0}/_{u_4} + {}^{0}/_{u_5} + {}^{0}/_{u_6} + {}^{0}/_{u_7} + {}^{0}/_{u_8} + {}^{0}/_{u_9} + {}^{0}/_{u_{10}} + {}^{0}/_{u_{11}} \right\}$$

$$A_2 = \left\{ {}^{0.5}/_{u_1} + {}^{1}/_{u_2} + {}^{0.5}/_{u_3} + {}^{0}/_{u_4} + {}^{0}/_{u_5} + {}^{0}/_{u_6} + {}^{0}/_{u_7} + {}^{0}/_{u_8} + {}^{0}/_{u_9} + {}^{0}/_{u_{10}} + {}^{0}/_{u_{11}} \right\}$$

$$A_3 = \left\{ {}^{0}/_{u_1} + {}^{0.5}/_{u_2} + {}^{1}/_{u_3} + {}^{0.5}/_{u_4} + {}^{0}/_{u_5} + {}^{0}/_{u_6} + {}^{0}/_{u_7} + {}^{0}/_{u_8} + {}^{0}/_{u_9} + {}^{0}/_{u_{10}} + {}^{0}/_{u_{11}} \right\}$$

⋮

$$A_{11} = \left\{ {}^{0}/_{u_1} + {}^{0}/_{u_2} + {}^{0}/_{u_3} + {}^{0}/_{u_4} + {}^{0}/_{u_5} + {}^{0}/_{u_6} + {}^{0}/_{u_7} + {}^{0}/_{u_8} + {}^{0}/_{u_9} + {}^{0,5}/_{u_{10}} + {}^{1}/_{u_{11}} \right\}$$

Furthermore, this section will explain the formation of fuzzification based on intervals and obtain linguistic values according to the intervals formed. Determination of the fuzzification value by defining the data into the appropriate interval. For example, the first data in this study, January 2022, is 100.79, so the data is included in the *u6* class interval. In the fuzzification process, the data will be converted into a linguistic value of *A6* because in the fuzzification process a data will enter into a linguistic value that has a membership degree value equal to 1 which indicates a true value. The fuzzification results can be seen in Table 5.

Table 5. Fuzzification

t	Month	FER	Fuzzification
1	Jan-22	100.79	A_6
2	Feb-22	100.5	A_5
3	Mar-22	100.58	A_5
⋮	⋮	⋮	⋮
22	Okt-23	104.92	A_{10}
23	Nov-23	106.23	A_{11}
24	Des-23	106.47	A_{11}

In Table 5, the results of the fuzzification process on the FER value can be explained that the January 2022 period is 100.79, can be defined into the interval [100.58; 101.01] which is included in the range of linguistic values *A6*. Furthermore, in the February 2022 period worth 100.5, can be defined into the interval [100.15; 100.58] which is included in the range of linguistic values *A5*, and so on until the December 2023 period worth 106.47 with the interval [105.29; 106.57] which is included in the range of linguistic values *A11*.

e. Formation of Fuzzy Logic Relationship and FLR Group

From Table 5, it is known that in January 2022 and February 2022, the FER values were fuzzified into sets A_6 and A_5, respectively, so this relationship can be notated as $A_6 \rightarrow A_5$. Economically, this relationship indicates a tendency for a decline in farmers' purchasing power in the subsequent period, which could be caused by rising production costs or falling prices for agricultural commodities.

Table 6. FLR

Data Sequence	FLR	Data Sequence	FLR
1	-	12→13	$A_3 \rightarrow A_1$
1→2	$A_6 \rightarrow A_5$	13→14	$A_1 \rightarrow A_1$
2→3	$A_5 \rightarrow A_5$	14→15	$A_1 \rightarrow A_2$
3→4	$A_5 \rightarrow A_6$	15→16	$A_2 \rightarrow A_4$
4→5	$A_6 \rightarrow A_4$	16→17	$A_4 \rightarrow A_4$
5→6	$A_4 \rightarrow A_6$	17→18	$A_4 \rightarrow A_7$
6→7	$A_6 \rightarrow A_4$	18→19	$A_7 \rightarrow A_7$
7→8	$A_4 \rightarrow A_5$	19→20	$A_7 \rightarrow A_8$
8→9	$A_5 \rightarrow A_3$	20→21	$A_8 \rightarrow A_9$
9→10	$A_3 \rightarrow A_2$	21→22	$A_9 \rightarrow A_{10}$
10→11	$A_2 \rightarrow A_2$	22→23	$A_{10} \rightarrow A_{11}$
11→12	$A_2 \rightarrow A_3$	23→24	$A_{11} \rightarrow A_{11}$

The results of the fuzzy logic relationship (FLR) formation presented in Table 6 show that dominant relationships such as $A_6 \rightarrow A_4$ indicate that when FER is in the medium range, the probability of FER in the next period will tend to decrease to a lower value group. Meanwhile, the relationship $A_{11} \rightarrow A_{11}$

shows stability at high FER levels, where the value tends to remain in the same category in the next period. Thus, the dominant FLRG provides an overview of the most frequent patterns of change in FER. If the dominant FLRG shows a declining transition, this indicates economic pressure on farmers. Conversely, a stable or increasing FLRG reflects relatively maintained or improved farmer welfare conditions.

Furthermore, to form the FLRG obtained from the FLR results. If there is a fuzzy set that has a relationship or can predict with more than one fuzzy set, it can be combined. Based on Table 6, it can be seen that fuzzy A_1 has a relationship that can predict A_1, A_2, so for FLRG can be formed with the notation $A_1 \rightarrow A_1 \;\; A_2$. Complete results for the formation of FLRG can be seen in Table 7.

Tabel 7. FLRG

Current State		*Next State*
A_1	$\rightarrow$	$A_1 \;\; A_2$
A_2	$\rightarrow$	$A_2 \;\; A_3 \;\; A_4$
A_3	$\rightarrow$	$A_1 \;\; A_2$
A_4	$\rightarrow$	$A_4 \;\; A_5 \;\; A_6 \;\; A_7$
A_5	$\rightarrow$	$A_3 \;\; A_5 \;\; A_6$
A_6	$\rightarrow$	$A_4 \;\; A_5$
A_7	$\rightarrow$	$A_7 \;\; A_8$
A_8	$\rightarrow$	A_9
A_9	$\rightarrow$	A_{10}
A_{10}	$\rightarrow$	A_{11}
A_{11}	$\rightarrow$	A_{11}

f. Weighting

After the FLRG construction is completed, the weighting process is carried out by identifying the frequency of identical relationships within the FLRG. This process, which involves assigning weights to each fuzzy relation, is presented in Table 8. Suppose there is a fuzzy set $A_1 \rightarrow A_1, \; A_2$ then it can be known for the fuzzy relation $A_1 \rightarrow A_1$ as much as one and $A_1 \rightarrow A_2$ as much as one. Then based on the FLRG, the weighted $w_{11} = 1$ (from A_1) and $w_{12} = 1$ (from A_2) are obtained. So that a weight matrix is formed which can be written as $W_t = [w_1 \;\; w_2] = [1 \;\; 1]$. If written in the form of a weighted fuzzy relation, the result is $A_1 \rightarrow A_1, \; A_2$. Where the weighting matrix can be seen in Table 9.

Table 8. FLRG weighting

Current State		*Next State*
A_1	$\rightarrow$	$A_1 \;\; A_3$
A_2	$\rightarrow$	A_3
A_3	$\rightarrow$	$A_1 \;\; A_2 \;\; A_3 \;\; A_4$
A_4	$\rightarrow$	$A_4 \;\; A_5 \;\; A_6 \;\; A_7$
A_5	$\rightarrow$	$A_3 \;\; A_5 \;\; A_6$
A_6	$\rightarrow$	$2(A_4) \;\; A_5$
A_7	$\rightarrow$	$A_7 \;\; A_8$
A_8	$\rightarrow$	A_9
A_9	$\rightarrow$	A_{10}
A_{10}	$\rightarrow$	A_{11}
A_{11}	$\rightarrow$	A_{11}

Table 9. Weighting matrix

FLRG	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}
A_1	1	1	0	0	0	0	0	0	0	0	0
A_2	0	1	1	1	0	0	0	0	0	0	0
A_3	1	1	0	0	0	0	0	0	0	0	0
A_4	0	0	0	1	1	1	1	0	0	0	0
A_5	0	0	1	0	1	1	0	0	0	0	0
A_6	0	0	0	2	1	0	0	0	0	0	0
A_7	0	0	0	0	0	0	1	1	0	0	0
A_8	0	0	0	0	0	0	0	0	1	0	0
A_9	0	0	0	0	0	0	0	0	0	1	0
A_{10}	0	0	0	0	0	0	0	0	0	0	1
A_{11}	0	0	0	0	0	0	0	0	0	0	1

The next step is to transfer the FLRG weights into the form of a standardised weight matrix (W^*). Suppose there is a fuzzy set $A_1 \to A_1,\ A_2$. which has weighted $w_{11} = 1$ (from A_1)) and $w_{12} = 1$ (from A_2) with matrix $W_t = [w_{11}\ \ w_{12}] = [1\ \ 1]$, so that the standardised weight matrix becomes.

$$W_{ij}{}^* = \frac{w_{ij}}{\sum_{j=1}^{n} w_{ij}}$$

$$W_{11}{}^* = \frac{1}{1+1} = 0.5$$

$$W_{12}{}^* = \frac{1}{1+1} = 0.5$$

So for the fuzzy set in $A_1 \to A_1,\ A_2$after transferring the FLRG weights into a standardised weighting matrix form, the standardised weighting matrix value is obtained, namely $W_{ij}{}^* = [W_{11}{}^*\ \ W_{12}{}^*] = [0.5\ \ 0.5]$. The step applies onwards for other fuzzy sets to transfer the standardised weighting matrix values which can be seen in Table 10.

Table 10. Standardisation weighting matrix

FLRG	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}
A_1	0.5	0.5	0	0	0	0	0	0	0	0	0
A_2	0	0.3333	0.3333	0.3333	0	0	0	0	0	0	0
A_3	0.5	0.5	0	0	0	0	0	0	0	0	0
A_4	0	0	0	0.25	0.25	0.25	0.25	0	0	0	0
A_5	0	0	0.3333	0	0.3333	0.3333	0	0	0	0	0
A_6	0	0	0	0.6667	0.3333	0	0	0	0	0	0
A_7	0	0	0	0	0	0	0.5	0.5	0	0	0
A_8	0	0	0	0	0	0	0	0	1	0	0
A_9	0	0	0	0	0	0	0	0	0	1	0
A_{10}	0	0	0	0	0	0	0	0	0	0	1
A_{11}	0	0	0	0	0	0	0	0	0	0	1

g. Forecasting Value Defuzzification Process

In the Cheng model forecasting method, after the FLRG generation process is formed, weights are added to calculate defuzzification. In the calculation process, it will use a standardised weight matrix

(W^*) and the middle value in the interval or midpoint (m_i) for each relation in fuzzy $A_i = A_1, A_2, \ldots, A_n$.

Suppose the researcher will calculate the defuzzification result of the forecasting value in the fuzzy set A_1. Then according to the calculation of the Cheng model formula for the F_i forecasting value defuzzification process as follows.

$$F_1 = w_{11}^*(m_1) + w_{12}^*(m_2)$$

$$= 0.5(99.03) + 0.5(99.35)$$

$$= 99.19$$

From the results of the forecasting calculation above, the defuzzification result of the forecasting value in the fuzzy set A_1 is 99.19. This step applies to each fuzzy set relation A_i to get the results or future forecasting values. The complete results of the forecasting value defuzzification process on all fuzzy set relations, namely 11 groups, can be seen in Table 11.

Table 11. Defuzzification result forecasting value

Current State		*Next State*	Defuzzification
A_1	→	A_1 A_3	99.19
A_2	→	A_2 A_3 A_4	99.67
A_3	→	A_1 A_2	99.19
A_4	→	A_4 A_5 A_6 A_7	100.59
A_5	→	A_3 A_5 A_6	100.28
A_6	→	$2(A_4)$ A_5	100.12
A_7	→	A_7 A_8	101.65
A_8	→	A_9	103.36
A_9	→	A_{10}	104.65
A_{10}	→	A_{11}	105.93
A_{11}	→	A_{11}	105.93

After the defuzzification process was carried out. the predicted FER value for January 2024 was obtained using the FTS Cheng method. based on the FER data from January 2022 to December 2023 presented in Table 12. However. the Fuzzy Time Series Cheng method has limitations. namely that the prediction results tend to stabilize after several periods. making it less than optimal for long-term forecasting. Additionally. this method has not yet considered external factors such as planting seasons. climate change. and food price policies. which can significantly affect the FER value.

Table 12. Data estimation

t	Month	Actual Data	Estimation
1	Jan-22	100.79	
2	Feb-22	100.5	100.12
3	Mar-22	100.58	100.28
⋮	⋮	⋮	⋮
22	Okt-23	104.92	104.65
23	Nov-23	106.23	105.93
24	Des-23	106.47	105.93

h. Calculating the MAPE Value

The purpose of calculating the Mean Absolute Percentage Error (MAPE) value is to determine the level of accuracy in forecasting by measuring the accuracy of the forecasting results. In a forecasting situation. it contains a degree of uncertainty or a level of error (Error). So, what must be done is to find the level of error or error obtained from the difference between actual data and forecasting data. The MAPE value of 0.3027% and the accuracy of the forecasting results is 99.6973%. From these results, it can be concluded that forecasting using the fuzzy time series method in forecasting FER in Southeast Sulawesi can be said to be 'Very Good' because it has a MAPE value of less than 10%.

i. Forecasting Farmer Exchange Rate in Southeast Sulawesi Province in 2024

FER data for future periods can be forecasted by considering each forecasting output produced as input data to forecast the next period. For example. forecasting in January 2024 (t=15). It is known that the forecast result in December 2023 was 105.93. This result will be used as actual data in January 2024 as well as in the February and March 2024 periods. Because 105.93 is in the u_{11} interval and by looking at the previous period. December 2023 (t=14). it is fuzzified to A_{11}. So the FLR obtained is $A_{11} \rightarrow A_{11}$. and the FLRG obtained is $A_{11} \rightarrow A_{11}$. so the following forecasting results are obtained.

$$F_{11} = w^{*}_{1111}(m_{11})$$

$$= 1(105.93)$$

$$= 105.93$$

In this study. FER forecasting will be carried out in Southeast Sulawesi Province for the next three months. namely January. February. March 2024. The forecast results can be seen in Table 13.

Table 13. Forecast results for the next three months

t	Month	Fuzzification	Forecast
25	Jan-24	A_{11}	105.93
26	Feb-24	A_{11}	105.93
27	Mar-24	A_{11}	105.93

The plot of actual data and FER forecast results for the next three months can be seen in Figure 3.

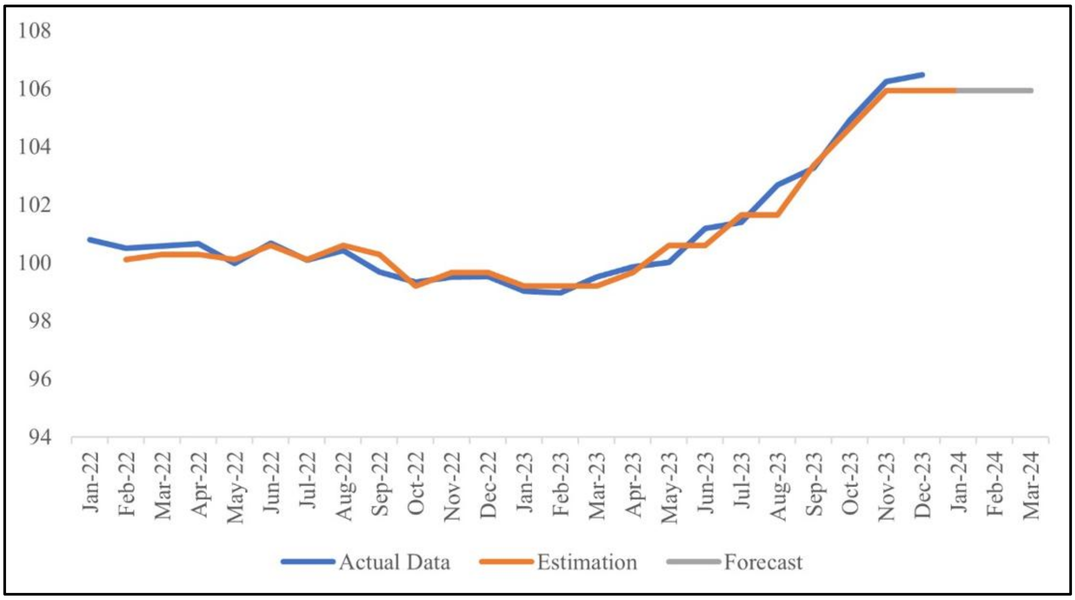

Figure 3. FER forecast result

In Figure 3, it can be seen that the actual data plot is shown with a blue line. the estimated value is shown with an orange line. and the forecast results are shown with a grey line. The forecast results produce the same fuzzification value for the next three periods. namely A_{11}. The forecasting results graph shows that the FER value for the next three periods tends to be stable. This condition indicates that farmers' purchasing power is expected to remain at a moderate surplus level as long as there are no significant changes in commodity prices and consumption costs. Fluctuations in FER in the previous period were primarily influenced by changes in income from commodity sales and the level of production costs and household needs. When the selling price of agricultural products decreased or production costs increased. FER tended to fall. weakening farmers' purchasing power. Conversely. when income increased or costs could be kept down. FER rose and farmers' welfare improved. Thus. the pattern of FER fluctuations reflects the level of vulnerability of farmers' welfare in Southeast Sulawesi

Province to price and cost of living dynamics. Although the forecasting results show a stable trend. periodic monitoring is still necessary to anticipate future changes in economic conditions.

4. Conclusion

The conclusion that can be drawn in this study is that forecasting with the fuzzy time series cheng method can be used to forecast the Farmer Exchange Rate (FER) in Southeast Sulawesi Province in 2024. The FER forecast results in January 2024 were obtained at 105.93 and the FER was predicted to be the same as in February and March 2024. The forecast results of FER > 100. which means that farmers experience a surplus. the price of production rises greater than the increase in consumption prices. Farmers' income increased more than their expenditure. Accuracy by looking at the accuracy of the mean absolute percentage error (MAPE). The MAPE obtained is 0.3027%. which means that the accuracy of the model obtained is 99.6973%. from these results it can be concluded that the criteria for forecasting results using the Cheng fuzzy time series method are included in the ‘very good’ criteria. because they have a MAPE value of less than 10%.

Ethics approval

Not required.

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Not required.

Competing interests

All the authors declare that there are no conflicts of interest.

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This research uses secondary data from BPS-Statistics Indonesia.

Credit Authorship

Rastina: Conceptualization, Methodology, Writing, Editing, Visualization. **Lilis Laome:** Conceptualization, Methodology, Editing, Validation. **Bahriddin Abapihi:** Methodology, Reviewing. **Gusti Ngurah Adhi Wibawa:** Methodology. **Mukhsar:** Reviewing. **Makkulau:** Reviewing. **Gama Putra Danu Sohibien:** Editing, Reviewing, Supervision. **Sukim:** Supervision. **Fathurrahman Yahyasatrio:** Supervision.

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