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Forecasting Models Based on Fuzzy Logic: An Application on International Coffee Prices

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Abstract: In recent decades, Fuzzy Time Series (FTS) has become a competitive, sometimes complementary, approach to classical time series methods such as that of Box-Jenkins. This study has two different purposes: a theoretical purpose, presenting an overview of the fuzzy logic and fuzzy time series models, and a practical purpose, which is to estimate and forecast monthly international coffee prices during the period 2000-2022. Analysing and forecasting the dynamics of coffee prices is of great interest to producers, consumers, and other market actors in managing and making rational decisions. The findings showed that international coffee prices exhibited significant fluctuations, with large increases and decreases influenced mainly by the level of top-ranked producers. The forecasted results revealed that a decrease in prices during the next six months (Jan 2023 to June 2023) is expected. Based on the results, it is also clear that the FTS models are more flexible and can be applied in forecasting time-series variables. At the same time, volatility and, sometimes, the unexpected swingsin coffee prices continue to draw more criticism and raise different issues regarding the roles of the markets and countries in ensuring food security.

Keywords: fuzzy logic, time series, forecasting, coffee prices, FTS models.

1. Introduction

Forecasting is a crucial task in various fields of research. Statistical forecasting techniques have also been a fertile field for research and development for many years. However, in time series analysis, the well-known parametric Box-Jenkins approach is the method most widely used by researchers which requires different assumptions on the characteristics of the time series process, such as stationarity and linearity (Box &

Jenkins, 1976); in practice, these assumptions were considered as drawbacks and key limitations.

Another strategy based on fuzzy logic was proposed to bypass these statistical assumptions (Zadeh, 1978). The concept of fuzzy logic is founded on the notion that variable truth values, rather than being true or false, are ranged between 0 and 1. In this way, this expands conventional Boolean logic by allowing for fractional truth values. Several forecasting models were developed based on this assumption, including the following: (Chen, 1996; Song & Chissom, 1993), heuristic (Abbasov & Mamedova, 2003; Chen & Hsu, 2004; Huarng, 2001; Singh, 2008).

This study had two main objectives: a theoretical one, by briefly presenting the concepts of fuzzy logic, and the most commonly used fuzzy time series models in forecasting. The second objective of the application is to analyse and forecast the pattern of coffee prices over a relatively long period (2000-2022). The author focused on studying this agricultural commodity, because coffee for several countries (and besides export yields) is among the most important crops; in other words, it is an important factor in economic development, where this crop is accompanied by significant investments, such as the construction of railways (logistics chain) and providing manpower.

Different studies attempted to analyse and forecast the dynamics of coffee prices. As an indication, Novanda et al. (2018) used different methods to forecast coffee prices and found that the ARIMA model was the appropriate model for this purpose. Using a hybrid model based on ARIMA and artificial neural network models, Naveena, Singh, Rathod, and Singh (2018) estimated and forecasted the dynamics of Robusta coffee prices in India. Recently, Deina et al. (2022) proposed a new feature for forecasting based on extreme learning machines to forecast coffee prices, compared to ARIMA and exponential smoothing models, and the results showed that the proposed method had higher accuracy. In the application of the FTS models, the study mainly followed the lines of the study conducted by Chellai et al. (2019) to model and forecast the dynamics of olive oil prices, as well as the study by Chellai et al. (2020), which estimated and forecasted the trajectory the spread of COVID-19 in African countries.

As a general framework of analysis, the study by Labys (2017) was of great interest, as it developed in detail how to model and forecast the trajectory of primary commodity prices. The remainder of this paper is organized as follows: Section 2 presents the methodology of the research, Section 3 reports the results of the application of the FTS models, Section 4 discusses the main findings of the estimation, and finally, the conclusion.

2. Methods

2.1. The concept of fuzzy logic

Fuzzy logic (FL) is defined as a multi-valued logic where the truth values of variables are reels numbers in the unit interval, rather than true or false. In this way, it stretches classical Boolean logic by allowing for partial truth values. The FL method imitates the method of decision-making in a human that considers all the possibilities between the true and false digital values. Fuzzy logic is regarded as a decision-making aid. As illustrated by Asli, Aliyev, Thomas, and Gopakumar (2017), all levels of truth and probabilities range from 0 and 1, and thus may appear similar at first, but fuzzy logic uses degrees of truth as a mathematical model of vagueness, whereas probability is a mathematical model of ignorance.

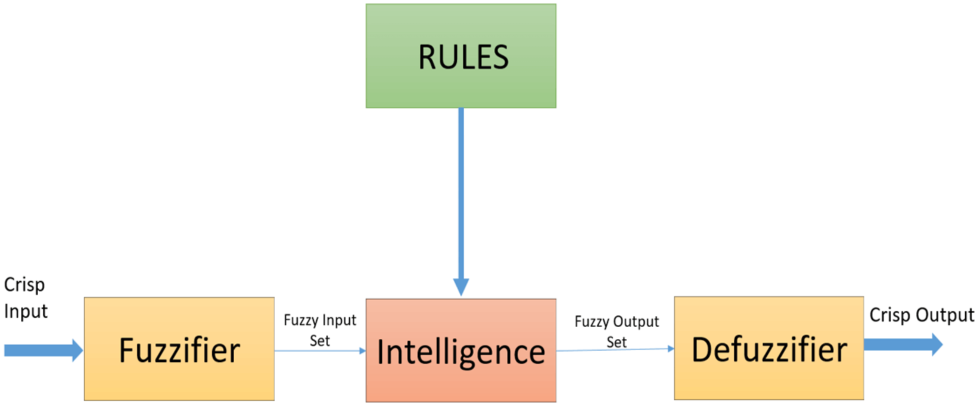

Fig. 1. A structure of fuzzy logic

Source: own elaboration.

Figure 1 illustrates a structure of the fuzzy system. The system receives a precise value x_t as input, which is fuzzified, i.e. converted into the degree of membership in the input fuzzy set. Using the fuzzy IF-THEN rules contained in the rule base, the inference engine generates a fuzzy value that is defuzzified, resulting in a useful output. Partitioning the crisp dataset (Figure 1), identifying fuzzy logical linkages, and defuzzification all play a significant role in the model's predicting performance (Bose & Kalyani, 2019).

In this regard, the Mamdani system (Mamdani, 1974) is the most common system used. To summarise, the system performs the following steps: initially, it fuzzifies all input data into fuzzy membership functions, then it executes all the rules to calculate the fuzzified functions, and finally, it de-fuzzifies the fuzzified functions to obtain ‘crisp’ output values.

2.2. The concept of fuzzy time series

This part discusses the essential ideas of fuzzy time series (FTS). The information for this objective was mostly derived from the research by Chen (1996), Chen and Hsu (2004), and Huarng (2001). The major distinction between fuzzy and conventional time series is that the values of the FL are fuzzy numbers, whereas the latter values are numbers (reels and/or integers).

Fuzzy sets and universe of discourse

Define U as the universe of discourse containing$n$ elements, and put $U = \{u_1, u_2, \dots, u_n\}$. Accordingly, fuzzy set $\mathcal{M}$ based on universe U is defined as

$$\mathcal{M} = \left\{\frac{u_{\mathcal{M}}(u_1)}{u_1}, \frac{u_{\mathcal{M}}(u_2)}{u_2}, \dots, \frac{u_{\mathcal{M}}(u_n)}{u_n}\right\},$$

where $u_{\mathcal{M}}(u_i)$ is the membership function of U, takes values within the range [0,1]. Each element u_i exhibits three different conditions in connection to the universe of discourse U:

1) $u_i$is not a member (***not included***),
2) u_i is *a full member* (***fully included***),
3) $u_i$is*a fuzzy member* (***partially included***).

Fuzzy Time Series

However, if we define subset $\mathcal{H}_t, (t = 1, 2, \dots, n)$ of real numbers representing the universe of discourse, whereby we construct fuzzy sets $m_i(t),$ and if $\mathcal{M}$ (t) is a set of elements of $m_i(t),$ then $\mathcal{M}$ (t) is referred to as FTS defined on Ht. According to (Chen, 1996), fuzzy time series is a new idea in statistics which may be utilised in forecasting where the historical data represent linguistic values.

Based on time scale, in literature, there are two types of fuzzy time series (FTS) models, a time-variant FTS and a time-invariant FTS model (Song & Chissom, 1993). As a result, $\mathcal{M}$(t) is referred to as a time-invariant fuzzy time series If $R(t, t - i)$ is independent of t, where $R(t, t - i)$ is the fuzzy connection with both $F(t - i)$ and $F(t)$. In contrast, $\mathcal{M}$(t) can be a time-variant fuzzy time series model, for such a subcategorynumerous studies were conducted, e.g. (Jiang, Dong, Li, & Lian, 2017; Liu & Wei, 2010). For more details see (Chellai, 2022).

2.3. Main models of FTS

The purpose of this subsection is to provide a brief overview of the most used fuzzy time series models, in particular those provided by (Chen, 1996; Singh, 2008; Song & Chissom, 1993).

The Song & Chissom (1993) model

Song and Chissom (1993) proposed a new approach to forecast university enrollments, and their concept is based on the following method,

$$Y_i = Y_{i-1} \times R.$$

Based on fuzzification, Y_{i-1} and Y_i represent, respectively, the current and predicted observations, and the sign ∘" is just the max-min composition operator, while R is a fuzzy relationship representing fuzzy connections between FTS. The technique described in (Song & Chissom, 1993) requires a significant number of calculations to generate fuzzy relation R, and the max-min composition operations of this method takes a huge amount of computing time whenever fuzzy relation R is extremely large, according to (Chen, 1996).

The Chen (1996) model

Chen (1996) offered a novel approach that was mainly a refinement of the Song and Chissom (1993) approach. The optimality of this technique is attributable to the fact that it employs simplified arithmetic operations rather than the complex max-min composition processes described in the formula above when presenting the Song and Chissom (1993) approach.

Chen used the University of Alabama's historical enrollments to demonstrate the forecasting processes of the new technique. Initially, we determined D min and D max to be the smallest and largest values and the highest in the dataset, defining the universe of discourse U as $[D_{min} - D_1, D_{max} + D_2]$. Briefly, the steps of the approach are as follows:

(1) *Step 1:* decompose the universe of discourse $U = [D_{min} - D_1, D_{max} + D_2]$ into equal length intervals $u_1, u_2, \dots, u_m$.

(2) *Step 2*: determine the fuzzy sets $A_1, A_2, \dots, A_k$ as follows:

$$\begin{array}{l} A_1 = a_{11}/\mu_1 + a_{12}/\mu_2 + \dots + a_{1m}/\mu_m\,, \\ A_2 = a_{21}/\mu_1 + a_{22}/\mu_2 + \dots + a_{2m}/\mu_m\,, \\ \vdots \\ A_k = a_{k1}/\mu_1 + a_{k2}/\mu_2 + \dots + a_{km}/\mu_m\,, \end{array} ;\ a_{ij} \in [0,1], 1 \le i \le k \text{, and } 1 \le j \le m$$

(3) *Step 3:* based on the current states of the enrollments of fuzzy logical connections, split the resulting fuzzy logical relations into subgroups.

(4) *Step 4:* forecasting.

The Singh (2008) model

Singh (2008) proposed this model to address the issue of uncertainty of fluctuations within sequential values of chronological time series data. In short, the process to fit and predict time series with such a method are as follows:

(1) Establish the universe of discourse U using the provided historical time series data $U = [Dmin - D1, Dmax + D2]$, where D1 and D2 are both positive numbers.
(2) Divide the universe of discourse into fixed intervals, where the number of intervals to be investigated would be proportional to the number of fuzzy sets.
(3) Create the fuzzy sets in line with the intervals in Step 2 and implement the triangle membership criterion for each interval for each fuzzy set.
(4) Fuzzify the temporal data and construct the fuzzy inference using the principle: If Ai is the fuzzy output of year n and Aj is the fuzzify output of year n + 1, therefore the fuzzy logical relationship is indicated as $A_i \rightarrow A_j$, here Ai is termed present state and Aj is future state.
(5) Forecast the rules.

The other three FTS models are not discussed here, namely the Heuristic model (Huarng, 2001), the model by (Abbasov & Mamedova, 2003), and the Chen & Hsu (2004) model; for more details see (Fatih, 2022).

2.4. Accuracy comparison criterion

The performance and forecast accuracy of fuzzy time series models are measured and evaluated in terms of well-known accuracy statistics: ME – Mean Error, RMSE – Root Mean Squared Error, MAE – Mean Absolute Error, MPE – Mean Percentage Error, MAPE – Mean Absolute Percentage Error, and MAPE – Mean Absolute Percentage Error. Nevertheless, the Root Mean Square Errors criterion was the default criterion employed throughout this chapter (RMSE). The RMSE formula is as follows:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n}}; \quad U = \frac{\sqrt{\sum_{t=1}^{n-1}\left(\frac{\hat{y}_{i+1} - y_i}{y_i}\right)^2}}{\sqrt{\sum_{t=1}^{n-1}\left(\frac{y_{i+1} - y_i}{y_i}\right)^2}}.$$

In the above formulas, $\hat{y}_i$: are expected values, and y_i are observed values. We can sometimes apply Theil's *U* statistics for Fuzzy Time Series models; this statistic takes value equalto 1 under the naive forecasting strategy. If *U* is smaller than 1, the suggested models predicting accuracy is better than the naive predictions, and if *U* is bigger than 1, it indicates the reverse of the second situation.

3. Results

3.1. Changes in coffee prices during the study period

To fit the proposed FTS models, the study analysed the trajectory of coffee prices over the period January 2000-December 2022). The main purpose was to model and forecast the dynamics of monthly coffee prices. The dataset was provided by Yahoo! Finance (accessed on December 8, 2022; link: https://finance.yahoo.com). Figure 2 shows the evolution of monthly prices (blue line) and changes in prices (brown line) during the studied period.

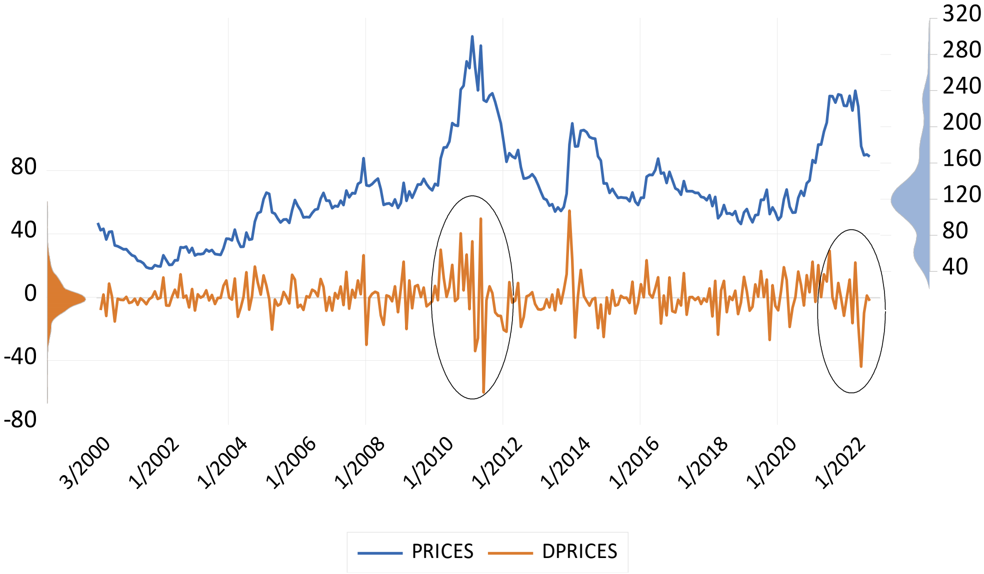

Fig. 2. Evolution and variation of monthly coffee prices during the study period

Source: own elaboration.

Accordingly, one can see two waves of rising coffee prices; the first wave in the period from Jan2010 to Feb2012 known as "Food Price Crisis" which was caused by a range of factors. During this sub-period, by February 2011, coffee prices crossed the 300$/100lb mark. After that, and during the period 2015-2020, coffee prices ranged from 90 to 140$/100lb. The second wave, and the most recent one, was in 2021-2022, where the prices crossed the threshold of 239$/100lb. Nevertheless, this upward trend in prices did not last long compared to the first wave, when the prices reached a very low level in the last two months of 2022, at around 166$ in September 2022.

3.2. Application of FTS Models to forecast monthly coffee prices

As previously stated, the author intended to proceed with fitting the Fuzzy Time Series to this dataset, and then compare the FTS models. Hence, the R program's "AnalyzeTS" package was used to show the estimate and forecasting phases. Next, the estimated procedure was divided into different steps based on the logic of the FTS models described in Section 2.

Step 1: Determination of universe of discourse

The first step determined the universe of discourse that contains all observations in the dataset $\Omega = [Min(y_t) - d_1; Max(y_t) + d_2]$. Descriptive analysis showed that the lowest value recorded for the monthly coffee price was 42.6$/100lb, hence $Min(y_t) = 42.6$ and the highest monthly price during the study period was 299$/100lb, and $Max\ (y_t) = 299$. In the literature, there was no specific method to select the values of d_1 and d_2, consequently they were arbitrarily selected, where $d_1 = 2.6$ and $d_2 = 1$. According to this selection, the universe of discourse of the monthly coffee prices during the study period was $\Omega = [40, 300]$.

Step 2: Determination of fuzzy sets

The difficulty in working with FTS is determining the *number of fuzzy sets* in the universe of discourse. In this study, the discourse universe $\Omega = [40, 300]$ is split into equal sub-intervals using the well-known statistical procedure, $k = 1 + 3.32 \times log(T)$ with k being the appropriate number of sub-intervals and T: the sample size. The dataset of this study covers the period 2000-2022 with a monthly frequency, so the number of observations $T = 276$. The author replaced the value into the formula $k = 1 + 3.32 \times log(276) \approx 20$, which is the number of fuzzy sets.

Table 1. Summary of the selected fuzzy sets

Set	Dow	Up	Mid	Num
A1	40.00	53.02	46.51	14
A2	53.02	66.04	59.53	22
A3	66.04	79.05	72.54	12
A4	79.05	92.07	85.56	7
A5	92.07	105.09	98.58	33
A6	105.09	118.11	111.60	37
A7	118.11	131.12	124.61	52
A8	131.12	144.14	137.63	28
A9	144.14	157.16	150.65	8
A10	157.16	170.18	163.67	14
A11	170.18	183.19	176.68	11
A12	183.19	196.21	189.70	7
A13	196.21	209.23	202.72	6
A14	209.23	222.25	215.74	3
A15	222.25	235.26	228.75	12
A16	235.26	248.28	241.77	5
A17	248.28	261.30	254.79	0
A18	261.30	274.32	267.81	3
A19	274.32	287.33	280.82	0
A20	287.33	300.25	293.84	2

Source: own calculation based on R program.

As a practical indication, hereafter we put the command that can be used in R program to fit different FTS models, such as the Chen model (Chen, 1996), the Singh model (Singh, 2008), the Huarng model (Huarng, 2001), and also the model proposed by Chen and Hsu (2004).

```
fuzzy.ts1(coffee, n = 20, D1 = 2.6, D2 = 1, type = c("Chen", "Singh",
"Heuristic", "Chen-Hsu"), bin = NULL, trace = TRUE, plot = TRUE,
grid = TRUE)
```

In the command *type* means that we should select one model.

Step 3. Fuzzification of coffee prices

This stage consists of converting the original data set to a fuzzy series, thus each monthly price becomes a linguistic value rather than a positive reel number.

Step 4: Definition of fuzzy logic relationships

After fuzzification, this step defines fuzzy logical relationships between the fuzzyfied data and then forms fuzzy relationship groupings. In this step, fuzzy logical relationships are defined between the fuzzyfied data, and next fuzzy relationship groups are formed. One can see that the A17 and A19 fuzzy sets have no relations with the other fuzzy sets; this is a sign that we can reduce the number of fuzzy sets defined previously.

Table 2. Results of fuzzy relationships used the 20 fuzzy sets

"A1->A1,A2"	"A2->A1,A2,A3"
"A3->A2,A3,A4,A5"	"A4->A3,A4,A5"
"A5->A4,A5,A6,A7"	"A6->A5,A6,A7,A8"
"A7->A5,A6,A7,A8,A11"	"A8->A6,A7,A8,A9,A10"
"A9->A8,A9,A10"	"A10->A8,A9,A10,A11"
"A11->A9,A10,A11,A12,A13"	"A12->A10,A12,A13"
"A13->A11,A13,A15,A16"	"A14->A11,A13,A16"
"A15->A14,A15,A16"	"A16->A14,A15,A16,A18,A20"
"A17->NA,"	"A18->A16,A18,A20"
"A19->NA,"	"A20->A15,A18"

Source: author calculations using R.

Before summarising the assessments of each model, the performance of the Abbasov and Mamedova (2010) model has some specific features and instructions in R. For this reason the author included two of these command lines hereafter; the first concerns the main instruction to fit and estimate the models.

```
fuzzy.ts2(coffee, n = 20, D1 = 2.6, D2 = 1, C = 0.001, forecast = 5, r = 12, trace =
TRUE, plot = TRUE, grid = TRUE, type = "Abbasov-Mamedova")
```

The second instruction enables to determine the optimal C value (through simulation). This estimation is based on some accuracy of the predicting criterion, such as "ME", "MAE", "MPE", "MAPE", "MSE" (as option), or "RMSE".

```
GDOC(coffee, n = 20, w = 7, D1 = 2.6, D2 = 1, error = 1e-06, k = 500, r = 13,
CEF = "MSE", type = "Abbasov-Mamedova", show.complete = TRUE)
```

However, Abbasov and Mamedova (2004) developed this formula to select the optimal value

$$\boldsymbol{\mu_{A_i}(\mu_i) = \frac{1}{1 + \left[C\,.\left(U - \mu_m^i\right)\right]^2}}.$$

As developed by Abbasov and Mamedova(2004), the optimal value of this component C should be chosen to enable the transformation of the original dataset into fuzzy values or their interval membership.

Step 5: Forecasting

The final step of each fuzzy time series model was to predict the pattern of the original time series. This study fitted five FTS models and reported the forecast results for each model, where different blocks of Figure 3 (a-e) depict the observed and predicted coffee prices using the five fuzzy time series models. In the same way, Table 3 presents the forecasting accuracy metrics of these models. At first sight, and according to accuracy metrics, the Singh FTS model appears to outperform the other models.

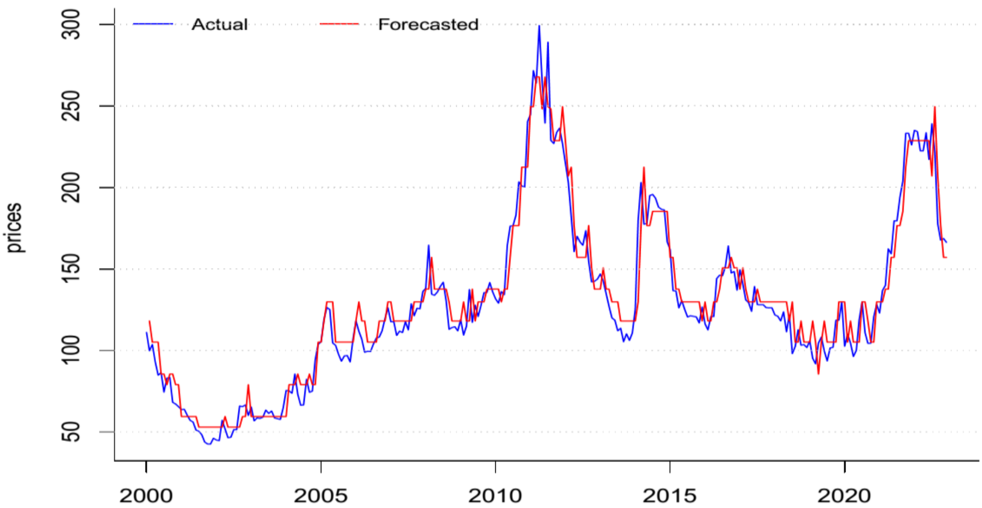

Fig. 3a. Actual vs. forecasted coffee prices by the Chen model of 20 fuzzy sets

Source: own elaboration.

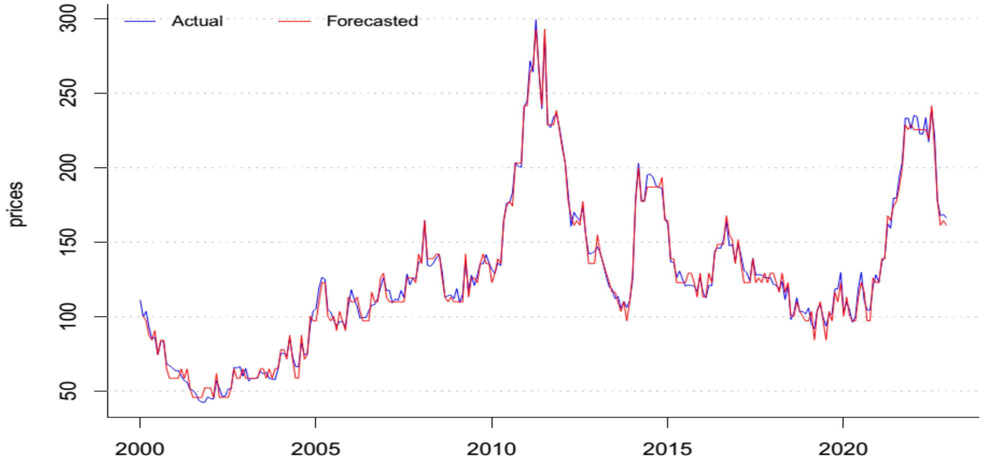

Fig. 3b. Actual vs. forecasted coffee prices by the Chen-Hsu model of 20 fuzzy sets

Source: own elaboration.

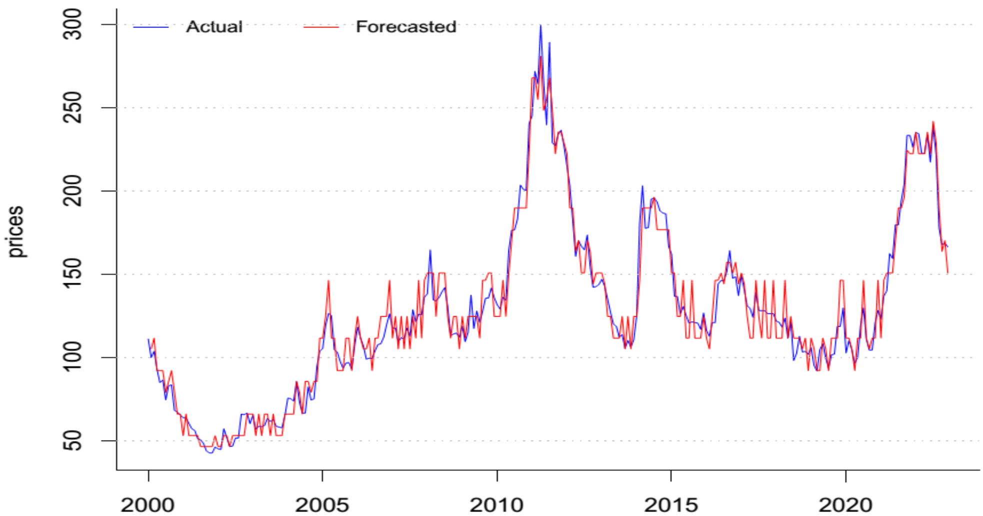

Fig. 3c. Actual vs. forecasted coffee prices by the Heuristic model of 20 fuzzy sets

Source: own elaboration.

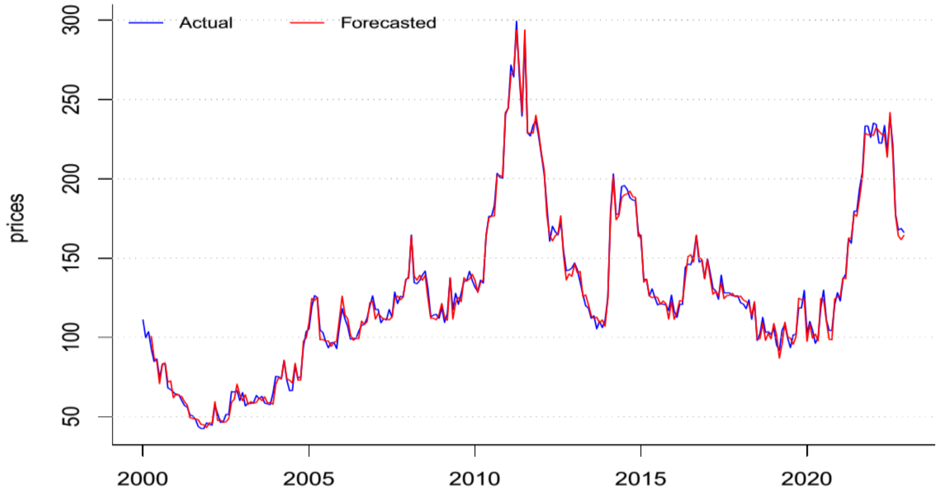

Fig. 3d. Actual vs. forecasted coffee prices by the Singh model of 20 fuzzy sets

Source: own elaboration.

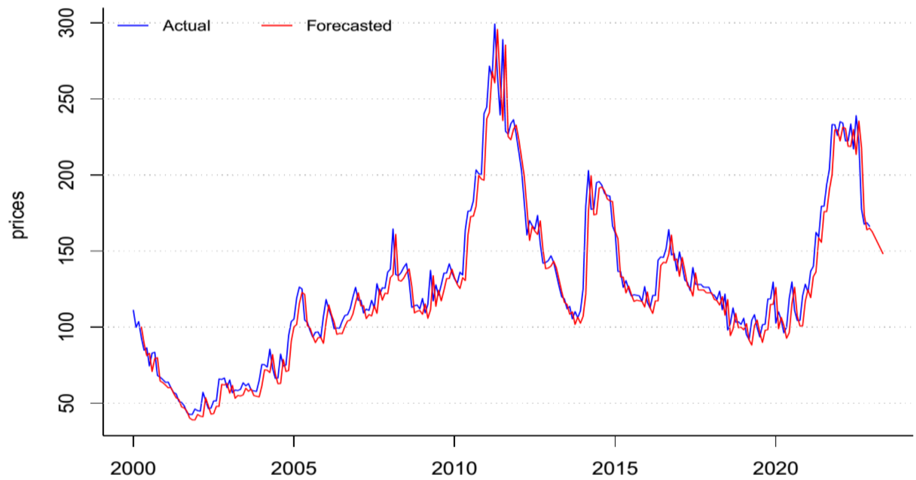

Fig. 3e. Actual vs. forecasted coffee prices by the Abbasov−Mamedova model of 20 fuzzy sets

Source: own elaboration.

Selecting the optimal model

Except for the Mean Errors (ME) and Mean Percentage Errors (MPE) indicators, one can observe that the Singh model recorded the lowest values of the accuracy measures (ME, MAE...). The second best model that suited better the dataset was the Chen & Hsu model (2004).

Table 3. Accuracy measures of the fuzzy time series models

FTS models	MAE	MAPE	ME	MSE	RMSE	MPE	U
Heuristic Huarng (2001)	8.04	6.73	–0.674	97.951	9.897	–0.94	0.802
Chen (1996)	9.34	7.84	–2.19	152.25	12.34	–3.07	1.001
Abbasov&Mamedova (2010)	8.97	7.01	3.81	167.12	12.92	3.13	1.046
Chen & Hsu (2004)	3.83	3.56	0.89	21.785	4.667	0.59	0.378
Singh (2008)	3.06	2.75	0.36	13.741	3.707	0.17	0.301

Source: author's calculation using R program.

4. Discussion

The main aim of this study was to present fuzzy time series models and to estimate and forecast the dynamics of international coffee prices. The estimation results reveal that the Singh model (Singh, 2008) outperformed all the other estimated FTS models. However, the forecasts provided by the estimated models showed the same pattern and future dynamics of coffee prices, see Figure 3 (a-e). According to the forecast results, one can expect a decline in coffee prices over the next six months, from January to June 2023. In part, the expected decrease in coffee prices can be linked (but without confirmed causality) to the recent improvement in the supply chain in the international coffee market.

The FTS models in several applied studies were better than the classical timeseries models, such as the ARIMA family models (Fatih et al., 2020). However, in some cases, FTS models are not preferable if the hypotheses of the linear models (such as the Box-Jenkins) are respected, even though FTS models can provide an alternative forecasting scenario for other methods. For example, in this study the author fitted the ARIMA model to the same dataset and the estimation revealed that the time series exhibited a seasonal component. The forecast of the ARIMA model showed nearly stable coffee prices during the next six months (results not shown here).

Recent reports have shown an improvement in coffee production in Brazil, which is considered the biggest international producer of coffee (Reuters, 2022). On the production side, countries leading in coffee exports (such as Brazil, Vietnam, and Colombia) are behind the net wealth creation to the global food economy (Koh, Garrett, Janetos, & Mueller, 2020). However, the coffee farms in these countries are operated by 'smallholders', producers with relatively small properties and primarily reliant on family labour; this production system is very sensitive to price fluctuations. For example, in 2019 low prices combined with an oversupply of coffee in international markets punished millions of farmers in different regions, mostly in East Africa and Central America.

However, the most likely scenario is that we will see a significant inflationary trend in the prices of agricultural commodities in the coming months. The reasons for this scenario are based on a mixed of different factors, such as economic factors (increased demand, global stocks, inflation, increased supply costs) – a recent study showed the impact of supply-chain on the global inflationary pressure (Di Giovanni, Kalemli--Özcan, Silva, & Yildirim, 2022); climatic factors (drought, floods) – see the study by (Pham, Reardon-Smith, Mushtaq, & Cockfield, 2019) to analyse the impact of climate change on coffee production. This scenario is also supported by geopolitical factors such as regional conflicts, especially those happening in food producing countries such as Ukraine and Russia (Saâdaoui, Jabeur, & Goodell, 2022). The effects of this expected increase in prices will be significant in the economies of importing countries, particularly in underdeveloped regions.

5. Conclusions

This study contributes to filling the gap in the field of forecasting time series using fuzzy logic models. FTS is considered a competitive and alternative method to non-FTS models (such as the Box-Jenkins method) in forecasting. However, the main conclusion and policy implications of the study are based on the fact that price fluctuations of agricultural commodities were a significant generator of poverty and food insecurity, and favoured the net-exporters' countries by increasing their income, a situation that widens the economic inequality between nations. These considerations make forecasting a strategic tool in the hands of policymakers.

References

Abbasov, A. M., & Mamedova, M. H. (2003). Application of fuzzy time series to population forecasting (*Proceedings of 8th Symposium on Information Technology in Urban and Spatial Planning*, Vienna University of Technology, February 25-March 1, pp. 545-552).

Asli, K. H., Aliyev, S. A. O., Thomas, S., & Gopakumar, D. A. (2017). *Handbook of research for fluid and solid mechanics: Theory, simulation, and experiment*. CRC Press.

Bose, M., & Kalyani, M. (2019). Designing fuzzy time series forecasting models: Asurvey. *International Journal of Approximate Reasoning*, (111), 78-99.

Box, G., & Jenkins, M. (1976). *Time series analysis. Forecasting and control*. Hoboken: Wiley.

Chen, S. M. (1996). Forecasting enrollments based on fuzzy time series. *Fuzzy Sets and Systems*, (81), 311-319.

Chen, S. M., & Hsu, C. C. (2004). A new method to forecast enrollments using fuzzy time series. *International Journal of Applied Science and Engineering*, (12), 234-244.

Deina, C., do Amaral Prates, M. H., Alves, C. H. R., Martins, M. S. R., Trojan, F., Stevan Jr, S. L., & Siqueira, H. V. (2022). A methodology for coffee price forecasting based on extreme learning machines. *Information Processing in Agriculture*, *9*(4), 556-565.

Di Giovanni, J., Ka, A., & Yildirim, M. A. (2022). *Global supply chain pressures, international trade, and inflation* (No. w30240). National Bureau of Elemli-Özcan, Ṣ., Silvaconomic Research.

Fatih, Ch. (2022). *Forecasting using Fuzzy Time Series (MPRA Paper)*. University Library of Munich, Germany. Retrieved from https://EconPapers.repec.org/RePEc:pra:mprapa:113848

Fatih, Ch., Charfeddine, L., & Mishra, P. (2020). Modeling and forecasting olive oil price using Fuzzy Time Series and a Fractional Integrated Stochastic Process. *Middle East J. Sci. Res.*, *28*, 322-336. doi: https://dx.doi.org/10.5829/idosi.mejsr.2020.322.336

Fatih, Ch., Hamimes, A., & Mishra, P. (2019). Covid-19 statistics, strange trend and forecasting of total cases in the most infected African countries: An ARIMA and Fuzzy Time Series approaches. *African Journal of Applied Statistics*, *7*(2), 967-982.

Huarng, H. (2001). Huarng models of fuzzy time series for forecasting. *Fuzzy Sets and Systems*, (123), 369-386.

Hyndman, R. J., & Killick, R. (2022). CRAN task view: Time series analysis. Version 2022-06-02. Retrieved from https://CRAN.R-project.org/view=TimeSeries

Jiang, P. Dong Q., Li, & Lian, L. (2017). A novel high-order weighted fuzzy time series model and its application in nonlinear time series prediction. *Appl. Soft Comput*. (55), 44-62.

Koh, I., Garrett, R., Janetos, A., & Mueller, N. D. (2020). Climate risks to Brazilian coffee production. *Environmental Research Letters*, *15*(10), 104015.

Labys, W. C. (2017). *Modeling and forecasting primary commodity prices*. Routledge.

Liu, H.-T., & Wei M.-L. (2010). An improved fuzzy forecasting method for seasonal time series. *Expert Syst. Appl.*, *37*(9), 6310-6318.

Mamdani, E. H. (1974). Application of fuzzy algorithms for control of simple dynamic plant. *Proceedings of the Institution of Electrical Engineers*, *121*(12), 1585-1588. doi:10.1049/PIEE. 1974.0328

Naveena, K., Singh, S., Rathod, S., & Singh, A. (2017). Hybrid ARIMA-ANN modelling for forecasting the price of Robusta coffee in India. *Int. J. Curr. Microbiol. Appl. Sci*, *6*(7), 1721-1726.

Novanda, R. R., Sumartono, E., Asriani, P. S., Yuliarti, E., Sukiyono, K., Priyono, B. S., ... & Octalia, V. (2018, November). A comparison of various forecasting techniques for coffee prices. *Journal of Physics: Conference Series*, *1114*(1).

Pham, Y., Reardon-Smith, K., Mushtaq, S., & Cockfield, G. (2019). The impact of climate change and variability on coffee production: A systematic review. *Climatic Change*, *156*(4), 609-630.

Reuters. (9 Nov. 2022). *Rabobank sees growing coffee crop in Brazil, more sugarcane crushing*. Retrieved from www.reuters.com/markets/commodities/rabobank-sees-growing-coffee-crop-brazil-more-sugarcane-crushing-2022-11-09

Saâdaoui, F., Jabeur, S. B., & Goodell, J. W. (2022). Causality of geopolitical risk on food prices: Considering the Russo-Ukrainian conflict. *Finance Research Letters*, *49*, 103103.

Singh, S. R. (2008). A computational method of forecasting based on fuzzy time series. *Mathematics and Computers in Simulation*, (79), 539-554.

Song, Q., & Chissom, B. S. (1993). Forecasting enrollments with fuzzy time series-part 1. *Fuzzy Sets and Systems*, (54), 1-9.

Theil, H. (1966). *Applied economic forecasts*. Amsterdam: North Holland.

Tran, T. N. H., Doan, H. N., Mai, T. H. D., Nguyen, T. D. M., Hong, V. M., Vo, V. T. & Pham, M. T. (2016). *Analyze TS: Analyze Fuzzy Time Series. R package version 2.2*. Retrieved from https://CRAN.R-project.org/package=AnalyzeTS

Zadeh, L. A. (1978). Fuzzy sets as a basis for a theory of possibility. *Fuzzy Sets and Systems*, *1*(1), 3-28.

Modele prognostyczne oparte na logice rozmytej: aplikacja dotycząca międzynarodowych cen kawy

Streszczenie: W ostatnich dziesięcioleciach rozmyte szeregi czasowe stały się konkurencyjnym, czasem uzupełniającym, podejściem wobec klasycznych metod analizy szeregów czasowych, takich jak metoda Boxa-Jenkinsa. Prezentowane badanie ma dwa różne cele: cel teoretyczny, w którym przedstawiono przegląd logiki rozmytej i modeli rozmytych szeregów czasowych, oraz cel praktyczny, którym jest oszacowanie i prognoza miesięcznych międzynarodowych cen kawy w okresie 2000-2022.

Analiza i prognozowanie dynamiki cen kawy ma duże znaczenie dla producentów, konsumentów i uczestników rynku w zarządzaniu i podejmowaniu racjonalnych decyzji. Wyniki pokazały, że międzynarodowe ceny kawy wykazywały duże wahania, z dużymi wzrostami i spadkami, na które wpływ miał głównie poziom czołowych producentów. Zgodnie z wynikami prognoz należy spodziewać się spadku cen w ciągu najbliższych sześciu miesięcy (od stycznia do czerwca 2023 r.). Na podstawie uzyskanych wyników można stwierdzić, że modele FTS są bardziej elastyczne i mogą być stosowane w prognozowaniu zmiennych szeregów czasowych. Z drugiej strony zmienność, a czasami nieoczekiwane zmiany cen kawy nadal powodują coraz większą krytykę i sygnalizują, że należy zwrócić uwagę na różne kwestie dotyczące roli rynków i państw w zapewnianiu bezpieczeństwa żywnościowego.

Słowa kluczowe: logika rozmyta, szeregi czasowe, prognozowanie, ceny kawy.