Forecasting Commodity Prices in Brazil Through Hybrid SSA-Complex Seasonality Models

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Abstract. Forecasting agricultural prices is of paramount importance to assist producers, farmers, and the industry in the decision-making process. We propose a hybrid forecasting approach combining Singular Spectrum Analysis (SSA) with complex seasonality methods, machine learning, and auto-regressive models to predict monthly corn, soybean, and sugar spot prices in Brazil.

Keywords: Forecasting, Singular Spectrum Analysis, Commodities.

1 Introduction

Reliable price forecasting for agricultural commodities is of paramount importance to assist farmers, producers, and the industry in the decision-making process. Thus, having efficient mechanisms to predict price trends may support optimal input allocation, agricultural investments, and hedging decisions. However, forecasting agricultural commodities is challenging; besides the supply and demand effects and the seasonal patterns involved, exogenous factors may influence prices, such as climate changes, technology, exchange rates, political and macroeconomic events.

The forecasting literature provides several different approaches to capture the dynamic and complexity of the commodities prices. For instance, Gibson and Schwartz [1] and Schwartz [2] described the behavior of commodity prices through differential stochastic models, and the latter study applied the Kalman Filter to estimate the parameters of the unobserved state variables. Based on these previous findings, Ribeiro and Oliveira [3] proposed a hybrid model for forecasting the prices of agricultural commodities considering the structure of the Schwartz [2] stochastic process, which describes the price evolution following selected activation functions for Neural Networks (NNs), thus allowing the incorporation of nonlinear dynamics into the models.

Further studies showed the importance of the combination approaches to capture linear and nonlinear information of the time series. Xiong et al. [4] proposed a combination of vector error correction (VEC) and multi-output Support Vector Regression (SVR) to forecast interval-valued agricultural commodity futures prices. Maia et al. [5] introduced a new approach based on a hybrid ARIMA and ANN model. They showed that the proposed model outperformed the AR and ARIMA single approaches. Li et al. [6] proposed two hybrid methods for monthly crude oil price forecasting using support vector machine (SVM) optimized by genetic algorithm (GA) and backpropagation neural network optimized by GA. The variational model decomposition with artificial intelligence provided more accurate results than all benchmark models.

Decomposition methods were also employed to improve model forecasting performance. Wang et al. [7] applied a NN forecasting model based on SSA for corn, gold, and crude oil. They used SSA to decompose the price series, and the smoothed commodity prices series was reapplied into NN model. Overall, the SSA method decomposes the original series data into trend, oscillatory, and noise components. Meira et al. [8] considered the use of Seasonal Trend Decomposition using Loess (STL) [9] to isolate key components of electricity supply time series before using exponential smoothing models, thus improving forecasting performance over several benchmarks. Athoillah et al. Athoillah et al.[10] applied the support vector regression (SVR) to predict rainfall based on reconstruction series from SSA free from noise elements. Results showed that the SVR with the filtered data outperformed the SVR model.

Motivated by the previous findings, we propose a hybrid model to predict spot prices for sugar, soybeans, and corn in the Brazilian market. Particularly, we combine the Singular Spectrum Analysis (SSA) with complex seasonality methods, machine learning algorithms, and auto-regressive models to predict monthly prices up to 2 and 3 steps ahead. In addition, we compare whether using the SSA decomposition method outperforms single benchmarks. The results are of particular importance considering the global role that Brazil plays as the leading exporter of sugar and soybeans and the fourth-largest supplier of corn. Notably, the country accounted for 38% of the total sugar exported in 2020, followed by India with 11%. The country is also a leading exporter of soybean, accounting for 37% of total world production. Although the country is not the main corn exporter, it is one of the top four countries that provides 70% of corn supply worldwide. Noteworthy, corn production has increased over the years due to the crop rotation named “2a Safra”. Therefore, agricultural commodities constitute a crucial driver of the Brazilian economy, corresponding to a large portion of the country’s GDP [11][12].

The rest of the paper is organized as follows. Section 2 describes the Singular Spectrum Analysis method and its implementation. Section 3 briefly overviews the forecasting benchmarks considered for comparison. Section 4 describes the data and the setup to train and test the data. Section 5 presents and discusses the empirical results. Section 6 concludes and presents suggestions for futures studies.

2 Singular Spectrum Analysis (SSA)

SSA is a nonparametric method to analyze time series that do not require the classical assumptions over the normality of the residuals or the stationarity of the time series. Not only this technique overcomes the traditional approaches, but it also incorporates elements of classical time series analysis, multivariate statistics, and signal processing [13].

SSA involves two stages of decomposing and reconstructing the time series, and each one consists of two steps:

2.1 Embedding

The embedding step consists of mapping a one-dimensional time series $Y_N = (y_1, \dots, y_N)$ into the multidimensional series $X_1, \dots, X_K$ with vectors $X_i = (x_i, \dots, x_{i+L-1})^T \in \Re^L, (1 \leq i \leq k)$, where *K=N-L+1.* The X_1vectors are called *L*-lagged vectors. L is an integer and describes the window length; its size should not exceed *N/2*. The single choice of L in the embedding step results in the trajectory matrix **X** formed by the sub-series X_i, which is also a Hankel matrix,

$$X = \begin{bmatrix} x_1 & \cdots & x_{K-1} \\ \vdots & \ddots & \vdots \\ x_{L-1} & \cdots & x_{N-1} \end{bmatrix} \tag{1}$$

2.2 Singular Value Decomposition (SVD)

The SVD of the trajectory matrix X denotes the sum of rank-one bi-orthogonal elementary matrices. Let $\boldsymbol{S} = \mathbf{X}\mathbf{X}^{\mathbf{T}}$ and $\boldsymbol{\lambda}_{\mathbf{1}}, \dots, \boldsymbol{\lambda}_{\mathbf{L}}$ be the eigenvalues **S** ordered by its magnitude$(\boldsymbol{\lambda}_{\mathbf{1}} \geq \cdots \geq \boldsymbol{\lambda}_{\mathbf{L}})$ and $\boldsymbol{U}_{\mathbf{1}}$,…,$\boldsymbol{U}_{\boldsymbol{L}}$ be the orthogonal eigenvectors of S related to the eigenvalues $\boldsymbol{V}_{\boldsymbol{i}} = \frac{\mathbf{X}^{\mathbf{T}}\mathbf{U}_{\mathbf{1}}}{\sqrt{\boldsymbol{\lambda}_{\mathbf{1}}}}$ (*i*=1,…,*d*). We can denote the SVD as the trajectory of the matrix X represented as follows:

$$X = X_1 + \cdots + X_d \tag{2}$$

2.3 Grouping

The first step of stage 2 involves separate the elementary matrices $\boldsymbol{X}_{\boldsymbol{i}}$ into several groups and sums each group of matrices. The indices 1,…,d is organized into groups $\mathbf{I}_{\mathbf{1}}, \dots, \mathbf{I}_{\mathbf{m}}$; thus, the matrix $\boldsymbol{X}_{\mathbf{1}}$associated with the group, I can be defined as $\boldsymbol{X} = \boldsymbol{X}_{\boldsymbol{I1}} + \cdots + \boldsymbol{X}_{\boldsymbol{Im}}$. The process of selecting the sets $\boldsymbol{I}_{\mathbf{1}}, \dots, \boldsymbol{I}_{\boldsymbol{m}}$ is called eigentriple grouping, such that the contribution of group I to the $\boldsymbol{X}_{\mathbf{1}}$component is gauged by the share of the corresponding eigenvalues: $\frac{\sum_{i=1} \boldsymbol{\lambda}_{\mathbf{1}}}{\sum_{i=1}^{d} \boldsymbol{\lambda}_{\mathbf{1}}}$.

2.4 Diagonal Averaging (DA)

DA consists of transforming each matrix I into an additive component of the original series. The transformation of the resulting matrices into the series occurs by applying the Hankealization (H) linear operator. This operator acts on an arbitrary matrix transforming it into a Hankel matrix - trajectory matrix – resulting in a time series.

2.5 Choosing the parameters L and r

The purpose of the SSA method is to filter the data so that the new data can be applied in the time series forecasting models minimizing the error measures. Thus, the choice of the length of the window (L) and the reconstruction grouping (r) will be defined during the decomposition process. There are no strict rules for selecting the L parameter; we follow [14] procedure.

Let us consider a time series $Y = (y_{(1,1)} + \cdots + y_{(1,S)}, \ldots, y_{(N,S)})$ with NS observations and a seasonal period of lenght S. Further, we split the data into two parts: a training set $Y = (y_{(1,1)} + \cdots + y_{(1,S)}, \ldots, y_{(K,S)})$ with size $T = KS$, and a calibration set $Y = (y_{(K+1,1)} + \cdots + y_{(K+1,S)}, \ldots, y_{(N,S)})$ with $h = (N - K - 2)S$ observations.

Then, the following steps are conducted for $L = S, 2S, \ldots, \frac{KS}{2}$:

i. construct the trajectory matrix $\boldsymbol{X} = [X_1 + \cdots + X_K]$ using the training set;
ii. obtain the SVD by calculating the $\mathbf{XX^T}$;
iii. for $m = 1, \ldots, L$, group the first components $X = X_1 + \cdots + X_m$, then apply the diagonal average in $\boldsymbol{X}$ to obtain the filtered series - $\tilde{Y}$. Choose the forecasting model (ETS, ARIMA, NN, NNETAR, ELM, and Fourier in our study) and apply it in the $\tilde{Y}$ to get the h steps ahead $\tilde{Y} = (\tilde{y}_{(1,1)} + \cdots + \tilde{y}_{(1,S)}, \ldots, \tilde{y}_{(N,S)})$. Finally, compute the error when comparing the forecast $\tilde{Y}$ with the validation set. The L and r vector parameters will be selected as being the ones presenting the lowest forecasting errors.

We employ the Mean Absolute Percentage Error (MAPE) to identify the optimal L for decomposing the commodities prices and the optimal r for reconstructing the denoised series to be further applied into the forecasting models. We use the L and r combination that presents the lowest MAPE. The MAPE ca be defined as follows:

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{d_t - \overline{y_i}}{d_t} \right| \qquad (3)$$

Where N is the total number of the data estimated, d represents the actual (observed) prices of the commodity, and y comprises the forecasts generated by each forecasting model.

3 Forecasting benchmarks

3.1 Exponential smoothing methods

To account for seasonal patterns in the commodities prices, we apply three forecasting models. First, we employ the Exponential Smoothing (ETS) algorithm that considers error, trend, and seasonal components selecting the best exponential smoothing model from several combinations. The best-fit model is selected by default by minimizing the Akaike Information Criterion (AIC) with corrections [15]. This automatic algorithm can be implemented through the *forecast* package for the R software [16].

In addition, we consider the additive Holt-Winters' method, which can be written as:

$$\hat{y}_{t+1} = L_t + kT_t + S_{t+k-m} \quad (4)$$

where L_t represents the level component, T_t is the trend, and S_t the seasonality. These, in turn, can be represented as follows:

$$L_t = \alpha(y_t - S_{t-m}) + (1-\alpha)(L_{t-1} + T_{t-1}),$$
$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1},$$
$$S_t = \gamma(y_t - L_t) + (1-\gamma)S_{t-m} \quad (5)$$

where α, β e γ are the smooth parameters corresponding to the level, trend, and seasonality components. The *forecast* package in R also provides the implementation of the additive Holt-Winters' method.

3.2 Seasonal Autoregressive, Integrated, Moving Average (SARIMA) formulations

Two SARIMA formulations are considered for comparisons. The popular automatic version of the Box and Jenkins – ARIMA model is provided in the forecast R package. The auto.arima( ) function automatically selects the number of differences d, and p and q are estimated by minimizing the AICc, p, and q, respectively referring to the orders of the autoregressive and moving-average parts of the selected SARIMA model.
Lastly, to deal with possible multiple seasonal patterns in the involved time series, we also consider the extension of the traditional, univariate SARIMA formulation to a dynamic harmonic regression framework. This consists of adding Fourier terms in the SARIMA formulation as regressors (exogenous factors), thus other possible seasonal patterns that may be present in the involved time series [17].

3.3 Artificial Neural Networks (ANNs)

Artificial neural network models have become popular in many areas of applied sciences since the development of data availability and computing power. A neural

network is organized into several layers: input, output, and hidden layers. In the hidden layer, the neurons assume estimated values (weights). Each signal is multiplied by a weight, which indicates the influence on the unit's output. The weights are selected through an algorithm that minimizes a forecast error measure.
We compare three different ANN approaches to forecast commodities prices. First, we consider the multilayer perceptron (MLP), which comprises a system of interconnected neurons that map input data sets onto a set of outputs, representing a nonlinear mapping. The MLP makes no prior assumptions regarding its distribution [18]. We use the mlp( ) function from the nnetar package [16] to estimate the feedforward networks; this function employs a supervised learning method called backpropagation for training the networks. Second, we compare the mlp( ) with the nnetar( ) function in the forecast package that fits a NN to a nonlinear auto-regressive model [16]. Finally, we compare these approaches with the extreme learning machine (ELM) function in the nnfor package. The elm( ) function is a training method that neither requires iterative tuning nor setting the hyperparameters and can be faster than other methods [19].

4 Experimental setup

The training and test set data were used to choose the best L and r parameters, described in section 2.5. The L and r selection is used to reconstruct the denoised series. Thus, the new reconstructed time series is the training 2 set that is used to predict the remaining observation with the benchmark forecasting models and compare it with the test 2 set (see Fig.1.).

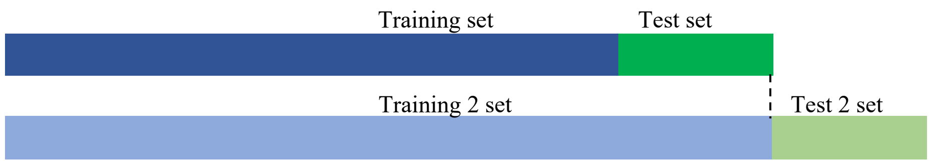

Fig. 1. Training and test set to perform the forecasting models.

This study considers the monthly spot prices of corn, soybean, and sugar in the Brazilian commodity market. The database was retrieved from CEPEA/Esalq website [20] from November 2013 to March 2021. Since the forecasts will be generated considering a lead time of two and three steps ahead, the training set ranges from November 2013 to October/November 2020, and the test set consists of the following 2 and 3 months. Further, training set 2 in Fig. 1 begins in November 2013 and ends in December 2020 and January 2021.

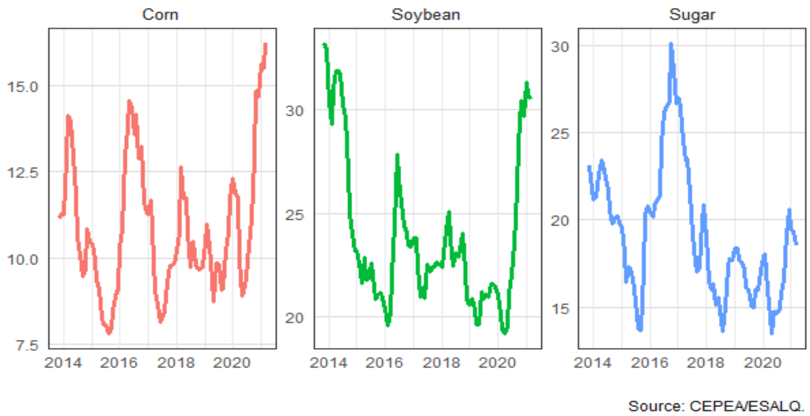

Fig. 2. Time series plots of corn, soybean, and sugar spot prices.

5 Empirical Results

This section compares the accuracy of the Hybrid approach, which consists of reconstructing the denoised series using SSA and applying seven different models (ARIMA, ELM, ETS, Fourier, HW, NN, NNETAR), with the accuracy of the seven different models when directly applied to the original series, i.e., with no SSA involved. In addition, we examine which forecasting approach performs the best. To measure the forecasting accuracy, we employ the MAPE. We use 2 and 3 months in advance to forecast the commodities prices for the test set and the validation set. Fig. 3 and Fig. 4 show the accuracy of different forecasting methods for 2 and 3 steps ahead (h=2 and h=3, respectively).

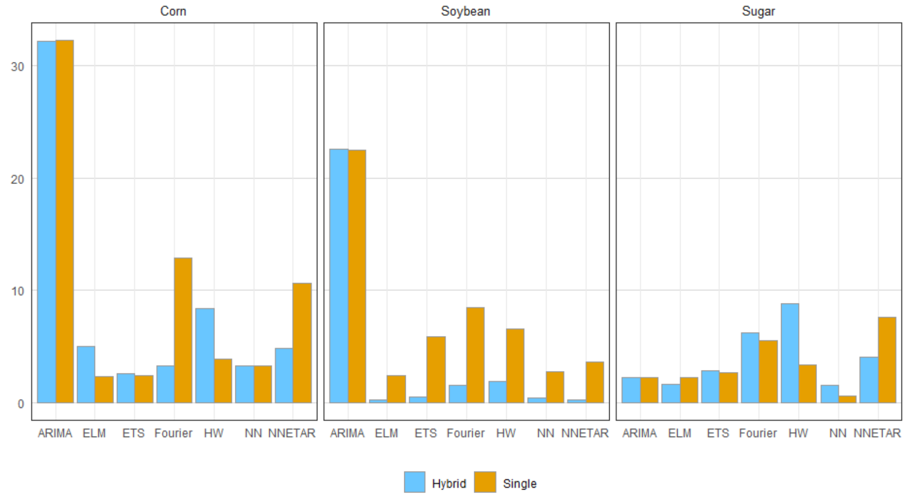

Fig. 3. Forecast errors (MAPE) comparison between the hybrid and the Single model with h=2.

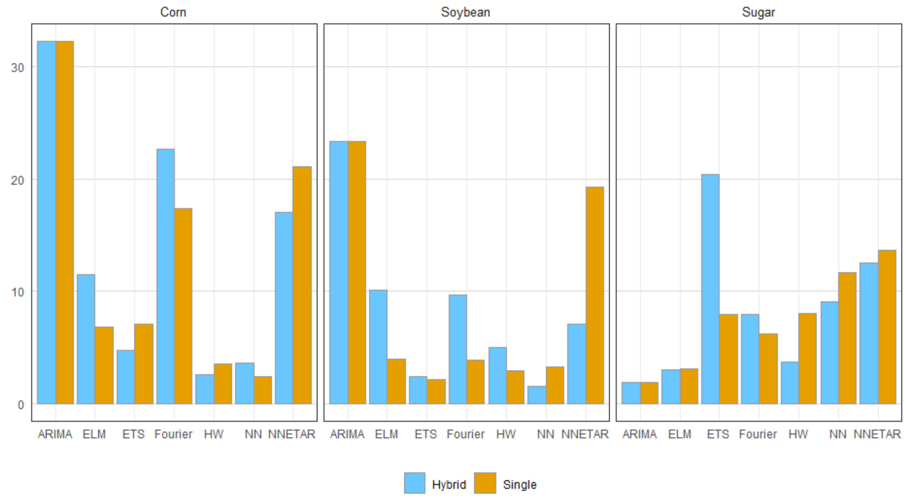

Fig. 4. Forecast errors (MAPE) comparison between the hybrid and the Single model with h=3.

Overall, the Hybrid approaches outperforms the Single models. The better performance of the hybrid models when compared to single methods is less evident when the forecasting lead time is $h = 3$. The hybrid SSA-exponential smoothing method had an average performance, while the ARIMA model almost had the worst performance - both the hybrid approach and the single model had similar performances. On the other hand, the results showed that the machine learning algorithms presented minor forecast errors. For instance, the NNETAR and ELM Hybrid models, presented the lowest MAPE values when forecasting up to 2 months ahead.

Moreover, the forecasting models for the soybean prices had a better performance than the other commodities. Noteworthy, the corn price had a steep spike in the last observations while sugar prices declined. We also include the Mean Average Error (MAE) and the Mean Absolute Scale Error (MASE) methods to measure the forecast accuracy. Tables 1 and 2 illustrate the forecast errors using these metrics (MAE, MAPE, and MASE) [21]. The empirical results remained similar using MAE and MASE.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \overline{y_i}|$$

$$MAE_{naive} = \frac{1}{N-1}\sum_{i=1}^{n}|y_i - y_{i-1}|$$

$$MASE = \frac{MAE}{MAE_{naive}} \quad (6)$$

Sugiura [14] found similar results. The authors compared the SSA forecast with ETS, ARIMA, and NNETAR. They showed that SSA performed better than the alternative approaches providing a significant advantage to forecast tourist arrivals in the US. Also, Lima et al. [22] compared the ARIMA-GARCH and the NN forecasting models for the Brazilian soybean log returns. However, they applied the wavelet decomposition to filter the time series and reapply into the econometric models. Results showed that using wavelet decomposition improved the forecasts, and the NN presented better forecasts than the ARIMA-GARCH. Ribeiro and Oliveira [3] also found that using NN can reduce forecast errors.

Table 1. Performance evaluation criteria for Hybrid and Single model using 2 steps (h=2)

Sugar	**Hybrid model**			**Single model**		
	MAE	**MAPE**	**MASE**	**MAE**	**MAPE**	**MASE**
ETS	0.52	2.79	0.12	0.50	2.67	0.12
ARIMA	0.42	2.22	0.10	0.42	2.22	0.10
HW	1.65	8.80	0.39	0.63	3.31	0.15
NN	0.29	1.55	0.07	0.12	0.60	0.03
NNETAR	0.76	4.03	0.18	1.45	7.60	0.34
ELM	0.31	1.65	0.07	0.43	2.22	0.10
Fourier	1.15	6.17	0.27	1.04	5.50	0.24
Soybean	**Hybrid model**			**Single model**		
	MAE	**MAPE**	**MASE**	**MAE**	**MAPE**	**MASE**
ETS	0.16	0.51	0.05	1.78	5.82	0.51
ARIMA	6.91	22.59	2.37	6.86	22.44	1.96
HW	0.57	1.87	0.18	2.01	6.58	0.58
NN	0.13	0.42	0.04	0.83	2.73	0.24
NNETAR	0.06	0.21	0.02	1.10	3.59	0.31
ELM	0.08	0.25	0.02	0.73	2.38	0.21

Fourier	0.48	1.57	0.16	2.59	8.48	0.74

Corn	**Hybrid model**			**Single model**		
	MAE	**MAPE**	**MASE**	**MAE**	**MAPE**	**MASE**
ETS	0.40	2.56	0.17	0.38	2.36	0.16
ARIMA	5.11	32.20	2.19	5.11	32.21	2.15
HW	1.33	8.40	0.56	0.62	3.91	0.26
NN	0.53	3.24	0.23	0.51	3.24	0.22
NNETAR	0.76	4.85	0.33	1.70	10.63	0.72
ELM	0.78	4.98	0.33	0.36	2.27	0.15
Fourier	0.51	3.23	0.22	2.05	12.90	0.86

Table 2. Performance evaluation for Hybrid and Single models when forecasting 3 months ahead (h=3)

Sugar	**Hybrid model**			**Single model**		
	MAE	**MAPE**	**MASE**	**MAE**	**MAPE**	**MASE**
ETS	3.88	20.43	0.89	1.51	7.96	0.35
ARIMA	0.36	1.90	0.08	0.36	1.91	0.08
HW	0.70	3.68	0.16	1.52	8.01	0.35
NN	1.72	9.06	0.40	2.23	11.68	0.51
NNETAR	2.37	12.54	0.55	2.57	13.61	0.59
ELM	0.57	2.98	0.13	0.59	3.10	0.14
Fourier	1.51	7.96	0.35	1.17	6.25	0.27
Soybean	**Hybrid model**			**Single model**		
	MAE	**MAPE**	**MASE**	**MAE**	**MAPE**	**MASE**
ETS	0.72	2.36	0.22	0.66	2.14	0.20
ARIMA	7.20	23.35	2.12	7.20	23.35	2.11
HW	1.53	5.00	0.46	0.89	2.90	0.26
NN	0.47	1.55	0.14	1.00	3.23	0.29
NNETAR	2.17	7.08	0.67	5.92	19.24	1.74
ELM	3.10	10.07	0.91	1.22	3.96	0.36
Fourier	2.95	9.63	0.87	1.19	3.86	0.35
Corn	**Hybrid model**			**Single model**		
	MAE	**MAPE**	**MASE**	**MAE**	**MAPE**	**MASE**
ETS	0.75	4.76	0.32	1.12	7.06	0.47
ARIMA	5.09	32.23	2.17	5.09	32.23	2.15
HW	0.40	2.57	0.18	0.56	3.53	0.24
NN	0.58	3.61	0.25	0.38	2.41	0.16
NNETAR	2.70	17.03	1.15	3.35	21.14	1.42
ELM	1.82	11.52	0.78	1.08	6.79	0.46
Fourier	3.59	22.69	1.53	2.74	17.35	1.16

6 Concluding remarks

Forecasting models play an important role in estimating future price behavior in the commodity markets. Producers, farmers, and commodity traders can benefit from accurate models to support input allocation and optimal hedging and investment decisions. Moreover, agricultural commodities represent an important driver of the Brazilian economy.

The present study contributes to improving the forecasting model accuracy by combining different approaches. We apply the Singular Spectrum Analysis (SSA) to decompose the time series into signals: trend, oscillatory, and noise components, and then reconstruct the denoised series. We use the denoised series into the econometric models to compare whether filtering the time series with the SSA reduces forecasting errors. We employ a range of methods that deals with seasonality and nonlinearity. It is worth noting that the main characteristic of agricultural commodities is the seasonality component. Therefore, we compare several seasonal models - ETS, Fourier; SARIMA formulations - with machine learning algorithms - ELM, NNETAR, and NN.

In most cases, the hybrid approaches, i.e., those that combine the SSA technique with the selected econometric methods - outperform those that do not take into account previous filtering with SSA. Among single models, the machine learning algorithms presented better performances than competing approaches. We compare the forecasting error using the MAPE, so for the soybean price, the ELM had the best performance, while the ARIMA models presented the highest forecast error.

A possible avenue for future research is to explore alternative decomposition schemes for time series filtering besides SSA, such as wavelet decomposition. In addition, further studies could extend the forecasting investigation using a multivariate framework.

References

1. Gibson R, Schwartz ES (1990) Stochastic Convenience Yield and the Pricing of Oil Contingent Claims. J Finance 45:959–976. https://doi.org/10.1111/j.1540-6261.1990.tb05114.x
2. Schwartz ES (1997) The stochastic behavior of commodity prices: Implications for valuation and hedging. J Finance 52:923–973. https://doi.org/10.1111/j.1540-6261.1997.tb02721.x
3. Ribeiro CO, Oliveira SM (2011) A hybrid commodity price-forecasting model applied to the sugar–alcohol sector. Aust J Agric Resour Econ 55:180–198. https://doi.org/https://doi.org/10.1111/j.1467-8489.2011.00534.x
4. Xiong T, Li C, Bao Y, et al (2015) A combination method for interval forecasting of agricultural commodity futures prices. Knowledge-Based Syst 77:92–102. https://doi.org/10.1016/j.knosys.2015.01.002
5. Maia ALS, de Carvalho F de AT, Ludermir TB (2008) Forecasting models for interval-valued time series. Neurocomputing 71:3344–3352. https://doi.org/https://doi.org/10.1016/j.neucom.2008.02.022
6. Li J, Zhu S, Wu Q (2019) Monthly crude oil spot price forecasting using variational mode decomposition. Energy Econ 83:240–253. https://doi.org/https://doi.org/10.1016/j.eneco.2019.07.009
7. Wang J, Li X (2018) A combined neural network model for commodity price forecasting with SSA. Soft Comput 22:5323–5333. https://doi.org/10.1007/s00500-018-3023-2
8. Meira E, Cyrino Oliveira FL, de Menezes LM (2021) Point and interval forecasting of electricity supply via pruned ensembles. Energy 232:121009. https://doi.org/https://doi.org/10.1016/j.energy.2021.121009
9. Cleveland RB, Cleveland WS, McRae JE, Terpenning I (1990) STL: A Seasonal-Trend Decomposition Procedure Based on Loess (with Discussion). J Off Stat 6:3–73
10. Athoillah I, Wigena AH, Wijayanto H (2021) Hybrid Modeling of Singular Spectrum Analysis and Support Vector Regression for Rainfall Prediction. J Phys Conf Ser 1863:12054. https://doi.org/10.1088/1742-6596/1863/1/012054
11. CONAB, Companhia Nacional A (2021) Informações Agropecuárias. https://www.conab.gov.br/info-agro. Accessed 7 Sep 2021
12. Centro de Estudos Avançados em Economia Aplicada C (2021) PIB do Agronegocio Brasileiro. https://www.cepea.esalq.usp.br/br/pib-do-agronegocio-brasileiro.aspx. Accessed 7 Sep 2021
13. Rodrigues PC, Tuy PGSE, Mahmoudvand R (2018) Randomized singular spectrum analysis for long time series. J Stat Comput Simul 88:1921–1935. https://doi.org/10.1080/00949655.2018.1462810
14. Hassani H, Webster A, Silva ES, Heravi S (2015) Forecasting U.S. Tourist arrivals using optimal Singular Spectrum Analysis. Tour Manag 46:322–335. https://doi.org/https://doi.org/10.1016/j.tourman.2014.07.004
15. Sugiura N (1978) Further analysts of the data by akaike' s information criterion and the finite corrections. Commun Stat - Theory Methods 7:13–26. https://doi.org/10.1080/03610927808827599
16. Hyndman RJ, Athanasopoulos G (2021) Forecasting: principles and practice, 3rd editio.

Melbourne

17. Box GEP, Jenkins GM (1970) Time Series Analysis: Forecasting and Control. Holden-Day
18. Gardner MW, Dorling SR (1998) Artificial neural networks (the multilayer perceptron)—a review of applications in the atmospheric sciences. Atmos Environ 32:2627–2636. https://doi.org/https://doi.org/10.1016/S1352-2310(97)00447-0
19. Huang G-B, Zhu Q-Y, Siew C-K (2006) Extreme learning machine: Theory and applications. Neurocomputing 70:489–501. https://doi.org/https://doi.org/10.1016/j.neucom.2005.12.126
20. Cepea (Center for Advanced Studies on Applied Economics) (2020) Price Index. http://www.cepea.esalq.usp.br/. Accessed 1 Jul 2020
21. Hyndman RJ, Koehler AB (2006) Another look at measures of forecast accuracy. Int J Forecast 22:679–688. https://doi.org/https://doi.org/10.1016/j.ijforecast.2006.03.001
22. Lima FG, Kimura H, Neto AA, Perera LCJ (2010) Previsão de preços de commodities com modelos ARIMA-GARCH e redes neurais com ondaletas: velhas tecnologias - novos resultados. Rev Adm 45:188–202. https://doi.org/10.1590/S0080-21072010000200008