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Co-movements and causalities between ethanol production and corn prices in the USA: New evidence from wavelet transform analysis

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ABSTRACT

The literature has been increasingly examining the existence of possible compatibility or conflict hypotheses between biofuels and food security in recent years. While current research outputs do not provide a consensus, the new evidence can guide sustainable development policies. In this context, this paper investigates the co-movements between fuel ethanol production and corn prices for the US employing oil production, population, and real exchange rate control variables via the Morlet wavelet analysis from 1990:m1 to 2021:m4. The results of the analysis provide empirical evidence for the dynamics of the relationship between ethanol production and corn prices in the short and long term. However, the striking output of this paper is that increases in corn prices have followed increases in fuel ethanol production in the US markets since 2010. Especially in the long-term (from 2010:m3 to 2019:m12), the increase in ethanol production caused an increase in corn prices. From a sustainable development perspective, this paper points to the existence of a conflict between ethanol production and corn prices in the US over the past decade.

1. Introduction

Global warming and climate change are still the most important global problems that the world should face. The global community continues to experience the economic, social, political, and environmental impacts of climate change [1]. Theoretical and empirical studies reveal that the source of the problem is greenhouse gas emissions (especially CO_2) based on fossil fuel use [2–4]. The effects of fossil resources are not limited to greenhouse gas emissions. Fossil fuels cause various pollutant gas emissions such as nitrogen oxides (NO_x), sulfur oxides (SO_x), carbon monoxide (CO), volatile organic compounds (VOCs), dust, and other particles, causing acid rain, soil pollution, and surface water and underground water emissions leads to changes in water quality [5]. This unsustainable situation causes significant pressure on political leaders to combat global warming and climate change [6]. On the other hand, currently, fossil resources such as oil, natural gas, and coal are the main natural resources to meet the energy demand in the world [7]. To cope with global warming and climate change and to reduce greenhouse gas emissions, the transition and transformation to renewable-clean energy in societies is now a necessity [8].

Biofuels are considered a promising alternative to replace fossil resources and transition to a sustainable energy system [9]. Biofuels, especially ethanol and biodiesel, offer great potential in combating climate change, energy security, sustainability of the transportation sector, increasing agricultural diversity, and supporting rural development [10]. Biofuels have three types of production technologies: first, second, or third-generation biofuels. First-generation biofuels are produced from various agricultural raw materials, primarily corn and sugar cane. Second-generation biofuels are obtained from non-food crops (lignocellulosic materials) such as wheat straw, and sugarcane meal. Third-generation biofuels are produced from algae, yeast, fungi, and cyanobacteria [5]. However, the dependence of biofuel production on agricultural raw materials can lead to fierce competition or a conflict between food demand and biofuel production. Assuming agricultural land is stable, the transition from food production to biofuel production may adversely affect the supply and price of commodities such as sugarcane, sugar beet, cassava, corn, rapeseed, soybeans, palm oil, and wheat [6]. In recent years, there has been a public concern and question marks about the potential effects of biofuel production on food security [11].

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When the literature on the relationship between biofuel production and food is evaluated, findings that support two opposing hypotheses, compatibility, and conflict, are observed. According to the conflict approach, biofuel production and incentives cause the use of agricultural raw materials for food production for energy production, and a transition from food agriculture to energy agriculture [12]. As the biofuel market expands, the use of water, fertilizer, farm machinery, capital, pesticides, and labor required for agri-food production is likely to shift to energy generation [13]. Therefore, biofuel production can put serious pressure on food prices and the security of supply. According to the compatibility approach, biofuel production indirectly affects food supply positively by lowering oil prices. Biofuels are economically feasible and the most viable-competitive option to replace fossil fuels [14]. The main input of product processing and transportation processes in the food and agriculture sector is crude oil [13]. The increase in oil prices has a direct effect on food prices due to cost pressure and indirectly through the exchange rate channel [15,16]. Table 1 presents the empirical literature results on the biofuel-food relationship. According to the literature findings (i) the first group of papers shows that biofuel production causes pressure on food supply, security, and prices and supports the conflict approach [13,17–21]. (ii) The second group shows that biofuels do not have a significant effect on food, but even positively affect food supply and security (Compatibility approach supported) [6,22–27]. (iii) There is no consensus on the biofuel-food relationship in the literature [13,25,28,29]. In terms of sustainability, new evidence or information on biofuel-food competition has become increasingly important in the literature.

From the relevant importance, this paper aims to investigate the co-movements between fuel ethanol production and corn prices for the US employing oil production, population, and real exchange rate control variables via the wavelet analysis from 1990:m1 to 2021:m4. The method followed estimates the relationships between ethanol and corn prices in periods corresponding to both low frequency and high frequency, considering all possible structural changes between the co-movements of the variables.

The organization of the paper is as follows. After the introduction, the importance of the research, motivation, and contributions are presented in the second section. The third section gives information about the method. The fourth section provides data and summary statistics. The fifth section reports the estimation outputs. The sixth section depicts discussion and political implications. The final section presents the conclusion.

2. Importance of research, motivation, and contributions

The importance of the research topic of this paper, motivation, and contributions are fourfold in terms of literature and policy recommendations.

First, the studies launched on the relationship between biofuels and food have very close links with the United Nations Sustainable Development Goals (SDGs). The use of biofuels is directly related to the blue economy, climate action, clean and sustainable energy transformation, circular economy, inclusive development, and prosperity [30–32]. Food-biofuel research is also directly related to the fight against poverty and hunger, and the objectives of responsible production and consumption [33–36]. Food security is one of the biggest challenges for the global community. It is reported that around 700 million people worldwide do not have access to healthy food [7].

On the other hand, there are few papers in the literature that discuss the relationship between biofuels and food within the scope of the SDGs [5]. Moreover, empirical evidence for the relationships between biofuels and food is insufficient. Current research covers the last decade (see Table 1). This paper contributes to the literature by revealing new information about the short-term and long-term dynamics between ethanol production and corn prices using the wavelet transform method. The empirical outputs of the paper are extensively evaluated in the final

Table 1
Literature summary.

Author	Time span	Method	Country/ region	Findings
Serra et al. [17]	1980–2008	Vector error correction model (VEC)	USA	The strong relationship between ethanol and corn prices and between gasoline and corn prices
Tokgoz et al. [18]	2005–2030	International model for policy analysis of agricultural commodities and trade	Different regions	Biofuels positively influence food prices.
Monteiro et al. [19]	1980–2007	Ordinary least squares (OLS)	USA and Brazil	Ethanol production increases food prices in Brazil and does not affect food prices in the USA.
Bahel et al. [20]	–	General equilibrium model	–	Biofuels increase food prices.
To and Grafton [37]	1981–2013	Autoregressive models	USA	Food prices are positively related to biofuels and oil prices.
Koizumi [21]	–	OLS	China, Thailand, Indonesia, Brazil, Malaysia, USA	Biofuel production negatively influences food security.
Dick and Wilson [38]	1995–2010	Partial equilibrium analysis	Nigeria	Ethanol production negatively affects food security and land use.
Martinez et al. [39]	2010–2030	Predictions with the system dynamics model	Colombia	Biofuel production raises food prices.
Lima et al. [40]	2000–2016	Detrended partial cross-correlation	Brazil	A strong and positive correlation between ethanol and sugar prices.
Maitah et al. [41]	2008–2016	Cointegration analysis	Brazil	Ethanol production positively affects food prices.
Gilbert and Mugera [42]	2000–2016	Regression method with the structural break	USA	Ethanol production enhances corn prices.
Ajanovic [22]	2000–2007	Comparative analysis with various statistics	The USA and Europe	Biofuels have little impact on food prices.
Gilbert [23]	1970–2008	Granger causality	Global data	Biofuels do not affect commodity prices.
Zilberman et al. [24]	–	Simulations and other theory-	–	Food prices are not

(continued on next page)

Table 1 (*continued*)

Author	Time span	Method	Country/ region	Findings
		based calculations		affected by biofuels.
Tyner [43]	Different periods	Graphical analysis	USA, Europe, and Brazil	Increases in food prices are not related to biofuels.
Bentivoglio et al. [28]	2007–2013	VEC, Granger causality	Brazil	Food prices are not influenced by the ethanol market.
Dutta [25]	2003–2016	Autoregressive distributed lag model and causality analysis	Brazil	Ethanol price fluctuations do not affect sugar prices, whereas sugar prices affect ethanol prices.
Taghizadeh et al. [26]	2000–2016	VEC	Eight Asian countries	Oil prices and biofuel prices respectively explain 65% and 2% of the increases in food prices.
Shrestha et al. [44]	1991–2016	Machine learning	USA	Global food prices are strongly affected by crude oil and population. Increases in food prices are not associated with biofuels. Biofuels do not change agricultural land use.
Subramaniam et al. [6]	2011–2016	Generalized method of moments	51 countries	Biofuels do not affect food prices. Biofuels increase food security.
Bilgili et al. [13]	1981–2008	Wavelet analysis	USA	Biofuels reduce food prices over the period 2011–2017.

section under the SDGs links. Thus, the paper can guide the development of sustainable development policies.

Second, currently, radical increases in global food prices are observed after the COVID-19 pandemic. The pandemic shock has devastating effects on food supply-demand dynamics and the food supply chain. Policy authorities began to impose restrictions on the food trade. International organizations such as the World Food Program (WFP), Food and Agriculture Organization (FAO), and International Food Policy Research Institute (IFPRI) are constantly calling for the abandonment of practices that will disrupt food trade balances [45]. Moreover, with globalization, energy, food, agriculture, and financial markets have become unprecedentedly interconnected. The interdependence between markets also pushes food prices upwards [46]. Therefore, the stability of food prices is one of the main agendas of the global society today [47]. However, even before the pandemic, global food prices had an upward trend. The global food price index value rose from 97.7 in 2003 to 201.4 in 2008, and 174.6 in 2017. Therefore, revealing the dynamics that drive global food prices is critical for the development of policies to ensure price stability [13]. Until recent years, the existing literature explained the increases in food prices with dynamics such as economic growth, population, urbanization, changes in precipitation and temperature regime, global warming and climate change, lack of agricultural land, or oil prices [48–51]. More specific indicators should be focused on to explain the reason for changes in global food prices. Is ethanol production in the USA a significant reason for the increase in corn prices? The related research question may help understand food price dynamics. Searching for an answer to a relevant research question is an important motivation for the creation of this paper.

Third, this paper focuses on the US ethanol market for research. This is a reasonable choice. The USA continues to lead the global biofuel industry with increasing demand for ethanol. The United States produced 6521 million gallons of ethanol in 2007, increasing to 15,379 million gallons in 2017. The USA accounts for about 60% of global ethanol production [52]. The USA is also a leading country in biofuel support and incentives. Comprehensive biofuel support and incentives such as the Environmental Protection Agency (EPA), Renewable Fuel Standard (RFS), and Low Carbon Fuel Standard (LCFS) play an important role in the growth of the ethanol market. Corn ethanol is an important renewable fuel in the USA, with its contributions to reducing greenhouse gas emissions from the transportation sector, energy security, agricultural gains, and rural development [53]. Although some studies suggest that the increase in global corn prices is due to the US ethanol market, there is a research gap on this issue [54]. Thus, this research can provide useful policy implications about the US ethanol market and its impact on food prices.

There have been papers that focus directly on the ethanol market for the past few years. For example, Dutta et al. [55] examine the links between the corn and ethanol markets in the United States with GARCH-jump models. The findings show that ethanol price changes respond positively to maize market volatility shocks after controlling for the impact of oil price uncertainty. It also reveals that the effect of volatility in paper corn prices on US ethanol prices is asymmetrical. In the other paper focusing on the ethanol market in Brazil, Dutta and Bouri [56] evaluate the effect of carbon emission prices on ethanol prices with GARCH-jump models. According to the findings, (i) carbon emission prices positively affect Brazilian ethanol prices. (ii) Increasing emissions prices cause an increase in the price of ethanol. (iii) Time-varying jumps occur in the ethanol price index. (iv) The effect of emissions prices on the ethanol market is asymmetrical. Bouri et al. [57] estimate ethanol price volatility by considering structural breaks in the US ethanol market. Forecasts show that the persistence of price volatility tends to decrease under structural breaks. On the other hand, this paper uses the wavelet transform method to estimate the ethanol-corn price relationship and differs from other papers in the literature in this respect. Existing research frequently demonstrates the effects of energy on food prices using correlation analyses, time series, and panel data models [13]. Such parameter calculations are average conditional estimators and do not change over time and frequency [58]. The wavelet transform method is a robust estimator and has significant advantages over other methods. The method provides information on real exchange rate, oil, and population control variables, as well as possible causal relationships between variables in the entire sample and all sub-samples about ethanol-corn prices. It also captures dynamic co-movements and causality at different time frequencies [59]. The following section provides detailed information about the method.

One can observe, throughout the literature, the applications of frequency and/or frequency-time analyses such as Fourier transform (FT) analyses, FT causality analyses, discrete wavelet transform (DWT), shift-invariant discrete wavelet transform (SIDWT), maximum overlap discrete wavelet transform (MODWT) and continuous wavelet (CWT).

FT can analyze the cyclical nature of a time series in the frequency domain. However, under FT, the time domain properties of a time series might be lost. FT and wavelet transform are commonly used methods in frequency analyses. The FT is a suitable method for the analysis of stationary time series. FT Granger causality analyses also require stationary time series variables. For instance, Breitung and Candelon [60] conduct causality tests in the frequency domain to observe if there exists a causality from term spread to economic growth by employing I(1) variables of growth and spread. However, taking differences in a time series to reach stationarity might also result in losses in the original time series. Differencing (with the possibility of throwing information away) may not provide gain in asymptotic efficiency and can not capture the long-run relationship between the variables [61]. So, the FT may not be an efficient method for researchers using non-stationary time series. For this reason, this paper used the wavelet transformation technique, which allows the analysis of non-stationary time series.

Wavelet analysis is a technique using a mathematical representation of the Fourier transform together with a new feature of the transform called scaling. Wavelet has the advantage of localizing signals both in the time and frequency domain simultaneously. The wavelet transforms, as the best technique for the non-stationary time series, are filtered into different frequency bands, which are divided into segments in the time domain.

DWT computes the transform for a very special discrete choice of the parameter values for time and frequency. This provides a very efficient and simple iterative procedure to compute the transform. The DWT applications, hence, are popular due to their simplicity and low computational cost [62–64].

As opposed to the DWT, SIDWT is time-invariant which provides some translation in time even after applying a "signal extension" process. Bekiros and Marcellino's paper [65] follows the SIDWT methodology and relies on wavelet multiresolution analysis to investigate the dependence structure and predictability of currency markets across different timescales. Their research presents an invariant discrete wavelet transform that contains no phase shifts and enables multiscale point-to-point comparison.

We employed continuous wavelet transform (CWT) and partial continuous wavelet transform (PCWT) analyses. CWT requires more computational time — but provides researchers with large freedom in selecting the wavelets, while this choice is more limited in the discrete setting. CWT can make it much easier to interpret the results obtained and to draw conclusions from the data. The MODWT can be considered a compromise between the DWT and the CWT as it is a redundant transform, because while it is efficient with the frequency parameters it is not selective with the time parameters, but is not as redundant as the CWT [63,66]. Finally, the PCWT methodology provides us with the employment of some most relevant control variables in the wavelet model. Instead of bivariate models, the employment of control variables as well as main variables leads us to better defined(specified) models. The methodology section will present CWT in detail through relevant functions.

3. Methodology

The wavelet analysis is a widely used frequency-analysis technique [67–72]. Wavelet analysis is a method that allows frequencies to evaluate their correlation levels at different frequency scales and at different moments in time. In practice, each time series is decomposed at different frequencies in a time-frequency space, and this decomposition can be done using different wavelet transforms [73]. Thus, wavelet transforms can be provided not only the time-varying power spectrum but also the phase spectrum needed for coherence calculation [74].

Continuous wavelet transform (CWT) is used to transform the signal with a resolution appropriate to its scale and provides both spectral and temporal information [75] between a given signal $x(t)$ and the wavelet function $\widetilde{\alpha}^*_{\tau,\&}(t)$. The CWT of $\{X\} \in L^2(\mathbb{R})$ with relating to wavelet $\widetilde{\alpha}^*_{\tau,\&}(t)$ is written as follows:

$$W_{x(\tau,\&)}(t) = 1 \Big/ \sqrt{\&} \int_{-\infty}^{\infty} x_{(t)} \widetilde{\alpha}^* \left(\frac{t-\tau}{\&}\right) dt \begin{cases} \& \neq 0 \\ \tau, \& \in R \end{cases} \tag{1}$$

In Eq. (1), the $W_x(\tau,\&)$ represents wavelet coefficients at translation (τ) and scale ($\&$) in the time-scale band. The asterisk (*) indicates the complex conjugate. The term $1/\sqrt{\&}$ denotes the normalization parameter providing unit variance of wavelet. The term & is the scaling parameter, which depicts the position in the frequency domain of the wavelet. The term τ is the translation parameter, which checks the location of the wavelet in the time domain.

Morlet wavelet transform, one type of the CWT, is defined as a set of functions in the form of small waves created by dilations and translations as a tapering sine wave by a Gaussian [76]. The Morlet wavelet was first formulated by Grossmann and Morlet [77] as follows.

$$\widetilde{\alpha}_{\omega 0}(t) = \pi^{-\frac{1}{4}} e^{i\omega_0 t} e^{-\left(t^2/2\right)} \tag{2}$$

Here, the term ω represents the central frequency term of the Morlet wavelet $\widetilde{\alpha}_{\omega 0}(t)$. For examining the covariance between two-time series, Torrence and Compo [78] defined x_t and y_t, with continuous wavelet transforms W_x and W_y, as is given in Eq. (3).

$$W_{xy}(\tau,\&) = W_x(\tau,\&) W_y{}^*(\tau,\&) \tag{3}$$

The wavelet coherency of two-time series $\mathscr{W}_x(\tau,\&)$ and $\mathscr{W}_y(\tau,\&)$ can be defined as follows [63].

$$\Re_{xy}(\tau,\&) = \frac{\left|\mathbb{S}\left(W_{xy}(\tau,\&)\right)\right|}{\sqrt{\mathbb{S}\left(\left|W_{xx}(\tau,\&)\right|\mathbb{S}\left(\left|W_{yy}(\tau,\&)\right|\right)\right)}} \tag{4}$$

Here, the $\Re_{xy}$ demonstrates the correlation, it ranges from strong consistency to no coherency (1–0) in both time and frequency bands. Parameter $\mathbb{S}$ is the smoothing parameter that restricts the coherency from being an optimal performance at all scales and times.

The wavelet phase difference between $\{X\}$ and $\{Y\}$ can be obtained with the complex-valued $\delta_{xy}\ (t)$ functions as indicated by Eq. (5).

$$\delta_{xy}(\tau,\&) = tan^{-1}\left(\frac{\mathfrak{Im}\left(W_{xy}(\tau,\&)\right)}{\mathfrak{Re}\left(W_{xy}(\tau,\&)\right)}\right) \tag{5}$$

$\mathfrak{Re}(.)$ and $\mathfrak{Im}(.)$ in Eq. (5) are respectively the real, and imaginary parts of the W_{xy}, and hence the co- and quadrature wavelet spectra of $x(t)$ and $y(t)$.

4. Data and summary statistics

This paper investigates the co-movements between fuel ethanol production and corn prices for the US employing oil production, population, and real exchange rate control variables via the Morlet wavelet analysis from 1990:1 to 2021:4. Corn prices (U.S. Dollars per bushel), real exchange rate, and population (total) data are obtained from the United States Department of Agriculture National Agricultural Statistics Service (USDA NASS) and the US, Bureau of Labor Statistics. Ethanol (Trillion Btu) and oil production (Thousand Barrels) data is obtained from the US, Energy Information Administration (EIA). Table 2 shows descriptive statistics. The trend graphs of the variables are shown in

Table 2
Summary statistics.

Statistics	Fuel ethanol product.	Corn price	Oil production	Population	Real exchange rate
Mean	50.35	3.21	214619.17	294675.08	109.57
Median	28.61	2.79	196,992	296,472	109.46
Std. Dev.	42.87	1.32	60281.99	24423.48	8.44
Minimum	3.92	0.29	119,208	248,743	93.06
Maximum	119.99	7.63	400,219	331,126	129.03
Observation	376	376	376	376	376

figures from 1 to 5 to provide visual information.

From Fig. 1 to Fig. 5., there are trend graphs of the US fuel ethanol production, the US corn price, the US oil production, the US population, and the US real exchange rate variables, respectively. Figs. 1, 3 and 4 indicate that the fuel ethanol production, oil production, and population tend to increase for the whole sample period. According to Fig. 5 it is seen that the real exchange rate data points fluctuate around the average until the end of the period. One may observe from Fig. 2 that realized data points of corn price demonstrate more severe fluctuations than fuel ethanol production data do. Table 3 reveals the trend equations of the variables.

Although CWT does not require unit root tests as it can analyze nonstationary time series, one might wonder if the variables have unit roots with structural breaks. We conducted Lumsdaine-Papell unit root tests considering structural breaks The outputs yield that except for population, all variables are found stationary in differences I(1) with two breaks (Appendix A). We performed Lumsdaine-Papell unit root tests considering structural breaks through RATS program lines. The program code and output are as follows. The outputs reveal that except for population, all variables are found stationary in differences with two breaks. We launched also the Lee-Strazicich unit root test with structural breaks and LS found DPOPULATION I(1) as well. Later, we analyzed the cumulative sum of recursive residuals or the cumulative sum of OLS residuals to determine to test whether there is a structural break. Under the null hypothesis, the cumulative sum of residuals will have a mean of zero. We found that the main variables of ethanol production and corn price and control variables have structural breaks by rejecting the null hypothesis of no structural breaks at 1% levels (Appendix B).

5. Estimation output

In this paper, we investigate the co-movements of the US fuel ethanol production and the US corn price through the Morlet wavelet analysis. Fig. 6 shows the wavelet analysis of fuel ethanol production and corn prices. Fig. 9 illustrates the wavelet analysis between fuel ethanol production and corn prices with the inclusion of the control variables of oil production, population, and real exchange rate in the model.

Thick black curves in Fig. 6 and 7 show the cone of influences introducing the border distortions. In the colour bar, the dark blue colour demonstrates the weakest consistency, and the dark red colour represents the strongest consistency. Figs. 7 and 10 yield the phase difference outputs in 1–3 frequency bands, and Figs. 8 and 11 reveal the phase difference results in 3–8 frequency bands. 1–3 frequency bands display lead-lag correlations in relatively short-term cycles and 3–8 frequency bands exhibit lead-lag correlations in relatively longer-term cycles. One might define the lead variable as the variable which can predict the shifts in the lagging variable. Or, one may consider a lead-lag relationship a causality relationship between the variables.

Notes: Description of phase difference figures:

(a) The vertical axes show the phase differences with lead-lag relations of the variables.

Phase difference	Lead-lag relationship
pi/2; pi	Negative correlation and y is leading
0; pi/2	Positive correlation and x is leading
0	Positive correlation and x-y move together
0;-pi/2	Positive correlation and y is leading
-pi/2;- pi	Negative correlation and x is leading

(b) The horizontal axes show the monthly period from January 1990 to April 2021.

The interpretation of the outputs of figures step by step:

1 We consider blue regions weak associations between the variables and red regions strong associations between the variables (1995–2001, 2012–2015, and 2018–2021 at 1–3 year cycle).
2 After observing the strong associations between the variables (Fig. 6), we analyze phase difference outputs at the 1–3 frequency band (Fig. 7) and the 3–8 frequency band (Fig. 8). In this step, (a) lead-lag relations between the variables and (b) negative or positive associations between the leading variable and lagging variable are monitored through phase difference analyses which show lead-lag relations and positive/negative associations between the variables.

According to Figs. 6 and 7, (a) corn price is leading fuel ethanol production and a reduction in ethanol production is associated with corn prices during 1995–2001, (b) fuel ethanol production is leading corn prices and declines in corn prices are associated with increases in fuel ethanol production for the period 2012–2015, (c) fuel ethanol production is again leading corn prices and increases in corn prices are accompanied by increases in fuel ethanol production for the period 2018–2021. Since Fig. 6 does not reveal strong movement between the variables at a 3–8-year cycle, it will not be meaningful to interpret Fig. 8.

One might, however, claim that the wavelet estimation output is given in Fig. 6 cannot capture the co-movements between the variables well. Since the relationship between the fuel ethanol production and corn price is not demonstrated in the wavelet coherence analysis, the control variables (oil production, population, and real exchange rate) will be included in the model and the partial wavelet coherence analysis will be launched.

With the control variables, the outputs of partial wavelet analyses are given in Fig. 9. And, the phase difference analyses are given in Fig.s. 10 and 11. As Fig. 10 expresses the leading-lagging correlations in the short-term cycle (frequency of 1–3 years), Fig. 11 exhibits the lead-lag association between the variables in the long-term cycle (frequency of 3–8 years).

When Figs. 9, and Fig 10 are evaluated simultaneously at 1–3 frequency band (sort term), the main outcomes are as follows:

- In the period 1991:1–1999:7, there exists a negative association between the variables and the corn prices lead ethanol production. A

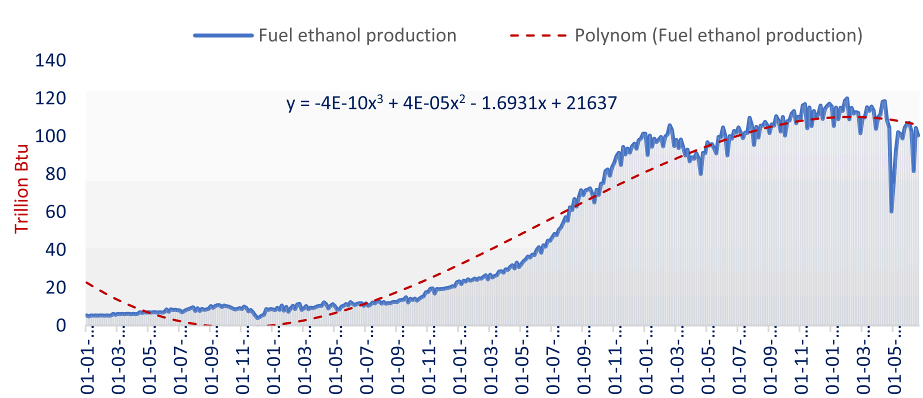


Fig. 1. The US fuel ethanol production. **Data source:** EIA.

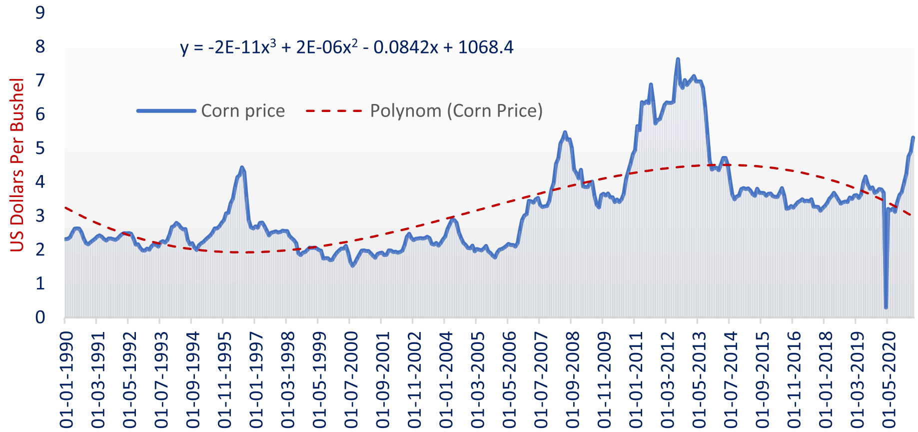


Fig. 2. The US corn price. **Data source:** USDA NASS.

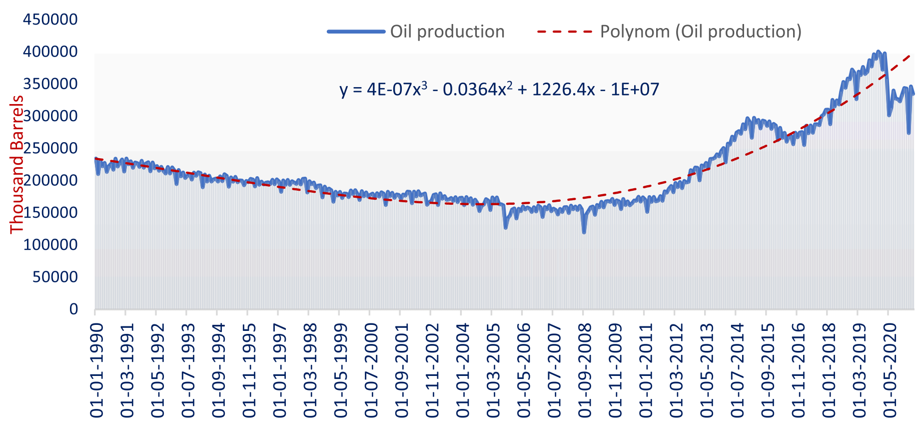


Fig. 3. The US oil production. **Data source:** EIA.

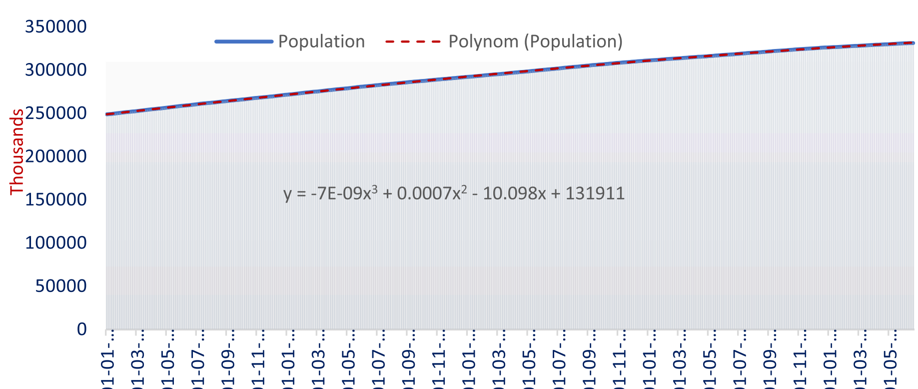


Fig. 4. The US population. **Data source:** U.S. Bureau of Economic Analysis.

decrease in ethanol production is associated with increases in corn prices.

- In the periods 2005:3–2011:12, and 2018–2019, there is a positive association between the variables, and fuel ethanol production leads to corn prices. An increase in fuel production is accompanied by an increase in corn price.

When Figs. 9, and Fig 11 are evaluated simultaneously (3–8 frequency band/long term):

- In the periods 1992:1–1995:10, and from 2010:3 to the end of the sample, fuel ethanol production is the leading variable, and corn price is the lagging variable. An increase in ethanol production is accompanied by increases in corn price.
- In the periods 1995:11–1996:1, and 2007:1–2008:2, there exist positive co-movements. Corn prices are leading. An increase in corn prices is accompanied by an increase in fuel ethanol production.

In summary, one might observe from the wavelet coherence analyses that.

(a) In the shorter term (1–3 year cycle), during 2005–2011and 2018–2019, ethanol production is the leading variable as corn

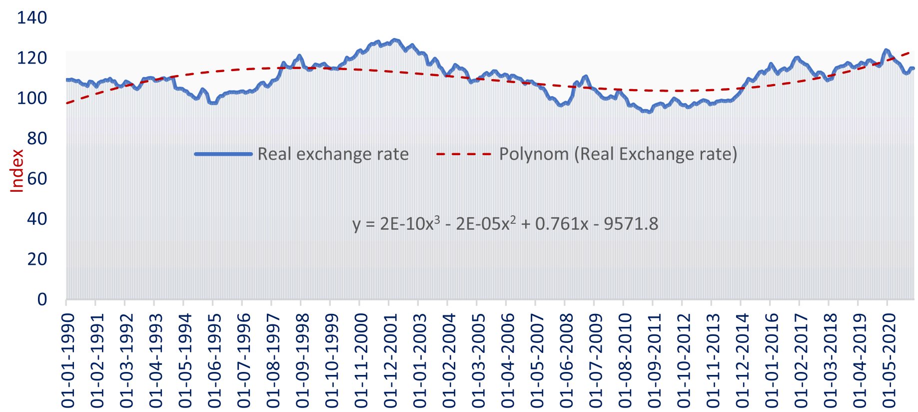


Fig. 5. The US real exchange rate. **Data source:** USDA NASS.

Table 3
Trend equations.

Variables	Trend Graph	Trend Equation
Fuel ethanol product.	Fig. 1.	-4E-10 × ^{3} + 4E-05 × ^{2} - 1.6931x + 21,637
Corn price	Fig. 2.	-2E-11 × ^{3} + 2E-06 × ^{2} - 0.0842x + 1068.4
Oil production	Fig. 3.	4E-07 × ^{3} - 0.0364 × ^{2} + 1226.4× - 1E+07
Population	Fig. 4.	-7E-09 × ^{3} + 0.0007 × ^{2} - 10.098x + 131,911
Real exchange rate	Fig. 5.	2E-10 × ^{3} - 2E-05 × ^{2} + 0.761× - 9571.8

Source: Author's calculation

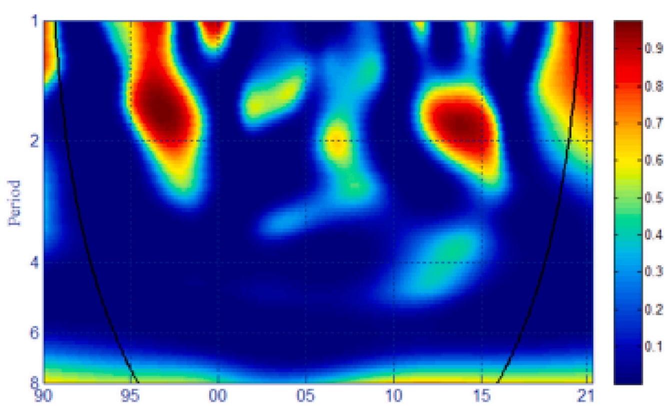


Fig. 6. Wavelet coherence (Fuel ethanol product, corn price). Notes: (a) Fig. 6 presents the wavelet coherency between fuel ethanol production and corn prices; (b) The vertical axis includes cycles of 1, 2, 4, 6, and 8 years; (c) the horizontal axis shows the monthly period from January 1990 to April 2021; (d) The thick black curves show the cone of influences introducing the border distortions; (e) In the color bar, the dark blue colour demonstrates the weakest consistency, and the dark red colour represents the strongest consistency.

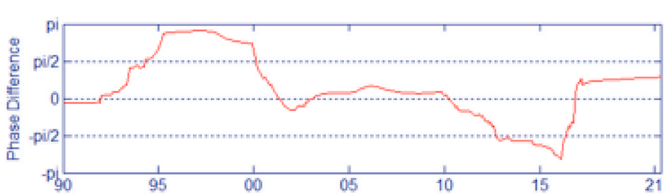


Fig. 7. 1–3 frequency band.

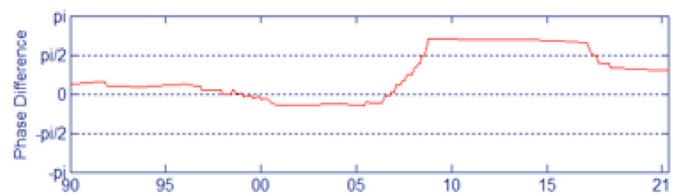


Fig. 8. 3–8 frequency band. Notes: Description of phase difference figures.

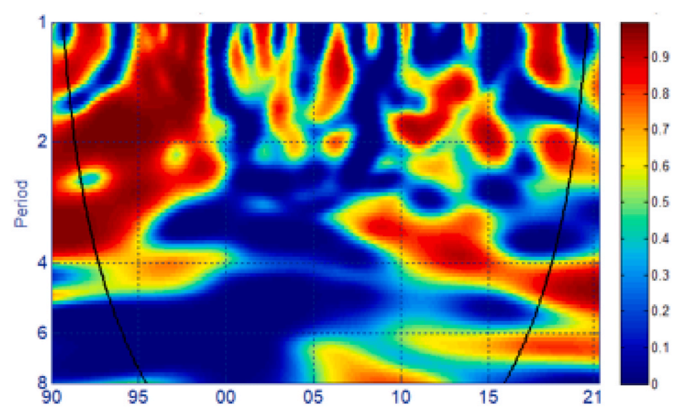


Fig. 9. Partial wavelet coherence (Fuel ethanol product, corn price//oil production, population, real exchange rate).

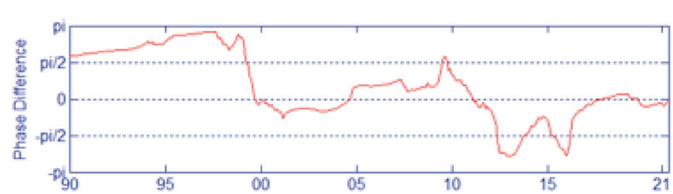


Fig. 10. 1–3 frequency band.

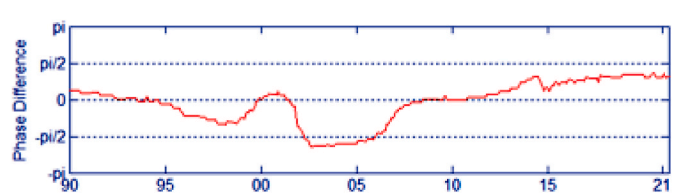


Fig. 11. 3–8 frequency band.

prices are lagging. And, an increase in corn prices is associated with an increase in ethanol production.

(b) In the longer term (3–8 year cycle), especially for the period; from 2010 till the end of the sample, ethanol production is again the leading variable as corn prices are lagging. And, an increase in corn prices is associated with an increase in ethanol production.

Eventually, the striking output of partial wavelet computation is that increases in corn prices follow the increases in fuel ethanol production since 2010 in the US markets. Especially in the long-term (from 2010:m3 to 2019:m12), the increase in ethanol production caused an increase in corn prices. Table 4 reports summary information on co-movements and causal relationships between ethanol production and corn prices. In other words, Table 4 is the summary of the analysis results in Figs. 9–11. Table 4 is evaluated in general, there is a negative co-movement between the variables in the period 1991:7–1999:7, which shows the phase angles π, $\pi/2$ in 1–3 frequency bands, while there is a positive co-movement in the other periods (2005:3–2011:12; 2018:12–2019:12; 1992:1–1995:10 2010:3–2019:12; 1995:11–1996:1; 2007:1–2008:2). (i) In the phase difference where there is a negative co-movement in the 1~3 frequency bands, the increase in corn price in the period 1991:7–1999:7 causes (leads) a decrease in fuel ethanol production. (ii) The increase in fuel ethanol production in the phase angle $\pi/2$,0 in the 1–3 frequency bands (2005–2011, and 2018–2019 periods) causes (leads) an increase in corn price. (iii) In the phase difference where there is a positive co-movement in the 3–8 frequency bands, the increase in fuel ethanol production in the period 1992:1–1995:10, and 2010:3–2019:12 causes (leads) an increase in corn prices. (iv) The increase in corn prices in the phase angle 0,-$\pi/2$ in the 3–8 frequency bands (1995:11–1996:1, and 2007:1–2008:2 periods) causes (leads) an increase in fuel ethanol production.

In some seminal papers in the literature, the frequencies are determined through short-term cycles (1–2 year or 1–3 year frequency bands) and long-term cycles (2–4 year or 3–7, or 3–8 year frequency bands) as given in Aguiar-Conraria, Soares [79]. The business cycle frequencies might range from 1.5 to 8 years and hence the frequencies might be chosen in the range of 1.5–8 or 8+ year time periods or similar periods (time cycles) as is explained in Gallegati and Gallegati [80], Aguiar-Conraria and Soares [79], Kilian and Park [81], and Baumeister and Peersman [82].

Hence, in summary, frequencies were chosen to observe the co-movements between the variables within the range of the short time cycle and long-term cycles. Short-term cycles (or highest frequency) might represent spot prices as well and long-term cycles (lower frequencies) might refer also to the future prices in the markets. Producers, consumers, and government authorities in the ethanol and corn markets need to follow rationally both short-run and long-run cycles to assess the market data, price assessments for major export positions, crop forecasts in key exporting countries, based on weather conditions, and many other factors and market trends [83–87]. For instance, Demirer et al. [86] reach the evidence that ethanol has a positive impact on both price and volatility in the corn market (especially in the spot and the shorter maturity futures contracts). It is clear that the futures prices of bio-ethanol and the two agricultural commodities, corn, and sugarcane, have stronger co-volatility spillovers than their spot price counterparts. Chang et al. [87] reach the evidence that the futures prices of bio-ethanol and corn and sugarcane follow stronger co-volatility spillovers than their spot price counterparts.

Table 4
Summary of partial wavelet coherence analysis results.

Term	Periods	Phase	Co-movement	Causality
1–3	1991:7–1999:7	π, $\pi/2$	−	corn prices → fuel ethanol production
1–3	2005:3–2011:12 2018:1–2019:12	$\pi/2$,0	+	fuel ethanol production → corn prices
3–8	1992:1–1995:10 2010:3–2019:12	$\pi/2$,0	+	fuel ethanol production → corn prices
3–8	1995:11–1996:1 2007:1–2008:2	0,-$\pi/2$	+	corn prices → fuel ethanol production

Throughout wavelet coherency estimations one might consider Frequency domain causality tests as well to compare with the outputs of wavelet coherency analyses. The results are given in Appendix C.

We obtained also (a) Decomposition trees from estimated CWT computations by Shannon entropy at different levels (1, 2, 3, 4, and 5) and (b) Best Level Decomposition trees by Shannon entropy. Computing the best tree makes the de-noising calculations more efficient. The outputs are presented in Appendix D.

6. Discussion, and political implications

Biofuels attract attention as an important alternative source against concerns about energy supply, energy security, and environmental pollution. Technical and economic feasibility studies show biofuels as an important and potential renewable resource in terms of sustainability. The fact that it has a high storage capacity and does not have a reserve problem further increases the importance of biofuels [14,88]. However, the increase in global food prices observed in recent years raises concerns about biofuels. Although researchers have identified many variables that affect food prices, oil prices or production shocks are the most prominent indicators. On the other hand, its fluctuations in the energy market and the food market always attract great attention in the literature [46]. The literature has been following the impact of oil production or price shocks on food prices since the oil price shocks of the 1970s [89,90]. The upward trend in global food prices has been observed in the last two decades. There has been a sharper rise in the last ten years. In the same period, a serious decrease is observed in oil prices, especially after 2011 [13]. In the same period, there was an unprecedented increase in global biofuel production, especially in the USA, China, and Brazil. The arguments that biofuel production may be another important reason for the increase in food prices are consistent. Some papers advocate views to the contrary. The compatibility approach emphasizes that biofuel production lowers fossil energy prices and lowers food production costs.

Our findings show that ethanol production in the USA has had an increasing effect on corn prices after 2010. Ethanol production in the USA in the last decade is an important reason for the increase in corn prices. Our outputs are similar to the findings of papers supporting the conflict approach [13,17–21]. We can argue that there are two possible reasons behind these results, both theoretical and political. The pressure of ethanol production on corn prices can be explained by the deterioration in supply and demand balances. Demand-side arguments emphasize that the reason for food price increases is not only population, urbanization, and increased nutritional needs, but also increasing demand for biofuels. According to this approach, the main sources of raw materials for biofuel production are agricultural products such as corn, sugar, sugarcane, wheat, straw, sorghum, rice, potatoes, rye, and barley. With the biofuel production boom, agricultural raw materials that were previously produced for the food sector are diverted to the energy sector. Hence, additional demand from the energy sector puts pressure on food prices, and food prices may rise [21]. Supply-side arguments draw attention to biofuel and food competition. The growth in the biofuels market leads to competition with the food market in the use of land, water, fertilizers, agricultural physical capital, pesticides, and labor. Competition triggers the rise in food prices by causing difficulties in using inputs and increasing costs in food production [91]. Therefore, the increase in food prices through supply and demand-side channels of biofuels is in line with theoretical expectations.

In the political context, the possible reason for ethanol production to increase corn prices in the USA is renewable energy incentives and subsidies. In the USA, especially ethanol is the most prominent fuel among renewable energy sources to meet the increasing energy demand and sustainable economy [92]. Ethanol is a first-generation biofuel, and its main raw material is corn. The federal government's directive of ethanol production for renewable fuel standards affects the supply and consumption of corn for food. Some studies argue that corn prices increase due to ethanol production and incentives [93].

Although biofuels compete with the food market, they are undoubtedly a very important renewable energy source for a sustainable energy transformation. Incentives, support, and subsidies from governments for biofuel production are indispensable. However, the pressures of biofuels on food can be alleviated with some optimistic approaches. Practices that will increase efficiency in the use of agricultural lands can direct the production of more food, energy, and raw materials. Researchers confirm that innovative farming practices, agricultural technology advances, and large-scale agricultural investments in recent years have resulted in tremendous yield increases in land use [94]. The second optimistic implication is the fact that biofuels can lower food production costs by reducing fossil fuel prices, especially crude oil prices. It underlines the increasing use of biofuels in the transportation sector as a possible reason for the decline in oil prices over the last decade [95].

Finally, advances in biofuel technologies also have critical implications for biofuel-food competition. The world has now reached the third generation of biofuel technologies. First-generation biofuels are produced with agricultural products such as corn, sugarcane, soy, mushrooms and sunflowers. The most serious objections to biofuels are that these products are used as fuel raw materials and cause a food crisis. While the raw material of second-generation biofuels is wheat straw, cellulose, wood and biomass wastes, algae are among the third-generation biofuel raw material sources. The need for raw materials to produce second and third-generation biofuels is not large enough to put pressure on food production, and its energy efficiency is much higher than for first-generation biofuels [96–98]. Hence, second and third-generation biofuels appear to be an important option for renewable energy conversion. Considering that ethanol is mostly produced from corn in the USA, it can be stated that agricultural wastes, corn stalks, trees or algae are much more suitable sources for ethanol production. After all, this paper suggests that policy authorities consider possible pressures on food prices when developing strategies for biofuel production.

7. Conclusion

This paper examines the co-movements and causal relationships between fuel ethanol production and corn prices for the United States using Morlet wavelet analysis from 1990:m1 to 2021:m4. Oil production, population, and real exchange rate control variables are included in the model as control variables. Estimations provide insights into the dynamics of the relationship between ethanol production and corn prices in the short and long term. The striking output of the paper is that since 2010, increases in fuel ethanol production in the US markets are followed by increases in corn prices. In the long run, from 2010:m3 to 2019:m12, the increase in ethanol production is observed to drive the increase in corn prices. Our findings confirm that there is a conflict or trade-off relationship between the ethanol market and corn prices in the USA. Biofuels have a central role in energy security, climate change, and rural development goals. As alternative and competitive fuels to fossil fuels, it is critical for a clean and sustainable energy transition. However, this research provides robust evidence that biofuels affect food security by putting pressure on food prices. The output of the paper has important implications for ethanol investors and policymakers. First, demand and supply-side approaches in the biofuel-food competition should be considered in all their dimensions. Second, renewable energy incentives and subsidies from governments are critical to a renewable energy transition. More efficient use of farmland prerequisites for related supports can alleviate the pressure of biofuel production on food prices. Third, developments in second and third-generation biofuel technologies are promising for the future renewable energy transformation.

There is no doubt that more research is needed on the biofuel-food relationship. Future research may initiate research on other important Chinese and Brazilian markets besides the US market. Researchers can test conflict or compatibility approaches with different empirical methods. Within the framework of the interaction between global markets, the effects of biofuels on food can be focused on. Finally, empirical research, particularly in biofuel markets, may consider long-range dependence. Long-range dependence is a phenomenon that can occur in the analysis of spatial or time-series data and is related to the increasing time interval or the spatial distance between points and the rate of deterioration of the statistical dependence of two points [99]. Hence, papers that take long-range dependence into account can provide new and robust information to the literature on the biofuel-food nexus. All initiatives will guide a more sustainable global society.

Credit author statement

Conceptualization: EK, FB, UB; **Methodology:** EK, UB, SK; **Software**: UB, SK; **Validation:** EK, FB, UB, SK, Investigation: EK, FB, UB, SK, Resources: EK, FB, UB, SK; **Data Curation:** UB, SK; **Writing - Original Draft**: EK, FB, UB, SK; **Writing - Review & Editing**: EK, FB, UB, SK; **Visualization:** FB, EK; **Supervision**: FB, EK; **Project administration:** FB, EK; EK: Emrah Koçak; FB: Faik Bilgili; UB: Umit Bulut; SK: Sevda Kuskaya.

Declaration of competing interest

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

Data availability

Data will be made available on request.

Appendix

Appendix A. Lumsdaine-Papell Unit Root Tests considering structural breaks

Table A1
Lumsdaine-Papell Unit Root Test With Structural Breaks, Series ETHANOL

Variable	Coefficient	T-Stat
Y{1}	−0.1701	−4.1788
DT(2004:12)	0.1973	4.1822
DT(2010:03)	−0.2072	−4.8043

(*continued on next page*)

Table A1 (*continued*)

Variable	Coefficient	T-Stat
Constant	0.4287	0.6807
Trend	0.0178	3.0553

Table A2
Lumsdaine-Papell Unit Root Test With Structural Breaks, Series CORNPRICE

Variable	Coefficient	T-Stat
Y{1}	−0.0694	−3.3189
DT(2004:09)	0.0033	2.2445
DT(2011:02)	−0.0045	−2.3984
Constant	0.1774	2.5171
Trend	−0.0002	−0.4442

Table A3Lumsdaine-Papell Unit Root Test With Structural Breaks, Series OILPROD

Variable	Coefficient	T-Stat
Y{1}	−0.1524	−3.8930
DT(1995:04)	38.2301	0.6312
DT(2008:08)	275.0052	3.5517
Constant	35262.5848	3.7381
Trend	−83.2039	−1.5108

Table A4
Lumsdaine-Papell Unit Root Test With Structural Breaks, Series POPULATION

Variable	Coefficient	T-Stat
Y{1}	−0.0023	−2.7236
DT(2007:05)	−0.1498	−2.8755
DT(2016:04)	−0.2328	−3.4695
Constant	612.5692	2.9181
Trend	0.5229	2.4992

Table A5
Lumsdaine-Papell Unit Root Test With Structural Breaks, Series EXCHANGERATE

Variable	Coefficient	T-Stat
Y{1}	−0.0517	−4.1113
DT(2001:04)	−0.0216	−3.5038
DT(2010:09)	0.0240	3.7438
Constant	5.1135	4.0379
Trend	0.0090	3.0184

We also conducted the Lee-Strazicich Unit Root Test with structural breaks for the Population series. Wd reached the evidence of I(1) for the population series.

Table A6
Lee-Strazicich Unit Root Test With Structural Breaks, Series POPULATION

Variable	Coefficient	T-Stat
S{1}	−0.0043	−2.3999
Constant	271.6439	217.1153
D(1997:08)	25.3145	2.1358
DT(1997:08)	−39.4952	−18.4190
D(2012:08)	51.0588	4.3222
DT(2012:08)	−69.6131	−47.1996

Table A7
Lumsdaine-Papell Unit Root Test With Structural Breaks, Series DETHANOL

Variable	Coefficient	T-Stat
Y{1}	−3.0002	−9.7825
DT(2003:08)	0.0478	2.4407
DT(2008:03)	−0.0808	−3.9369
Constant	−0.0160	−0.0242
Trend	0.0031	0.4927

Table A8
Lumsdaine-Papell Unit Root Test With Structural Breaks, Series DCORNPRICE

Variable	Coefficient	T-Stat
Y{1}	−1.1533	−22.3861
DT(2010:10)	−0.0031	−2.3539
DT(2015:05)	0.0062	2.6593
Constant	−0.0229	−0.6144
Trend	0.0003	1.2347

Table A9
Lumsdaine-Papell Unit Root Test With Structural Breaks, Series DOILPROD

Variable	Coefficient	T-Stat
Y{1}	−1.9253	−8.6018
DT(2008:09)	97.1194	2.1927
DT(2013:07)	−167.6646	−2.5845
Constant	−777.0284	−0.5618
Trend	1.5269	0.1559

Table A10
Lumsdaine-Papell Unit Root Test With Structural Breaks, Series DPOPULATION

Variable	Coefficient	T-Stat
Y{1}	−0.1060	−3.2240
DT(2007:01)	−0.0145	−0.7340
DT(2015:12)	−0.0941	−2.0061
Constant	30.0724	3.1697
Trend	−0.0331	−2.6639

Table A11
Lumsdaine-Papell Unit Root Test With Structural Breaks, Series DEXCHANGERATE

Variable	Coefficient	T-Stat
Y{1}	−0.7704	−12.9914
DT(1997:12)	−0.0153	−2.1365
DT(2003:05)	0.0105	2.2016
Constant	−0.2876	−1.1429
Trend	0.0066	1.7046

Table A12
Lee-Strazicich Unit Root Test With Structural Breaks, Series DPOPULATION

Variable	Coefficient	T-Stat
S{1}	−0.2429	−10.9338
Constant	19.0711	8.4337
D(1994:02)	40.3388	4.3902
DT(1994:02)	−13.0027	−6.5758
D(2005:02)	8.3818	0.9093
DT(2005:02)	7.2182	5.8593

Table A13
LP Critical Values

Sig Level	Crit Value
1%(**)	−7.1900
5%(*)	−6.6200
10%	−6.3700

Table A14
LS Critical Values

Sig Level	Crit Value
1%(**)	−5.7416
5%(*)	−5.1784
10%	−4.9252

If the T-stat of Y(1) or S1 is less than the critical value in absolute value, we can reject the null of a unit root. Throughout Lumsdaine-Papell, except population, all variables are found stationary in differences [I(1)] with two breaks. Lee-Strazicich unit root test with structural breaks found DPOPULATION I(1). as well.

Appendix B. Cumulative Sum of Recursive Residuals or the Cumulative Sum of OLS Residuals to Determine to Test Whether There is A Structural Break

We found that the main variables of ethanol production and corn price and control variables have structural breaks by rejecting the null hypothesis of no structural breaks at 1% levels. The relevant statistical outputs can be provided upon request of the potential reader.

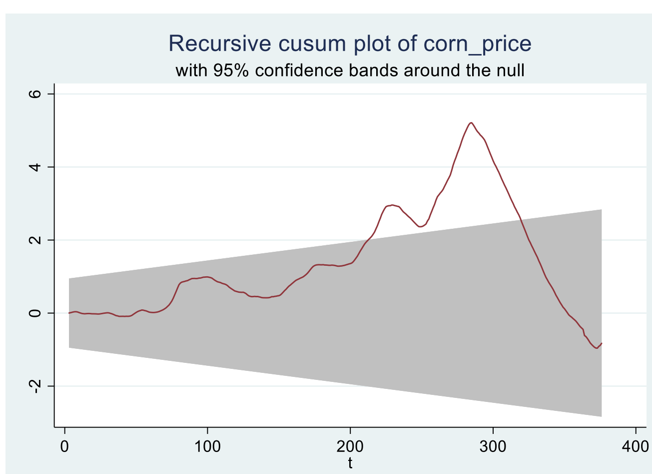


Fig. B1. Corn_Price: Ho: No structural break

The red line is the cumulative sum. If the red line is in the shaded area, the test would have not rejected the null hypothesis at the 5% level. The graph for the corn_price indicates that corn_price has a structural break(s) by rejecting the null of no structural break.

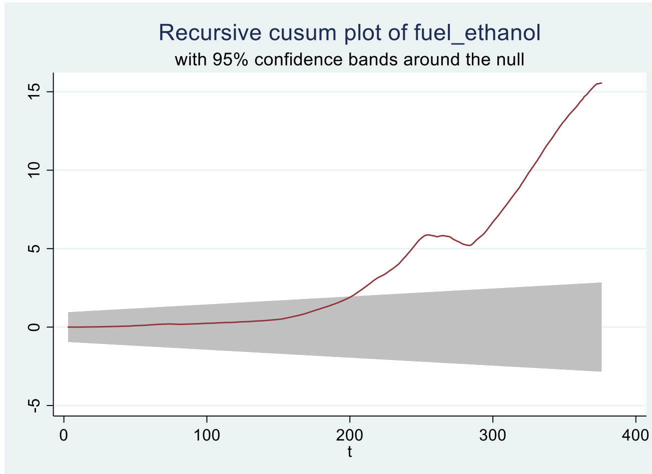


Fig. B2. Fuel_Ethanol: Ho: No structural break

The red line is the cumulative sum. If the red line is in the shaded area, the test would have not rejected the null hypothesis at the 5% level. The graph for the fuel_ethanol reveals that fuel_ethanol has a structural break(s) by rejecting the null of no structural break.

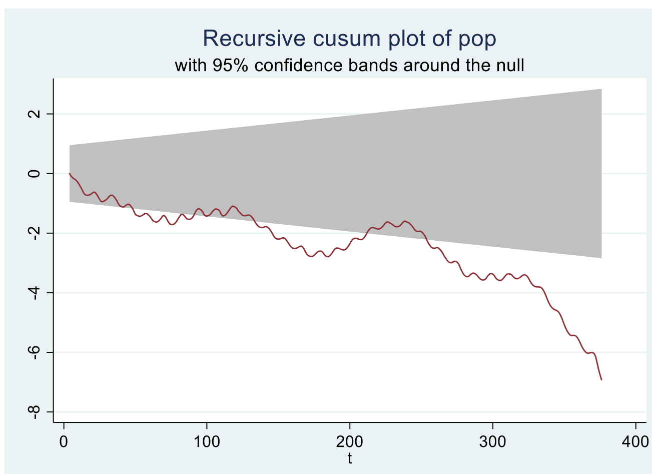


Fig. B3. POP: Ho: No structural break

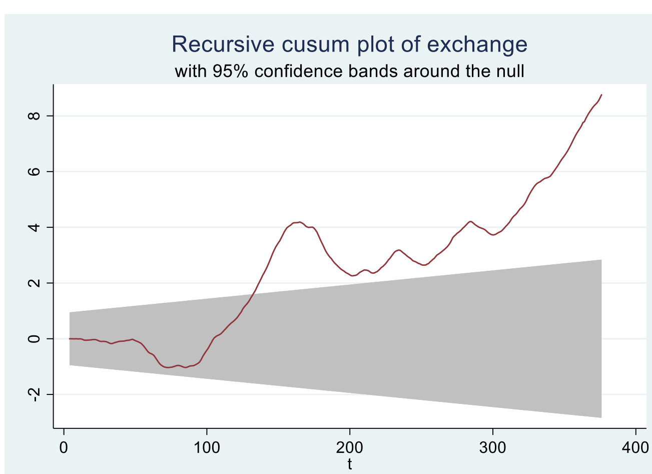


Fig. B4. Exchange: Ho: No structural break

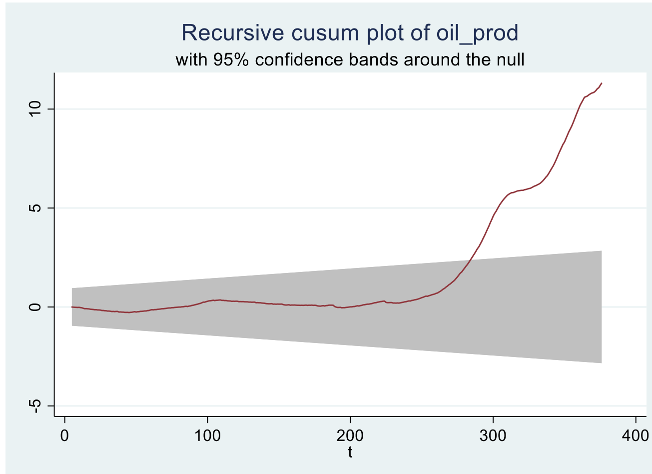


Fig. B5. Oil Prod: Ho: No structural break

All variables are found that they have a statistically significant structural break(s) through the Cumulative sum test for parameter stability. The null of no structural breaks is rejected at 1% for all variables employed in partial wavelet analyses.

Appendix C. Frequency Domain Causality Tests

Frequency domain causality tests require stationary data. Our data were found nonstationary [$I(1)$]. The continuous wavelet Coherence analyses, on the other hand, can handle nonstationary data. That's why we conducted wavelet Coherence analyses by employing our data at their levels.

For example, Fourier transform analyses, which decompose functions depending on space or time into functions depending on the spatial frequency or temporal frequency and which can capture the cyclical natüre of a time series analyses are efficient if the time series is stationary [62,100,101]. Wavelet analyses can capture transient cycles that are not stable across time and frequencies between non-stationary time series (The wavelet transform analyses can decompose the non-stationary time series into the time-frequency domain) [79,102].

However, for the potential reader to be able to follow the manuscript, frequency domain causality tests, by considering Taştan [103] and Breitung and Candelon [60] were conducted and the results of the analyses for comparison purposes (with Figure A1) are presented as follows.

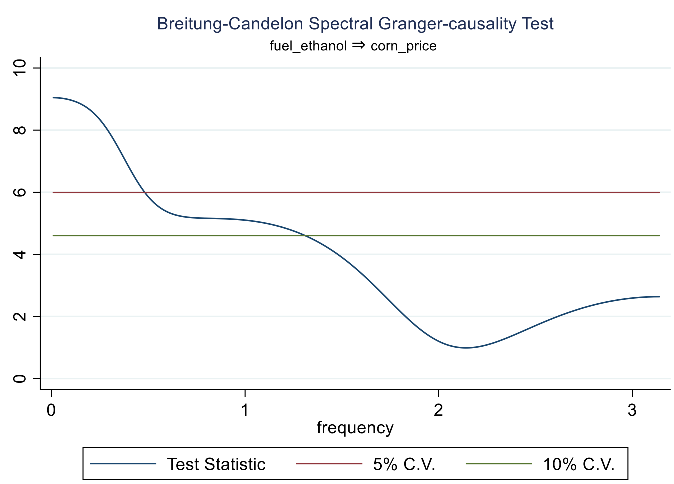


Fig. C1. Frequency domain Granger causality test results from income to consumption (conditional on the exchange rate, oil production, and population).

The causality tests at low frequencies are found significant since they are above the 5% line and later causality tests are found significant at w = 0,49 to w = 1.3.

Within the range w = 0.001 and w = 0.48, ethanol Granger causes corn prices at 5% conditional on exchange rate, oil production, and population. As the wavelength = 2π/w, i.e., w(0.48) corresponds to the wavelength of 3.1 years or 13 quarters.

Within the range w = 0.49 and w = 1.3 (corresponding to a wavelength between 12.8 quarters and 4.8 quarters), ethanol Granger causes corn prices at 10%, (conditional on the exchange rate, oil production, and population).

The partial wavelet coherency analyses also result in strong co-movements between ethanol product and corn price at low frequencies (3–8 year cycle) for the period 2007–2021 (with control variables exchange rate, oil production, and population).

The Frequency domain Granger causality test results on the other hand reveal that ethanol production does not Granger cause corn prices at high frequencies (from w = 1.31 to w = 3.14, corresponding to wavelength = 4.79 quarters and wavelength = 2 quarters). The partial wavelet coherency results, however, yield strong coherencies between ethanol product and corn price at high frequencies (1–3 year cycle) for the periods 1991:1–1999:7, 2005:3–2011:12, and 2018–2019.

Table C1
Frequency domain Granger causality tests, frequency, t stats, prob values

w	2*pi (=2*3,14= 6,28)	corresponding quarter /year	r(W)[314,3]	Frequency	tstat	pvalue
...	...	...	...			
0,46	6,28	13,65217	r46	.46	6.1864545	.04535534
0,47	6,28	13,3617	r47	.47	6.0961898	.04744923
0,48	6,28	13,08333	r48	.48	6.0107639	.04951984
...	...	...	...			
1,28	6,28	4,90625	r128	1.28	4.6832395	.09617174
1,29	6,28	4,868217	r129	1.29	4.6577051	.09740745
1,3	6,28	4,830769	r130	1.3	4.6313036	.09870183
...	...	...	...			
3,12	6,28	2,012821	r312	3.12	2.6364896	.26760459
3,13	6,28	2,00639	r313	3.13	2.6372437	.26750371
3,14	6,28	2	r314	3.14	2.6375433	.26746364

Appendix D. Decomposition Trees, Denoising Analyses at Different Levels

1- We obtained (a) decomposition trees from estimated CWT computations by Shannon entropy at different levels (1, 2, 3, 4, and 5) and (b) Best Level Decomposition trees by Shannon entropy. Computing the best tree makes the de-noising calculations more efficient. The below program lines in the wavelet package gives the best level.

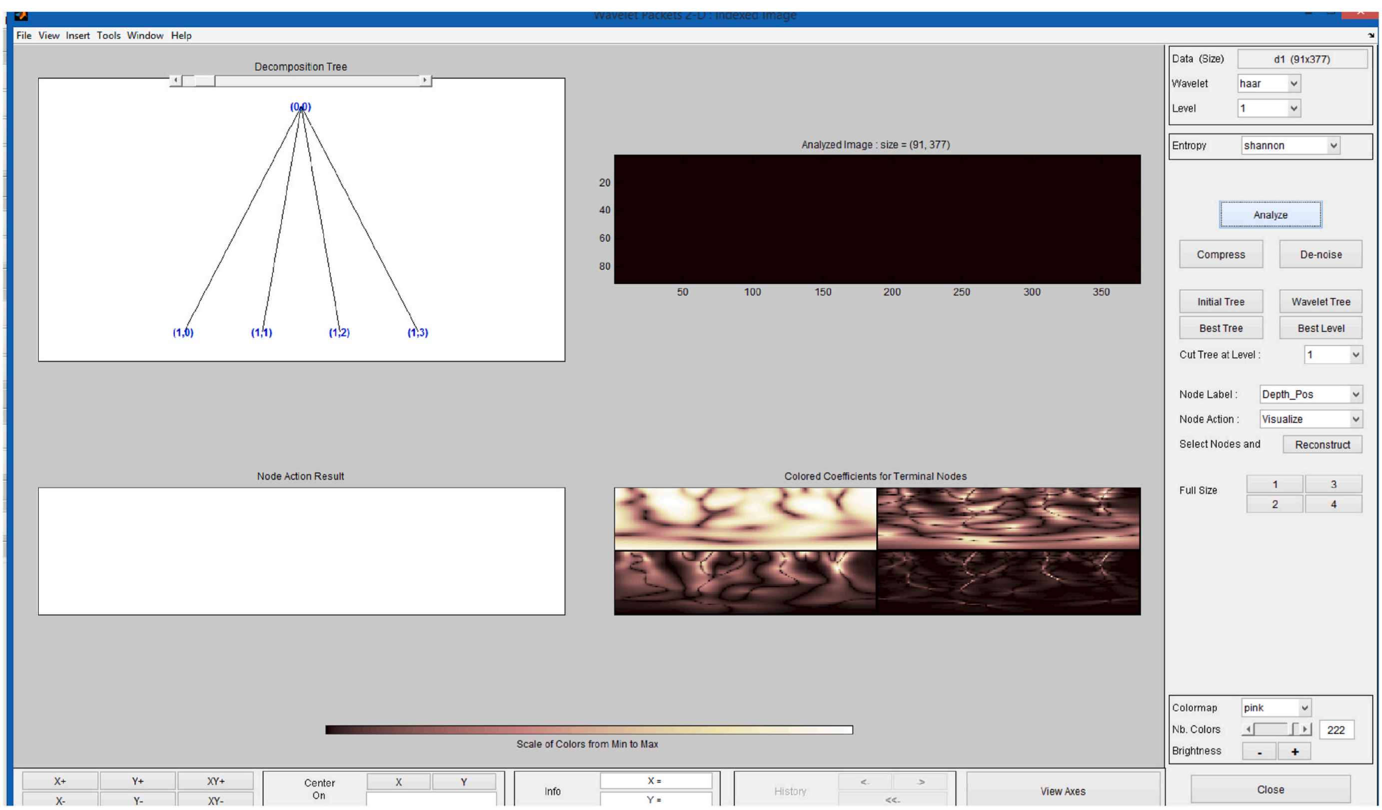


Fig. D1. Level 1: Decomposition trees by Shannon entropy

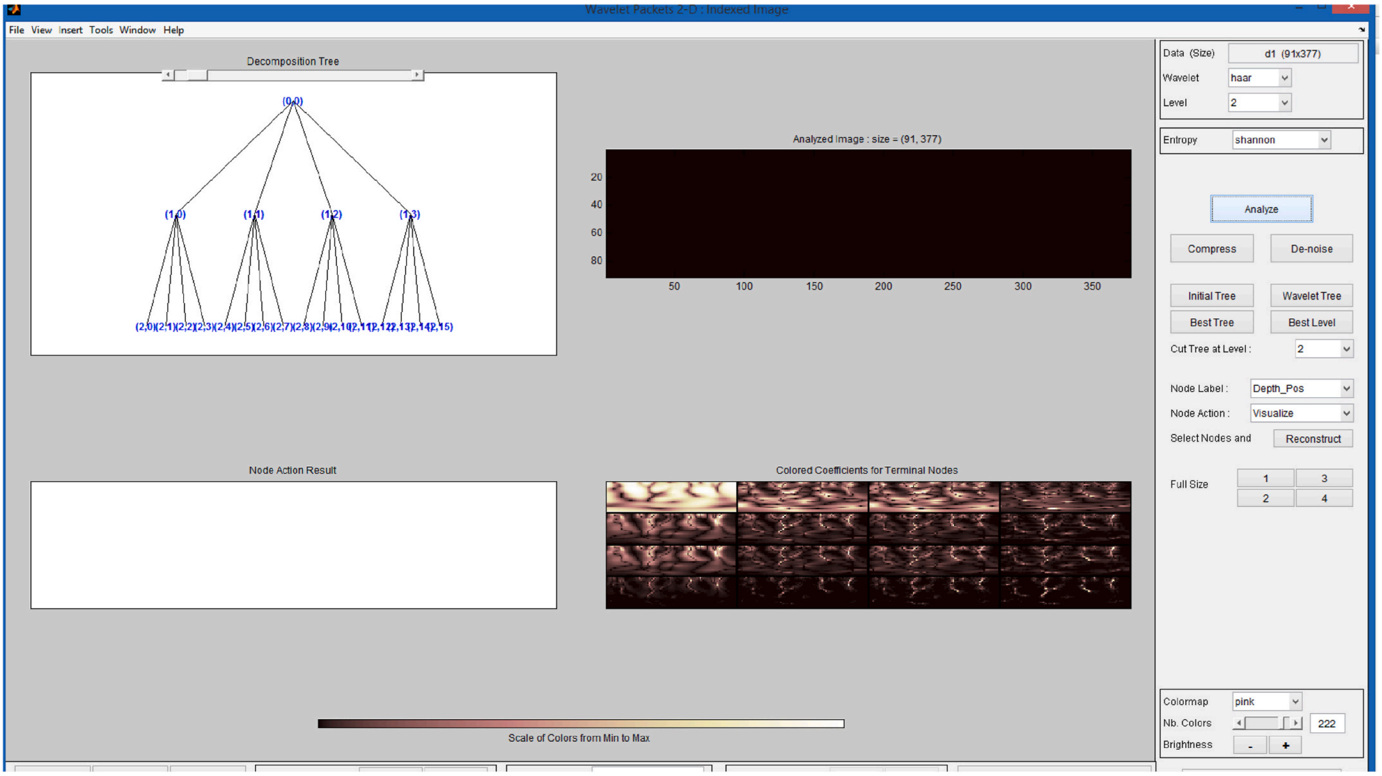


Fig. D2. Level 2: Decomposition trees by Shannon entropy

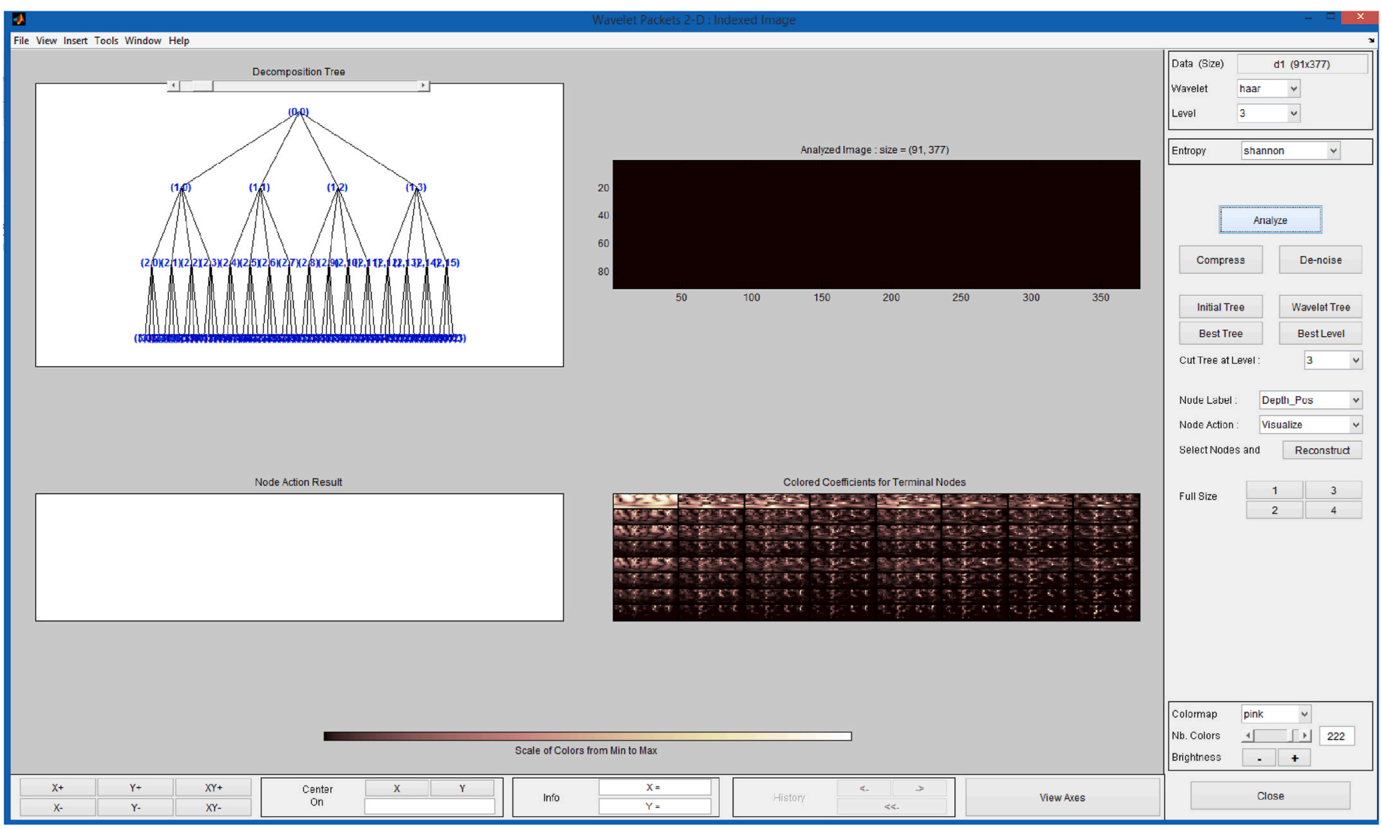


Fig. D3. Level 3: Decomposition trees by Shannon entropy

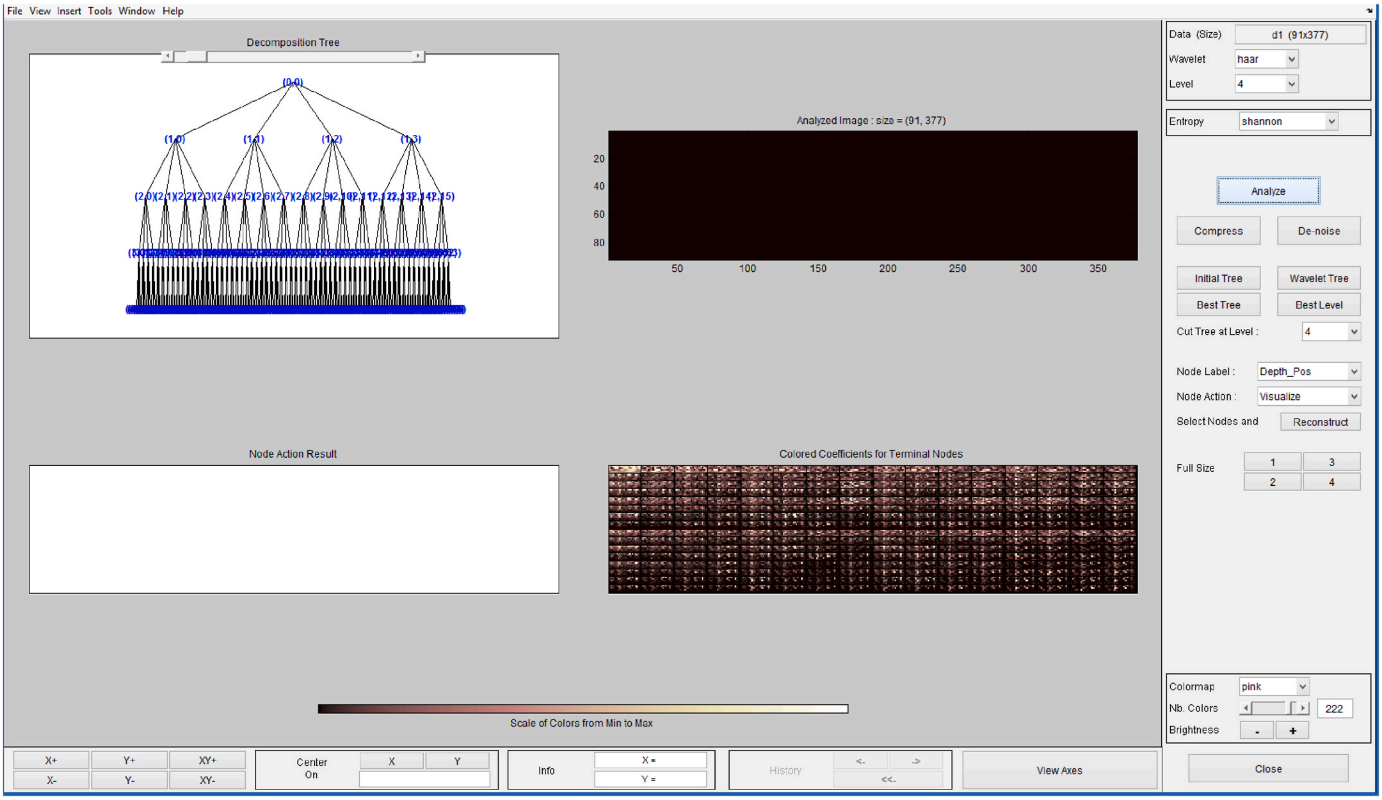


Fig. D4. Level 4: Decomposition trees by Shannon entropy

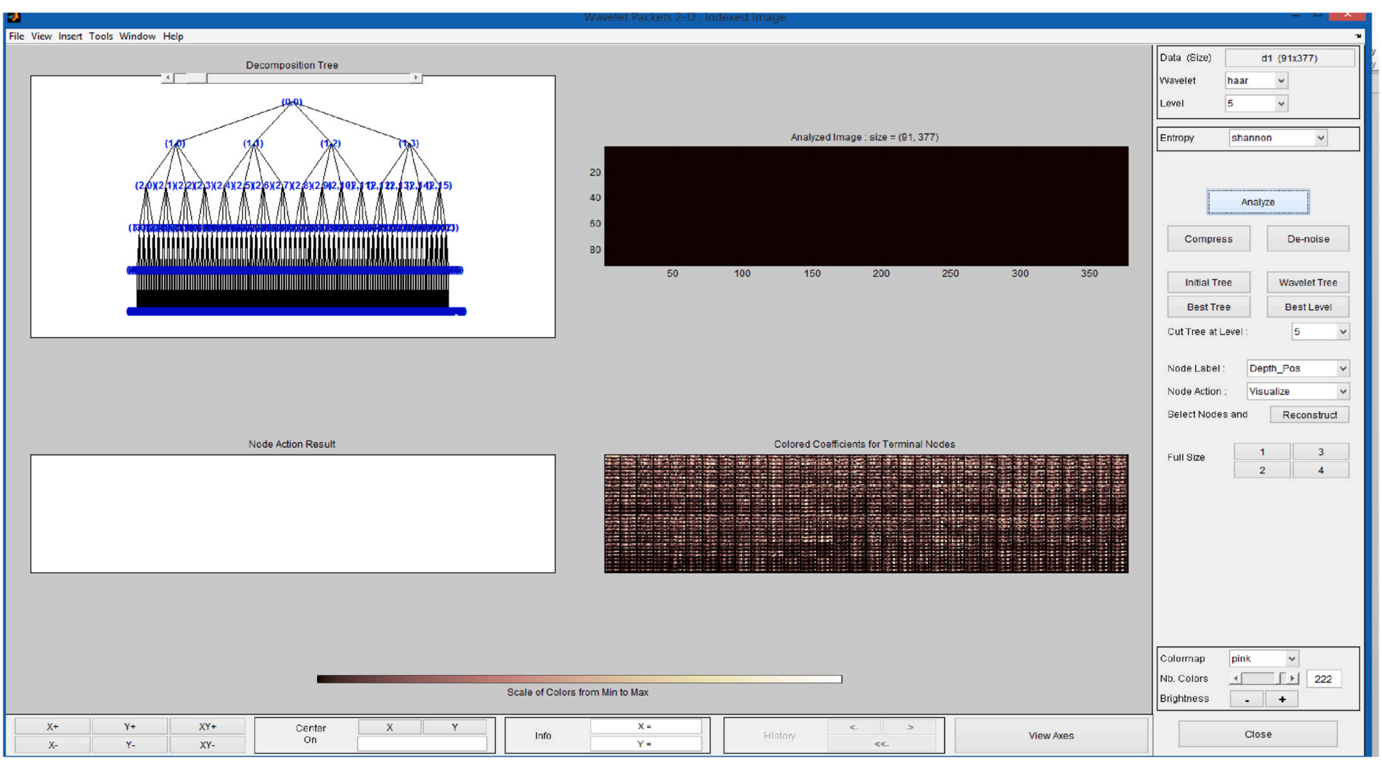


Fig. D5. Level 5: Decomposition trees by Shannon entropy

Best Level: Decomposition trees by Shannon entropy.
Computing the best tree makes the de-noising calculations more efficient. The below program lines in the wavelet package gives the best level.

- bestlevt

Purpose Best level tree wavelet packet analysis.
Syntax.
T = bestlevt(T).
[T,E] = bestlevt(T).
Description.

- bestlevt is a one- or two-dimensional wavelet packet analysis function.
- bestlevt computes the optimal complete subtree of an initial tree concerning an entropy type criterion. The resulting complete tree may be of smaller depth than the initial one.

T = bestlevt(T) computes the modified wavelet packet tree T corresponding to the best level tree decomposition.
[T,E] = bestlevt(T) computes the best level tree T, and in addition, the best entropy value E.
The optimal entropy of the node, whose index is j-1, is E(j).
% The current extension mode is zero-padding (see dwtmode).
% Load signal.
load noisdopp; x = noisdopp; % Decompose x at depth 3 with db1 wavelet, using default.
% entropy (shannon).
wpt = wpdec(x, 3,'db1′);
% Decompose the packet [30].
wpt = wpsplt(wpt [30]);
% Plot wavelet packet tree wpt.
plot(wpt).
% Compute best level tree.
blt = bestlevt(wpt);
% Plot best level tree blt.
plot(blt).

Algorithm is explained in besttree algorithm section. The only difference is that the optimal tree is searched among the complete subtrees of the initial tree, instead of among all the binary subtrees (Mathworks, 1984–2009, 2022).

(©) 1984–2009 The MathWorks, Inc https://www.mathworks.com/

Mathworks (2022) Support, https://www.mathworks.com/support.html?s_tid = gn_supp

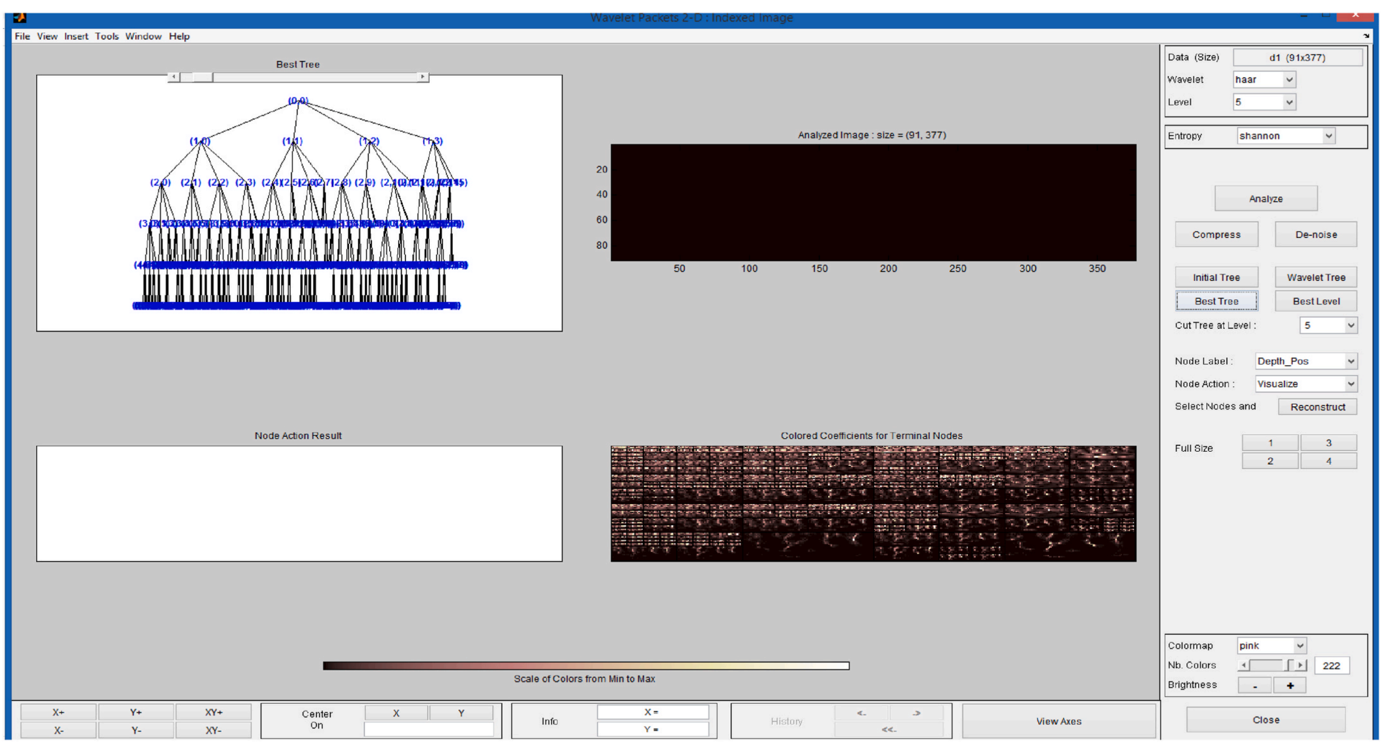


Fig. D6. Best Tree: Decomposition trees by Shannon entropy

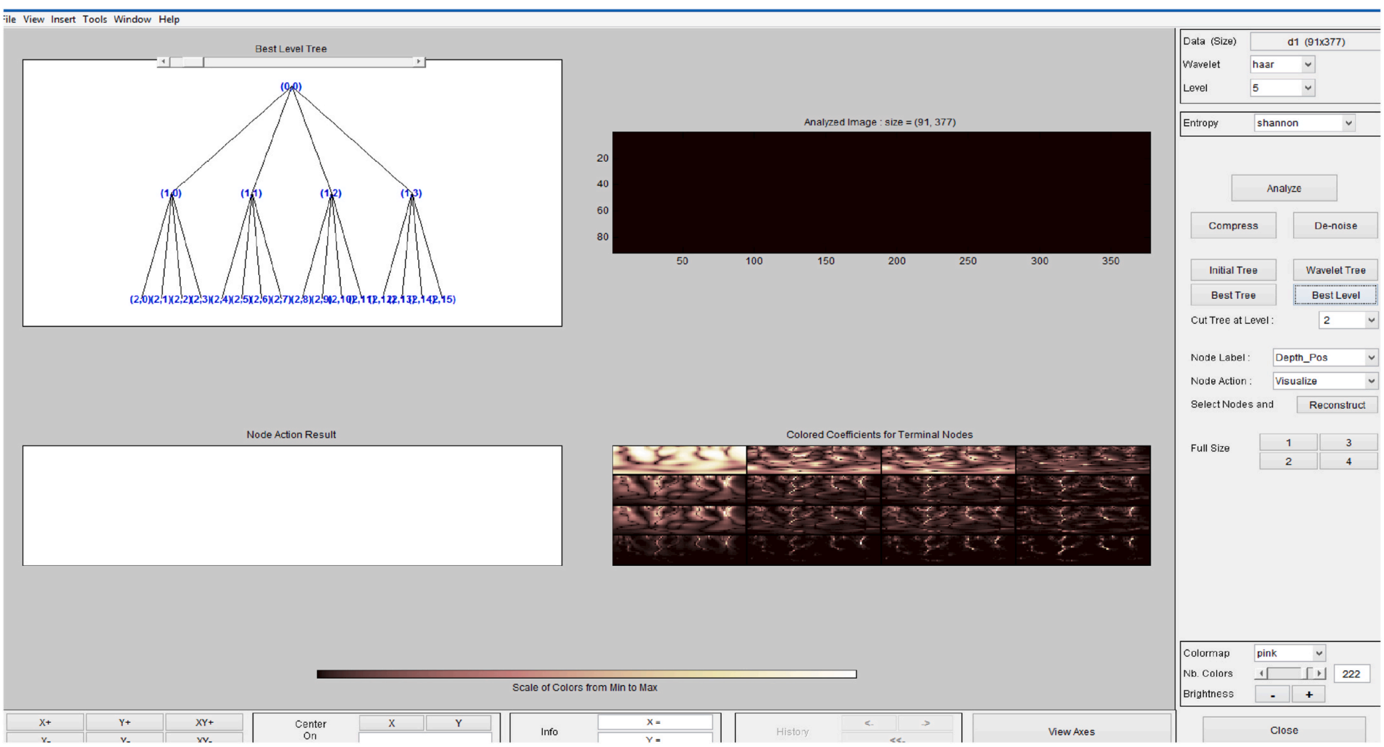


Fig. D7. Best Level Tree: Decomposition trees by Shannon entropy

2- We also conducted Wavelet 1-D Multi signal analyses-Denoising at different levels.

To observe the residuals from wavelet estimations, we used the One-Dimensional Multi signal Analysis of MatlabR2099b, a wavelet toolbox. This program provides us with the features of one-dimensional multisignal wavelet analysis, compression, and denoising using the Wavelet Toolbox™ software. The rationale is the same as in the 1-D single signal case. To view residuals, Ctrl-click the Orig. Signal, the Denoised, and the Residuals items in the list on the left of the Selection of Data Sets pane. The original, denoised, and residual signals are selected ($3 \times 91 = 273$ signals). We have chosen the Asc. at the bottom of the Selection of Data pane to sort the signals using the Idx Sig parameter through Separate Mode.

Selecting the ALL button in the Thresholding pane, The threshold for each level (ThrD1, …, ThrD4), the program computes and displays in the Selection of Data pane. Then click the Denoise button at the bottom of the Thresholding pane and by Ctrl-click the Denoised item in the list on the left of the Selection of Data Sets pane, the original signals, and the corresponding denoised ones are selected ($3 \times 91 = 273$ signals). We clicked the Asc. button at the bottom of the Selection of Data pane to sort the signals according to the Idx Sig parameter.

We, first, selected the first nine signals. They correspond to the original signals 1, 2, 3 the corresponding denoised signals 92, 93, 94, and the residuals 183, 184, and 185. Then, we need to choose the Separate Mode.

We, later, selected the last nine signals. They correspond to the original signals 89, 90, 91 the corresponding denoised signals 180, 181, 182, and the residuals 271, 271, and 185. Then, we need to choose the Separate Mode.

The output might reveal that the original signals (1, 2, 3) are depicted well by the denoised signals (92, 93, 94) and the expected values of residuals (183, 184, 185) are close to zero.

The output might also yield that the original signals (89, 90, 91) are depicted well by the denoised signals (180, 181, 182) and the expected values of residuals (271, 271, and 185) are close to zero.

Overall, multisignal denoising analyses can indicate that the original signals are observed well by the denoised signals and the residuals tend to be normally distributed and the expected values of residuals are close to zero.

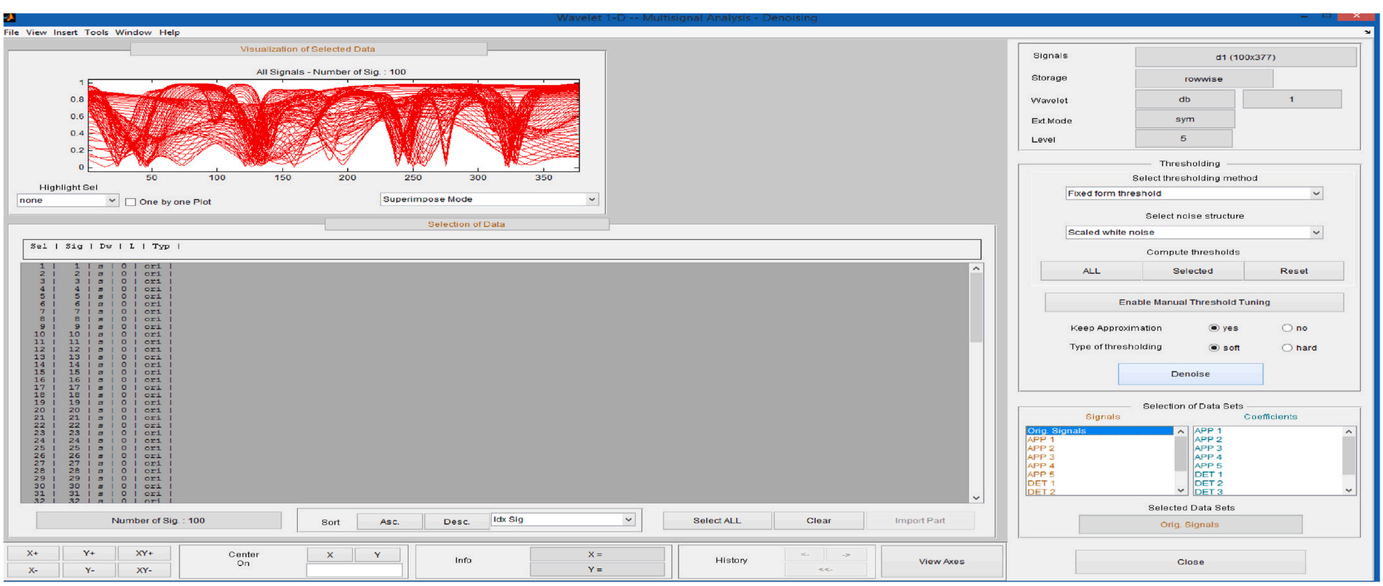


Fig. D8. Superimpose mode

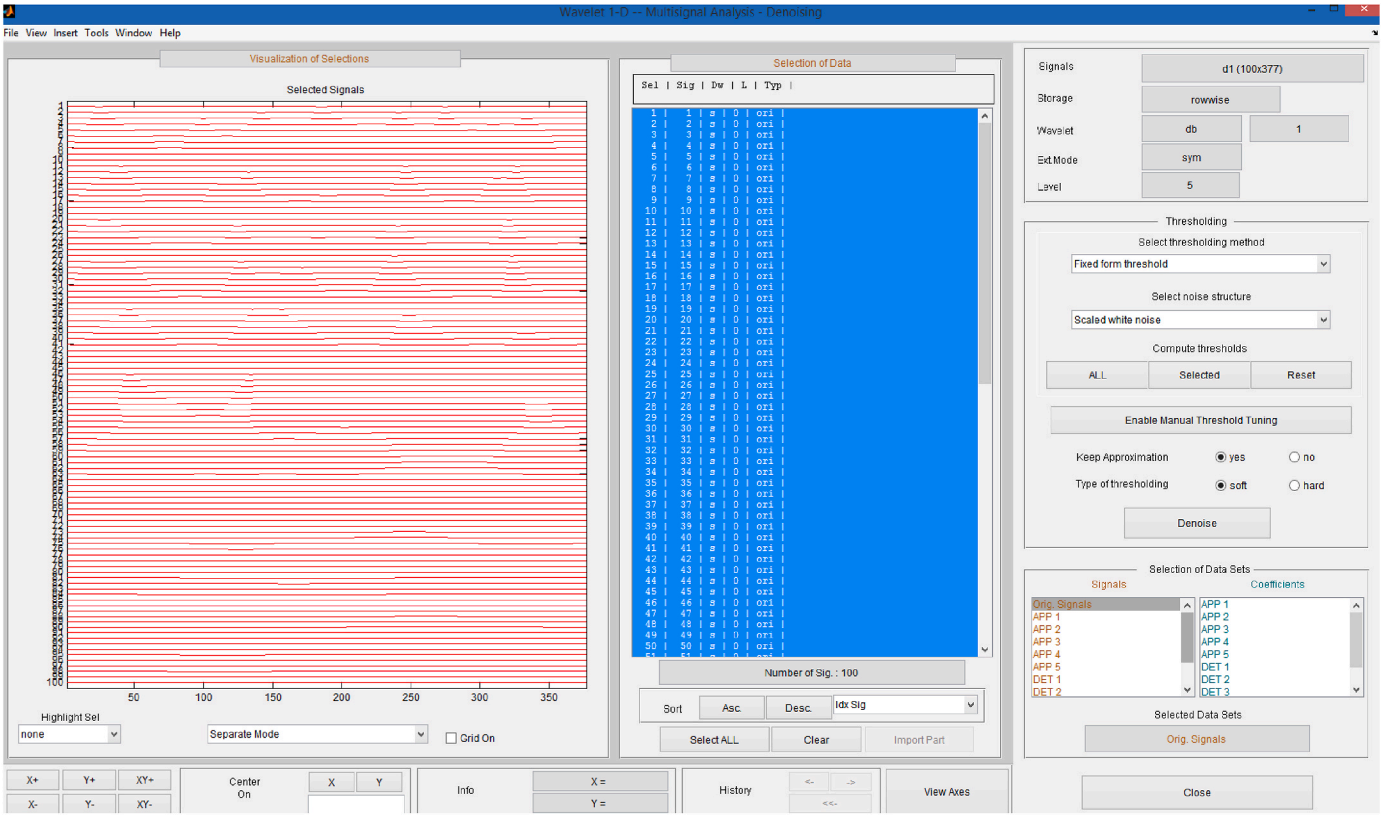


Fig. D9. Separated mode

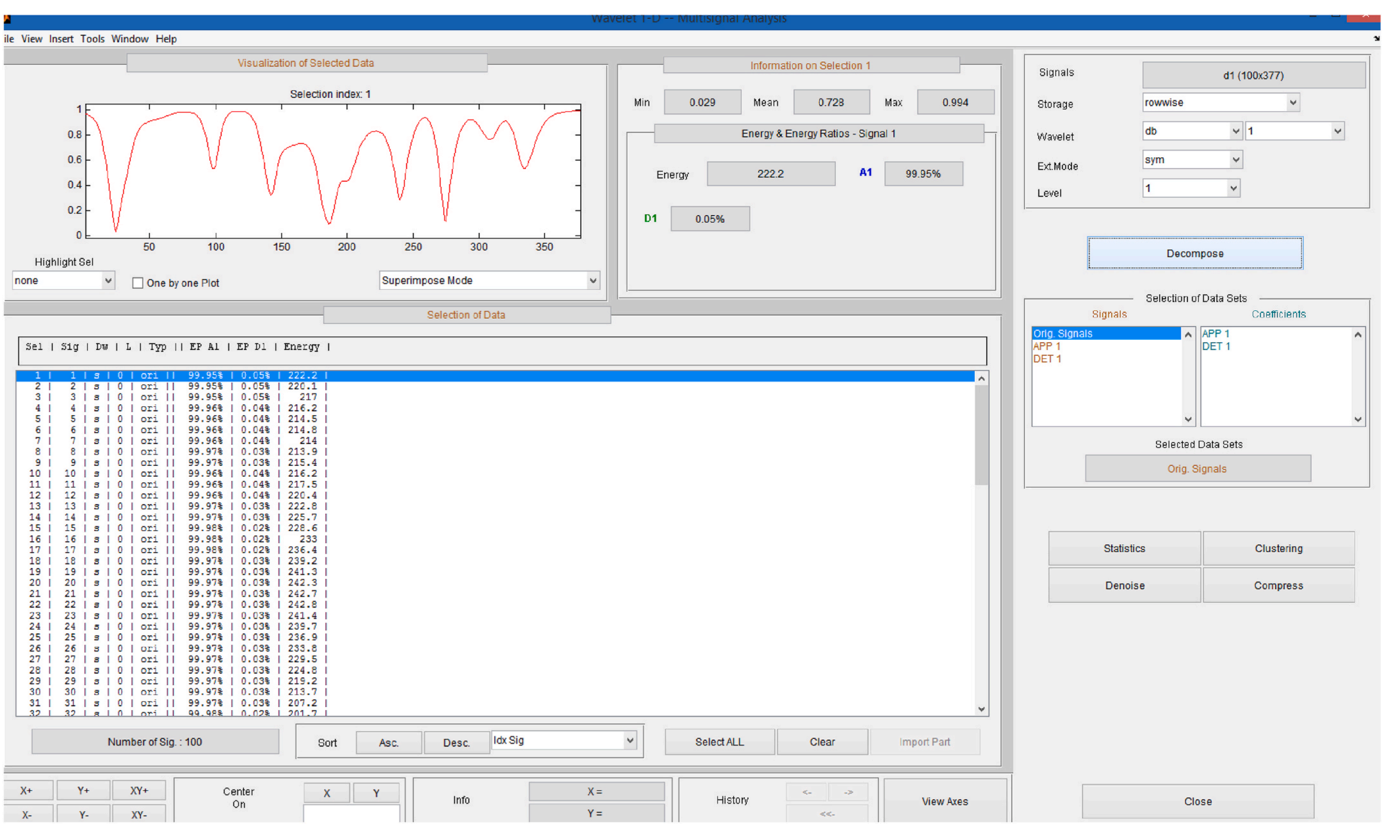


Fig. D10. Level 1

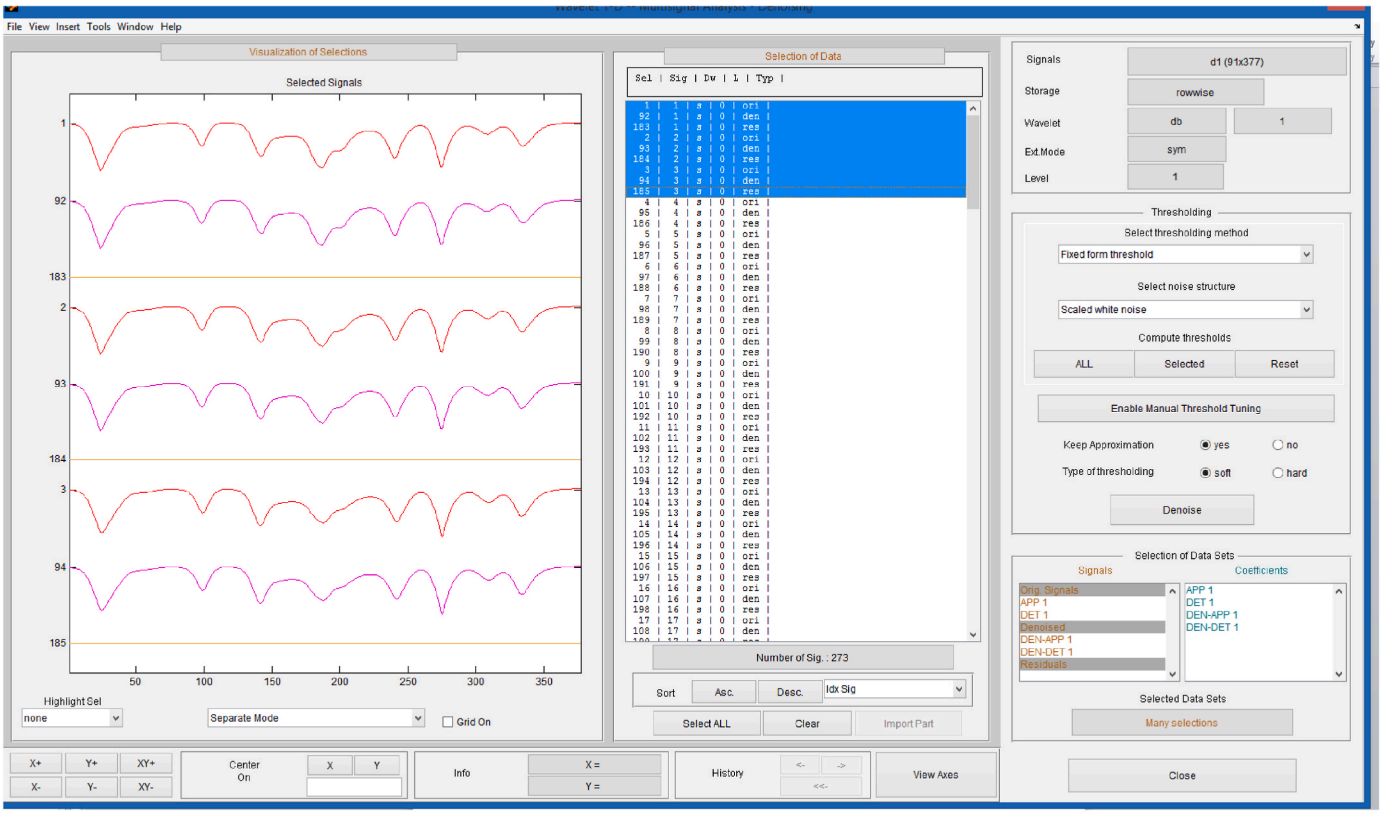


Fig. D11. Level 1: Decomposition/ Denoising

We, first, selected the first nine signals. They correspond to the original signals 1, 2, 3 the corresponding denoised signals 92, 93, 94, and the residuals 183, 184, and 185. Later, we need to choose the Separate Mode.

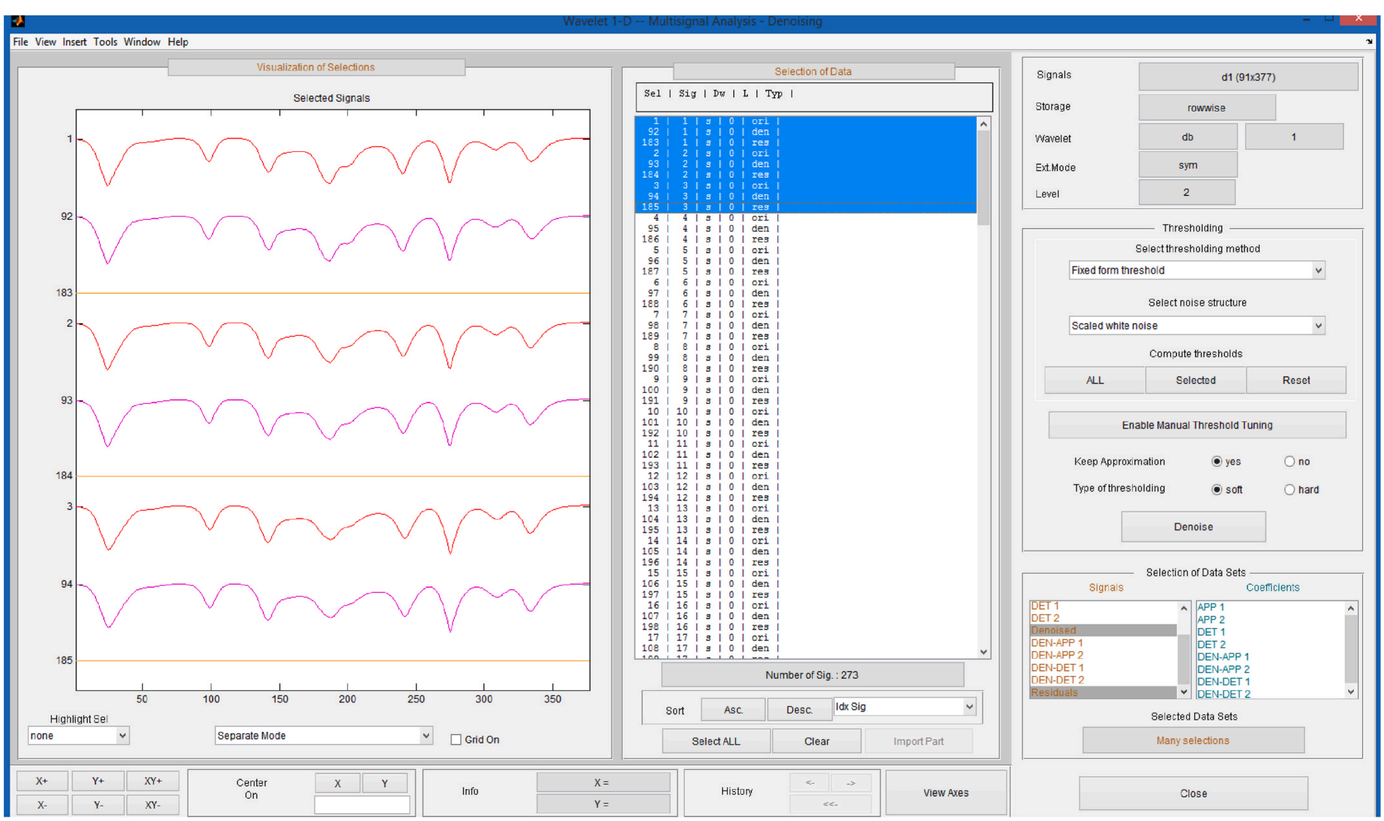
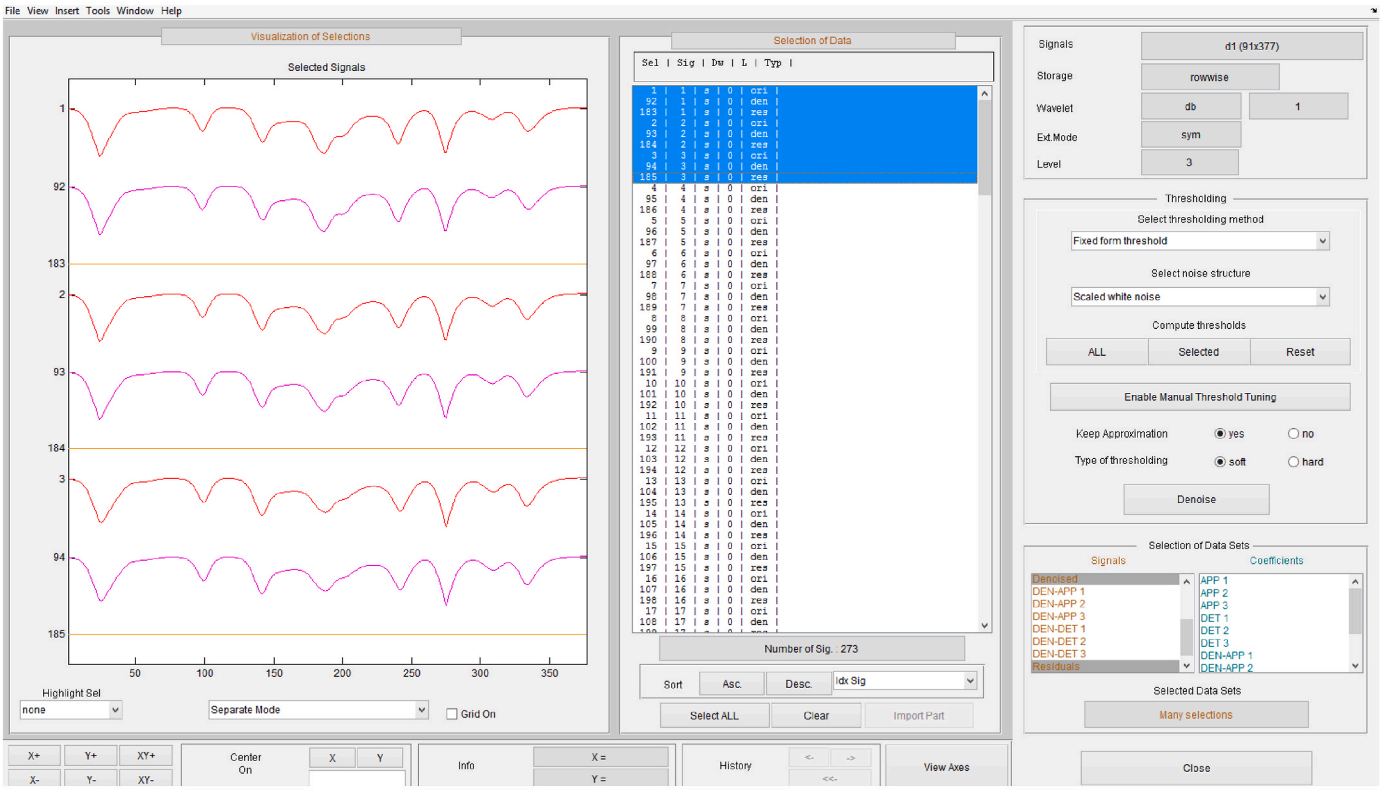


Fig. D12. Level 2: Decomposition/ Denoising

(a)



(b)

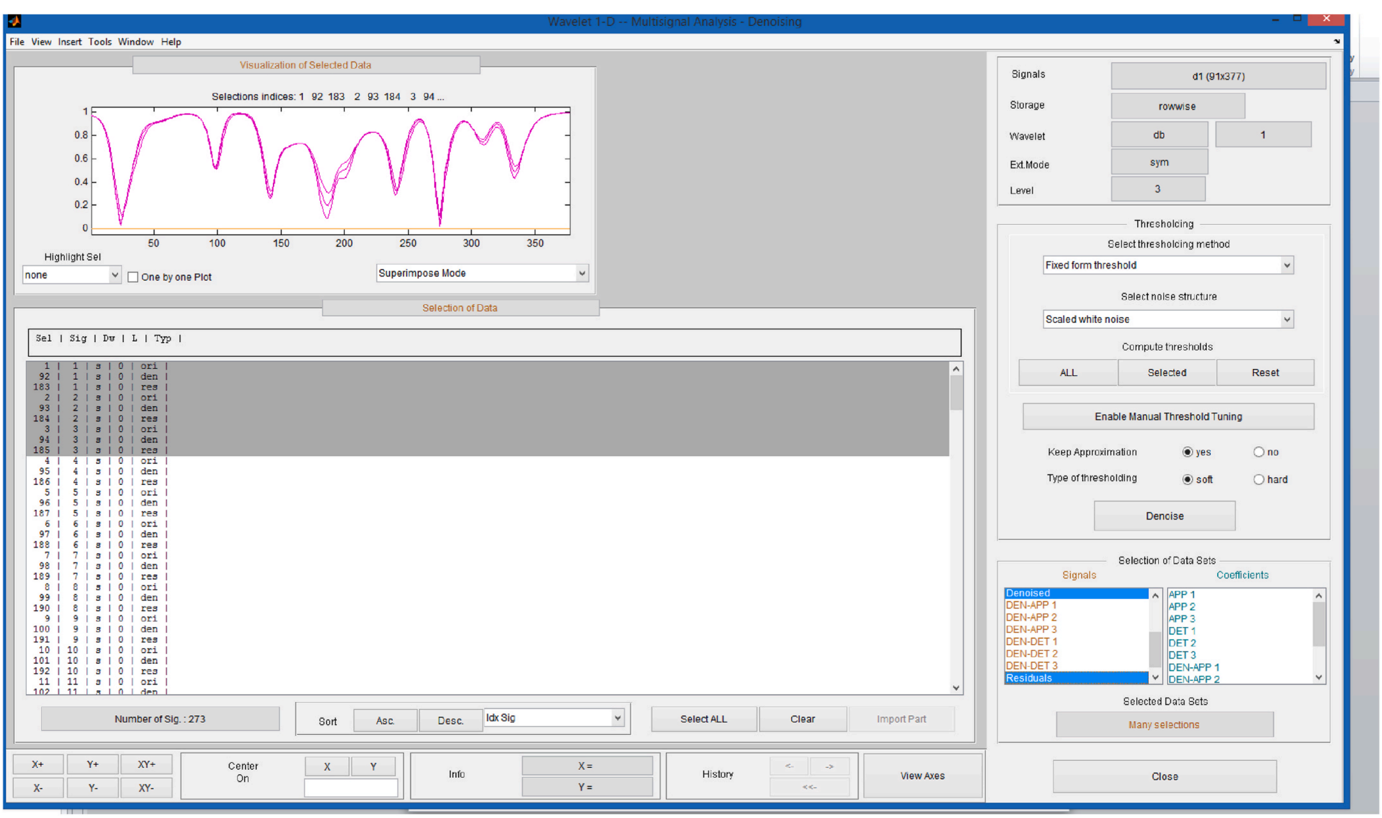
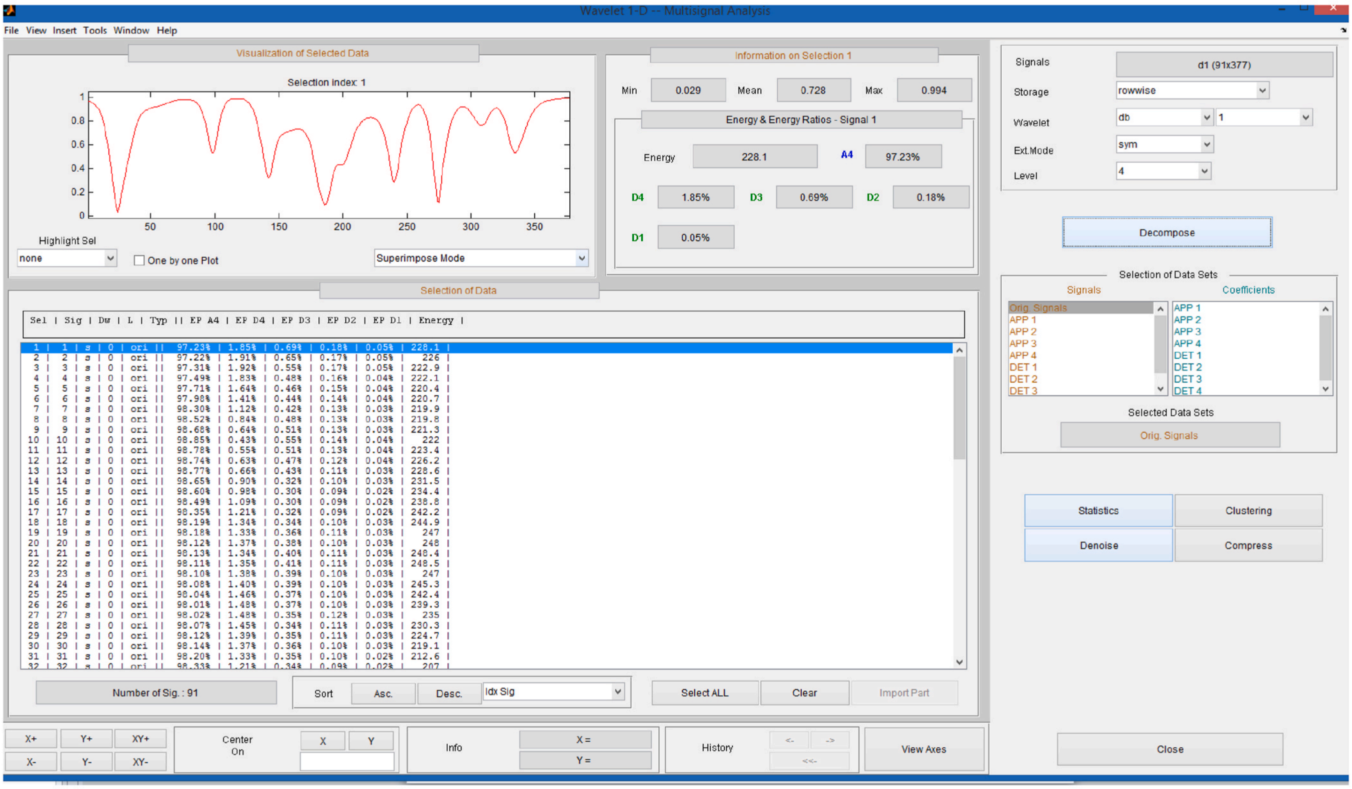


Fig. D13. Level 3: Decomposition/ Denoising

(a)



(b)

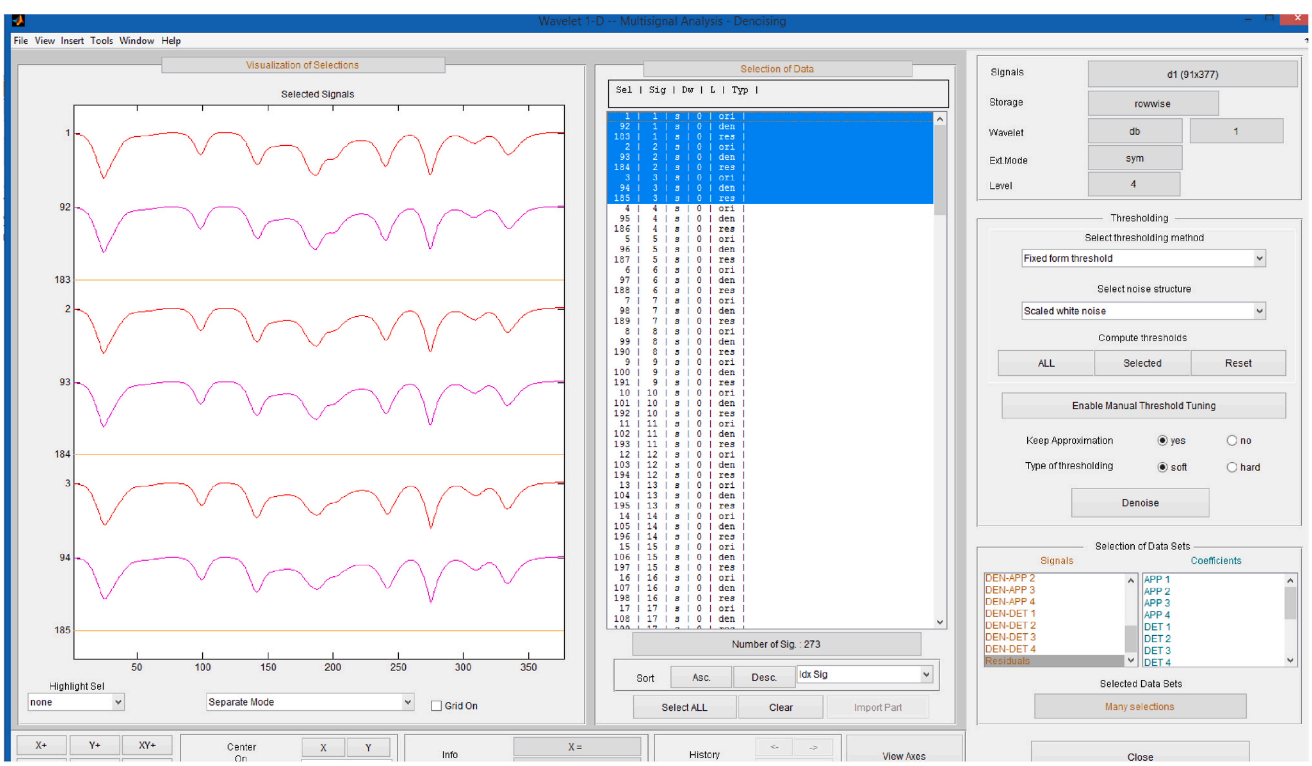
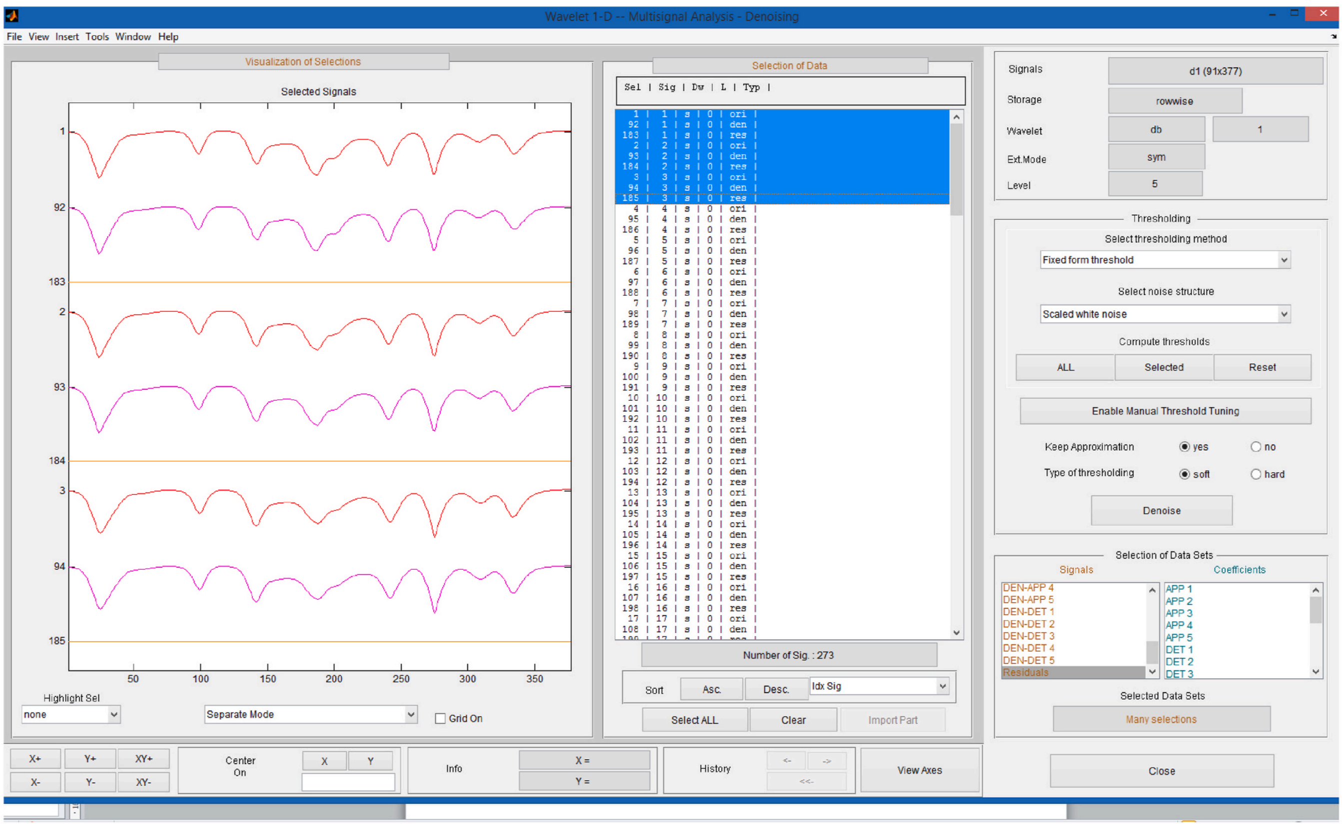


Fig. D14. Level 4: Decomposition/ Denoising

(a)



(b)

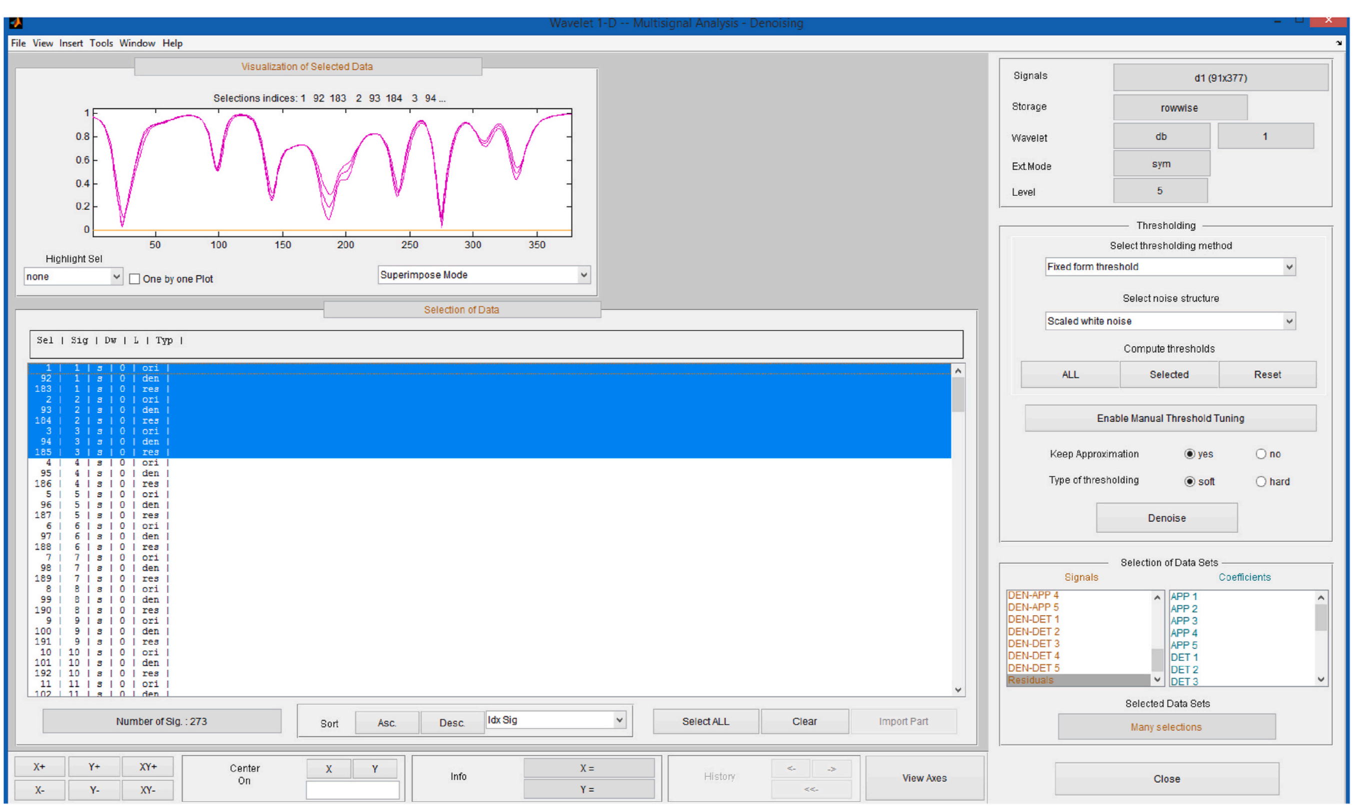
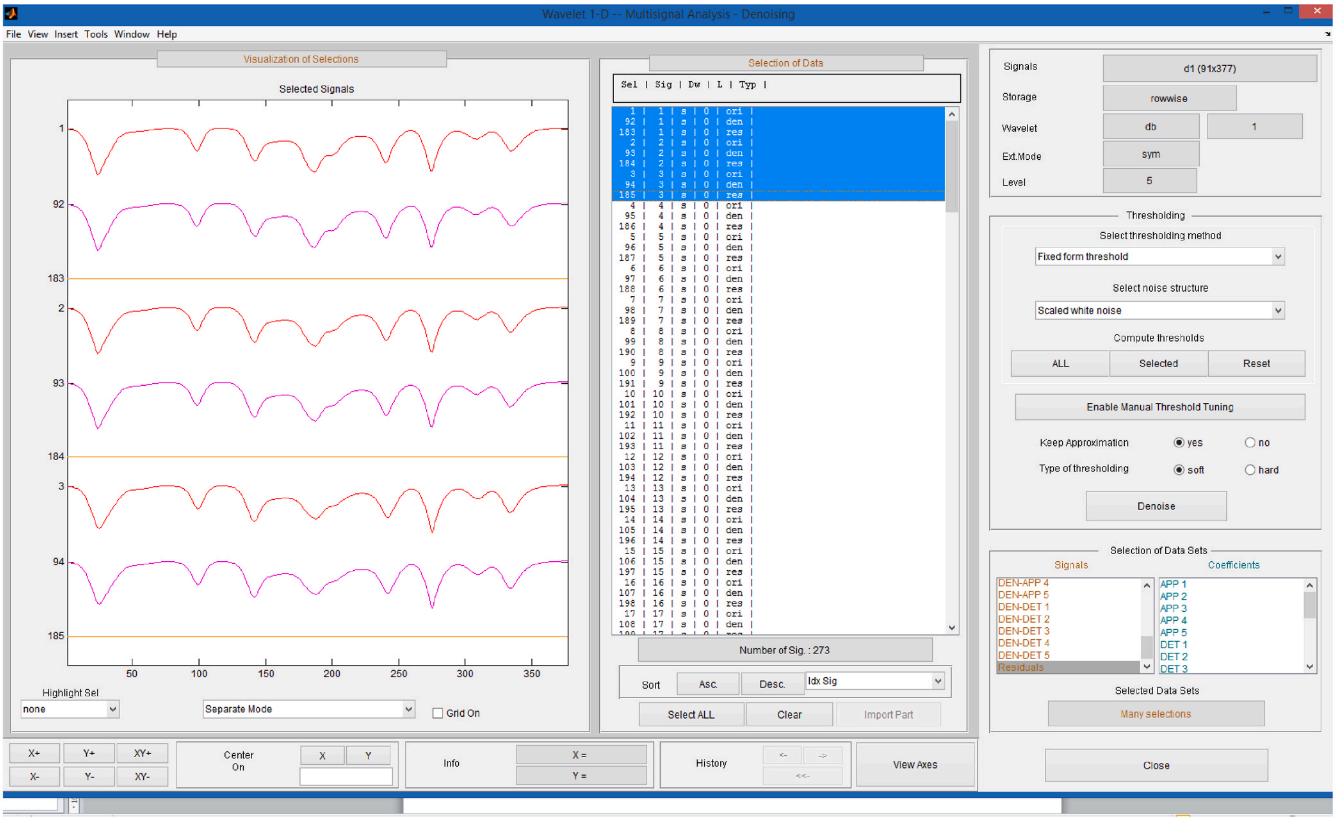


Fig. D14. (*continued*).

(a)



(b)

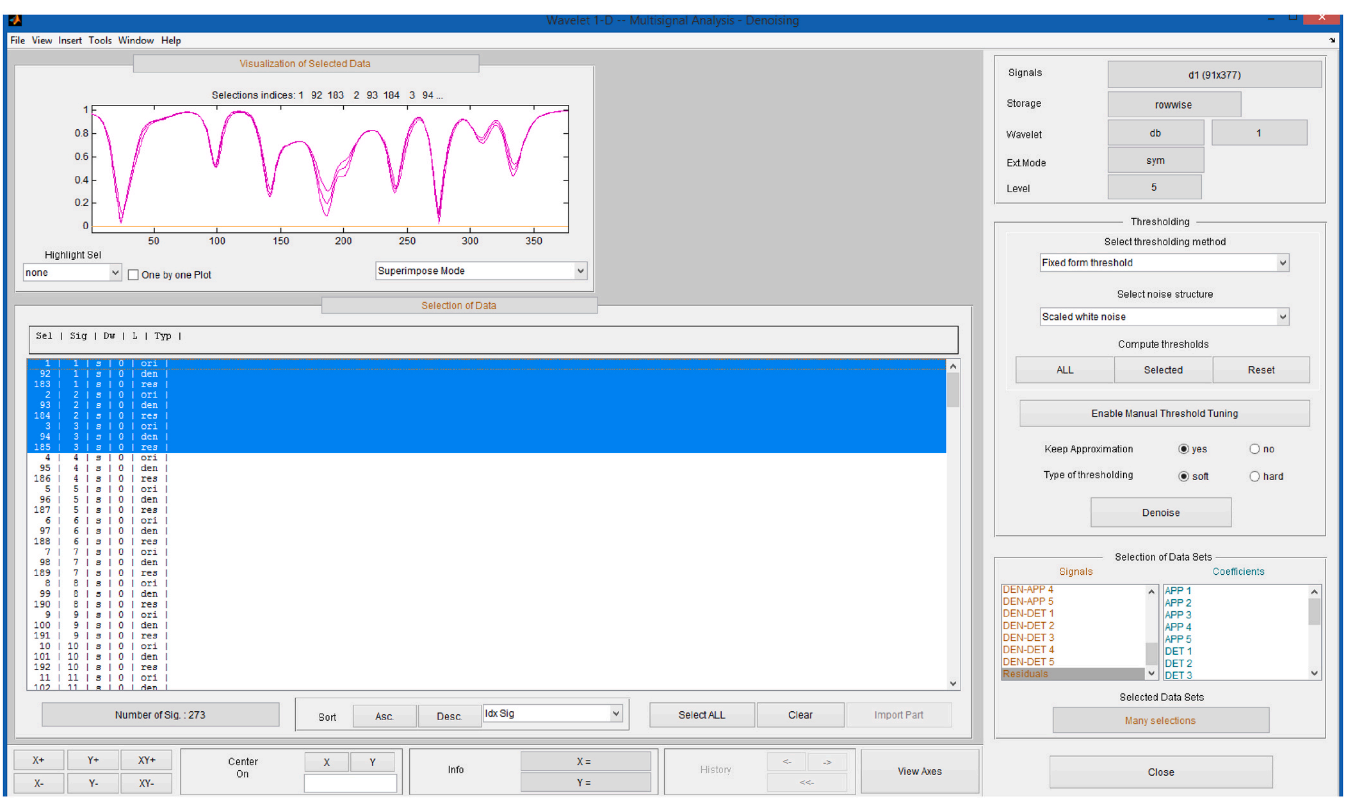
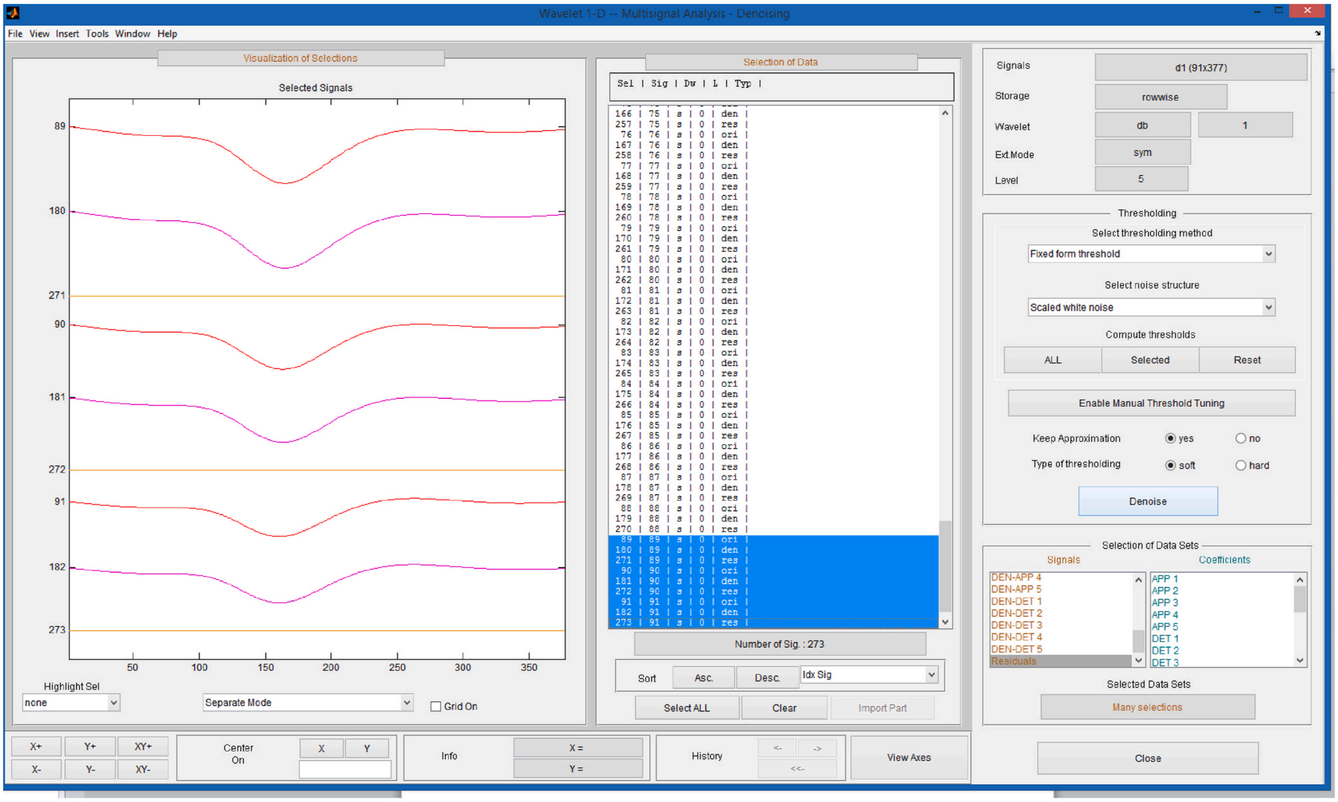


Fig. D15. Level 5: Decomposition/ Denoising

(c)



(d)

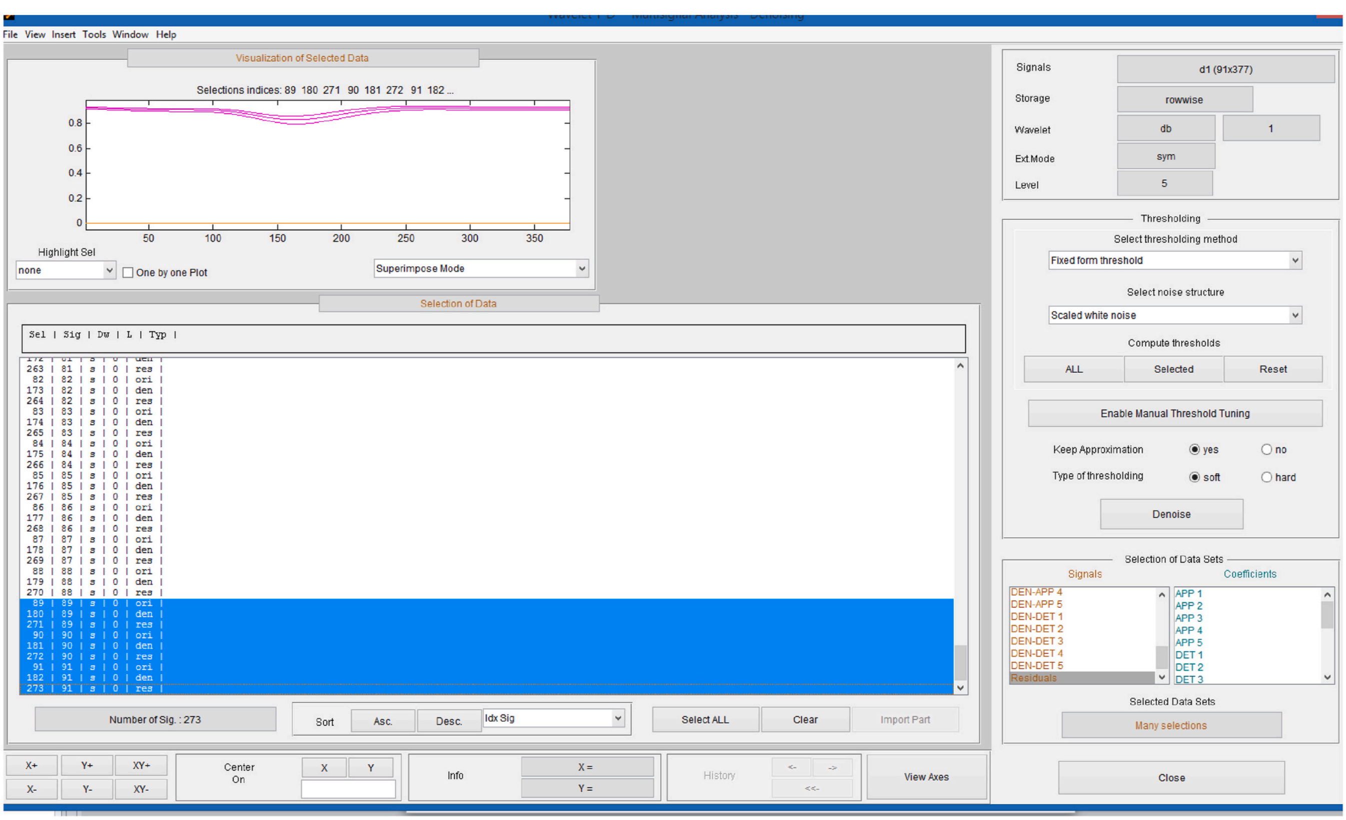


Fig. D15. (*continued*).

We, later, selected the last nine signals. They correspond to the original signals 89, 90, 91 the corresponding denoised signals 180, 181, 182, and the residuals 271, 271, and 185. Then, we need to choose the Separate Mode.

The output might reveal that the original signals (1, 2, 3) are depicted well by the denoised signals (92, 93, 94) and the expected values of residuals (183, 184, 185) are close to zero. This later output might refer to the unbiasedness of the denoising at all levels.

References

[1] Bilgili F, Kuşkaya S, Toğuç N, Muğaloğlu E, Koçak E, Bulut Ü, Bağlıtaş HH. A revisited renewable consumption-growth nexus: a continuous wavelet approach through disaggregated data. Renew Sustain Energy Rev 2019;107:1–19. https://doi.org/10.1016/j.rser.2019.02.017.
[2] Koçak E, Önderol S, Khan K. Structural change, modernization, total factor productivity, and natural resources sustainability: an assessment with quantile and non-quantile estimators. Resour Pol 2021;74:102433. https://doi.org/10.1016/J.RESOURPOL.2021.102433.
[3] Abbasi KR, Shahbaz M, Jiao Z, Tufail M. How energy consumption, industrial growth, urbanization, and CO2 emissions affect economic growth in Pakistan? A novel dynamic ARDL simulations approach. Energy 2021;221. https://doi.org/10.1016/j.energy.2021.119793. 119793.
[4] rong Ren F, Tian Z, sheng Chen H, ting Shen Y. Energy consumption, CO2 emissions, and agricultural disaster efficiency evaluation of China based on the two-stage dynamic DEA method. Environ Sci Pollut Res 2020:1–18. https://doi.org/10.1007/s11356-020-09980-x.
[5] Nazari MT, Mazutti J, Basso LG, Colla LM, Brandli L. Biofuels and their connections with the sustainable development goals: a bibliometric and systematic review. Environ Dev Sustain 2021;23:11139–56. https://doi.org/10.1007/S10668-020-01110-4/TABLES/1.
[6] Subramaniam Y, Masron TA, Azman NHN. Biofuels, environmental sustainability, and food security: a review of 51 countries. Energy Res Social Sci 2020;68:101549. https://doi.org/10.1016/j.erss.2020.101549.
[7] Kurowska K, Marks-Bielska R, Bielski S, Kryszk H, Jasinskas A. Food security in the context of liquid biofuels production. 13 Energies 2020 2020;13:6247. https://doi.org/10.3390/EN13236247. 6247.
[8] Qadir SA, Al-Motairi H, Tahir F, Al-Fagih L. Incentives and strategies for financing the renewable energy transition: a review. Energy Rep 2021;7:3590–606. https://doi.org/10.1016/J.EGYR.2021.06.041.
[9] Shahid MK, Batool A, Kashif A, Nawaz MH, Aslam M, Iqbal N, Choi Y. Biofuels and biorefineries: development, application and future perspectives emphasizing the environmental and economic aspects. J Environ Manag 2021;297:113268. https://doi.org/10.1016/J.JENVMAN.2021.113268.
[10] Nakamya M. How sustainable are biofuels in a natural resource-dependent economy? Energy Sustain. Dev. 2022;66:296–307. https://doi.org/10.1016/J.ESD.2021.12.012.
[11] Brinkman M, Levin-Koopman J, Wicke B, Shutes L, Kuiper M, Faaij A, van der Hilst F. The distribution of food security impacts of biofuels, a Ghana case study. Biomass Bioenergy 2020;141:105695. https://doi.org/10.1016/j.biombioe.2020.105695.
[12] Benites-Lazaro LL, Giatti LL, Sousa Junior WC, Giarolla A. Land-water-food nexus of biofuels: discourse and policy debates in Brazil. Environ. Dev. 2020;33:100491. https://doi.org/10.1016/J.ENVDEV.2019.100491.
[13] Bilgili F, Koçak E, Kuşkaya S, Bulut Ü. Estimation of the co-movements between biofuel production and food prices: a wavelet-based analysis. Energy 2020;213. https://doi.org/10.1016/j.energy.2020.118777.
[14] Bilgili F, Koçak E, Bulut Ü, Kuşkaya S. Can biomass energy be an efficient policy tool for sustainable development? Renew Sustain Energy Rev 2017;71:830–45. https://doi.org/10.1016/J.RSER.2016.12.109.
[15] Nazlioglu S, Soytas U. Oil price, agricultural commodity prices, and the dollar: a panel cointegration and causality analysis. Energy Econ 2012;34:1098–104. https://doi.org/10.1016/J.ENECO.2011.09.008.
[16] Wei Su C, Wang X-Q, Tao R, Oana-Ramona L. Do oil prices drive agricultural commodity prices? Further evidence in a global bio-energy context. Energy 2019;172:691–701. https://doi.org/10.1016/J.ENERGY.2019.02.028.
[17] Serra T, Zilberman D, Gil JM, Goodwin BK. Nonlinearities in the U.S. corn-ethanol-oil-gasoline price system. Agric Econ 2011;42:35–45. https://doi.org/10.1111/j.1574-0862.2010.00464.x.
[18] Tokgoz S, Zhang W, Msangi S, Bhandary P. Biofuels and the future of food: competition and complementarities. Agriculture 2012;2:414–35. https://doi.org/10.3390/agriculture2040414.
[19] Monteiro N, Altman I, Lahiri S. The impact of ethanol production on food prices: the role of interplay between the U.S. and Brazil. Energy Pol 2012;41:193–9. https://doi.org/10.1016/j.enpol.2011.10.035.
[20] Bahel E, Marrouch W, Gaudet G. The economics of oil, biofuel and food commodities. Resour Energy Econ 2013;35:599–617. https://doi.org/10.1016/j.reseneeco.2013.02.005.
[21] Koizumi T. Biofuels and food security: IFPRI Publications. Renew Sustain Energy Rev 2015;52:829–41. https://doi.org/10.1016/J.RSER.2015.06.041.
[22] Ajanovic A. Biofuels versus food production: does biofuels production increase food prices? Energy 2011;36:2070–6. https://doi.org/10.1016/j.energy.2010.05.019.
[23] Gilbert CL. How to understand high food prices. J Agric Econ 2010;61:398–425. https://doi.org/10.1111/j.1477-9552.2010.00248.x.
[24] Zilberman D, Hochman G, Rajagopal D, Sexton S, Timilsina G. The impact of biofuels on commodity food prices: assessment of findings. In: Am. J. Agric. Econ. John Wiley & Sons, Ltd; 2013. p. 275–81. https://doi.org/10.1093/ajae/aas037.
[25] Dutta A. Cointegration and nonlinear causality among ethanol-related prices: evidence from Brazil. GCB Bioenergy 2018;10:335–42. https://doi.org/10.1111/gcbb.12495.
[26] Taghizadeh-Hesary F, Rasoulinezhad E, Yoshino N. Energy and food security: linkages through price volatility. Energy Pol 2019;128:796–806. https://doi.org/10.1016/J.ENPOL.2018.12.043.
[27] Shrestha DS, Staab BD, Duffield JA. Biofuel impact on food prices index and land use change. Biomass Bioenergy 2019;124:43–53. https://doi.org/10.1016/j.biombioe.2019.03.003.
[28] Bentivoglio D, Finco A, Piedade Bacchi MR. Interdependencies between biofuel, fuel and food prices: the case of the Brazilian ethanol market. Energies 2016;9:1–16. https://doi.org/10.3390/en9060464.
[29] Kinda SR. Does the green economy really foster food security in Sub-Saharan Africa? Cogent Econ. Financ. 2021;9. https://doi.org/10.1080/23322039.2021.1921911.
[30] Costa JAV, de Freitas BCB, Lisboa CR, Santos TD, Brusch LR de F, de Morais MG. Microalgal biorefinery from CO2 and the effects under the blue economy. Renew Sustain Energy Rev 2019;99:58–65. https://doi.org/10.1016/J.RSER.2018.08.009.
[31] Kaşdoğan D. Designing sustainability in blues: the limits of technospatial growth imaginaries. Sustain Sci 2020;15:145–60. https://doi.org/10.1007/S11625-019-00766-W/FIGURES/3.
[32] Weng Y, Chang S, Cai W, Wang C. Exploring the impacts of biofuel expansion on land use change and food security based on a land explicit CGE model: a case study of China. Appl Energy 2019;236:514–25. https://doi.org/10.1016/J.APENERGY.2018.12.024.
[33] Streimikis J, Baležentis T. Agricultural sustainability assessment framework integrating sustainable development goals and interlinked priorities of environmental, climate and agriculture policies. Sustain Dev 2020;28:1702–12. https://doi.org/10.1002/sd.2118.
[34] Hasegawa T, Havlík P, Frank S, Palazzo A, Valin H. Tackling food consumption inequality to fight hunger without pressuring the environment. Nat Sustain 2019;2:826–33. https://doi.org/10.1038/s41893-019-0371-6.
[35] Nikas A, Koasidis K, Köberle AC, Kourtesi G, Doukas H. A comparative study of biodiesel in Brazil and Argentina: an integrated systems of innovation perspective. Renew Sustain Energy Rev 2022;156:112022. https://doi.org/10.1016/J.RSER.2021.112022.
[36] Gasparatos A, Mudombi S, Balde BS, von Maltitz GP, Johnson FX, Romeu-Dalmau C, Jumbe C, Ochieng C, Luhanga D, Nyambane A, Rossignoli C, Jarzebski MP, Dam Lam R, Dompreh EB, Willis KJ. Local food security impacts of biofuel crop production in southern Africa. Renew Sustain Energy Rev 2022;154:111875. https://doi.org/10.1016/J.RSER.2021.111875.
[37] To H, Grafton RQ. Oil prices, biofuels production and food security: past trends and future challenges. Food Secur 2015;7:323–36. https://doi.org/10.1007/s12571-015-0438-9.
[38] Dick NA, Wilson P. Analysis of the inherent energy-food dilemma of the Nigerian biofuels policy using partial equilibrium model: the Nigerian Energy-Food Model (NEFM). Renew Sustain Energy Rev 2018;98:500–14. https://doi.org/10.1016/J.RSER.2018.09.043.
[39] Martínez-Jaramillo JE, Arango-Aramburo S, Giraldo-Ramírez DP. The effects of biofuels on food security: a system dynamics approach for the Colombian case. Sustain Energy Technol Assessments 2019;34:97–109. https://doi.org/10.1016/J.SETA.2019.05.009.
[40] Lima CRA, de Melo GR, Stosic B, Stosic T. Cross-correlations between Brazilian biofuel and food market: ethanol versus sugar. Phys. A Stat. Mech. Its Appl. 2019;513:687–93. https://doi.org/10.1016/j.physa.2018.08.080.
[41] Maitah M, Procházka P, Smutka L, Maitah K, Honig V. Analysis of the impact of ethanol production on agricultural product prices in Brazil. Sugar Tech 2019;21:773–9. https://doi.org/10.1007/s12355-019-00709-w.
[42] Gilbert CL, Mugera HK. Competitive storage, biofuels and the corn price. J Agric Econ 2020;71:384–411. https://doi.org/10.1111/1477-9552.12362.
[43] Tyner WE. Biofuels and food prices: separating wheat from chaff. Global Food Secur 2013;2:126–30. https://doi.org/10.1016/j.gfs.2013.05.001.
[44] Shrestha DS, Staab BD, Duffield JA. Biofuel impact on food prices index and land use change. Biomass Bioenergy 2019;124:43–53. https://doi.org/10.1016/j.biombioe.2019.03.003.
[45] Pu M, Zhong Y. Rising concerns over agricultural production as COVID-19 spreads: lessons from China. Global Food Secur 2020;26:100409. https://doi.org/10.1016/J.GFS.2020.100409.

[46] Tiwari AK, Nasreen S, Shahbaz M, Hammoudeh S. Time-frequency causality and connectedness between international prices of energy, food, industry, agriculture and metals. Energy Econ 2020;85:104529. https://doi.org/10.1016/J.ENECO.2019.104529.

[47] Laborde D, Martin W, Swinnen J, Vos R. COVID-19 risks to global food security. Science 2020;369(80):500–2. https://doi.org/10.1126/SCIENCE.ABC4765/ASSET/2D2555D9-845F-4BB7-8095-09B9051F73D9/ASSETS/GRAPHIC/369_500_F1. JPEG.

[48] Andersson Djurfeldt A. Urbanization and linkages to smallholder farming in sub-Saharan Africa: implications for food security. Global Food Secur 2015;4:1–7. https://doi.org/10.1016/J.GFS.2014.08.002.

[49] Tubiello FN, Fischer G. Reducing climate change impacts on agriculture: global and regional effects of mitigation. Technol Forecast Soc Change 2007;74:1030–56. https://doi.org/10.1016/J.TECHFORE.2006.05.027. 2000–2080.

[50] Fowowe B. Do oil prices drive agricultural commodity prices? Evidence from South Africa. Energy 2016;104:149–57. https://doi.org/10.1016/J.ENERGY.2016.03.101.

[51] Brinkman M, Levin-Koopman J, Wicke B, Shutes L, Kuiper M, Faaij A, van der Hilst F. The distribution of food security impacts of biofuels, a Ghana case study. Biomass Bioenergy 2020;141:105695. https://doi.org/10.1016/J.BIOMBIOE.2020.105695.

[52] Dutta A. Forecasting ethanol market volatility: new evidence from the corn implied volatility index. Biofuels, Bioprod. Biorefining. 2019;13:48–54. https://doi.org/10.1002/BBB.1931.

[53] Lee U, Kwon H, Wu M, Wang M. Retrospective analysis of the U.S. corn ethanol industry for 2005–2019: implications for greenhouse gas emission reductions. Biofuels, Bioprod. Biorefining. 2021;15:1318–31. https://doi.org/10.1002/BBB.2225.

[54] Hao N, Pedroni P, Colson G, Wetzstein M. The linkage between the U.S. ethanol market and developing countries' maize prices: a panel SVAR analysis. Agric Econ 2017;48:629–38. https://doi.org/10.1111/AGEC.12362.

[55] Dutta A, Bouri E, Junttila J, Uddin GS. Does corn market uncertainty impact the US ethanol prices? GCB Bioenergy 2018;10:683–93. https://doi.org/10.1111/GCBB.12527.

[56] Dutta A, Bouri E. Carbon emission and ethanol markets: evidence from Brazil. Biofuels, Bioprod. Biorefining. 2019;13:458–63. https://doi.org/10.1002/BBB.1950.

[57] Bouri E, Dutta A, Saeed T. Forecasting ethanol price volatility under structural breaks. Biofuels, Bioprod. Biorefining. 2021;15:250–6. https://doi.org/10.1002/BBB.2158.

[58] Bilgili F, Lorente DB, Kuşkaya S, Ünlü F, Gençoğlu P, Rosha P. The role of hydropower energy in the level of CO2 emissions: an application of continuous wavelet transform. Renew Energy 2021;178:283–94. https://doi.org/10.1016/J.RENENE.2021.06.015.

[59] Kuşkaya S, Bilgili F. The wind energy-greenhouse gas nexus: the wavelet-partial wavelet coherence model approach. J Clean Prod 2020;245:118872. https://doi.org/10.1016/J.JCLEPRO.2019.118872.

[60] Breitung J, Candelon B. Testing for short- and long-run causality: a frequency-domain approach. J Econom 2006;132:363–78. https://doi.org/10.1016/J.JECONOM.2005.02.004.

[61] Current Release, (n.d.) RATS Econometric Software 2017 (accessed June 21, 2022), https://www.estima.com/ratslatest.shtml.

[62] Soares MJ. The continuous wavelet transform: a primer. 2010. http://www.eeg.uminho.pt/economia/nipe. [Accessed 30 August 2020].

[63] Aguiar-Conraria L, Magalhães PC, Soares MJ. The nationalization of electoral cycles in the United States: a wavelet analysis. Publ Choice 2013;156:387–408. https://doi.org/10.1007/s11127-012-0052-8.

[64] Joanna B. On some problems in discrete wavelet analysis of bivariate spectra with an application to business cycle synchronization in the euro zone — economics E-journal. 2011. accessed June 21, 2022), http://www.economics-ejournal.org/economics/discussionpapers/2011-5/.

[65] Bekiros S, Marcellino M. The multiscale causal dynamics of foreign exchange markets. J Int Money Finance 2013;33:282–305. https://doi.org/10.1016/J.JIMONFIN.2012.11.016.

[66] Aguiar LF, Soares MJ. The continuous wavelet transform: a primer. 2010 (accessed June 21, 2022), https://ideas.repec.org/p/nip/nipewp/23-2010.html.

[67] Bilgili F. Business cycle co-movements between renewables consumption and industrial production: a continuous wavelet coherence approach. Renew Sustain Energy Rev 2015. https://doi.org/10.1016/j.rser.2015.07.116.

[68] Wang Z, Liu Z, Deng Z, Deng W, Jia X. Phase extraction of non-stationary interference signal in frequency scanning interferometry using complex shifted Morlet wavelets. Opt Commun 2018;420:26–33. https://doi.org/10.1016/J.OPTCOM.2018.03.032.

[69] Shehzad K, Bilgili F, Zaman U, Kocak E, Kuskaya S. Is gold favourable than bitcoin during the COVID-19 outbreak? Comparative analysis through wavelet approach. Resour Pol 2021;73:102163. https://doi.org/10.1016/j.resourpol.2021.102163.

[70] Bilgili F, Kuşkaya S, Ünlü F, Gençoğlu P. Does waste energy usage mitigate the CO2 emissions? A time-frequency domain analysis. Environ Sci Pollut Res 2020;27:5056–73. https://doi.org/10.1007/s11356-019-07253-w.

[71] Duan P, Huang C. Application of normal Morlet wavelet transform method to the damped harmonic analysis: on the isolation of the seismic normal modes (0S0 and 0S5) in time domain. Phys Earth Planet In 2019;288:26–36. https://doi.org/10.1016/J.PEPI.2019.01.005.

[72] Chang CC, Yu CP, Lin Y. Distinction between crack echoes and rebar echoes based on Morlet Wavelet Transform of impact echo signals. NDT E Int 2019;108:102169. https://doi.org/10.1016/J.NDTEINT.2019.102169.

[73] Tiwari AK, Cunado J, Gupta R, Wohar ME. Are stock returns an inflation hedge for the UK? Evidence from a wavelet analysis using over three centuries of data. Stud Nonlinear Dynam Econom 2019;23. https://doi.org/10.1515/SNDE-2017-0049/PDF.

[74] Jena SK, Tiwari AK, Roubaud D. Comovements of gold futures markets and the spot market: a wavelet analysis. Finance Res Lett 2018;24:19–24. https://doi.org/10.1016/J.FRL.2017.05.006.

[75] Zheng Y, Rinoshika A. Wavelet multi-resolution analysis on particle dynamics in a horizontal pneumatic conveying. Adv Powder Technol 2018;29:2404–15. https://doi.org/10.1016/J.APT.2018.06.019.

[76] Neto OP, Oliveira Pinheiro A, Pereira VL, Pereira R, Baltatu OC, Campos LA. Morlet wavelet transforms of heart rate variability for autonomic nervous system activity. Appl Comput Harmon Anal 2016;40:200–6. https://doi.org/10.1016/J.ACHA.2015.07.002.

[77] Grossmann A, Morlet J. Decomposition of hardy functions into square integrable wavelets of constant shape. SIAM J Math Anal 1984;15:723–36. https://doi.org/10.1137/0515056.

[78] Torrence C, Compo GP, Torrence C, Compo GP. A practical guide to wavelet analysis. Bull Am Meteorol Soc 1998;79:61–78. https://doi.org/10.1175/1520-0477(1998)079<0061:APGTWA>2.0.CO. 2.

[79] Aguiar-Conraria L, Soares MJ. Oil and the macroeconomy: using wavelets to analyze old issues. Empir Econ 2011;40:645–55. https://doi.org/10.1007/s00181-010-0371-x.

[80] Gallegati M, Gallegati M. Wavelet variance analysis of output in G-7 countries. Stud Nonlinear Dynam Econom 2007;11. https://doi.org/10.2202/1558-3708.1435/DOWNLOADASSET/SNDE1435_SUPPLEMENTARY_1.ZIP.

[81] Kilian L, Park C. The impact of oil price SHOCKS ON the U.S. Stock market. Int Econ Rev (Philadelphia) 2009;50:1267–87. https://doi.org/10.1111/J.1468-2354.2009.00568.X.

[82] Baumeister C, Peersman G. Time-varying effects of oil supply shocks on the US economy. Am Econ J Macroecon 2013;5:1–28. https://doi.org/10.1257/MAC.5.4.1.

[83] Agricultural Markets | Refinitiv, (n.d.). https://solutions.refinitiv.com/agriculturalmarkets? (accessed June 21, 2022).

[84] Condon N, Klemick H, Wolverton A. Impacts of ethanol policy on corn prices: a review and meta-analysis of recent evidence. Food Pol 2015;51:63–73. https://doi.org/10.1016/j.foodpol.2014.12.007.

[85] USDA ERS - Charts of Note, (n.d.). https://www.ers.usda.gov/data-products/charts-of-note/charts-of-note/?topicId=b614d82c-461d-4572-8bb8-29bc2a0868a4 (accessed June 21, 2022).

[86] Demirer R, Kutan AM, Shen F. The effect of ethanol listing on corn prices: evidence from spot and futures markets. Energy Econ 2012;34:1400–6. https://doi.org/10.1016/J.ENECO.2012.06.018.

[87] Chang CL, McAleer M, Wang YA. Modelling volatility spillovers for bio-ethanol, sugarcane and corn spot and futures prices. Renew Sustain Energy Rev 2018;81:1002–18. https://doi.org/10.1016/J.RSER.2017.07.024.

[88] Teske S, Pregger T, Simon S, Naegler T, Graus W, Lins C. Energy [R]evolution 2010-a sustainable world energy outlook. Energy Effic 2011;4:409–33. https://doi.org/10.1007/S12053-010-9098-Y/FIGURES/5.

[89] Huang X, Liu X. The time-frequency evolution of multidimensional relations between global oil prices and China's general price level. Energy 2022;244:122579. https://doi.org/10.1016/J.ENERGY.2021.122579.

[90] Dalheimer B, Herwartz H, Lange A. The threat of oil market turmoils to food price stability in Sub-Saharan Africa. Energy Econ 2021;93:105029. https://doi.org/10.1016/J.ENECO.2020.105029.

[91] Goswami K, Choudhury HK. Biofuels versus food: understanding the trade-offs between climate friendly crop and food security. World Dev. Perspect. 2019;13:10–7. https://doi.org/10.1016/j.wdp.2019.02.004.

[92] Mohanty SK, Swain MR. Bioethanol production from corn and wheat: food, fuel, and future. Bioethanol Prod. from Food Crop 2019:45–59. https://doi.org/10.1016/B978-0-12-813766-6.00003-5.

[93] Walker K, Vadlani P, Madl R, Ugorowski P, Hohn KL. Ethanol fermentation from food processing waste. Environ Prog Sustain Energy 2013;32:1280–3. https://doi.org/10.1002/EP.11700.

[94] Rada NE, Fuglie KO. New perspectives on farm size and productivity. Food Pol 2019;84:147–52. https://doi.org/10.1016/J.FOODPOL.2018.03.015.

[95] Naylor RL, Higgins MM. The political economy of biodiesel in an era of low oil prices. Renew Sustain Energy Rev 2017;77:695–705. https://doi.org/10.1016/J.RSER.2017.04.026.

[96] Ganguly P, Sarkhel R, Das P. The second- and third-generation biofuel technologies: comparative perspectives. Sustain. Fuel Technol. Handb 2021:29–50. https://doi.org/10.1016/B978-0-12-822989-7.00002-0.

[97] Chowdhury H, Loganathan B. Third-generation biofuels from microalgae: a review. Curr. Opin. Green Sustain. Chem. 2019;20:39–44. https://doi.org/10.1016/J.COGSC.2019.09.003.

[98] Eggert H, Greaker M. Promoting second generation biofuels: does the first generation pave the road? Energies 2014;7:4430–45. https://doi.org/10.3390/EN7074430. 7 (2014) 4430–4445.

[99] Ferreira P. Long-range dependencies of Eastern European stock markets: a dynamic detrended analysis. Phys. A Stat. Mech. Its Appl. 2018;505:454–70. https://doi.org/10.1016/J.PHYSA.2018.03.088.

[100] Aguiar-Conraria L, Azevedo N, Soares MJ. Using wavelets to decompose the time–frequency effects of monetary policy. Phys. A Stat. Mech. Its Appl. 2008;387:2863–78. https://doi.org/10.1016/J.PHYSA.2008.01.063.

[101] Aguiar-Conraria L, Joana Soares M. Business cycle synchronization and the Euro: a wavelet analysis. J Macroecon 2011;33:477–89. https://doi.org/10.1016/J.JMACRO.2011.02.005.

[102] Rhif M, Ben Abbes A, Farah IR, Martínez B, Sang Y. Wavelet transform application for/in non-stationary time-series analysis: a review. Appl Sci 2019;9:1345. https://doi.org/10.3390/APP9071345. 9 (2019) 1345.

[103] Tastan H. Testing for spectral Granger causality. STATA J 2015;15:1157–66. https://doi.org/10.1177/1536867X1501500411.