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Estimation of the co-movements between biofuel production and food prices: A wavelet-based analysis

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A B S T R A C T

Recently, the significance of biofuel production on food prices has become an important topic of discussion within the framework of sustainable development. Based on the relevant discussions, this work aims at observing the influence of biofuel production on food prices in the US for the monthly period 1981–2018 by considering all possible structural changes between the co-movements of the variables. In the analyses, oil prices and population variables are also employed as control variables. To this end, we use continuous wavelet model estimations for the whole sample period and sub-sample periods at different frequencies. All computations have considered the potential changes in co-movements of the variables at different sub-sample periods corresponding to high and low frequencies of observed time series data. Estimation results show that there exist significant relationships between biofuel production and food prices in the short-term and long-term cycles. The outcomes of the research hence may provide some insights into the design of sustainable energy and food policies in the United States.

1. Introduction

The global food prices increased considerably in early 2008 since the shock in food prices appeared at the beginning of the 1970s [1]. The market price of many types of foods doubled in real terms from 2005 to mid-2008. Until the peak in July 2008, the main increases were in prices of palm oil (140%), rice (110%), corn (102%), wheat (101%), and soybean (86%) [2]. While the food prices crisis led to food uprisings in many countries, some countries banned grain and food exports and reduced tariffs on imported products [3]. More importantly, the food crisis led to poverty, food insecurity, and hunger in many households all around the world [4,5]. Increases in food prices deeply affected specifically low-income countries and net grain importers, such as sub-Saharan African countries, as households in these countries have to allocate 50–90% of their incomes to food expenditures [6]. Due to these effects, the food crisis has become an essential agenda of public policy [7].

In the following years, global increases in food prices could not be controlled. According to the Food and Agriculture Organization of the United Nations (FAO), while the food price index value was 97.7 in 2003, it was 201.4 in 2008, 211.9 in 2011, and 174.6 in 2017. Remarkably, prices were higher in 2011 compared to 2008, which was considered as the crisis year. While the prevalence of malnutrition in the world decreased in the 2000s, the rise in food prices re-raised this prevalence. The number of undernourished people in 2017 is estimated to be one-ninth of the world's population, approximately 821 million people [8]. These figures increase the risk of not achieving the goal of removing hunger, which is the second one of the United Nations Sustainable Development Goals (SDG-2) by 2030 [8].

In order to provide adequate and specific solutions to the price shocks, first of all, the reasons for the increase in food prices need to be revealed [7]. For this reason, many international organizations, such as the IATP (Institute for Agriculture and Trade Policy) and the World Bank, have focused on the reasons for the increase in global food prices in recent years [6]. Similarly, the food crisis has led many academicians to theoretically and empirically examine the reasons for the rise in food prices [7,9]. When one observes the outputs of these studies, he/she can classify the causes of the increases in food prices under a few groups.

The first and foremost reason for the increase in food prices is

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considered as the high growth rates and the urbanization process in the 2000s [10,11]. Countries with a high population, namely China and India, notedly exhibited a remarkable growth performance in the 2000s. According to the World Bank, the Chinese economy grew by 14% and 9.6% in 2007 and 2008, while the Indian economy grew by 7.6% and 3.8% in the same period. The world's most impoverished region, namely sub-Saharan African countries, grew by 6.6% and 5.5% in 2007 and 2008. These high growth rates have a significant influence on the demand side of the world food balance, resulting in much higher food consumption than expected. The urbanization process also changed the consumption structure and increased the demand for foods [12,13].

The second reason for the pressure on food prices is extreme weather conditions stemming from global warming and climate change [14–17]. Due to global warming and climate change, significant deviations occur in rainfall and temperature, and many regions face droughts and floods. The yield in agricultural production is substantially reduced in the areas that are exposed to extreme weather conditions [18].

Researchers point out crude oil prices as a third and essential factor that led to increases in food prices, and many empirical studies explore findings supporting co-movement between crude oil prices and food prices [1,19–22]. Crude oil is the primary input of the product processing and transportation processes in the agricultural sector. Increases in crude oil prices have a direct impact on agricultural production costs, leading to a rise in food prices [23]. Additionally, crude oil prices also influence the food prices via exchange rate channel because an increase in oil prices may bring about the current account deficit, which in turn can result in a depreciation of the national currency. The increase in the exchange rate affects the prices of many agricultural inputs and leads to increases in food prices [21].

Last but not least, the literature emphasizes the relationship between food prices and biofuel production. Biofuels are regarded as an essential policy tool for sustainable economic development [24,25]. There are several reasons for this feature of biofuels: (i) The raw material needed to produce biofuels is found in all parts of the world. In recent years, public support and technological developments for biofuels have made the production of biofuels economically reasonable [26]. (ii) Biofuels have the potential to mitigate transport-induced CO_2 emissions to fight global warming [27,28]. (iii) Fossil fuels can be substituted with biofuels that support countries' energy security [29]. (iv) Bioenergy might help rural areas increase employment, and hence, can improve agricultural production, and so reduce poverty in developing countries [30].

Despite the enormous potential of biofuels, the causality from biofuel production to food prices and the competition between biofuels market and food market have become an essential issue for economic and political debates due to the boom of global biofuel production after the year 2005 [31,32].

Contributing to the economic and political debates on the competition between biofuels and food with robust empirical evidence motivates us for this research. In this paper, following these discussions, we observe the co-movements of biofuel production and food prices. The literature explains the burden of biofuel production on food prices with the deterioration in the mechanism of food supply and demand. According to demand-side approaches, the reason for increasing food demand in recent years has been not only related to nutrition but also related to biofuel production. As is known, basic foods are used as raw materials in biofuel production. Ethanol is produced from various grains (in Africa), corn (in the US), and sugarcane (in Brazil), while biodiesel is obtained from rapeseed (in EU) and soybeans (in the US and Brazil) [33]. With the boom of biofuel production, demand for these products can increase significantly, and food prices can rise [34].

On the other hand, according to supply-side approaches, farmers tend to grow energy crops on the lands previously used for food production due to the increasing interest in biofuels and the supports provided by states [9,35]. Moreover, as the biofuel market grows out of land competition, demand for water use, fertilizer, agricultural machinery, and capital, pesticides, and labor are increasing for food and feed production [34]. For this reason, the use of lands for energy crops leads to decreases in food supply and can lead to difficulties for sustainable food production both globally and locally [32]. Finally, it is important to note that the increase in biofuel production may cause pressures on agricultural productivity. The use of cultivation areas for the production of biofuel raw materials reduces land productivity due to reasons such as soil degradation, erosion, reduction of biodiversity, monoculture cultivation, and increased chemical emissions.

We can explain the possible contributions of our paper to the literature as follows:

(1) The results of these studies are expected to help policy-makers decide whether to maintain biofuel production [36]. Despite the extensive literature that reveals that biofuels are clean, renewable, and eco-friendly, opinions have also begun to increase that biofuels have adverse effects on food prices and land use [37]. These contradictory results cause confusion among researchers, policy-makers, and people. Empirical evidence regarding the consequence of biofuels on food prices seems not to be sufficient, and lack of research is observed [38]. Considering the importance of the increase in biofuel production on the future of the environment along with food prices, it is essential to unravel the impacts of biofuel production to determine the policies of food, energy, and environment [32,37]. In this paper, we aim to provide new empirical evidence for the correlation between biofuels and food prices with a focus on the research gap in the literature. Within this scope, we use monthly data spanning from January 1981 to January 2018 in the USA to investigate the possible co-movement between biofuel production and food prices via the wavelet coherence method considering some control variables, such as oil prices, and population. We focus specifically on the US in the paper as the US is the world's greatest biofuel producer and grain exporter. The US alone dominates the global biofuels market [39]. The US currently accounts for 57% of global ethanol production [40]. According to the USDA Food Database, the share of the US in wheat, corn, and soybean exports in 2017 is 15%, 39%, and 40%, respectively. Therefore, we hope that the empirical results of the paper will provide significant conclusions to the literature and administrators due to the impact of the US on global food and biofuel markets.

(2) Lastly, in terms of research methodology, this paper differs from the available papers in the literature. The papers available in the literature, in general, pursue the field analyses, or, correlation analyses or, time series models, or panel data models to investigate the possible potential impact(s) of energy products on food prices. These analyses obtain in general the parameter estimations which either don't change or might change due to two-three structural breaks during the entire example period. This paper, on the other hand, employs continuous wavelet model estimations for (a) whole sample period, and (b) sub-sample periods at different frequencies in the US for the monthly period 1981:1–2018:1. The following papers about the robust aspects of the method can be viewed separately [41–44]. To this end, this work addresses the interaction between biofuel production and food prices by investigating all potential structural changes

between the co-movements of the variables. All computations, therefore, have considered the possible changes in interactions of the variables at sub-sample periods corresponding to both low frequency (3-8-year cycle) and high frequency (1-2-year cycle) of observed time series data. Therefore, the method followed in this research increases the original value of the paper.

2. Literature

It is of great interest for economists to examine the interrelationship between the energy market and the food market. Especially after the oil price shocks in the 1970s, the impact of oil prices on many macroeconomic indicators began to be examined [45]. One of the crucial indicators affected by the energy crisis is food prices. Then, in 2008, a common movement was observed between oil prices and food prices [46]. Thus, researchers have sought to reveal the possible impact of changes in energy prices on food prices. Many studies mainly investigate the relationship between global food prices and oil prices with various analysis methods. Apart from global food prices, there are also some studies on oil price-food prices in a single/specific country. Therefore, in the literature review, we first evaluated the studies that empirically investigate the correlation between energy/oil prices and food prices.

In this context, Esmaeili and Shokoohi [47] analyze the connection between macroeconomic indicators, oil prices, and world food prices in 1961–2005 with the principal component analysis. The paper considered the market prices of 7 main products, including wheat, rice, sugar, eggs, milk, meat, and oilseeds. Research indicates that oil prices increase food prices. However, it reveals that macroeconomic indicators have a more significant influence on food prices. Nazlioglu and Soytas [21] explored the dynamic link between oil prices and agricultural product prices for the period 1980–2010 through the panel vector error correction model (VEC) estimations. Test results indicate that the volatility in world oil prices has significant consequences on food prices. Wang et al. [48] monitored the dependence between oil prices and global agricultural commodity prices with monthly data by using the structural VAR method. The results confirm the significant effect of oil shocks on food prices. Ibrahim [49] evaluates the relationship between oil prices, GDP, and food price index in Malaysia for the period 1971–2012 with the NARDL method. The study indicates that there exists a strong positive correlation between oil prices food prices in the long and short run.

On the other hand, it shows that the fall in food prices is not related to the fall in oil prices. Cheng and Cao [50] tested the relationship between global oil prices and food prices for the period 1990–2017 using the threshold VECM. The test results confirm the validity of a nonlinear relationship between global oil prices and food prices. Taghizadeh-Hesary et al. [51] examine the impulse-response relationship between energy (oil) prices and food prices in Asian countries for the period of 2000–2016 by using panel structural VAR method. The research findings reveal a significant causality from oil prices to food prices and emphasize that the move in oil prices explains 64% of the variance in food prices.

On the other hand, global food prices peaked in 2011, while oil prices tended to decline. The boom in biofuel production, which began in 2005, continued in 2011 as well [52]. Researchers began to emphasize that another important reason for the increase in food prices might be biofuel production. Then, the literature engages in the relationship or competition between the biofuel market and the food market. Therefore, we secondly review studies focusing solely on the relationship between biofuel production/prices and food prices. In the related literature, it is seen that researchers follow different analysis methods. For example, Ajanovic [11] examines the relationship between biofuel production, production costs, oil prices, land use, and food prices in the USA and Europe with descriptive statistics and comparative analysis methods. The main findings of the study are as follows: (1) Biofuel production may put pressure on raw material prices due to high raw material demand and high marginal costs. (2) However, the most crucial reason for the volatility in raw material prices in the period 2000–2009 was not the production of biofuels, but the oil prices and speculative movements. This situation shows that the recent increases in biofuel production have no significant impact on raw material prices. Tokgoz et al. [39] explored the relationship between biofuel production growth and agricultural commodity prices, uncertainties in OECD energy and fuel policies. The results of the analysis have shown that biofuels growth has a significant impact on the prices of agricultural products and that these effects may change consumption, calorie availability, and food safety. Araujo Enciso et al. [53] research the impact of biofuel policies on global food safety for the period 2015–2024. The analysis findings of the model show that the abolishment of biofuel policies does not yield an increasing effect on global food security. Martínez-Jaramillo et al. [54] explore the repercussion of biofuels on food safety and land usage in Colombia for the period 2016–2030 with a system dynamics model. The outputs underline that production of biofuel affects food production and food prices by reducing the land supply allocated to agriculture. In other respects, Yan et al. [55] conduct a comprehensive life cycle assessment and economic analysis of ethanol produced from agave in the context of water-energy-food-environment. Research results show that agave is promising for biofuel production in the water-energy-food-environment context. Moreover, agave outperforms corn and sugar cane on environmental impact.

In the literature, a group of researchers presents the relationship between biofuels and food prices with partial equilibrium, dynamic partial equilibrium, and general equilibrium approaches. These approaches are market models created by simulation techniques by various international organizations. Partial equilibrium models estimate the impact of taxes and subsidies in the biofuels market on the agricultural sector. General equilibrium models investigate the interaction between the biofuels market and other markets and the bi-directional relationship. In particular, the general equilibrium model analyzes to focus on the effects of biofuels and carbon emission targets on economic and international trade [56]. In this context, Tokgoz [57] examines the relations between crude oil prices, biofuel market, and the agriculture sector in EU-27 countries with a general equilibrium approach. The first scenario indicates that crude oil prices have increased bioethanol production, consumption, and grain prices. The second scenario reveals that trade liberalization decreases grain prices, and this effect is greater than the burden of crude oil prices. Timilsina et al. [36] explore the significance of oil prices on biofuels expansion and food supply. The research shows that the rise in oil prices has reduced agricultural production. The negative impact of the increase in oil prices on agricultural production appears to be relatively less in the major biofuel producing countries. Bahel et al. [59] observe the relationship between oil prices, biofuel production, and global food prices with the decentralized equilibrium model. Model results argue that biofuel production increases food prices by affecting land scarcity. Chakravorty et al. [60] employed a Ricardian model with different land quality to show that world food prices may enlarge by 32% by 2022. They take into account the multi-national, multi-sectoral, dynamic, and global computable general equilibrium model. In this way, they evaluate the relationships between biofuel supply, agricultural supply, global food supply, and land-use change. Research shows that biofuels production might contribute to an increase in food prices. The study also draws attention to demand-side factors such as population, dietary preferences, and income level. Dick and Wilson [61] inspect the effect of ethanol production on land use and food safety in Nigeria during the period 1995–2010 with the partial equilibrium model. The model points to two important outcomes: (1) Nigeria may meet the demand for ethanol without compromising food safety. (2) The doubling of current ethanol demand adversely affects land use and food safety. Weng et al. [63] analyze the influence of biofuel production on land use and food safety in China. Model findings reveal that biofuel production leads to reallocation of land for rice, cereals and other crops, forests, and grassland. Brinkman et al. [64] examine the effects of biofuel production on food security, availability, access, use, and stability for urban and rural households in Ghana with the computable general equilibrium (CGE) model. The results show that the most critical effect of biofuel production in terms of food security is to increase the pressure on food prices and import dependency.

Finally, we evaluate the literature that examines the relationship between biofuels and food prices with econometric estimations such as time series and panel data analysis. Applanaidu et al. [65] search the effects of the increases in biodiesel demand in Malaysia on the palm oil market between 1980 and 2007 with the nonlinear two-stage least squares (2SLS) method. Research findings indicate that a 70% increase in biodiesel demand results in an increase of 110% on the price of raw palm oil. Bastianin et al. [66] investigate the interactions of biofuels, field crops, and cattle prices in the USA for the period of 1987–2012 with Granger causality and asymmetric least squares methods (OLS). Estimation findings do not provide significant evidence of an association between cattle prices, field crops, and biofuels in the United States. Bayramoğlu et al. [56] observe the connection between corn prices and bioethanol production in the USA between 1993 and 2011 by using Three-Stage Least Squares (3SLS) method. In contrast to the results of Bastianin et al. [66]. Bayramoğlu et al. [56] reveal that bioethanol production has a significant and increasing effect on corn prices. They also emphasize that bioethanol production in the US is a considerable fact in explaining the increase in world corn prices. Similarly, To and Grafton [1] estimate the relationship between oil prices, per capita income, biofuel production, and food prices using autoregressive models using the US and global data. The results of the investigation show that food prices are affected by crude oil prices and biofuel production in the US and globally.

Koizumi [34] evaluates the correlation between agricultural development, food safety, and crude oil prices in Brazil, USA, Indonesia, Malaysia, Thailand, and China with the least squares (OLS) method for the period 1990–2012. Research findings indicate that biofuel production might yield an adverse effect on food safety. The results also show that biofuel production creates essential opportunities for agricultural developments. Bentivoglio et al. [9] test the relation between sugar prices, ethanol, and gasoline in Brazil during 2007–2013 by causality analysis, impulse-response functions, and variance decomposition. The test findings show that gasoline and sugar prices influence the ethanol prices, while ethanol prices don't affect on sugar prices. Aké [67] evaluates the link between global food prices and biofuel production for the period 1992–2016 using dynamic conditional correlation and phase synchronization methods. Analysis findings confirm that increases in profits in biofuel production have an increasing impact on the prices of oily cereals. Paris [68] examines the connection between agricultural commodity prices, oil prices, and biofuel production in the US and Europe for the period 1986–2014 with a cointegration model approach. The results of the research show that biofuel production contributes to the price of agricultural products positively. Lima et al. [33] examined the co-movements of ethanol production and sugar prices in Brazil by partial cross-correlation analysis (DPCCA).

In contrast to the findings of Bentivoglio et al. [9], Lima et al. [33] show a positive and significant correlation between ethanol production and sugar prices in Brazil. Shrestha et al. [69] estimate the association between food prices, biofuel production, and land-use change in the United States for the period 1991–2016 by employing correlation analysis. The findings emphasize that biofuel production does not cause food prices to increase. According to the research, the two main factors affecting food prices are oil prices and population. Gilbert et al. [70] investigate the effect of ethanol production on corn prices in the US by using regression analysis with structural breaks using monthly data for the period 2000–2016. Regression findings show that ethanol production causes upward pressure on corn prices. Subramaniam et al. [71] resolve the effect of the interaction between biofuels and environmental quality on food security with a generalized method of moments (GMM) for fifty-one countries. The paper shows that biofuels may initially bring competition to food security, but at a later stage may lead to a favorable situation for agriculture.

Table 1 describes a summary of the literature findings. For example, in terms of the nexus between bio-energy demand and food prices, there exist different outputs in the literature. Applandau et al. [65] indicate that an increase in biodiesel demand increases the price of raw palm oil. Müller et al. [72] reveal, on the other hand, that the growing demand for bio-energy might influence the food production/food prices positively and negatively. In terms of the nexus between bio-energy production and food prices, the literature reveals different outputs as well. Some works exhibit that biofuel production has no impact on food prices [11,66], and some other papers yield that biofuel production has a significant effect on food prices [1,34,39,56,59,60,67].

After all these evaluations, (1) we may state that there is no consensus between the empirical findings in the relevant literature considering the dependence between biofuel production and food prices. (2) The literature findings differ according to the country/countries, period, and method. (3) Due to the dominant role of Brazil and the US in the biofuel market, the literature focuses either on these two countries or on the global market. (4) The findings of all researches aim to contribute to the development of biofuels and food policies. The first main factor that motivates us to prepare this paper is the lack of enough empirical evidence in the literature on the relationship between biofuel production and food price. The second factor is to contribute to the development of global food and energy policies.

3. Methodology: wavelet analyses

Fourier transform and wavelet transform are the most used methods in frequency analysis. The Fourier transform is a suitable method for the analysis of stationary time series. So, the Fourier transform is not an effective method for researchers using non-stationary time series. For this reason, this paper used the wavelet transformation technique, which allows analysis of non-stationary time series.

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

This research differs from other researches available in the literature of biofuel product-food price nexus in terms of the time dimension and frequency dimension. In general, the seminal

Table 1
Summary of literature.

Author(s)	Country	Period	Method	Results
Applandau et al. [65]	Malaysia	1980–2007	Nonlinear 2SLS	A 70% increase in biodiesel demand results in an increase of 110% on the price of raw palm oil.
Müller at al [72].	Global	1970–2006	Statistical comparisons	Demand for bio-energy might influence food production and food prices negatively or positively.
Tokgoz [57]	EU-27 countries	2008–2017	General equilibrium approach	Oil prices increase bioethanol production, consumption, and grain prices.
Esmaeili and Shokoohi [47]	Global	1961–2005	Principal component analysis	Oil prices and macroeconomic indicators significantly affect food prices.
Ajanovic [11]	The USA and Europe	2000–2007	Descriptive statistics and comparative analysis	Biofuel production does not influence the raw material prices. The prominent increase in food prices stems from oil prices.
Timilsina et al. [36]	Global	2009–2020	Computable general equilibrium	The rise in oil prices reduces agricultural production. This negative effect of oil prices on agricultural output appears to be relatively less in biofuel producing countries.
Nazlioglu and Soytas [21]	Global	January 1980 to February 2010	Panel co-integration and panel VEC causality	The world oil price yields a significant consequence on agricultural commodity prices.
Tokgoz et al. [39]	OECD	2005–2020	IMPACT analyses	Biofuel production has a considerable effect on agricultural commodity prices.
Bahel et al. [59]	Global	–	Decentralized equilibrium model	Biofuel production increases food prices by affecting land scarcity.
Gardebroek and Hernandez [73]	USA	1997–2001	GARCH models	There is a significant interaction between the ethanol market and the corn market. However, oil prices have no major impact on the corn market.
Bastian et al. [66]	USA	1987–2012	Asymmetric OLS and Granger causality	There is no meaningful association among cattle prices, biofuels, and field crops in the US.
Wang et al. [48]	Global	January 1980 to December 2012	Structure VAR.	Agricultural commodity prices respond to oil price shocks.
Koizumi [34]	Brazil, USA, Indonesia, Malaysia, Thailand, and China	1990–2012	OLS	Food safety is affected negatively by biofuel production.
To and Grafton [1]	Global and USA	1981–2013	Autoregressive model	Food prices are influenced by biofuel production and oil prices in the US and globally.
Ibrahim [49]	Malaysia	1971–2012	NARDL model	There is an asymmetric relationship between oil prices and food prices.
Bayramoğlu et al. [56]	USA	1993–2011	3SLS	Bioethanol production has a significant and increasing effect on corn prices.
Bentivoglio et al. [9]	Brazil	2007–2013	Causality, impulse-response functions and variance decomposition.	Changes in ethanol prices do not affect sugar prices.
Enciso et al. [53]	Global	2015–2024	Recursive-dynamic agricultural multi-commodity model	The abolition of biofuel policies has no impact on increasing global food security.
Aké [67]	Global	1992–2016	Dynamic conditional correlation and phase synchronization	As biofuel production becomes profitable, it has an increasing effect on oily cereal prices.
Chakravorty et al. [60]	Global	2007–2030	Ricardian model	Biofuels account for about half of the increase in food prices.
Dick and Wilson [61]	Nigeria	1995–2010	Partial equilibrium model	The demand for ethanol negatively influences land-use and food security.
Paris [68]	The USA and Europe	1986–2014	Smooth transition regression	Biofuel production contributes to the price increase in agricultural products.
Cheng and Cao [50]	Global	January 1990 to June 2017	TVECM	Oil and food prices follow a nonlinear causality.
Lima et al. [33]	Brazil	2000–2016	DPCCA	Ethanol production and sugar prices have a positive correlation.
Shrestha et al. [69]	USA	1991–2016	Correlation analysis	Oil prices and population influence food prices, while biofuel production is not the real reason for the rise in food prices.
Taghizadeh-Hesary et al. [51]	Asian countries	2000–2016	Panel structure VAR	Oil price fluctuations powerfully explain the rise in food prices.
Martínez-Jaramillo et al. [54]	Colombia	2016–2030	System dynamics model	Biofuels change land use and reduce the land supply allocated to agriculture. This situation brings about a shortage of food supply and boosts food prices.
Weng et al. [63]	China	2012–2020	Computable general equilibrium	Biofuel production causes a reallocation of land for rice, cereals and crops, forest, and grassland.
Yan et al. [55]	Australia	–	Comprehensive life cycle assessment	Agave is promising for biofuel production in the water-energy-food-environment context.
Brikman et al. [64]	Ghana	2010–2030	Computable general equilibrium model	The most critical effect of biofuel production in terms of food security is to increase the pressure on food prices and import dependency.
Gilbert et al. [70]	US	2010–2016	Regression analysis with structural breaks	Ethanol production causes upward pressure on corn prices.
Subramaniam et al. [71]	Fifty-one countries.	2011–2016	GMM	Biofuels may initially bring competition to food security, but at a later stage may lead to a favorable situation for agriculture.

papers in the literature economics and/or engineering yield relevant model estimations in which (i) parameter estimations do not change through time or (ii) the parameter estimations consider at most two or three potential structural breaks of the series. This paper, however, reveals (a) the impact of the leading variable on the lagged variable in the estimated model that might change through time, and, (b) the effect of the leading variable on the lagged variable in the estimated model that might change from high frequency to low frequency. By following the motivation of this research, this paper employs a continuous wavelet approach, which can address the issues given in (i) and (ii).

Fourier transform and wavelet transform are the leading signal analysis methods. The Fourier Transform (FT) is an effective technique to observe the frequency components of the signal. But, when we consider the FT over the entire time axis, we cannot monitor a certain frequency clearly [74]. To overcome such a limitation, the wavelet analysis has been proposed. Wavelet computation is to use a mathematical representation of the FT through its new feature of scaling. Wavelet analysis provides an advantage since it has flexibility in using different non-stationary signals. Wavelet analysis is a powerful tool well-suited to study multiscale, nonstationary processes occurring over finite spatial and temporal domains [75]. Wavelet analysis has been used successfully in signal processing analysis in the last thirty years [76–81].

In this paper, wavelet analysis allows us to effectively measure the correlation between the food price index and biofuel production indicators for the USA at a specific scale and at a specific time. Also, Wavelet analysis provides advantages that enables us to detect sudden structural changes that may occur over time [81].

Wavelets have the features of being localized over time scale because they move homogeneously over time and are structured over finite time intervals [82]. This analysis considers both time and scale domains simultaneously. This is the reason why ripples can discrete data into varied frequency components [83]. A wavelet follows an oscillating, complex or real function $\mathbb{X}(t) \in L^2(\mathbb{R})$ [84]. The factor $\mathbb{X}_{(\ell,s)}(t)$ used to create the wavelet family is called the mother wavelet and it can be written as below:

$$\mathbb{X}_{(\ell,s)}(t) = \frac{1}{\sqrt{|s|}}\mathbb{X}_t\left(\frac{t-\ell}{s}\right) \qquad \ell, s \in \mathbb{R} \text{ and } s \neq 0 \tag{1}$$

where the term $1/\sqrt{|s|}$ defined as the normalization factor. The mother wavelet $\mathbb{X}(.)$ includes scaled (s) and located (ℓ) parameters. The mother wavelet $\mathbb{X}(t)$ is designed to balance between the time and frequency domains resolution. The term ℓ is the translation parameter which represents the position of the wavelet in the time domain. The term s is the scaling parameter which represents the position of the wavelet in the frequency domain.

An increase in s detects the low-frequency feature of time series, as a descending s compacts it to observe the high-frequency properties of the time series. This means that there is a negative association between scale and frequency. This allows the creation of a $\mathfrak{X}(t)$ time-series through Continuous Wavelet Transform (CWT) $\mathfrak{w}_x(s,\ell)$ The CWT provides a repetitious depiction of a function obtained through the mother wavelet [85]. Thereby, the wavelet-based transformation can be depicted by $\mathfrak{X}(t)$ using Eq. (2).

$$\mathfrak{X}(t) = \left(\frac{2}{\mathfrak{m}_{\mathbb{X}}}\right)\int_0^{\infty}\left[\int_{-\infty}^{\infty}\mathfrak{w}_x(\ell,s)\,\mathbb{X}_{\ell,s}(t)d_s\right]\frac{d\ell}{\ell^2} \tag{2}$$

Hence, the CWT of $\mathfrak{X}(t)$ in terms of $\mathbb{X}^*(t)$ is denoted by Eq. (3).

$$\mathfrak{w}(\ell,s) = \frac{1}{\sqrt{|s|}}\int_{-\infty}^{+\infty}x(t)\mathbb{X}^*\left(\frac{t-\ell}{s}\right)dt \tag{3}$$

where the ℓ is the translation or position the factor, s is the expansion or scale factor, and asterisk (*) represents complex conjugation.

Wavelets generally don't have identical properties. They might have different features. One form of the wavelet is Morlet. As it is presented firstly by Morlet et al. [86], the Morlet wavelet provides both phase and amplitude analysis because it contains imaginary and real parts. The Morlet wavelet analysis offers several features-advantages for time-frequency analysis. One of these advantages is that the Morlet wavelet is Gaussian-shaped in the frequency domain. Due to this feature, the absence of sharp edges minimizes ripple effects that can be misinterpreted as oscillations. Another important advantage is the results of Morlet wavelet convolution, preserving the temporal resolution of the original signal [87]. The Morlet wavelet can be exhibited in Eq. (4).

$$\mathbb{X}_w(t) = \pi^{-1/4}e^{i\omega_0 t}e^{-t^2/2} \tag{4}$$

When $\mathbb{X}_0 = 6$ the wavelet scale, s, is negatively correlated with frequency, $f \approx s^{-1}$, clarifying the exposition of the wavelet transform [88]. It is possible to obtain the cross-wavelet power (CWP) by using the CWT as $|\mathfrak{w}_{xy}(s,\ell)|$. The CWP expresses the region's covariance of {X} and {Y} series at different scales [89]. The correlation {X} and {Y} series, then, is defined as in Eq. (5).

$$\Im_{xy}(\ell,s) = \frac{|\mathbb{S}(\mathfrak{w}_{xy}(\ell,s))|}{\sqrt{[\mathbb{S}(\mathfrak{w}_x(\ell,s))\mathbb{S}(\mathfrak{w}_y(\ell,s))]}} \tag{5}$$

where $\Im_{xy}$ represents the correlation between variables. It takes a value ranging from zero to one in both the time and frequency domain. The phase difference analysis is used to detect the negative/positive correlation and the lead-lag relationship among the components. The visual expression of the lead-lag relationship between the variables is given in Fig. 1.

The phase difference (with $\mathfrak{m}_{x,y} \in [-\pi,\pi]$) between {X} and {Y} series can be written as follows:

$$\mathfrak{m}_{xy} = Arctan\left[\frac{\mathfrak{F}(\mathfrak{w}_{xy}(\ell,s))}{\Re(\mathfrak{w}_{xy}(\ell,s))}\right] \tag{6}$$

where $\mathfrak{F}(\mathfrak{w}_{xy})$ and $\Re(\mathfrak{w}_{xy})$ represent the real part and imaginary part of the smooth power spectrum, respectively. If $\mathfrak{m}_{x,y} \in \left(0, \frac{\pi}{2}\right)$

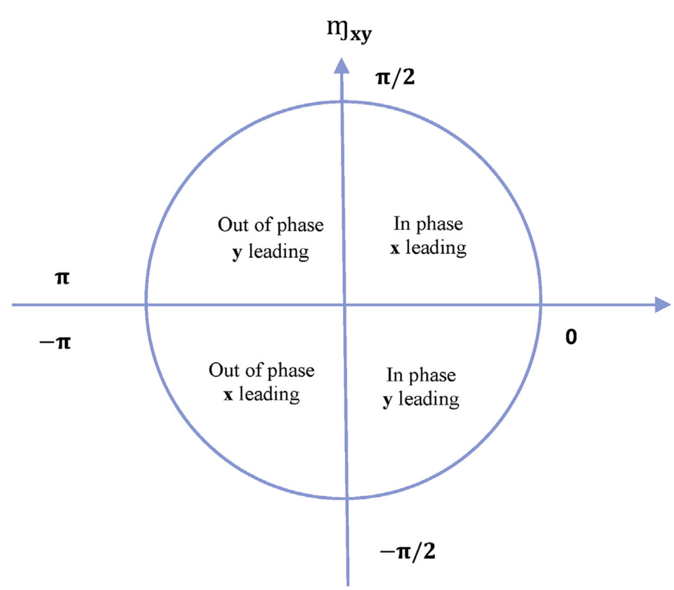

Fig. 1. Phase difference circle. **Source:** [90].

the series move in phase, {X} leads {Y} If $\eta_{x,y} \in \left(0, -\frac{\pi}{2}\right)$ the series move again in phase, then {Y} is leading. If $\eta_{x,y} \in \left(\frac{\pi}{2}, \pi\right)$ there is anti-phase relation, in this case, the series move again out of the phase where y(t) is leading. There exists anti-phase relation when the phase difference is π or $-\pi$. If $\eta_{x,y} \in \left(-\pi, -\frac{\pi}{2}\right)$ the series is following anti-phase relation as {X} is leading. A phase difference of zero indicates that {Y} and {X} move together.

4. Data and descriptive statistics

This research analyses the co-movements between food prices index and biofuel production together with the control variables of oil price and population for the USA. Table 2 reveals the descriptive statistics of the variables.

Figs. 2–5 depict the polynomial trends to demonstrate the slope of the variables. Food price index, biofuel production, oil price, and population data are estimated well with their polynomial trends as shown in Eqs. (7)–(10).

$$\text{Food price index} = 2E - 07x^2 - 0.0026x - 12.921 \quad (7)$$

$$\text{Biofuel production} = -7E - 14x^4 + 1E - 08x^3 - 0.0005x^2 + 12.759x - 113703 \quad (8)$$

$$\text{Oil price} = -7E - 18x^5 + 1E - 12x^4 - 8E - 08x^3 + 0.0028x^2 - 48.738x + 333218 \quad (9)$$

$$\text{Population} = -3E - 05x^2 + 9.491x - 33285 \quad (10)$$

The trend lines of the variables from Figs. 2–5 have the goodness of fit measures (R^2) of [0.996], [0.973], [0.831], and [0.997], respectively. Figs. 2 and 5 indicate that the food price index and population tend to increase for the whole sample period. Fig. 3 explores that, although there exist some fluctuations in observed data for biofuel production during the whole sample data, the 4th degree of polynomial representation of the data demonstrates an increase in biofuel production after 1996 till the end of the period. One may monitor from Fig. 4 that realized data points of oil price exhibit more severe fluctuations than biofuel production data do. Although it fluctuates around its mean with several considerable ups and downs, the 5th degree of polynomial representation of the data yields first a decline (during the period 1981:01–1997:06), later an increase (for the period 1997:07–2012:06), and later again a decrease in oil price index till the end of the period.

Although observed data and their polynomial equations provide some visual inspections about historical movements of the variables, they do not provide specific co-movement information at specific sample period(s) between the variables. The next section intends to analyze the co-movements and lead-lag relations between time series $x(t)$ and $y(t)$ for the whole sample data period and sub-sample periods at high and low frequencies.

5. Wavelet-time and frequency domain-estimation results

In this section, we investigate the co-movements of the food price index and biofuel production of the USA through continuous wavelet model, time domain, and frequency domain computations.

Fig. 6a illustrates the wavelet analysis of the food price index and biofuel production (without control variables). Fig. 7a shows the wavelet coherency between the food price index and biofuel production, together with the control variables of population and oil prices. All figures show the co-movements of the respective variables. In Figs. 6a and 7a, the thick black curves depict the cone of influences that monitor the border distortions. In the color bar, blue indicates weak coherence and red represents strong coherency. The dark blue color demonstrates the weakest coherence and the dark red indicates the strongest coherence.

Finally, Fig. 6b-c and 7b-7c expose the phase difference outputs of 1~2 years and 3~8 years frequencies.

Fig. 6a, monitoring the co-movements between biofuel product and food price (index), and phase difference analysis given in Fig. 6b, denoting lead-lag relations, reveal that, in short term cycle (1~2 years frequency):

(a) During 1981–1986, biofuel production and food price move together; as biofuel production (food price) increases, food price (biofuel production) increases as well. In his period there is no lead-lag relation between the variables.
(b) During 1995–2000, as food price index goes up, the biofuel production goes up as well. This association of the variables at this period seems, however, to be relatively weaker than that of variables at the period 1981–1986.
(c) Another relationship that is not very strong but worth interpreting is realized in periods 2000–2003 and 2006–2008. At these periods, biofuel production leads to an increase in the food price index.
(d) In the period 2014–2017, the increase in food prices leads to an increase in biofuel production.

Fig. 6a and c shows that in the 3~8 years frequency band (in the long-term cycle), the variables move together; as food price index boosts, the biofuel production also boosts (or vice versa). In the long term (at the low-frequency period), it appears that there is no lead-lag association between variables.

When the controlled variables of oil price and population are observed additionally in the wavelet analyses (Fig. 7a), the co-movements of the food price index and biofuel production

Table 2
Variable definitions, data sources, and descriptive statistics: 1981:1–2018:1.

Variable	Definitions	Sources	Mean	Median	Min.	Max.	Obs.
Food Price Index	The consumer price index for all urban consumers (Index 1982–1984 = 100)	U.S. Bureau of Labor Statistics	169.12	163.80	91.50	252.36	445
Biofuel Production	Total biomass inputs to the production of fuel ethanol and biodiesel (trillion BTU)	U.S. Energy Information Administration (EIA)	58.85	18.45	0.97	252.36	445
Oil price	Crude Oil Domestic First Purchase Price (Dollars per Barrel)	U.S. Energy Information Administration (EIA)	37.66	26.04	8.03	128.08	445
Population	Total population (Thousands)	U.S. Bureau of Labor Statistics	278140.1	279,448	229,004	327,265	445

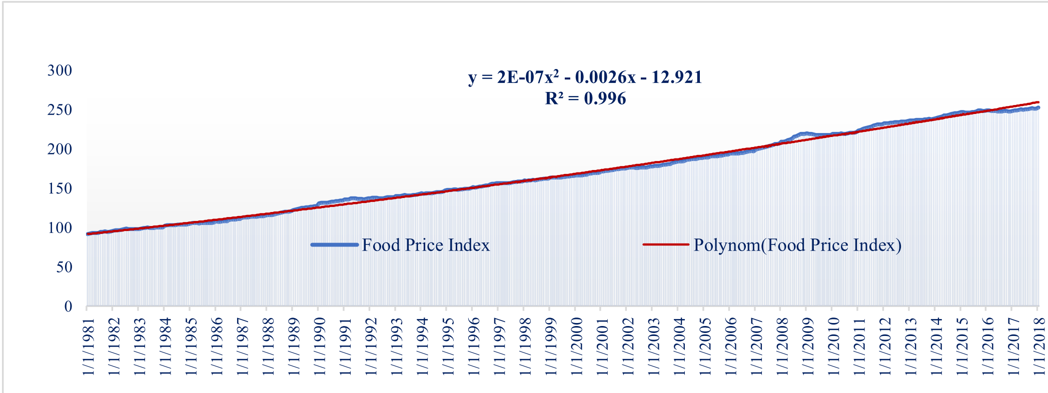

Fig. 2. The food price index of the US (1981:1 to 2018:1). **Data source:** [91].

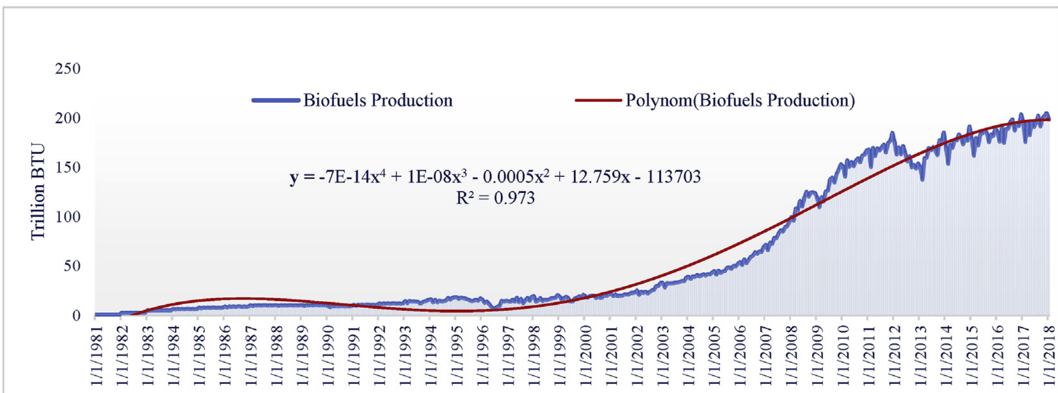

Fig. 3. The biofuel production of the US (1981:1 to 2018:1). **Data Source:** [92].

Data Source: [92]

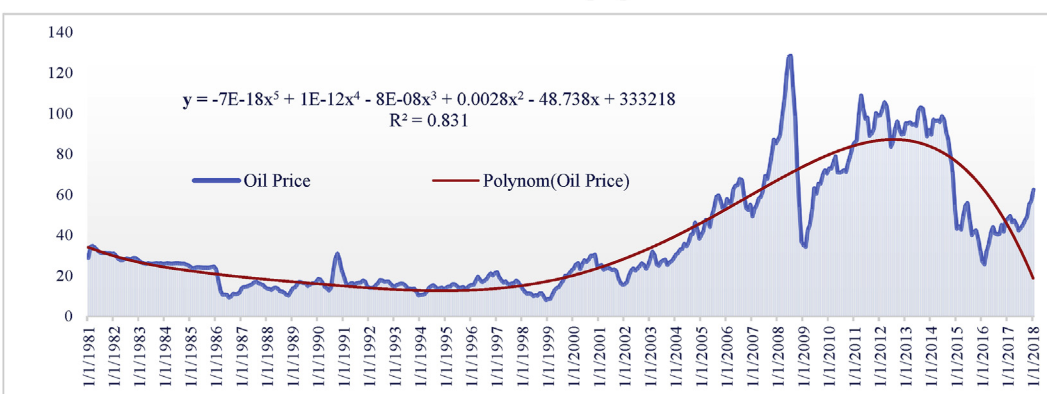

Fig. 4. The oil price in the US (1981:1 to 2018:1). **Data Source:** [92].

become clearer and more accurate than Fig. 6a.

In Fig. 7a, a strong co-movement association between biofuel production and food prices is observed. Fig. 7a and b indicate that in the short-term cycle (1~2 years frequency):

(a) During 1983–2000, an increase in food price results in an increase in biofuel production.
(b) In 2000–2010, biofuel production causes the food price index to increase.
(c) On the other hand, the biofuel production brings about a decrease in the food price index for the period 2011–2017.

Fig. 7a and c yield that in the 3~8 years frequency band (in the long-term cycle), during 2001–2017, the biofuel production brings about an increase in the food price index.

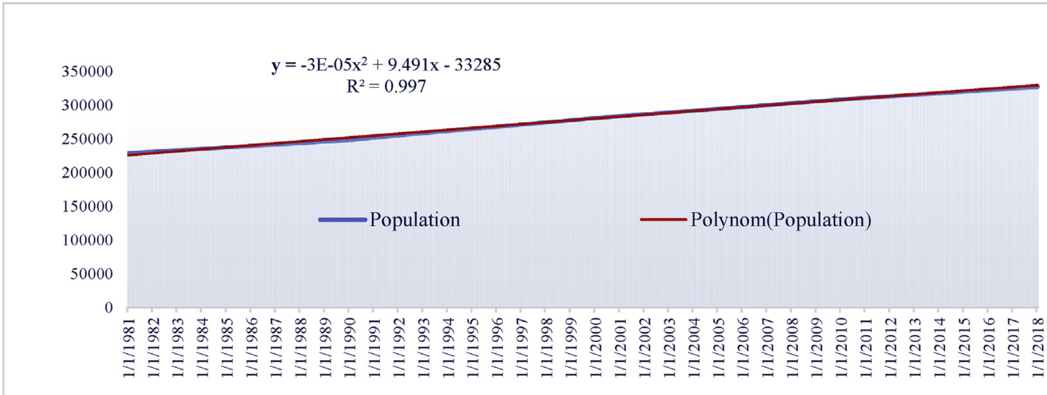

Fig. 5. The population of the US (1981:1 to 2018:1). **Data Source:** [92].

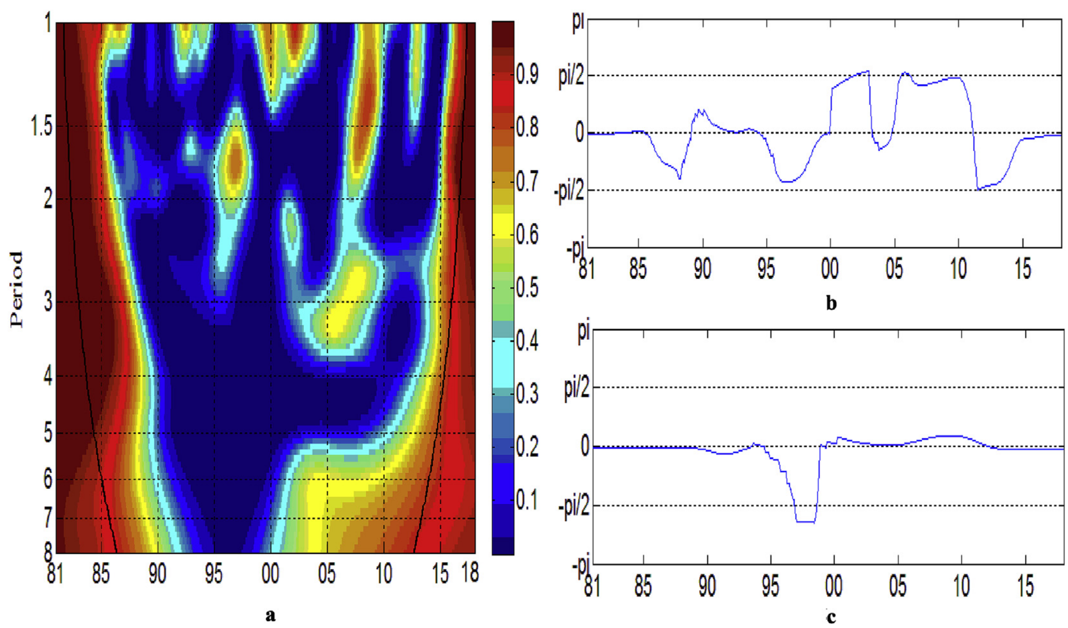

Fig. 6a. wavelet coherency [biofuel production/food price] computation. Fig. 6b: 1~2 Years frequency band. Fig. 6c: 3~8 Years frequency band.

The considerable remarks obtained from Fig. 7a, b, and 7c are that.

(i) In short cycle, (1~2 years frequency), biofuels increased food prices for the period 2000–2010 but decreased food prices for the period 2011–2017.
(ii) However, when longer cycle (3~8 years frequency) is considered, it is observed that, during 2001–2017, the biofuel production brings about an increase in the food price index.

Overall, wavelet analyses indicate that, at high-frequency intervals, the biofuels supply first increased food prices during the 2000s, later, decreased the price of food after 2010s. The biofuels, however, affect the prices of food positively both during the 2000s and after 2010s at low frequency (at longer cycle periods) in the US.

6. The verification, sensitivity, residual and extension analyses of wavelet estimations

The wavelet computations of this paper might need to explore the verification, sensitivity, residual, and extension analyses.

To verify the model, we obtained the wavelet estimations at 5% and 10% significance levels by Monte Carlo simulations. We launched the Monte Carlo simulations with 500 and 1000 replications to reach significant partial wavelet computations at 5% and 10% significance levels. The relevant figures (Figs. A1 and A2) are given in the appendix. The significant regions were obtained based on Monte Carlo simulations by following an ARMA (p, q) model by creating new samples through drawn errors from a Gaussian distribution by following Aguiar-Conraria and Soares [88,93] and Torrence and Compo [94]. The Monte Carlo simulations were launched by following Matlab lines of [nsur: 1000,

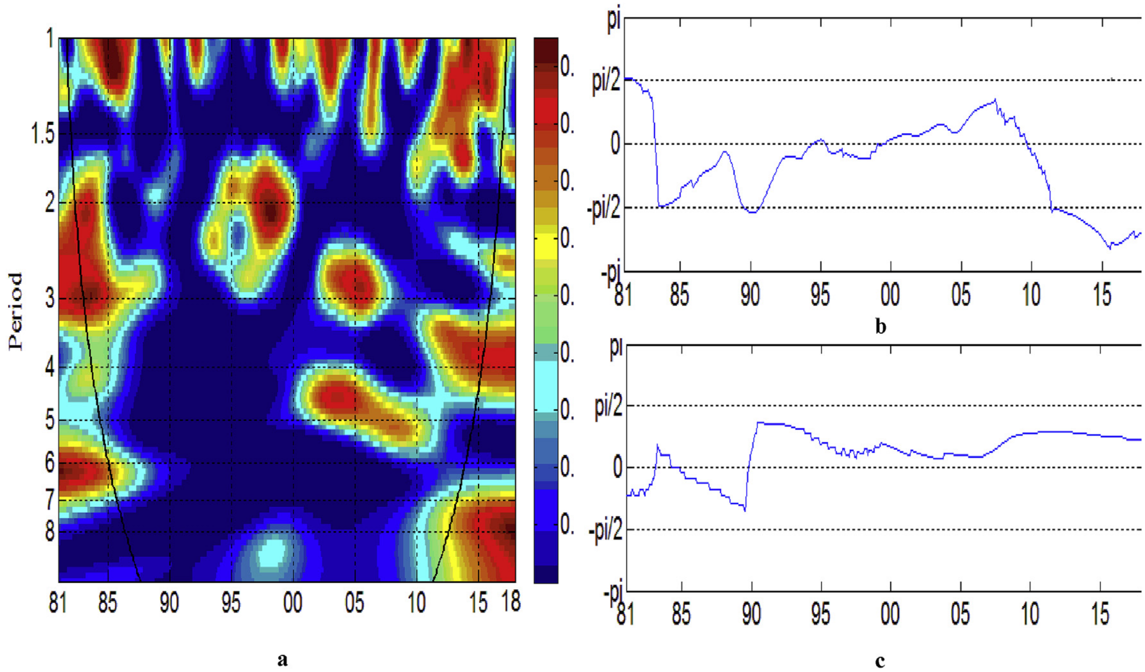

Fig. 7a. wavelet coherency [biofuel production/food price/oil price/population] computation. Fig. 7b: 1~2 Years frequency band. Fig. 7c: 3~8 Years frequency band.

nsur_type = 'ARMAEcon'; p = 1; q = 1] trough Econometrics and Signal Processing Toolboxes of Matlab as explained in Aguiar - Conraria and Soares [93]. In Figs. A1, and A2, the black contour depicts the 5% significance level and grey contour yields the 10% significance level based on the null of ARMA (p = 1, q = 1). The region influenced by edge effects is depicted by the cone of influence denoted by thick black lines.

Figs. A1 and A2 have just small differences. Fig. A2 differs from Fig. A1 in terms of the island shown at a 1-year frequency band in 2013 which becomes now more significant at 5% level. In Fig. A2, the 5% significance of co-movements during 2014–2016 at a 1.5-year frequency band has become more apparent. The association between the variables during 2006–2008 at the high-frequency band in Fig. A1, on the other hand, is more significant (5% level) than the relevant association in Fig. A2.

In a comparison of Fig. A1 and A2 with 7a, the outcomes are almost similar at a higher frequency band (1~2 years). The outcomes of the lower frequency band (3~8 years), however, indicate that the red color region (strong coherency) for the period 2014–2017 is found insignificant at 5% and 10% significance levels.

Next, we performed the sensitivity analyses by considering the works of Zhong and Oyadiji [95], Aguiar-Conraria and Soares [96] and Shen and Li [97].

Zhong and Oyadiji [95] indicate that the sampling intervals (different sampling distances; Si of 5, 25, 50, and 125 mm) considerably influence the peak value of the stationary wavelet transform (SWT) detail coefficient and, hence, affect the crack sensitivity, which in turn affect the damage detection capability.

Aguiar-Conraria, Martins and Soares [96] underline the potential sensitiveness to frequency and time in wavelet analyses as revealed in the work of Verona [98] that assessed the investment-Q sensitivity at different frequencies and its evolution over time.

Therefore, to conduct the sensitivity analyses, we re-estimated our wavelet work by following different periods to observe if the main outputs of our wavelet analyses are sensitive to different sampling intervals. Our wavelet estimations were performed for the period 1981:1–2018:1.

To this end, we conducted the relevant wavelet analyses for the monthly periods of 1982:1–2018:1 (Fig. A3), 1983:1–2018:1 (Fig. A4), 1984:1–2018:1 (Fig. A5), and 1985:1–2018:1 (Fig. A6).

One might state through re-estimated partial wavelet coherencies that, as the period is shortened, the strong energy (co-movements) between the biofuel production and food prices (together with control variables of population and oil price) in the US is diminishing and finally disappearing in the 1985–2018 period. Phase difference analyses, on the other hand, do not change significantly as the initial period varies. The re-computed phase difference analyses are not shown here to save the space.

Overall, the partial wavelet estimations seem to be sensitive to different sampling sizes at initial periods. The main findings of wavelet coherency and phase difference predictions given in Fig. 7a remained the same. Decreasing the period by one year at each step, and, eventually, after subtracting 5 years from the main data (by decreasing the number of observations from 445 to 397), the outputs at higher frequency (1-year cycle) did not change. The findings at a lower period of frequencies (3-8-year cycle) yielded some slight changes. Figs. from A3 to A6 are given in the appendix section.

To observe the residuals from wavelet estimations, we used the One-Dimensional Multi signal Analysis of MatlabR2099b, 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. 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. Overall, multisignal denoising analyses can indicate that the original signals are observed well by the denoised signals and the expected values of residuals are close to zero. The relevant figs. (A7 and A8) are presented in the appendix section.

We also thoroughly searched to realize the signal extension analyses through MatlabR2009b toolbox. The extension of analysis as a sample deals with the border distortion. It is defined for sequences with length of some power of 2, and different ways of extending samples of other sizes are needed as explained in MatlabR2009b. Eventually, we did run signal extension analyses. We utilized Signal Extension Tool dguisext. It demonstrates Signal extension GUI tools in the Wavelet Toolbox. This is a slideshow file for use with wshowdrv.m. To observe it, we did run the analyses by following 'wshowdrv dguisext'. Throughout signal extension analyses, we considered the frame from Matlabr2019b.

First, the signal has been extended by zero-padding (see Fig. A9 in appendix section). Later, we have extended the signal for SWT (see Fig. A10 in appendix section). Since the decomposition at level k of a signal using SWT requires that 2ˆk divides evenly into the length of the signal, the tool provides a special option dedicated to this kind of extension. Then we did select the for SWT option from the Extension mode menu. Since the signal from SWT is of length 40,496 = 2ˆ12, there is no need to apply the extension of signal. In this case the Extension tool is ineffective as shown in Fig. A10.

Overall, all these analyses indicate that the wavelet analyses and several products of the estimations worked well so that no worries were needed.

Besides, we simulated the wavelet reconstruction program obtained from our wavelet workplace and our wavelet workplace in which bootstrapping with 1000 replications were conducted. We reached the identical 'wavelet-input signals', 'wavelet-output signals', and 'wavelet-difference signals'. All checks yielded the 'Passed' result.

7. Discussion and conclusion

One might observe that there has been a great interest in the literature of energy, energy economics, and agricultural economics to observe the fluctuations in the energy market, energy prices, and food market. The researchers have been monitoring specifically the influence of oil production shocks on food prices since the oil price shocks of the 1970s.

Then, the relevant literature has focused on the impacts of the productions of fossil energy and renewable energy on food markets. One might also observe throughout literature evidence that there might be a correlation between disaggregated renewables' production and food prices since the boom of global biofuels production of 2005. Based on these discussions, this paper aims at observing the potential impacts of biofuel production on food prices in the US by using monthly data from 1981 to 2018 through a continuous wavelet method. Throughout wavelet analyses, this paper reveals that, at high frequency (1~2 years) intervals, the biofuels supply first increased food prices during the 2000s, later, decreased the price of food after 2010s. The biofuels, however, affect the prices of food positively both during the 2000s and after 2010s at low frequency (3~8 years) in the US.

Our results, especially obtained from 3~8 years frequency analyses, support the literature evidence [29,32–34,73] that biofuel production increases food prices by causing additional pressure on food supply and demand. Moreover, the findings support the arguments that biofuels production may be a possible cause of high increases in global food prices [11,100], called the 2007–2008 World Food Crisis. In addition, our findings are consistent with the results of To and Grafton [1], Tokgoz et al. [38], Bahel et al. [58], and Paris [68].

Contrary to the dominant view in the literature, this paper presents also new evidence that biofuels have a reducing effect on food prices in the United States during the period 2011–2017 at high frequency (at 1~2 years cycle). This may support more optimistic views that more food, more energy, and more raw materials can be produced if the land surface is used efficiently. Especially in the United States, there exist some literature evaluations in the last decade finding that large scale production in the agricultural sector, the use of more advanced agricultural technologies and innovations increase the land-use efficiency [101–103]. Therefore, in recent years, both agricultural developments and developments in biofuel production may explain the background of such a result. The second reason behind this result may be the decline in oil prices due to the rapid increase in biofuel production in the USA. In the last decade, biofuels production increases in leading countries such as the USA, Brazil, and Argentina led to a sevenfold expansion of the global biofuels sector. The rapid growth in the biofuel sector has led to a dramatic drop in oil prices since mid-2014 [104,105]. The decline in oil prices may be the cause of the decline in food prices, as oil is the main input for production in food prices.

Despite the potential contribution of this study to the current literature, this paper has some limitations. First, we analyzed the interactions of biofuel production and food prices in the United States. However, the possible future researches may consider investigating the co-movements of relevant variables for other major producing countries such as Brazil, Canada, Germany, China, France, and Australia. Second, we followed the wavelet analysis method for empirical analysis. Future research may follow both linear and nonlinear time series methods, such as structural fracture cointegration and granger causality analyses, for further empirical evidence. Besides, potential future works may apply panel data methods by evaluating the major producer countries together. Thirdly, we concluded that biofuels put pressure on food prices in the USA during 2000–2010. On the other hand, we found that biofuel production in the USA has a decreasing effect on food prices for the period 2011–2017. Future research (es) might evaluate and compare the energy and food policies, sectoral dynamics, and structural changes in the USA for the relevant period.

For future works, this paper invites potential future researches to analyze the impacts of biofuel production on food prices (a) in other developed countries such as the UK, Canada, Japan, Germany, etc., (b) in developing countries and/or new emergent markets. Besides, the paper might invite the future works to observe the association between biofuel market and food markets through (i) dynamic time series models with structural changes or regime shifts (i.e. cointegration models with structural changes, Markov regime-switching (MS) models, MS-VAR models, structural VAR models, (ii) dynamic panel methodologies such as dynamic panel GMM, panel structural VAR models, panel dynamic cointegration models, clustering algorithm and convergence clubs, panel smooth transition regression or panel spatial regressions to reveal the time-varying co-movements, or direct and indirect causalities between biofuel production and food prices, if exist.

Finally, our research work might suggest that future works consider the variables of energy efficiency, energy security, urbanization, ruralization, and economic-political or pandemic uncertainties in determining the interactions between biofuel markets and food markets.

CRediT authorship contribution statement

Faik Bilgili: Conceptualization, Methodology, Software, Writing - original draft, Writing - review & editing, Visualization, Project administration. **Emrah Koçak:** Conceptualization, Validation, Resources, Data curation, Writing - original draft, Writing - review & editing, Supervision, Project administration. **Sevda Kuşkaya:** Methodology, Investigation, Data curation, Writing - original draft, Visualization. **Ümit Bulut:** Validation, Investigation, Resources, Writing - original draft, Supervision.

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.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.energy.2020.118777.

Appendix

Table A1
Nomenclature

Nomenclature	
Ϫ	Mother wavelet
$1/\sqrt{\lvert\mathscr{s}\rvert}$	Normalization factor
$\mathscr{s}$	A scaling or dilation factor that controls the width of the wavelet
ℓ	A translation parameter controlling the location of the wavelet
t	Time
$Ϫ_w$	Morlet wavelet function
{X}	A time-series variable
{Y}	A time-series variable
$\mathfrak{w}_{xy}$	Cross wavelet power
$\mathfrak{w}_x$	Wavelet transform of X
$\mathfrak{w}_y$	Wavelet transform of Y
FT	Fourier Transform
CWP	Cross-wavelet power
CWT	Continuous wavelet transform
e	Exponential
π	Pi
$\mathfrak{I}_{xy}$	Wavelet coherency
$\mathbb{S}$	Smoothing operator
$\mathfrak{I}_{xy}$	Phase difference
$\mathfrak{R}(\mathfrak{w}_{xy})$	The imaginary part of smoothed cross wavelet power
$\mathfrak{F}(\mathfrak{w}_{xy})$	The real part of smoothed cross wavelet power
*	Complex conjugation
SWT	Stationary wavelet transform

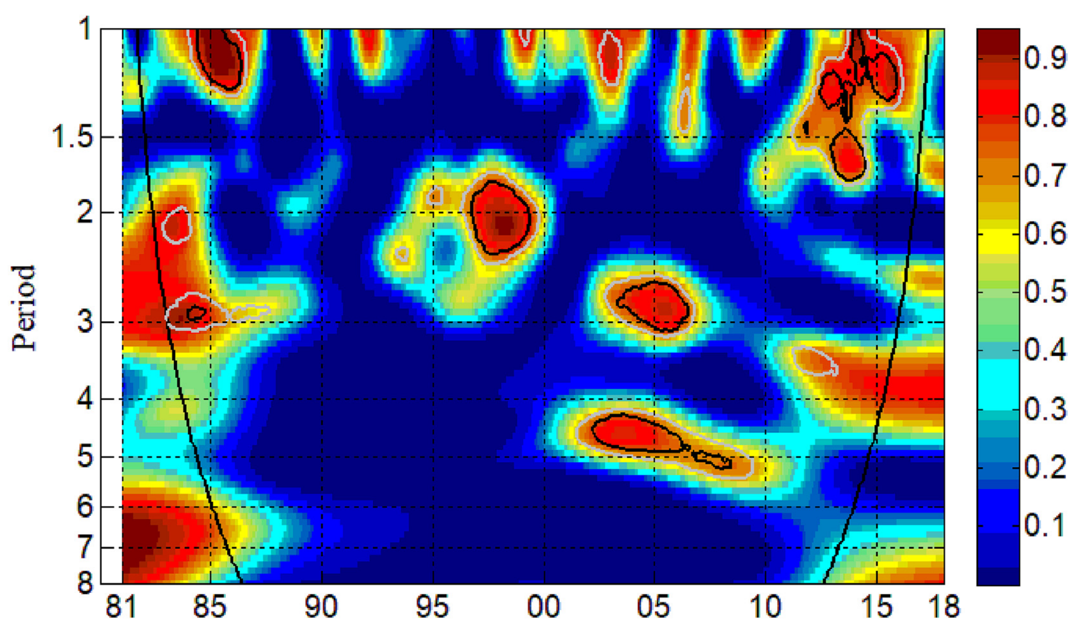

Fig. A1. Wavelet Coherency [Biofuel Production/Food Price/Oil Price/Population] Computation with Monte Carlo estimations through 500 replications.

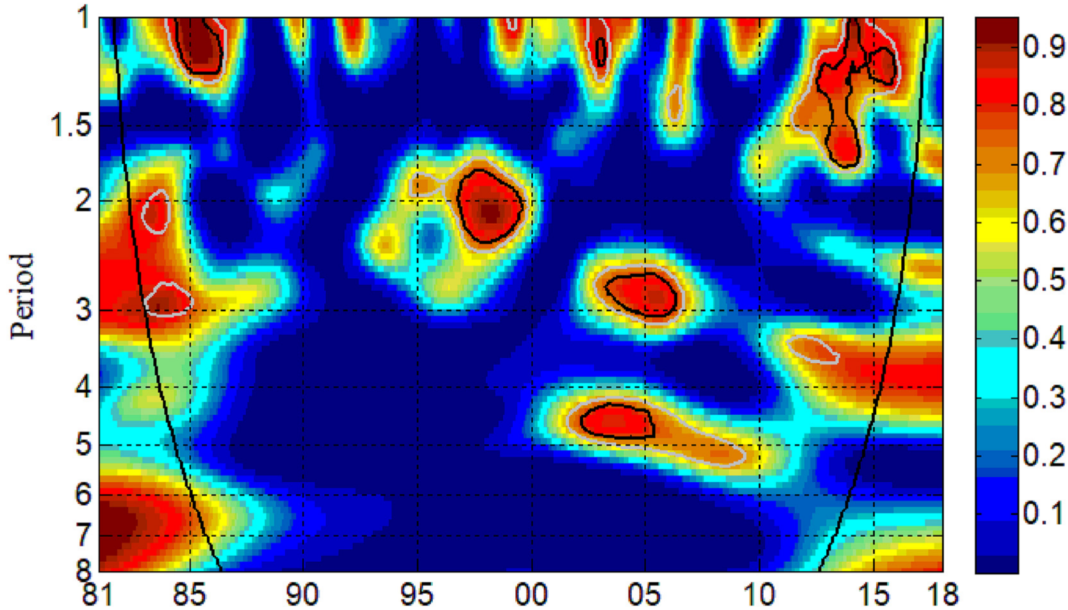

Fig. A2. Wavelet Coherency [Biofuel Production/Food Price/ Oil Price/Population] Computation with Monte Carlo estimations through 1000 replications.

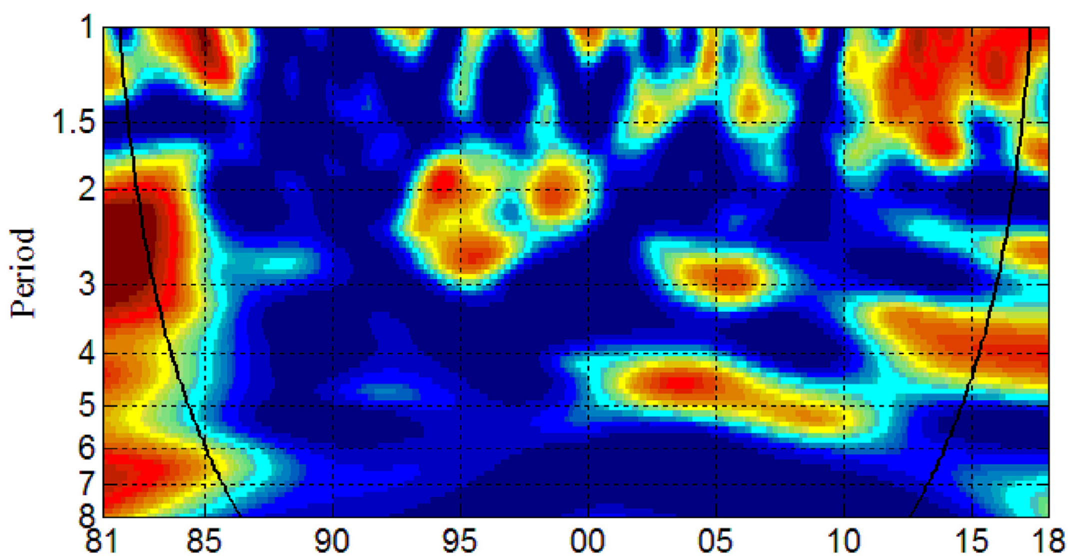

Fig. A3. Wavelet Coherency [Biofuel Production/Food Price/ Oil Price/Population] Computation (1982:1–2018:1).

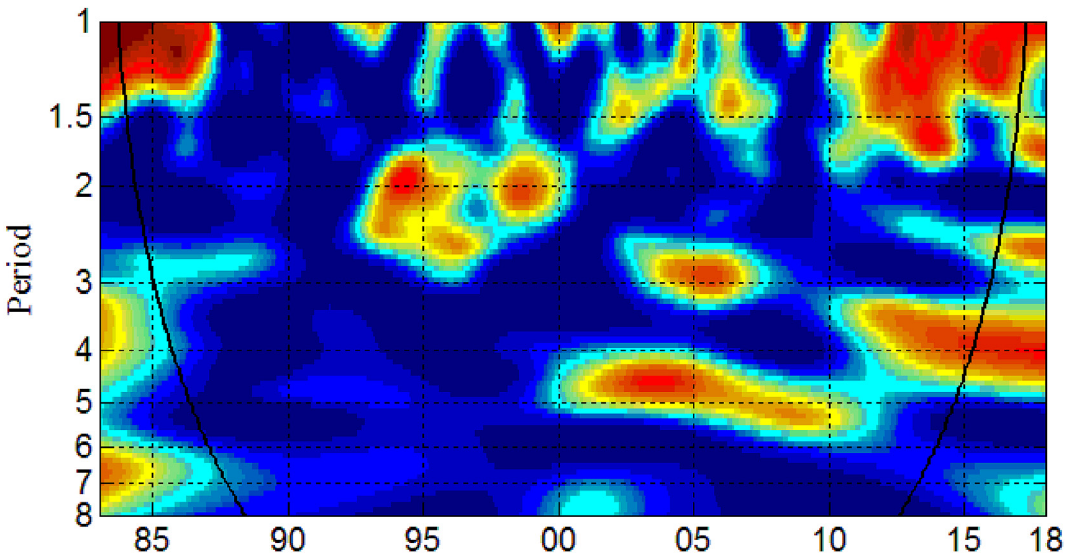

Fig. A4. Wavelet Coherency [Biofuel Production/Food Price/ Oil Price/Population] Computation (1983:1–2018:1).

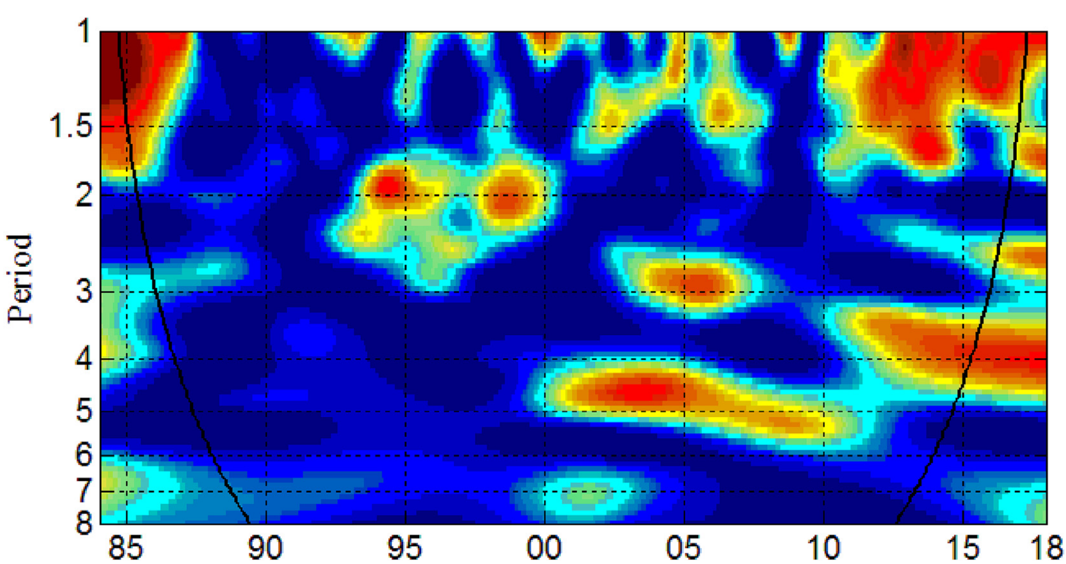

Fig. A5. Wavelet Coherency [Biofuel Production/Food Price/ Oil Price/Population] Computation (1984:1–2018:1).

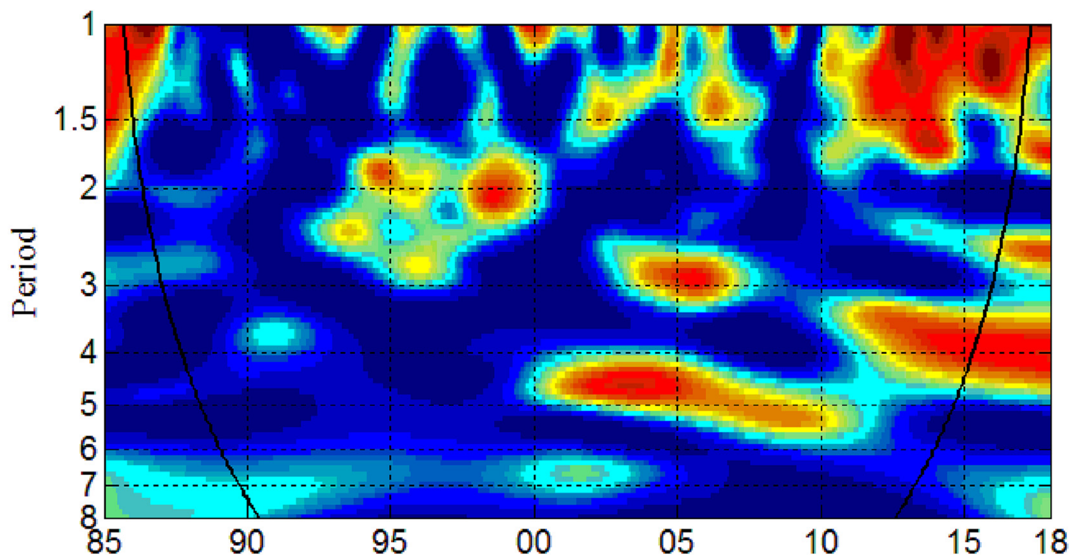

Fig. A6. Wavelet Coherency [Biofuel Production/Food Price/ Oil Price/Population] Computation (1985:1–2018:1).

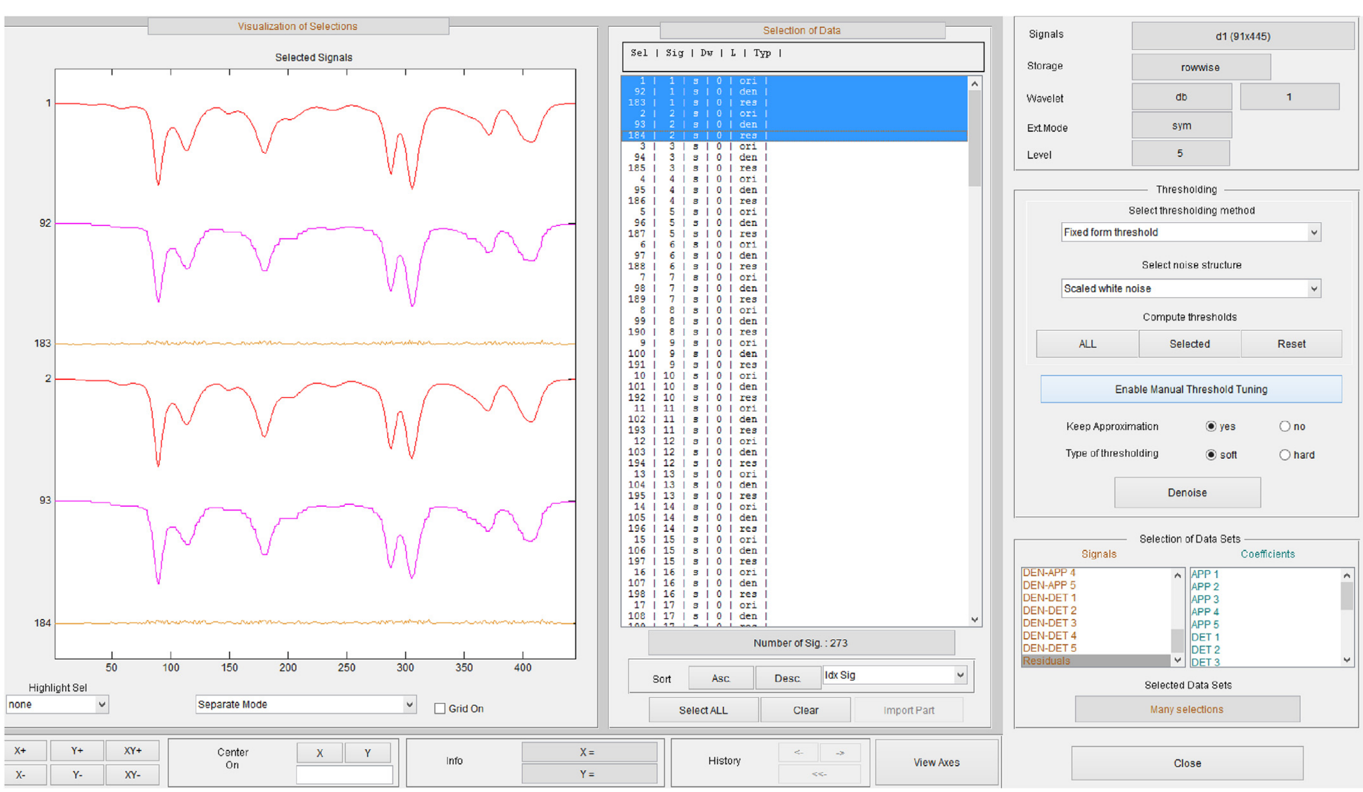

Fig. A7. The residual analyses: Original signals 1, 2, the corresponding denoised signal 92, 93, and the residuals 183 and 184.

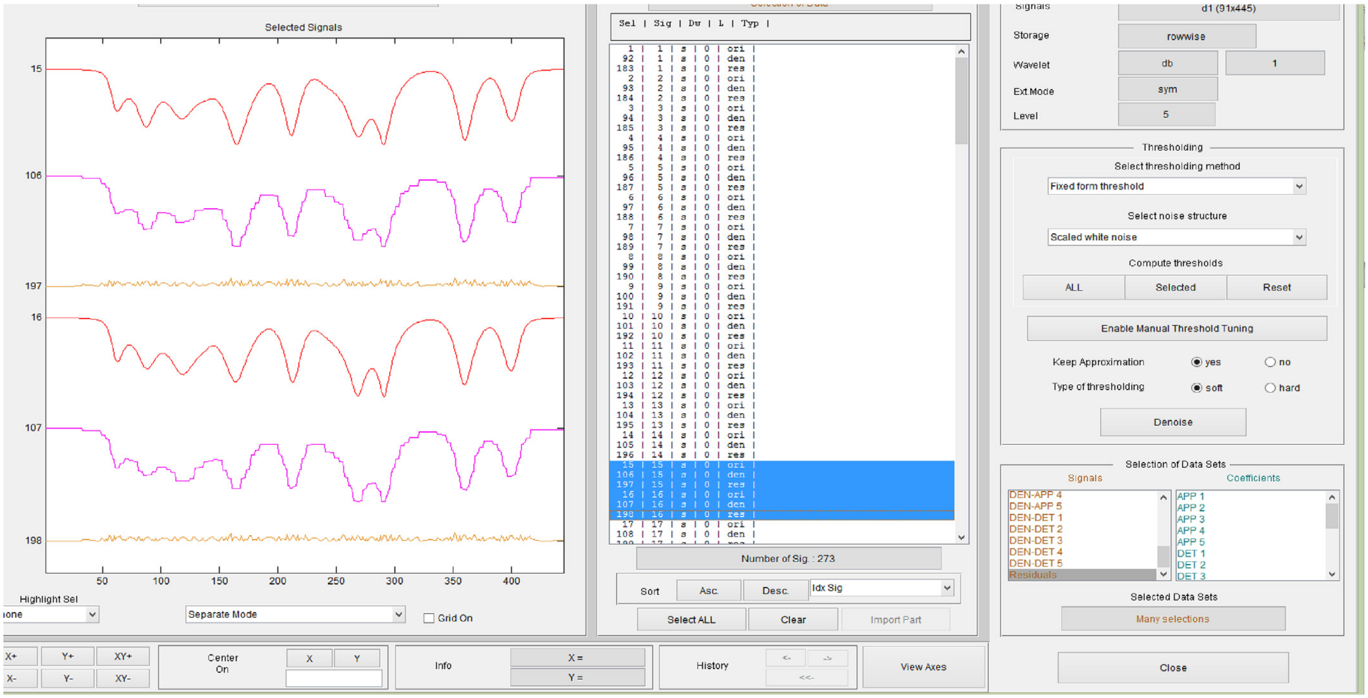

Fig. A8. The residual analyses: Original signals 15, 16, the corresponding denoised signal 106, 107, and the residuals 197, 198.

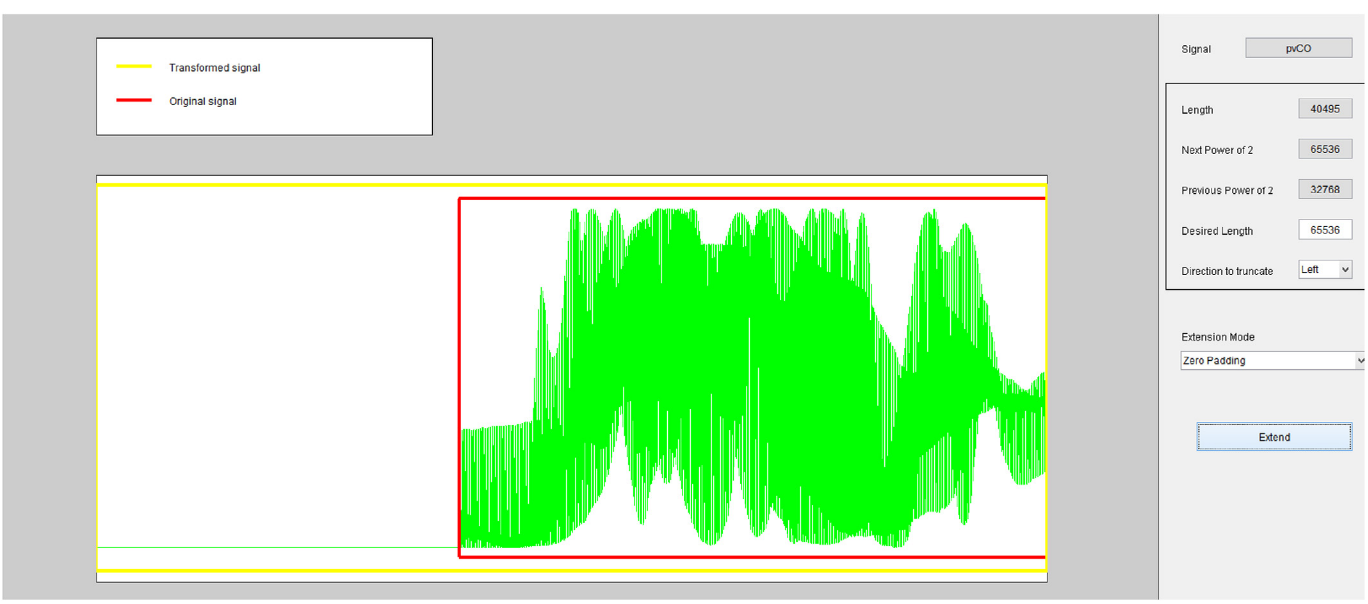

Fig. A9. The signal extension by zero-padding.

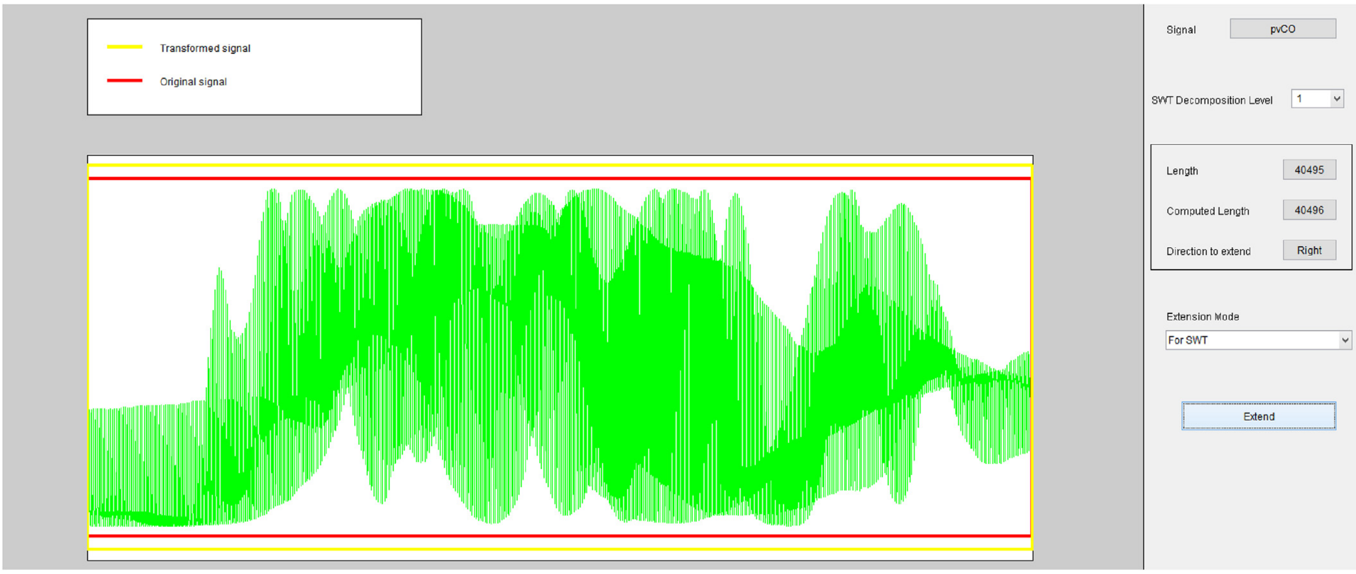

Fig. A10. The signal extension by stationary wavelet transforms.

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