Connection between Climatic Change and International Food Prices: Evidence from Robust Long-range Cross-correlation Coefficient with Sliding Windows Approach

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Abstract

Due to its fundamental connection to food prices, climate change is crucial to the development of the countries. Although the widespread influence of climate change on the crop yields of the main agricultural commodities are well known, the impact of climatic change on the price of food still remains uncertain. This study explores the impact of the most well-known climate index, the North Atlantic Oscillation (NAO) index, on the international food prices. For this goal, a new robust power-law cross-correlation coefficient is used. First, we determine the statistically critical value for power-law cross-correlation coefficient. Second, we obtain the color map of such coefficient by using the sliding windows approach for different time scales, and we deduce a time-varying version of such coefficient. Our results suggested that large increments of the NAO index are followed by large increments of the different international food prices for short and long-term scales. Accordingly, the NAO index influences the international foods price.

Keywords: Food security, robust long-range cross-correlation coefficient, bivariate Hurst exponent, NAO index, international food prices.

1. Introduction

Compared with pre-pandemic forecasts, 75 million people are expected to fall into extreme poverty by the end of 2022 and global hunger remains alarmingly high (USAID, 2022). Before the onset of the covid-19 pandemic, the number of people affected by hunger rose to 828 million in 2021, an increase of about 46 million since 2020 and an increase of 150 million since 2019. The global food crisis has been exacerbated in part by the growing number of food trade restrictions that countries have imposed to boost domestic supplies and drive down prices (Mari and Axel, 2022; Kristalina and Sebastián Sosa, 2022). In addition, to export restrictions, some countries have eased import restrictions, which could put additional pressure on food prices as demand increases. Global food production is also being impacted by rising temperatures, shifting precipitation patterns, and increasingly frequent extreme weather events (EPA, 2022; C.Worldwide, 2022). Since 1961, climate change has caused a 21% decrease in worldwide agricultural productivity. This stunts growth, reduces labor productivity and threatens economic development, especially in developing countries (W.Bank, 2022).

Extreme weather events like scorching temperatures or torrential rain are becoming more common due to the effects of climate change. Agricultural supply is highly weather-dependent and the North Atlantic Oscillation (NAO) index, which represents the redistribution of atmospheric mass between the arctic or subarctic regions and the subtropical regions of the Atlantic, has a strong bearing on world crop production (Porter and Semenov, 2005; Heino et al., 2018). Moreover, NAO index prominently influences the intensity of winter conditions in Asia, Europe, and the United States (Visbeck et al., 2001; Wang and You, 2004) and they then influence agriculture production (Shah et al., 2021). Based on food and agricultural organization, in 2020, the United States is the largest producer of corn in the world with 31.8% of global production followed by China with 23% of global production, Brazil with 9.6% of global production, Iowa with 5.1% of global production and Argentina with 4.8% of global production. Additionally, the world produced 760 million tons of wheat, with China, India, and Russia being the three biggest producers, together making up roughly 41% of the total. The world's fourth-largest producer of wheat is the United States. However, if we count the European Union as one country, it produces more wheat than any other country except China. Regarding the production of oats, in 2020, the European Union was the largest producer of oats in the world with 36.4% of global production followed by Canada with 17.95% of global production, Russia with 16.19% of global production, Australia with 6.57% of global production and United States with 3.72% of global production. Furthermore, the total world soybean production in 2020 was 353,463,735 tons. Brazil is the largest producer, with his 34% of global production, followed by the United States with 32% of global production.

The largest producing countries of wheat, oats, corn and soybean are near to the North Atlantic. On the other hand, and similarly the NAO index measures a phenomenon affecting the climate system of the North Atlantic Ocean. Also, the NAO index describes the variations in the ocean atmosphere regime over the region and is, generally, the difference in atmospheric pressure between the Azores High and the Iceland Low. NAO index is a determining climatic factor on a regional scale because it is related to the position and trajectory of meteorological disturbances that affect Western Europe as well as ocean temperatures in the North Atlantic basin. It is natural to find , in the NAO index, outlier observations causing by a strongly positive values linked to warm conditions across the U.S. East and Northern Europe, and cold conditions across southern Europe. As well, outlier observation in the NAO index can be caused by a strongly negative values linked to cold conditions in the U.S. East and Northern Europe, and warm conditions in Southern Europe. To study a possible nexus between the NAO index and the international food price it is necessary to apply a robust method to test for outliers observations. It's proved that the Granger causality test is sensitive to additive outliers observations (Baldd Rodrez, 2005; Bojanic and Lo, 2016), as well for vectorial autoregressive model (Funke, 1992). This study addresses the potential relationship between the NAO index and international food prices through a novel approach dealing with robust power-law cross-correlation coefficient within a sliding windows framework. For this objective, data includes the daily time series of the NAO index, and the international price of wheat, corn, soybean, and oats, respectively. In addition, we apply the robust power-low cross-correlation coefficient proposed by (Dhifaoui, 2022) that can prove if the fluctuations of the process X is followed by the fluctuations of the process Y or not. Moreover, we use a sliding windows approach to study a possible connection between NAO index and the international food prices over the time-scale. Our findings have implications, first, for how careful investors should be when assessing climate

risk. Additionally, they need to have portfolios that are well-diversified and have a hedging strategy in place, for the food markets, which could suffer if the climate risk increases. Second, for responsible authorities, to prepare well for food crises due to climate change, by storing food products, or replacing some food products with others available and at low prices.

The following describes the structure of this article: Section 1 is devoted to the introduction. The review of the literature is located in Section 2. We introduce the methods employed in this research in Section 3. We describe the sample data and provide descriptive statistics for the chosen sample in Section 4. Section 5 outlines the results. A robustness exercise is presented in Section 6. Theoretical and empirical implications is given in section 7. We present our conclusion in Section 8.

2. Literature review

Despite the fact that the impact of the NAO index on agricultural production is discussed in various studies, at the time of writing of the present article, we have not found a study focussed on the impact of the NAO index on any international food prices. Nevertheless, there are some works interested in the connection between some other climate change indices, like El Niñ0 or La Niña indices, and some food products. Peri (2017) discusses the effect of the El Niño and La Niña events according to the Spring-Summer and Autumn-Winter weather seasons, and shows that both events increase the expected volatility of corn price, showing the strongest impact during the El Niño phase in Spring-Summer. Also, soybean price volatility tends to decrease slightly during the fall and winter weather seasons and increase during the Spring-Summer period. As well, Ubilava (2017) showed, by studying the monthly spot prices of wheat from the United States, the European Union, Australia, Canada, and Argentina, that wheat price tend to increase after La Niña events and decrease after El Niño events. In addition, Gutierrez (2017) showed that wheat export prices are positively linked to the events in La Niña, demonstrating once again its constant impact in the short and long term. By studying the dynamics of the fishmeal-soybean flour price ratio, Ubilava (2014) showed the significant impacts of the bi-monthly multivariate El Niño Southern Oscillation (ENSO) on the dynamics of the price ratio, and indicated the statistical significance of these effects up to one year after the ENSO shocks. Moreover, Hasudungan et al. (2021) showed that the price of rice is positively related to the El Niño index and negatively related to the shocks of La Niña.

Although there is no study that has dealt with a possible relationship between NAO index and some international food price, several research studies are interested in the impact of NAO index on some food price for different regions or countries. Heino et al. (2020a) showed that the NAO index has an impact on the soybean production in Australia and Europe. With other different climate change indices, Salinger et al. (2022) proves the connection between NAO index and soybean production in Italy. Also, Anderson et al. (2019) demonstrated that the global aggregated variability in corn, soybean, and wheat output is accounted for by the ENSO index, the Indian Ocean Dipole, tropical Atlantic variability, and the NAO index, respectively. As well, Najafi et al. (2019) showed that large-scale changes in the NAO index are strongly correlated with soybean yield variability in north and south America, Oceania and south of Asia. The relationship between variability of NAO index and corn production is studied in different works. Zhou et al. (2012) showed that the springtime NAO index is significantly correlated to the increment of corn and rice yield in Northeast China. The study in (Brown,

Table 1: Summary of previous research.

Study	Climatic indices	Method	Causality
Zhou et al. (2012)	NAO index	Correlation coefficient	Yes
Brown (2012)	Meteorological data, bioclimatic metrics, and the NAO index	Correlation coefficient	Yes
Ubilava (2014)	El Niño index	A smooth transition autoregressive model	Yes
Peri (2017)	El Niño index	Volatility impulse response function from a multivariate GARCH model.	Yes
Ubilava (2017)	El Niño index	Vector smooth transition autoregressive model	Yes
Gutierrez (2017)	El Niño index	Global dynamic model	Yes
Anderson et al. (2019)	NAO, Indian Ocean Dipole, tropical Atlantic variability, and ENSO indices	Maximum covariance analysis	Yes
Najafi et al. (2019)	NAO index	Robust principal component analysis	Yes
Heino et al. (2020a)	NAO index	Multivariate linear regularisedridge regression	Yes
Hasudungan et al. (2021)	El Niño index	The vector error correction model	Yes
Salinger et al. (2022)	NAO index	Simulated Annealing classification and principal component transversa	Yes

2012) reveals that a significant relationship between wheat, barley, oats, and potatoes and climate vary depending on the crop type and month. Table 1 briefly summarizes the past research focused on the relationship between some climatic change indices and food prices.

3. Methodology

In this section, we recall the robust outliers power-law cross-correlation coefficient proposed in (Dhifaoui, 2022). This coefficient is named the bivariate Hurst exponent and permits to testing if the fluctuations of the process X is followed by the fluctuations of the process Y when these two processes are cross correlated contaminated by outlier observations. In addition, we use the bootstrap method to obtain the statistical critical value of such coefficient, and the sliding windows approach is used to obtain the nexus between X and Y over time and timescale.

3.1. Robust bivariate Hurst exponent

The robust bivariate Hurst exponent (BHE) is based on the use of the deterended cross-correlation function. Let a zero means stochastic processes X and Y and are long-range tem-

porally autocorrelated with power-law auto-correlations as:

$$\mathbb{E}[X(\ell)X(\ell+s)] \sim s^{2H_X-2} \text{ and } \mathbb{E}[Y(\ell)Y(\ell+s)] \sim s^{2H_Y-2}, \tag{1}$$

where $(H_X, H_Y) \in [0.5, 1[^2$ are the Hurst exponents and $\sim$ denotes proportionality. The power-law cross-correlations are defined by:

$$\mathbb{E}[X(\ell)Y(\ell+s)] \sim As^{2\gamma-2} \text{ and } \mathbb{E}[Y(\ell)X(\ell+s)] \sim Bs^{2\gamma-2}, \text{ where } (A, B) \in \mathbb{R}_+^2, \tag{2}$$

and the scaling exponent γ characterizes the cross-correlation properties of X and Y.

For computing cross-correlation function, considering two time series $\{X_i\}_{i=1,\ldots,N}$ and $\{Y_i\}_{i=1,\ldots,N}$. Each time series is covered with $N_s = [N/s]$ non overlapping boxes of size s where [.] is a lower integer sign. The profiles in the v-th box $[\ell_v + 1, \ell_v + s]$, where $\ell_v = (v-1)s$, are determined to be:

$$X_v(k) = \sum_{j=1}^{k} X(\ell_v + j) \text{ and } Y_v(k) = \sum_{j=1}^{k} Y(\ell_v + j), \text{ for } k = 1, \ldots, s. \tag{3}$$

Assume that the local trends of $X_v(k)$ and $Y_v(k)$ are respectively $\widetilde{X_v}(k)$ and $\widetilde{Y_v}(k)$. According to (Xiaojun et al., 2014), the cross-correlation for each box is given by:

$$f_v^{X,Y}(s) = \frac{1}{s}\sum_{k=1}^{s}(X_v(k) - \widetilde{X_v}(k))(Y_v(k) - \widetilde{Y_v}(k)), \text{ for } v = 1, \ldots, N_s, \tag{4}$$

and the q-th order cross-correlation function is calculated as follows:

$$F_{X,Y}(q,s) = \begin{cases} \Big(\frac{1}{N_s}\sum_{v=1}^{N_s}(f_v^{X,Y}(s))^{\frac{q}{2}}\Big)^{\frac{1}{q}}, & \text{when } q \neq 0; \\ \exp\Big(\frac{1}{2N_s}\sum_{v=1}^{N_s}\log(f_v^{X,Y}(s))\Big), & \text{when } q = 0. \end{cases} \tag{5}$$

Then, when s is large enough, we expect the following scaling relation:

$$F_{X,Y}(q,s) \sim s^{\gamma_{X,Y}(q)}, \tag{6}$$

where $\gamma_{X,Y}(q)$ characterizes the long-range cross-correlation properties of processes X and Y. If $\gamma_{X,Y}(2) = 0.5$ or $F_{X,Y}(2,s)$ oscillates around zero suggested that no cross-correlation. If $\gamma_{X,Y}(2) > 0.5$, then there is a positive power-law cross-correlation, which indicates that a large increment in one process is more likely to be followed by a large increment in the other process. If $\gamma_{X,Y}(2) < 0.5$, then X and Y are anti-correlated.

In the case where the processes X and Y are cross-correlated and contaminated with outliers observations, the BHE, $H_X + H_Y$, is established from the behavior of $\mathbb{E}[F_{X,Y}(2,s)^2]$, for large values of s, given in the following relation (Dhifaoui, 2022):

$$\mathbb{E}[F_{X,Y}(2,s)^2] = \frac{\sigma_X\sigma_Y\rho_{XY}}{2}s^{H_X+H_Y}\mathcal{O}(1) + \frac{\sigma_X\sigma_Y\rho_{XY}}{2}s. \tag{7}$$

where $\sigma_X = \sqrt{\text{var}(X(1))}$, $\sigma_Y = \sqrt{\text{var}(Y(1))}$ and $\rho_{XY} = \text{cor}(X(1), Y(1))$.

3.2. Statistical critical value of bivariate Hurst exponent

It is proved, in (Dhifaoui, 2022), that $\gamma_{X,Y}(2) = (H_X + H_Y)/2$, then, according to last interpretations of $\gamma_{X,Y}(2)$, if $H_X + H_Y = 1$ then their is no cross-correlation, if $H_X + H_Y > 1$ then there is a positive power-law cross-correlation, and if $H_X + H_Y < 1$ then X and Y are anti-correlated. Herein, we note by $H_{X,Y}$ the BHE and we determine their critical value and the associated p-value using the procedure given in (Podobnik et al., 2011). Then, we will follow the steps:

1. We generate pairs of i.i.d time series ($H_X = H_Y = 1/2$) of length N taken from a Gaussian distribution.
2. We estimate the BHE using the procedure proposed in (Dhifaoui, 2022).
3. We repeats steps 1 and 2 for $N_{rep} = 10000$ times.
4. We calculate the probability density function (PDF) of BHE.

The descriptive statistics of 10000 times BHE for different N are given in Table 2 and the associated probability density functions are illustrated in Figure 1. According to Table 2, the Kurtosis coefficient is near to zero for all N values which implies that the distribution of BHE is flattened. The Skewness coefficient revels that, for $N = 300$, the distribution of BHE is symmetric whereas for $N = 500$ and $N = 1000$ the distribution of BHE is not symmetric. We applied Kolmogorov-Smirnov (K.S) and Jarque-Berra (J.B) tests for testing the normality distribution of BHE. The results of K.S test shows that the BHE is normally distributed for all N values. This results is confirmed by J.B test for $N = 300$ and $N = 500$, whereas the distribution of BHE is not normal for $N = 1000$. Then, according to this results we assume that the probability distribution of BHE is normal and we test the null hypothesis against the alternative hypothesis, that is:
H0: $H_X + H_Y = 1$ (no cross-correlation),
H1: $H_X + H_Y > 1$ (positive power-law cross-correlation).
Therefore, for each N, we found the critical value $H^c_{X,Y}(N)$ of BHE for 90%, 95%, and 99% of confidence level, as follows:

$$H^c_{X,Y}(N) = m_{H_{X,Y}} + Z_\alpha \sigma_{H_{X,Y}}, \tag{8}$$

where $m_{H_{X,Y}}$ is the mean value of 10000 times BHE, $\sigma_{H_{X,Y}}$ is the standard deviation and Z_α is fractile of standard normal distribution for the desired confidence level $1 - \alpha$. In addition, the p-value of $H_{X,Y}$ is given by:

$$\text{pv}(H_{X,Y}) = \frac{1}{N_{rep}} \sum_{\ell=1}^{N_{rep}} \mathbf{1}_{\{H_{X,Y} \leq (\widehat{H}_{X,Y})_\ell\}}, \tag{9}$$

where $(\widehat{H}_{X,Y})_\ell$ is the estimated value of BHE of ℓ-th simulated two i.i.d time series and $\mathbf{1}_{\{H_{X,Y} \leq (\widehat{H}_{X,Y})_\ell\}} = 1$ if $H_{X,Y} \leq (\widehat{H}_{X,Y})_\ell$ and 0 otherwise. Then, we reject the hypothesis **H0** if $H_{X,Y} > H^c_{X,Y}(N)$ and we consider that the positive power-law cross-correlation is statistically significant. The obtained critical values $H^c_{X,Y}(N)$ for different confidence level (CL) $1 - \alpha$ and some descriptive statistics of $H_{X,Y}$ for different N are given in Table 2.

Figure 1: Probability distribution of BHE for i.i.d time series ($H_X = H_Y = 1/2$).

Table 2: Descriptive statistics of BHE for $N = 300$, $N = 500$ and $N = 1000$, respectively.

	$N = 300$	$N = 500$	$N = 1000$
Mean	0.983	0.998	1.01
Median	0.984	1.0009	1.011
Std.D	0.191	0.143	0.102
Skewness	0.001	-0.021	-0.053
Kurtosis	-0.038	-0.046	-0.058
K.S test	$0.004(0.969)^{***}$	$0.009(0.329)^{***}$	$0.011(0.152)^{***}$
J.B test	$0.585(0.746)^{***}$	$1.662(0.435)^{***}$	$6.209(0.044)^{***}$
$H^c_{X,Y}(N)$			
C.L=90%	1.227	1.182	1.142
C.L=95%	1.297	1.234	1.179
C.L=99%	1.427	1.332	1.249

Note: The value between parenthesis is the associated p-value and *** indicates that the value is statistical significant for 1%. C.L is the abbreviation of confidence level.

3.3. Sliding windows approach of BHE

The proposal of this article consisting to take the robust long-range cross-correlation coefficient $H_{X,Y}$ with sliding windows approach. Let N the length of the initial time series, h the size of window where $1000 \leq h \leq N/2$, n the time scale and T the time period where $1 \leq T \leq N - h$, then we obtain the color map of $H_{X,Y}(T, n)$ using sliding windows framework as follows:

1. We fixe $h = N/2$ and, for fixed T in $[1, h + 1]$, we consider the pairs of time series $\{X_i\}_{i=T,\ldots,h+T-1}$ and $\{Y_i\}_{i=T,\ldots,h+T-1}$.
2. For fixed n, each time series is covered with $N_s^* = [(h - n)/s]$ non overlapping boxes of size s. We compute the profiles in the v-th box $[\ell_v + 1, \ell_v + s]$, where $\ell_v = (v - 1)s$ using Eq. (3).
3. We compute the cross-correlation ${f_v}^{X,Y}(s)$ for each box using Eq. (4) for $v = 1, \ldots, N_s^*$, and the second order cross-correlation function $F(T, n)_{X,Y}(2, s)$ by Eq. (5) as:

$$F(T, n)_{X,Y}(2, s)^2 = \frac{1}{N_s^*} \sum_{v=1}^{N_s^*} f_v^{X,Y}(s).$$

4. We obtain $H_{X,Y}(T, n)$ by the liner regression of $\log(F(T, n)_{X,Y}(2, s)^2)$ on $\log(s)$.
5. We repeat steps 1–4 for $T = 1, \ldots, h + 1$ and for $n = 50, 100, 150, 200$.

4. Data and descriptive statistics

The analyzed time series are the North Atlantic Oscillation (NAO) index time series downloaded from the website https://www.cpc.ncep.noaa.gov/products/precip

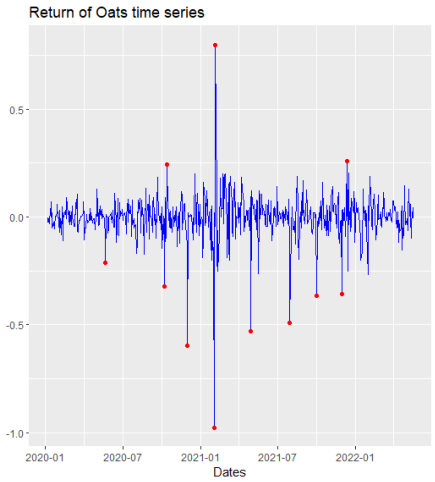
/CWlink/pna/nao.shtml and the international price of corn, soybean, oats and wheat in U.S. Dollars per bushel downloaded from the Bloomberg Terminal. The time series cover the period from January 06, 2020 until May 18, 2022, then we have a daily time series of 600 observations. Except the NAO index, in order to study the fluctuation of such time series, we analyze its return given by $x_{t+1} - x_t$. The studied time series are shown in Figure. 2 with the blue continued curve and where the red points represented the detected outlier observations. Some descriptive statistics of studied time series are given in Table 3. According to Table 3, the NAO index is characterized by a negative mean and by a high value of variance, whereas other time series have a zero means and low variances.

The bivariate Hurst exponent proposed in (Dhifaoui, 2022) need that the used processes are a fractional Gaussian noise (fGn) processes contaminated with additive outliers observations. In this study, to compute the bivariate Hurst exponent, we proceed as follow: we prove the presence of outliers in studied time series, then we remove outliers from time series, and we test the normality and stationarity of time series without outliers, as well we test if the process without outliers is stochastic. If the time series without outliers is stochastic, stationary, and normally distributed we can assimilate that it is a fractional Gaussian noise.

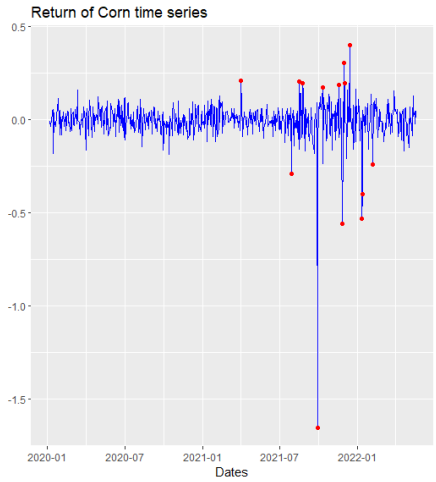
In order to detecting outlier observations in the studied time series, the extreme value theory test of Holesovský et al. (2018) is used. The result of this test is given in Table 3 where the value between parenthesis indicate the percentage of outliers observations in each time series. On the other hand, it is known that the augmented Dickey-Fuller (ADF) or the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests are very sensible to the effect of outliers observations (Franses and Haldrup, 1994; Otero and Smith, 2005). To overcome this problem, the unit root test based upon the Breitung's variance ratio (Breitung, 2002) is used. In addition, the robust Jarque-Bera (robust J.B) test (Gel and Gastwirth, 2008) is used to testing normality distribution of the studied time series. The results of the above tests are given in Table 3.

The result of detection of outliers test reveals that the NAO index, the return of oats, the return of corn, the return of soybean and the return of wheat time series contains 3.5%, 3.291%, 3.041%, 2.083% and 1.958% of outliers observations, respectively. In addition, the robust stationarity test rejects the initial hypothesis of non-stationarity against the alternative hypothesis of stationarity using that all p-values are less than 1%, then, the studied time series are stationary. The no-normality distribution of studied time series is confirmed using the robust Jarque-Berra (J.B) test where the corresponding p-values given between parenthesis are less than 1% which indicates the rejection of initial hypothesis of normality.

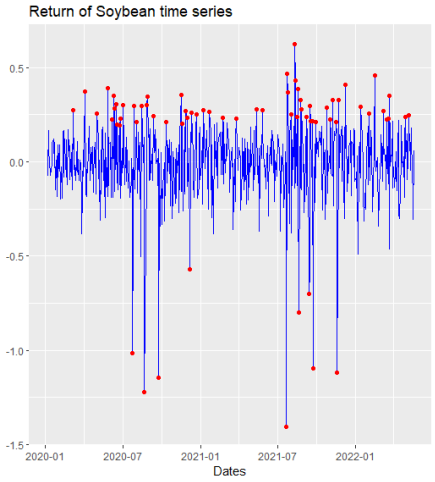
The results of stationarity and normality tests of studied time series without outliers are reported in Table 4, these time series are shown in Figure 8. According to the results of ADF and J.B tests given in Table 4, the studied time series without outliers are stationary and Gaussian distributed. In addition, the estimated value of Hurst exponent (H), using corrected rescaled range (R/S) approach (Hurst, 1951; Weron, 2002), are more than 0.5 which implies that the time series without outliers have a long memory. On the other hand, in order to test if the studied time series after removing outliers are a fractional Gaussian noise processes, we conduct a graphical comparison between their autocorrelation functions and the autocorrelation function of fractional Gaussian noise process using the estimated value of Hurst exponent H. The autocorrelation function of fractional Gaussian noise process is given by $\rho(k) = V_H\big(|k+1|^{2H} + |k-1|^{2H} - 2|k|^{2H}\big)$ where $V_H = \Gamma(1-2H)\cos(\pi H)/(2\pi H)$ and k is the time lag. Based on Figure 9, we remark that the autocorrelation function (in blue color)



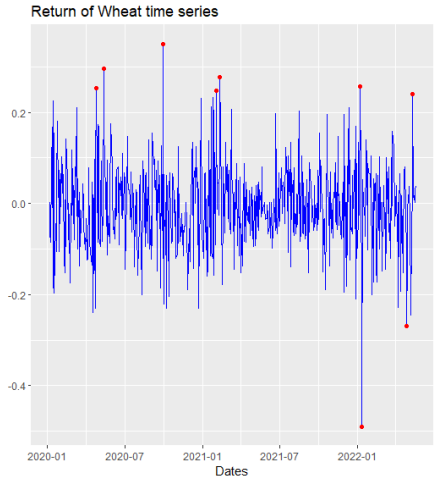
(a) Return of international price of oats.



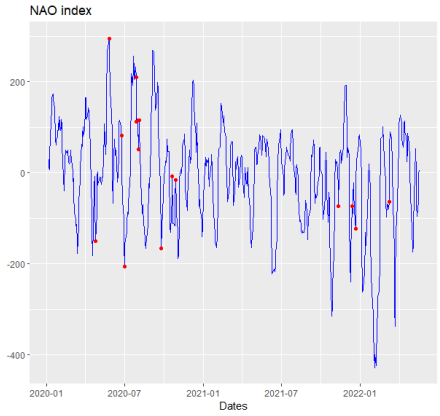
(b) Return of international price of corn.



(c) Return of international price of soybean.



(d) Return of international price of wheat.



(e) NAO index.

Figure 2: Studied time series.

Table 3: Descriptive statistics of studied time series.

Time series	Mean	Std. Dev	Extreme value variance theory test	Breitung ratio test	Robust J.B test
NAO index	-1.839	110.543	47(1.958%)	0.005(0.001)***	98.554(0.000)***
Return of Corn	0.0001	0.084	79(3.291%)	0.0002(0.001)***	631128.2(0.000)***
Return of Soybean	0.001	0.16	73(3.041%)	0.0001(0.001)***	11679.66(0.000)***
Return of Wheat	0.001	0.127	50(2.083%)	0.0002(0.001)***	376399.5(0.000)***
Return of Oats	0.001	0.081	84(3.5%)	0.0001(0.001)***	39656.19(0.000)***

*Note: The value between parenthesis is the associated p-value and *** indicates that the value is statistical significant for 1%.*

of all studied time series without outliers and autocorrelation function of fractional Gaussian noise process (in red color) have almost the same behavior. In addition, the stochasticity of studied time series without outliers are tested using the robust correlation dimension estimator proposed in (Dhifaoui, 2016) where is based on the use of Gaussian kernel correlation integral (Diks, 1996; Yu et al., 2000; Dhifaoui, 2018) (for application of this method, reader can se (Zouhaier, 2022)). The results of the used stochasticity test are shown in Figure 10, where we remark that the correlation dimension increase when the embedding dimension (m) increase, then we can conclude that the studied time series after removing outliers are stochastic, this results are also confirmed by evolution of confidence interval of estimated correlation dimension. Based on the above results, we can consider that the studied time series are a fractional Gaussian noise processes corrupted by outliers.

Table 4: Results of stationarity and normality tests and the Hurst exponent (H) of the studied time series without outliers.

Time series	ADF test	J.B test	H
NAO index	-7.384(0.010)***	3.494(0.174)***	0.683
Return of Corn	-7.276(0.010)***	0.947(0.622)***	0.595
Return of Soybean	-7.366(0.010)***	2.472(0.290)***	0.545
Return of Wheat	-6.777(0.010)***	0.051(0.974)***	0.575
Return of Oats	-7.786(0.010)***	0.413(0.813)***	0.583

*Note: The value between parenthesis is the associated p-value and *** indicates that the value is statistical significant for 1%.*

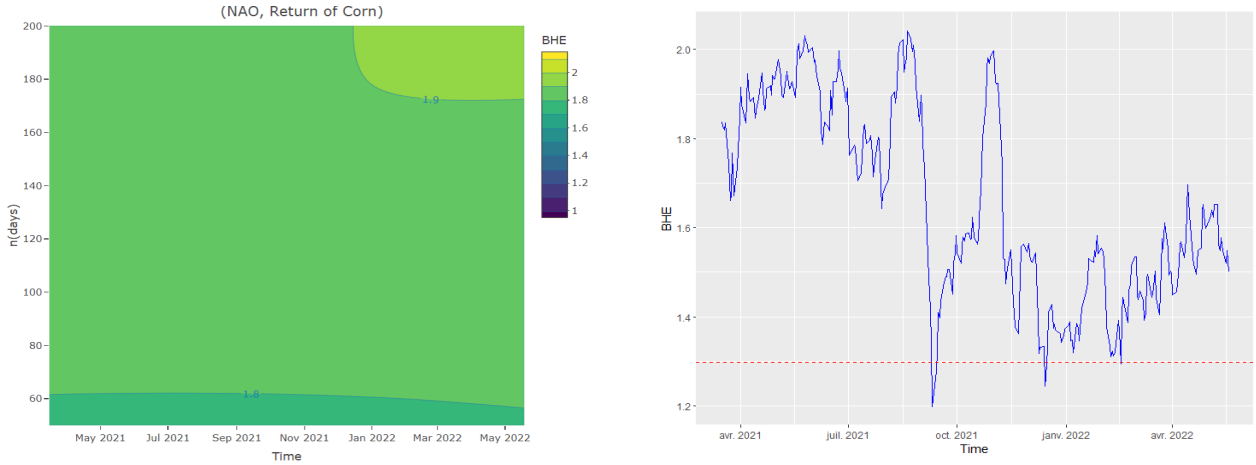
5. Empirical results and discussions

The sliding window approach for long-range cross-correlation between NAO index and the return of different international food prices is obtained for $1 \leq T \leq 300$ i.e for time period from March 16, 2021 until May 18, 2022 and for time scale n equal to 50, 100, 150 and 200 days. Herein, we consider n from 50 days to 100 days as a short-term scale, and when n from 150

days to 200 days as a long-term scale. Additionally, we propose the time-varying long-range cross-correlation as the average of $H_{X,Y}(T,n)$ for all n as follows:

$$H(T)_{X,Y}(2) = \frac{1}{4} \sum_{n=\{50,100,150,200\}} H_{X,Y}(T,n). \tag{10}$$

Furthermore, we take 1.297 as a statistical critical value for $H_{X,Y}$ for confidence level equal to 95% (see Table 2), then we consider each $H_{X,Y} \geq 1.297$ is statistically significant and then their is a positive power-law cross-correlation. The sliding windows long-range cross-correlation, illustrated by contour plot, and the corresponding time-varying long-range cross-correlation coefficient (the dashed red line represent $H(T)_{X,Y} = 1.297$) for different pairs are given in figures 3, 4, 5 and 6.



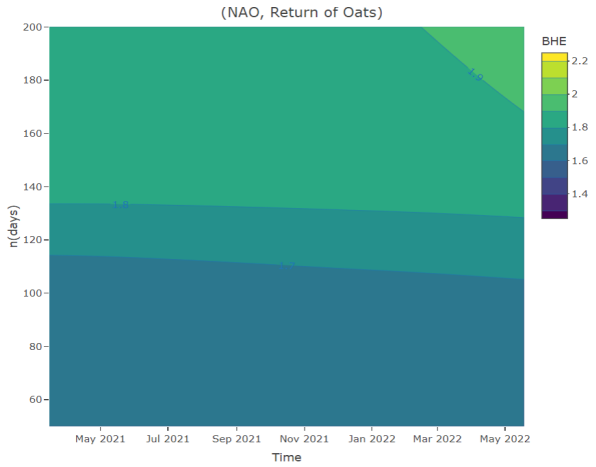
(a) Sliding windows BHE.

(b) Time-varying BHE.

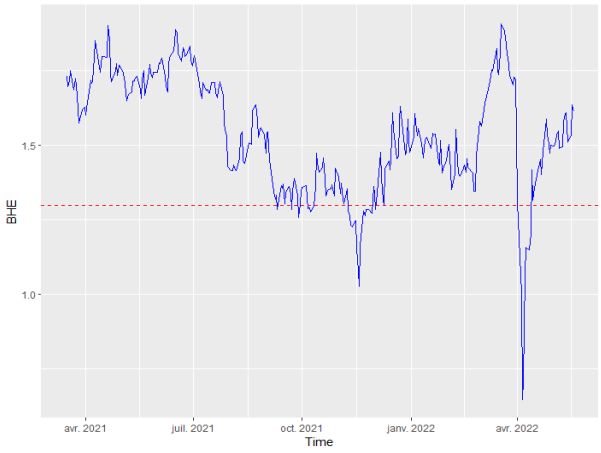
Figure 3: Sliding window and time-varying BHE for NAO and return of Corn time series.

Our principal finding, of this section, is that there is a significant positive power-law cross-correlation, for different time scale n and all time period T, between the fluctuation of NAO index and the fluctuation of studied international food prices. These results suggests that there is a long-range cross-correlation between NAO index and different return of international food prices. Therefore, a large change in the NAO index is followed by a large change in the return of wheat, soybean, corn and oats prices, respectively.

Figure 3a represent the color map of $H_{X,Y}$ for pairs NAO index and the return of corn price. From this figure we remark that $H_{X,Y}$ is greater than 1.9 for short and long term scale and for all studied time period. On the other hand, Figure 3b showed that the time-varying long-range cross-correlation coefficient is greater than the critical value 1.297 for all time periods except in the middle of September 2021 and the middle of December 2021. This result implies that a large change in the NAO index is followed by a large change in the return of corn price, so we

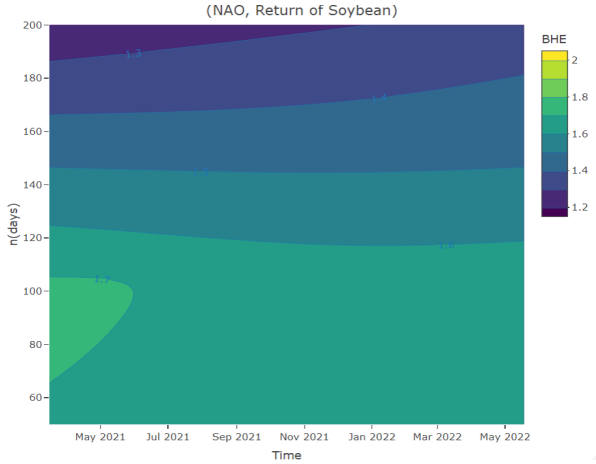


(a) Sliding windows BHE.

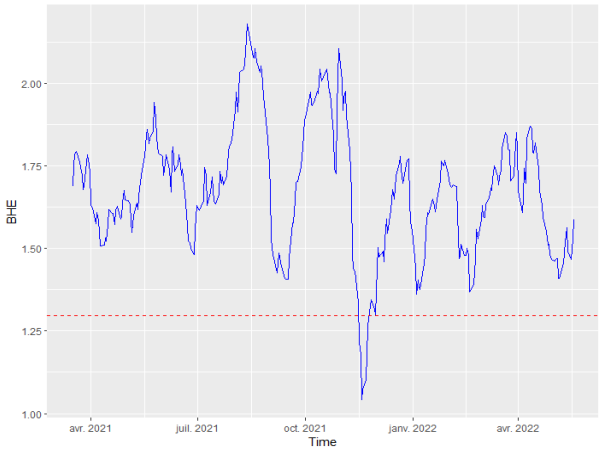


(b) Time-varying BHE.

Figure 4: Sliding window and time-varying BHE for NAO and return of Oats time series.

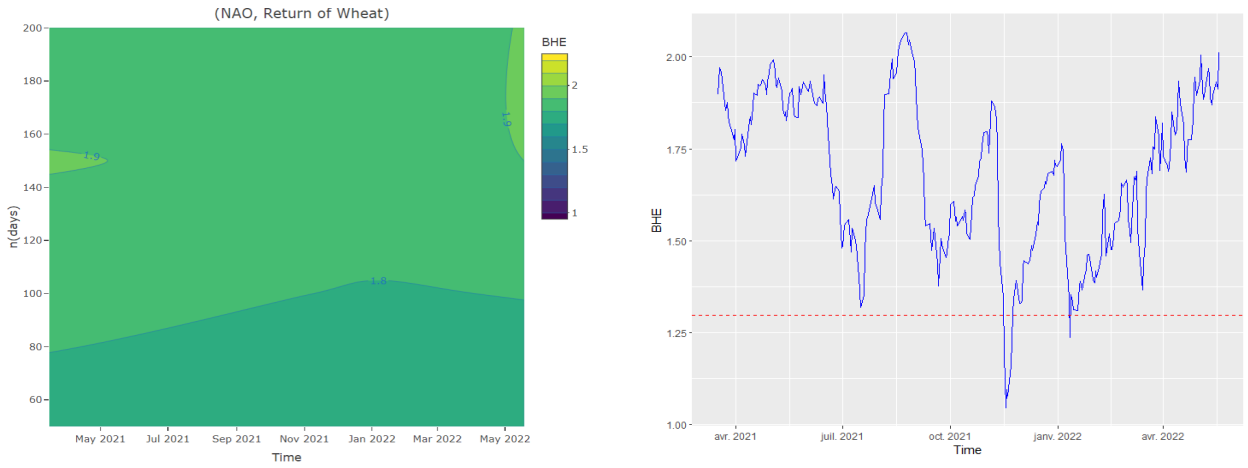


(a) Sliding windows BHE.



(b) Time-varying BHE.

Figure 5: Sliding window and time-varying BHE for NAO and return of Soybean time series.



(a) Sliding windows BHE.

(b) Time-varying BHE.

Figure 6: Sliding window and time-varying BHE for NAO and return of Wheat time series.

conclude that NAO index influences the fluctuation of corn price. In our knowledge, there is no scientific research proves the connection between fluctuation of NAO index and the return of corn price. This finding is due, probably, to the impact of NAO index on the corn yield (Malone et al., 2009; Zhou et al., 2012; Heino et al., 2020a) which influence the corn price. Furthermore, the relationship between NAO index and the return of corn price can be due to relationship between NAO index and some other climatic change indices which impacts the fluctuation of corn price or corn yield (Noah S. et al., 2012; Hatfield and Dold, 2018; Moschini et al., 2021). Moreover, different studies showed the impact of NAO index on the quality of water (Sarafanov, 2009; Rust et al., 2022) or the rainfall (Rust et al., 2021), and it is known the importance of the irrigation and the rainfall on the corn productivity (Ren et al., 2008; Florio et al., 2014; Xu et al., 2021). Accordingly, we can, probably, associate our finding about the relationship between NAO index and the corn price to the impact of NAO index on production of corn which is sensitive to the quality of the used water for irrigation and to the rainfall.

According to Figure 4a which represents the color map of $H_{X,Y}$ for pairs NAO index and the return of oats price, we remark that $H_{X,Y}$ is greater than 1.7 for short term scale ($50 \leq n \leq 100$). Whereas $H_{X,Y}$ is greater than 1.9 for long term scale ($150 \leq n \leq 200$) for all studied time period. In addition, the lang-range cross-correlation coefficient given by Figure 4b showed that it is not constant and it is time-varying for all studied time period. As well, $H_{X,Y}$ is greater than 1.297 for all studied time period expect in the middle of November 2021 and in the begin of April 2022 where $H_{X,Y}$ is less than 1.297. The obtained result reveals that a large change in the NAO index is followed by a large change in the return of oats price. Like the previous finding, in our knowledge there is no work studying the relationship between NAO index and the fluctuation of oats price. We associate our finding, possibly, with the connection between NAO index and oats yield (Kim and McCarl, 2005; Brown, 2013), or to the relationship between NAO index and some climatic changes which influence the oats price (Gordeev et al., 2022; Ljungqvist et al., 2022). Also, based on the connection between NAO index and water or rainfall, we thought to explain the relationship between NAO index and the oats price to the impact of water and rainfall on the yield of oats (Jia et al., 2019; Klink et al., 2014)

The color map of long-range cross-correlation of pairs NAO index and the return of soybean price is given by Figure 5a which showed that $H_{X,Y}$ is greater than 1.297 for short- and long term scales. In addition, evolution of long-range cross-correlation coefficient over time, given in Figure 5b, is not constant and it is time-varying. As well, $H_{X,Y}$ is greater than 1.297 expect in the middle of November 2021. According to this finding we conclude that a large change in the NAO index is followed by a large fluctuation in soybean price. Our finding is consistent with other research showing a significant relationship between NAO index and the fluctuation of soybean price (Najafi et al., 2019; Heino et al., 2020b).

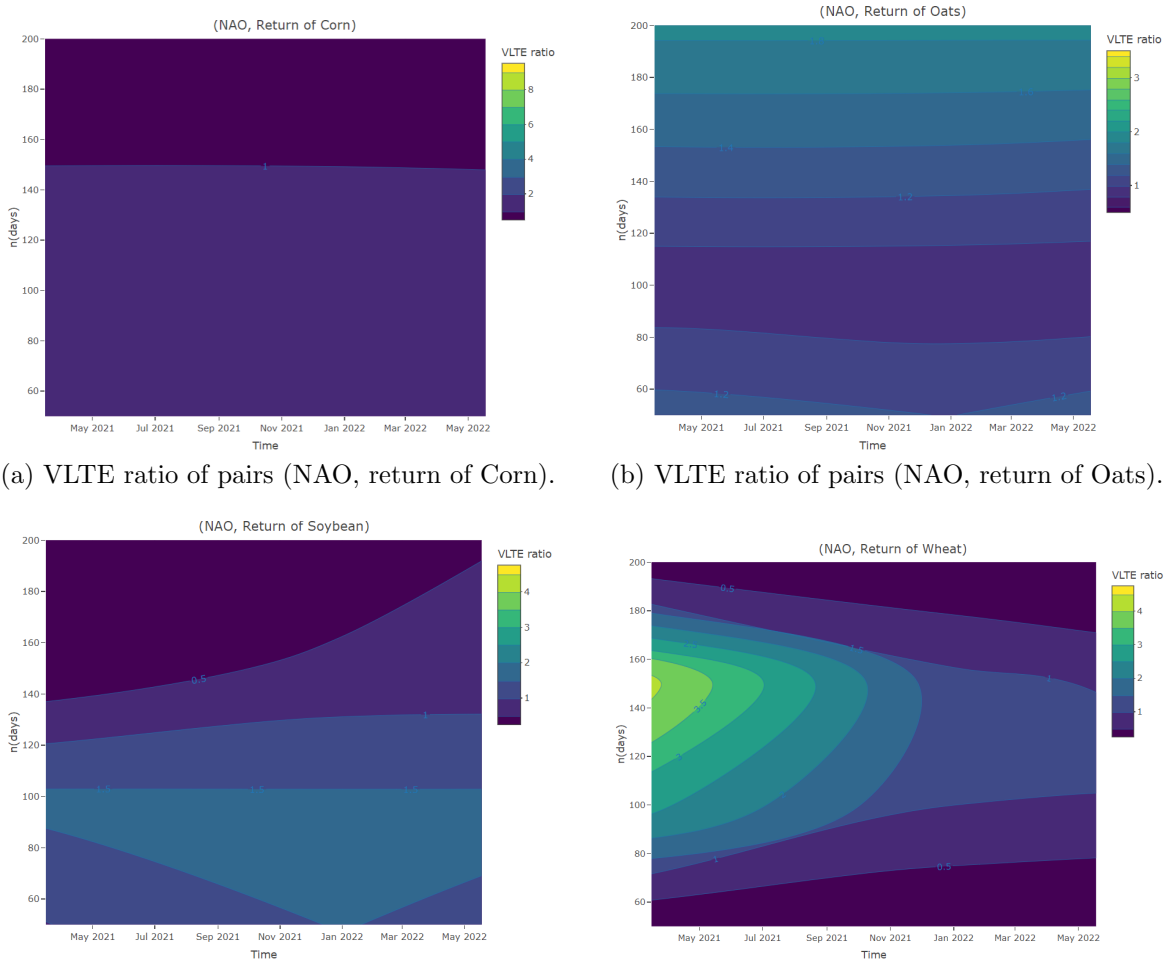
The color map of $H_{X,Y}$ for pairs NAO index and the return of wheat price, given by Figure **??**, revealed that $H_{X,Y}$ is greater than 1.8 for all time period and for short- and long-term scales. Figure **??** showed that the long-range cross-correlation coefficient is time-varying and it is greater than 1.297 expect in the middle of November 2021 and in the beginning of January 2022. These results suggested that a large change in the NAO index is followed by a large change in the return of wheat price. This finding is consistent with different other works showing significant relationship between NAO index and the fluctuation of wheat price (Kettlewell et al., 1999; Gimeno et al., 2002; Shmelev et al., 2021).

6. Robustness check

In this section, we conduct a robustness check for the obtained results. For this goal, a variable-lag transfer entropy (VLTE) causality test (Amornbunchornvej et al., 2021) with sliding windows approach is used. The same sliding windows and scales us for the power-low cross-correlation coefficient with sliding window approach are used. Barnett et al. (2009) found complete equivalence between the Granger causality test and the transfer entropy approach for Gaussian time series. Also, Edinburgh et al. (2021) advocated the usage of the transfer entropy approach and the nonlinear Granger causality test after comparing the transfer entropy method to ten causality methodologies and causality tests. On the other hand, the effectiveness of transfer entropy method when their are a outliers observations in studied time series is proved in (Falkowski and Domanski, 2020). Furthermore, transfer entropy has found practical applications (Dhifaoui et al., 2022, 2023). We employ the VLTE method that can infer a causal relationship of Granger or transfer entropy where a cause impacts an effect with arbitrary dynamically delays. According to (Amornbunchornvej et al., 2021), the VLTE method consists to compute the transfer entropy from X to Y noted $\mathcal{T}_{X\to Y}$ and from Y to X noted $\mathcal{T}_{Y\to X}$ and if VLTE ratio $= \mathcal{T}_{X\to Y}/\mathcal{T}_{Y\to X}$ is greater than 1 then we state that the variable X transfer entropy cause the variable Y. For our studied time series, the obtained results of VLTE ratio are reported in figures 7a, 7b, 7c and 7d.

According to Figure. 7a, the VLTE ratio is greater than 1 for short-term scale and all studied time period, then we conclude that the NAO index transfer entropy causes the fluctuation of international price of corn. The color map of VLTE ratio for pairs NAO index and the return of corn price is given in Figure. 7b, where we remark that the VLTE ratio is greater than 1 for short- and long-term scale which implies that the NAO index transfer entropy causes the fluctuation of the international price of oats. Figure. 7c report the VLTE ratio for pairs NAO index and the return of international price of soybean where VLTE ratio is greater than 1 for short-term scale and all studied time period. As well, VLTE ratio is greater than 1 for long-term scale but for time interval from the beginning of the studied time period to the

begin of November 2021. This result suggested that the NAO index transfer entropy causes the fluctuation of the international price of soybean. Based on Figure. 7d, the VLTE ratio is greater than 1 for short-term scale and almost long-term scale ($90 \leq n \leq 180$) and for time interval from beginning of studied time period to the end of November 2021. This result indicated that the NAO index transfer entropy causes the fluctuation of the international price of wheat. The obtained results using VLTE causality test with sliding windows approach confirms the obtained results using the bivariate Hurst exponent with sliding widows approach.



(a) VLTE ratio of pairs (NAO, return of Corn).

(b) VLTE ratio of pairs (NAO, return of Oats).

(c) VLTE ratio of pairs (NAO, return of Soybean).

(d) VLTE ratio of pairs (NAO, return of Wheat).

Figure 7: Time-scale VLTE ratio for different pairs of time series.

7. Implications for theory and practice

7.1. Theoretical implications

The purpose of this article is to find out if the NAO index will have an impact on the international food prices at both time and time scales. The robust power-law cross-correlation coefficient, which allows for capturing effects of the NAO index on international food prices, was used in this study to advance the field. This study makes several contributions to the

climate change-food price impact literature. First, this study extended the literature by using an innovative robust power-law cross-correlation coefficient. Second, we propose the color map of power-law cross-correlation coefficient obtained by sliding window framework, and we deduce the time-varying robust power-law cross-correlation coefficient. As far as we know, no academic researcher has presented this novelty from theoretical and empirical perspectives, despite the cross-correlation method is used in different works (He and Chen, 2011; Wei et al., 2017).

7.2. Empirical implications

The global food crisis has worsened as a result of the covid-19 pandemic, which has disrupted food prices in almost all countries. Different studies shows that the food prices are negatively affected during the pandemic compared to the pre-pandemic period (Bairagi et al., 2022; Beckman et al., 2021). The covid-19 pandemic continues to have devastating effects on hunger and poverty around the world, particularly on the poorest and most vulnerable communities. On the other hand, the persistent consequences of the COVID-19 epidemic, combined with the Russian-Ukrainian conflict, have already contributed to soaring food costs on both domestic and international markets (Behnassi and Haiba, 2022). So, rising food prices could become the new normal as a result of covid-19 pandemic and conflicts creating endemic and ubiquitous hazards to global food security. Our study suggested that their is a positive power-law cross-correlation between fluctuation of NAO index and that's of international price of oats, soybean, corn and wheat, respectively for short- and long terms. For this goal, a robust bivariate Hurst exponent is used. First, we give the statistical critical value of such exponent. Second, we obtain a color map by computing the bivariate Hurst exponent for different time scale and using the sliding window approach. Our result reveals that a large fluctuations of NAO index is followed by a large fluctuations of studied international foods price. Accordingly, the NAO index can be considered as an explain variable of international food price, which increase the level of uncertainty on the international food markets.

Although that the NAO index increase the level of uncertainty in the international food markets, but our study finds that the NAO index and the international food price rest essentially on a single modelling framework. So, we prove that the NAO index is a explicative factor of the fluctuation of international food price. Then, to mitigate food market uncertainty can be done by actions on the fluctuation of NAO index. It is well known that the NAO index is related to temperature, then decreasing the temperature can help to control NAO index and then the international price of food (Bandara and Cai, 2014; Chen and Villoria, 2019). The Paris Agreement signed in 2015 to prevent severe climate change by keeping global warming well below $2°C$ and pursuing efforts to keep it below $1.5°C$ is considered in this objective. For decreasing global temperature, different strategies are used. Employing decarbonization techniques and technologies that reduce carbon dioxide emissions, such as nuclear power, renewable energy, and the use of alternative fuels, are traditional mitigation measures (Bataille et al., 2018; Bustreo et al., 2019). On the other hand, a new set of technologies and techniques that have just been developed. These processes are known as negative emissions technologies, and they have the potential to be used to capture and sequester carbon dioxide from the atmosphere (Ricke et al., 2017). The main negative emissions technologies that have received a lot of attention in the literature are bioenergy carbon capture and storage, biochar, enhanced weathering, direct air carbon capture and storage, ocean fertilization, ocean alkalinity enhancement, soil carbon sequestration, afforestation and reforestation (Lawrence et al., 2018; Palmer, 2019; Goglio et al.,

2020). Since industrial sectors have gotten more focus on greenhouse gas mitigation efforts than the food industry, by the middle of the century, emissions from agriculture can become the main source of emissions worldwide (Lynch et al., 2021; Crippa et al., 2021). Therefore, it is very important to applied different strategies to mitigate emissions given from food industry, like a shift to more plant-based diets (Shukla et al., 2022), less food waste (Fund, 2022) and improvements in crop yields and farming practices (Northrup et al., 2021; Islam et al., 2022).

Our findings suggested that, for short- and long-term scale, changes in the NAO index can spread to changes in the international price of food, and that one large increment in the NAO index is likely to result in further large increment in the international food prices. Accordingly, different strategies can be applied by policymakers to insure the alimentary security. To secure food and nutrition security in the face of a warming climate, governments, private companies, and international partners must work toward more productive, resource-efficient, varied, and nutrient-rich farming systems. Produce more varied and nutrient-dense food with less water and fertilizer for a growing population, while reducing land use change and greenhouse gas emissions. Other temporary measures that can be considered by governments include import levies or price subsidies with clear sunset provisions for basic food commodities. Additionally, governments should assist food production, refrain from stockpiling, and utilize food reserves when they are available in an effort to improve the food supply.

8. Conclusion

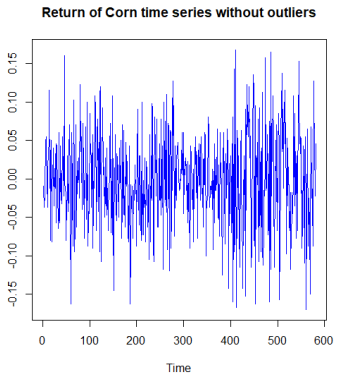
Even prior to the covid-19 pandemic, rising levels of food insecurity were noted throughout the world. These levels were attributed to a variety of issues, including rising food prices, declining wages, broken supply chains and climate change. This study examined the impact of fluctuations of the NAO index on the fluctuations of international price of wheat, corn, soybean and oats, respectively. We remind that wheat and corn with rice comprise a major component of the human diet. As well, oats is the most ingredient in the manufacture of healthy food products. As a significant source of both human and animal protein, demand for soybeans, on the other hand, is currently correlated with the world's meat consumption and is anticipated to increase. The used data are the daily time series over the period from January 06, 2020 until May 18, 2022. After proving, by robust statistical tests, the existence of outliers observations in our studied time series, a new robust power-law cross-correlation coefficient with sliding windows approach is used as the analysis method. Before obtaining a color map and the time-varying version of power-law cross-correlation coefficient, we determine the statistical critical value of such coefficient, for different confidence levels and different length of time series and windows, by bootstrap method. We find that, for short- and long terms, the power-law cross-correlation coefficient of pairs of time series (NAO index, wheat), (NAO index, soybean), (NAO index, oats) and (NAO index, corn) is above the critical value 1.297 for 95% confidence level. Accordingly, our major result is that there is a statistically significant impacts of fluctuations of the NAO index on the fluctuations of different international food price, since we showed a significant positive power-law cross-correlation meaning that large increments of the NAO index are followed by large increments of each international food price. Our finding are confirmed using variable-lag transfer entropy causality test.

In practice, our findings can be used by the responsible authorities for creation of some public policies to reduce the effects of the NAO index on the international food prices. Fur-

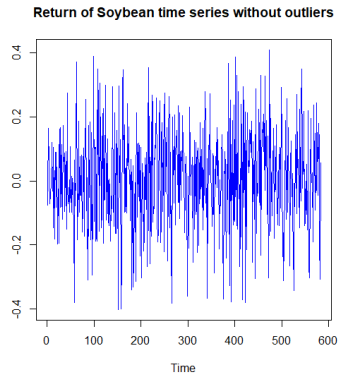
thermore, the prediction of international food price using the evolution of NAO index can give satisfactory results. For this goal, univariate models like the autoregressive model (AR) with NAO index as an exogenous variable (AR-NAO) model or the time-varying AR-NAO model can be used. For multivariate models, the vector autoregressive fractionally integrated moving average (VARFIMA) model can be applied to capture both long-range and short-range dependence dynamics between NAO index and international food prices, as well for forecasting. In addition, different scenarios can be simulated for the future evolution of studies of different food prices which can be done using these suggested econometric models.

Our proposed method being based on the robust power-law cross-correlation coefficient. Recall that, the outliers' observations can be caused by the occasional events such as in climate change time series or on the international food price. As well, in our method, we can choose the time scale we need. Our proposed method proves, if there is a power-law cross-correlation between two processes X and Y, that a large increment in X is followed by a large increment in Y, but our method does not give the time interval when the large increment in X is followed by large increment in Y which is very important in practice for preventive actions. To overcome this problem, future research will first continue to explore the robust power-law cross-correlation coefficient with time interval localization. Second, we can combine our proposed method with a decomposition technic, like wavelet decomposition or empirical mode decomposition, to test power-law cross-correlation between time series in both time and frequency.

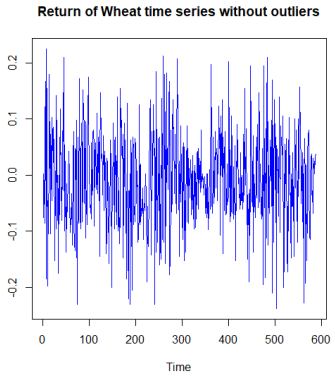
Appendix



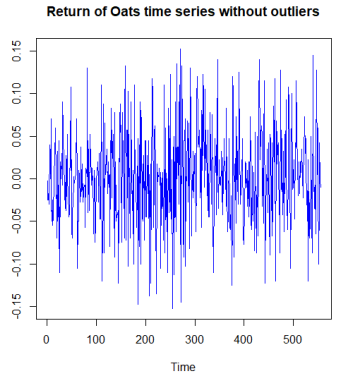
(a) Return of international price of corn time series.



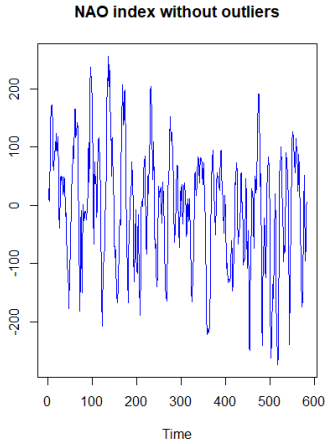
(b) Return of international price of soybean time series.



(c) Return of international price of wheat time series.

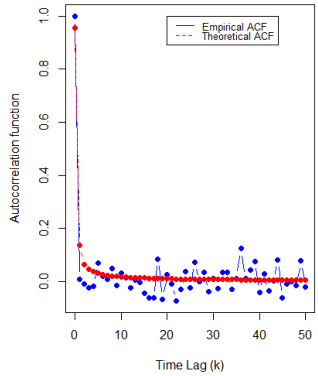


(d) Return of international price of oats time series.

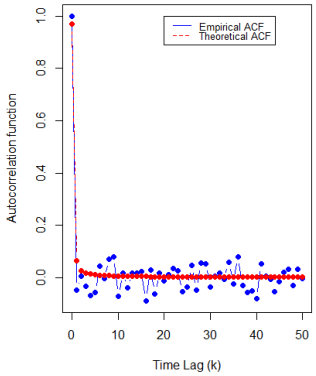


(e) NAO index.

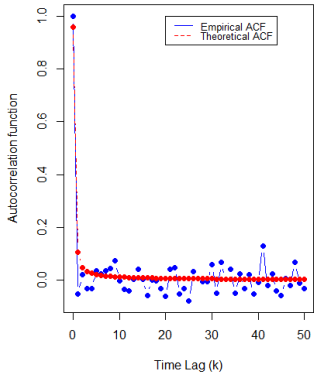
Figure 8: Studied time series after removing outliers observations.



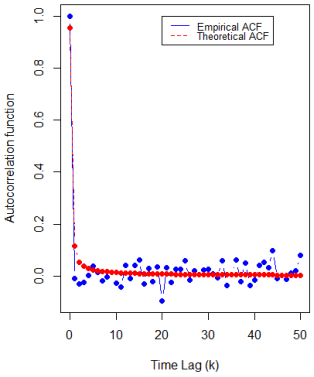
(a) ACF of return of international price of corn and of fGn with $H = 0.595$.



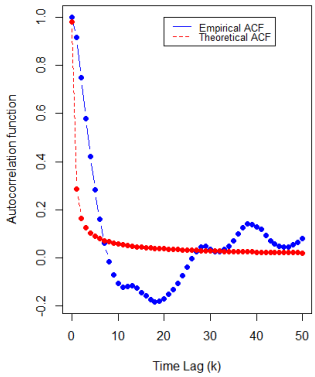
(b) ACF of return of international price of soybean and of fGn with $H = 0.545$.



(c) ACF of return of international price of wheat and of fGn with $H = 0.575$.

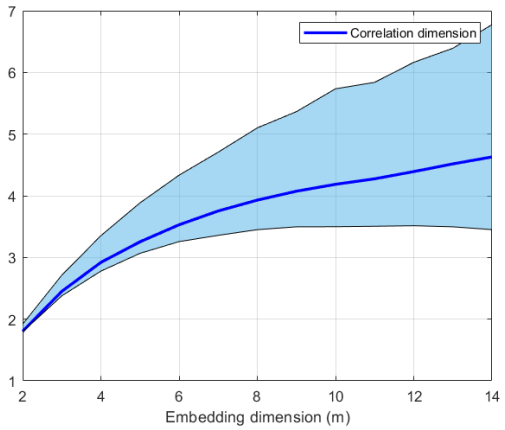


(d) ACF of return of international price of oats and of fGn with $H = 0.583$.

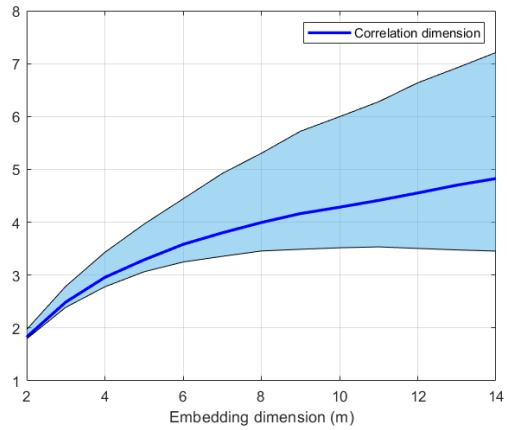


(e) ACF of NAO index and of fGn with $H = 0.683$.

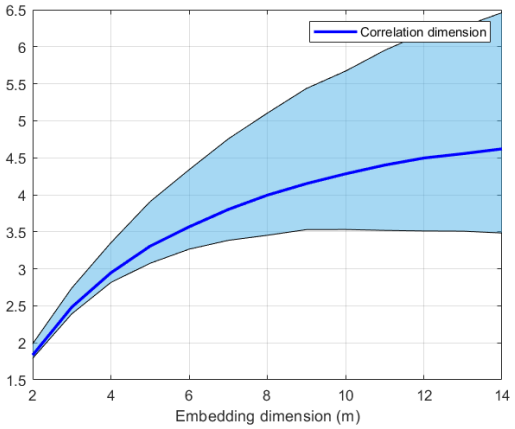
Figure 9: Autocorrelation functions of studied time series without outliers and of associated fGn process.



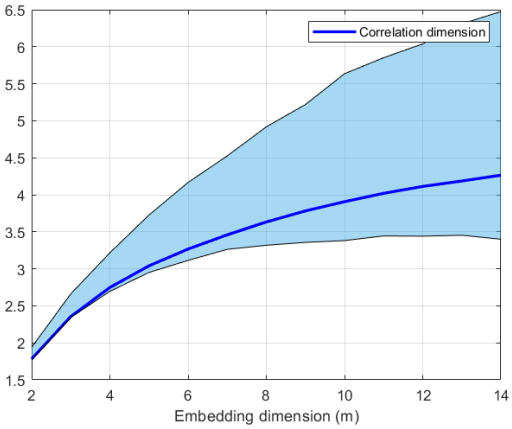
(a) Evolution of correlation dimension of return of international price of corn time series.



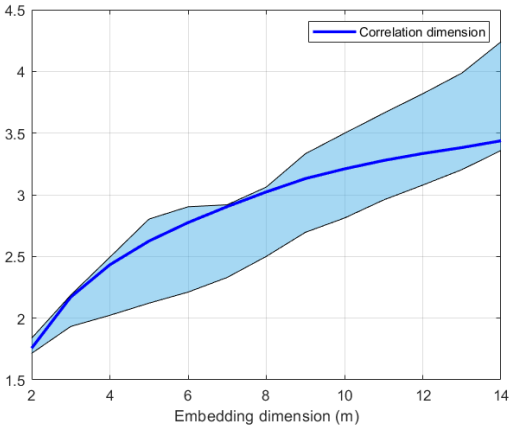
(b) Evolution of correlation dimension of return of international price of soybean time series.



(c) Evolution of correlation dimension of return of international price of wheat time series.



(d) Evolution of correlation dimension of return of international price of oats time series.



(e) Evolution of correlation dimension of NAO index.

Figure 10: Results of test of stochasticity.

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