Journal of Environmental Management 326 (2023) 116789

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

Research article

Exploring the effect of climate risk on agricultural and food stock prices: Fresh evidence from EMD-Based variable-lag transfer entropy analysis

Zouhaier Dhifaoui [a], Rabeh Khalfaoui [b], Sami Ben Jabeur [c], Mohammad Zoynul Abedin [d,e,*]

[a] Department of Family and Community Medicine, Faculty of Medicine of Sousse, University of Sousse, Mohamed Karoui Street, 4002 Tunisia
[b] ICN Business School, CEREFIGE, Université de Lorraine, France
[c] Institute of Sustainable Business and Organizations, Confluence: Sciences et Humanités - UCLY, ESDES, 10 place des archives, 69002, Lyon, France
[d] Department of Finance, Performance & Marketing, Teesside University International Business School, UK
[e] TUIBS Sustainable Finance Research Group, Teesside University, Middlesbrough, TS1 3BX Tees Valley, UK

ARTICLE INFO

Keywords:
Variable lag transfer entropy
Empirical mode decomposition
El Niño34
Food index
Agricultural index

ABSTRACT

Climate has traditionally played an important role in the development of countries, owing to its inherent relationship with agricultural output and pricing. This study explores one such association between the most well-known climate anomaly, the El Niño34 Southern Oscillation, and international commodity prices of agriculture and food indexes. This study addresses the potentially causal effect of El Niño34 on international agricultural and food stock prices. To do so, we develop a novel approach: the empirical mode decomposition variable-lag transfer entropy (EMD-VL transfer entropy) by combining the variable-lag transfer entropy framework and the empirical mode decomposition. The evidence reveals the following major results. First, climate shocks affect global agricultural stock prices in the short-term. Second, significant transfer entropy from El Niño34 to food index appeared at mid- and long-term business cycles. Third, unidirectional causal effect from climate shocks to agricultural and food stock prices is more intense in the short business cycle attesting to the impact of climate shocks on the food market, which is especially visible in the short-term horizon. Finally, our proposed method exceeds the traditional variable-lag transfer entropy by detecting such causal interplay at various business cycles, which is useful for investors and policymakers.

1. Introduction

Each year, the global temperature continues to rise. Since 1971, the average rate of increase was 0.18 °C–0.19 °C per decade while the 2014–2019 period led to an increase of 0.32 °C–0.39 °C above the mean of the 2000–2009 decade (Dunn et al., 2020). Compared to the 2001–2010 period, the 2011–2020 period was the warmest decade on record for the globe where the average rate of increase was 0.82 °C (NCEI, 2021). Unfortunately, changes in climate have a negative impact on the quality and availability of soil moisture and water required for agricultural production (Arora, 2019; Backlund et al., 2020). According to the 2019 report of the European Environment Agency, more extreme weather and climate events are expected to increase the risk of crop losses across Europe, and due to the effects of climate change on agriculture, the average decrease in the gross domestic product is expected to amount to 1% by 2050 (Jacobs et al., 2019). Moreover, as a result of the high temperatures and high levels of carbon emissions, Jonas et al. (2021) there is a predicted 24% decrease in maize productivity by the end of the century.

In general, in the long term, environmental degradation is expected to lead to a decline in the output of the agricultural sector. Such supply contraction may put pressure on the prices of food. On this matter, Sally et al. (1992) suggested that the price of agricultural commodities should rise whenever climate change effects are very adverse. By relying on the El Niño34 index which is used to capture changes in the sea surface temperature, different studies confirmed a harmful impact on the prices of world primary commodities (Brunner, 2002), fishmeal-soya bean meal (David, 2014), wheat David (2017), maize and soybean (Massimo, 2017). In this frame, David (2018) argues that such impact is mainly explained through the channel of production because the weather anomalies directly affect the regional suppliers of agricultural commodities. Additionally, climate change-induced land productivity changes can also lead to a rise in the price of rice, wheat, and cereal grains (Bandaraa and Cai, 2014). To inhibit the consequences of global warming one food prices, some adaptation costs may be required to enhance the productivity of the agriculture

* Corresponding author at: Department of Finance, Performance & Marketing, Teesside University International Business School, UK.
E-mail addresses: zouhaierdhifaoui@ymail.com (Z. Dhifaoui), rabeh.khalfaoui@gmail.com (R. Khalfaoui), sbenjabeur@gmail.com (S. Ben Jabeur), m.abedin@tees.ac.uk (M.Z. Abedin).

https://doi.org/10.1016/j.jenvman.2022.116789
Received 20 June 2022; Received in revised form 21 October 2022; Accepted 12 November 2022
Available online 26 November 2022

sector that can embrace the form of (public) investments in rural roads, research, and irrigation infrastructure (Nelson et al., 2009).

As consumer surplus can be affected by the volatility in food prices, addressing how climate change impacts the agricultural producers in terms of stocks and performance represents a major question in the environmental literature. This article contributes to the strand of climate change literature along several key directions. First, this study investigates the nexus between the effects of global warming, agricultural and food commodities prices in relation to El Niño34 cycles. Second, this research addresses the potentially causal relationship between El Niño34, agricultural, and food commodities prices through a novel approach dealing with the variable-lag transfer entropy. In fact, a new method, termed EMD-VL transfer entropy is proposed to exhibit the nonlinear behavior between variables. According to Barnett et al. (2009), transfer entropy method and the Granger causality test are entirely equivalent under the Gaussian time series. In addition, through comparative study between the transfer entropy method and ten causality methods, (Edinburgh et al., 2021), recommended the use of the transfer entropy method and nonlinear Granger causality test. However, all causality methods are based on hypothesis testing procedure, where a statistic test is computed, and the existence of causality is determined based on the value of this statistic. Therefore, these methods do not measure the strength of causality with a numerical value. Transfer entropy, can measure the strength of the causality (see, Schreiber, 2000; Milan et al., 2001) and can also detect nonlinear causality relationships.

To the best of our knowledge, no research has attempted to use the EMD-VL transfer entropy in this nexus. Empirical mode decomposition (EMD) is a popular time–frequency signal decomposition technique for evaluating nonstationary and nonlinear data (Yaguo et al., 2013). Such methodology achieved greater results when dealing with nonstationary signals (Tian et al., 2018). In our study, for each attribute, EMD is used for decomposition with different time scales. EMD is more suited for decomposing nonlinear and nonstationary time series than other decomposition methods, such as wavelet and the Fourier decomposition method (Chang et al., 2021). In addition, we apply the VL transfer entropy approach proposed by Amornbunchornvej et al. (2021) that can infer a causal relation of Granger or transfer entropy where a cause impacts an effect with arbitrary delays that can change dynamically, and also to report the similarity of time series patterns between the cause and the delayed effect, for arbitrary delays. Moreover, our research is also connected to the body of literature that examines the consequences of natural disasters (Berkman et al., 2011; Tsai and Wachter, 2015; Huang et al., 2018; Keleş et al., 2018; Chang and Jennifer, 2022; Chen et al., 2022). In related studies, climate change may be used as a gauge of risk. Disaster risk has a negative impact on stock returns dating back to 1919 (Berkman et al., 2011). Indeed, the relevance of this risk has become more evident since the recent Ukrainian crisis. Food prices reach their greatest level ever as a result of the Ukraine conflict. Our findings provide practical implications for investors that should be cautious when evaluating climate risk. They should also have well-diversified portfolios with a hedging strategy in place, particularly for food and agricultural markets that might be harmed if the climate risk intensifies.

This paper is organized as follows; Section 2 is dedicated to the literature review. In Section 3, we introduce the methodology adopted in this article. In Section 4, we describe the sample data and provide descriptive statistics for the selected sample. The results are provided in Section 5. In Section 6 we discus our findings and we bring forth our conclusion in Section 7.

2. Literature review

In many regions of the globe, El Niño34 is a major cause of inter-annual variability in weather and climate change (Bebonchu and Naafey, 2021). An enormous amount of work has been carried out on the effect of El Niño34 on economic and financial market. According to Brunner (2002), El Niño34 indices are useful indicators for analyzing the causal inferences of medium-frequency climatic anomalies on global economic activity. Berry and Okulicz-Kozaryn (2008) investigated the linkage between the El Niño34 fluctuations, the rates of inflation and economic growth over the period 1894–1999. The authors found that extreme El Niño34 occurrences may have a short-term influence on the pricing of certain commodities produced in specific locations during specific time periods. Berry and Okulicz-Kozaryn (2008) employed a dynamic multi-country framework to examined the effects of El Niño34 shocks on growth, inflation, energy, and non-fuel commodity prices. Their findings revealed that the reactions of various countries to the El Niño34 shocks are very heterogeneous. While El Niño34 causes a temporary drop in economic activity in Australia, Chile, Indonesia, India, Japan, New Zealand, and South Africa, it has a growth-enhancing influence in other nations (including the United States and the European area). Generoso et al. (2020) examined the effect of weather patterns in affecting the transmission of global climatic cycles to economic development. The authors found negative effects of El Niño34 events on economic growth.

Several studies have explored the effects of El Niño34 on agricultural and food prices (Barrett, 1998; Podesta et al., 2002; Chen et al., 2002; Sivakumar et al., 2005). According to Bebonchu and Naafey (2021), the influence of El Niño34 on agricultural production and pricing differs between the El Niño34 and La Niña stages of the El Niño34 cycle. Adams et al. (1999) used a stochastic economic model to estimate the economic consequences of El Niño34 events on US agriculture. The authors found that both phases cause economic harm to US agriculture, with El Niño34 causing a \$1.5 to \$1.7 billion loss and La Niña causing a \$2.2 to \$6.5 billion loss. David (2012) employed a smooth transition autoregression framework to investigate nonlinear dynamics of El Niño34 and coffee prices. Their results found that during El Niño34 episodes, coffee prices are affected in the near term. David (2014) analyzed the regime-dependent dynamics of the fish meal-soya bean meal price ratio and investigates it in conjunction with the El Niño34 shocks. The author demonstrated that El Niño34 has an economically significant influence on price ratio dynamics, and that these effects are statistically significant for up to a year following the El Niño34 shocks. Tack and Ubilava (2013) estimated the El Niño34's effect on U.S. county-level corn yield distributions. Their findings showed that the influence of global climate on agriculture cannot be summarized by temperature and precipitation alone. For the mean, variation, and downside risk of corn yields, they show that acreage-weighted aggregate effects disguise substantial geographic variability at the county level. El Niño34 has a −24 to 33% impact on mean yields, whereas La Niña has a −25 to 36% impact, with the geographic center of losses moving from the Eastern to Western corn belt. According to Iizumi et al. (2014), El Niño34 boosts world average soybean output by 2.1–5.4% while decreasing corn, rice, and wheat yields by −4.3% to 0.8%. On the other hand, they revealed lower yields of between 0% and −4.5% for all four crops during La Niña years. David (2018) used a time-varying smooth transition autoregressive modeling approach to account for dynamic interactions between sea surface temperature anomalies and pricing that may be complicated. The authors found more amplified price responses during El Niño34 events, and at the onset of the El Niño34 cycle and a significant relationship between sea surface temperature anomalies and a subset of agricultural commodity prices. As pointed out by Bebonchu et al. (2020), agricultural yields are projected to be reduced as a consequence of an El Niño34 shock, which would reduce present and future cash flows to food and agricultural industries, resulting in a reduction in their stock values and/or profits. More recently, (Bebonchu and Naafey, 2021) used state-dependent local projection methods to investigate whether El Niño34 has asymmetric effects on the pricing of food and agricultural stocks in the United States. The authors documented that food and agricultural stock prices react asymmetrically to El Niño34 shocks. Also, the authors found that El Niño shocks frequently lower or have no impact on food and agricultural stock prices in the United States, but La Nina shocks generally raise prices.

3. Methodology

3.1. Variable-lag transfer entropy

Transfer entropy was developed by Schreiber (2000) and independently under the name conditional mutual information by Katerina et al. (2007). Transfer entropy can be conceived as a parameter which can be used for describing the interaction between time series X and Y and to detect the directionality of the flow of information between them. Furthermore, transfer entropy is a measure to evaluate dynamic, nonlinear, and non-symmetric relationships between time series (Xuegeng and Pengjian, 2017). On the other hand, transfer entropy is the nonlinear extension of Granger causality (Schreiber, 2000; Barnett et al., 2009).

Let X and Y two time series and k, ℓ are two lag constants, the transfer entropy from X to Y is defined thus:

$$T_{X\to Y} = H\left(Y_t|Y_{t-1}^{(k)}\right) - H\left(Y_t|Y_{t-1}^{(k)}, X_{t-1}^{(\ell)}\right), \tag{1}$$

where $H(.|.)$ is a conditional entropy and $Y_{t-1}^{(k)} = (Y_{t-1}, \dots, Y_{t-k})$. Amongst the most known types of entropy is Shannon entropy (Shannon, 1948) where the function H is defined as:

$$H(X) = -\sum_t f(X_t)\log_2(f(X_t)), \tag{2}$$

where f is the probability density function. Based on Eqs. (1) and (2), the Shannon transfer entropy from X to Y (Behrendt et al., 2019) is given by:

$$T_{X\to Y} = \sum_t f\left(Y_t, Y_{t-1}^{(k)}, X_{t-1}^{(\ell)}\right)\log_2\left(\frac{f(Y_t|Y_{t-1}^{(k)}, X_{t-1}^{(\ell)})}{f(Y_t|Y_{t-1}^{(k)})}\right). \tag{3}$$

Typically, we infer whether X causes Y by computing the transfer entropy ratio $T(X,Y) = T_{X\to Y}/T_{Y\to X}$, if $T(X,Y) > 1$ then we state that X causes Y.

However, Amornbunchornvej et al. (2020) proves that the Granger causality test is limited by the fixed-lag assumption, then, to overcome this problem, the authors propose a variable-lag Granger causality test (Amornbunchornvej et al., 2020). In addition, since transfer entropy is a nonlinear extension of Granger causality test, Amornbunchornvej et al. (2021) show that transfer entropy is also limited by the fixed-lag assumption. In fact, Eq. (1) shows a comparison between Y_t and $Y_{t-1}^{(k)}$ and $X_{t-1}^{(\ell)}$ and no variable lags are allowed. Therefore, the variable-lag transfer entropy or VL transfer entropy function is defined as below:

$$T_{X\to Y}^{VL}(P) = H\left(Y_t|Y_{t-1}^{(k)}\right) - H\left(Y_t|Y_{t-1}^{(k)}, \widetilde{X}_{t-1}^{(\ell)}\right), \tag{4}$$

where $\widetilde{X}_{t-1}^{(\ell)} = (X_{t-1-\Delta_{t-1}}, X_{t-2-\Delta_{t-2}}, \dots, X_{t-\ell-\Delta_{t-\ell}})$, P is the alignment sequence between X and Y (see definition 5.1 in Amornbunchornvej et al., 2021) and $\Delta_t \in P$ where $\Delta_t > 0$. Based on Eqs. (2) and (4), the variable-lag Shannon transfer entropy is given by:

$$T_{X\to Y}^{VL} = \sum_t f\left(Y_t, Y_{t-1}^{(k)}, \widetilde{X}_{t-1}^{(\ell)}\right)\log_2\left(\frac{f(Y_t|Y_{t-1}^{(k)}, \widetilde{X}_{t-1}^{(\ell)})}{f(Y_t|Y_{t-1}^{(k)})}\right) \tag{5}$$

and the variable-lag transfer entropy ratio $T^{VL}(X,Y) = T_{X\to Y}^{VL}/T_{Y\to X}^{VL}$. If $T^{VL}(X,Y) > 1$ then we state that X transfer entropy causes Y.

An appropriate alignment P can be given by:

$$P^* = \underset{P}{\operatorname{argmax}}\left(\operatorname{sim}(\widetilde{X}, Y)\right), \tag{6}$$

where $\widetilde{X}_t = X_{t-\Delta_t}$ and $\Delta_t \in P$. P^* represents a sequence of time delay that matches the most similar pattern of time series X with the pattern in time series Y where the pattern of X comes before the pattern of Y. "Sim" can be any function that measures the similarity between two time series, for example, using distance function dist: $\mathbb{R}^2 \times [0,1]$, the similarity between X and X' can be given by:

$$\operatorname{sim}(X, X') = \frac{1}{T}\sum_t 1 - \operatorname{dist}(X_t, X'_t). \tag{7}$$

The procedure for the variable-lag transfer entropy causality test is as follows: given two time series X and Y, first, using the Dynamic Time Warping (DTW) method (Amornbunchornvej et al., 2020, 2021), the time series X^{DTW} is reconstructed based on X which is most similar to Y. DTW calculates the distance between two time series by aligning sufficiently similar patterns between them, while allowing for local stretching. Thus, it is particularly well suited for calculating the variable lag alignment. Second, the variable-lag transfer entropy given by Eq. (5) is computed using X^{DTW} and Y. Finally, the variable-lag transfer entropy ratio is computed. On the other hand, the approach proposed in Dimpfl and Peter (2013) to perform Markov block bootstrap on transfer entropy is used to obtain the p-value of variable-lag transfer entropy ratio. The dependency within the time series while performing bootstrapping using the approach proposed in Dimpfl and Peter (2013) is retained.

3.2. Empirical mode decomposition method

Empirical Mode Decomposition (EMD) is an adaptive method proposed by Wu and Huang (2009) for dealing with nonlinear and nonstationary time series. EMD method allows the decomposition of a time series into finite intrinsic mode functions (IMFs), which stand for different time-scale oscillating components ranging from high frequency to low frequency without overlapping. IMFs components fully embody the details of the original signal. On the other hand, each IMF satisfy the following conditions:

(i) The number of extreme points and zero-crossings must be equal or differ by one at most.
(ii) At any point, the mean value of the envelope determined by the local maxima and minima is zero.

For determining IMFs and residual part (R_t) of a time series $\{X_t\}$ $t \in T$, the following steps are used:

1. We locate local extreme, minima, and maxima.
2. By connecting local extreme with a cubic spline line, we generate the upper envelope X_t^{upper} and lower envelope X_t^{low}.
3. The envelope mean $M_t = (X_t^{\text{upper}} + X_t^{\text{low}})/2$ is computed.
4. We obtain the detailed component $D_t = X_t - M_t$.
5. If D_t satisfies conditions (i) and (ii), we replace X_t with $R_t = X_t - D_t$, if not we replace X_t with D_t.
6. Steps 1–5 are repeated for X_t until R_t satisfies $\sum_{t=1}^{T}(D_{j,t} - D_{j+1,t}/D_{j,t})^2 < SC$, then $D_{j,t}$ is the result of the jth iteration, where $SC \in [0.2, 0.3]$.

At the end of this process, X_t is decomposed into the sum of IMF components and a residual part as follows:

$$X_t = \sum_{j=1}^{K} D_{j,t} + R_t. \tag{8}$$

3.3. EMD-VL transfer entropy

Let x and y two time series, IMFs, obtained by EMD method, of each time series are grouped together, using fine to coarse method, in two terms; the short-term scale $\mathbf{H}$ and the medium-term scale $\mathbf{L}$. The long-term scale of each time series is the residual part $\mathbf{R}$ obtained directly by the EMD method. Then, for the time series x these different parts are respectively $\mathbf{H}^x$, $\mathbf{L}^x$ and $\mathbf{R}^x$, while for the time series y they are $\mathbf{H}^y$, $\mathbf{L}^y$ and $\mathbf{R}^y$.

We define, the empirical mode decomposition variable-lag transfer entropy (EMD-VL transfer entropy) as the variable-lag transfer entropy given by Eq. (5) between short-term scales, medium-term scales and long-term scales respectively as below:

$$T_{\mathbf{H}^x\to\mathbf{H}^y}^{VL} = \sum_t f\left(\mathbf{H}_t^y, \mathbf{H}_{t-1}^{y(k)}, \widetilde{\mathbf{H}^x}_{t-1}^{(\ell)}\right)\log_2\left(\frac{f(\mathbf{H}_t^y|\mathbf{H}_{t-1}^{y(k)}, \widetilde{\mathbf{H}^x}_{t-1}^{(\ell)})}{f(\mathbf{H}_t^y|\mathbf{H}_{t-1}^{y(k)})}\right), \tag{9}$$

Table 1
Studied time series.

Time series	Ticker	Description
NOAA optimum interpolation sea surface temperature index	El Niño34	Is the average sea surface temperature anomaly in the region bounded by 5°N to 5°S, from 170°W to 120°W.
S&P Food & Beverage Select Industry Index	SPSIFBN	Means the companies constituting the S&P Food & Beverage Select Industry Index as of the beginning of the Performance Period.
MSCI Agri & FC Index	M2WO0AGF	Is a free float-adjusted market cap index designed to track the performance of companies which are producers of agricultural products, fertilizers & agricultural chemicals, packaged foods and food distributors.
Nasdaq US Smart Food & Beverage Index	NQSSFB	Is designed to provide exposure to US companies within the Food & Beverage sector.
Bloomberg World Agriculture Index	BWAGRI	Is a capitalization-weighted index of the leading agriculture stocks in the World.

$$T^{VL}_{\mathbf{L}^x\to\mathbf{L}^y} = \sum_t f\left(\mathbf{L}^y_t, \mathbf{L}^{y(k)}_{t-1}, \widetilde{\mathbf{L}^x}^{(\ell)}_{t-1}\right) \log_2\left(\frac{f(\mathbf{L}^y_t|\mathbf{L}^{y(k)}_{t-1}, \widetilde{\mathbf{L}^x}^{(\ell)}_{t-1})}{f(\mathbf{L}^y_t|\mathbf{L}^{y(k)}_{t-1})}\right), \tag{10}$$

and

$$T^{VL}_{\mathbf{R}^x\to\mathbf{R}^y} = \sum_t f\left(\mathbf{R}^y_t, \mathbf{R}^{y(k)}_{t-1}, \widetilde{\mathbf{R}^x}^{(\ell)}_{t-1}\right) \log_2\left(\frac{f(\mathbf{R}^y_t|\mathbf{R}^{y(k)}_{t-1}, \widetilde{\mathbf{R}^x}^{(\ell)}_{t-1})}{f(\mathbf{R}^y_t|\mathbf{R}^{y(k)}_{t-1})}\right) \tag{11}$$

where $\widetilde{\mathbf{H}^x}^{(\ell)}_{t-1} = \mathbf{H}^x_{t-1-\Delta_{t-1}}, \mathbf{H}^x_{t-2-\Delta_{t-2}}, \ldots, \mathbf{H}^x_{t-\ell-\Delta_{t-\ell}}$.

The EMD-VL transfer entropy ratios are $T^{VL}(\mathbf{H}^x, \mathbf{H}^y) = T^{VL}_{\mathbf{H}^x\to\mathbf{H}^y}/T^{VL}_{\mathbf{H}^y\to\mathbf{H}^x}$, $T^{VL}(\mathbf{L}^x, \mathbf{L}^y) = T^{VL}_{\mathbf{L}^x\to\mathbf{L}^y}/T^{VL}_{\mathbf{L}^y\to\mathbf{L}^x}$ and $T^{VL}(\mathbf{R}^x, \mathbf{R}^y) = T^{VL}_{\mathbf{R}^x\to\mathbf{R}^y}/T^{VL}_{\mathbf{R}^y\to\mathbf{R}^x}$ respectively. If the ratio is greater than 1 then we state that the scale part of x transfer entropy causes the scale part of y.

Herein, we decompose all studied time series using the EMD method. The EMD method decomposes any time series in different IMFs and a long-term scale (residual part **R**). Second, from IMFs, we reconstruct the high frequency part (**H**) and the low frequency part (**L**) using fine to coarse method. The high frequency part or the short-term scale (**H**) reflect how the time series is touched by irregular events of short duration. The low frequency part or the medium-term scale (**L**) reflects how time series is touched by major shocks. Whereas, the long-term scale (**R**) is the fundamental trend. The principle of the fine to coarse method is as follows: from the first IMF, we add the next IMF and we test if this sum is statistically different from zero using Student t-test. From the IMF where there is a statistically significant difference from zero, we then consider that this sum of IMFs is the height frequency part (**H**) and the sum of the rest of IMFs represent the low frequency part (**L**). The flow of information between different scales are computed using Eqs. (9), (10) and (11). On the other hand, the causality relationships are tested via different ratio statistical tests $T^{VL}(\mathbf{H}^x, \mathbf{H}^y)$, $T^{VL}(\mathbf{L}^x, \mathbf{L}^y)$ and $T^{VL}(\mathbf{R}^x, \mathbf{R}^y)$ where the corresponding p-value is obtained by the bootstraping method proposed in Dimpfl and Peter (2013).

4. Data

The analyzed time series are the El Niño34 index (El Niño34), the S&P food and beverage select industry index (SPSIFBN), the MSCI agricultural & FC index (M2WO0AGF), the Nasdaq US Smart Food & Beverage Index (NQSSFB), and the Bloomberg world agricultural index (BWAGRI). All time series were collected in the period from March 04, 2015 until November 27, 2021 and downloaded from the Bloomberg Terminal. A detailed definition of our variables is provided in Table 1. We select the observations from the same days in the studied period, then we have a time series of 1659 observations. All studied time series are shown in Fig. 1 (black continued curves) and some of their descriptive statistics are given in Table 2.

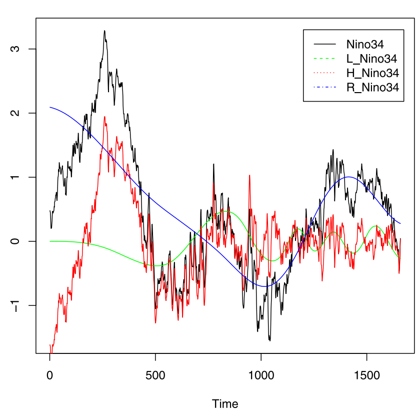
From Table 2, we see that El Niño34 time series have a negative minimum value and the lowest values of maximum, mean, and standard deviation (sd) compared to other time series. On the other hand, we remark that all agricultural studied time series are characterized by high values of mean and sd. In order to test the stationarity of time series and check the robustness of the stationarity results, two statistical tests are used which are the Augmented Dickey–Fuller (ADF) unit root test (Dickey and Fuller, 1979) and the Phillips–Perron (PP) test (Phillips and Perron, 1988). The PP test is resistant to general forms of heteroscedasticity in standard error terms which is an advantage over the ADF test. The Akaike Information Criterion (AIC) was used to select the lag length in the ADF test, while the Newey–West Bartlett kernel was used to select the bandwidth for the PP test. The results of ADF and PP tests demonstrate that none of the studied time series are stationary. Further, Jarque Bera (JB) (Jarque and Bera, 1980) and Shapiro–Wilk (SW) (Shapiro and Wilk, 1965) normality tests show that all time series are not normally distributed.

The studied time series are not distributed according to the normal distribution test, then we use the Spearman correlation coefficient to test correlation between them. The results of the Spearman correlation coefficient are given in Table 3 which indicates a negative correlation between the El Niño34 index and other time series (p-values are less than 0.05), but no correlation between the El Niño34 index and the BWAGRI index (p-value is greater than 0.05). On the other hand, the transfer entropy is used to measure the information transmission flow from El Niño34 to other time series. The results of transfer entropy are given in Table 3, where the smallest pairwise information transmissions are from El Niño34 to NQSSFB (0.0015), from El Niño34 to SPSIFBN (0.0022) and from El Niño34 and M2WO0AGF (0.0039). While the largest pairwise information transmission is from El Niño34 to BWAGRI (0.0054).

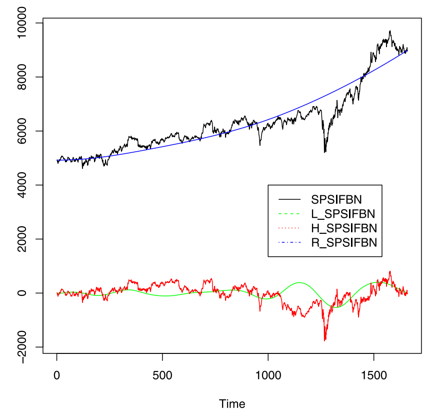
5. Results

5.1. VL transfer entropy results

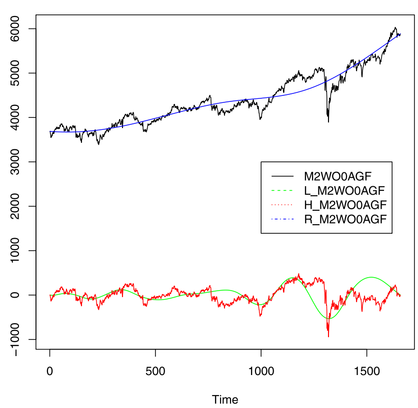
The results of the causality test using transfer entropy with fixed lag (Amornbunchornvej et al., 2021) and by the variable-lag transfer entropy are given in Table 4 and Table 5 respectively. For the computation of the transfer entropy, we use a maximum lag equal to 20% of length of the time series. In addition, to compute the p-value of the transfer entropy ratio test, we use the number of bootstrap samples equal to 300. According to Tables 4 and 5, all values of the transfer entropy ratio are less than 1 with corresponding p-value greater than 0.05. This finding indicates that there is no causality relationship from the El Niño34 index to each agricultural time series. Conversely, in the case of transfer entropy with fixed lag, for pairs (El Niño34, NQSSFB) the value of transfer entropy ratio is less than 1, but the corresponding p-value is greater than 0.05, which proves that there is no causality relationship from the El Niño34 index to the NQSSFB index.



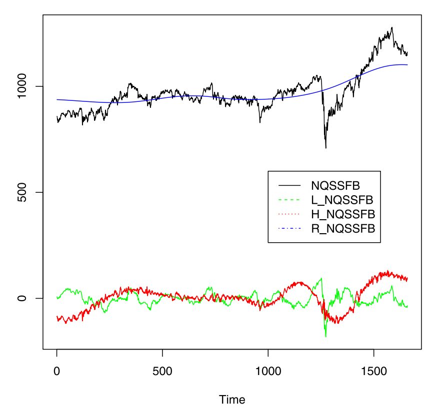
(a) El Niño34 index and their multiscale feature extraction.



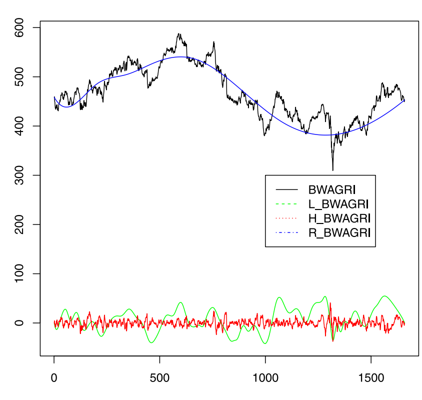
(b) SPSIFBN index and their multiscale feature extraction.



(c) M2WO0AGF index and their multiscale feature extraction.



(d) NQSSFB index and their multiscale feature extraction.



(e) BWAGRI index and their multiscale feature extraction.

Fig. 1. Original series and multiscale feature extraction.

5.2. EMD-VL transfer entropy results

The previous causality results that we found made us think that there may be causal relationships between different scales of studied time series, i.e there are causality relationships, but masked in different scales. In this regard, we decompose each time series using the EMD method where a selection criteria (SC) is equal to 0.2, then we reconstruct the high frequency part **H** and the low frequency part **L**

Table 2
Descriptive statistics of studied time series.

Time series	Min	Max	Mean	Sd	Stationarity tests		Normality tests	
					ADF test	PP test	JB test	SW test
El Niño34	−1.554	3.287	0.479	1.009	−2.012(11)***	−2.236(8)***	61.46***	0.975***
SPSIFBN	4609.792	9719.409	6316.137	1202.21	−1.898(11)***	−1.952(8)***	863.67***	0.872***
M2WO0AGF	3388.64	6033.5	4390.255	601.766	−2.833(11)***	−2.851(8)***	130.48***	0.942***
NQSSFB	707.85	1278.89	970.945	95.843	−2.444(11)***	−2.487(8)***	1740***	0.883***
BWAGRI	309.47	587.99	466.574	53.028	−2.386(11)***	−2.206(8)***	27.582***	0.983***

Note: The lag length and bandwidth for ADF and PP test is given between parenthesis.
***Denote the statistical significance at 1%.

Table 3
Correlation and transfer entropy.

Pair of time series	Spearman correlation coefficient		Transfer entropy
		p-value	
(El Niño34,SPSIFBN)	−0.268***	$<10^{-3}$	0.0022
(El Niño34,M2WO0AGF)	−0.301***	$<10^{-3}$	0.0039
(El Niño34,NQSSFB)	−0.141***	$<10^{-3}$	0.0015
(El Niño34,BWAGRI)	−0.014	0.542	0.0054

***Denote the statistical significance at 1%.

Table 4
Transfer entropy causality test.

	Transfer entropy test	
	Transfer entropy ratio	*p*-value
El Niño34 → SPSIFBN	0.171	1
El Niño34 → M2WO0AGF	0.193	1
El Niño34 → NQSSFB	1.335	0.64
El Niño34 → BWAGRI	0.537	1

Table 5
Variable-Lag transfer entropy causality test.

	Transfer entropy test	
	Transfer entropy ratio	*p*-value
El Niño34 → SPSIFBN	0.256	1
El Niño34 → M2WO0AGF	0.494	1
El Niño34 → NQSSFB	0.748	0.84
El Niño34 → BWAGRI	0.542	1

Table 6
Variance contributions for different time scales.

Time series	Variance as percentage of original time series			Variance as percentage of sum of IMFs and residual			Main scales
	H	**L**	**R**	**H**	**L**	**R**	
El Niño34	14.4	38.1	44.9	14.5	38.3	45.08	Short-term; medium-term; long-term
SPSIFBN	4.337	2.356	91.824	4.415	2.399	93.484	Short-term; long-term
M2WO0AGF	8.686	4.291	95.234	5.173	4.167	92.616	Short-term; long-term
NQSSFB	9.647	62.348	24.427	10.553	68.213	26.725	Short-term; medium-term; long-term
BWAGRI	10.094	12.064	72.321	10.623	12.695	76.106	Short-term; medium-term; long-term

(the trend part **R** is a residual part given by EMD method) using the fine to coarse method, and we apply the variable-lag transfer entropy method to different time scales.

In Table 6, for each time series, we show the different contribution of the various time scales to the original time series and to all their sums and we identify the main time scales. The results of the variable-lag transfer entropy in short-term scales, medium-term scales, and long-term scales are given in Table 7, Table 8, and Table 9 respectively.

According to Table 7, there is a causality relationship from the high frequency part of the El Niño34 index to the high frequency part of the M2WO0AGF index and the BWAGRI index where the transfer entropy ratio are 3.986 and 2.195 respectively with corresponding p-values less than 0.05. In addition, the largest pairwise information transmissions are from the high frequency part of the El Niño34 index to the high frequency part of the M2WO0AGF index (0.014) and from the high frequency part of the El Niño34 index to the high frequency part of the BWAGRI index (0.008). The smallest pairwise information transmissions are from the high frequency part of El Niño34 index to the high frequency part of the SPSIFBN index (0.004) and from high frequency part of the El Niño34 index to the high frequency part of NQSSFB index (0.0075).

According to Table 8, the largest pairwise information transmission is from the low-frequency part of the El Niño34 index to the low-frequency part of the NQSSFB index (0.0038). The pairwise information transmissions from the low-frequency part of the El Niño34 index to the low-frequency part of the SPSIFBN index and from the low-frequency part of the El Niño34 index to the low-frequency part of the BWAGRI index is 0.0007. The smallest pairwise information transmission is from the low-frequency part of the El Niño34 index to the low-frequency part of the M2WO0AGF index (0.0003). On the other hand, there is a causality relationship from the low-frequency part of the El Niño34 index to the low-frequency part of the NQSSFB index where the transfer

Table 7
Causality in the short term scale.

	Transfer entropy	VL transfer entropy test	
		Transfer entropy ratio	*p*-value
El Niño34 → SPSIFBN	0.004	2.183	0.680
El Niño34 → M2WO0AGF	0.014	3.986***	$<10^{-3}$
El Niño34 → NQSSFB	0.0075	1	0.666
El Niño34 → BWAGRI	0.008	2.195**	0.020

***Denote the statistical significance at 1%.
**Denote the statistical significance at 5%.

Table 8
Causality in the medium-term scale.

	Transfer entropy	VL transfer entropy test	
		Transfer entropy ratio	*p*-value
El Niño34 → SPSIFBN	0.0007	0.204	0.65
El Niño34 → M2WO0AGF	0.0003	0.741	0.900
El Niño34 → NQSSFB	0.0038	31.849***	$<10^{-3}$
El Niño34 → BWAGRI	0.0007	2.336	0.420

***Denote the statistical significance at 1%.

Table 9
Causality in the long-term scale.

	Transfer entropy	VL transfer entropy test	
		Transfer entropy ratio	*p*-value
El Niño34 → SPSIFBN	0.0053	19.225***	$<10^{-3}$
El Niño34 → M2WO0AGF	0.0037	4.809**	0.030
El Niño34 → NQSSFB	0.0002	1	1.235
El Niño34 → BWAGRI	0.0002	27.512***	$<10^{-3}$

***Denote the statistical significance at 1%.
**Denote the statistical significance at 5%.

entropy ratio is equal to 31.849 with a corresponding *p*-value less than 10^{-3}.

The results of the variable-lag transfer entropy on long-term scales given in Table 9 show that there is a causality relationship from the trend of the El Niño34 index to the trend of the SPSIFBN index, from the trend of the El Niño34 index to the trend of the M2WO0AGF index, and from the trend of the El Niño34 index to the trend of the BWAGRI index where values of transfer entropy ratio are greater than 1 and the p-values are less than 0.05. In addition, the largest pairwise information transmission is from the trend of the El Niño34 index to the trend of the SPSIFBN index (0.0053) and from the trend of the El Niño34 index to the trend of the M2WO0AGF index (0.0037). The smallest pairwise information transmission is from the trend of the El Niño34 index to the trend of the NQSSFB index and from the trend of the El Niño34 index to the trend of the BWAGRI index (0.0002).

6. Discussion of the major results and implications

6.1. Discussion

Our aim in this empirical work is to investigate the causal effect of the El Niño34 temperature index on agricultural and food indexes in the U.S. at both time and frequency domains. El Niño34 is considered as an appropriate indicator to revisit the causality inferences of climate anomalies on world economic interest (Brunner, 2002). In recent years, and owing to different crises: health pandemic, economic disaster, financial crisis, wars, and so forth, agricultural and food price changes have become a realm of concern by investors, hedgers, market operators, and regulators. Notably, one of the most important indicators that has affected food and agricultural price changes is climate change (Brunner, 2002; Massimo, 2017). In accordance with this research, we aimed to investigate the causality interplays between the climate change index: the temperature of the El Niño34 index and agricultural indexes. By combining the Variable-lag Transfer Entropy and EMD methods, and using daily data on El Niño34, S&P 500 food and beverage, MSCI agricultural & FC, packaged foods & food distributors, and world agricultural indexes, we found a time and frequency causal relationship structure between El Niño34 and others indexes. The VL transfer entropy showed that on the short-term horizon, El Niño34 significantly affected both MSCI agricultural & FC and Bloomberg world agricultural market indexes. Furthermore, at the mid-term horizon, causality is running from El Niño34 to packaged food & food distributors index, indicating that for moderate business cycles the majority of food and agricultural indexes do not receive risk information from climate change. On the other hand, at the long-term horizon El Niño34 had significantly and highly contributed to food & beverage select industry (19.225) and packaged food & food distributors (27.512) indexes. Compared to the short-term horizon, the unidirectional causal effect from El Niño34 to the Bloomberg world index is more intense as given by transfer entropy ratio 27.512. These above mentioned findings are not surprising as climate change had strongly affected and still affects food and agricultural prices at all frequency business cycles. Therefore, the causal flows running from climate change to food and agriculture at all frequency bands indicated that regulators should consider useful technical and political measures to mitigate higher risk transmission from climate change to food and agricultural markets.

6.2. Implications for theory

This study aims to respond to the question whether climate change anomalies significantly influence food and agricultural markets in the U.S. at both time and frequency domains. However, it makes several contributions to the climate change-food-agricultural nexus literature. First, this study extended the literature by using an innovative framework: the variable-lag transfer entropy that allows capturing non-linear causal dependence between markets as well as the direction and strength of information transfer from one market to another (Schreiber, 2000; Katerina et al., 2007). Second, we developed a novel technique: the EMD-VL transfer entropy by combining the variable-lag transfer entropy and the EMD method in order to investigate the nonlinear dependence between markets in the sense of Granger causality over time–frequency space. Furthermore, from theoretical and empirical prospects, to the best of our knowledge, no academic researcher has introduced this novelty. Third, as for the economic attitude, our study extended a state-of-the-art way for assessing the strength and direction of causal effects running from climate change to food and agricultural markets throughout various investment horizons. Fourth, information transfer from climate change to food and agricultural prices has received little attention, this study thus extended the literature by examining climate-food and climate-agricultural nexus at various time horizons.

6.3. Implications for practice

Can our proposed technique (EMD-VL transfer entropy) really work, and is it useful for investors, economic agents, and policymakers? i.e., can investors, portfolio managers, hedgers, and policy designers gain from the EMD-VL transfer entropy method?. We have stated that causal interplay from climate change to food and agricultural indexes varies over time and frequency. However, timely recognition and expectation of adverse scenarios in the financial system should be a summit priority for different kinds of investors as well as policymakers (Romn et al., 2018). For investors' perspective, our findings have afforded interesting implications for short-, medium-, and long-term economic agents. It is important for investors to encompass commitments in their term sheets to handle states of high and low frequency shocks when designing optimal investment and portfolio diversification strategies from food and agricultural markets. According to our EMD-VL transfer entropy method, short-term investors and portfolio managers should pay further attention to the causal flows of El Niño34 on MSCI agricultural & FC and Bloomberg world agricultural market indexes based on its high impact on these agricultural markets, while long-term investors and hedgers should be cautious for changes in El Niño34 and its significant effect on the food & beverage select industry, MSCI agricultural & FC, and Bloomberg world agricultural markets. Hitherto, no study has been reached in the literature regarding the causal relationship and transfer pathways between El Niño34, and food and agricultural market indexes using our innovative method EMD-VL transfer entropy, and taking into account that the El Niño34 temperature index is a well-known and forecastable event, our findings are also relevant for policymakers. However, regulators can use the current research to consider convenient actions due to significant effect of climate anomalies on food and agricultural markets.

7. Conclusion

This paper examined the historical effects of El Niño34 on U.S. food and agricultural stock prices. In particular, using daily data over the period from March 04, 2015 until November 27, 2021 and EMD-VL transfer entropy, we explore if the magnitude, sign, significance, and persistence of the reactions of U.S. food and agricultural stock prices to El Niño34 are substantially different from each other. The major results are summed up as follows. First, combined with the EMD method, the VL transfer entropy shows information transfer flow running from El Niño34 to agricultural and food market indexes at all scales. However, at short-term scales, El Niño34 significantly and highly transfer entropy causes agricultural indexes (MSCI Agri & FC Index and Bloomberg World Agriculture Index). The information transfer entropy is lesser from El Niño34 to both S&P food & beverage (0.004), and Nasdaq US smart food & beverage (0.0075). Second, El Niño34 yields high transfer entropy flow to Nasdaq US smart food & beverage and weak transfer entropy information to MSCI agri & FC index. Third, at long-term scales, the greatest transfer entropy information flow from El Niño34 appears with S&P food & beverage and MSCI agri & FC indexes, while the lowest one assumes to be with Nasdaq US smart food & beverage and Bloomberg agricultural indexes.

Our findings have a wide range of policy implications, and our model can be applied in various ways. First, the model may be used as an input for the creation of public policies to alleviate the consequences of weather changes. For example, given the recent advances in climate modeling (Davinson et al., 2020), our model enables to assess the causal relationship between the times series variables as well as to understand the predictability propagation mechanism of weather shocks. Second, in terms of macroeconomic policy, the government should implement programs that encourage farmers to invest in irrigation systems as well as in the development of more efficient food value chains. Third, on the monetary policy side, Davinson et al. (2020) stated that in the event of rising consumer inflation, the identification of weather shocks helps central banks to avoid overreacting by tightening the monetary stance, even in the event of possible second-round consequences, thus our model may serve as a tool to assist anchor inflation expectations by describing the effect of El Niño34 on agriculture and food prices. Fourth, given the recent rise in surface temperatures, the increased frequency of severe climatic extremes, melting glaciers and arctic sea ice, raising sea levels, and declining snowpacks globally, strong Niño34 occurrences will significantly impact local and regional locations by severe wave. Therefore, our study may be utilized to forecast possible production levels, allowing agricultural managers at the local and regional levels to better prepare for the upcoming season. In fact, the relationship between Niño34 and food and agriculture stock prices may be considered as an important channel through which climatic shocks might influence the well-being of citizens, specifically in countries with a lower income. As a result, the findings of this research contribute to the body of knowledge about the worldwide economic impact of climatic anomalies, which will aid in the debate of this topic. This work contributes to a better knowledge of the economic impact of the El the Niño34, which may be a significant tool in minimizing the unfavorable consequences of climatic anomalies, especially in developing countries.

El Niño34 anomalies will become more common as a result of climate change, and agricultural production will be affected as well. Climate change, food security, and commodity financing are all important topics that will become more important in the near future, making it imperative that experts from several disciplines work together to examine the issue thoroughly. To this goal, future research, will first make use of a variety of methodological techniques, including quantile connectedness proposed by Ando et al. (2022), or examination of different markets, or El Niño34 indexes. Additional research could continue to explore the variable-lag transfer entropy causality method by comparing it with asymmetric causality tests proposed by Hatemi-J (2012, 2014) and Lee et al. (2021). The empirical mode decomposition can be combined with these causality tests to examine the causality between different scales. Moreover, it would be interesting as part of future research to extend our analysis to the asymmetric effects of the El Niño34 cycle on agricultural and food stock prices, based on the asymmetric causality test, which allows for consideration of the positive and negative shocks.

CRediT authorship contribution statement

Zouhaier Dhifaoui: Conceptualization, Methodology, Formal analysis, Writing – original draft, Reviewing, Software. **Rabeh Khalfaoui:** Conceptualization, Data curation, Formal analysis, Writing and reviewing. **Sami Ben Jabeur:** Conceptualization, Methodology, Formal analysis, Writing and reviewing. **Mohammad Zoynul Abedin:** Conceptualization, Formal analysis, Writing and editing.

Declaration of competing interest

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

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jenvman.2022.116789. Data Deposite and Software Source Code are available in supplementary materials.

References

Adams, R.M., Chi-Chung, C., McCarl, B.A., Rodney, F.W., 1999. The economic consequences of ENSO events for agriculture. Clim. Res. 13 (03), 165–172.

Amornbunchornvej, C., Zheleva, E., Berger-Wolf, T., 2020. Variable-lag Granger causality and transfer entropy for time series analysis. CoRR abs/2002.00208.

Amornbunchornvej, C., Zheleva, E., Berger-Wolf, T., 2021. Variable-lag Granger causality and transfer entropy for time series analysis. ACM Trans. Knowl. Discov. Data (TKDD) 15, 1–30.

Ando, T., Greenwood-Nimmo, M., Shin, Y., 2022. Quantile connectedness: Modeling tail behavior in the topology of financial networks. Manage. Sci. 68 (4), 2401–2431.

Arora, N.K., 2019. Impact of climate change on agriculture production and its sustainable solutions. Environ. Sustain. 02, 95–96.

Backlund, P., Buja, L., Walsh, M., Degaetano, A., Takle, E., Todey, D., Melnick, R., Prokopy, L., Ziska, L., 2020. USDA climate change indicators for agriculture: A new framework for understanding climate risks and impacts to U.S. agriculture. In: AGU Fall Meeting Abstracts, Vol. 2020. pp. SY044–03.

Bandaraa, J.S., Cai, Y., 2014. The impact of climate change on food crop productivity, food prices and food security in South Asia. Econ. Anal. Policy 44 (04), 451–465.

Barnett, L., Barrett, A.B., Seth, A.K., 2009. Granger causality and transfer entropy are equivalent for Gaussian variables. Phys. Rev. Lett. 103, 238701.

Barrett, C.B., 1998. The value of imperfect ENSO forecast information: Discussion. Am. J. Agric. Econ. 80 (5), 1109–1112.

Bebonchu, A., Michael, M., Baomei, M., Emily, M., 2020. The impact of El Nio-Southern oscillation on U.S. food and agricultural stock returns. Water Resourc. Econ. 32, 100157.

Bebonchu, A., Naafey, S., 2021. Exploring asymmetries in the effects of El Niño-Southern oscillation on U.S. food and agricultural stock prices. Q. Rev. Econ. Finance 81, 1–14.

Behrendt, S., Dimpfl, T., Peter, F.J., Zimmermann, D.J., 2019. RTransferEntropy quantifying information flow between different time series using effective transfer entropy. SoftwareX 10, 100265.

Berkman, H., Jacobsen, B., Lee, J.B., 2011. Time-varying rare disaster risk and stock returns. J. Financ. Econ. 101 (2), 313–332.

Berry, B.J., Okulicz-Kozaryn, A., 2008. Are there ENSO signals in the macroeconomy? Ecol. Econom. 64 (3), 625–633.

Brunner, A.D., 2002. El Niño and world primary commodity prices: Warm water or hot air? Rev. Econ. Stat. 84, 01.

Chang, H.O., Jennifer, O., 2022. Multinational enterprises and natural disasters: Challenges and opportunities for IB research. J. Int. Bus. Stud. 1–24.

Chang, L., Xiaolei, S., Jun, W., Jianping, L., Jianming, C., 2021. Multiscale information transmission between commodity markets: An EMD-based transfer entropy network. Res. Int. Bus. Finance 55 (10131), 8.

Chen, C.-C., McCarl, B., Hill, H., 2002. Agricultural value of ENSO information under alternative phase definition. Clim. Change 54, 305–325.

Chen, J., Yao, J., Zhang, Q., Zhu, X., 2022. Global disaster risk matters. Manage. Sci..

David, U., 2012. El Niño, La Niña, and world coffee price dynamics. Agric. Econ. 43 (1), 17–26.

David, U., 2014. El Niño southern oscillation and the fishmealsoya bean meal price ratio: Regime-dependent dynamics revisited. Eur. Rev. Agric. Econ. 41 (4), 583–604.

David, U., 2017. The ENSO effect and asymmetries in wheat price dynamics. World Dev. 96, 490–502.

David, U., 2018. The role of El Nino Southern Oscillation in commodity price movement and predictability. Am. J. Agric. Econ. 100 (1), 239–263.

Davinson, S.A.-S., Luis, F.M.-V., Daniel, P.-A., 2020. Nonlinear relationship between the weather phenomenon El Nino and Colombian food prices. Aust. J. Agric. Resource Econ. 64 (4), 1059–1086.

Dickey, D.A., Fuller, W.A., 1979. Distribution of the estimators for autoregressive time series with a unit root. J. Amer. Statist. Assoc. 74 (366a), 427–431.

Dimpfl, T., Peter, F.J., 2013. Using transfer entropy to measure information flows between financial markets. Stud. Nonlinear Dyn. Econom. 17 (1), 85–102.

Dunn, R.J., Stanitski, D., Gobron, N., Willett, K., Ades, M., Adler, R., 2020. Global Climate. Technical Report 8, Bulletin of the American Meteorological Society.

Edinburgh, T., Eglen, S.J., Ercole, A., 2021. Causality indexes for bivariate time series data: A comparative review of performance. Chaos 31, 083111.

Generoso, R., Ccile, C., Olivier, D., Kamiar, M., 2020. The growth effects of El Nio and La Nia: Local weather conditions matter. Ann. Econ. Stat. (140), 83–126.

Hatemi-J, A., 2012. Asymmetric causality tests with an application. Empir. Econ. 43, 447–456.

Hatemi-J, A., 2014. Asymmetric generalized impulse responses with an application in finance. Econ. Model. 36, 18–22.

Huang, H.H., Kerstein, J., Wang, C., 2018. The impact of climate risk on firm performance and financing choices: An international comparison. J. Int. Bus. Stud. 49 (5), 633–656.

Jacobs, C., Berglund, M., Kurnik, B., Dworak, T., Marras, S., Mereu, V., Michetti, M., 2019. Climate Change Adaptation in the Agriculture Sector in Europe. European Environment Agency.

Jarque, C.M., Bera, A.K., 1980. Efficient tests for normality, homoscedasticity and serial independence of regression residuals. Econom. Lett. 06 (03), 255–259.

Jonas, J., Christoph, M., Ruane, A.C., Joshua, E., Juraj, B., Oscar, C., Babacar, F., Ian, F., Christian, F., Franke, J.A., Kathrin, F., Guarin, J.R., Jens, H., Gerrit, H., Toshichika, I., Jain, A.K., David, K., Nikolay, K., Stefan, L., Lin, T.S., Wenfeng, L., Oleksandr, M., Sara, M., Moyer, E.J., Masashi, O., Meridel, P., Cheryl, P., Rabin, S.S., Clemens, S., Schneider, J.M., Schyns, J.F., Rastislav, S., Andrew, S., Tommaso, S., Haynes, S., Heidi, W., Florian, Z., Cynthia, R., 2021. Climate impacts on global agriculture emerge earlier in new generation of climate and crop models. Nature Food 02 (11), 873–885.

Katerina, H.-S., Milan, P., Martin, V., Joydeep, B., 2007. Causality detection based on information-theoretic approaches in time series analysis. Phys. Rep. 441 (1), 1–46.

Keleş, B., Gómez-Acevedo, P., Shaikh, N.I., 2018. The impact of systematic changes in weather on the supply and demand of beverages. Int. J. Prod. Econ. 195, 186–197.

Lee, D.J., Kim, T.-H., Mizen, P., 2021. Impulse response analysis in conditional quantile models with an application to monetary policy. J. Econom. Dynam. Control 127, 104102.

Massimo, P., 2017. Climate variability and the volatility of global maize and soybean prices. Food Secur. 9 (4), 673–683.

Milan, P., Vladimir, K., Zbynek, H., Katalin, S., 2001. Synchronization as adjustment of information rates: Detection from bivariate time series. Phys. Rev. E 63, 046211.

NCEI, N., 2021. State of the Climate: Monthly Global Climate Report for Annual 2020. Technical Report.

Nelson, G., Rosegrant, M., Koo, J., Robertson, R., Sulser, T., Zhu, T., Ringler, C., Msangi, S., Palazzo, A., Batka, M., Magalhaes, M., Valmonte-Santos, R., Ewing, M., Lee, D., 2009. Climate Change: Impact on Agriculture and Costs of Adaptation. Food Policy Reports 21, International Food Policy Research Institute (IFPRI).

Phillips, P.C., Perron, P., 1988. Testing for a unit root in time series regression. Biometrika 75 (02), 335–346.

Podesta, G., Letson, D., Messina, C., Royce, F., Ferreyra, R., Jones, J., Hansen, J., Llovet, I., Grondona, M., OBrien, J., 2002. Use of ENSO-related climate information in agricultural decision making in Argentina: A pilot experience. Agric. Syst. 74 (3), 371–392.

Romn, F., Rania, J., Vicente, J.B., Rafael, B., 2018. Interactions between financial stress and economic activity for the U.S.: A time and frequency-varying analysis using wavelets. Physica A 492, 446–462.

Sally, K., John, R., James, T., 1992. An empirical study of the economic effects of climate change on world agriculture. Clim. Change 21 (01), 17–35.

Schreiber, T., 2000. Measuring information transfer. Phys. Rev. Lett. 85, 461–464.

Shannon, C.E., 1948. A mathematical theory of communication. Bell Syst. Tech. J. 27 (3), 379–423.

Shapiro, S.S., Wilk, M.B., 1965. An analysis of variance test for normality (complete samples). Biometrika 52 (3–4), 591–611.

Sivakumar, M.V., Das, H., Brunini, O., 2005. Impacts of present and future climate variability and change on agriculture and forestry in the arid and semi-arid tropics. Clim. Change 70 (1–2), 31–72.

Tack, J.B., Ubilava, D., 2013. The effect of the El Nino southern oscillation on U.S. corn production and downside risk. Clim. Change 121 (04), 689–700.

Tian, C., Sihang, J., Xiaohui, Y., Mohamed, E., Fuji, R., Mingyan, F., Zhangang, C., 2018. Emotion recognition using empirical mode decomposition and approximation entropy. Comput. Electr. Eng. 72, 383–392.

Tsai, J., Wachter, J.A., 2015. Disaster risk and its implications for asset pricing. Annu. Rev. Finan. Econ. 7, 219–252.

Wu, Z., Huang, N.E., 2009. Ensemble empirical mode decomposition: A noise-assisted data analysis method. Adv. Adapt. Data Anal. 01 (01), 1–41.

Xuegeng, M., Pengjian, S., 2017. Transfer entropy between multivariate time series. Commun. Nonlinear Sci. Numer. Simul. 47, 338–347.

Yaguo, L., Jing, L., Zhengjia, H., Ming J., Z., 2013. A review on empirical mode decomposition in fault diagnosis of rotating machinery. Mech. Syst. Signal Process. 35 (01), 108–126.