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Aiswarya S, Muthumeenakshi Muralikrishna*

Vellore Institute of Technology
India
**Corresponding author*

TIME-FREQUENCY ANALYSIS OF GEOPOLITICAL RISK AND FOOD COMMODITY MARKET: A WAVELET BASED INVESTIGATION

Purpose. *The most recent conflicts have demonstrated that geopolitical risk has evolved into a significant issue that has an impact on the global food markets. Through the use of bi-wavelet coherence analysis, the study aimed to establish the ways in which geopolitical risk and climate policy uncertainties influences the food commodity market using Geopolitical Risk Index (GPR index), Climate Policy Uncertainty Index (CPU index) and the five components that make up the FAO Food Price Index (FPI).*

Methodology / approach. *The study used monthly data spanning from January 1990 to March 2024. Geopolitical risk was measured using the GPR index developed through textual analysis of news articles. CPU index, developed using similar textual analysis, is used to represent the uncertainties related to climate change risk. The FAO's FPI constituents were used to represent global food commodity market. The research applied advanced econometric methods including Johansen cointegration tests, Toda-Yamamoto causality analysis, Brock-Dechert-Scheinkman (BDS) nonlinearity tests, and bi-wavelet coherence analysis. Wavelet coherence analysis was particularly focused due to its capability to capture dynamic, time-frequency relationships among non-stationary data series.*

Results. *The study found two significant long-run cointegrating relationships among GPR, CPU and FPI constituents. Causality tests indicated that geopolitical risk significantly influenced climate policy uncertainty but not vice versa. Wavelet analysis revealed that GPR and vegetable oil has more strong co-movement, and it is also the same in the case of CPU. CPU has a leading influence on GPR, which means that policy uncertainties lead to increased geopolitical tensions. Uncertainties in climate policies have an effect on food commodity market in the short run. Whereas, GPR affects cereals during geopolitical tension periods. In the case of dairy products, time varying co-movements in the short run could be witnessed whereas in the long run medium co-movement could be seen. Volatilities occur in the prices of vegetable oils during periods of crisis which can exacerbate prices of other food commodities, which can lead to food security issues.*

Originality / scientific novelty. *The originality of the study lies in the fact that the main focus is on GPR, CPU and five constituents of FAO's FPI. Moreover, the study uniquely incorporates CPU index as a proxy to climate change risk and its impact on food commodity market. Most of the studies focus on the spillover effect of geopolitical risk on different classes of asset. Significant number of literatures focus on the spillover effect on oil market, stock market and commodities market. However, there are only limited studies that focus on food commodity market. In addition, analysing these factors provides a deeper understanding of how they affect food security and market dynamics. This innovative approach offers valuable insights to policymakers, investors and stakeholders of food commodity market.*

Practical value / implications. *Creating a more economically sustainable environment is the goal of every country, which requires joint efforts by various sectors of the financial market, government officials and economic regulators. These findings are of great importance to* *policymakers and stakeholders in global food systems, highlighting the need to create adapted policy frameworks, focus on the vulnerability of individual commodities, and carefully implement climate policies to mitigate potential negative impacts on food security.*

Key words: *geopolitical risk, food security, climate policy uncertainty, bi-wavelet analysis, Food Price Index.*

1. INTRODUCTION

Geopolitical tensions become serious issues that need to be addressed as they affect international peace, security, cause disruption in the demand and supply of commodities and ultimately it can hamper the economic growth of nations. On the eve of the Russian-Ukrainian war and the ongoing conflict between Israel and Palestine, geopolitical issues and related risks have attracted the attention of politicians, government agencies and researchers seeking to intervene in a timely manner and develop appropriate policies. Caldara & Iacoviello (2018) identified geopolitical risk, measured it, and developed an index using the frequency of news publications in 10 leading newspapers in the United States, Great Britain, and Canada. In their opinion, geopolitical risk is a threat, the realisation and escalation of adverse events related to wars, terrorism and any tensions between states and political actors that affect the peaceful course of international relations.

There are extensive number of studies that focus on the impact of geopolitical risk on various sectors of financial market and macroeconomic variables. Based on the research works, it is evident that geopolitical risk impacts oil market (Antonakakis et al., 2017; Liu et al., 2019; Bouoiyour et al., 2019; Mei et al., 2020; Plakandaras et al., 2019), stock market (Sharif et al., 2020; Balcilar et al., 2018; Kannadhasan & Das, 2020), and commodity market (Baur & Smales, 2020; Wang et al., 2022; Gong & Xu, 2022). In addition, it is worth noting another important point – this is a study of the impact of geopolitical risks on green bonds. Sheenan et al. (2023) note in their study that green bonds are more susceptible to geopolitical issues than conventional bonds. Granger causality can be evidenced at the lower quantiles from Geopolitical Risk Index to the Green Bond Index.

Food prices are increasingly affected by geopolitical trade disputes, unstable weather conditions, and negative events related to terrorism and wars. According to IMF’s (Special Feature..., 2022), supply chain disruptions, trade restrictions on border, export restrictions on large food exporters are significant sources of upside risk for food prices. Chatzopoulos et al. (2020) specified that the extreme agroclimatic changes which can bring supply disruptions in the agricultural commodity markets. Ultimately this can lead to food security issues which is a hindrance to the achievement of UN’s Sustainable Development Goal (SDG) 2 “Zero Hunger”.

The rise in geopolitical risks hinders global cooperation between countries in combating climate change and leads to an increase in climate change-related risks (Jin et al., 2023). There is an asymmetrical and uneven impact of geopolitical risk on reserves related to climate change (Demiralay et al., 2024). Le et al. (2023) explains that the climate policy uncertainty (transition risk) tends to have more effect on the connectedness among water, energy and agricultural market than physical risk.

Research shows that geopolitical tensions can disrupt international cooperation, which is essential for managing the risks associated with climate change. In addition, it causes volatility in the prices of commodities. On the eve of escalating geopolitical problems, it is necessary to analyse the impact of geopolitical risks on the commodities market in connection with the increasing financialisation of commodities. Essential food commodities are receiving much attention among the researchers in the context of ongoing conflicts and inflated food prices.

Geopolitical incidents and climate policy uncertainties are important drivers influencing world food markets. Recent wars and climate policy shifts have shown the potential for high price volatility. Although the issue of energy commodities and the role of the Geopolitical Risk Index (GPR) in energy transformation, as well as sustainable access to clean energy sources, have been discussed previously, the implications for agricultural commodities, particularly food commodities, also need to be addressed (S & Muralikrishna, 2024).

This paper aims to identify and assess the relationship among Geopolitical Risk Index, Climate Policy Uncertainty Index (CPU) and food prices. Five constituents of Food Price Index (FPI) of Food and Agriculture Organization of the United Nations (FAO) have been considered. FPI represents the basket of five major food commodities traded on a global level. The global Food Price Index eliminates the influence of interest rate changes, which could affect the food prices (Sun & Su, 2024). The reasons that distinguish this work from others are as follows:

(i) to begin with, existing studies focus on the volatility of stock prices, individual commodity prices, especially energy commodities. Research works on food commodities have only recently begun;

(ii) there is significant number of studies highlighting the contribution of geopolitical risk on the climate change issues. However, works using climate policy uncertainty as the proxy for climate change risk is limited;

(iii) studies that take into account geopolitical risks, climate policy uncertainty and the five components of the food price index are rare. It is significant to understand the relationship among these variables to have insights about how geopolitical tensions affect the climate change issues and food security. Therefore, to know about the relationship among these variables, wavelet analysis was conducted. This study focuses on identifying the co-movement between GPR and food commodities and the co movement between CPU and food commodities are also studied using wavelet analysis.

The ability of wavelet coherence analysis to overcome the limitations of traditional econometric approaches in capturing dynamic, scale-dependent correlations in non-stationary data prompted the use of this method. Presenting a time-frequency viewpoint helps to better understanding the changing linkages among food commodity market, climate policy uncertainties, and geopolitical hazards.

This work is structured as follows: section 2 is devoted to a review of the available literature, and section 3 – to the methodology used. Section 4 deals with results for the analysis and discussion is presented in section 5. Conclusions drawn from the study are outlined in section 6 and the details of limitations and future scope are included in section 7.

2. LITERATURE REVIEW

Geopolitical risk could have notable negative consequences on the economy and doubled after the September 11 attacks (Carney, 2016). It affects both the developed and developing countries in a negative manner (Solarin et al., 2021). GPR has long term spillover effect and Russia is the main transmitter of risk to other BRICS nations (Vo & Dang, 2023). High geopolitical risk may force consumers to limit their consumption and companies to postpone investments (Caldara & Iacoviello, 2018). Most number of studies address the time varying connectedness among GPR, oil returns and gold returns. BRICS geopolitical risk, oil and gold markets have a time-varying relationship and when geopolitical events occur, gold and oil have a hedging function (Li et al., 2021). Accommodating Geopolitical Risk Index improves predicting oil futures volatility (Asai et al., 2020). The authorities should take measures to mitigate the impact of geopolitical risks, as they could lead to a decline in oil demand and a slowdown in overall economic activity (Cunado et al., 2019).

Pindyck & Rotemberg (1990) were the first to investigate correlation among the price changes of seven commodities, which are unrelated to each other and stated that there is a co-movement in the prices of commodities. The price changes happen due to the changes in the macroeconomic variables. The rise in geopolitical risk increases the volatility in the prices of energy commodities like crude oil, heating oil and natural gas (Liu et al., 2021). Because commodities have become more financial in nature, as they have the ability to hedge against risky situations in the financial market, research has begun to focus on the commodities market. During key periods of financial instability, such as the global financial crisis, the European debt crisis, and market crashes caused by COVID-19, commodity yields and prices are impacted (Armah et al., 2022).

Out of the sub-indices of the GPR index (GPR Act index and GPR Threat index), GPR Act index reveals the connectedness of commodities market (Gong & Xu, 2022). Results of their study indicated that the energy, industrial metal and precious metal commodity markets are the information transmitters and agriculture and livestock commodity markets are information receivers. Grains are more susceptible to geopolitical risk than soft commodities. Arab Spring and Russia-Ukraine war are the main events that moved agricultural market during the period 2000–2022 (Micallef et al., 2023). COVID-19 pandemic event has surged the food prices and FAO's Food Price Index reached its highest level (Frimpong et al., 2021). Geopolitical issues among countries influence the commodity price dynamics (Foglia et al., 2023). There is a heterogeneity in the price between energy and agricultural commodities during financial crisis period (Han et al., 2015). World uncertainty, global pandemics and geopolitical risk has one directional effect on world food, energy and stock markets (Chowdhury et al., 2021).

Adverse weather conditions can lead to falling prices for agricultural products, ultimately leading to rising food prices (Matošková, 2011). Climate change induced productivity issues cause reduced food production and food price increase in the five major South Asian countries like Bangladesh, India, Nepal, Pakistan and Sri Lanka (Bandara & Cai, 2014). According to a study conducted in Uganda, increase in temperature causes variability in food prices than rainfall shocks. Policies concentrating on mitigating weather changes can bring food price variability down (Mawejje, 2016). Climate induced natural disasters cause low agricultural production and surge in food prices (Cevik, 2023).

It is clear from existing literature that geopolitical issues can hinder economic flows within a country, leading to disruptions in the supply and demand for food commodities. Climate change issue is another factor which accounts for food price spikes results in food security issues.

It is evident from the literature that food market needs to be analysed in the context of flaring geopolitical tensions and climate change risk. Climate change issues are measured by assessing physical risks such as rising temperatures, extreme precipitation, and the number of deaths during natural disasters. Studies considering climate policy uncertainty as the proxy for measuring climate changes are very rare to find. In this paper, GPR index, CPU index and the FAO's specific commodity indices, e.g. FAO Meat Price Index, Dairy Price Index, Cereal Price Index, Vegetable Oil Price Index and Sugar Price Index were used to decipher the impact of GPR and CPU on food prices.

3. METHODOLOGY

This study's conceptual framework is based on the hypothesised connections between geopolitical risk (GPR), climate policy uncertainty (CPU), and global agricultural commodity prices. Geopolitical risk, characterised by threats and disruptions stemming from international conflicts, terrorism, and political tensions, can profoundly affect global commodities markets via supply chain disruptions and trade volatility (Caldara & Iacoviello, 2018; Gong & Xu, 2022). Simultaneously, uncertainty about climate policy – specifically, ambiguity about governmental climate mitigation strategies – can affect commodity prices by modifying market expectations and production expenses (Gavriilidis, 2021; Sarker et al., 2022).

Recent work indicates that geopolitical conflicts may hinder international collaboration on climate measures, hence exacerbating uncertainty in agriculture markets (Jin et al., 2023). This paper proposes a system in which GPR and CPU serve as external determinants affecting global agricultural commodity prices. The study used Johansen cointegration and Toda-Yamamoto causality tests to examine empirically these linkages, identifying long-term equilibrium and directional causalities among the variables. Wavelet coherence analysis was used to identify dynamic, nonlinear interactions over several time scales, overcoming the constraints of conventional econometric techniques in examining non-stationary data with structural discontinuities (Grinsted et al., 2004; Vacha et al., 2013).

3.1. Data. The study has resorted monthly data of GPR index, CPU index and FPI of FAO for a period of 34 years starting from 1st January, 1990 to 1st March,2024. The GPR index and CPU index data are freely available in the policy uncertainty website, while the FPI data can be downloaded from the FAO's database which is made freely accessible.

As we noted, the study has resorted monthly GPR data available to measure the impact of geopolitical events. The GPR index construction involves definition, measurement and validation. Caldara & Iacoviello (2018) constructed this index using an algorithm that counts the number articles related to geopolitical events published in the 10 leading newspapers of the US, the UK and Canada.

To capture the climate change issues, Climate Policy Uncertainty developed by Gavriilidis (2021) is used. Similar to the construction of GPR index, Climate Policy Uncertainty Index is also developed using textual analysis method from the eight major newspapers like the Boston Globe, Chicago Tribune, Los Angeles Times, Miami Herald, the New York Times, Tampa Bay Times, USA Today and the Wall Street Journal. CPU index could be used in examining the role of climate policy uncertainty in climate sensitive industries.

FAO has developed an index to measure the prices of globally traded commodities. This index is a weighted average of 5 commodity groups, whose weights are determined by shares of exports over 2014–2016. The constituents of the Food Price Index include meat, dairy, cereals, oils and sugar (Sun & Su, 2024). In this paper we consider the monthly real prices of these individual commodities indices to understand the long-term co-movement between GPR as well as CPU. Table 1 outlines the details of the specifications of the variables and details of the data sources.

Table 1

Data specification and sources

Variables	Proxy	Data sources
Geopolitical risk	GPR index	www.policyuncertainty.com
Climate change	Climate policy uncertainty	www.policyuncertainty.com
Food prices	Real prices of Food Price Index Constituents: Meat Dairy Cereals Oils Sugar	Food and Agriculture Organization (FAO) fao.org

Source: compiled by the authors.

3.2. Cointegration test. This section highlights the econometric model used to study the relationship between GPR and constituents of FPI as well as CPU and FPI and constituents. We have used Johansen cointegration approach and the causality testing procedure (Toda & Yamamoto, 1995).

Cointegration is described as the long-term or equilibrium relationship between two series. Cointegration serves as an optimal analytical method to determine the presence of a long-term relationship among GPR, CPU and FPI constituents. This study uses the cointegration method developed by Johansen (1995). The Vector

Autoregression (VAR) cointegration test methodology established by Johansen is delineated as follows. The process is based on a VAR of order *p*:

$$yt \ = \ A1\,yt - 1 + \ldots + Ap\,yt - p \ + \ Bzt \ + \ \varepsilon t \ , \tag{1}$$

where *yt* represents a vector of non-stationary I (1) variables (GPR, CPU, meat, dairy, cereals, oils and sugar), *zt* denotes a vector of deterministic variables, and *εt* signifies a vector of innovations. The VAR may consequently be redefined as:

$$\Delta yt = \ \pi y_{t-1} + \ \sum_{i=1}^{p-1} + \Gamma_i \,\Delta y_{t-p} + \mathrm{B} z_t + \varepsilon_t, \tag{2}$$

$$\text{where } \pi = \sum_{i=1}^{p} A_i - I,$$

$$\text{and } \Gamma_i = \sum_{j=i+1}^{p} A_j.$$

Estimates of *Γi* contain information on the short-run adjustments, while estimates of *Π* contain information on the long-run adjustments, in changes in *yt*. The number of linearly dependent cointegrating vectors that exist in the system is referred to as the cointegrating rank of the system. This cointegrating rank may range from 1 to *n*-1 (Greene, 2000).

3.3. Causality analysis. Since testing techniques are prone to integration, Toda and Yamamoto (1995) propose an interesting but simple method that requires the estimation of an extended VAR, which guarantees the asymptotic distribution of the Wald statistic (asymptotic chi-square distribution) that includes the cointegration characteristics of the process.

3.4. Brock, Dechert and Scheinkman test. To address the issue of nonlinearity, the BDS test introduced by Broock et al. (1996) was used for the residual series produced by the Vector Error Correction Model (ECM). This test evaluates the assumption of identically and independently distributed (i.i.d.) error terms. If the i.i.d. assumption is failed, it can be concluded that a nonlinear relationship exists between the variables.

3.5. Wavelet analysis. This allows analysing the relationship between two signals (Cazelles et al., 2008). Wavelet coherence plots help in analysing the co-movements between two markets in a time-frequency domain (Harikumar & Muralikrishna, 2024). The wavelet coherence can be measured using the following formula:

$$WCOI(a,b) = \frac{|R(a,b)|2}{S\_x(a) \cdot S\_y(b)}, \tag{3}$$

where $WCOI(a, b)$ represents wavelet coherence at scale *a* and *b*;

|(a, b)|^2 is the squared magnitude of the cross correlation between two signals;

$S\_x(a)S\_y(b)$ product of the signals *x* and *y* at scale *a* and *b*.

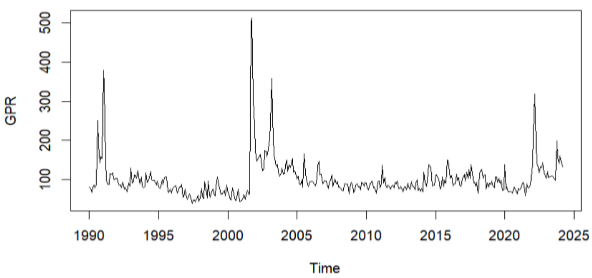
Real-world data are frequently non-stationary, which may result in estimations that are not entirely accurate. Moreover, if any structural break occurs within the time series, the outcomes derived using a conventional time domain method with fixed parameters may be erroneous. Under these specific circumstances, we necessitated an approach that facilitated the localisation of such disruptions in empirical probing. Conversely, the principal issue with a standalone frequency domain technique, notably the Fourier transform, is that it entirely disregards information from the time domain by concentrating exclusively on the frequency domain. The unit root of the time series is quite significant. Wavelet analysis is innovative in that it enables the decomposition of unidimensional temporal data into a bidimensional time-frequency domain (Pal & Mitra, 2017).

As wavelet coherence provides special benefits in studying time-frequency connections in non-stationary data, this work uses bi-wavelet coherence analysis instead of conventional techniques such as Vector Autoregression or Structural Vector Autoregression (SVAR). Wavelet coherence enables the simultaneous investigation of time and frequency components unlike VAR and SVAR, which operate only in the time domain. As is the case with geopolitical risk (GPR), climate policy uncertainty (CPU), and food commodity indices, this capacity is especially helpful when examining correlations that change over time and over many frequencies. Effective capturing of such dynamic, scale-dependent interactions is not possible with conventional techniques (Vacha et al., 2013).

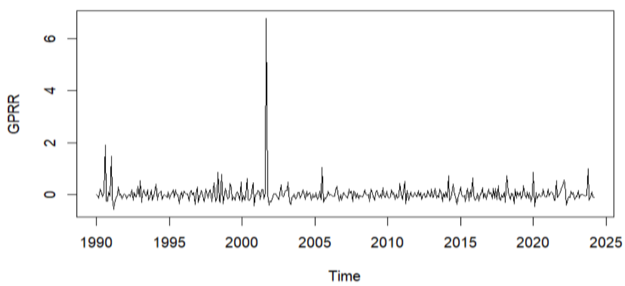
4. RESULTS

Figure 1 shows the graphical representation of trend of the time series plot of two indices and five agricultural commodity indices. A quick inspection of the plots reveals that the indices increased gradually up until the year 2000. And shortly after that, it continues to demonstrate an upward trend, which began in 2008. That could be marked as a period of beginning of financial crisis. The GPR index has a rising trend when major geopolitical events take place. The CPU index is one indicator that is clearly trending upward over time. All five commodities show similar price dynamics after 2005. The reasons for the change in commodity prices may include increased financialisation of commodities, climate change and policies related to biofuel production.

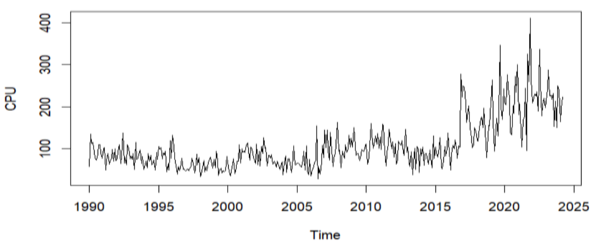
Raw series *Return series*



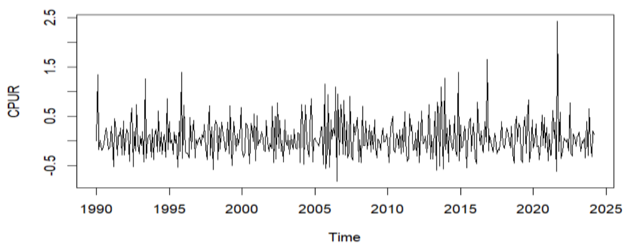
GPR raw series



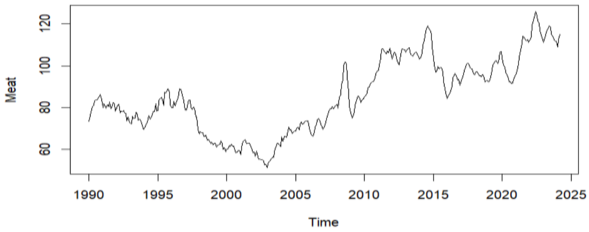
GPR return series



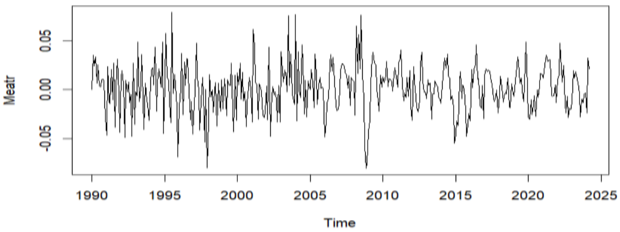
CPU raw series



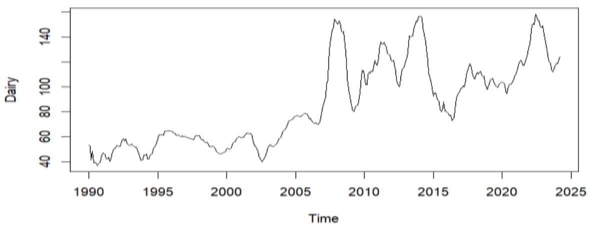
CPU return series



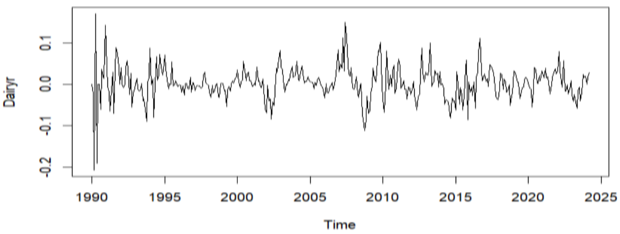
Meat raw series



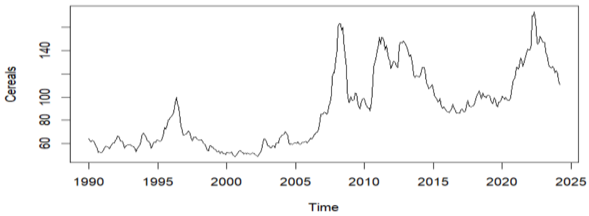
Meat return series



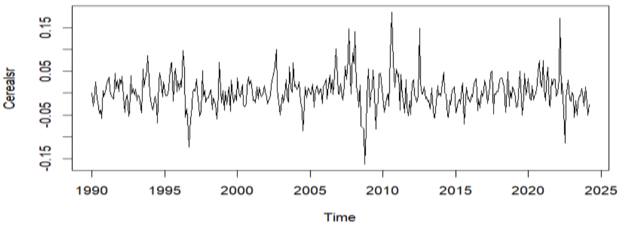
Dairy raw series



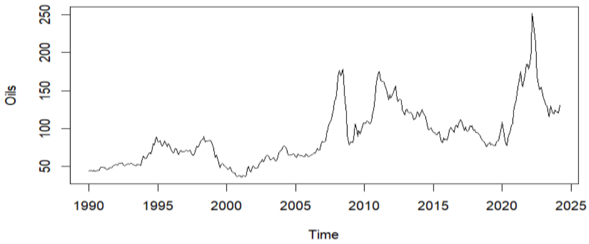
Dairy return series



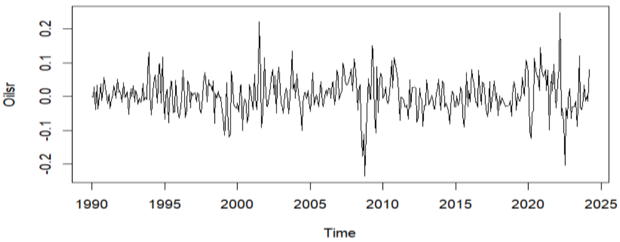
Cereals raw series



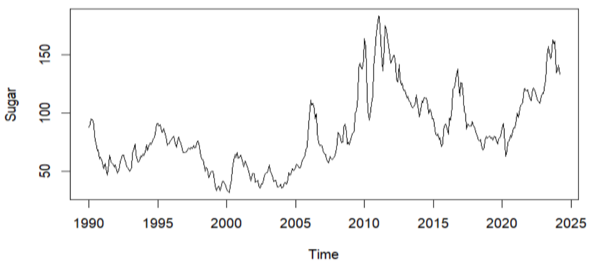
Cereals return series



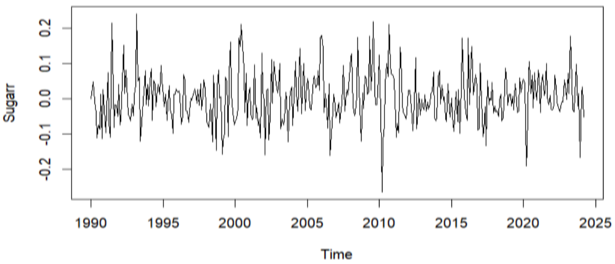
Oils raw series



Oils return series



Sugar raw series



Sugar return series

Figure 1. Plots of raw series (left) and return series (right)

Source: generated using R programming.

Table 2 illustrates the descriptive statistics of the GPR, CPU and the five constituents of the Food Price Index. It is clear that vegetable oils give the highest return compared to the other six variables and have the highest standard deviation. This means that oil is subject to greater risk and serious price fluctuations may occur. All the variables have positive skewness, except for meat, which means that, negative returns are most likely to occur. The kurtosis value of GPR, CPU and Meat Price Index indicates that they have sharper peaks, heavier tails meaning the presence of heavy outliers. Whereas, price indices of dairy, cereals, oils and sugar have flatter peaks, indicating a smaller number of outliers.

Table 2

Descriptive statistics

Indicators	GPR	CPU	Meat	Dairy	Cereals	Oils	Sugar
Observations	411	411	411	411	411	411	411
Minimum	-0.562	-0.818	0.000	0.000	0.000	0.000	0.000
Maximum	6.778	2.430	122.205	160.445	168.776	245.396	172.846
Mean	0.037	0.071	89.980	89.129	92.018	94.116	86.783
Median	-0.009	0.017	91.471	85.899	90.229	86.620	80.851
Sum	15.125	28.993	36981.978	36632.038	37819.260	38681.639	35667.636
Variance	0.171	0.158	145.956	763.966	632.887	1068.498	774.474
St. dev.	0.413	0.398	12.081	27.640	25.157	32.688	27.829
Skewness	11.014	1.266	-0.821	0.392	0.665	1.200	0.671
Kurtosis	170.904	3.517	6.395	-0.504	0.097	2.262	0.239
KPSS test	0.0008	0.007	0.172	0.089	0.116	0.062	0.046

Source: calculated using R programming.

The correlation among the variables given in the Table 3 shows that GPR has a weak negative correlation with all the food commodities and a positive correlation with CPU. The negative correlation with the food commodities shows that there is no significant relationship between prices of food commodities and geopolitical risk in the data analysed. The very weak positive correlation between GPR and CPU indicates that changes in GPR have little or no direct relevance to CPU. While examining the correlation between CPU and all food commodities except cereals, we could see a very weak positive correlation.

Table 3

Correlation matrix

Variables	GPR	CPU	Meat	Dairy	Cereals	Oils	Sugar
GPR	1.000	0.043	-0.011	-0.018	-0.041	-0.032	-0.016
CPU	-	1.000	0.007	0.016	-0.006	0.003	0.021
Meat	-	-	1.000	0.504	0.611	0.526	0.562
Dairy	-	-	-	1.000	0.856	0.789	0.497
Cereals	-	-	-	-	1.000	0.889	0.601
Oils	-	-	-	-	-	1.000	0.578
Sugar	-	-	-	-	-	-	1.000

Source: authors' compilation.

The stationarity of the studied variables was determined based on the results of unit root tests conducted using the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) methods, and is presented in Table 4. The ADF and PP tests show that the GPR variable is stationary and the KPSS test confirms this conclusion. The ADF test is ambiguous for the CPU and the PP test indicates stationarity, but the KPSS test strongly rejects stationarity, thereby demonstrating non-stationarity. Likewise, throughout all three tests, the price indices for meat, cereals, and sugar show constant non-stationarity. Regarding Dairy Price Index, ADF and PP tests indicate stationarity. KPSS contradicts this finding, thereby pointing possible problems with level stationarity. Ultimately, oils are found steady by ADF and PP tests; KPSS denies level stationarity, indicating perhaps trend-related issues. These results show the need of using several unit root tests to guarantee strong results on stationarity in time series data.

Table 4

Unit root test result

Variable	ADF test (p-value)	PP test (p-value)	KPSS test (p-value)	Stationarity interpretation
GPR	0.010	0.010	>0.10	Stationary (ADF & PP confirm; KPSS inconclusive)
CPU	0.127	0.010	<0.01	Non-stationary (ADF inconclusive; PP & KPSS confirm non-stationarity)
Meat	0.465	0.247	<0.01	Non-stationary (All tests confirm non-stationarity)
Dairy	0.010	0.029	<0.01	Stationary (ADF & PP confirm; KPSS indicates stationarity rejection at level)
Cereals	0.072	0.051	<0.01	Non-stationary (ADF & PP inconclusive; KPSS confirms non-stationarity)
Oils	0.016	0.035	<0.01	Stationary (ADF & PP confirm; KPSS indicates stationarity rejection at level)
Sugar	0.073	0.029	<0.01	Non-stationary (ADF inconclusive; PP & KPSS confirm non-stationarity)

Source: authors' compilation.

Investigated the existence of long-run correlations among the variables GPR, CPU, meat, cereals, dairy, oils, and sugar using the Johansen cointegration test. The test findings show that among these factors there are probably two significant cointegrating connections.

The trace statistic value (219.08) and maximum eigenvalue (76.29) exceed the critical limit of 1 %. This suggests the rejection of the null hypothesis, absence of cointegrating relationship ($r = 0$). The test results for the alternative hypothesis ($r \leq 2$) is below the 1 % threshold limit, indicating a maximum of two cointegrating relationships among GPR, CPU, meat, dairy, cereals, oils and sugar.

The first two eigenvalues are the most important since they show the strength of every possible cointegrating relationship. This helps to confirm that among the variables there exist two significant long-run correlations.

Though their interpretation is convoluted by normalisation, the eigenvectors offer understanding of the structure of these interactions. Usually, the eigenvectors' coefficients indicate how each variable helps to achieve the long-term equilibrium. For example, variables with opposite signs move in separate directions, while variables with the same signs in their own vectors often move together in time. Overall, the presence of two cointegrating relationships implies that there are underlying long-run dynamics that link these economic variables together. Table 5 shows the results of Johansen cointegration test.

Table 5

Summary of Johansen cointegration test results

Test details	Trace statistic	Maximum eigenvalue	Interpretation
Number of cointegrating relationships	2	2	Indicates two significant long-run relationships among the variables
Eigenvalues	First: 0.170164, Second: 0.1169486	First: 0.170164, Second: 0.1169486	Represent the strength of each cointegrating relationship
Test statistic for $r = 0$	219.08	76.29	Rejects the null hypothesis of no cointegrating relationships
Critical value for $r = 0$ at 1%	143.09	51.91	Threshold for rejecting the null hypothesis at the 1% significance level
Test statistic for $r <= 1$	142.79	50.87	Indicates more than one cointegrating relationship
Critical value for $r <= 1$ at 1%	111.01	46.82	Threshold for rejecting the null hypothesis at the 1% significance level
Test statistic for $r <= 2$	91.92	31.15	Indicates at most two cointegrating relationships
Critical value for $r <= 2$ at 1%	84.45	39.79	Threshold for rejecting the null hypothesis at the 1% significance level

Source: authors' compilation.

After knowing that there is a cointegrating link among GPR, CPU, meat, cereals, dairy, oils and sugar, the next stage of this research is to confirm whether GPR and CPU Granger cause food commodity indices as posed by Fisher hypothesis applying the Toda and Yamamoto causality test. If so, it can be argued that food commodity market reacts to fluctuations in GPR and CPU. Using methodology by Toda & Yamamoto (1995), the empirical findings of Granger Causality test are approximated by modified Wald (MWALD) test and given in Table 6.

The Toda-Yamamoto causality test reveals numerous noteworthy correlations between food commodity prices, climate policy uncertainty (CPU), and geopolitical risk (GPR). While the reverse causation (CPU causing GPR) is not statistically significant, GPR greatly affects CPU, demonstrating that changes in geopolitical risk greatly influence climate policy uncertainty. This points to a unidirectional link whereby geopolitical uncertainty influences climate policy direction. GPR also greatly affects Dairy Price Index, hence stressing its influence on this particular food commodity maybe due to the vulnerability of dairy markets to geopolitics influencing trade and production.

Regarding CPU, it greatly affects Dairy Price Index demonstrating a bidirectional relationship between climate policy uncertainty and dairy prices and significantly causes dairy. This interaction means that, perhaps through emissions regulations and sustainable development projects, dairy markets are both affected by and contribute to uncertainty in climate-related policy.

Table 6

Toda-Yamamoto causality test result

Causal relationship	Chi-squared statistic, XÂ²	Degrees of freedom, df	P-value	Interpretation
GPR to CPU	63.4	2	$1.70e^{-14}$	Significant causality from GPR to CPU
CPU to GPR	5.6	2	0.06	No significant causality from CPU to GPR (at 5% level)
GPR to meat	1.1	2	0.59	No significant causality from GPR to meat
Meat to GPR	5.6	2	0.06	No significant causality from Meat to GPR (at 5% level)
GPR to cereals	0.67	2	0.72	No significant causality from GPR to cereals
Cereals to GPR	5.6	2	0.06	No significant causality from Cereals to GPR (at 5% level)
GPR to dairy	672.1	2	<0.001	Strong evidence of causality from GPR to dairy
Dairy to GPR	5.6	2	0.06	No significant causality from Dairy to GPR (at 5% level)
GPR to oils	1.3	2	0.51	No significant causality from GPR to oils
Oils to GPR	5.6	2	0.06	No significant causality from Oils to GPR (at 5% level)
GPR to sugar	0.2	2	0.91	No significant causality from GPR to sugar
Sugar to GPR	5.6	2	0.06	No significant causality from Sugar to GPR (at 5% level)
CPU to meat	1.1	2	0.59	No significant causality from CPU to meat
Meat to CPU	63.4	2	<0.001	Strong evidence of causality from meat to CPU
CPU to dairy	672.1	2	<0.001	Strong evidence of causality from CPU to dairy
Dairy to CPU	63.4	2	<0.001	Strong evidence of bidirectional causality between dairy and CPU
CPU to cereals	0.67	2	0.72	No significant causality from CPU to cereals
Cereals to CPU	63.4	2	<0.001	Strong evidence of causality from cereals to CPU
CPU to oils	1.3	2	0.51	No significant causality from CPU to oils
Oils to CPU	63.4	2	<0.001	Strong evidence of causality from oils to CPU
CPU to sugar	0.2	2	0.91	No significant causality from CPU to sugar
Sugar to CPU	63.4	2	<0.001	Strong evidence of causality from sugar to CPU

Source: authors' compilation.

These results highlight the reciprocal impacts between CPU and several food commodities like cereals, oils, and sugar, as well as the important part geopolitical risk plays in determining climate policy uncertainty and its downstream effects on particular food commodity markets, especially dairy. These dynamics should be taken into account by policymakers and interested parties developing plans to reduce hazards in world food systems and climate policy frameworks.

Table 7 presents the BDS test results for the GPR, CPU, meat, dairy, cereals, oils and sugar series. These results show that irrespective of different dimensions, the null hypothesis of independent and identically distributed (i.i.d.) can be rejected at 5 % level of significance. This indicates the presence of nonlinearity in the residuals, rendering the use of a linear model unsuitable. A significant deviation from linearity indicates that the use of nonlinear modelling methods or complex analytical methods, such as wavelet analysis, is justified and necessary to effectively reflect the inherent complexity and structural shifts of these variables.

Table 7

Brock, Dechert and Scheinkman test

Embedding dimension, m	Standard normal	P-value
2	82.3039	0.000
3	130.8748	0.000

Source: authors' compilation.

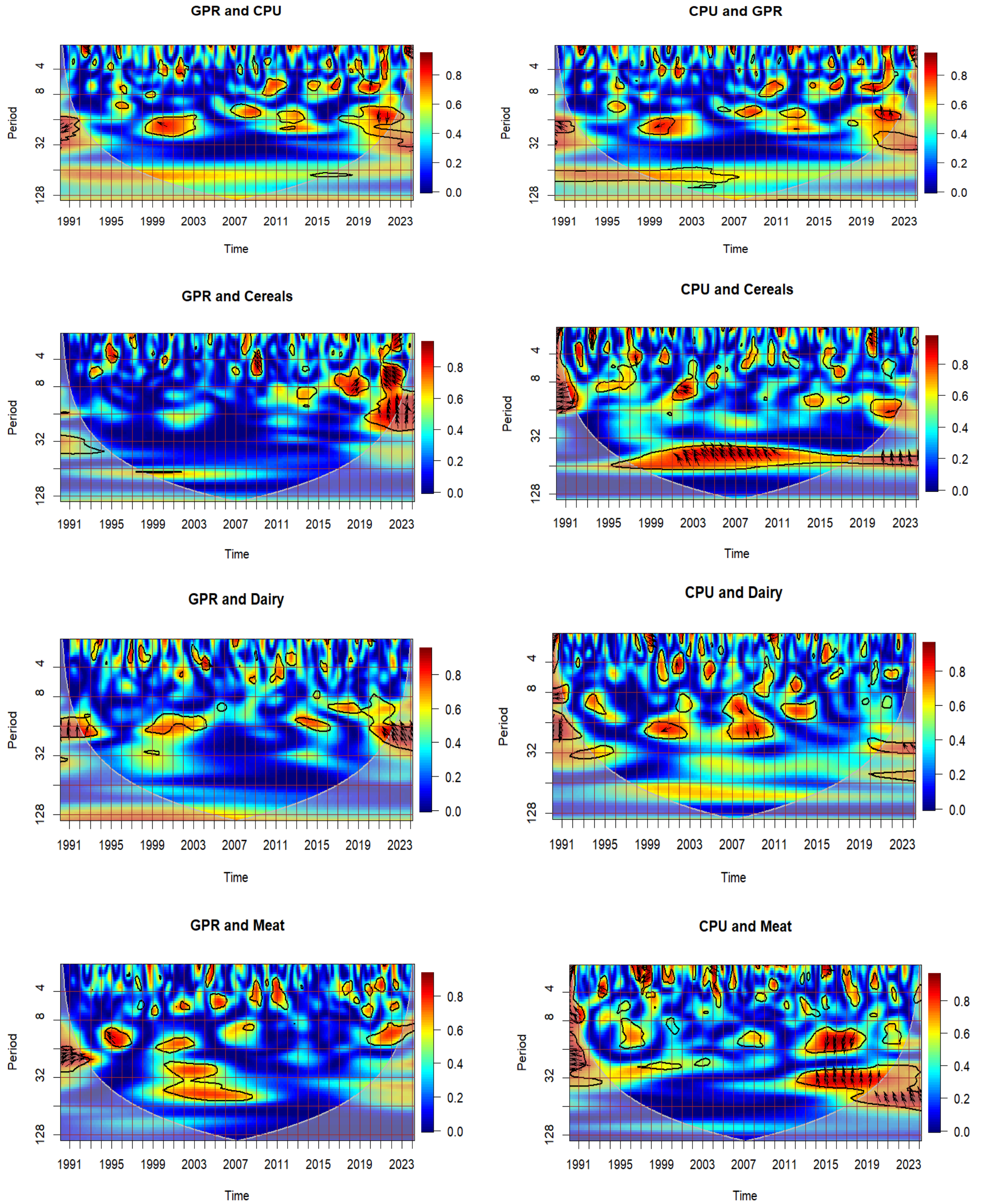
Context plots are used in wavelet analysis to show the time-frequency correlations between markets. This helps in developing insights about the variables under study and the deeper understanding of their relationship dynamics. Three colours are used in dimensional graphs to indicate the strength or weakness of co-movement over various time intervals (horizontal axis, generally years) and frequency ranges (usually not explicitly labelled). In addition, the plot's arrows illustrate how these associations are causative. The leading and lagging associations, as well as their positive or negative direction, are shown by the arrows. These wavelet coherence plots, which resemble heat maps, are an efficient way to display the co-movement patterns across markets in the time-frequency domain.

The degree of co-movement between two variables or signals in different regions is shown graphically in heat maps. These maps use a colour spectrum, with warmer tones (red) denoting significant co-movement and cooler tones (blue) denoting poor co-movement. The direction of the arrow is very important when studying the relationships between variables. It shows the possible relationship between the variables over time. More specifically, a positive relationship is indicated by a rightward arrow, which means that the variables have a tendency to move in tandem. Furthermore, an arrow in the wavelet coherence plot shows the lead/lag relations between the examined series. Arrows pointing towards left indicate that they are in anti-phase. Anti-phase means they move in opposite direction. Right-down or left-up pointing arrows indicate that the first variable is leading, while right-up or left-down pointing arrows indicate that the second variable is leading. By analysing the direction, we can better understand the relationship between variables and the order in which they change.

Figure 2 shows the plots of wavelet analysis of both GPR and CPU with five individual commodities.

The bi-wavelet coherence maps presented on the left reveal the co-movement between GPR and CPU as well as GPR and five commodities, while the right side shows the relationship between CPU and five commodities. When we analyse the co-movement between GPR and CPU, it is clear that small areas were observed between 1990 and

2021 in 4–32 frequency bands, which indicate that there is a co-movement ranging from short run to long run. Observing the directions of the arrows points out a downward trend, where it can be concluded that climate policy uncertainty causes geopolitical risk. GPR affects Cereal Price Index which is evident during the period 2019 and 2024. The heat maps show a strong co-movement between these two series which is evident with the directions of the arrows and the warmer colour tones in that particular period.



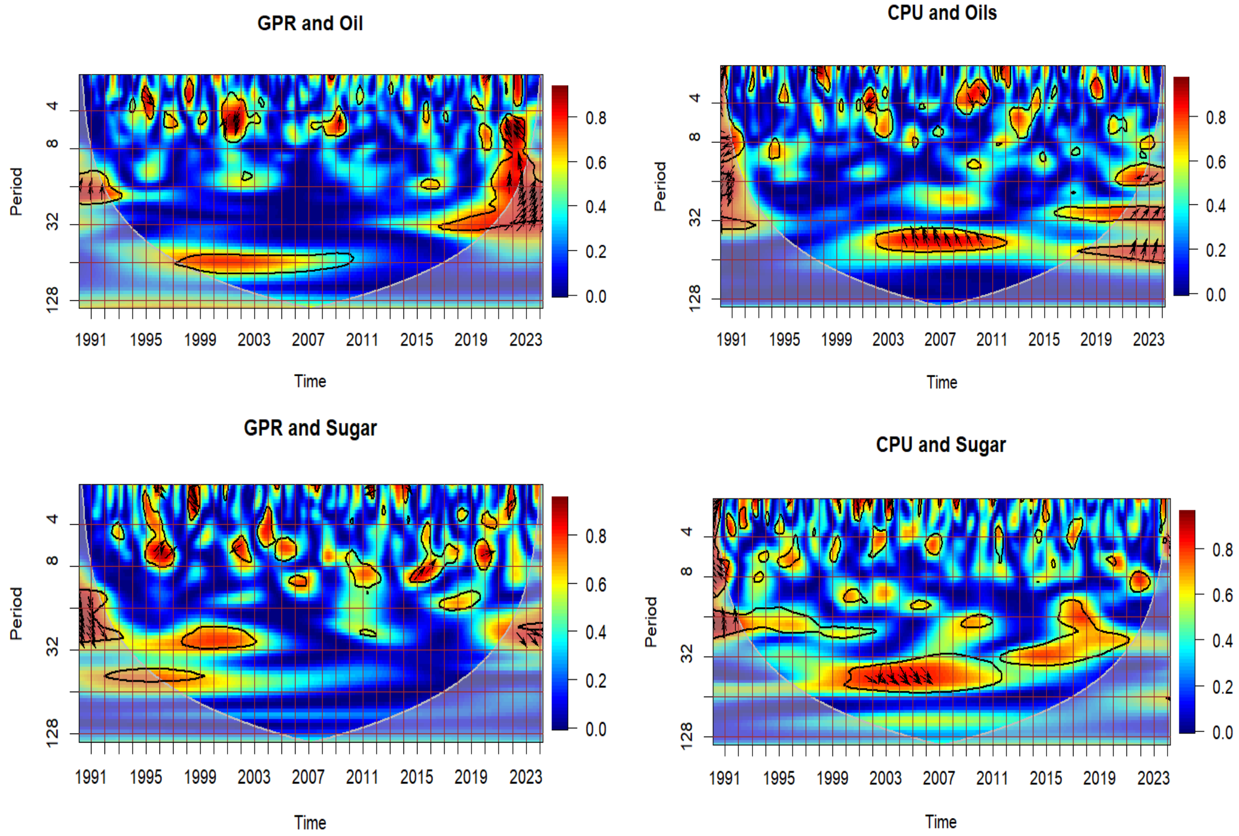


Figure 2. Wavelet coherence plots

Source: generated using R programming.

As the upward pointing arrows indicate the first variable causing changes in the second variable, it can be concluded that geopolitical tensions cause changes in the prices of cereals. In addition, the period in which strong collective movements are observed coincides with the onset of the global pandemic, followed by the Russian-Ukrainian war and ongoing conflicts between Israel and Palestine.

In the case of dairy commodities, it can be concluded that effect of geopolitical risk was observed only in the year of 1990 to 1993 and in the period from late 2019 to 2024. Between 1990 and 1993, there was a strong positive correlation, whereas from 2019 to 2024, the correlation is negative, and Dairy Price Index have leading effect on GPR index. GPR is exhibiting a leading effect on Meat Price Index during 1990–1992, and there is also significant co-movement. After that, there was strong overall growth between 1998 and 2008. Since the start of the global pandemic, there has been a short-term effect, as small areas are in the 4–8 frequency range. The co-movement analysis of GPR and oils (which includes palm oil, rapeseed oil, soybean oil and sunflower oil) requires a special attention as there exists a long run effect and it has peaked during pandemic and Russian-Ukraine war. As these vegetable oils are used in production of many food products, volatilities in their prices could affect the costs of various food commodities.

In the case of GPR and the Sugar Price Index, which fluctuates in the frequency range from 4 to 32, periods of both leading and lagging effects are observed. In most of the cases Sugar Price Index is having a leading effect on GPR. The available heat maps show that the impact of GPR varies for different commodities, and uncertainty in climate policy leads to GPR. There is a significant co-movement between GPR and vegetable oils. As the existing strands of literature put forward the effect of climatic changes on agricultural commodities, its effect on food commodities needs to be addressed as it can cause food security issues. In addition to that, as CPU has a leading effect on GPR, setting CPU as first variable another analysis was also conducted along with other food commodity indices.

The heat maps of wavelet coherence functions on the right show the joint dynamics of the CPU index return series and the five food index return series. From 1990 to 2006, there was a long-term correlation between CPU and GPR. However, strong co-movement with leading effect of CPU is evident during the period from 2019 till 2024. During this period, small areas of warm colours could be observed for a short time. From 1990 to 2006, there was a prolonged correlation between CPU and GPR. Cereals and dairy commodities and CPU are not showing any significant co-movement in the long run and CPU is the leading variable. In the short run, there is a strong interdependence co-movement. Whereas in the case of oils, from 2019 to 2024, there is a strong co-movement in the long run and CPU has leading effect on vegetable oils. However, in the case of sugar, there is a strong co-movement in the long run and CPU is leading. Table 8 outlines the summary of the significant results of the analysis.

Table 8

Crux of wavelet analysis

Variables	Co-movement results
GPR and CPU	Climate policy uncertainty leads geopolitical risk
GPR and cereals	Geopolitical risk leads cereal prices
GPR and dairy	Strong negative co-movement and dairy commodities leads
GPR and meat	Strong co-movement in the short run
GPR and oils	GPR leading oil prices in the long run
GPR and sugar	Strong co-movement in the short run
CPU and cereals	Strong co-movement with leading effect of CPU
CPU and dairy	Significant co-movement in the short run
CPU and meat	Strong co-movement in the short run and CPU has leading effect
CPU and oils	Strong co-movement and CPU leads vegetable oils
CPU and sugar	CPU leading sugar and co-movement in the long run

Source: authors' compilation.

5. DISCUSSION

Interpreting the results reveals findings that can be compared and contrasted with previous literature. The presence of two cointegrating connections among GPR, CPU, and food commodities suggest underlying long-run equilibrium dynamics linking these variables. This backs up research like (Goyal & Steinbach, 2023), which underlined the need of knowing long-term geopolitical effects on agricultural markets for successful policy actions. The necessity of nonlinear modelling techniques to reflect the intricacy of the interactions is highlighted by the rejection of linearity in residuals via the BDS test. Recent research using nonlinear approaches – such as quantile regressions by Mo et al. (2023) or time-varying parameter models by Goyal & Steinbach (2023) have similarly underlined the need of considering nonlinearity in analysing food price dynamics under global hazards.

By applying bi-wavelet analysis to understand the time-frequency relationship as well as long and short run relationship among variables, the study was able to bring out the time varying relationship between GPR and food commodities as well as CPU and food commodities. This aligns with work by Mastroeni et al. (2022) where they have tried to differentiate short run and long run dynamics between oil and food prices. From the results, it is known that, the GPR index increases during crisis period and it has shown a dramatic increase during Gulf war, September 11, during 2003 invasion of Iraq as rightly pointed by Caldara & Iacoviello (2018), and recently during the Russian-Ukraine war.

The most pronounced peak occurred after 2019 which coincides with the periods of global events such as COVID-19, Russian-Ukraine war, ongoing Israel-Palestine issue and increasing climate related discussions and policies. This shows the sensitivity of Climate Policy Uncertainty Index to external factors and potential for it to create uncertainty in policy framework.

Given the clearly demonstrated long-term causality in the case of oils, the data show that GPR significantly affects some food products, especially dairy products and vegetable oils. This finding is consistent with the study by Hudecová & Rajčániová (2023), which demonstrated the asymmetric impact of GPR on rapeseed, sunflower oil and wheat prices during geopolitical issues like the Russian-Ukraine war. The bidirectional causation noted between CPU and dairy prices points to a feedback loop whereby climate policies not only influence agriculture markets but also help to shape them.

The co-movement analysis between GPR and CPU shows that GPR does not cause climate change. The result is in contrast to the findings by Zhao et al. (2023), where they have demonstrated that subside the demand for renewable energy and threaten climate change mitigation policies. The results show that uncertainty surrounding climate policy and climate change-related risk issues increases geopolitical risk. This is in line with the findings by Bohl et al. (2017), where they state that natural risk transcends to political risk, which results in financial risk. Furthermore, GPR affects cereals during major global issues. The Cereal Price Index, which is one of the constituents of Food Price Index, is compiled using the International Grains Council (IGC) wheat price index, the IGC maize price index, the IGC barley price index, one sorghum export quotation and the FAO All Rice Price Index. An increase in prices of cereals like wheat, which is used in the production of varieties of food products like bread, buns, biscuits and cakes due to geopolitical tensions, can interrupt accessibility (Hudecová & Rajčániová, 2023). This can lead to food security issues.

Depending on the time period, the contrasting effects on dairy commodities suggest a complex relationship where geopolitical risk has leading and lagging effects in different time periods. The findings highlight the importance of vegetable oils in the food supply chain, as their price volatility can have broader implications for food security. Vegetable Oil Price Index consists of soy, rapeseed, palm and sunflower oil prices. Rising prices due to supply disruptions could affect industries that use these oils as raw materials for other goods. Soybean and rapeseed are used in production of biofuels which is an alternative to conventional energy sources.

In the long term, sugar and geopolitical risk show little or no common dynamics, while in the short term, there is a strong common dynamic, with sugar having the leading influence. During the period of COVID-19 and Russian-Ukraine war GPR is leading sugar prices with strong co-movement, which is confirmed by the findings of Hudecová & Rajčániová (2023).

The weak link between GPR and other commodities, such sugar and meat, however, indicates that not all agricultural markets are similarly responsive to geopolitical events. These differences highlight how crucial commodity-specific elements – such trade dependencies and production techniques – are in reducing the influence of geopolitical concerns.

When it comes to CPU and cereals, the presence of co-movement with leading effect of CPU could be identified in the long run, which is consistent with the findings of Liu et al. (2023) who argue that CPU affect grains in the long run but not in the short run. In 2005, the US has introduced the biofuel production policies in order to bring reduction in the use of fossil fuel energy sources as part of mitigating climate change issues. This has caused surges in the prices of grains causing food security issues but studies also show that later on it can positively contribute to food security through preservation of environmental quality (De Gorter et al., 2013; Subramaniam et al., 2020).

CPU has strong co-movement with dairy and meat in the short run whereas ranging from strong to low co-movement with oil and strong co-movement in the long with sugar having leading effect in all these cases. According to Khalfaoui et al. (2024), the relationship between climate change, agriculture, and food prices is impacted by environmental and climate policies. For instance, policies that impede a nation's efforts to address climate change, such as carbon emission levies and emissions trading schemes, may increase producer costs and have an impact on food prices and agricultural exports. As a result, climate change implies unfavourable weather, which increases market uncertainty in agriculture. Altogether, the results press on the need for further research into the effects of climate change on agricultural commodities and their implication for food security.

The Toda-Yamamoto test found that geopolitical risk significantly caused climate policy uncertainty, but wavelet coherence revealed that CPU led GPR during certain periods, particularly from 2019 to 2024. In addition, GPR demonstrated a strong causality with dairy commodities in the causality analysis, whereas, wavelet coherence has shown a negative co-movement with dairy commodities during the same period, with dairy leading GPR. The reasons could be first, causality tests assume linear relationships, while wavelet coherence explores both time and frequency domains, capturing scale-dependent and non-linear interactions (Grinsted et al., 2004; Baruník et al., 2011). Furthermore, wavelet coherence is responsive to structural breaks and exogenous shocks, such as the COVID-19 pandemic or the Russian-Ukraine war, which are frequently disregarded by static causality tests (Pal & Mitra, 2017). Following that, causality tests assess average associations throughout the whole sample period, thereby obscuring short-term or developing dynamics that wavelet coherence might elucidate. Wavelet analysis revealed significant co-movement between GPR and wheat during global crises, a phenomenon not observed in causation results.

The bidirectional causation identified between CPU and dairy prices in the Toda-Yamamoto test underscores feedback loops that wavelet coherence does not directly represent. Wavelet analysis primarily concentrates on detecting intervals of significant co-movement and lead-lag dynamics across various frequencies. Both methodological distinctions highlight the complementing characteristics of both approaches. Causality tests provide statistical evidence of directional relationships, but wavelet coherence provides deep insight into dynamic interactions over time and across scales.

6. CONCLUSIONS

This paper explored the co-movements between global geopolitical risk and five constituents of FAO's Food Price Index. In addition, the impact of policy uncertainties regarding climate change issues on food commodities is also analysed using bi-wavelet coherence analysis. The results indicate several critical insights: two cointegrating relationships among GPR, CPU, and food commodities, underscoring long-term equilibrium dynamics; the requirement for nonlinear modelling techniques due to the BDS test's rejection of linearity; and time-varying relationships among GPR, CPU, and food commodities evidenced by bi-wavelet analysis. The research identified bidirectional causality between CPU and dairy prices, indicating a feedback loop in which climate policy influences and are influenced by agriculture markets. Uncertainty in climate policy significantly affects a number of commodities, such as grain, oil, and sugar. Significantly, CPU was identified as a precursor to GPR, suggesting that uncertainty in climate policy could intensify geopolitical concerns.

The results revealed that vegetable oils such as palm oil, rapeseed oil, soybean oil and sunflower oil has a strong co-movement with GPR especially during the period of extreme events. In the period from 2019 to 2024 there is a strong positive co-movement in the case of GPR and cereals whereas there is a negative relationship with dairy commodities during the same period. Long run effect between GPR and CPU is illustrated using the plot. Another important thing to be noted is CPU leading GPR. CPU not only has a leading effect on GPR but also on vegetable oils that from the period 2019 to 2024. Time varying significant co-movements between CPU and food commodities could be witnessed in the short run. It is understood that policy uncertainties regarding climate change issues affect food commodities in the short run. As political tensions among states can affect the functioning of an economy and can lead to supply chain issues, which may in turn affect the prices of essential commodities especially food commodities. This can lead to food security problems, which is an obstacle to achieving the Sustainable Development Goal 2: "Zero Hunger".

The results highlight the great need of proactive governmental actions to protect world food systems. First of all, the great influence of geopolitical concerns, especially on basic commodities like oil, calls for more global collaboration to maintain supply chains during crises. Second, integrated climate-agriculture policies are essential to properly balance environmental goals with food security since climate policy uncertainty drives food costs in a major part. At last, policymakers should use advanced nonlinear modelling approaches to improve their ability to predict market reactions under challenging and changing risk scenarios, hence supporting better informed and successful policy decisions.

7. LIMITATIONS AND FUTURE RESEARCH

While the study used the wavelet analysis to decompose the data into signals of different time scales, several limitations need to be addressed. To start with, the study does not account for other external factors such as economic policy uncertainties, trade agreements and natural disasters. Additionally, the study does not focus on geopolitical issues or climate changes specific to a geographical area. There can be particular regions where such issues will be persistent and need attention. There are 44 country-specific indices that can be used as indicators of geopolitical events specific to each country. As well as, new index explicitly to a country or region could also be developed for even more effective analysis. Furthermore, overall market dynamics cannot be deciphered only with the five constituents of FAO's Food Price Index.

Climate Policy Uncertainty Index is used to find out effect of climatic changes on food commodities. The physical risk indices or new measures of climate change issues can be used and a greater number of food commodities can also be used for better results. The return series of five constituents of Food Price Index is used in this study. Conducting studies on various economic unions or trade blocs like BRICS, G20 nations and MENA countries is also suggested. Econometric methods embedded with machine learning tools can be used for data analysis in the future studies. Daily food commodity futures prices, together with the GPR index and the CPU index, can provide effective results for timely action to address food security issues, which can help create more sustainable growth and development.

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