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Research article

The impact of Russo-Ukrainian war, COVID-19, and oil prices on global food security

Nadia AL-Rousan [a,*], Hazem AL-Najjar [b], Dana AL-Najjar [c]

[a] SEEIT, Computer Engineering Department, German Jordanian University, Amman, Jordan
[b] Computer Science Department, University of Petra, Amman, 317, Jordan
[c] Department of Finance and Banking Sciences, Faculty of Business, Applied Science Private University, Amman, 11931, Jordan

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ABSTRACT

Context: Light of recent global upheavals, including volatile oil prices, the Russo-Ukrainian conflict, and the COVID-19 pandemic this study delves into their profound impact on the import and export dynamics of global foodstuffs. With rising staple food prices reminiscent of the 2010–2011 global food crisis, understanding these shifts comprehensively is imperative.
Objective: Our objective is to evaluate this impact by examining six independent variables (year, month, Brent crude oil, COVID-19, the Russo-Ukrainian conflict) alongside six food indicators as dependent variables. Employing Pearson's correlation, linear regression, and seasonal autoregressive integrated moving averages (SARIMA), we scrutinize intricate relationships among these variables.
Results and conclusions: Our findings reveal varying degrees of association, notably highlighting a robust correlation between Brent crude oil and food indicators. Linear regression analysis suggests a positive influence of the Russo-Ukrainian conflict, Brent oil on food price indices, and COVID-19. Furthermore, integrating SARIMA enhances predictive accuracy, offering insights into future projections.
Significance: Finally, this research has a significant role in providing a valuable analysis into the intricate dynamics of global food pricing, informing decision-making amidst global challenges and bridging critical gaps in prior research on forecasting food price indices.

1. Introduction

Preceding the advent of the COVID-19 pandemic, the Food and Agriculture Organization (FAO) predicted the prevalence of hungers in 2021 would afflict a demographic ranging between 702 and 828 million individuals [1]. After the COVID-19 pandemic era, this numerical prediction surged beyond more than 900 million. This escalation is attributed to the customary ramifications of global COVID-19 regulations. Despite the FAO's anticipation of enhanced food security in 2021, the actuality witnessed a worsening global hunger in the same year, substantiated by the ramifications of the COVID-19 impact [2–4].

Food security, defined as an assessment of the availability of sustenance and an individual's capacity to procure nutrition of commendable quality consistently, is measured across four foundational dimensions: availability, access, utilization, and stability [5]. Numerous researchers employ global food price indices for approximating the valuation of international food commodities. The index

* Corresponding author.
E-mail address: nadia.rousan@yahoo.com (N. AL-Rousan).

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of food price is a pivotal metric, gauging the mean monthly fluctuations in international food commodities and groceries. Various food price indices may also be applied to evaluate specific comestibles (i.e., meat, oils, eggs, dairy) [6–8].

The Russo-Ukrainian war, fluctuations in crude oil prices, and the COVID-19 pandemic have great impact on global food security, which cause complex challenges for policymakers [9,10]. The Russo-Ukrainian war began in 2014, and it has disrupted the agricultural sector in the region and led to a decline in global food security [11]. The war has caused supply chain interruptions, affecting the global availability of essential food commodities and groceries [12]. Besides, the war between Russia and Ukraine, and the coronavirus pandemic impacted the existing food systems, leading to grocery shortages and price increases [13]. The fluctuations in oil prices, influenced by geopolitical tensions and economic crises, have increased production costs and transportation expenses. As a result, they caused strain on global food markets and decision makers as well [14].

Interconnecting all mentioned crises together led to underscore the need for comprehensive policies to address the current challenges in food security sector [15]. However, policymakers are facing the task of mitigating the adverse effects of supply chain disruptions, invest in agricultural technologies, and diversify sources of food production to ensure the stability in food prices to prevent widespread hunger. Shortages in critical commodities and groceries (i.e. wheat, flour, etc.) have increased by war, pandemic, and other crises [16]. This increased the urgent necessity for strategic planning and international cooperation to secure food supplies and save humanities. Furthermore, the socio-economic impacts of these crises should be considered especially on vulnerable populations inline to protect them from the consequences of rising food prices, facilitate the movement of goods, and prevent further disruptions [17]. Additionally, policymakers can play an essential role in supporting local farmers, ensuring fair trade practices, promoting sustainable agricultural practices, and contribute long term food security problems [18].

Exacerbation of the global challenges consequences policymakers to adopt adaptive strategies that address the evolving nature of the crises. They should find robust solutions that safeguard global food security, mitigate the impact of geopolitical events, pandemics, and fluctuations on vulnerable populations, and foster a more sustainable and resilient global food system.

Ihle et al. [19] investigated how the war between Russia and Ukraine in February 2022 influenced global commodity and energy prices. This crisis disrupted supply chains, and increased grocery and commodity price synchronization worldwide. The study analyzed 15 key price indices for several global commodities from January 2010 to July 2022. The study revealed that grain, energy, and fertilizer supply chain disruptions increased international prices. In addition, these crises pose challenges for consumers to mitigate the effects of Russia's inflation by finding cheaper alternatives. Therefore, policymakers are urged to enhance the resilience of global chains of food to minimize the impact of international crises and work towards achieving sustainable development goals. The study emphasizes the need for market interventions, such as strategic staple food stocks and sustainable improvements in food supply chain resilience globally.

Izzeldin et al. [20] assessed the impact of the Russia- Ukraine war on international financial market, comparing it to the effect of Covid-19 and 2008 economic crisis. The study analyzed the intensity metrics of global stock markets and commodities to find that financial markets responded rapidly to the current war and other crises compared to previous crises. In addition, Wheat and nickel were particularly affected due to Russia's and Ukraine's prominent exporter status. The short-term consequences include rising inflation and lower economic growth with potential long-term implications for energy security, affordability, and the low-carbon transition economy. The study highlights the need for policymakers to address the challenges posed by ongoing commodity pressure and the potential global recession resulting from the war.

Previous and current research has highlighted the impact of the Russo-Ukraine war, COVID-19, and oil prices on the food security problem. Therefore, policymakers should undertake firm measures to handle all risks associated with food shortages and increase its costs. Several studies discussed the interconnections between crude oil, the COVID-19 pandemic, and the Russia-Ukraine war, particularly concerning food price indices [21].

Earlier investigations have focused on studying the relationships between global crises and food security (i.e., exploring the correlation between the food price index and Brent oil, etc.) [22]. In contrast, this research seeks to elevate the scope of research by delving into the multifaceted impacts of pivotal geopolitical and economic factors—specifically, crude oil prices, the COVID-19 epidemic, and the global Russia-Ukraine war—on the international food price index [23].

The primary objective of this research is to discern and scrutinize the intricate relationships and potential causal links among these variables, acknowledging their significant influence on the dynamic nature of food prices on a global scale.

The idea of this research is to provide a deep, nuanced overview of the intricate interplay among geopolitical, economic, and public health events, particularly their impact on the global food price index. This can be done by shedding light on how factors like Russia, the crude oil price fluctuation, and COVID-19 pandemic, collectively shape and impact the fluctuations in international food prices and affect food security.

This depth of insight would be crucial for various stakeholders and decision-makers globally. It would enable them to face complex and interconnected global events. The research further serves as a foundation for devising strategic plans to tackle the challenges of various discussed crises. Thus, ultimately contributing to the development of effective and adaptive measures to address the problems of global food markets.

In addition to investigating the impact of crude oil prices, COVID-19, and the Russo-Ukrainian war on the global food price index, this research makes substantial contributions to the audience and policymakers through diverse analytical approaches. Primarily, this study engages in a meticulous examination of the intricate relationships among vital independent variables (i.e., year, month, WTI oil, Brent oil, COVID-19, and the Russo-Ukrainian war) and six dependent variables (i.e., meat, dairy, cereals, oils, sugar, and the overall food price index) utilizing Pearson correlation analysis. This comprehensive exploration is designed to unveil nuanced connections and dependencies between the studied factors to provide a profound understanding of their influence on specific food categories and the broader food market.

Furthermore, this research seeks to enhance predictive accuracy by developing linear regression models integrating year, month, Brent oil, COVID-19, and the Russo-Ukrainian war as significant predictors for estimating global food indices. This approach would help decision-makers, policymakers, and authors to identify the key drivers influencing food prices and their respective impacts on various food categories. Additionally, this research contributes forecasting methodologies by implementing seasonal autoregressive integrated moving averages (SARIMA) models that operate without reliance on specific independent variables.

This approach offers an alternative perspective on predicting future trends in food prices. In addition to a comprehensive understanding of the underlying dynamics. Therefore, it provides valuable insights and contributes to the complex dynamics of global food pricing. Therefore, providing valuable insights into the complex dynamics of global food pricing. By uncovering complex relationships, enhancing predictive accuracy, and offering alternative forecasting methodologies, our research aims to facilitate more informed decision-making and policy planning in response to the challenges posed by these multifaceted global events. However, to the best of the authors' knowledge, prior research has yet to employ predictive models to forecast upcoming global food price indices, despite other studies that have explored the impact of political crises on global food security.

2. Literature review

The current conflict between Ukraine and Russia has resulted in immediate food insecurity and brought to light inherent weaknesses in the global food security system [24]. Husain [25] focused on addressing the current crisis and implementing decisive measures to prevent all challenges and avoid economic and humanitarian catastrophes. Hassen and ElBilali [26] investigated the indirect and direct ramifications of the Russian invasion on global food security, significantly since the conflict adversely affected crop yields. The study underscores the urgent need for long-term policies to strengthen sustainable food systems. Abay et al. [27] investigated the repercussions of the Russo-Ukrainian war on North Africa and the Middle East (MENA) food security. Their research revealed a swift and substantial spike in food prices during the war. On the other hand, the study also sheds light on the essential policies that countries in the region should contemplate to mitigate the impact on food security.

Moreover, a notable upsurge in the food price index occurred in March 2022. This was a direct outcome of the Russian invasion of Ukraine. This escalation was anticipated considering their significant roles as two major exporters of grain and wheat referred to by the FOA (2022). Due to the current conflict and as a strategy to increase leverage in international forums, Russia has imposed restrictions on most food shipments from Ukraine, which is considered a major global wheat producer. Furthermore, they have initiated attacks on the country's energy grid, leading to disruptions in the food supply chain [28].

Assous et al. [5] introduced forecaster models to predict the yields of four crops (wheat, dates, watermelon, potatoes, and maize) in Gulf countries. The research employed a neural network model. The prediction model incorporated five independent variables: temperature, year, nitrogen fertilizer, pesticide, and rainfall. At the same time, the outcomes demonstrated the importance of the proposed model in predicting crop yields in the Gulf countries. Furthermore, the results highlighted the distinct responses of each crop to the independent variables.

Ye et al. [29] studied the influence of oil prices index and supply chain pressures on the consumer from 1997 to 2022 globally. The study utilized nonlinear and linear autoregressive distributed models. The research revealed that oil prices indirectly impacted the inflation rate across all examined countries. Besides, the research identified an asymmetric effect of the supply chain on inflation in both developed and developing economies. The study recommended using green energy and technology to address inflation issues caused by elevated oil prices and foster economic growth and sustainable development.

Deininger et al. [30] collected information on agricultural fields in Ukraine using satellite imagery. This detected the damage to agriculture caused by the incursion of Russian forces into Ukraine. The study considered four years between (2019 and 2022), and 10, 125 Ukraine's village councils. This study utilized a machine learning model to classify the collected data and then to calculate the Normalized Difference Vegetation (NDV) Index. The research revealed that the war increased the loss in winter wheat.

Feng et al. [31] investigated the impact of the Russian dispute on global agriculture, prices, trade, and food security. The research revealed that the higher farm produce prices reduced trading volume and severed Food scarcity, particularly for importing countries depend on Russia and Ukraine. Besides, producer countries like Canada and the United States may benefit, but energy and fertilizer restrictions could worsen food insecurity.

Das et al. [32] investigated the effect of the dispute between Russia and Ukraine on Russian and European stock markets. The research considered nine European countries and Russia between November 2021 and May 2022. The study used Ordinary Least Squares (OLS) model to understand the influence of war on the selected stock markets. The research found that the conflict disturbed the stock markets in all the studied countries. The results showed that the mining, construction, and manufacturing sectors were the most affected due to the conflict. In addition, it was emphasized the fact that the effect of new sanctions as a result of Russia-Ukraine conflict can have fatal impacts on systems worldwide. Strategic approaches for this purpose were recommended that will facilitate preserving food security and avoid a long-term catastrophic situation.

Zhou et al. [33] assessed the influence of the war between Ukraine and Russia on food security and global energy using a refined model for cascading failures under load. The research showed that the upper limit of node load has a notable effect, whereas the lower limit parameter has a minor influence. The study suggested enhancing production ability and energy diversity to mitigate risks and strengthening global organizations' role in balancing security demand.

Tajaddini and Gholipour [34] assessed the relationship between the Ukraine- Russia crisis and stock markets in 83 countries. The analysis showed that the war strongly impacted countries with stronger trade ties. Besides, the results revealed a weak relationship between market drop and trade dependency in countries' trade openness.

Mroua and Bouattour [35] studied the influence of the Coronavirus and the Ukrainian- Russo war on stock markets in the USA and

Gulf Council Cooperation (GCC) regions. The research considered oil prices, precious metals and renewable energy. The study utilized a Time Varying Parameter Vector Autoregression approach (TVP-VAR) to examine the connectedness between these markets. The results indicated the renewable energy stock markets in United States were consistently emitted significant shocks throughout the study period. Moreover, the oil market acted as both receiver and emitter of shocks concerning the Gulf countries and United States market, suggesting a possible shift towards renewable energy.

Sohag et al. [36] studied the geopolitical events in Russia and their impact on global energy and food prices in Western and Eastern of Europe in the period between (January 2001 and March 2022). The research used Both Cross-Quantilogram (CQ) and sophisticated econometric methods to analyze the monthly data properties to uncover the causality relationships between variables, considering long, medium, and short memories. The study revealed that aggregated geopolitical risk reduces the food prices in Eastern Europe in the short-term but increases them in Western Europe. Additionally, decomposed measures of geopolitical threat exhibit diverse effects. The study suggested urgent policy implications, including joint measures to address the detrimental impact of geopolitical risks, utilizing unused agricultural lands, supporting smallholder farmers, safeguarding supply chains, and mitigating fuel scarcity. Moreover, the study emphasized the potentially disastrous consequences of new restrictions in reaction to the Russia and Ukraine war on global food systems, urging strategic actions to ensure food security and avert long-term cataclysms.

Zhang et al. [37] Investigated the unequal influence of energy prices shocks on welfare, drawing on household data from various developing and developed nations, which collectively represent over 87% of the global population. Analysis revealed that the nonmaterial and material dimensions, “Creation” and “Protection,” respectively, were the most significantly affected needs globally, experiencing declines ranging from 3.7% to 8.5% and 3.6%–8.4%. Among these dimensions, households in BRICS countries faced the greatest impact, encountering drops ranging from 2.0 to 2.2 times of the global average due to energy-dependent consumption and higher price patterns. Conversely, low-income groups in poorer countries experienced more severe declines in meeting human needs satisfaction. The study underscored the importance of addressing both non-material and material dimensions of wellbeing in response to the effect of energy price shocks, particularly in vulnerable households.

Inacio et al. [38] examined the influence of the Russia-Ukraine war on global energy prices, particularly crude oil and refined product prices, employing dynamic cross-correlation analyses. Three distinct periods were studied: pre-COVID 19 and pre-war, during COVID 19 and pre-war, and both COVID 19 and the war from 2019 to 2023. The results reveal significant differences between pre-COVID 19, and pre-war periods compared to other periods, with varying impacts on different energy commodities. Besides, the war influences diesel prices in European more than diesel prices in US. The study employed multivariate and bivariate cross-correlation methods emphasizing each market’s complexity and unique dynamics.

Lin et al. [39] explored the consequences of the Russia and Ukraine war on global food insecurity, focusing on the substantial impact on wheat production and trade disruption. As major grain producers and exporters, Ukraine and Russia’s conflict reduced wheat production in Ukraine, thus affecting global wheat markets. The study presents three different scenarios ranging from slight to severe to assess the impact of the conflict on wheat harvest and trade disruption. The research used a general equilibrium trade model and revealed potential trade drops, escalating wheat prices, and intense food in-security, particularly for countries heavily reliant on importing wheat from Ukraine. The conflict led to price increases and welfare decline for affected countries, impacting around 1.7 billion people in hunger, and around 276 million people in food in-security. The study suggested an increase in wheat production and export by major wheat-producing countries to reduce the global wheat crisis, emphasizing the need for cooperation and exemption from unnecessary trade restrictions to mitigate the far-reaching consequences of the conflict.

Nerlinger et al. [40] investigated the influence of the conflict between Ukraine and Russia on energy companies’ stock prices through a sample of 1630 global energy companies, conducting short-term events studying the Russia’s invasion in February 2022. The findings revealed positive cumulative average abnormal returns, indicating that energy companies outperformed the stock market after the invasion. On the other hand, the energy companies in North American exhibited the highest outperformance compared to European and Asian counterparts, with regional results aligning with current gas and oil trade agreements. The study concluded that the participants of stock markets anticipate profitability in traditional energy segments. Despite the ongoing global push for renewable energy, The reaction of capital markets to shifts in supply chains prompted by significant events like wars and potential opportunities for competitor markets to capitalize on disruptions is increased. The study emphasized the need for further research to explore the effect of long-term pressure on traditional supply chains.

Behnassi and El-Haiba [24], underscored the profound consequences of the Russia and Ukraine struggle on global food security, emphasizing the complex relationship between food insecurity and armed conflicts. The war disrupts key aspects of food systems, hindering production, supply chains, and market dynamics, leading to increased food prices and decreased accessibility. The study discovered that the war between Russia and Ukraine disrupted corn, wheat, and barley exports in both Russia and Ukraine which are the main producers for global wheat and calorie. This surged in food and fertilizer prices worldwide. On the other hand, the consequences extended beyond economic factors and affected the capacity of international organizations to offer food aid and potentially rise in global hunger. The study endorsed promoting human rights compliance during conflicts by taking urgent measures and strategic food reserves for efficient food assistance implementation to address the crisis’s human security implications. Besides, it revealed the urgent need for new rules for international humanitarian law to protect food systems and develop a comprehensive multidisciplinary research program for mitigating the complex interplay between food insecurity and conflicts.

Duho et al. [41] studied the influence of the Russia and Ukraine conflict on Africa region, pertaining to regional economic communities. The study employed time-line analysis to trace the significant events that occurred during the war and impacted on the food security in the region. The study examined eight economic communities in African to address the financial effects, energy and food policy implications, trade effects, and diplomatic relations with Russia. The study exposed the need for proactive solutions and strategic investments in food policy and the energy sector for African self-reliance.

Tetteh et al. [42] measured the performance of macro-economic indicators in Ghana economy during the three significant global shocks (Global Financial Crisis (GFC), Coronavirus, and Russian and Ukraine war). The study used a descriptive approach to conduct the investigation. The study identified trends in various indicators under each shock using comparative analysis. The research revealed that gold and cocoa prices increased significantly during the GFC, resulting in more favorable exports. In contrast, it was found that timber exports and gas and oil imports declined. On the other hand, timber exports and gas and oil imports increased during COVID 19, while gold exports and the trade equilibrium decreased. However, the Russian-Ukraine war impacted unprecedentedly high values in gas and oil prices, the exchange rate, and non-food and food inflation, reflecting the worst economic growth record compared to other shocks. The study suggested curbing inflation, enhancing domestic production, and adding value to goods exports to foster economic evolution and improve the trade equilibrium.

Adi et al. [43] discussed that the recent Russian invasion of Ukraine posed a considerable threat to both global economic growth and humanity. The research focused on the challenges such as financial market disruptions, rising food and energy prices, supply chain and inflation issues that caused by all catastrophic events like COVID 19, climate change, and the Russo–Ukrainian war. The study revealed that these crises have further supply and demand tensions, affecting consumer behavior and global economic development. Besides, it explored the motives behind the conflict and its profound implications on humanity and the global economy. The research emphasized the need to explore diplomatic solutions over war and engage the civil society and international community.

Saâdaoui et al. [44], studied the correlation between the prices of vital food commodities and geopolitical risks during Russia-Ukraine crise. The study used a multiscale analysis to unveil patterns obscured by noise in prices of commodity during various conflicts like Brexit, COVID 19, and the conflict between Ukraine and Rissa. The study revealed that the geopolitical factors influence food prices with one-way causal relationship. This research is considered as valuable research among other research due to its importance for scholars studying global development, international aid organizations and policymakers.

Kozielec et al. [44], investigated the influence of importing food from Russia or Ukraine on the security of food in the GCC countries. The article studied the negative influence of the crises on global food security. The study used linear regression and correlation analysis to explore the relationship between importing food from Ukraine and Russia and the total food imports to the Gulf countries. The findings revealed a strong positive correlation and a moderately positive relationship. However, GCC countries showed good efforts to enhance agricultural independence and bolster food security.

Olayungbo et al. [45], studied the co-integration and causal correlation between oil and food prices in different 21 countries characterized by being food-importers and oil-exporters. The study employed yearly data between 2001 and 2015. It used the Panel Autoregression Distributed Lag (ARDL) model to assess the long-run relationship between variables in panel data settings. The short-term analysis revealed that there is a negative effect between food and oil prices, while a positive effect emerged in the long term. The study revealed a unidirectional flow from food prices to oil prices in causality analysis. Besides, to underscore the value of implementing agricultural strategies to foster favorable food prices and exploring alternative energy options.

Cheng et al. [46] investigated the dynamic interaction between both indices of food price and the global price of crude oil using monthly dataset between 1990 and 2017. The study used initial linear methods to assess stationarity, linear Granger causality, and co-integration. Besides, it used a nonlinear framework to assess the nonlinearity between univariate food and oil price connections. The study analyzed asymmetric adjustment, integrating Threshold Vector Error Correction (TVECM) and Threshold Vector Autoregressive (TVAR) mechanisms to comprehend the dynamic variation mechanism based on different regimes. The study revealed a non-linear causality relationship between the price of food and indices of the global crude oil, highlighting structural break features and a continual adjustment process of food price indices approaching equilibrium when a threshold is reached, outpacing oil price growth.

Ding et al. [47], assessed the influence of the current fluctuation of oil price on the food market, particularly in oil exporting economies, during two distinct periods: before the Ukraine-Russia crisis (2000–2013) and during the Ukraine- Russia crisis (2013–2019). The study observed a long-term inverse relationship between oil and food prices in high income countries that exporting oil across all examined periods. However, during the shocks, low-income countries and the overall dataset revealed a co-movement of food and oil prices in the long-run. The study underscored the economic structure and crisis events are crucial in shaping the dynamics and relationships between food and oil markets. In contrast, for short term divergence market factors propel them to equilibrium in the over the long term, with countries of low-income showing indifference because of their limited ability to manage the rising of food supply and demand.

Zmami et al. [48] assessed the macroeconomic implications of fluctuations in oil price, especially the relationship between the prices of oil and food. The study examined aggregated and disaggregated studies of the relationship between the price of West Texas Intermediate (WTI) and Brent oil and the price of food globally using linear connections between January 1990 and October 2017. The study utilized autoregressive distributed lag (ARDL) models, both nonlinear and linear, to investigate the correlations among the variables under investigation. The findings showed that, over time, positive shocks to oil prices are the only factors that affect the overall price of food. Additionally, specific agricultural commodity prices display short-term asymmetries, responding solely to the decreases of oil price. The study suggested that assuming an equal impact in both directions of food and oil prices might be oversimplified, emphasizing the need for nuanced considerations in future research and policy formulations to address food insecurity.

Tárik [49] addressed the escalating food security crisis in North Africa and in the Middle East. In addition, this research emphasized the impact of Western sanctions on Russia and their impact in causing a surge in the global energy and food prices. The research also highlighted the Russian invasion which prompts Ukraine to restrict wheat and grain exports, posing a substantial challenge as the two countries contribute significantly to global wheat exports. It also examined the impact of COVID 19 pandemic on the global supply chains, public health, and food and energy security. It also highlighted the Economic challenges, conflicts, and the current crisis. It revealed the urgent necessity for solutions that can find alternative wheat sources.

Table 1
Comparison between different previous studies.

Ref	Theory Discussed	Effective Crises	Studied Variables	Region/Countries	Period of Time Covered	Model Used	Findings
[36]	Food price transmission theory	geopolitical events in Russia	global energy, and food prices	Eastern and Western Europe	January 2001 to March 2022	Cross-quantilogram (CQ) approach sophisticated econometric method	Geopolitical risks lead to a decrease in short term food prices in Eastern Europe, but conversely, they result in an increase in prices in Western Europe.
[37]	Food price transmission theory Keynesian Economics:	Russian-Ukrainian (RU) conflict	Energy price shocks on wellbeing And eight dimensions of human needs	both developed and developing countries (49 countries/ regions)	Data of 2022	An integrated framework is proposed (to merge the Extended Linear Expenditure System (ELES) model, the output-input price model, and the quantification of basic human needs).	The material dimension “Protection” and Non-material dimension “Creation” are the human needs most profoundly impacted on a global scale, witnessing declines ranging from 3.7% to 8.5% and 3.6%–8.4%, respectively.
[38]	Price Transmission Theory:	Russia-Ukraine war COVID-19 Pandemic	global energy prices (crude oil and refined product prices)	major exchanges in the United States and the European Unions	pre-COVID-19 and pre-war, Feb. 2019 to Feb. 2020), P1 (during COVID 19 and pre-war, Feb. 2021 to Feb. 2022), and P2 (during both COVID 19 and the war, Feb. 2022 to Feb. 2023)	dynamic cross-correlation analyses bivariate and multivariate cross-correlation methods	the war’s impact on European diesel prices is higher compared to the US diesel. significant differences between P0 and the other periods
[39]	Supply and Demand Theory Microeconomics	Russia-Ukraine conflict	global food security, focusing on the substantial impact on wheat production in Ukraine and trade disruption.	Global markets	wheat production in Ukraine in 2022	the general equilibrium trade model	reveals potential trade drops, soaring wheat prices, and severe food insecurity
[40]	Supply Chain and Demand Theory	Russia-Ukraine conflict	energy companies’ stock prices through a sample of 1630 global energy companies	Global energy firms and Capital Market	Russia’s invasion on Feb. 24, 2022	Cumulative Average Abnormal Returns (CAAR), Robustness Test	North American energy firms exhibited the highest outperformance compared to European and Asian counterparts
[24]	Supply Chain and Demand Theory Price Transmission Theory:	Russia-Ukraine conflict Covid-19 Energy crises	global food security, emphasizing the intricate relationship between armed conflicts and food insecurity	global food security	February 2020–February 2022	Price volatility analysis	food and fertilizer prices have rapidly increased, affecting every farmer on Earth. The fluctuation of major food goods and fertilizers lead a distinct threat as it produced greater market uncertainty, which may impact on the production decisions and spur speculative actions.

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Table 1 (*continued*)

Ref	Theory Discussed	Effective Crises	Studied Variables	Region/Countries	Period of Time Covered	Model Used	Findings
[19]	Supply Chain and Demand Theory Price Transmission Theory:	Russia's invasion of Ukraine	global commodity prices, particularly in food and energy markets (15 key global commodity price indices)	Global Prices	January 2010 to July 2022,	complementary dimensions of synchronization analysis vector, correlation, and autoregressive models by applying the Harding and Pagan synchronization measurement	disruptions in grain, energy, and fertilizer supply chains heightened the co-movement of prices globally
[20]	Price Transmission Theory,	Russian-Ukrainian war, Covid 19 pandemic, and 2008 global financial crisis, the collapse of Lehman Brothers bank on Sep. 2008, the announcement of lockdown in Italy on Sep. 2020, and the invasion day on Feb. 2022, respectively.	global financial markets (stock markets and commodities)	Global Financial Crisis	Between 2008 and 2022	Synchronization, duration, and intensity measures, Descriptive statistics, heterogeneous autoregressive model, *Realised variance* (RV) markov-switching HAR model on volatility proxies, estimates are made of synchronization, duration and intensity measures for each event	The war's short-term consequences include lower economic growth and rising inflation, with potential long-term implications for energy security, affordability, and the transition to a low carbon economy
[49]	Supply Chain and Demand Theory Price Transmission Theory,	Western sanctions on Russia and their impact in causing a surge in the global energy and food prices, Russian invasion which prompts Ukraine to restrict wheat and grain exports, influence of COVID 19 pandemic	food security crisis, Russian invasion which prompts Ukraine to restrict wheat and grain exports. public health, global supply chains, energy security, and food	North Africa and in the Middle East (Arab World)	2020–2022	Statistical reports	the urgent necessity for solutions that can find alternative wheat sources
[41]	Price transmission theory Supply and Demand Theory	Ukraine-Russia war	food security in the region. The study examined eight regional economic communities in Africa to address the food and energy policy implications, economic consequences, trade effects, and diplomatic relations with Russia.	African countries, especially on regional economic communities Daily WTI Spot Price and Brent Spot Price	2020–2022	timeline analysis	emphasized the need for proactive measures, warned against a passive approach, and focus on the value of strategic investments in food policy and the energy sector for African self-reliance amid global geopolitical complexities.
[42]	Theory of Comparative Advantage Keynesian Economics Price transmission theory Supply chain and Demand Theory	Global Financial Crisis (GFC), the COVID 19, and the Ukraine-Russia war	cocoa and gold prices timber exports and oil and gas imports timber exports and gas and oil imports	macroeconomic indicators in the Ghanaian economy	2008 M1 to 2023 M	descriptive approach comparative analysis	the Russian-Ukraine war impacted unprecedentedly high values in the exchange rate, non-food and food inflation, and gas and oil prices, reflecting the worst economic growth

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Table 1 (*continued*)

Ref	Theory Discussed	Effective Crises	Studied Variables	Region/Countries	Period of Time Covered	Model Used	Findings
							record compared to other shocks
[43]	Price transmission theory	Russo–Ukrainian conflict Brexit, COVID-19	geopolitical risk and the prices of vital food commodities (rice, corn, and wheat)	Global economy	2012–2022	Correlation analysis, causality relationships between the prices of rice, corn, and wheat and time series of geopolitical risks	The results demonstrated a one-way causality relationship. Geopolitical forces notably impact the prices of food
[44]	Keynesian Economics Institutional Economics Supply and Demand Theory	Russia-Ukraine conflict	Import food from Ukraine and Russia on the food insecurity	Gulf countries	2000 to 2021	correlation and linear regression analysis descriptive statistics	revealed a strong positive correlation and a moderately positive relationship. GCC showed a good effort to enhance agricultural independence and bolster food security
[45]	Price transmission theory Supply and Demand Theory	food crises	causal cointegration relationship between oil and food prices	21 countries characterized by being both food-importing and oil-exporting economies	2001 to 2015	Panel Autoregressive Distributed Lag (panel ARDL) model to analyze the long run relationship between variables in panel data settings	there are short-term favorable impacts but long-term negative implications between the price of food and oil
[46]	Price transmission theory	oil price shock	dynamic interaction between the global crude food price and oil price indices		monthly dataset (Jan. 1990–June 2017)	linear (co-integration, stationarity, and linear Granger causality), nonlinear framework (asymmetric adjustment analyses, integrating (TVAR) and (TVECM) mechanisms)	food and oil prices have negative consequences, but over time, there are good effects as well.
[47]	Price transmission theory	oil price shock	food market, particularly in oil-exporting economies,	Selected countries from Africa, America and Middle East	before the crisis (2000–2013) and during the crisis (2013–2019)	aggregate analysis	economic structure and crisis events play crucial roles in shaping the dynamics and relationships between food and oil markets.
[48]	Price transmission theory	oil price shock	oil price fluctuations, with a specific focus on oil-food price relationship	Assessments both combined and separated, of how the price of (WTI) and Brent oil affects the price of food worldwide	January 1990 to October 2017	macroeconomic implicationsl inear and nonlinear autoregressive distributed lag (ARDL) multiresolution analysis timeseries forecasting	food price is affected only by positive shocks to oil prices in the long-run. Additionally, certain agricultural commodity prices display short-term asymmetries, responding solely to oil price decreases

On the other hand, various researchers have investigated the effects of international and local events on stock markets, food security indices, and prices. Many events have been considered by these researchers, such as air quality [50], Ramadan Effects [51], Syrian Refugee Influx [52], Crop yield indices [5], and oil prices [53]. Table 1 shows several studies that discussed food security issues and several crises that occurred recently. The table presents the theory discussed in these presented research (i.e. Supply and Demand Theory, Price Transmission Theory, Keynesian Economics, Classical Economics, Monetarism, Neoclassical Economics, Behavioral Economics, etc.), the studied crises, the studied variables, the analytical model used, and the main findings of the presented research.

3. Research methodology

3.1. Ethical statement

We confirm that ethical approval was not required for this study as it involved secondary data analysis and did not involve direct interaction with human participants. However, informed consent was obtained for datasets included in the study. The study adhered to the principles outlined in the Declaration of Helsinki.

3.2. Data collection

The dataset was collected from different resources to achieve the objective of the study. Food price indices are calculated based on the monthly fluctuations in global prices of a basket of a variety food commodity. The food price indices contain Meat, Dairy, Cereals, Oils, Sugar, and Food Price Index. The first five indices are the primary food indices of food commodities. The indices are collected from the Food and Agriculture Organization (FAO) of the United Nations website [54]. In addition, two leading monthly and yearly crude oil indices, particularly West Texas Intermediate (WTI) Crude and Brent crude, are used to predict the food indices. The crude oils are collected from the link finance.yahoo.com.

Moreover, the Russo-Ukrainian war and COVID-19 events are considered in this research to understand the influence of the war on monthly food prices. The events are dummy variables (i.e., 0 and 1). In this study, a COVID-19 dummy variable is used to eliminate the influence of COVID 19 on food price indices. The selected data resources are characterized by their innovativeness reliability, originality, and dependability. This is due to their importance for international economic communities, organizations, stakeholders, and policymakers. This will add to the valuable role of this research and its impact on decision making globally.

As a first step in maintaining the integrity of statistical analyses and ensuring the robustness of results, it is imperative to identify and exclude outlier data points that exhibit substantial deviation from the central tendency of the dataset. The removal of such outliers, characterized by their considerable distance from the mean or median, aims to enhance the reliability of subsequent statistical inferences and prevent undue influence on the overall analysis. Employing established methods such as Z-scores, interquartile range (IQR), or machine learning models designed for anomaly detection facilitates a systematic and scientifically grounded approach to identify and appropriately handle outliers, thereby fostering the accuracy and validity of statistical outcomes. In addition, measuring the dispersion of the employed dataset is essential to guarantee the normal distribution of the variables, which will help smoothly use several statistical approaches (i.e., Pearson Correlation analysis, etc.). Besides, descriptive statistics analysis for the selected dataset is calculated to understand the nature of data in order to find the main characteristic of the dataset. This would help in selecting the appropriate statistical and regression models and to ensure the robustness of the results. Afterward, median, maximum, minimum, variance, standard deviation, and mean were calculated, then feature engineering was implemented to construct features with predictive power from the collected dataset. Consequently, following the completion of all preceding mentioned procedures, a total of 129 observations of data samples persists in the dataset. The descriptive statistics analysis is shown in Table 2. The descriptive statistics analysis showed that eleven years from 2012 to 2022 are used with a monthly value for each independent variable. However, various variables were adopted (i.e. year, month, Cushing OK WTI Price in ($/Barrel), Europe Brent Spot Price in ($/Barrel), COVID_19, Russian Ukraine Conflict, the index of Meat price in (points), the index of Dairy price in (points), the index of Cereals price in (points), the index of Oils price in (points), the index of Sugar price in (points), and the index of Food price in (points).

Table 2
Descriptive statistics for the selected dataset.

	N	Minimum	Maximum	Mean	Std. Deviation	Variance
Year	129	2012	2022	2016.88	3.117	9.713
Month	129	1	12	6.40	3.433	11.788
Cushing OK WTI Price ($/Barrel)	129	16.55	114.84	68.0204	23.36099	545.736
Europe Brent Spot Price ($/Barrel)	129	18.38	125.45	74.0424	26.79526	717.986
COVID_19	129	0	1	0.27	0.446	0.199
Russian Ukraine Conflict	129	0	1	0.06	0.242	0.059
Meat (points)	129	84.9	159.7	108.472	17.0316	290.077
Dairy (points)	129	84.2	125.9	102.076	8.9369	79.869
Cereals (points)	129	72.7	156.5	111.571	20.5595	422.695
Oils (points)	129	86.00	173.50	112.2202	21.60320	466.698
Sugar (points)	129	76.6	251.8	115.836	35.2118	1239.873
Food Price Index (points)	129	63.2	149.3	99.800	19.8994	395.985

3.3. Phase one: correlation analysis and feature selection

After the data collection, the collected datasets are merged into one dataset to extract the relationship between dependent and independent variables. To examine the correlation between variables, Pearson correlation analysis and linear regression analysis are used to select the features that must be employed in constructing a predictive model. The feature selection method aims to enhance the prediction model of the proposed model by minimizing the number of effective independent variables in the proposed predictive model. In addition, the linear regressive model is used to show the most affected crude oil index on the food price indices. To calculate the correlation between two variables A and B, Pearson correlation can be calculated using Equation (1).

$$Pearson\ Correlation = \frac{N\sum ay - (\sum a)(\sum b)}{\sqrt{\left[N\sum a^2 - (\sum a)^2\right]\left[N\sum b^2 - (\sum b)^2\right]}} \tag{1}$$

3.4. Phase two: the influence of the independent variable on the indices of food price

The output of the first phase is forwarded to the second phase to build a linear regression model and to find the influence of independent variables on the indices of food price. The second phase aims to understand and extract the linear relationship between dependent and independent variables. The test adopted determination coefficient (R^2), error, analysis of variance (ANOVA), variables coefficients, variance inflation factor (VIF), t-value, F-value, and *P*-value. The aim of using VIF is to avoid the multicollinearity problem in the created models since two crude oils are used. For each food price index, one linear regression equation is created using year, month, one of the crude oil, Russo-Ukrainian war dummy variable, and COVID-19 dummy variable. Based on the collected results of the previous models, the study can explain the influence of the war between Russia and Ukraine on the food indices.

Therefore, the linear regression equation of the Food Index for dairy, meat cereals, sugar, oils and food price index is calculated using equations (2) and (3).

$$Food\ \ Index = \beta_0 * 1 + \beta_1 * v_{i1} + \ldots + \beta_n * v_{in} + \varepsilon_i \tag{2}$$

$$Food\ \ Index = \beta * {v_i}^T + \varepsilon \tag{3}$$

where Food Index is the vector of one of the food price indices values, T denotes the transpose operation for either a vector or a matrix, so that $\beta * {v_i}^T$ is the inner product. The β values are generated from the linear regression model, where v is the independent variable used in the study. The variables are mainly year, month, one of the crude oil, Russo-Ukrainian war dummy variable, and COVID-19 dummy variable.

The statistical hypotheses test is computed for the proposed model to draw inferences about the characteristics of a population based on information obtained from a sample and provide a systematic and formalized approach to decision-making in the presence of uncertainty as the following:

$$\beta_i = \{\text{Year, Month, COVID} - 19, \text{Russian Ukraine, and Europe Brent Price}\}$$

H0.1. The regression coefficients (β_i) for variables in the Food Price Index model are zero.

H0.2. The regression coefficients (β_i) for variables in the Meat Index model are zero.

H0.3. The regression coefficients (β_i) for variables in the Dairy Index model are zero.

H0.4. The regression coefficients (β_i) for variables in the Cereals Index model are zero.

H0.5. The regression coefficients (β_i) for variables in the Oils Index model are zero.

H0.6. The regression coefficients (β_i) for variables in the Sugar Index model are zero.

3.5. Phase three: forecast the food price indices using the SARIMA model

Linear regression shows a linear relationship between input and output variables. To construct a comprehensive forecasting model capable of predicting food price indices accurately, this study employed the Seasonal Autoregressive Integrated Moving Average model (SARIMA). SARIMA, recognized for its effectiveness in short-term forecasting, necessitates a minimum of 40 historical data points for robust performance. The underlying assumption of SARIMA is that the data lacks a trend and is non-stationary. The model utilizes the errors and observations from the preceding period to inform the current one.

Utilizing SARIMA involves a series of key steps, encompassing the identification of the Seasonal Cycle, recognition of Autoregressive (AR) and Moving Average (MA), as well as Seasonal Autoregressive (SAR) and Seasonal Moving Average (SMA) Terms. The SARIMA model comprises several parameters, namely d, p, and q, representing the degree of differencing, autoregressive model order, and the moving-average model order, respectively. Additionally, the parameters P, Q and D, signifying the seasonal autoregressive process, seasonal moving process, and seasonal difference process were determined. It is crucial to consider standard seasonal cycles, such as monthly, quarterly, or yearly patterns. In this investigation, a meticulous examination of the data was conducted, with the monthly determination of data seasonality using equation (4) [55]:

$$SARIMA(Food\ Index) = AR(1,1)_{e_{t-1}} + AR(1,2)_{e_{t-2}} \ldots\ldots + AR(1,p)_{e_{t-p}} + MA(1,1)_{y_{t-1}} + + AR(2,2)_{e_{t-2T}} + AR(2,P)_{e_{t-TP}} + MA(2,1)_{y_{t-T}} + MA(2,Q)_{y_{t-TQ}} \quad (4)$$

The model is then estimated using Historical data that are used to estimate the model, and to compute its performance using statistical metrics and diagnostic checks. This step ensures the model accuracy and robustness for forecasting. By employing PACF and ACF to determine AR and MA terms, and specifying the seasonality monthly, the methodology aims to construct a SARIMA model tailored to the temporal dynamics of the data. The seasonal cycle was calculated for the proposed SARIMA model as 12. While other terms including MA and AR will be presented in the next tables.

4. Results analysis and discussion

This section presents Pearson correlation, linear regression, and SARIMA results for food price indices as dependent variables and year, month, crude oils, Russian-Ukrainian war, and COVID-19 as independent variables. Notably, to avoid the similarity and redundancy of the results, only the proposed model's primary results are presented in the paper from Tables 4–6, besides the multi-collinearity test is presented in Table 6.

4.1. Correlation analysis and feature selection results

To understand the linearity relationship between dependent variables namely Food price index Dairy, Meat, Oils, Sugar, and Cereals and independent variables including Year, Month, Cushing OK WTI, Europe Brent, COVID 19, and Ukraine Russian war, the Pearson correlation is used. A *P*-value is considered in this study to avoid the chances of a correlation relationship. The correlation results are shown in Table 3; the year variable showed no significant relationship with food, meat, dairy, and cereals, whereas, with oils and sugar, the model is significant with a low relationship. The month variable showed no significant relationship with all variables. The COVID-19 variable is significant with all dependent variables except sugar. The strength of the relationship is between low and medium, with a correlation coefficient of no more than 0.6.

The Russo-Ukrainian war variable showed a significant correlation of more than 0.5 for the price index of food, cereals, meat, and oils, where sugar and diaries did not show a significant and significant decrease (i.e., 0.421), respectively. Moreover, both crude oils showed a medium to high correlation with the dependent variables; all the significant relationships between independent and dependent variables are positive. The analysis showed that WTI and Brent crude have a strong relationship that will create a multi-collinearity problem, so using both crude oils to develop the linear regression model will create an incorrect linear regression model.

This study uses Month, year, Russian-Ukraine, COVID-19, and Brent as independent variables to develop linear regression models for the Food price index, Oils, dairy, Cereals, meat, and Sugar. Brent is chosen over WTI since Brent reflects the core price of oil better than WTI.

4.2. Phase two: food indices linear regression models

The significant results indicated that COVID 19 and the war between Ukraine and Russia positively affected all food indices, including the food price index, oils, dairy, cereals, meat, and sugar, where the index of sugar did not show any significant changes—the result s variables on dependent variables. Five independent variables are used to build linear regression models: year, month, brent oil index, COVID-190, and Russian Ukraine war dummy variable. The independent variables are used to build food indices, namely the Food price index, oils, dairy, cereals, meat, and sugar, as shown in Table 4. The R^2 values for Food Price Index, oils, dairy, cereals, meat, and sugar models are 0.88, 0.73, 0.71, 0.84, 0.71, and 0.43, respectively, with the error values ranging from 5 to 19. Linear regression

Table 3
Correlation analysis.

		Food price index	Oils	Dairy	Cereals	Meat	Sugar
Year	Corr	0.280[a]	0.280[a]	0.006	0.032	0.070	−0.351[a]
	Sig.	0.001	0.001	0.950	0.718	0.433	0.000
Month	Corr	−0.108	−0.108	−0.053	−0.071	0.056	−0.043
	Sig.	0.222	0.222	0.551	0.424	0.527	0.625
Cushing OK WTI	Corr	0.588[a]	0.588[a]	0.807[a]	0.771[a]	0.752[a]	0.591[a]
	Sig.	0.000	0.000	0.000	0.000	0.000	0.000
Europe Brent	Corr	0.544[a]	0.544[a]	0.771[a]	0.772[a]	0.711[a]	0.583[a]
	Sig.	0.000	0.000	0.000	0.000	0.000	0.000
COVID_19	Corr	0.554[a]	0.554[a]	0.209[b]	0.391[a]	0.319[a]	−0.028
	Sig.	0.000	0.000	0.017	0.000	0.000	0.757
Russian Ukraine	Corr	0.632[a]	0.632[a]	0.421[a]	0.549[a]	0.559[a]	0.198[b]
	Sig.	0.000	0.000	0.000	0.000	0.000	0.024

[a] Significant at the 0.01 (2-tailed).
[b] Significant at the 0.05 (2-tailed).

Table 4
The regression models summary.

Model	Name	R	R^2	Adjusted R^2	Error
1	Food Price Index	0.940	0.88	0.88	5.91
2	Oils	0.853	0.73	0.72	18.75
3	Dairy	0.841	0.71	0.69	11.36
4	Cereals	0.919	0.84	0.84	8.70
5	Meat	0.842	0.71	0.70	4.91
6	Sugar	0.659	0.43	0.41	15.26

Table 5
The ANOVA analysis for all developed models.

		Sum Squares	df	Mean Square	F	Sig.
Food Price Index	Reg.	32,834	5	6567	188	0.000[b]
	Res.	4295	123	35		
	Tot.	37,130	128			
Oils	Reg.	115,478	5	23,096	66	0.000[b]
	Res.	43,225	123	351		
	Tot.	158,704	128			
Dairy	Reg.	38,245	5	7649	59	0.000[b]
	Res.	15,860	123	129		
	Tot.	54,105	128			
Cereals	Reg.	50,431	5	10,086	133	0.000[b]
	Res.	9307	123	76		
	Tot.	59,737	128			
Meat	Reg.	7253	5	1451	60	0.000[b]
	Res.	2970	123	24		
	Tot.	10,223	128			
Sugar	Reg.	22,036	5	4407	19	0.000[b]
	Res.	28,651	123	233		
	Tot.	50,686	128			

models showed that the independent variables effectively predicted the food, meat, dairy, oils, and cereals price index, whereas the sugar index showed a very low prediction rate. All linear regression models are linearly significant, as shown in Table 5.

For all the developed linear regression models, the VIF values did not exceed 10, indicating no multicollinearity problem is found, as shown in Table 6. The coefficients' analysis of the food price index, meat, and oils models showed that the most three important variables (from most to least) are Brent, COVID 19, and war between Ukraine and Russia. The top three variables for the diary model are brent, year, and COVID-19, whereas for cereals model, the top variables are brent COVID-19, and year. For the sugar model, the results showed a significant relationship with a constant value, which indicates that the model is rejected, and additional variables should be added or removed to optimize the performance of the linear-regressive model. On average, the results showed a positive influence of the Brent oil, COVID- 9, and Ukraine-Russia war on food price indices. Finally, to improve the linear equations of previous models and forecast for the next six years, SARIMA models are adopted without dependent variables. The authors utilized the Variable Inflation Factor (VIF) to evaluate the presence of multi-collinearity in the developed model. Consistent with recommendations from previous research, a VIF value below 10 indicates the absence of problematic multi-collinearity issues [56,57]. Table 6 shows that all model variables have VIF values below 10, suggesting that the interactions between the independent variables are negligible.

To test the credibility and stability of the model's assumptions. The modified Breusch-Pagan Test is used to validate the stability of the developed models, as shown in Table 7.

The findings of the Modified Breusch-Pagan Test for Heteroskedasticity are outlined in Table 7, offering valuable insights into the assumption of consistent variance within regression models for diverse variables. Operating under the premise of homoscedasticity, the null hypothesis (H0) asserts that the variance of errors remains uniform across all levels of the independent variables. Conversely, the alternative hypothesis (Ha) posits the existence of heteroskedasticity, suggesting variable variances. The table details each variable, including the chi-square statistic, degrees of freedom, and corresponding p-values. Rejecting the null hypothesis is evident for the "Food Price Index," supported by a chi-square statistic of 3.968 at a significance level of 0.046. Similar conclusions are drawn for variables such as Cereals, Oils, and Sugar, where markedly low p-values substantiate the presence of heteroskedasticity. However, Meat's marginal p-value of 0.077 indicates a less decisive indication of heteroskedasticity.

To solve the heteroscedasticity problem in the previous dataset, researchers have suggested using a logarithmic transformation to the Brent variable, prompting an evaluation through the Modified Breusch-Pagan Test. For the Food Price Index, a marginal deviation from homoscedasticity is implied by a chi-square statistic of 3.192 at a significant level of 0.074. In contrast, Meat exhibits more persuasive evidence, featuring a chi-square of 4.523 and a significant level of 0.033. *P*-values exceeding 0.05 for variables like Dairy and Cereals indicate homoscedasticity in these independent variables. Conversely, Oils and Sugar demonstrate very low p-values, signifying robust evidence of heteroskedasticity. These results underscore potential variations in error variance among commodities, underscoring the imperative of integrating robust regression modeling to account for the presence of heteroskedasticity effectively.

Table 6
The coefficient values of the developed models.

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	VIF
		B	Std. Error	Beta			
1	(Constant)	1010	681		1.48	0.14	
	Year	−0.47	0.34	−0.09	−1.39	0.17	4
	Month	−0.10	0.15	−0.02	−0.62	0.54	1
	COVID_19	18.43	1.94	0.48	9.48	0.00	3
	Russian Ukraine	14.34	2.92	0.20	4.91	0.00	2
	Europe Brent Price	0.46	0.03	0.73	17.09	0.00	2
2	(Constant)	−203	566		−0.36	0.72	
	Year	0.14	0.28	0.05	0.50	0.62	4
	Month	0.28	0.13	0.11	2.22	0.03	1
	COVID_19	5.41	1.62	0.27	3.35	0.00	3
	Russian Ukraine	7.70	2.43	0.21	3.17	0.00	2
	Europe Brent Price	0.23	0.02	0.70	10.36	0.00	2
3	(Constant)	−3974	1308		−3.04	0.00	
	Year	2.00	0.65	0.30	3.09	0.00	4
	Month	0.04	0.29	0.01	0.15	0.88	1
	COVID_19	4.18	3.73	0.09	1.12	0.27	3
	Russian Ukraine	−3.00	5.61	−0.04	−0.53	0.59	2
	Europe Brent Price	0.70	0.05	0.91	13.42	0.00	2
4	(Constant)	2673	1002		2.67	0.01	
	Year	−1.29	0.50	−0.19	−2.61	0.01	4
	Month	−0.20	0.23	−0.03	−0.90	0.37	1
	COVID_19	26.00	2.86	0.54	9.09	0.00	3
	Russian Ukraine	15.75	4.30	0.18	3.66	0.00	2
	Europe Brent Price	0.56	0.04	0.70	14.18	0.00	2
5	(Constant)	1814	2158.93		0.84	0.40	
	Year	−0.87	1.07	−0.08	−0.81	0.42	4
	Month	−0.71	0.49	−0.07	−1.45	0.15	1
	COVID_19	43.48	6.17	0.55	7.05	0.00	3
	Russian Ukraine	39.81	9.26	0.27	4.30	0.00	2
	Europe Brent Price	0.64	0.09	0.48	7.41	0.00	2
6	(Constant)	7962	1758		4.53	0.00	
	Year	−3.91	0.87	−0.61	−4.49	0.00	4
	Month	−0.26	0.40	−0.05	−0.66	0.51	1
	COVID_19	18.07	5.02	0.41	3.60	0.00	3
	Russian Ukraine	14.62	7.54	0.18	1.94	0.05	2
	Europe Brent Price	0.25	0.07	0.33	3.53	0.00	2

Table 7
Modified Breusch-Pagan test for heteroscedasticity.

Variables		Chi-Square	df	Sig.
Year	Food Price Index	3.968	1	0.046
Month	Oils	13.265	1	0.000
COVID_19	Dairy	0.113	1	0.736
Russian Ukraine	Cereals	9.915	1	0.002
Europe Brent Price	Meat	3.134	1	0.077
	Sugar	26.846	1	0.000
Year	Food Price Index	3.192	1	0.074
Month	Oils	11.875	1	0.001
COVID_19	Dairy	0.595	1	0.441
Russian Ukraine	Cereals	1.036	1	0.309
log (Europe Brent Price)	Meat	4.523	1	0.033
	Sugar	29.290	1	0.000

This indicates that linear regression models for Food Price Index, Meat, Dairy, and Cereals are robust compared to other models in Table 7.

4.3. *Forecast the food price indices using the SARIMA model*

SARIMA models aim to develop an optimized linear equation without independent variables using a complex linear equation based on moving average and autoregression variables. The optimized equation allows us to forecast the next six years without extra independent variables. The SARIMA models are built for all the food price indices, as shown in Table 8.

To validate the capability of the SARIMA models in food indices prediction, R^2 and Root Mean Square error (RMSE) are used, as

Table 8
The developed SARIMA models.

	Model	Model Type
Food_Price_Index	1	ARIMA (1,1,0) (0,0,0)
Oils	2	ARIMA (1,1,0) (0,0,0)
Dairy	3	ARIMA (1,1,0) (0,0,0)
Cereals	4	ARIMA (0,1,1) (0,0,0)
Meat	5	ARIMA (1,1,0) (1,0,1)
Sugar	6	Simple Seasonal

shown in Table 9. The results showed that all the models have R^2 more than 0.9 with RMSE values between 1 and 9. Dairy, Food_Price_Index, and Meat are the top three models with the highest prediction rate, with 97.5%, 97.2%, and 96.6, respectively. Moreover, to check the autocorrelation problem, the Ljung-Box test is used. The results of all the SARIMA models showed that a p-value >0.05 gives enough statistical events not to reject the null hypothesis. The null hypothesis defined that the time series isn't autocorrelated. The results of the Ljung-Box test showed that all food price indices models rejected the possibility of autocorrelation, as shown in Table 9. On the other hand, the full information of AR and MV values for all the models are shown in Table 10.

All SARIMA models are forecasted until December 2027, as shown in Table 11 and Fig. 1. The expected values for food indices, oils, dairy, cereals, meat, and sugar were 109, 157, 131, 142, 141, and 180, respectively, at the end of 2027. In addition, the results showed the upper control limit and the lower control limit for the next six years. The upper control limit for meat, dairy products, cereals, oils, sugar, and food price indices are 241, 210, 246, 295, 512, and 199, respectively, at the end of 2027. Forecasting models predict that the values of the lower control limit for all models will range from 20 to 76 at the end of 2027. The lowest value in the case of the lower control limit is the food price index, with an index value equal to 20.

4.4. Results discussion

In order to enhance the depth of our conclusions, and provide more comprehensive insights, a detailed analysis of the achieved results is imperative. Studying the reflected-on forces behind the observed outcomes, understanding the implications, and exploring potential applications are crucial for deriving meaningful conclusions.

The correlation analysis between independent variables (year, month, WTI, Brent, COVID-19, Russo-Ukrainian war) and dependent variables (food indices) revealed weak to moderate correlations. While a strong relationship was found between Brent and WTI, posing a potential multicollinearity challenge if both variables are employed in developing food indices. The study utilized Brent oil for developing linear equations, considering its dominance in determining global oil prices.

On the other hand, in constructing linear regression model food indices, all dependent variables, except WTI, were employed. The outcomes showcased promising results, particularly for the food price index and cereals, exhibiting R^2 values of 0.88 and 0.84, respectively, with associated error values of 5.91 and 11.39. Coefficient analysis revealed a positive and significant relationship with Brent, COVID 19, and the Ukraine and Russia war. Notably, the impact of Brent was found to be higher than that of COVID-19, with the latter exerting a stronger influence than the Russo-Ukrainian war. Furthermore, the linear regression models demonstrated that the influence of the Russo-Ukrainian war persists.

In acknowledging the instability in oil prices and its cascading effect on food indices, it becomes evident that linear regression models, while providing valuable insights, may require more complex equations for predicting the next six years. Consequently, SARIMA models were adopted as time series models, leveraging minimal independent variables for enhanced prediction accuracy, robustness, and efficiency.

The forecasting results from SARIMA models predict the indices for the overall food price, oil, dairy, cereals, meat, and sugar at 109, 157, 131, 142, 141, and 180, respectively, by the end of 2027. These outcomes underscore the potential ramifications of unchecked food price escalation, suggesting a rising global inflation rate if regulatory measures are not implemented to curb the upward trend. This deeper analysis contributes to a more nuanced understanding of the intricate dynamics influencing global food prices and inflation.

However, the findings are in line with previous and ongoing conducted research, all global crises are influenced positively on the food insecurity, besides the results posed an urgent necessity for strategic planning and international cooperation to secure food

Table 9
The SARIMA models summary.

Model	Fit statistics		Ljung-Box Q (18)			Num. Outliers
	R^2	RMSE	Statistics	DF	Sig	
1	0.972	2.848	11.812	17	0.811	0
2	0.946	8.193	16.622	17	0.480	0
3	0.975	3.238	13.753	17	0.684	0
4	0.960	4.345	8.536	17	0.954	0
5	0.966	1.656	16.649	15	0.340	0
6	0.918	5.711	25.158	16	0.067	0

Table 10
The estimation values for the developed models.

				Estimate	SE	T	Sig.
Food_Price_Index	Natural Logarithm	AR	Lag	0.388	0.082	4.749	0.000
		Difference		1			
Oils	Natural Logarithm	AR	Lag	0.336	0.084	4.004	0.000
		Difference	1				
Dairy	No Transformation	AR	Lag	0.519	0.076	6.865	0.000
		Difference	1				
Cereals	Natural Logarithm	Difference	1				Cereals
		MA	Lag	−0.298	0.085	−3.512	
Meat	No Transformation	AR	Lag	0.591	0.072	8.267	0.000
		Difference		1			
		AR, Seasonal	Lag	0.768	0.238	3.230	0.002
		MA, Seasonal	Lag	0.603	0.294	2.052	0.042

Table 11
The forecast, upper control, and lower control limit values for the developed models until the end of December 2027.

	Meat	Dairy	Cereals	Oils	Sugar	Food price index
Forecast	141	131	142	157	180	109
Upper Control Limit	241	210	246	295	512	199
Lower Control Limit	76	51	37	75	43	20

supplies and save humanities. Additionally, policymakers can play an essential role in supporting local farmers, ensuring fair trade practices, and promoting sustainable agricultural practices to contribute long term food security problems [24,36,37,39,41,44].

5. Conclusion and future work

This study examined the influence of Brent crude prices, coronavirus, and the Russia and Ukraine war on meat, dairy products, grains, oils, sugar, and food price indices. To extract the relationship between dependent and independent variables, the study used Pearson correlation, linear regression, and SARIMA models. For the SARIMA models, food price indices without independent variables were developed to forecast the next six years until the end of 2027. Correlation analysis showed that the relationship between dependent and independent variables ranged from low to medium. The most correlated variable was a brent oil. Afterward, the linear regression model is used to build a regression model to extract the most important variables on food indices. The average results showed that the most important variables in developing a linear equation are (from most to least important) the crude Brent oil, the COVID-19 variable, and the Russo-Ukrainian war. Moreover, the best result of the food price index was recorded using the year, month, crude brent oil, COVID 19, and Ukrainian-Russo war with R^2 and error rate of 0.88 and 6, respectively.

For SARIMA model, the average result showed that SARIMA models are more accurate, robust, and efficient than linear regression with a minimum R^2 was 0.958 and RMSE of 4.33. The results indicated that the time series linear equation fits the food indices more accurately than the linear regression equation. However, the authors believe that more comprehension and expanded study should be conducted. This is due to various limitations that scope in the current study. Particularly, the limitation in selecting the variables that limited number of variables were considered in this study based on their availability in the time of conducting the research, which may have overlooked other important influencing factors. In addition, the time span of this study is only 11 years of monthly data, which reflects short term impact and does not reflect the long-term impact. Besides, the study only focuses on the global food price index and does not consider regional differences. On another hand, the study is limited to correlation and prediction models, and does not explore the deep causal mechanism between the selected variables. As a result, the study's projection period is only up to 2027, and the medium- and long-term impacts are not clear because as clarified earlier it's only a short-term study. Putting all these together will concentrate on the current study.

In future work, extra food indices must be considered with other independent variables (i.e., air pollution, international stock indices, the inflation rate, and so forth). Besides, nonlinear forecasting models should be implemented to validate and enhance future prediction. The study could be expanded to include data from other countries and regions to analyze the heterogeneity and regionality of global food safety. In addition, long-term impact should be considered.

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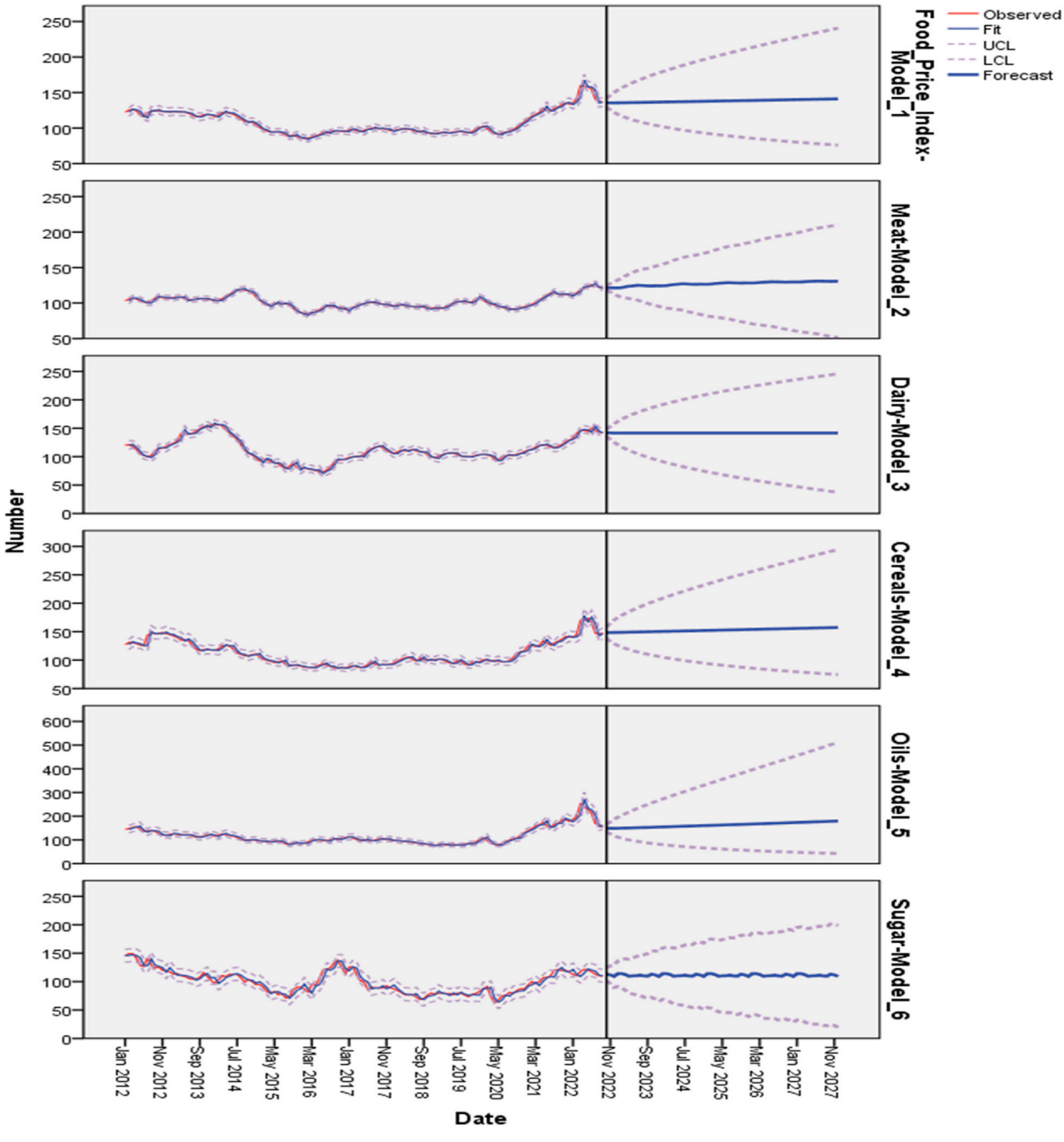

Fig. 1. Forecast the developed models using the SARIMA model.

Data availability statement

All data that can reproduce the results in this study are available upon request.

CRediT authorship contribution statement

Nadia AL-Rousan: Writing – review & editing, Writing – original draft, Software, Resources, Methodology, Investigation, Formal analysis, Data curation. **Hazem AL-Najjar:** Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Formal analysis, Data curation. **Dana AL-Najjar:** Investigation, Funding acquisition.

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.

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