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Predicting the differences in food security with and without the Russia–Ukraine conflict scenarios over different regions of the world

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Abstract

The Russia–Ukraine conflict has caused a global food security crisis, impacting sustainable development goals. Predicting the crisis's impact on food security is crucial for global stability by 2030. From a macro-perspective, this paper constructs a food security evaluation indicator system and a food security composite index (FSCI), and using the autoregressive integrated moving average model to predict the variations in the FSCI for different regions of the world from 2023 to 2030 under scenarios with or without the "Russia–Ukraine conflict." By quantitatively analyzing the differences in these variations, the potential impact of the conflict on regional food security is assessed. The results conclude that the global food security level progressively improved over the past 20 years. The FSCI in Europe, Latin America and Caribbean increased at a faster pace than the global average, with growth rates of 0.035/(10 years) and 0.034/(10 years), respectively. However, the FSCI in the Sub-Saharan Africa showed a declining trend. By 2030, it is expected that the Russia–Ukraine conflict will have a significant impact on the food security of Europe and Sub-Saharan Africa, with a contribution of 1.49% and 0.29%, respectively. However, the impact of the conflict on food security levels in Asia and Latin America and Caribbean is relatively small. This study introduces a new quantitative method to assess and project the overall influence of the Russia–Ukraine conflict on food security. The findings contribute crucial scientific support for effectively evaluating and monitoring the sustainable development objectives related to global food security.

Keywords: Russia–Ukraine conflict, Food security, Sustainable development, Indicator system, ARIMA model

Introduction

Since the outbreak of the Russia–Ukraine conflict in February 2022, global food production has been reduced, food price has exceeded historical high, and the food layout has changed. Moreover, the COVID-19 pandemic and other factors continue to threaten global food security. Predicting future changes in world food security trends is of great significance for achieving UN sustainable development goals (SDGs). With the escalating conflict between Russia and Ukraine, the dominant position of the two countries in the global food landscape has been gradually weakened, and the global food security situation has been deteriorating (Belik 2020; Carriquiry et al. 2022; Nasir et al. 2022; Lang and McKee 2022). Countries that are highly dependent on Russia and Ukraine are at risk of food shortages, and the international community generally believes that a global food crisis has occurred (Osendarp et al. 2022; FAO 2022; Poertner et al. 2022). The conflict, combined with other factors, will perpetuate global food insecurity and will have a profound impact on the future development of the world order, making food security an urgent issue for current global governance.

At present, there are many valuable views on the effect of the Russia–Ukraine conflict on food security at home and abroad. For instance, Nasir et al. (2022) employed a descriptive analysis approach to evaluate the influence of the conflict on global food situation from aspects such as food production, prices, and trade. Feng et al. (2023) utilized a general equilibrium trade model to analyze the potential impacts of the conflict on global food production, trade, and prices, suggesting that the conflict may result in soaring agricultural prices and reduced trade volumes, particularly for Egypt and Turkey, while major food-producing countries such as the USA and Canada may even benefit from the conflict. Lin et al. (2023) employed satellite observation data and combined it with a general equilibrium trade model to analyze the potential effects of the conflict on global wheat production and prices. Besides, food security is a comprehensive issue involving multiple dimensions, factors and hierarchies (Santeramo 2015; Upton et al. 2016). Although there have been numerous studies evaluating the impact of the Russia–Ukraine conflict on food security in the past, there is a lack of researches that systematically evaluate it as a multidimensional integrated composite indicator of food security, as well as a lack of predictions on the potential future impacts of the conflict.

Firstly, based on the previous researches, a macro-level evaluation indicator system for food security is constructed from three dimensions, namely quantity security, economic security, and resource security, using a multidisciplinary approach. Secondly, the evaluation indicators from the three dimensions are integrated into a food security composite index (FSCI) using a mixed weighting method that combines the analytic hierarchy process (AHP) and criteria importance through intercriteria correlation (CRITIC) weighting method. Additionally, a scenario analysis method is attempted to predict the variation in the FSCI between the scenarios with and without the "Russia–Ukraine conflict" during the period of 2023–2030. This aims to reflect the potential impacts of the Russia–Ukraine conflict on food security.

Construction of a macro food security evaluation indicator system

Food security has four dimensions: availability, access, utilization and stability (AAUS), which means that a situation that exists when all people, at all times, have physical, social and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life (FAO 1996; FAO 2012). The Food and Agriculture Organization (FAO) has selected 31 indicators ("Appendix": Table 6) to measure these four dimensions and has developed a set of indicators for food security, which includes both macro-level elements and micro-level nutritional security indicators (FAO 2015). Cai et al. (2020) adopted the AAUS dimensions and selected indicators such as per capita food production, average protein supply, average dietary energy supply adequacy, GDP per capita, percentage of children under 5 with stunted growth, political stability, and absence of violence/terrorism. They used a multi-indicator composite evaluation method to assess the food security levels of 172 countries from 2000 to 2014. Caccavale and Giuffrida (2020) selected indicators such as average protein supply, average dietary energy supply adequacy, rail-lines density, prevalence of undernourishment, people using at least basic sanitation services, and value of food imports over total merchandise exports. They developed a Proteus index to measure the multidimensional concept of food security and analyzed the food security situation of 185 countries over 28 years. Although the indicators selected and the constructed indicator systems in these studies cover multiple dimensions and aspects of food security, the composition of the indicators is complex and includes both macro- and micro-elements. We know that the understanding of food security varies at different scales and dimensions. The macro-level of food security emphasizes the supply and demand aspects at the national or regional scale, while the micro-level of food security focuses on the dietary needs for the health and well-being of households or individuals (Hwalla et al. 2016; Zhao and Zhong 2020). If different scale indicator elements are mixed together to construct a comprehensive index, it will inevitably overshadow the variation trends that each scale seeks to represent. Therefore, this study started from a macro-perspective and selected appropriate indicators to construct a food security evaluation indicator system and composite index.

Food security encompasses several characteristics, encompassing the aspects of quantity, economy, and resource. This multidimensionality establishes it as a comprehensive indicator system. Among them, quantity security and economic security are the fundamental components, as their sufficient supply and economic capability are essential for overall food security. In practice, quantity security, economic security, and resource security are usually interconnected and compatible with each other. Cui and Nie (2019) evaluated the evolution of food security in China from 2000 to 2018, starting from the new connotation and new goals of the concept of food security in the new era. They concluded that quantity security and economic security made greater contributions to the overall development level of food security, while the attention to resource security was relatively low. Zhang et al. (2022), based on a sustainable development perspective, found that the importance of resource security for food has been increasing. Sustainable agricultural practices have the potential to enhance yields, lower production costs, and safeguard land and water resources. Conversely, unsustainable resource management can result in reduced yields, price volatility, and economic instability, thereby exerting adverse effects on all three aspects of food security. Hence, maintaining a harmonious equilibrium among these three dimensions is of paramount importance in attaining holistic food security and offers a significant framework for envisioning the macro-pattern of food security.

This study is focused on the macro-scale of food security and, guided by principles such as systematicity, hierarchy, representativeness, operability, and scientific guidance, it constructs an evaluation indicator system for food security. Taking reference from the food security indicator system developed by FAO (Appendix Table 6), evaluation indicators are selected from three dimensions: quantity, economic, and resource security, resulting in a set of 15 specific indicators for food security evaluation (Table 1). This indicator system perceives food security as a target system, breaking it down into three key dimensions (quantity, economic, and resource security, abbreviated as QER),

Table 1 An evaluation indicator system for food security

First-layer index	Second-layer indices	Third-layer indicators	Properties
Food security composite index (FSCI)	Quantity security index (Y_1)	X_{11} : Cereal production per capita	Positive
		X_{12} : Domestic cereal supply quantity	Positive
		X_{13} : Net cereal imports	Negative
		X_{14} : Food loss	Negative
		X_{15} : Per capita food production value variability	Negative
	Economy security index (Y_2)	X_{21} : Gross domestic product per capita, PPP	Positive
		X_{22} : The agriculture orientation index for government expenditures	Positive
		X_{23} : Food consumer price index (CPI)	Negative
		X_{24} : Food price inflation	Negative
	Resource security index (Y_3)	X_{31} : Percentage of arable land area	Positive
		X_{32}: Rail line density	Positive
		X_{33} : Port container traffic	Positive
		X_{34} : Political stability and absence of violence index	Positive
		X_{35}: Control of corruption index	Positive
		X_{36} : Percentage of agricultural freshwater	Positive

A positive indicator indicates a positive influence on food security, meaning that the greater the value is, the higher the food security level. A negative indicator indicates a negative influence on food security, meaning that the greater the value is, the lower the food security level

further refined into 15 specific evaluation indicators. The weights of each indicator are calculated using a combination of AHP and CRITIC weighting methods, and the Food Security Composite Index (FSCI) is computed. This index plays a critical role as an assessment indicator for gauging the comprehensive level of food security.

Materials and methods

Data

This study aims to assess the historical trends and make future predictions regarding food security levels in Asia, Europe (EU), Latin America and Caribbean (LAC), and Sub-Saharan Africa (SSA) (Countries are listed in the appendix Table 7). It examines indicators such as food quantity, prices, trade, land area, and transportation in 86 countries worldwide from 2001 to 2022. The data used for this study are obtained from reputable sources, including the Food and Agriculture Organization of the United Nations (FAOSTAT, https://www.fao.org/faostat/), World Bank (DataBank, https://data.worldbank.org/), Agricultural Market Information System (AMIS, https://www.amis-outlook.org/home/en/), United Nations Commodity Trade Statistics Database (UNCTSD, https://comtrade.un.org/), and United Nations International Statistics Database (UNdata, http://data.un.org/Host.aspx?Content=About). Specific details of the indicators can be found in Table 2.

Table 2 Food security indicator description

Indicator	Unit	Description	Data resource
X_{11} : Cereal production per capita	Tons/1000 persons	Cereal production/total population number	FAOSTAT
X_{12} : Domestic cereal supply quantity	1000 tons	Cereal production + cereal imports—cereal exports + changes in cereal stocks (decrease or increase)	FAOSTAT; UNCTSD
X_{13} : Net cereal imports	Tons	Cereal imports—cereal exports	FAOSTAT; UNCTSD
X_{14} : Food loss	Tons	Amount of the commodity in question lost through wastage (waste) during the year at all stages between the level at which production is recorded and the household, i.e., storage and transportation	FAOSTAT
X_{15} : Per capita food production value variability	Dimensionless	Standard deviation of the per capita food production value / average per capita food production value	FAOSTAT
X_{21} : Gross domestic product per capita, PPP	$(constant 2017 international $)	Gross domestic product converted by purchasing power parity/total population number	FAOSTAT; DataBank
X_{22} : The agriculture orientation index for government expenditures	Dimensionless	Share of agriculture in government expenditures/share of agriculture in GDP	FAOSTAT
X_{23} : Food consumer price index (CPI)	Dimensionless	A measure of the monthly change in international prices of a basket of food commodities (2015 = 100)	FAOSTAT; UNdata; AMIS
X_{24} : Food price inflation	%	Fluctuation of food commodity price series in a certain period	FAOSTAT
X_{31} : Percentage of arable land area	%	Arable land area/ land area	FAOSTAT
X_{32}: Rail line density	km/(100km^2)	The total length of railway routes/ land area	FAOSTAT
X_{33} : Port container traffic	TEU: 20-foot equivalent	Port container traffic measures the flow of containers from land to sea transport modes	DataBank; UNCTSD
X_{34} : Political stability and absence of violence index	Dimensionless	One of the Worldwide Governance Indicators (WGI)	DataBank
X_{35}: Control of corruption index	Dimensionless	One of the Worldwide Governance Indicators (WGI)	FAOSTAT
X_{36} : Percentage of agricultural freshwater	%	Annual agricultural freshwater of total freshwater	FAOSTAT; DataBank

In data preprocessing, the min–max normalization method is applied to all indicators. This is done to eliminate the effects of scale, units, and variability range of variables, in order to integrate each indicator into a composite index (Chou et al. 2019; Xu et al. 2023). Positive indicators expected to have a positive impact on food security are calculated using formula 1, while negative indicators that may have a negative impact are calculated using formula 2. This study focuses on both global and regional scales, with regional data values obtained by calculating the regional average of national-level data, and global data values obtained by calculating the average of regional-level data.

$$X_{ij}^{'} = (X_{ij} - \min X_j)/(\max X_j - \min X_j) \tag{1}$$

$$X_{ij}\prime = (\max X_j - X_{ij})/(\max X_j - \min X_j) \tag{2}$$

where X_{ij} is the original data of the jth index of the ith province, $X_{ij}\prime$ is the corresponding normalized variable value, and $\max X_j$ and $\min X_j$ represent the maximum and minimum values of the jth index, respectively.

Determining the indices weights by the AHP-CRITIC mixed weighting method

Food security is a complex phenomenon, which needs to be comprehensively reflected by integrating multiple dimensions and indicators of multiple subsystems. The key to building a composite index is to determine the weight of each indicator or factor. The analytic hierarchy process (AHP) and criteria importance through intercriteria correlation (CRITIC) weighting method are used to combine food security evaluation indicators in this paper. The CRITIC weighting method is an objective weighting method that not only considers the influence of index variation on weight but also considers the conflict between indices (Krishnan et al. 2021). The AHP method is a method of subjectively determining the weight of indicators. It decomposes the evaluation objectives into different levels and indicators and compares and calculates the indicators at the same level to determine the weight of different evaluation indicators (Kim 2009; Li et al. 2018). Therefore, the AHP-CRITIC mixed weighting method adopts formula (3) to determine the weights of each indicator (Chang et al. 2019; Li et al. 2022; Zhang et al. 2022). Among them, ω_j represents the integrated weight of each indicator, $\omega_{j,1}$ represents weight calculated based on the AHP method, and $\omega_{j,2}$ represents weight calculated based on the CRITIC method.

$$\omega_j = \frac{\omega_{j,1}\omega_{j,2}}{\sum \omega_{j,1}\omega_{j,2}} \tag{3}$$

Based on the normalized data and the third-level indicators weights, the second-level index evaluation model is established to evaluate the quantity security (Y_1), economy security (Y_2) and resource security (Y_3):

$$Y_i = \sum (\omega_{ij} \cdot X_{ij}) \tag{4}$$

where Y_i represents the quantity security, economy security and resource security of the second-level indices and i represents the number of second-level indices, which is 1, 2, and 3. ω_{ij} represents the weight corresponding to third-level indicators, and j represents the number of corresponding tertiary indicators in the secondary indices. The final score of the FSCI is calculated as the sum of the scores of all three dimensions, and the final score of the FSCI is obtained. The evaluation model is:

$$FSCI = \sum (\omega_j \times Y_i) \tag{5}$$

ARIMA prediction model

The ARIMA model is used to predict the level of world food security in the future. The autoregressive integrated moving average (ARIMA) model is a widely used method in time series analysis and prediction, with a strong theoretical foundation and empirical support (Yuan et al. 2016; Ceylan 2020; Rajpoot et al. 2022). The model is based on the law and past and present historical data to estimate and infer the state of something at some point in the future (Adebiyi et al. 2014; Aasim 2019). In the ARIMA model, autoregressive (AR) and moving average (MA) components are two important constituents for modeling time series data. The autoregressive component (AR) represents the relationship between current and past observations, reflecting trends and inertia effects in the time series data. By considering the delayed effects within the time series itself, the autoregressive component can be used to predict future observations. On the other hand, the moving average component (MA) represents the relationship between current and past error terms, reflecting random fluctuations and noise in the time series data. The moving average component is utilized to capture the randomness and irregularity in the time series data. Using this model for prediction generally involves a data unit root test and stationary processing, model identification, model parameter estimation and testing steps. In the ARIMA model, the future value of the sequence is expressed as a linear function of the current and lag periods of the lag term and the random disturbance term. That is, the general form of the model is as follows:

$$\widehat{Y_t} = c + \alpha_1 Y_{t-1} + \cdots + \alpha_p Y_{t-p} + \epsilon_t + \beta_1 \epsilon_{t-1} + \cdots + \beta_q \epsilon_{t-q} \tag{6}$$

where $\widehat{Y_t}$ represents the predicted value of the model. Y_t represents the measured value of the original lagged sequence. $\alpha_1, \alpha_2 \ldots \alpha_p$ is the coefficient of the AR model, and p is the order of the AR model. $\beta_1, \beta_2 \ldots \beta_q$ denote the coefficients of the MA model, and q denotes the order of the MA model. c is a constant, and ε_t represents a white noise process.

Assumptions of scenario with or without the "Russia–Ukraine conflict"

This study employs the scenario analysis method to quantitatively examine the disparities in FSCI between two scenarios: one with the "Russia–Ukraine conflict" and the other without. Subsequently, the prospective influence of the Russia–Ukraine conflict on global food security is predicted.

The strategy for analyzing the influence of an external factor (such as a sudden event, climate change, etc.) on food security and predicting future scenarios is as follows: assuming other factors remain constant, food security has a certain developmental status (without considering the external factor). However, when factoring in the changes caused by this external factor, the developmental status of food security undergoes a distinct transformation, reflecting the impact of the variation in the investigated external factor. Chou et al. (2011) employed this approach to derive a yield impact of climate change model for predicting the economic consequences of future climate change using an economy-climate model. Taking China's major grain-producing regions as an example, they projected the potential effects of climate change on crop yields under different SSP-RCP scenarios (Chou et al. 2021). This methodology is commonly referred to as counterfactual analysis in the field of economics (Chen et al. 2016; Lin et al. 2023).

Taking the Russia–Ukraine conflict as an example, this study estimates the differences in the FSCI between the scenarios with and without the "Russia–Ukraine conflict." Specifically, using 2022 as the time point and based on the aforementioned future estimation strategies, two scenarios are set: the scenario with the "Russia–Ukraine conflict" and the scenario without the "Russia–Ukraine conflict."

The scenario without the R–U conflict refers to the fact that food security still changes based on the time series before the Russia–Ukraine conflict. The data from 2001 to 2021 are used to predict world food security in 2022–2030, which is recorded as $S1$. At this point, the FSCI is only influenced by factors other than the Russia–Ukraine conflict events. The scenario with the R–U conflict refers to the change in food security based on the time series change rule after the Russia–Ukraine conflict has occurred. By incorporating the data for the year 2022, the FSCI for the period from 2023 to 2030 is predicted using the data from 2001 to 2022, which is recorded as $S2$. The difference between $S2$ and $S1$ represents the impact caused by the Russia–Ukraine conflict, denoted as $\Delta Y = S2 – S1$, referred to as the yield impact of Russia–Ukraine conflict. Meanwhile, $\Delta Y/S2$ is referred to as the contribution of the Russia–Ukraine conflict impact to changes in food security. This study quantitatively analyzes the percentage between the multi-year average of the Russia–Ukraine conflict impact and the multi-year average of the FSCI with the "Russia–Ukraine conflict" scenario to characterize the contribution of the Russia–Ukraine conflict events to variations in food security (Fig. 1).

Results

Variations of food security in different regions during historical period

Based on the normalized dataset of various indicators from 2001 to 2021, the AHP-CRITIC mixed weighting method was employed to calculate the weights of 15 assessment indicators, as shown in Fig. 2. Firstly, based on the evaluation results of certain indicators by experts in existing research (Izraelov and Silber 2019; Guo et al. 2021; Cai et al. 2020), the relative importance of indicators such as per capita GDP, food loss,

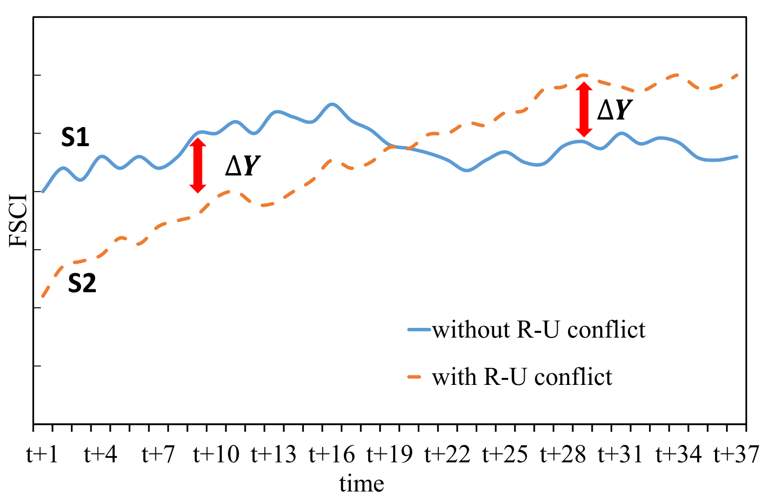

Fig. 1 Variations in food security with or without the "Russia–Ukraine conflict" ($S1$ represents the variations in food security without the "Russia–Ukraine (R–U) conflict," $S2$ represents variations in food security with the "Russia–Ukraine conflict." ΔY refers to as the yield impact of Russia–Ukraine conflict.)

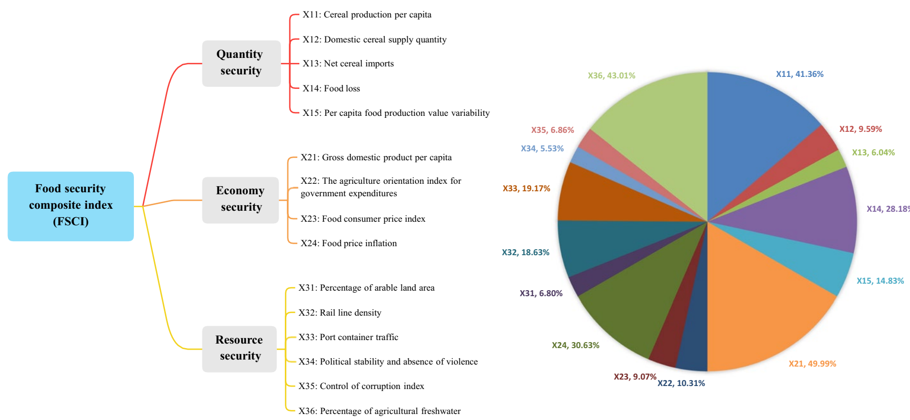

Fig. 2 Weights of the food security evaluation indicators by the AHP-CRITIC mixed weighting method

cereal price index, food price volatility, railway density, and corruption index were subjectively assessed using the AHP method, and the weights for each food security indicator were calculated (Appendix Table 8). According to the consistency test results, it can be concluded that all indicators pass the consistency test (Appendix Table 8).

Based on weights of the above calculation indicators, the second-level index evaluation model and comprehensive evaluation model of food security are calculated:

$$Y_{1,t} = 0.414X_{11,t} + 0.096X_{12,t} + 0.06X_{13,t} + 0.282X_{14,t} + 0.148X_{15,t} \tag{7}$$

$$Y_{2,t} = 0.5X_{21,t} + 0.103X_{22,t} + 0.091X_{23,t} + 0.306X_{24,t} \tag{8}$$

$$Y_{3,t} = 0.068X_{31,t} + 0.186X_{32,t} + 0.192X_{33,t} + 0.055X_{34,t} + 0.069X_{35,t} + 0.43X_{36,t} \tag{9}$$

$$FSCI = 0.428Y_{1,t} + 0.282Y_{2,t} + 0.29Y_{3,t} \tag{10}$$

Figure 3 displays the changes in FSCI at the global and regional scales from 2001 to 2022. The results reveal an increasing trend in global FSCI over the past two decades, with a growth rate of 0.018/(10 years). This indicates a gradual improvement in the global food security development level over time. At the regional level, the FSCI for Asia, EU, and LAC regions has shown a continuous increase over time, with growth rates of 0.006/(10 years), 0.035/(10 years), and 0.034/(10 years), respectively. It is noteworthy that the FSCI changes in the EU and LAC regions have occurred at a faster rate than the global average, suggesting an improving food security level in these regions. In contrast, the FSCI trend in the SSA region shows a decrease of 0.005 per decade, indicating a decline in food security in this region.

Simulation test of ARIMA model to predict FSCI

Based on global food security data from 2001 to 2021, the ARIMA model was used to predict the FSCI in different regions worldwide in the scenario without the "Russia–Ukraine conflict" for the period of 2023–2030. Firstly, the non-stationary data series were transformed into stationary series through unit root tests, and the results are shown in Table 3.

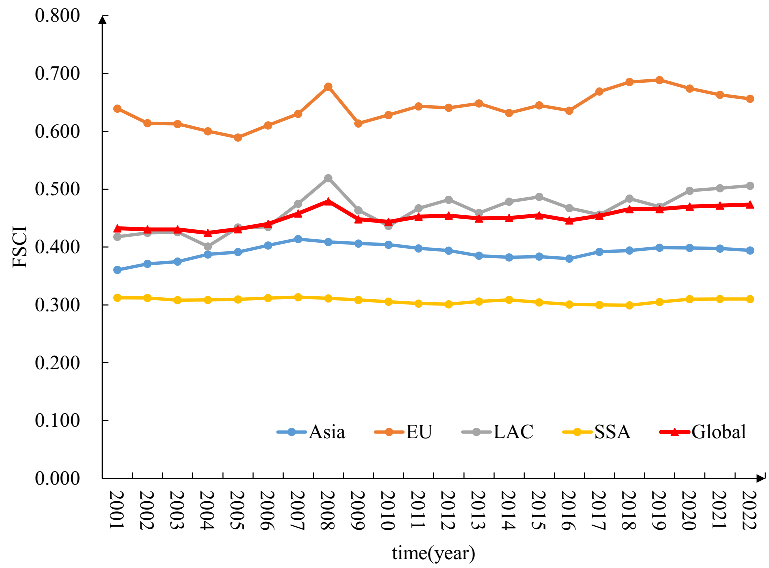

Fig. 3 Variations in the food security composite index in different regions from 2001 to 2022

Table 3 Unit-root test results of the FSCI without the "Russia–Ukraine conflict" scenario

Region	Difference order	*T*-test value	*P*-value	AIC	Critical value		
					1%	5%	10%
Asia	0	− 3.534	0.007***	− 108.375	− 4.138	− 3.155	− 2.714
EU	0	− 1.826	0.003***	− 66.923	− 3.809	− 3.022	− 2.651
LAC	0	− 4.096	0.001***	− 64.927	− 3.964	− 3.085	− 2.682
SSA	0	− 2.924	0.043**	− 110.228	− 3.833	− 3.031	− 2.656
Global	0	− 0.734	0.838	− 97.912	− 4.138	− 3.155	− 2.714
	1	− 21.743	0.000***	− 147.153	− 4.223	− 3.189	− 2.73

*** and ** denote statistical significance at 1%, 5%, respectively

Secondly, the ARIMA model was applied to forecast the stationary series, and the simulation results are depicted in Fig. 4. The results indicate a close resemblance between the simulated values and the actual values, with an average relative error ranging from 0.01% to 0.47%.

Based on global food security data from 2001 to 2022, the ARIMA model was used to predict the FSCI in different regions worldwide in the scenario with the "Russia–Ukraine conflict" for the period of 2023–2030. Firstly, the non-stationary data series were transformed into stationary series through unit root tests, and the results are shown in Table 4. Secondly, the ARIMA model was applied to forecast the stationary series, and the simulation results are depicted in Fig. 5. The results indicate a close resemblance between the simulated values and the actual values, with an average relative error ranging from 0.01% to 0.46%.

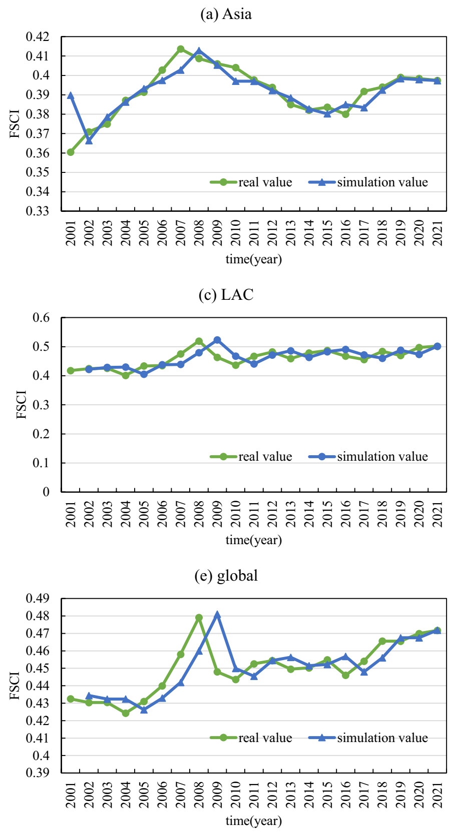

Fig. 4 Simulation results of FSCI from 2001 to 2021 based on ARIMA model without the "Russia–Ukraine conflict" scenario

Table 4 Unit-root test results of the FSCI with the "Russia–Ukraine conflict" scenario

Region	Difference order	*T*-test value	*P*-value	AIC	Critical value		
					1%	5%	10%
Asia	0	− 3.838	0.003***	− 121.023	− 4.138	− 3.155	− 2.714
EU	0	− 0.607	0.001***	− 71.225	− 4.138	− 3.155	− 2.714
LAC	0	− 2.895	0.046**	− 64.947	− 3.924	− 3.068	− 2.674
SSA	0	− 2.564	0.101	− 120.065	− 4.138	− 3.155	− 2.714
	1	− 3.707	0.004***	− 104.243	− 3.889	− 3.054	− 2.667
Global	0	− 1.619	0.002***	− 109.852	− 4.138	− 3.155	− 2.714

*** and ** denote statistical significance at 1%, 5%, respectively

Differences prediction of food security variation with or without the "Russia–Ukraine conflict" scenario

Firstly, the ARIMA model mentioned above was used to predict the FSCI values for different regions from 2023 to 2030 in two scenarios. Secondly, an analysis was conducted using the presence or absence of the "Russia–Ukraine conflict" scenario to calculate the average FSCI values for different regions from 2023 to 2030, and the differences in FSCI between the two scenarios were compared. Lastly, by analyzing the ratio between the differences in FSCI and the FSCI values with the "Russia–Ukraine conflict" scenario, the

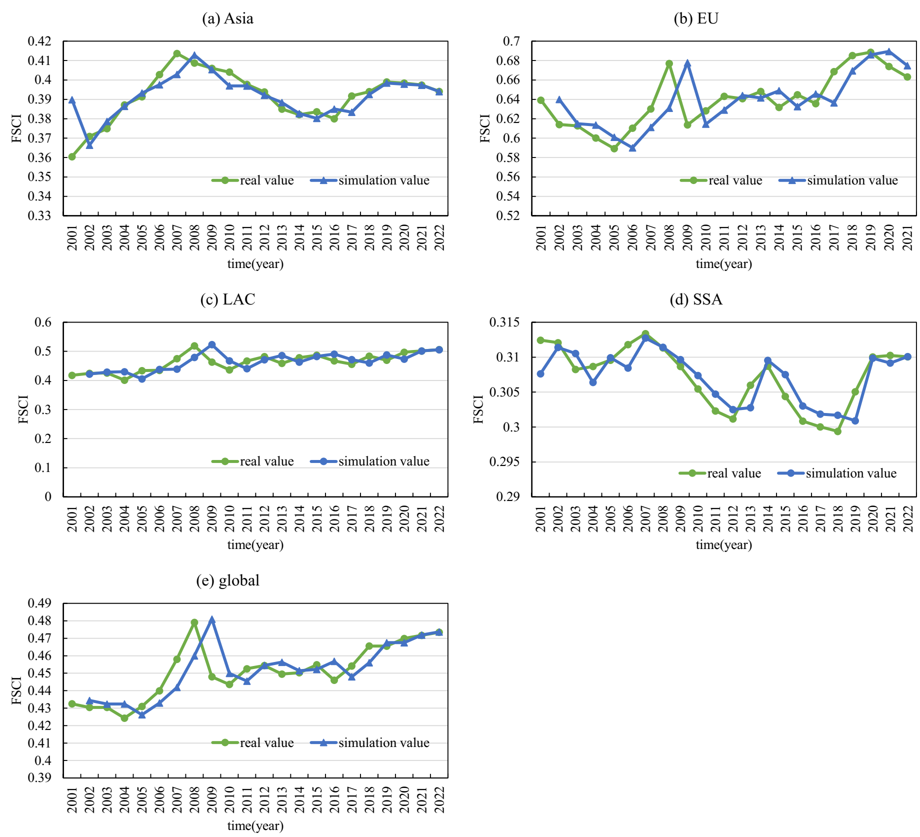

Fig. 5 Simulation results of FSCI from 2001 to 2021 based on ARIMA model with the "Russia–Ukraine conflict" scenario

Table 5 Difference of FSCI variation and its contribution degree under the scenario with or without "Russia–Ukraine conflict"

Scenario	Asia	EU	LAC	SSA	Global
Without the R–U conflict	0.38830	0.66971	0.52465	0.30712	0.48248
With the R–U conflict	0.38829	0.65989	0.52480	0.30801	0.48225
Difference (*ΔY*)	− 0.00002	− 0.00982	0.00014	0.00089	− 0.00023
Ratio (*ΔY/S2*)	0.00%	1.49%	0.03%	0.29%	0.05%

The difference represents the impact caused by the Russia–Ukraine conflict, denoted as $\Delta Y = S2 - S1$, referred to as the yield impact of Russia–Ukraine conflict. $\Delta Y/S2$ is referred to as the contribution of the Russia–Ukraine conflict impact to changes in food security

contribution of the conflict to the changes in the future food security composite index can be evaluated.

According to the results in Table 5, it is estimated that the contribution of the Russia–Ukraine conflict to the changes in FSCI for the regions of Asia, Europe, Latin America and Caribbean, and Sub-Saharan Africa from 2023 to 2030 is 0%, 1.49%, 0.03%, and 0.29%, respectively. This indicates that the conflict has the greatest contribution to the changes in food security in Europe, followed by the Sub-Saharan Africa region, while Asia and Latin America and the Caribbean have the lowest contribution. This is mainly due to the interruption of agricultural production caused by the conflict, including the destruction of arable land, difficulties in cultivation and harvesting, and the displacement of farmers, leading to a decrease in crop cultivation area, lower yields, and subsequently affecting food supply (Behnassi and El Haiba 2022; Osendarp et al. 2022). Additionally, the conflict may cause problems such as transportation blockages and border closures, resulting in the interruption or severe disruption of food supply chains in certain regions and countries (Carriquiry et al. 2022; Feng et al. 2023; Xu et al. 2023).

In a global perspective, it is estimated that the contribution of the Russia–Ukraine conflict to the changes in FSCI is 0.05%. This indicates that the impact of the Russia–Ukraine conflict on global food security is relatively small, which could be attributed to the resilience and elasticity of the global food supply chains, allowing them to withstand and mitigate the effects of localized conflicts and disasters to a certain extent (Ben Hassen and El Bilali 2022; Jagtap et al. 2022). Additionally, factors such as international trade and food reserves can compensate for the supply shortages in specific regions, ensuring the relative stability of global food supply (Chaudhary et al. 2018; Nasir et al. 2022).

Conclusions and discussion

This study adopts a macroscopic perspective and combines the AHP and CRITIC weighting methods to construct a food security evaluation indicator system and a FSCI from three dimensions, and utilizes the AMIRA model to predict the FSCI in different regions from 2023 to 2030 under two scenarios. The potential impact of the Russia–Ukraine conflict on regional food security is quantitatively analyzed. The main conclusions are as follows:

(1) By utilizing an interdisciplinary approach, a macro-level food security evaluation indicator system has been constructed from a top-down perspective, cleverly integrating the interrelationships between the dimensions of quantity, economic, and resource security. Through the assessment of the food security composite index, a comprehensive understanding of the global and regional levels of food security is obtained

(2) The FSCI showed an increasing trend in the past 20 years, with a growth rate of 0.018/(10 years). Among them, the FSCI of Asia, Europe, Latin America and Caribbean increased at a faster pace over time, while the GFSI of sub-Saharan Africa showed a declining trend, indicating uneven development of food security levels in different regions.

(3) It is expected that by 2030, the impact of the Russia–Ukraine conflict on global food security will be relatively small, but the effects on Europe and sub-Saharan Africa may be significant, while the impact on Asia and Latin America and Caribbean region will be less pronounced. Therefore, it is necessary to strengthen food security measures and cooperation in these affected regions.

Overall, there is still continued uncertainty due to the Russia–Ukraine conflict, and food security is related to national security, human security and global sustainable development. According to the data, it is anticipated that the conflict may have significant implications for food security in Europe and Sub-Saharan Africa by 2030. Due to the geographical proximity between Europe and Ukraine, the conflict might result in agricultural disruptions in Ukraine, consequently affecting the food supply in Europe. This could lead to an increase in food prices, causing economic pressure for European citizens. Governments may need to take measures to stabilize the food market and ensure food security for their populations. Although the data indicates a declining trend in the FSCI in Sub-Saharan Africa, the impact of the conflict on the region is expected to be more complex. On one hand, the conflict may affect the food supply in Europe, which could potentially lead European countries to shift their demand for food to the African region, thereby increasing the pressure for food imports in the area. On the other hand, the conflict might also contribute to increased political instability in Sub-Saharan Africa, impacting agricultural production and food supply in the region. Therefore, governments may need to take measures to address potential food shortages and social unrest.

The political impact of the conflict on the population and government will depend on the level of food security in the region, the stability of food supply, and the extent to which the conflict affects the economy and politics. To cope with the global food crisis, governments and international organizations should actively take actions. Each country needs to reassess the risks and difficulties of its own national food security from multiple dimensions of food security (such as quantity security, economic security and resource security), and restructure and improve its own food system so that it remains resilient in the long run and ensures food security in the face of rising climatic, conflict-related and economic risks. The international community needs to build a sustainable global food security architecture based on sustainable development goals. Only in this way can we ensure the survival of all humankind so that human security is the basic guarantee.

In addition, the food security evaluation indicator system has high consistency with the results of existing studies (Chen et al. 2016; Izraelov and Silber 2019; Cai et al. 2020; Guo et al. 2021), and it is more detailed and targeted, indicating that the evaluation model constructed is feasible. This paper explores the overall level of world food security only from a macro-global perspective, and provides global views and macro-ideas for the in-depth exploration of the spatial differences in food security risks within various countries and regions. Moreover, multidimensional and multi-indicator food security evaluation can provide a greater decision-making basis for formulating macro-level global food security policies than evaluation based on a single dimension or a single indicator. On the other hand, the food security composite index of world focuses on food security, which is established from the perspective of macro-conditions throughout the world, without fully considering the utilization of food by micro-individuals. In the future, incorporating government and micro-individual nutrition security into a comprehensive analytical framework will bring more insights into the development of food security strategies.

Appendix

See Table 6, 7, 8.

Table 6 FAO's Food security indicator system (FAO 2015)

Dimension	Food security indicators
Availability	Average dietary energy supply adequacy
	Average value of food production
	Share of dietary energy supply derived from cereals, roots and tubers
	Average protein supply
	Average supply of protein of animal origin
Access	Percentage of paved roads over total roads
	Road density
	Rail lines density
	Gross domestic product (in purchasing power parity)
	Domestic food price index
	Prevalence of undernourishment
	Share of food expenditure of the poor
	Depth of the food deficit
	Prevalence of food inadequacy
Stability	Cereal import dependency ratio
	Percent of arable land equipped for irrigation
	Value of food imports over total merchandise exports
	Political stability and absence of violence/terrorism
	Domestic food price volatility
	Per capita food production variability
	Per capita food supply variability
Utilization	Access to improved water sources
	Access to improved sanitation facilities
	Percentage of children under 5 years of age affected by wasting
	Percentage of children under 5 years of age who are stunted
	Percentage of children under 5 years of age who are underweight
	Percentage of adults who are underweight
	Prevalence of anemia among pregnant women
	Prevalence of anemia among children under 5 years of age
	Prevalence of vitamin A deficiency in the population
	Prevalence of iodine deficiency in the population

Table 7 List of countries in the study area

Number	Asia	Europe (EU)	Latin America & Caribbean (LAC)	Sub-Saharan Africa (SSA)
1	Azerbaijan	Austria	Argentina	Benin
2	Bangladesh	Belgium	Bolivia (Plurinational State of)	Botswana
3	China	Belarus	Brazil	Burkina Faso
4	India	Bulgaria	Chile	Democratic Republic of the Congo
5	Indonesia	Czechia	Colombia	Côte d'Ivoire
6	Israel	Denmark	Costa Rica	Ethiopia
7	Japan	Finland	Dominican Republic	Ghana
8	Jordan	France	Ecuador	Kenya
9	Kazakhstan	Germany	El Salvador	Madagascar
10	Kuwait	Greece	Guatemala	Malawi
11	Lebanon	Hungary	Honduras	Mali
12	Malaysia	Ireland	Mexico	Mozambique
13	Mongolia	Italy	Nicaragua	Niger
14	Nepal	Lithuania	Panama	Nigeria
15	Oman	Netherlands	Paraguay	Senegal
16	Pakistan	Norway	Peru	Sierra Leone
17	Philippines	Portugal	Uruguay	South Africa
18	Republic of Korea	Romania		Togo
19	Saudi Arabia	Russian Federation		Uganda
20	Sri Lanka	Slovakia		Zambia
21	Thailand	Spain		
22	Türkiye	Sweden		
23	Uzbekistan	Switzerland		
24	Viet Nam	Ukraine		
25		United Kingdom of Great Britain and Northern Ireland		

Table 8 Weight value of food security evaluation index

Indicator	Weight of the AHP method (%)	Weight of the CRITIC weighting method (%)	Weight of the mixed weighting method (%)	Coincidence indicator (CI) value	Random indicator (RI) value	Consistency ratio (CR) value	Consistency test
X_{11} : Cereal production per capita	42.52	19.38	41.36	0.121	1.26	0.096	Yes
X_{12} : Domestic cereal supply quantity	8.5	22.48	9.59				
X_{13} : Net cereal imports	9.42	12.78	6.04				
X_{14} : Food loss	27.82	20.18	28.18				
X_{15} : Per capita food production value variability	11.73	25.18	14.83				
X_{21} : Gross domestic product per capita, PPP	33.13	8.63	49.99	0.048	1.12	0.043	Yes
X_{22} : The agriculture orientation index for government expenditures	8.55	14.41	10.31				
X_{23} : Food consumer price index (CPI)	29.16	73.2	9.07				
X_{24} : Food price inflation	29.16	3.77	30.63				

Table 8 (continued)

Indicator	Weight of the AHP method (%)	Weight of the CRITIC weighting method (%)	Weight of the mixed weighting method (%)	Coincidence indicator (CI) value	Random indicator (RI) value	Consistency ratio (CR) value	Consistency test
X_{31} : Percentage of arable land area	34.28	2.99	6.8	0.025	1.26	0.02	Yes
X_{32}: Rail line density	16.7	16.85	18.63				
X_{33} : Port container traffic	16.7	17.33	19.17				
X_{34} : Political stability and absence of violence index	6.14	13.6	5.53				
X_{35}: Control of corruption index	6.14	16.86	6.86				
X_{36} : Percentage of agricultural freshwater	20.05	32.37	43.01				

Abbreviations

AHP	Analytic hierarchy process
CRITIC	Criteria importance through intercriteria correlation
FSCI	Food security composite index
FAO	Food and Agriculture Organization
AAUS	Availability, access, utilization and stability
QER	Quantity, economic, and resource security
ARIMA	Autoregressive integrated moving average model
R–U	Russia–Ukraine conflict

Supplementary Information

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Additional file 1. Time series values of the FSCI in different regions of the world for 2001-2022, as well as the predicted FSCI values for 2023-2030 with and without the "Russia-Ukraine conflict" scenario.

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Author contributions

YX involved in methodology, conceptualization, writing—original draft preparation, and writing—review and editing. JMC and WJD involved in validation, resources, supervision, project administration, and funding acquisition. YX and ZXW involved in software and formal analysis. YX and JMC involved in investigation and data curation. All authors have read and agreed to the published version of the manuscript.

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Availability of data and materials
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Declarations

Competing interests
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