# ARTICLE

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# Global environmental impacts of food system from regional shock: Russia-Ukraine war as an example

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Different responses to external interference, such as regional conflict, could have distinct sustainability outcomes. Here, we developed a novel framework to examine global food shortages from the Russia-Ukraine conflict and quantify the embodied environmental impacts of disturbed and alternative food supply chains. The conflict could soon bring a 50-120 Mt shortage of nine dominant food products and cause temporal global cropland abandonment and greenhouse gas emissions decline. By contrast, the partial agricultural recovery in the next cultivation season will raise global cropland use and greenhouse gas emissions by 9-10% and 2-4% (mainly in China and Europe). However, optimized food supply networks with prioritized agricultural expansion in higher-efficiency countries could minimize food shortages and food-mile expenses, offsetting the postwar environmental increments from agricultural recovery by 45-89%. These results validate a framework to simulate the global social-ecological system, and underline the resistance opportunities and tele-connected consequences of regional disturbance.

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# Introduction

niversal access to safe and nutritious food in an environmentally sustainable way by 2030 is the primary goal of the Sustainable Development Goal 2 (SDG2) (UN 2015). However, 2.3 billion people (29.3%) worldwide still suffer from a moderate or high level of food insecurity (FAO 2022b). Beyond the goal of zero hunger, the world faces the challenges of achieving the 1.5-degree warming target and staying with the planetary boundary for land use to protect the Earth's ecosystem stability. The global food system could be the lever of change since it accounts for approximately 1/3 of global Greenhouse gases (GHG) and 50% of habitat loss (Crippa et al. 2021; Ritchie and Roser 2022). However, external short-term (e.g., wars, extreme rainstorms, pandemics, etc.) and long-term (e.g., climate change, resource depletion, etc.) shocks (LaFleur et al. 2022) pose additional challenges to these sustainability goals by disturbing food production and trade. While long-term shocks, such as climate change, have been extensively studied, quantifying and alleviating short-term shocks remains an essential challenge for the global social-ecological system(Grafton et al. 2019; Kuemmerle and Baumann 2021; Revers et al. 2022; Virapongse et al. 2016). Given their increasing frequency, leaving short-term shocks unsolved will largely crackdown on global food security, the environment, and economic stability.

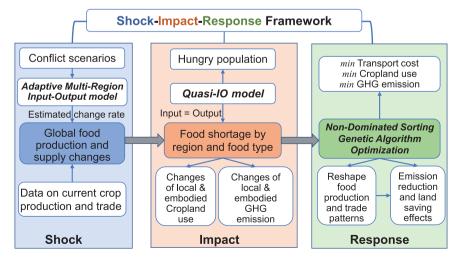
The ongoing Russia-Ukraine conflict is a typical external emergent shock event that has triggered global food shortages and hunger. It is estimated that 316.7 million people in 113 countries would suffer from extreme food insecurity (Deng et al. 2022). Food insecurity is rooted in food dependence on both countries, and Russia and Ukraine account for 12% of the world's total calorie trade (Caprile and Service 2022). Russia and Ukraine are the global breadbasket of barley, wheat, rye, sunflower seed, and many other crops, taking 15-58% of the global production. They exported approximately 57% of global seed oil, 28% of wheat, 24% of barley, 15% of sunflower seeds and 59% of sunflower products (FAOSTAT 2022; WTO 2022). Many countries are facing a shortage of fertilizers, which has led to a massive reduction in grain production (Mustafa 2022). As a result, export bans were enacted in over 20 major grain-producing countries to maintain domestic stability (Glauber et al. 2022). Moreover, food supplies and fertilizer shipments are greatly restricted due to the sanctions imposed on Russia (FAO 2022a; Mustafa 2022; UN 2022).

Due to trade restrictions and supply shortages, many foodimporting countries are struggling to restructure supply and demand in time to overcome food shortages (Husain et al. 2022). Although global food production and fertilizer markets might gradually recover in the next growing season, nonoptimal agricultural expansion and trade regimes to compensate for food shortages have increased GHG emissions, cropland transition and transport costs, and also undermined SDGs (Bin-Nashwan et al. 2022; Carriquiry et al. 2022; Foong et al. 2023). In response to the trilemma, many scholars have suggested ending the war to keep trade flowing (Hellegers 2022; Husain, et al. 2022; Khorsandi 2022; Lin et al. 2023), restructuring diets (Sun et al. 2022; Yazbeck et al. 2022), expanding global production (Bentley et al. 2022), establishing food orders and transforming the food system (Behnassi and El Haiba 2022; Ben Hassen and El Bilali 2022; Hellegers 2022; Mottaleb et al. 2022; Pörtner et al. 2022; Zhou et al. 2023). However, the specific environmental impacts of compensating for food shortages remain unknown, and how to balance the food supply with GHG emissions and cropland use mitigation has not been illuminated.

Here, we develop a novel shock-impact-response framework (Fig. 1) to model the environmental and food-shortage effects of external interference and to investigate the optimal transitions of food systems. Using this framework, we assess the distribution of food shortages under Russia-Ukraine conflict scenarios (Fig. 2). The impact on cropland use and GHG emissions of the affected food supply network is subsequently estimated. Finally, a multiobjective genetic algorithm is used to optimize the location of global production during agricultural recovery from postwar stages and propose optimization strategies to minimize GHG emissions, cropland use, and food transport costs. Nine dominant food products in Russia and Ukraine including rice, wheat, maize, barley, rye, beans, rapeseed, soybeans, and sunflower seed are considered in this study (IGC 2022). Our framework can be used to assess any short-term contingency on the specific socialecological systems involved. Our results provide a paradigm of a food production system that minimizes food shortages and economic costs while synergising with environmental policies.

#### Methods

**Quantify changes in food production and trade**. Predicting the impact of war on the agriculture sector is the first step in the three-step research framework of this paper. Due to the time lag in statistical data, it is often not possible to evaluate the true



**Fig. 1 Specific methods and thought of shock-impact-response framework.** The left panel shows the simulation of country-level change in food production and supply, the middle panel shows the estimated environmental impacts of type-specific food shortage, the right panel aims to optimize the food supply network with lower cost and environmental impacts.

Short term - Low Intension	Short term - High Intension
Duration:12 months	Duration:12 months
Severity:20% damage to Ukraine	Severity:40% damage to Ukraine
Sanction:20% limit to Russia export	Sanction:80% limit to Russia export
Countries Involved: unfriendly list	Countries Involved: all
Long term - Low Intension	Long term - High Intension
Duration:24 months	Duration:24 months
Severity:20% damage to Ukraine	Severity:40% damage to Ukraine
Sanction:20% limit to Russia export	Sanction:80% limit to Russia export
Countries Involved: unfriendly list	Countries Involved: all

**Fig. 2 The setting of the war scenarios.** Scenarios are set up on four levels: the duration of the war, the severity of damage to Ukraine, the intensity of sanctions on Russian exports, and the countries involved.

impact of emergencies, but targeted rescue measures require an assessment of the future impact of the emergency (Guan et al. 2020; Hallegatte 2008; Zeng et al. 2019). The IO (Input-Output Model) (Malik et al. 2022) and CGE (Yamazaki et al. 2018) (Computable General Equilibrium Model) are very popular in the impact assessment of emergencies because they can reflect the interdependence of economic sectors. Take the changing circumstances of war into consideration, the adaptive multi-regional input-output (AMRIO) model (Li et al. 2013; Shan et al. 2021) is more suitable than the CGE model for its simulating functions of short-term emergencies. AMRIO model is a tool to quantify the interdependencies between different sectors within the interregional economic system automatically. The well-established technique of AMRIO explicitly simulates the imbalance and shortage of supply and demand in different markets in weekly steps.

AMRIO model includes six modules: production function module, capital limitation, supply constraints, intermediate inputs module, labor supply module, and demand module. Our model further improves the previous version (Guan et al. 2020; Shan et al. 2021) and extends the impact of the Russia-Ukraine conflict to four controlling factors (Fig. 2): the duration of the Russia-Ukraine conflict, the restrictions on labor and transportation in Ukraine brought about by war, the intensity of sanctions in the nontheater zone against Russia, and the number of countries involved. Accordingly, we can assess the consequences of the Russia-Ukraine conflict on the global grain trade by considering different war factors and trade sanctions.

The process of growing, harvesting, processing, transporting, supplying, and marketing food in food system can be reflected through the structure and designed parameters in AMRIO model. The extent to which planting and harvesting are influenced can be represented indirectly through labor constraints. Processing constraints are implemented by altering the availability of labor and transportation, supply is modulated by restricting international trade, and consumption adjustments are made by reducing final demand. A detailed description of the model structure, equations, parameters, and model simulation is provided below.

**Production function module**. According to the Leontief function (Miller and Blair 2009), the output from sector *j* in region *i*  $(x_{j,i})$  can be expressed in the following equation:

$$x_{j,i} = \min\left(\text{for all } m, \frac{z_{j,i}^m}{a_{j,i}^m}; \frac{va_{j,i}}{b_{j,i}}\right) \tag{1}$$

where *m* denotes the type of intermediate product;  $z_{j,i}^m$  refers to the intermediate product *m* used in sector *j*; and  $va_{j,i}$  refers to the primary inputs for sector *j*, including labor and capital.  $a_{j,i}^m$  and  $b_{j,i}$  are the input coefficients of intermediate products *m* and primary inputs of sector *j*.

From the perspective of sectors, we believe that labor supply, intermediate inputs, and demand activities will be reshaped by the Russia-Ukraine war, so output across sectors will be affected.

**Capital limitation**. Due to the decline in available labor and the tightening of the global supply chain, the capital market has also received a serious impact, hindering production activities, making capital limitations one of the bottlenecks in production activities  $x_f^{Cap}(t)$ .

$$x_f^{Cap}(t) = \frac{Cap_{f,i}(t)}{b_{f,i}}$$
(2)

where  $x_f^{Cap}(t)$  refers to the maximum output when the capital market is restricted.  $Cap_{f,i}(t)$  the primary inputs for firm f at time step t.

**Supply constraints.** In terms of demand, there is a shortage of food production and supply due to the war. Hence, the total order demand for sector j in period t ( $TD_{j,i}$  (t)) equals the sum of intermediate demand and household demand.

$$TOD_{j,i}(t) = \sum_{q,s} FOD_{j,i}^{q,s}(t) + \sum_{s} HOD_{j,i}^{s}(t)$$
(3)

where  $FOD_{j,i}^{q,s}(t)$  refers to the order demand that sector q in region s requires from supplier sector j in region i;  $HOD_{j,i}^{s}(t)$  is the order demand that the household in region s requires from supplier sector j in region i.

**Intermediate inputs module**. The *mth* intermediate products at time *t* in sector *j* of region *i* are represented as  $\overline{z}_{j,i}^m(t)$ , which is determined by the inventory in the last time period  $Sup_{j,i}^m(t-1)$ :

$$\bar{z}_{j,i}^{m}(t) = Sup_{j,i}^{m}(t-1)$$
(4)

 $Sup_{j,i}^{m}(t-1)$  equals the inventory at time t-2 minus the usage  $Sup_{used j,i}^{m}(t-1)$  plus the inventory increase  $Sup_{added j,i}^{m}(t-1)$ :

$$Sup_{j,i}^{m}(t-1) = Sup_{j,i}^{m}(t-2) - Sup_{used j,i}^{m}(t) + Sup_{added j,i}^{m}(t)$$
(5)

Therefore, when the intermediate input products are restricted, the maximum output  $(x_{j,i}^{Sup}(t))$  is:

$$x_{j,i}^{Sup}(t) = \frac{Sup_{j,i}^{m}(t-1)}{a_{j,i}^{m}}$$
(6)

**Labor supply module**. War-induced labor constraints could have serious knock-on effects on food production and beyond. In the context of the Russia-Ukraine conflict, the inability of employees to work due to death or war constraints is a key factor to consider when assessing the impact of disasters. Following the assumption of the fixed proportion of production functions, the productive capacity of labor in each region after a disaster  $(x_j^{Lab}(t))$  represents a linear proportion of the available labor capacity  $(\sigma^{Lab}(t))$  at

a linear proportion of the available labor capacity  $\left(\sigma_{j}^{Lab}(t)\right)$  at each time step:

$$x_j^{Lab}(t) = \left(1 - \sigma_j^{Lab}(t)\right) \times \overline{x}_j \tag{7}$$

**Demand module**. To make a more realistic representation of the real production process, we assume that each sector holds some inventory of intermediate goods. In each time step, sectors use intermediate products from their inventories for production and purchase intermediate products from their supplying sectors to restore their inventories. We assume the inventory of

intermediate product *m* required by sector *q* in region *s* is  $Sup_{q,s}^{m,*}(t)$ , which could fulfil its consumption for  $n_{q,s}^m$  days:

$$Sup_{q,s}^{m,*}(t) = n_{q,s}^m \times a_{q,s}^m \times x_{q,s}^{max}(t)$$
(8)

Then, the order issued by sector q to its supplying sector j is:

$$FOD_{j,i}^{q,s}(t) = \begin{cases} \left(Sup_{q,s}^{m,*}(t) - Sup_{q,s}^{m}(t)\right) \times \frac{\overline{FOD}_{j,i}^{d,s} \times x_{j,i}^{max}(t)}{\sum_{q \to m} \overline{FOD}_{j,i}^{d,s} \times x_{j,i}^{max}(t)} & \text{if } Sup_{q,s}^{m,*}(t) > Sup_{q,s}^{m}(t) \\ 0 & \text{if } Sup_{q,s}^{m,*}(t) \le Sup_{q,s}^{m}(t) \end{cases}$$

$$(9)$$

 $FOD_{j,i}^{q,s}(t)$  is measured by the household order demand and the supply capacity of their suppliers. In this study, the demand for final products *q* by the demand of households in region *s*,  $HD_s^q(t)$ , is given exogenously at each time step. Then, the order issued by household *s* to its supplier *j* is:

$$HOD_{j,i}^{s}(t) = HD_{s}^{q}(t) \times \frac{\overline{HOD}_{j,i}^{s} \times x_{j,i}^{max}(t)}{\sum_{j \to q} \overline{HOD}_{j,i}^{s} \times x_{j,i}^{max}(t)}$$
(10)

Taking both forward effects and backward effects into consideration, the actual output of producer *j* in period *t*  $\left(x_{i,i}^{Act}(t)\right)$  is:

$$x_{j,i}^{Act}(t) = min\left(x_{j,t}^{Lab}(t), x_{j}^{Cap}(t), x_{j,i}^{Sup}(t), TOD_{j,i}(t)\right)$$
(11)

Alternative food supply's impacts. The Quasi Input-Output (QIO) is a model to establish interregional supply-demand relationships for different products, which is similar to the Input-Output (IO) model (Niu et al. 2020; Qu et al. 2017a; Qu et al. 2017b) and commonly employed for environmental footprint assessments. It can evaluate the embodied resources or emissions more accurately, as they were determined by the generation of all countries in the resource network. The QIO model accounts for both direct and indirect resource transfers (and associated virtual emission flows), and can be potentially applied as a standard tool in the important and emerging practices of measuring emission factors in resource networks (Qu et al. 2017b).

Although the QIO model was used for electricity tracking for the first time, the resource or emission transfers embodied in global agricultural trade is similar to the process of emission accounting from electricity production driven by specific electricity consumption (Qu et al. 2017b). Therefore, we use the QIO model to simultaneously track trade flows in the food sector mainly affected by war to track the tele-connected effect of the Russia-Ukraine conflict. The main target is to track changes in cropland use and GHG emissions under war and the transfer pattern of embodied cropland and GHG emissions among countries. Food sector includes rice, wheat, maize, barley, rye, beans, rapeseed, soybeans, and sunflower seeds, which have been more affected by the war.

Here, we borrow the framework of the QIO model to construct a global agricultural trade network. The global food trade can be viewed as a network of n nodes, with one node representing a country or region and the  $n \times n$  matrix T representing the trade flows between countries/regions. This equation can be written as follows:

$$T = \begin{bmatrix} 0 & T_{12} & \cdots & T_{1n} \\ T_{21} & \ddots & \ddots & T_{2n} \\ \vdots & \ddots & \ddots & \vdots \\ T_{n1} & \cdots & T_{n(n-1)} & 0 \end{bmatrix}$$
(12)

where  $T_{ij}$  is the flow of agricultural production exported from country *i* to country *j*. Within a country or region, the total

agricultural product consists of local agricultural production, changes in stocks and imports from other countries or regions, and it is equal to the sum of local agricultural consumption plus exports to other countries or regions. Thus, the total flow of agricultural products for country i can be written as:

$$x_i = p_i + \sum_{j=1}^n T_{ji} + s_i = c_j + \sum_{j=1}^n T_{ij}$$
(13)

where  $x_i$  is the total inflow or outflow of agricultural products in country *i*,  $p_i$  is the local agricultural production,  $s_i$  is the local agricultural stock, and  $c_i$  is the local agricultural consumption.

**Changes in cropland use and GHG emissions**. To calculate the share of international agricultural trade in total agricultural flows  $(x_i)$ , we define a direct outflow coefficient matrix *B*.

$$B = \widehat{x}^{-1}T = \begin{bmatrix} 0 & \frac{T_{12}}{x_1} & \cdots & \frac{T_{1n}}{x_1} \\ \frac{T_{21}}{x_2} & \ddots & \ddots & \frac{T_{2n}}{x_2} \\ \vdots & \ddots & \ddots & \vdots \\ \frac{T_{n1}}{x_n} & \cdots & \frac{T_{n(n-1)}}{x_n} & 0 \end{bmatrix}$$
(14)

where  $\hat{x}$  is the diagonal matrix with the elements of vector x on the diagonal, and  $B_{ij}$  is the proportion of agricultural product flow  $x_i$  that is exported to country j in country i. Then, the total outflow coefficient matrix, which quantifies direct and indirect agricultural trades, can be written as:

$$G = (I - B)^{-1} = 1 + B + B^{2} + \dots$$
(15)

where the element  $G_{ij}$  represents the agricultural product inflow to country *j* that is both directly and indirectly instigated by one unit of agricultural production in country *i*. In the equation, *I* indicates that international agricultural trade can occur directly (direct trade between two countries), *B* indicates that trade occurs through one pass-through country,  $B^2$  indicates trade through two pass-through countries and can also represent more passthrough countries.

In the Quasi-IO model, we assume that agricultural products imported from other countries are mixed with local products in a country, and then a portion of that total is used by local consumers. Thus, we define the production-consumption matrix H by linking agricultural production and consumption in different countries or regions

$$H = G\hat{c}\hat{x}^{-1} \tag{16}$$

where  $\widehat{cx}^{-1}$  is a diagonal matrix that captures the proportion of agricultural production consumed by every country in its total volume.  $H_{ij}$  represents the proportion of agricultural products produced in country *i* that are consumed in country *j* through all of the possible international trade paths.

The area of cropland used for certain crop production and GHG emissions within a country can be represented by vectors L and E, respectively, and  $L_i$  and  $E_i$  denote the total amount of cropland use and GHG emissions for a certain crop production in country *i*. Cropland use is calculated by dividing the production quantity by the yield per unit area, and GHG emissions account for the energy emissions of the agricultural production process. The crop production value per unit area in each country under the war is affected by fertilizer prices and labor inputs, which are always in a continuous process of change. Therefore, we obtained the NDVI values of agricultural land in each country for March-October 2022 and the same period in previous years to correct for the unit production value of agricultural products under the war scenario.

From the production-based perspective, embodied cropland use  $(L^P)$  and GHG emissions  $(E^P)$  occurred in food production within the country, which is used for local consumption and international trade. Therefore, the production-based cropland use and GHG emissions could be estimated separately by multiplying cropland use and emission quantity with the trade flow matrix (T) and local consumption vector (C). The formula can be written as:

$$L^{P} = diag\left(\frac{L}{X}\right) \times T + diag\left(\frac{L}{X}\right) \times C$$
(17)

$$E^{P} = diag\left(\frac{E}{X}\right) \times T + diag\left(\frac{E}{X}\right) \times C$$
(18)

where ./ denotes an element-by-element division.

Changes in embodied cropland use and GHG emissions. From the consumption perspective, embodied flows are caused by consumption activities from both direct and indirect imports. The production-consumption matrix H can link the cropland from food production to consumption, resulting in a matrix of cropland use transfers:

$$L^{c} = \widehat{L}H = diag\left(\frac{L}{X}\right) \times G \times diag(C)$$
(19)

In the above equation,  $\hat{L}$  is the diagonalized matrix of *L*. *L<sup>c</sup>* is a matrix that represents cropland use transfer from country *i* to *j*. Similarly, the embodied GHG emissions from country *i* to *j* can be calculated as follows:

$$E^{c} = \widehat{E}H = diag\left(\frac{E}{X}\right) \times G \times diag(C)$$
(20)

where  $\widehat{E}$  is the diagonalized matrix of *E*.

**Optimized food supply pattern**. The significance of reshaping global food supply has become apparent, here we provided a global food supply solution, which is divided into three processes: objectives and constraints, feasible solutions solving and multi-objective decision making. Firstly, the objectives are minimum transport fuel consumption, GHG emissions and cropland use from production (Poore and Nemecek 2018; Xue et al. 2021). The constraints limiting the optimization objectives are basis on the status quo. Besides, we choose the Elitist Nondominated Sorting Genetic Algorithm (NSGA-II) to get Pareto solution sets for multi-objective problems. Ultimately, Compromise Programming and Pseudo-Weights are used to find the global optimal solution balanced among food miles reduction, GHG emissions decrease, and cropland use conservation.

**Constraints and objectives in optimization**. We optimized world food production and trade under the war scenario to provide accurate production strategies for compensating world food shortages and reduce cropland use and GHG emissions in global food production. The objectives to be optimized and constraints of nine dominant food products can be expressed as follows:

$$f(T, P) = \min \left[ f(T * F), f(P * G), f(P * L) \right]$$
s.t. 
$$f(P) + f(Im) + f(S) = f(C) + f(Ex)$$

$$f(P) \ge f(Ex)$$

$$0 \le f(P) \le f(Ps); 0 \le f(T) \le f(Ts)$$

$$P_{Ukraine} \le P_{Ukraine 0}; P_{Russia} \le P_{Russia 0}$$

$$Ex_{Ukraine} \le Ex_{Ukraine 0}; Ex_{Russia 0}$$
(21)

where T is the food trade flow matrix between countries, P is the production quantity in 180 countries, F is the freight cost matrix

between countries and expressed as the minimum costs of fuel consumed by railway and shipping between countries. *G* is the GHG emissions required to produce a unit of food, *L* is the cropland used to produce a unit of food. f(T \* F), f(P \* G), and f(P \* L), correspond to the consumption for trade, production-based GHG gas emissions and cropland use respectively.

Im represents the country's imports, Ex represents exports, C is the total domestic consumption and S represents the change in Russia-Ukraine conflict.  $P_s$  is the maximum value of production quantity, which is 1.5 times higher than that before the conflict, and  $T_s$  represents the maximum value of the trade matrix, which is 1.5 times higher than that before the conflict. T and F are a 180\*180 matrix, in which the diagonal elements are 0. P, G, L, Im, Ex, C, S, and  $P_s$  are all column vectors with 180 national elements. In addition, both exports and production in Russia and Ukraine have reduced because of the war, so they are smaller than the current value in the optimization scenario.

**Feasible Pareto optimal solution set computation**. Since there are three objectives and multiple aspect constraints, we choose the well-known multi-objective algorithm: the Elitist Nondominated Sorting Genetic Algorithm (NSGA-II) to find the Pareto optimal solution set. With the properties of a fast nondominated sorting procedure, an elitist strategy, a parameterless approach, and a simple yet efficient constraint-handling method, NSGA-II is used to quickly find the Pareto solution sets that meet the constraints (Deb et al. 2002).

The main framework of the NSGA-II includes below content: population initialization, individual fitness evaluation, nondominated sorting, crowding distance calculation, selection operation, crossover operation, mutation operation, and iterative updating of the population (Blank and Deb 2020; Deb 2011; Deb et al. 2002). Initially, the solution space is initialized by randomly generating individuals, representing a potential solution. Then, the fitness of individuals is calculated to evaluate the individuals in the population and a non-dominated sorting algorithm is used to divide them into different fronts and determine their nondominance in the objective space. Subsequently, superior individuals are selected based on non-dominated sorting and crowding distance as parents and convey the repeated process of selection, crossover mutation, and updating, until the preset stopping conditions are met.

In NSGA-II, non-dominated individuals are classified by different fronts, but fronts need to be split due to the limitation of population size. However, the extreme points must be kept in every generation and assigned a crowding distance of infinity. Furthermore, to increase some selection pressure, NSGA-II uses binary tournament mating selection, which means every individual is compared by rank firstly and then is crowding distance.

We carry out this process using the pymoo algorithmic framework (https://pymoo.org/) by choosing a population size of 100 and only 10 in each generation and an implementation that is a greedier variant and improves convergence. In addition, we have enabled repeated checks to ensure that offspring after mating are different from themselves and existing populations by implementing space values. At the same time, 500 rounds of iterations are used, which is already a relatively high number of iterations in order to find more possible solutions. Ultimately, the results are a series of Pareto fronts that exhibit balanced performance across three objectives.

**Decision-making.** Pareto solution sets obtained in the previous step are used to find the global optimal solution. Considering the Pareto fronts can be both concave and convex (Messac 2015), we adopt two strategies to find the global optimal solution:

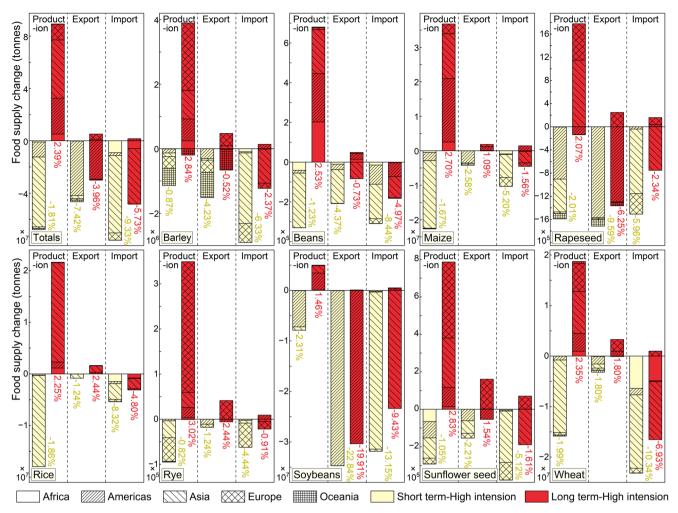


Fig. 3 Changes in global food production and import/export trade under a high level of war intensity. The different colors represent the war scenarios of short term-high intension and long term-high intension, where the filled stripes indicate the different continents in the stacked map. The numbers below the bars indicate the total world production and import/export change rate compared to the pre-war rate.

Compromise Programming and Pseudo-Weights. The optimal solutions obtained by both methods are the same in our study.

A simple way to choose a solution out of a solution set in the context of multi-objective optimization is the pseudo weight vector, especially for convex Pareto fronts (Deb 2011). The pseudo weight  $w_i$  for the *i*<sup>th</sup> objective function can be calculated by:

$$w_{i} = \frac{\left(f_{i}^{max} - f_{i}(x)\right) / \left(f_{i}^{max} - f_{i}^{min}\right)}{\sum_{m=1}^{M} \left(f_{i}^{max} - f_{i}(x)\right) / \left(f_{i}^{max} - f_{i}^{min}\right)}$$
(22)

where  $w_i$  represents the weight of the *i*<sup>th</sup> objective function,  $f_i^{max}$  represents the maximum value of that target and vice versa, and *M* is the total number of targets.

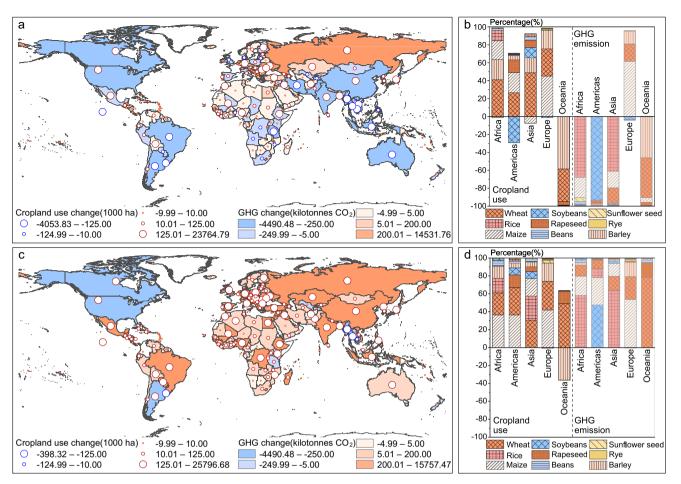
This equation calculates the normalized distance to the worst solution regarding every objective. For convex Pareto fronts, the pseudo weights indicate the location in the objective space. However, for nonconvex Pareto fronts, the pseudo weight does not correspond to the result of an optimization using the weighted sum. If we do not know the shape of the Pareto front, the thought of compromise programming is better suited to nonconvex Pareto priors to find global optimal solutions.

Compromise programming chooses the decomposition method called the augmented scalarization function (ASF), a well-known metric in the multi-objective optimization literature (Miettinen and Mäkelä 2002). Because ASF is supposed to be minimized, we choose the minimum ASF values calculated from all solutions to obtain the global optimal solution.

# Results

**Changes in global food production and supply.** The Russia-Ukraine conflict has affected global food production systems and supply chain operation properly and has mainly impeded activities in growing and harvesting, processing and transporting, and supplying and marketing food. Global food production faces a 0.6–1.8% reduction overall for the nine crops (Fig. 3, Supplementary Fig. 1). Asia accounts for the largest share, with over 75% of the global total reduction, followed by the Americas with a proportion of 18%. The greatest changes at present are rapeseed and soybeans, which face a yield reduction of over 2%. Global food exports are expected to fall by 3.5–7.2%. For most foods, exports from the Americas are expected to decrease ranging from 5.4 to 11.2%. Imports are expected to fall even more, by approximately 4.3–9.3%, with the reduction in imports occurring mainly in Asia and Europe.

In the next harvest season, we will see a brief recovery (2.4–3.0% increase compared to the first year of the war) in global production levels, but these levels still will not return to prewar levels. First, exports have recovered by 50% relative to the last year but are still facing a contraction of 4.0% compared to prewar



**Fig. 4 Changes in global cropland use and GHG emission of food production under different war intensities.** Panels show the changes, compared to prewar levels, under short term-high intension (**a**, **b**) and long term-high intension (**c**, **d**) by region (**a**, **c**) and food type (**b**, **d**). The size of the bubble indicates cropland use change, and the shade of the filling color indicates GHG emission change. In (**b**, **d**), the proportion of cropland use or GHG emissions changes were shown with black-bordered (left part) or gray-bordered columns (right part), respectively. The nine symbolic expressions represent different crops, and the length of the bar represents the proportion of crop contribution to changes in cropland use or greenhouse gas emissions within the same continent.

levels. In addition, import levels still face a decline of 0.8–5.7%, and more than 75% of the import decline may occur in Asia. Specifically, imports of rye will largely return to prewar levels, while imports of soybeans and wheat will remain low. Overall, food production will increase in the long term, but trade will tend to decrease, which will lead to an imbalance in the global distribution of food and worsen the shortage situation.

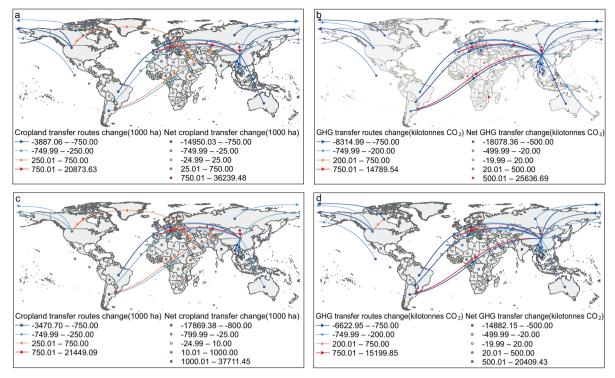
**Food shortage and food security**. The world is facing food shortages during the Russia-Ukraine conflict, and some regions will not be relieved by a timely restructuring of supply and demand. Currently, the world faces a food shortage of 53–130 million tons. The most severe food shortages are in Asia, Africa and Europe, with total shares of 80, 10 and 7%, respectively. The eastern coast of the Americas and countries in Oceania have relatively secure food supplies (Supplementary Fig. 2a, c). The countries with the worst per capita food shortages are Djibouti, Israel, the United Arab Emirates and Oman, where the grain shortages rise to more than 50 kg per capita. Wheat and rice remain the main types of shortages in all countries. The food shortage results in 360–490 million people facing nutrition security risks for the nine crops in the world (Supplementary Fig. 3a, c).

However, with the resumption of seeding activities, 36% of countries will see the number of at risk of nutrition insecurity drop to essentially zero (Supplementary Fig. 3e, g). As food production recovers, the food shortage will decrease by 62–73%,

but there will still be a food shortage of 1.4–4.9 million tons (Supplementary Fig. 2e, g). Northeast Africa and Middle East countries will still face a 25 kg per capita shortage due to the failure to adjust food supply and demand. Specifically, Africa and America will mainly lack wheat, Asia will lack soybeans, Europe will lack maize, and Oceania will lack rice.

**Increase in environmental impacts from agricultural recovery.** The Russia-Ukraine conflict has caused global cropland waste or desertion and GHG emission declines in the short term. Under the sudden shock of war, 3–11 million hectares (0.3–1% of global total) of cropland are at risk of abandonment. Cropland abandonment has occurred on the east coast of South America, Southeast Asia, and Oceania (Fig. 4a, Supplementary Fig. 4a). However, in Asia, Africa, and Europe, cropland is facing expansion, with a demand for 59–68 million hectares of cropland. The lack of timely fertilizer supplies may lead to a decline in yields, so cropland must be expanded to maintain total yields. The abandoned cropland is mainly for soybeans, while the cropland expansion is mainly intended for wheat and maize production. This situation also indicates that the Russia-Ukraine conflict has affected the production capacity of maize and wheat.

Meanwhile, a short-term shock on global food production slump will lead to temporal GHG emission reductions of approximately 24–60 million tons of CO2 (0.6–1.4% of global agricultural total). The Americas, Asia and Oceania have



**Fig. 5 Embodied cropland use and GHG transfer changes in trade under a high level of war intensity. a**, **c** indicate the implied cropland use changes and net cropland use outflow changes under short term-high intension and long term-high intension, respectively. **b**, **d** indicate the implied GHG changes and net greenhouse gas outflow changes for short term-high intension and long term-high intension, respectively. The trajectory and color of the line indicate the change in cropland use or GHG transfer between countries compared to pre-war, and the color of the dots indicates the change in cropland use or GHG transferred by one country to the others through trade.

contributed to emissions reduction. Rice is the largest contributor to emissions reductions in Africa and Asia, followed by soybeans in the Americas and barley in Oceania. Meanwhile, production continues in those countries less affected by Russia and Ukraine, which will create approximately 19–20 million tons of CO2.

Agricultural recovery will trigger a 2–4% GHG emissions increase and 9–10% cropland expansion in the long term. We estimate that 88% of the countries face an increase in gas emissions, and approximately 55–76 million tons of CO2 will be generated (roughly the total pre-war GHG emissions of Argentina). The increased GHG emissions primarily come from East Asia, Eastern Europe and the east coast of the Americas, mainly from wheat and rice. Similarly, 90% of the countries have a tendency of cropland expansion (Fig. 4c, Supplementary Fig. 4c) and generate 92–103 million hectares of cropland demand (roughly the total pre-war cropland use of Brazil). Global cropland expansion acts mainly on maize, wheat and rice. Rice is the main source of cropland expansion in Asia, followed by wheat in Oceania and maize in the Americas and Europe.

The general increase in cropland use and GHG emissions from global agricultural production is related to production recovery and filling the shortages brought by the conflict. Since different countries consume different cropland and GHG to produce a unit weight of food, the effects of cropland use and production changes vary by region. We have found that most countries have responded to food shortages resulting from the Russia and Ukraine conflict by expanding production and reducing exports. This situation is why countries should reduce trade barriers, make proper decisions and plan agricultural scale.

**Embodied environmental impacts of the shocked food trade patterns**. The Russia-Ukraine war has disrupted the structure of food supply networks, and changed the transfer pattern of cropland use or GHG emissions embodied in trade. Overall, embodied cropland use from food trade is mainly transferred to Asia. Due to the conflict and disturbed food trade network, the transfer from other continents to Asia declines more, but the transfer from other countries to the Americas intensified (Fig. 5a, c and Supplementary Fig. 5a, c). Net outflows from other countries to Asian countries increase by 23–59 million hectares, while net outflows from European countries to other countries increase by 27–52 million hectares. In terms of specific transfers between countries, the largest reductions in cropland use transfer are from Myanmar, Thailand and Argentina to China. However, transfers from Mongolia and Canada to China have been enhanced.

The pattern of embodied GHG emissions under the war scenario is similar to cropland use (Fig. 5b, d and Supplementary Fig. 5b, d). The net transfer of GHG emissions from the Americas and Oceania to other countries is continuously decreasing, while that from Africa and Europe is the opposite. Europe increases GHG emissions to other countries by 10-32 million tons. In addition, the transfer from Argentina and the United States to China shows the greatest decrease, over 4 million tons. However, the transfer of GHG emissions from Uruguay and Mongolia to China is enhanced. Net outflows from Argentina, China, Thailand and Brazil to other countries decrease the most. The net outflows from the Philippines, Togo, Mozambique, Mongolia and Uruguay may increase the most. In the long term, the cropland expansion and emissions increase in South America mainly because of the increased production to supply Asia. Meanwhile, Europe will decrease its dependence on Asia for food supply and environmental depletion.

**Options of sustainable food supply**. The Russia-Ukraine conflict highlights the vulnerability of the global food system. However, the reduction of exports from Russia and Ukraine

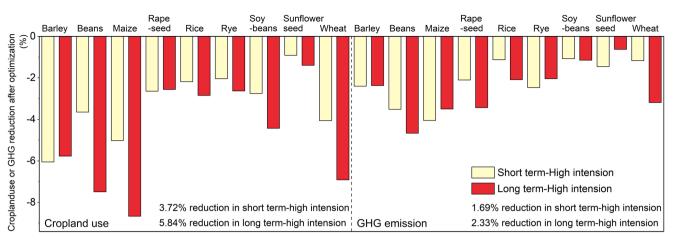


Fig. 6 Global cropland and GHG emission reduction potential selected from the Pareto frontier, with 25% increase in food transportation costs. Columns in different colors represent optimized reduction values under war scenarios of short term-high intension and long term-high intension.

opens a new window for a long-term sustainable food system transition toward a diversified food trade. It is also worth considering how world production would fill the food shortage in an environmentally friendly way. Food supply patterns are optimized using cropland use variability and GHG emissions required to produce units of food by country. The global food supply pattern optimized by the multi-objective genetic algorithm we use reduces global GHG emissions by 1.7–2.7% and cropland use by 3.7–4.5% compared to the war scenario (Fig. 6, Supplementary Fig. 6), and global transportation costs remain constant.

By optimizing, the reduced GHG emissions are approximately 34–49 million tons, which reaches those of agricultural production in countries such as Bangladesh or Indonesia (Ritchie et al. 2020). The cropland saved is approximately 37–61 million hectares, equal to the entire cropland use of Argentina. However, although rising freight costs could cause more GHG emissions from transportation, the overall GHG emissions in the food system are actually mitigated because production in low-emission countries can offset emissions and the efficiency of the food system is enhanced. Moreover, the mitigation benefit would be larger if agricultural productions further recover (Fig. 6 and Supplementary Fig. 6 red column), which is more practical for guiding production.

The optimization results can provide new solutions for the production of specific food crops (Supplementary Fig. 7). France could boost its 47% barley production, which may fill the Russian-Ukrainian shortage. As for beans, India could reduce its 15% production share, but Brazil and Myanmar could increase production share, thereby attaining more low-carbon and landsaving benefits. The production of maize requires the US to take advantage of its strengths and increase production by 39%. In addition, India could lower its production of rapeseed, rice, and wheat, which could be replaced by China. Poland could reduce its rye production share, while Germany, Denmark, and Belarus might replace it. As for soybeans, the USA could increase production by 18% on the current basis, while preferably reducing Argentina 43% of production. Sunflower seeds can only be transferred to Argentina, Romania and other possible places to compensate for the shortages. In terms of staple grains, the alternative supply of wheat and rice depends mainly on Asian countries, especially China and India. The alternative supply of maize relies more on American countries. If countries rely on their strength to produce food extensively and boost the resilience of the global food system, they will barely overcome shortages from external upheavals.

#### Discussion

Compensating for the food shortage caused by the Russia-Ukraine conflict while protecting ecosystem stability remains an urgent issue for all countries. Therefore, it is worthwhile to investigate how to build a resilient food system with land-saving and emissionreducing effects. Our research framework correlates multiple elements and regions and provides a good basis for overcoming hunger, improving cropland use efficiency, and reducing the burden of GHG emissions. We find that the Russia-Ukraine conflict declined crop production and led to a reduction in cropland waste and GHG emissions in the short term. However, agricultural recovery in the next cultivation season will cause additional global environmental pressure. In particular, the changing patterns of cropland use and GHG emissions transfer embodied in the food trade will place extra pressure on the sustainability agenda in China and Europe. Ultimately, we argue that an alternative food supply could minimize the global environmental impacts of the food system recovered from the Russia-Ukraine conflict.

**Widespread food production and barrier-free trade**. We find that the Russia-Ukraine conflict has reduced the food production of major crops by 0.6–1.8%. Cropland abandonment and food reduction first appeared because of higher food production costs and negative production psychology at the beginning of the conflict. Subsequently, we are facing a shortage of 50–120 million tons of food, while 360–490 million people may face food insecurity. While agricultural recovery could raise global production by over 2%, global trade remains below 97% of pre-war levels, meaning that food imbalances and hunger are still being perpetuated. Long-term food shortages may affect the social stability of countries, especially those with low-income levels (Deng et al. 2022).

The association between income levels and food shortages suggests that social instability may be higher in Asian and African countries, particularly Djibouti, Egypt, and Tunisia in Africa and Azerbaijan, Uzbekistan, and Afghanistan in Asia (Supplementary Fig. 8). Subtly, according to official reports in Iran, the ongoing protests over food prices in the country have resulted in deaths(https://new.thecradle.co/articles-id/4006). The food crisis in Egypt even caused economic turmoil, and the annual inflation rate soared to over 15% (Mamdouh 2023). These identified countries should receive more international help to overcome food shortages and prevent social extremes. In addition to international rescue, reducing waste and shifting diet can alleviate the food crisis by replacing domestic food consumption with other similar food types that are less emission-intensive (Navarre et al. 2023). At the

same time, agricultural yields can be increased by upgrading climate-resilient agriculture technologies, including crop improvement, changes in irrigation, planting and fertilization methods, and manure management (Foong et al. 2023; Lin et al. 2023).

Furthermore, the end of the Russia-Ukraine conflict is still unpredictable, and the conflict may develop into a long-term conflict and the fear-avoidance mentality of war instability could aggravate food security and trade diversification. Every country should leverage their production strengths to produce food with higher efficiency and lower emissions to ensure the adequacy and sustainability of global food production. At the same time, other countries could import specific food categories from those with production advantages, thereby reducing global GHG emissions and cropland use consumption. For instance, Russia and Ukraine are adept at producing sunflower seeds, China at rice, pork and seafood, and Thailand and India at rice.

However, the delay in reaching an agreement on food shipments between Russia and Ukraine further exacerbates the risk of global food shortages because the difficulty in transporting food out of Ukraine is ongoing. Considering that Russia and Ukraine are major agricultural producers of crops, it is crucial to combine policy and market measures to ensure production and remove trade barriers. Numerous studies have demonstrated that international trade reduces global environmental impacts (Hellegers 2022; Husain et al. 2022; Khorsandi 2022; Lin et al. 2023). Allowing agricultural products from both countries to enter the international market also aligns with the economic interests of agricultural producers in Russia and Ukraine. A conducive and liberal trade model requires dismantling trade barriers and promoting tax reductions to ensure food trade both within one country and among countries. Examples include China's green channels for food transportation on highways and the sustainable maize and soybeans trade between China and the USA.

Efficient and ecologically-protected agricultural expansion. Subsequent agricultural recovery will partially release the global food shortage but will lead to higher GHG emissions and increased cropland in most countries. Agricultural recovery will trigger 92–103 million hectares of cropland expansion and 55–76 Mt of  $CO_2$  emissions compared to prewar levels. In addition, restrictions on food trade are coupled with embodied environmental footprints. For example, reduced food imports in Asia will lead to an increase in local cropland use and GHG emissions but will reduce those embodied in imports. Food trade will place more pressure on climate action and biodiversity conservation in those countries.

Our results show that agricultural recovery would lead to an increase in global demand for cropland up to the total size of croplands in Brazil. This recovery would undoubtedly raise the risk of destroying other types of land, especially biodiversity hotspot (Guerrero-Pineda et al. 2022). Countries at risk of destroying biodiversity hotspot are mostly low-income and middle-income countries (Supplementary Fig. 9 'H-H' region), mainly including Morocco, Cape Verde, Ethiopia, Sri Lanka, the Philippines, El Salvador, Haiti, Nepal, Liberia, Azerbaijan, Lebanon, and Turkey. Countries identified as having a high risk of biodiversity hotspot destruction should guard the ecological bottom line and take appropriate protection measures. These countries face the risk of destroying biodiversity hotspot when expanding cropland, and should focus on increasing the unit yield of agricultural products to reduce the expansion of cropland. Optimizing photosynthesis and improving the efficiency of water and nutrient use can greatly improve the efficiency of food production (Bailey-Serres et al. 2019). It is also necessary to establish a circular food system to reduce the use of cropland and waste of resources (Vågsholm et al. 2020), which can improve food production efficiency, reduce food waste, and enhance the management of waste such as feces (Koppelmäki et al. 2021).

Adequate and sustainable food supply system. Our results show that the optimization of global production and trade could overcome food shortages while reducing GHG emissions by 1.7-2.7% and cropland use by 3.7-4.5%. The reduction in GHG emissions nearly equals agricultural production in countries such as Bangladesh or Indonesia, while the cropland saved is approximately the same size as that used for cropland in Argentina. However, the trade-off among lower cost, GHG emissions and cropland use is a tricky problem. Emission reduction or cropland use reduction targets alone may have greater single-target benefits but may undermine other targets (F. Melese and Solomon 2015). Moreover, trading freely and producing extensively determines the reference ability of the optimization. Even if we obtain options that may overcome food shortages, this process will create additional ecological security challenges for some countries. This situation is also a strong indication that the transformation of the global trade pattern is essential.

In the long run, we are facing the challenge of achieving sustainable food production and consumption by raising awareness of food issues (You et al. 2022). Therefore, measures such as food conservation, waste reduction, and food charity initiatives can efficiently alleviate the current food shortage. Food banks and food commons funding deserve to be organized and regularly maintained in social units of all scales around the world. Beyond the daily food waste, food loss and waste in the food trade process deserve extract attention. Upgrading transportation and preservation technologies can also contribute to food conservation and food system sustainability (Pradhan et al. 2020). Furthermore, adjusting the dietary structure is an important method to address food shortage. Some scholars have proven that in the EU and the UK, the EAT-Lancet, which means adopting a plant-based diet while limiting the intake of animal origin could cover almost all of the production deficit in Russia and Ukraine (Sun et al. 2022). Substitutions in food consumption and dietary changes can also help strengthen the resilience of food supply systems from global shocks by reducing the demand for grains needed for animal feed.

The current study has a few limitations. We assessed the current food shortage and the possible resource-environment impacts in the coming years, but the longer-term food system impact is not discussed. Due to the lag in real data, it was not possible to calibrate the simulated data. In addition, due to the lack of region-specific data, the potential for national improvement of environmental performance in agriculture was not considered in this study. The shock-impact-response framework can be widely used in the future to serve SDGs related to the food system better.

The occurrence of the Russia-Ukraine conflict has inspired us to transform global food system and ensure sufficient supply (Pradhan et al. 2021). To permanently ensure the maximum food supply, it is necessary to adjust the production distribution in a timely manner. All efforts are intended to keep the supply network's economic cost, global cropland occupation and GHG emissions as low as possible. If a timely transition is made to deal with one shock, there will be a chance to build better resilience in the future and more responsively adapt to other future shocks. The global impact of the Russia-Ukraine conflict is an opportunity to promote the long-term sustainable transformation of the food system, which contributes to achieving zero hunger, 1.5-degree climate goals and other SDGs.

# Data availability

All data needed to evaluate the conclusions in the paper are presented below. The base-year macroeconomic and sectoral data

is from the GTAP v.10 database(https://www.gtap.agecon.purdue. edu/databases/v10/index.aspx.). We linearly estimated the global population in 2022 using the 2020-2025 population data under the SSP2 path published by the International Institute for Applied Systems Analysis (IIASA) (https://secure.iiasa.ac.at/web-apps/ ene/SspDb/dsd?Action=htmlpage&page=about). Data for food balance sheets, cropland use for nine crops in each country, food production and trade data between countries are derived from the FAOSTAT database (https://www.fao.org/faostat/zh/#data). Income groups were divided according to the gross domestic product data published by the World Bank (https://data. worldbank.org/income-level). The nitrogen fertilizer applied by nation and food type is collected from the International Fertilizer Association (https://www.fertilizer.org/market-intelligence/ ifastat). Region- and food-specific GHG emissions are accounted for from the unified material flow analysis framework developed in previous studies (Hu et al. 2020; Lin et al. 2015). We track the annual agricultural inputs (e.g., fertilizer and water used per unit of cropland) and the resulting emissions in the various production processes with the most recent data. The agricultural inputs include biological nitrogen fixation, energy use, chemical fertilizer, manure and straw recycling, roots remaining in the cropland, seed, irrigation, and nitrogen deposition on cropland. The GHG emissions are then accounted for with the data of food production scale and region-specific emission factors from IPCC reports and other studies (Hong et al. 2021). Finally, the GHG emissions per unit of food product is obtained by dividing the total emissions by the corresponding production. As for optimizing food supply pattern, the freight cost calculation is based on rail and water transport routes between countries, using the minimum cost distance. In this case, the cost of fuel consumption by rail is 1.5 cents/ton-kilometer, while that of water transport is just 0.6 cents/ton·kilometer. Cost data comes from reports published by large international freight companies(https://www. szlongg.com/szsongg/vip\_doc/25915237.html) and (https://www. cnhli.com/news/hangye/57.html). The nautical route vector data is obtained by manually vectorizing from the world map with routes published by the Ministry of Natural Resources of the People's Republic of China. Rail route vector data is from the Data Centre for Resource and Environmental Sciences, Chinese Sciences (https://www.resdc.cn/data.aspx? Academv of DATAID=207). Global biodiversity hotspot spatial data is from (https://www.conservation.org/ Conservation International priorities/biodiversity-hotspots). Changes in global food production and trade under the Russia-Ukraine conflict are projected through the adaptive multi-regional input-output model (AMRIO), whose code is public (Li et al. 2013; Shan et al. 2021). We calculate the food shortage and alternative food supply's impacts via Quasi Input-Output (QIO) model (Niu et al. 2020; Qu et al. 2017a). We carry out multi-objective optimization using the pymoo algorithmic framework (https://pymoo.org/index. html) by choosing a population size of 100 and only 10 in each generation and an implementation that is a greedier variant and improves convergence.

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#### **Author contributions**

Y.H., L.J., Z.W., and H.Z. conceptualized the framework of the study. H.Z., C.L., and Z.D. calculated, processed and calibrated the data, contributing mainly to the modelling of the Russia-Ukraine conflict scenario and the calculation of environmental effects. H.Z., Y.H., L.J., Q.J., and X.L. developed the figures. H.Z., Y.H., L.J., and Z.W. wrote the first draft of the manuscript and L.J., Y.H., Z.W., and Y.L. supervised the study. All authors discussed the results of the study and revised the manuscript.

# **Competing interests**

The authors declare no competing interests.

#### Ethical approval

Ethical approval was not required as the study did not involve human participants. This research strictly adheres to international and national ethical guidelines and does not involve any human or animal experiments. All data used in the study comes from publicly available sources. In consideration of the subject matter, we have taken particular care to ensure fairness and objectivity in our analysis. Our research has not collaborated with any organizations or individuals that could pose a conflict of interest, and all findings are intended to promote scientific understanding and societal awareness of this issue.

#### Informed consent

All collaboration or consultation with experts, stakeholders, or participants was conducted with full transparency. Before engagement, all parties were provided with a clear explanation of the research's purpose, methods, potential implications, and the extent of their involvement. Written or verbal consent was obtained from all who contributed, ensuring that participation was voluntary and based on a full understanding of the research.

#### Additional information

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