Citation (APA)
Verschuur, J., Murgatroyd, A., Vittis, Y., Mosnier, A., Obersteiner, M., Godfray, C. J., & Hall, J. W. (2026). Assessing the resilience of global grain supplies to compound climatic and non-climatic shocks. *PLOS Climate*, *5*(5 May), Article e0000825. https://doi.org/10.1371/journal.pclm.0000825

PLOS Climate

RESEARCH ARTICLE

Assessing the resilience of global grain supplies to compound climatic and non-climatic shocks

Jasper Verschuur[1,2]*, **Anna Murgatroyd**[1,3], **Yiorgos Vittis**[4], **Aline Mosnier**[5], **Michael Obersteiner**[1,4], **Charles J. Godfray**[6], **Jim W. Hall**[1]

1 Environmental Change Institute, University of Oxford, Oxford, United Kingdom, **2** Department of Engineering Systems and Services, Faculty of Technology, Policy and Management, Delft University of Technology, Delft, the Netherlands, **3** School of Engineering, Newcastle University, Newcastle upon Tyne, United Kingdom, **4** Ecosystem Services and Management Program, International Institute for Applied Systems Analysis, Luxemburg, Austria, **5** Sustainable Development Solutions Network, Paris, France, **6** Oxford Martin School, University of Oxford, Oxford, United Kingdom

* J.Verschuur@tudelft.nl

Citation: Verschuur J, Murgatroyd A, Vittis Y, Mosnier A, Obersteiner M, Godfray CJ, et al. (2026) Assessing the resilience of global grain supplies to compound climatic and non-climatic shocks. PLOS Clim 5(5): e0000825. https://doi.org/10.1371/journal.pclm.0000825

Editor: Sejian Veerasamy, National Institute of Animal Nutrition and Physiology, INDIA

Received: January 17, 2026

Accepted: April 27, 2026

Published: May 12, 2026

Peer Review History: PLOS recognizes the benefits of transparency in the peer review process; therefore, we enable the publication of all of the content of peer review and author responses alongside final, published articles. The editorial history of this article is available here: https://doi.org/10.1371/journal.pclm.0000825

Abstract

The convergence of recent extreme-weather events and international conflicts has heightened concerns about the vulnerability of the global food system to shocks. Yet, it remains unclear what shocks most affect a country's food supply, and what role trade and other food system characteristics play in mitigating or amplifying negative impacts. Here, using a newly developed global bilateral trade model representing 177 countries and four major staple crops (maize, wheat, rice, soybean), we simulate the food supply, trade and price impacts resulting from climate-related yield variability, and shocks motivated by (i) the Ukraine war, (ii) the recent energy price shock, (iii) observed trade bans, as well as (iv) a compound shock (i-iii together). The energy price shock has the greatest effect of the first three shocks, and dominates the effect of the compound shock across most regions and crops. We find that in many instances trade adjustments can help cope with both supply and price shocks, but that this is shaped by a combination of factors that characterize a country's coping capacity. If the compound shock occurs at a time of poor global weather for agriculture, the total drop in consumer surplus that year can be over USD 600 billion and affect most countries simultaneously. The modelling approach developed here can be a useful tool to identify vulnerabilities in food systems and to develop targeted strategies to enhance resilience, such as strategic stockpiling, schemes to support domestic production or new trade agreements.

1 Introduction

The global agricultural system has become increasingly interconnected, providing food and feed for a growing global population [1]. At present, around 20% of all calories consumed globally are from traded food products [2], with trade of agricultural

Data availability statement: Crop yield and harvested area are taken from FAOSTAT (https://www.fao.org/faostat/en/#data/QCL). Crop production costs are taken from [37]. Demand and Supply elasticities are extracted from the IMPACT model [65], whereas total supply and demand estimates are taken from the FAO Food Balance Sheets (https://www.fao.org/faostat/en/#data/FBS). Trade data is from the BACI database [66], whereas tariffs are from the Mac-MAP-HS6 database [67]. Trade costs are based on [38] and stocks are taken from the USDA PSD database through their API (https://apps.fas.usda.gov/opendatawebV2/#/home). All code and data needed to rerun the model results, including a dummy model, is provided in [68].

Funding: This research has been conducted as part of the Oxford Martin School Programme on Systemic Resilience, for which JV, JWH and MO have received funding, and the FACT Alliance Jameel Index for Food and Trade Vulnerability, for which AMu and JWH have received funding. AMo acknowledges funding from the Global Environment Facility under project FOLUR. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

Competing interests: The authors have declared that no competing interests exist.

products more than doubling between 1995 and 2018 [3]. Trade is critical in balancing supply and demand across borders within and across years. However, an increasingly interconnected global food system also raises the possibility that local shocks become global ones, so-called systemic risks [4,5]. For instance, weather fluctuations during the growing season account for a third of the variation in global yields [6] and can cause crop failures in multiple ‘breadbasket’ regions simultaneously [7]. In addition to these climatic shocks, a variety of non-climatic shocks can impact production, prices and trade [8–10]. For example, global grain supplies were dramatically impacted by droughts in 2010–2011, whose effects were exacerbated by a Russian export ban and low stocks-to-use ratios, leading to a doubling of global wheat prices [11].

Evidence suggests that the frequency of droughts and other adverse weather events has increased in recent years [7]. Still, food price volatility over this period has been dominated by non-climatic factors, including the war in Ukraine and the consequent rise in fertilizer prices, locust outbreaks, and trade restrictions imposed by various countries [12–15]. These events, along with other factors such as the pandemic and an increasing number of civil and international conflicts, have doubled the number of people facing acute food insecurity in 2023 compared to 2019 [16]. This led to a range of interventions taken by governments in 2022 and 2023 (e.g., food and fertilizer subsidies, cash transfers and food vouchers), often at a considerable cost [13].

These recent events have led to renewed efforts to understand the resilience of the global food system to multiple, compounding shocks, i.e., those affecting production, trade and consumption at the same time across multiple countries. Food system resilience, in this context, refers to the ability of countries to buffer the variety of shocks that are impacting their domestic food system, and also their capacity to cope with shocks elsewhere. Low resilience can lead to food shortages and fluctuations in consumer prices, ultimately harming food consumers, in particular the poorest households in society [17].

Several studies have sought to explore the vulnerability and resilience of countries to food system shocks, using a variety of methodologies. A first set of approaches use econometrics to understand the factors that have affected past price fluctuations, primarily during crisis events [18–22]. These studies highlight the complex interplay of factors, such as stocks, demand and supply, speculation, exchange rates and fiscal responses that together shape global price spikes and its transmission to domestic prices. Others have empirically analyzed which countries have been most affected by historical trade shocks (defined as global export reductions). For instance, one study [5] found that low-income countries are disproportionately affected by such shocks.

A second strand of work uses trade data to reconstruct the global network of trade in different commodities, and then employ network analysis to identify country vulnerabilities to shocks [23–27]. Most of these studies use multiple network metrics as indicator of a country’s vulnerability, and compare those indicators across countries or track their evolution over time. Recent work has complemented trade data with information on national food balances to better characterize the vulnerability of different countries [17,28]. This research shows that a country's vulnerability to shocks cannot be explained by a simple indicator [29], but is shaped by a variety of interacting factors such as trade diversity, imports dependency, self-sufficiency ratio, and stocks-to-use levels [17].

A third set of approaches encompasses the use of dynamic food shock models, incorporating elements of the system's response to shocks such as supply adjustments or price fluctuations. For instance, Puma *et al.* added a simple trade reallocation algorithm to a trade model to evaluate the impacts of a supply shock and related export restrictions [27]. Burkholz and Schweitzer developed a "cascade model" in which a supply shock causes countries to reduce their exports, which consequently affects the supply to other countries, hence the cascade [4]. These models have been extended to include the use of stocks to buffer supply shocks, mainly based on heuristics [30]. In all these studies, price adjustments or substitution effects are not captured, and hence only supply shocks can be modeled. Others have developed dynamic models that can explicitly capture how multiple shocks impact global prices, and the resulting supply and demand adjustments taken by different countries [31,32]. However, these models do not explicitly represent bilateral trade flows between countries, preventing them from capturing trade adjustments such as import substitution that can mitigate or amplify impacts.

A fourth means of studying this issue is to use global food system models to assess the impact of a shock on food prices. Examples include a study of the effects of reduced supply due to the Ukraine war, either alone [33] or combined with the increase in fertilizer prices brought about by the war [34]. These models often assume a single global market and do not specify bilateral trade flows, so that trade substitution is unconstrained and rapid. Work that incorporates trade data in such models showed that price increases in the countries most affected by reduced wheat exports from Ukraine could be an order magnitude higher than global price impacts [35]. Still, such general- or partial-equilibrium models are designed to study long-run price and trade adjustments and hence tend to underestimate the impacts of short-run shocks.

Despite the significant body of research on food system resilience, a gap remains in our understanding of how bilateral trade flows dynamically shape a country's food system resilience to shocks. As highlighted above, existing methodologies fail to adequately capture either price or trade substitution adjustments. Price and trade adjustments are often the first response of many countries to a food system shock: to increase imports or reduce exports, and to forge new trading partnerships (which typically entails a cost). These trade adjustments can be country specific, requiring detailed modelling of how individual countries are affected by, or respond to, a disruption. Furthermore, most models do not fully explore the complex interactions of compounding climatic and non-climatic shocks. Yet, recent events have highlighted how supply shocks, trade restrictions, and input price spikes interact and possibly amplify each other. In doing so, it is important to explore these shocks and their interactions against the full distribution of possible weather scenarios: from those that result in a bumper harvest through "normal" years to adverse weather conditions leading to multiple production failures.

In this study, we utilize a newly developed bilateral trade model to study the effects of individual shocks and the compounding (i.e., simultaneously occurring and therefore interacting) nature of these shocks on global grain supply and prices. This dynamic food shock model explicitly represents bilateral trade, storage and price effects in a single, integrated framework. The approach allows us to go beyond network metrics and static analyses to directly model how trade adjustments can either buffer or amplify the impacts of a shock. By simulating a combination of compounding shocks (e.g., supply reductions, trade restrictions, and input price spikes) against a full distribution of possible weather scenarios, our research provides a more comprehensive assessment of global food system resilience than has been previously possible. Still, the shock scenarios tested in this study, inspired by the events of 2022–2023, are mainly to illustrate the use of the model, rather than a full global stress-testing of the food system.

We demonstrate how countries and regions differ in their exposure to the compound shock modelled, and in their capacity to cope with them by utilizing stocks, reducing exports, or changing trading partners. Our modelling framework provides insights into the vulnerability of different countries and the propagation of risks through global grain supply networks. We believe our modelling framework will enable more realistic stress-testing of global food supplies as well as the design of effective strategies to enhance the resilience of food supply systems.

2 Materials and methods

2.1 Overview

We developed a spatial price equilibrium model that simulates demand, supply, producer and consumer prices, and trade flows across 177 countries. Our model relies on standard datasets of yield, supply, demand and trade, and upon a food production and trade cost dataset constructed in previous research [36–38]. We considered four crops – maize, wheat, rice, soybeans – as they are strongly affected by the different shocks we modeled [34] and because of their importance for global food and feed consumption.

All key model parameters (involving yield, supply, demand, trade) were averaged over the period 2017–2021, our reference period, which we used for our model calibration. This specific time frame was chosen to exclude the effects of the food shocks that emerged from 2022 onward and because the necessary data for several of the cost components used in our model were only fully available for these years. Using a different period would introduce inconsistencies in our calibration procedure. We note that while this period overlaps with the COVID-19 pandemic, the data used for calibration is not greatly impacted by this event, given the averaging across non-COVID-19 years and because the demand and supply of cereals during the COVID-19 were still relatively stable [39]. The five-year averaging period was chosen to smooth year-to-year variations, as is common practice in general equilibrium modelling [40], because it is a good compromise between system representativeness and being able to smooth out interannual yield variability and external shocks. A longer period would have affected the consistency of our calibration, as mentioned above, while a shorter period would have been more susceptible to bias from events such as El Niño or the COVID-19 pandemic.

Our model can be considered a “one-time exogenous shock model” [4]. In other words, it is designed to explore the short-run impacts of a (hypothetical) shock whose impacts occur within a single year in which planting decisions have largely been made, leading to an inelastic supply. In this scenario of inelastic supply, countries can only respond by utilizing grain stocks, withholding exports, adjusting imports from existing suppliers and, at a cost, diversifying their trading partners.

We provide here a brief overview of the methodology in four subsections: (i) the spatial price equilibrium model, (ii) the implementation of the various shocks into the model, (iii) an overview of the factors determining the coping capacity of different countries, and (iv) the impact metrics we employ. Further details are provided in the Supporting Information.

2.2 Global spatial price equilibrium model

Our newly developed spatial price equilibrium model (SPEM) captures producer and consumer prices, supply, demand and trade flows. A SPEM is a multi-region partial equilibrium model that links producers and consumers across geographies [41]. The cost of trade sums all expenses incurred post farm gate including storage, within-country transportation, border and custom compliance, maritime transport, intermodal transfers, port fees, and import tariffs. These trade cost components have been derived separately in our previous work [38] which explored how trade costs contribute to the landed cost of grains, across crops and countries.

The benefits of a SPEM are fourfold. First, it explicitly captures bilateral trade flows, which are absent in most global food systems models. Second, it allows for trade substitution and the establishment of new trading partners. Third, it captures directional trade flows, meaning that countries can both import and export the same product. Fourth, it allows different types of shocks to be modeled, including price shocks, supply shocks, and trade shocks (e.g., tariffs, trade bans). SPEMs are usually constructed to address medium to long term questions such as the response of an economy to changing trade tariffs or demand patterns [40,42]. Here, we have adjusted the standard SPEM formulation to make it suitable for studying more short-term, typically one-off shocks (see Supporting Information). We have also incorporated commodity stock levels in the modelling framework, as these are essential to understand supply shortages in the short-term but are usually omitted in studies with a longer time horizon.

In our model, the decision to supply grain commodities from certain regions is purely based on differentials in the total landed cost of the goods (that is the cost to produce crops and ship them to consumers). However, there are real-world non-cost elements which influence where countries export to, and from where countries source imports. Hence, the model needs to be calibrated using existing trade data to capture these factors and create a representative cost chain for the trade network underpinning our reference period [40,43]. The model was calibrated to reproduce observed trade flows in our reference period (2017–2021) given the previous time period (averaged over 2012–2016) as a starting point (see Validation in S2 Text). This process yielded a calibration constant for each bilateral trade relationship, representing 'shadow trade costs' within the current trade network. Given that we imposed shocks to our reference food system, only one calibration constant is required instead of a multi-period calibration procedure. Moreover, only our reference trade system can be realistically calibrated, given that we do not have historical data on agricultural tariffs, production structures and costs, and transport connectivity and related costs.

In our model, countries have interconnected competitive markets between which there are directional trade flows in homogeneous goods. Producers in each country have a fixed amount of the good to supply to the market (either domestic or foreign), which is determined by that year's harvest and which they sell at the highest possible price. However, countries can utilize their stocks to bridge supply deficits, following their supply curve. Consumers have elastic demand for food commodities which they buy at the lowest possible price (following their demand curve). At equilibrium, we can find the trade flows between countries that determine the producer and consumer prices. For each country, the total production, stocks utilized and imports must match the total consumption and export at equilibrium.

The SPEM model thus required data on trade, transport and trade costs, stocks, prices, supply and demand, and information on the shape of the demand and supply curves (the demand and supply elasticities). We included 177 countries for which we could collect all the data required and provide an overview of the data sources in S1 Table. In the S1 Text, we describe the trade cost formulation used, the model set-up and the calibration process. A separate SPEM was constructed for each of the four crops, without considering any cross-grain substitution effects.

2.3 Shock implementation

Four shock scenarios were superimposed on a "weather-only" baseline scenario. It is important to clarify that our study used shocks that are motivated by the events of 2022–2023, rather than attempting to precisely reproduce the effects of these specific events. Instead, the main goal of this study is to explore the resilience of the food system to plausible and representative shocks against a wide range of simulated weather outcomes. Reproducing historical events would require more granular inputs than adopted in this paper. Below, we describe the different scenarios, with further details provided in the S1 Text.

Baseline "weather-only" scenario: Food production is influenced by year-to-year weather variations. Therefore, the impact of any additional shock depends upon the coincident weather in the year in which it occurs. To comprehensively analyze weather-related variability in food production, a baseline was adopted that incorporates weather variations from 54 years of observed global meteorological data, which was fed in a calibrated crop model [44]. For each grid cell, this resulted in a probabilistic yield realization based on past observed weather conditions. It should be emphasized that the resulting yield distribution should be interpreted as plausible variations in production based on historical weather, and not a historical reconstruction reflecting changes in productivity, harvest area and other factors [44]. Modeled grid-level crop yields were aggregated to country level to derive 54 samples of national crop yield (and hence production). Linear regression was used to filter out trends in the data and derive annual production deviations from the mean. These deviations were then added to the calibrated supply as input to the trade model (see S1 Text), after which the model equilibrium was re-evaluated.

Ukraine war scenario: For this scenario, three adjustments to the baseline model were added. First, the food supply from Ukraine was lowered to 60% of its baseline, in line with observed reductions in 2022/2023 [45]. Second, the trade costs of all food trade to and from Russia was increased by 50% to represent a surge in insurance costs for trade with Russia and rerouting costs given disruptions in Black Sea trade. Third, the effects of the blockage of Black Sea ports were modeled by doubling [46] the costs of trade from Ukraine to any non-European country. This captured the difficulty of sourcing Ukraine exports via sea and the additional costs to reroute goods via rail to alternative European ports.

Price shock scenario: In this scenario, a price shock was introduced to capture the increase in fertilizer, pesticide and diesel costs that occurred due to the energy crisis after Russia's invasion of Ukraine as well other supply issues over the last few years. We follow a similar methodology to that in our previous work [38] and estimated for every country the share of fertilizer, pesticide and diesel costs to total production costs. An input price shock was imposed in the model, increasing fertilizer costs by 200% and diesel costs and pesticide costs by 100% (see S2 Table). This input price shock was assumed to be passed on to consumers via an equivalent increase in producer prices (see S1 Text).

Trade bans scenario. In the trade ban scenario, the impacts of trade restrictions were evaluated in a similar way to those implemented by countries between 2022 and 2023. To do so, the Global Trade Alert (GTA) database (https://www.globaltradealert.org/) was utilized, which is considered the most comprehensive database on Non-Tariff Measures (NTM) available. The GTA database is constructed using an automated data collection system described in Evenett et al. [47,48]. The GTA database covers which countries imposed trade restrictions, which countries were affected by them, and for which commodities these restrictions were applied. Information on all implemented import and export trade bans (hereafter trade bans) was extracted for the four crops considered, and subsequently encoded in the model by preventing trade between the countries affected.

All "compound" shock scenario. In the compound shock scenario ("All"), all three shocks were implemented simultaneously on top of our "weather only" baseline.

2.4 Coping capacity indicators

There is a long-standing debate about the factors that determine a country's food system resilience, i.e., the factors that shape a country's capacity to cope and respond to shocks [17], including the role of trade [9,20]. A variety of indicators have been proposed to measure the coping capacity of countries. Here we considered five of these:

- **Import dependency** (ID) measures the percentage of consumption (production + imports – exports) derived from imports [17,27]. Higher ID makes countries vulnerable to shocks elsewhere, but reduces the impacts of domestic yield fluctuations (S1 Fig).
- **Supply diversification**, measured by the Herfindahl-Hirschman Index (HHI) which is an estimate of the degree to which supply is concentrated in a restricted number of countries (including from domestic production) [17,49]. Countries with larger supply diversification, so a lower HHI, can more easily substitute supply but are also more exposed to a greater number of shocks (42).
- **The stocks-to-use ratio** (S-t-U) measures the availability of stocks that can be used to meet shortfalls in supply and address domestic demand [18,29,50] (S3 Fig).
- **The export-to-production ratio** (E-t-P) is a proxy for a country's ability to withhold exports to meet shortfalls in domestic supply or withhold exports to lower domestic prices [17] (S4 Fig).
- **The demand elasticity** (DE) of countries determines its willingness to forego consumption if prices increase, and vice versa [18,51]. This is determined by a country's dietary preferences and GDP, among other factors (S5 Fig).

We tested the relationship between these coping capacity indicators and the impacts as a result of the shocks modeled (see Section 2.5).

2.5 Impact metrics

Food system resilience in this study is measured in terms of fluctuations in consumer surplus. The consumer surplus is a measure of welfare that captures the difference between consumers' willingness to pay for a given quantity of food and the price they actually have to pay. It has been used as an impact metric in a number of other studies of exogenous food system shocks [52–54]. Changes in consumer surplus track welfare impacts of price changes impacting both expenditure and consumption. A country's food system resilience can thus be defined as the ability to buffer impacts to its consumer surplus given the shocks imposed nationally and internationally.

Apart from country-level impacts, we also evaluated the globally systemic impacts of specific shock scenarios. We measured the globally systemic impacts as the simultaneous negative consumer surplus experienced across countries for a given shock scenario. A negative consumer surplus measures the deviation in consumer surplus for a certain weather realization compared to the mean consumer surplus experienced across the 54 weather years in the Baseline scenario. The global systemic impact is thus defined as the total number of countries experiencing a negative consumer surplus and the total cumulative negative consumer surplus across countries.

To explore how coping capacity, as measured by the different indicators (Section 2.4), influences a country's food system resilience, the relationship between the cross-country differences in the coping capacity indices and the modeled deviations in consumer surplus was evaluated. To do so, the severity of consumer surplus impacts per country were ranked across the stochastic shock scenarios (from 1 to 54). Then, the Spearman rank correlations between the modeled impacts and the five coping capacity indicators were evaluated. A non-parametric statistic was more appropriate than a standard Pearson correlation as the data was ordinal and to capture the potential non-linear relationship.

3 Results

3.1 The influence of weather on yields and hence consumer prices

We investigated the effects of typical patterns of weather fluctuations on domestic and foreign prices using 54 instances of annual weather data (*Baseline* scenario). In Fig 1 we show price volatility and average consumer prices for this scenario, for all four crops combined (Fig 1A) and for each crop separately (Fig 1B-1E). In S6-S7 Figs, we provide further information on fluctuations in supply and the degree to which domestic price fluctuations are influenced by global price fluctuations.

Despite weather-related variations in crop yield, most of Europe and North Africa exhibit low prices and low volatility, due to the deep and diverse grain markets operating in these regions. Regions with high production serving predominantly domestic markets (Central Asia, Eastern Europe, Australia, South Africa) have low prices but relatively high volatility, as domestic food prices are very sensitive to weather-related variation in domestic production (see S6 Fig). In contrast, some large importers (China, Bolivia, the Middle East and Sub-Saharan countries) have higher average prices because they are subject to large transport costs, but lower volatility because they can diversify across several food-producing trade partners. Countries in Sub-Saharan Africa face both high consumer prices and high volatility. This is caused by high transport costs [38], a dependence on suppliers whose production is highly variable (S6 Fig), and an isolation from global markets that prevents countries from buffering yield shocks (S7 Fig).

There are interesting differences between the four crops (Fig 1B-1E). For maize, low consumer prices and price fluctuations are predicted in Northern Africa (because of large and quite stable domestic supply) and in Eastern and Central Europe due to their proximity to major maize suppliers in Europe. In contrast, high transportation costs and reliance on variable production (AS6) leads to high prices and high price variability in most Sub-Saharan African countries and landlocked South America. For wheat, high import-dependency leads to high consumer prices in most of Africa, yet results in relatively stable supplies and prices due to imports from a diversity of countries (Eastern Europe, North America, Latin America and Western Europe). On the other hand, large wheat producers in South America, Eastern Europe and Central Asia are among the lowest cost producers, yet are subject to price fluctuations induced by production variability

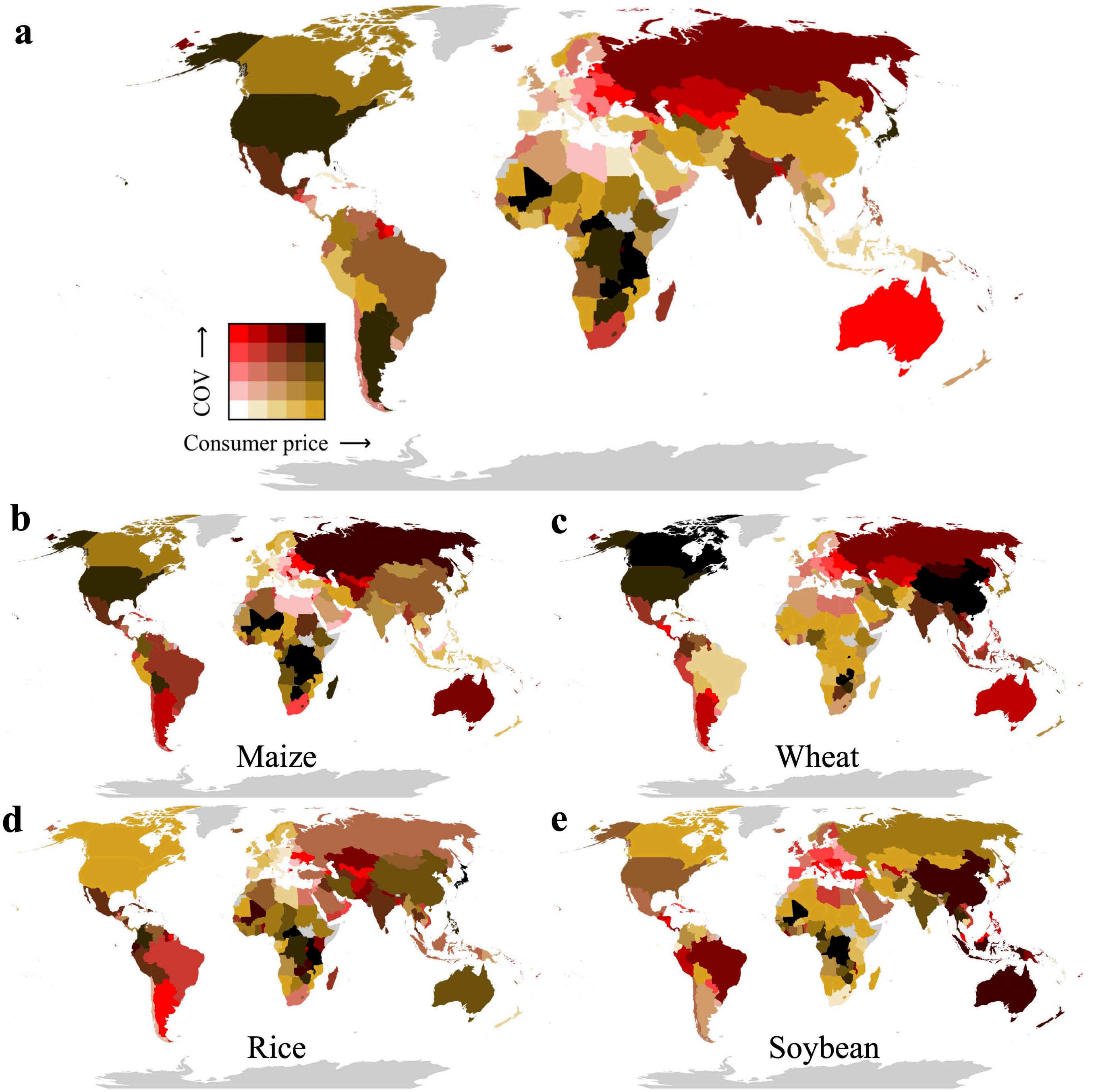

Fig 1. Risk profile of consumer prices related to climate-driven yield variations (A) Bivariate plot of the mean consumer price averaged across the 54 yield years, and the coefficient of variation (COV) of consumer prices over the same period across all four crops (weighted average), all under the baseline scenario. **(B-E)** Show the same as (A) but for Maize **(B)**, Wheat **(C)**, Rice (D) and Soybean (E) specifically. Darker red colors indicate that the price variability is high, but consumer prices low. Darker gold colors indicate that price variability is low, but prices are high. Black colors indicate that both are high. The basemap is from Global Administrative Areas project (gadm.org).

https://doi.org/10.1371/journal.pclm.0000825.g001

(see S6 Fig) For rice, lower consumer prices are experienced in parts of Latin America, Central Asia, and South Asia and South-East Asia, due to relatively low-cost production for domestic markets. Low price variability is found in Western Europe and North America because of stable imports from rice producing countries (S6 Fig). Soybean patterns are dominated by high prices and high price variability in most of Africa, East and South-East Asia, due to their reliance on soybean imports from Latin America where production volumes are quite sensitive to the weather (more so in Argentina than Brazil).

3.2 The impacts of compound shocks

The shocks to the global grain supply that we modeled affect consumer prices, leading to a loss in consumer surplus (see S8 Fig). When the compound shock (*All* scenario) is superimposed on weather-related production variability, it causes a median (taken across years with different weather) increase in global consumer price (weighted by demand) of 22.6% for soybean, 40.1% for maize, 47.8% for rice, and 51.5% for wheat. This results in a reduction of median global consumption of 4.4% for soybean, 4.1% for maize, 4.5% for rice, and 8.9% for wheat. Taken together, the compound shock reduces median global consumer surplus by 8.2% for soybean, 7.3% for maize, 7.9% for rice and 16.5% for wheat (S8 Fig). These reductions reflect the impact of food prices on domestic budgets and the food consumption of these crops that would be foregone because food is less affordable.

The drivers of consumer surplus losses differ across regions (Fig 2, equivalent plots for consumer prices and consumption are given in S9-S12 Fig and S13-S16 Fig, respectively). For maize, the energy price shock has the greatest effect in most regions, and is particularly severe for Central Asia, Oceania, and Sub-Saharan Africa where consumer prices rise by 50–100% (S9 Fig). For wheat, the energy price shock is also dominant, except in Eastern Europe (mainly Ukraine and Russia) where the supply shock associated with the Ukraine war is more important. The widespread effects of energy price shocks reflect the ubiquitous dependence of agriculture on fuel. Trade bans are predicted to have a large impact on wheat prices in Central Asia (due to export bans imposed by Russia, Kyrgyzstan, and India) and Oceania (largely due to an Indian trade ban). The latter has a knock-on effect on increased demand for wheat from Australia, which raises consumer prices locally, a dynamic that was also observed in 2022 [55].

For rice, the consumer surplus in Sub-Saharan Africa, East Asia, Central Asia, Western Asia, and Eastern Europe was found to be severely impacted by trade restrictions, particularly a rice export ban imposed by India. The same ban results in a reduction in domestic prices and so positively impacts domestic Indian consumer surplus, a response observed after India restricted rice exports in 2023 [56]. Consumer surpluses for rice in Central Asia are extremely sensitive to the different shocks. This can be explained by a combination of high weather-related production volatility in the region, combined with dependencies on trade from South Asia (affected by trade restrictions) and Eastern Europe (affected by the Ukraine war). Soybean consumer surpluses are most influenced by the energy price shock which is felt relatively uniformly across all regions.

Our country-level analysis (S17 Fig) further shows that, especially for wheat and rice, countries within the same region can be affected in quite different ways by the shocks, something that could not be studied using a more aggregated (regional) model.

3.3 Global systemic impact

Local or regional production shocks can give rise to systemic impacts that are felt everywhere because of the interconnected global food supply network. This may happen when shocks occur simultaneously (e.g., multiple breadbasket failures) or when a local shock is of such magnitude that it has global ramifications. To illustrate the potential worst case scenarios, we rank years from worst to best in terms of the cumulative negative consumer surplus (a log scale is used to highlight the effects of poor weather years) (Fig 3).

Under the *Baseline* scenario (Fig 3, grey curve), the worst annual consumer surplus loss is USD90.8 billion for maize, USD31.2 billion for wheat, USD64.4 billion for rice, and USD72.3 billion for soybean. This is equivalent to a 5% reduction in consumer surplus for maize, wheat and rice, and 10–15% for soybeans (S18 Fig). When this is compounded with the *All* shock scenario, the episodic loss can rise to up to USD246.4 billion, USD145.6 billion, USD135.6 billion, and USD78.6 billion for maize, wheat, rice, and soybean, respectively. In relative terms, this refers to a 10–15% reduction in consumer

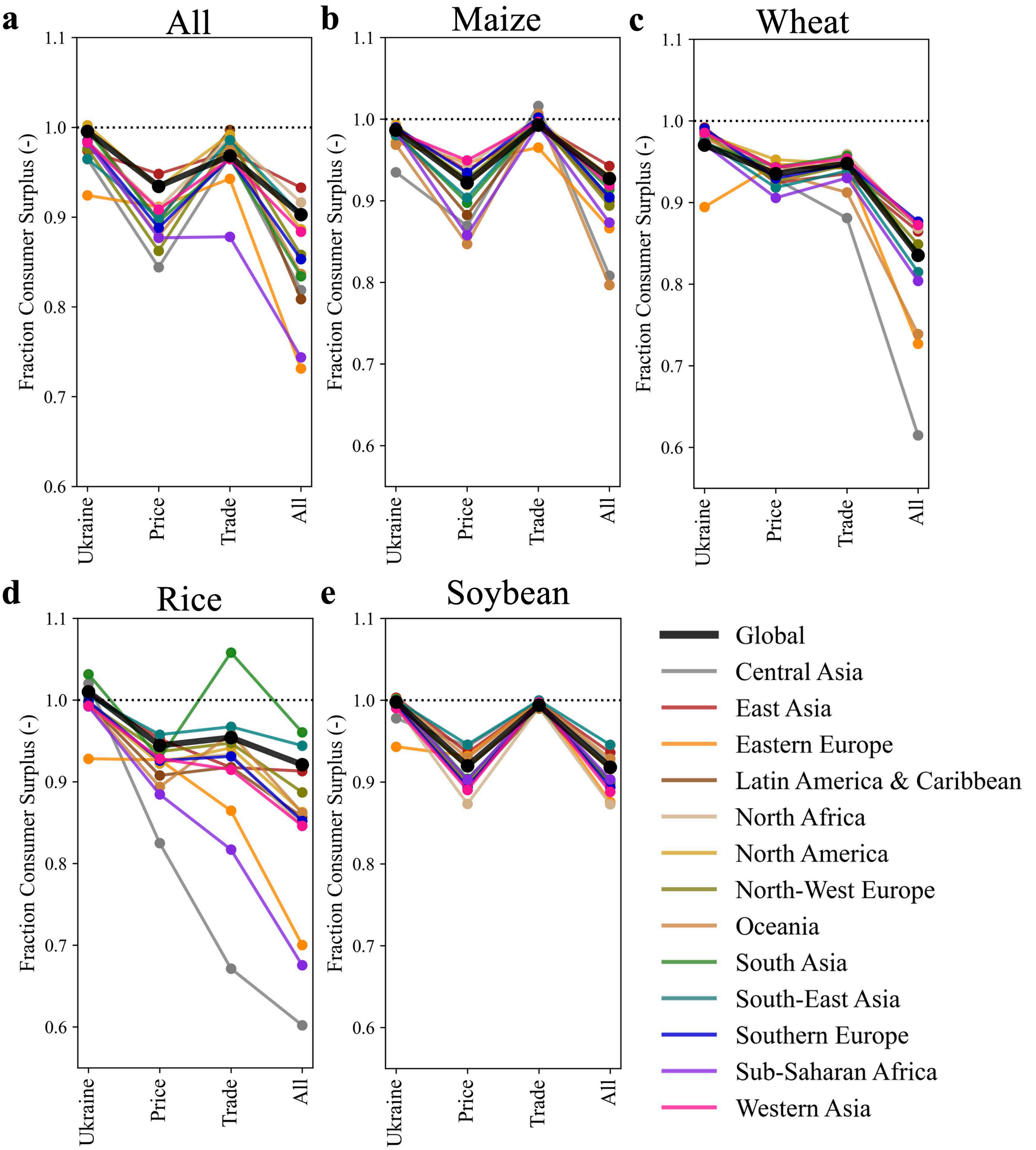

Fig 2. Regional impact of shocks to consumer surplus. (A) Median deviation (across the 54 events) of the normalized total consumer surplus (CS) under the various shock scenarios compared to the average regional consumer surplus for the baseline scenario (across the 54 events). **(B-E)** Show the same results but for the crop-specific CS. See S3 Table for a classification of the regions. A low fraction indicates a more severe impact on consumer surplus.

https://doi.org/10.1371/journal.pclm.0000825.g002

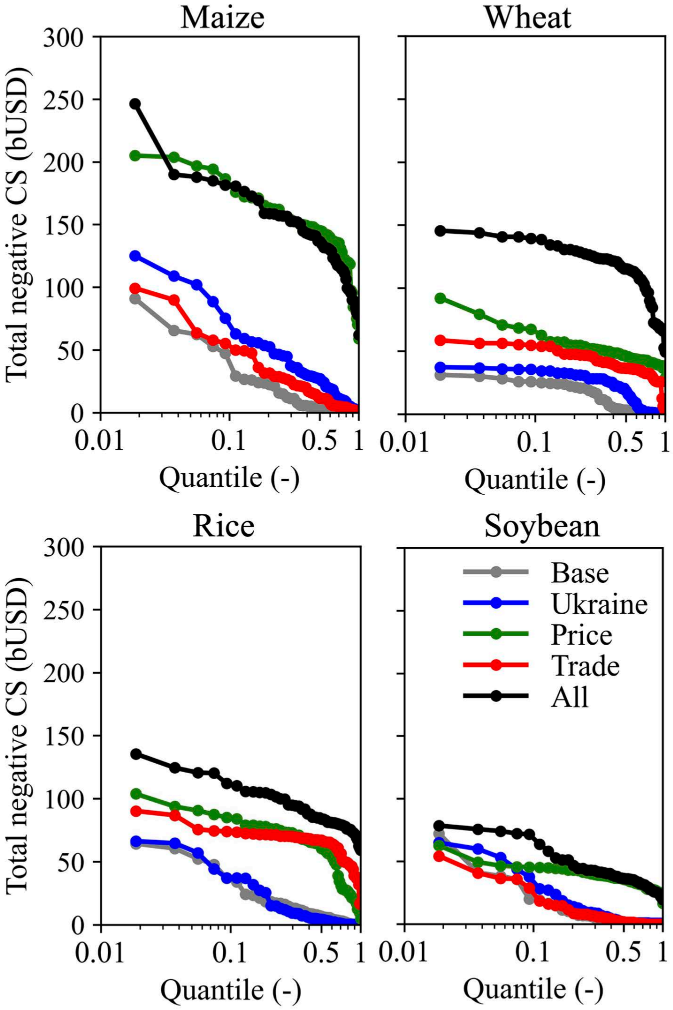

Fig 3. Global systemic impacts of shocks. Total amount of a negative consumer surplus (CS) during a single event (sum of all negative CS across countries). The quantiles indicates the rank of the weather year compared to the total number of weather years in our sample (N = 54), ordered by severity (rank 1 is worst case). A lower quantile indicates a higher severity event in terms of total negative consumer surplus.

https://doi.org/10.1371/journal.pclm.0000825.g003

surplus during the worst years for maize and rice, and 15 – 20% for wheat and soybeans (S18 Fig). Comparing *All* with the other three shock scenarios, we find that the energy price shock can explain most of the response for maize while for the other crops the different shocks all contribute to the drop in global consumer surplus. Trade restrictions for wheat and rice also cause widespread negative consumer surplus across countries. These shocks together can cause almost all countries to simultaneously experience a negative consumer surplus (S19 Fig).

What is also apparent from the results is the importance of weather-related variability as a driver of systemic risk. If the worst year represented in our weather data is compared with the median year (the 0.5 quantile), the difference in consumer surplus is in many cases larger than the additional effect of the shock scenarios. In other words, the impact of a very good harvest or breadbasket failure can be as great or greater than the additional effects of non-climatic shocks, emphasizing the importance of looking at them together.

We further test whether certain country groups are more prone to these systemic shocks than others. Small Island Developing States (SIDS), which are often import-dependent, are considered to be more vulnerable to shocks originating abroad. Our results (S20 Fig) shows that the systemic shock they face in terms of consumer surplus reduction is almost twice as high for maize and rice, but negligible for wheat and soybean. We perform the same test by grouping countries in terms of their income classification (Low and Lower Middle Income; Upper Middle Income; High Income), see S21 Fig. Here, again, crop-specific differences dominate. Upper Middle Income countries show lower impacts for wheat and rice, while Low and Lower Middle Income countries show higher systemic shock impacts for maize and soybean, but not for wheat and rice. In other words, crop-specific differences dominate specific characteristics of specific country groups, at least in our modelling framework.

3.4 Country food system resilience

A country's food system resilience is shaped by different country characteristics that influence its coping capacity (see S1-S5 Figs for the country characteristics). Here, we test to what extent the coping indicators help explain the between-country variations in consumer surplus impacts under the *Baseline* scenario (S22 Fig) and *All* scenario (Fig 4). In

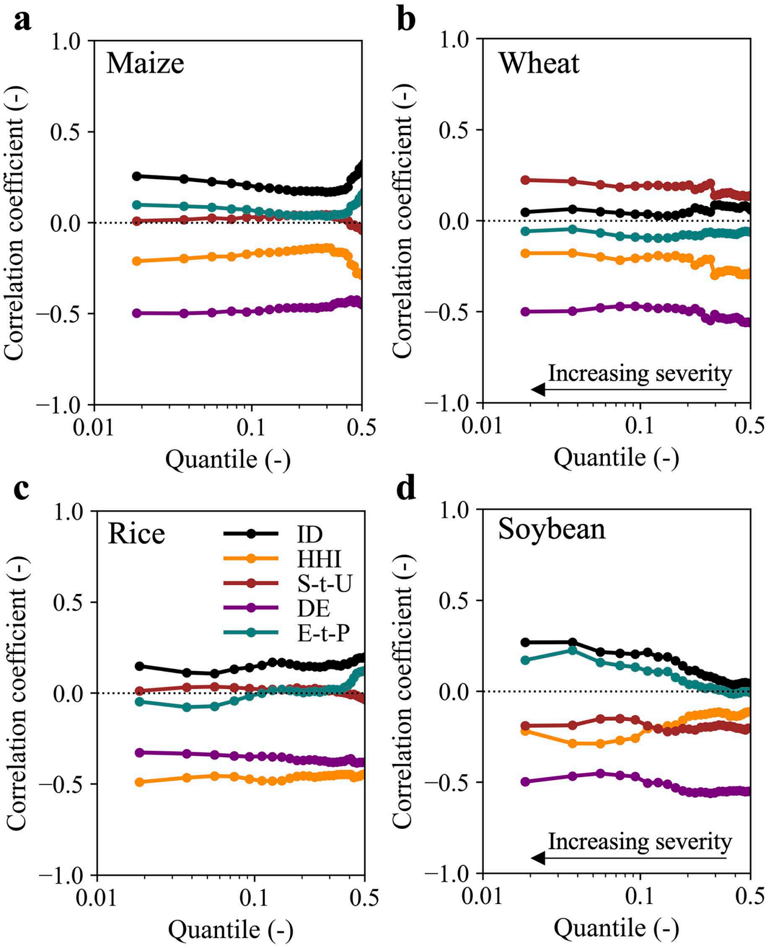

Fig 4. Country coping capacity to compound shock. (A) The Spearman rank correlation coefficient between country consumer surplus impacts and the different coping capacity indicators. **(B-D)** Show the same Figs but for Wheat **(B)**, Rice (C) and Soybean **(D)**. The quantiles indicate the rank of the shock year compared to the total number of years in our sample (N = 54), ordered by severity (event 1/54 is the worst case). ID = import dependency, HHI = the Herfindahl-Hirschman Index (HHI), S-t-U = stocks-to-use ratio, DE = demand elasticity and E-t-P = export to production ratio. All results are for the compound (*All*) shock scenario. A higher positive or negative coefficient indicates a stronger relationship between the coping capacity indicator and the across-country consumer surplus impacts.

https://doi.org/10.1371/journal.pclm.0000825.g004

particular, the HHI and ID indices measure the ability of countries to shift trade patterns, which were explicitly considered in our modelling framework as shown and discussed in S3 Text.

For maize, the impacts on consumer surplus increase for countries with a higher demand elasticity, a low diversity of suppliers, and low import dependency. These countries (such as Uganda, Afghanistan and Côte d'Ivoire) have a limited ability to replace domestic supplies with imports from different sources. For wheat, a combination of having high demand elasticity, high supply concentration and low stocks-to-use ratios was found to reduce food system resilience, while the effect of import dependency is less important. This explains the large impacts of the compound shock on countries such as Zambia, Madagascar and Mongolia. For rice, supply concentration is the leading factor driving between-country variation in consumer surplus, harming the ability of countries (such as Rwanda and Burundi) with a low diversity of suppliers to cope with systemic shocks. For soybean, countries with high self-sufficiency (through low export ratios, low import dependency, and high primarily domestic concentration) and high demand elasticities are most affected (for example Brazil, Serbia and Zambia). These results underline that a combination of factors together influence the food system resilience of a country to compounding global shocks.

4 Discussion

Fluctuations in food supplies and prices have been a growing cause of concern for governments and the international community since the 2007–2008 food crisis. Both empirical and model-based endeavors have sought to improve our understanding of the transmission of shocks through international food networks, its drivers, and the exposure and resilience of different countries to those shocks. Our work complements those studies by emphasizing the importance of trade dynamics in shaping the transmission of shocks and country's food supply resilience.

In our modeling framework, the compounding nature of weather and non-weather shocks was studied, including how this impacts countries globally within a food system interconnected by trade. This makes our study distinct from most earlier attempts that model a single shock [4,27,30], most often a supply shock or export restriction. Within our framework, the supply shock associated with the Ukraine war and the introduction of trade restrictions had the lowest global impacts across the scenarios studied. Still, the consequences for certain countries, in particular those with strong trade links to the Ukraine or dependent on countries introducing export bans, could be substantial, in line with previous work [35]. This underlines that a country-level analysis is key to distinguish the effects of exposure levels and impact pathways. Overall, we find that, within the set of scenarios we explored in our study, the indirect effects of the war in Ukraine via energy prices were greater than the direct effects through reduced production and trade disruptions. This has been found in other studies as well [31,34], and mainly occurs because energy prices affect all countries to some extent, irrespective of their position in the global trading system.

The relatively minor impact of the supply shock of the Ukraine war on global prices and consumption in our simulations arises because countries can source maize and wheat from international markets, either from existing trading partners or by establishing (at a cost) new trading relationships. This highlights the importance of trade substitution during shocks, which most existing food shock models do not capture. However, there is an ongoing debate about the short-run stickiness of trade flows after a shock [57]. In our model, each country could increase its imports from existing trade partners or establish a new trading relationship. However, there may be factors that favor or prevent such adjustments. For instance, previous work has shown that low-income countries often suffer disproportionately during trade shock, which has been hypothesized as due to lesser bargaining power [5,27]. Insights into the flexibility of trade adjustments and the factors that shape the winners and losers in securing supplies during "shortages" merit further research attention.

Our study contributes to the long-standing debate on whether reliance on trade is beneficial or not when it comes to food system resilience, given its potential to expose countries to systemic shocks [9,20]. We find that the global food system exhibits considerable resilience to mild shocks, with trade adjustments able to reduce impacts on consumer prices and consumer surplus. However, in years when the food system is already stressed due to weather-related crop failures, the food system becomes sensitive to the occurrence of further, non-climatic shocks. In particular, shocks such as a rise in energy prices can hit many producers at the same time, reducing the benefits of diversification. Stress-testing exercises, like our study, are therefore critical to understanding how systemic risks arise, how they propagate through food networks, and how they affect countries differently. Despite the fact that agricultural models have known biases in predicting the effects of climate extremes on future yields [58], estimating the likelihood of weather-related shocks is feasible. However, estimating the likelihood of non-climatic shocks is inherently much more difficult, requiring carefully crafted shock narratives that can inform policy.

Our study shows that a complex combination of factors, including import dependency, supply diversification, stock levels, and ability to withhold exports, shape a country's food system resilience. We find that the relative importance of these factors differs per crop, something that has also been noted in previous research [17,26]. For instance, we find that higher trade diversification positively impacts country resilience across all crops, but particular so for rice. Our results further point to the positive effect that a higher maize import dependency has on resilience, in line with earlier empirical findings [20]. On the contrary, access to stocks is most critical for wheat supplies in our simulations. Heslin *et al.* (2020) also found that United States stock levels were a key determinant of the international propagation of a major domestic supply shock [30]. In addition to the variations across crops, we find that for soybeans the importance of the different coping indicators changes with the severity of the shock. While the import dependency and export-to-use ratio do not explain the cross-country impacts observed under moderately extreme events, these two indicators become increasingly important in explaining the impacts across countries for the most extreme events. In other words, a country's food system resilience is not a static concept or a general attribute of a country, as often portrayed, but can differ across types of shocks and shock severity.

In addition to assessing the factors that shape a country's exposure and vulnerability to internationally transmitted shocks, it is important to understand the ability of a country to mitigate such shocks. Some countries have put in place mechanisms to transfer risk, or to recover quickly from exogenous supply or price shocks [13]. Based on our results, we see value in a layered approach to resilience in which the exposure and response to different types of shocks is matched to a set of specific interventions (such as agricultural system interventions, fiscal policies, and trade policies). Given the relative importance of these shocks in terms of their probability and severity, an optimal portfolio of interventions can then be determined.

5 Limitations

As with all global analyses, our modelling framework has several limitation. First, our model is supply constrained and does not allow for within-year adjustments by food producers. In reality, many farmers have few options to adapt to emerging shocks within a growing season, but there may be some opportunities to switch crops or alter crop management (including the application of fertilizers and pesticides) to reflect prevailing market conditions. For example, in 2022–2023 farmers chose to reduce the use of fertilizer and pesticide in response to rising input prices [59], which in turn would have reduced yields and supply and hence increased consumer prices. We believe the net effects of within-year responses will have only a minor effect on the broad patterns we found, but further analysis of this issue would be interesting to explore how enhancing within-year response agility may affect food system resilience.

Second, the price fluctuations we modeled only capture part of the price spike dynamics as observed during past events. In particular, on shorter time spans of days or weeks, global price fluctuations may be considerably higher due to aspects of grain markets that are not modeled here, such as speculation [60], derivatives trading, and cross-sectoral interactions with other markets (e.g., biofuels) [18]. In addition, we do not include government interventions, such as tariff adjustments and price subsidies, that affect the pass-through of global price spikes to domestic prices [61,62]. Including such policy responses in our model, and the feedback processes they may have with global markets, is an important future research avenue.

Third, we implemented a one-off exogenous shock to a single crop. In doing so, we omit how the implications of a shock are carried over to the following year(s), or how shocks to one crop may affect prices of, and demand for, other crops. For instance, during price spikes of grain crops, consumption patterns often change, leading to a higher consumption of unaffected or less-affected grain crops, or even other food groups [63,64]. Extending our modelling framework to a multi-year and multi-crop model can help address such questions but comes at the expense of higher computational complexity.

Fourth, the probabilistic set-up of our modelling framework, involving 54 years of weather-driven yield fluctuations, makes it computationally difficult to systematically explore variations in other model parameters. For instance, our analysis of the importance of various coping indicators indicated that demand elasticity is an important parameter shaping a country's food system resilience, but we have not been able to do a full sensitivity analysis of this parameter.

Fifth, the specificity of the compound shock modeled in this study limits us from making statements about the generalization of our findings beyond the context of these shocks. Future work could consider relaxing some of the model's granularity (e.g., number of countries) and test a larger subset of shock scenarios.

6 Conclusion

The world requires a globalized food system so that countries with a production surplus can provide food to countries with limited agricultural capacity to feed their population. Global trade in food is therefore essential to ensure global food security, and the food system needs to be stress-tested to ensure it is resilient to plausible worse-case shocks. We believe that the modeling approach we have adopted here, which can be extended to include further aspects of food system dynamics or different shocks (such as pest outbreaks, shipping disruption, or other conflicts), can be a useful tool to locate food systems' strengths and vulnerabilities, and identify strategies to increase resilience, such as strategic stockpiling, schemes to support domestic production or new trade agreements.

Supporting information

S1 Text. Supplementary methods. In the following, we describe the trade cost formulation used, the calibration process, and the model set-up for incorporating different types of shocks into it.
(DOCX)

S2 Text. Validation. This section provides additional validation exercises for the global supply model.
(DOCX)

S3 Text. Modelled shift in trade. This section describes how the compound shock affects trade patterns in the model.
(DOCX)

S1 Fig. Country variations in the import dependency ratio per crop considered. The basemap is from the Global Administrative Areas project (gadm.org).
(TIFF)

S2 Fig. Country variations in the Herfindahl-Hirschman Index (HHI) per crop considered. The basemap is from the Global Administrative Areas project (gadm.org).
(TIFF)

S3 Fig. Country variations in the stocks-to-use ratio per crop considered. The basemap is from the Global Administrative Areas project (gadm.org).
(TIFF)

S4 Fig. Country variations in the export-to-production ratio per crop considered. The basemap is from the Global Administrative Areas project (gadm.org).
(TIFF)

S5 Fig. Country variations in the demand elasticity per crop considered. The basemap is from the Global Administrative Areas project (gadm.org).
(TIFF)

S6 Fig. The coefficient of variation (standard deviation divided by mean) of country supply across 54 years of weather-driven yield fluctuations. Blue colours indicate higher fluctuation, whereas yellow colours indicate lower variability. The basemap is from the Global Administrative Areas project (gadm.org).
(TIFF)

S7 Fig. Correlation coefficient between the global consumer price (weighted by demand) and domestic consumer prices across 54 weather years, indicating the level of global integration of prices. Darker colours indicate strong integration, whereas lighter colours indicate a lack of integration. The basemap is from the Global Administrative Areas project (gadm.org).
(TIFF)

S8 Fig. Global average consumption, consumer price, and consumer surplus across the 54 scenarios. The uncertainty bars indicate the minimum and maximum value across the 54 scenarios.
(TIFF)

S9 Fig. Regional weighted average consumer price for each of the 54 counterfactual runs for maize. See S3 Table for a classification of the regions.
(TIFF)

S10 Fig. Regional weighted average consumer price for each of the 54 counterfactual runs for wheat. See S3 Table for a classification of the regions.
(TIFF)

S11 Fig. Regional weighted average consumer price for each of the 54 counterfactual runs for rice. See S3 Table for a classification of the regions.
(TIFF)

S12 Fig. Regional weighted average consumer price for each of the 54 counterfactual runs for soybean. See S3 Table for a classification of the regions.
(TIFF)

S13 Fig. Regional change in demand for each of the 54 counterfactual runs compared to the average demand under the baseline scenario for maize. See S3 Table for a classification of the regions.
(TIFF)

S14 Fig. Regional change in demand for each of the 54 counterfactual runs compared to the average demand under the baseline scenario for wheat. See S3 Table for a classification of the regions.
(TIFF)

S15 Fig. Regional change in demand for each of the 54 counterfactual runs compared to the average demand under the baseline scenario for rice. See S3 Table for a classification of the regions.
(TIFF)

S16 Fig. Regional change in demand for each of the 54 counterfactual runs compared to the average demand under the baseline scenario for soybean. See S3 Table for a classification of the regions.
(TIFF)

S17 Fig. The left panels indicate the mean change in consumer surplus for the 54 counterfactual runs compared to the average consumer surplus under the baseline scenario. The right panel shows the dominant shock per country that drives the compound impacts in the All shocks scenario. The basemap is from the Global Administrative Areas project (gadm.org).
(TIFF)

S18 Fig. Global systemic impacts of shocks in relative terms. (a) Total reduction in negative consumer surplus during a single event (sum of all negative consumer surplus across countries). The quantiles indicate the rank of the weather year compared to the total number of weather years in the sample (N = 54), ordered by severity (rank 1 is the worst case). A lower quantile indicates a higher severity event in terms of total negative consumer surplus.
(TIFF)

S19 Fig. Global systemic impacts of shocks in terms of the number of countries. (a) The fraction of countries that experience a negative consumer surplus during a single event (sum of all negative consumer surplus across countries). The quantiles indicate the rank of the weather year compared to the total number of weather years in the sample (N = 54), ordered by severity (rank 1 is the worst case). A lower quantile indicates a higher severity event in terms of total negative consumer surplus.
(TIFF)

S20 Fig. Global systemic impacts of shocks across SIDS and non-SIDS. (a) Total reduction in negative consumer surplus during a single event (sum of all negative consumer surplus across countries). The quantiles indicate the rank of the weather year compared to the total number of weather years in the sample (N = 54), ordered by severity (rank 1 is the worst case). A lower quantile indicates a higher severity event in terms of total negative consumer surplus. This is for the All scenario. SIDS = Small Island Developing States. SIDS classification is based on the UN classification system.
(TIFF)

S21 Fig. Global systemic impacts of shocks across income groups. (a) Total reduction in negative consumer surplus during a single event (sum of all negative consumer surplus across countries). The quantiles indicate the rank of the weather year compared to the total number of weather years in the sample (N = 54), ordered by severity (rank 1 is the worst case). A lower quantile indicates a higher severity event in terms of total negative consumer surplus. This is for the All scenario. LI = low income, LMI = lower middle income, UMI = upper middle income, and HI = high income. Based on the 2025 World Bank classification.
(TIFF)

S22 Fig. Spearman rank correlation coefficient between country consumer surplus anomaly and the different coping capacity factors. (a) This correlation is run per ranked consumer surplus anomaly across countries. (b–d) Show the same Figs for wheat (b), rice (c), and soybean (d). The quantiles indicate the rank of the weather year compared to the total number of weather years in the sample (N = 54), ordered by severity (rank 1 is the worst case). ID = import dependency, HHI = Herfindahl-Hirschman Index, S-t-U = stocks-to-use ratio, DE = demand elasticity, and E-t-P = export-to-production ratio. All results are for the weather-only (Base) shock scenario.
(TIFF)

S23 Fig. Validation plots of the trade model in terms of the Spearman rank coefficient and hit ratio between observed and modelled bilateral trade flows, both as a function of the size of the trade flow. The x-axis includes the threshold used to extract a subset of the bilateral trade network for validation (for example, only trade flows over 1–100,000 tonnes). The hit ratio is the ratio between the correctly modelled number of bilateral trade flows above a certain threshold and the total number of bilateral trade flows above this threshold.
(TIFF)

S24 Fig. Chord diagram of global international trade flows between regions under the baseline scenario (average over 54 years). The size of the outer band indicates the export share that regions have, and the size of the lines indicates the size of traded volume. See S3 Table for a classification of the regions.
(TIFF)

S25 Fig. Regional shifts in trade flows under the compound risk scenario. Absolute change in average interregional trade in the All shocks scenario (average over 54 events) compared with the Baseline scenario. The matrix indicates regional international trade, while the last column indicates change in domestic supply for countries within the region. Entries on the bottom-left to top-right diagonal of the matrices indicate changes in within-region international trade flows. See S3 Table for a classification of the regions. Darker red colours indicate larger negative trade volume, whereas darker blue colours indicate larger positive trade volume.
(TIFF)

S1 Table. Overview of the different data sources used in this study.
(DOCX)

S2 Table. Price shock specification.
(DOCX)

S3 Table. Region classification between the regions mentioned in the paper and the UN sub-region classification.
(DOCX)

S4 Table. Validation metrics for the global supply model. HHI stands for Herfindahl-Hirschman Index, an indicator of market concentration in this case supply concentration.
(DOCX)

Author contributions

Conceptualization: Jasper Verschuur, Aline Mosnier, Michael Obersteiner, Charles J. Godfray, Jim W. Hall.

Data curation: Yiorgos Vittis.

Formal analysis: Jasper Verschuur, Anna Murgatroyd.

Methodology: Jasper Verschuur, Aline Mosnier.

Project administration: Jim W. Hall.

Supervision: Jim W. Hall.

Writing – original draft: Jasper Verschuur, Anna Murgatroyd.

Writing – review & editing: Yiorgos Vittis, Aline Mosnier, Michael Obersteiner, Charles J. Godfray, Jim W. Hall.

References

1. D'Odorico P, Carr JA, Laio F, Ridolfi L, Vandoni S. Feeding humanity through global food trade. Earth's Future. 2014;2(9):458–69. https://doi.org/10.1002/2014ef000250
2. Martin W, Laborde D. The free flow of goods and food security and nutrition. Global Food Policy Report. 2018. https://doi.org/10.2499/9780896292970_03
3. FAO. The state of agricultural commodity markets 2022. The geography of food and agricultural trade: policy approaches for sustainable development. Rome: FAO; 2022. https://doi.org/10.4060/cc0475en
4. Burkholz R, Schweitzer F. International crop trade networks: the impact of shocks and cascades. Environ Res Lett. 2019;14:114013. https://doi.org/10.1088/1748-9326/ab4864
5. Distefano T, Laio F, Ridolfi L, Schiavo S. Shock transmission in the International food trade network. PLoS One. 2018;13(8):e0200639. https://doi.org/10.1371/journal.pone.0200639 PMID: 30089103

6. Ray DK, Gerber JS, MacDonald GK, West PC. Climate variation explains a third of global crop yield variability. Nat Commun. 2015;6:5989. https://doi.org/10.1038/ncomms6989 PMID: 25609225
7. Gaupp F, Hall J, Hochrainer-Stigler S, Dadson S. Changing risks of simultaneous global breadbasket failure. Nature Climate Change. 2020;10:54–7. https://doi.org/10.1038/s41558-019-0600-z
8. Nelson GC, Valin H, Sands RD, Havlík P, Ahammad H, Deryng D, et al. Climate change effects on agriculture: economic responses to biophysical shocks. Proc Natl Acad Sci U S A. 2014;111(9):3274–9. https://doi.org/10.1073/pnas.1222465110 PMID: 24344285
9. Brown ME, Carr ER, Grace KL, Wiebe K, Funk CC, Attavanich W, et al. Do markets and trade help or hurt the global food system adapt to climate change?. Food Policy. 2017;68:154–9. https://doi.org/10.1016/j.foodpol.2017.02.004
10. Davis KF, Downs S, Gephart JA. Towards food supply chain resilience to environmental shocks. Nat Food. 2021;2(1):54–65. https://doi.org/10.1038/s43016-020-00196-3 PMID: 37117650
11. Gaupp F, Pflug G, Hochrainer-Stigler S, Hall J, Dadson S. Dependency of crop production between global breadbaskets: a copula approach for the assessment of global and regional risk pools. Risk Anal. 2017;37(11):2212–28. https://doi.org/10.1111/risa.12761 PMID: 28032659
12. Behnassi M, El Haiba M. Implications of the Russia-Ukraine war for global food security. Nat Hum Behav. 2022;6(6):754–5. https://doi.org/10.1038/s41562-022-01391-x PMID: 35637299
13. Amaglobeli D, Hong GH, Hanedar E, Thevenot C, Gu M. Policy responses to high energy and food prices. IMF Working Papers. 2023;2023(074):1. https://doi.org/10.5089/9798400237768.001
14. 2023 Global report on food crisis: mid-year update. GRFC; 2023. https://www.fsinplatform.org/sites/default/files/resources/files/GRFC2023-MYU.pdf
15. Roussi A. Why gigantic locust swarms are challenging governments and researchers. Nature. 2020;579(7799):330. https://doi.org/10.1038/d41586-020-00725-x PMID: 32184472
16. WFP. A global food crisis. 2023. Accessed 2023 November 1. https://www.wfp.org/global-hunger-crisis
17. Kummu M, Kinnunen P, Lehikoinen E, Porkka M, Queiroz C, Röös E, et al. Interplay of trade and food system resilience: gains on supply diversity over time at the cost of trade independency. Global Food Security. 2020;24:100360. https://doi.org/10.1016/j.gfs.2020.100360
18. Kalkuhl M, von Braun J, Torero M. Food price volatility and its implications for food security and policy. Kalkuhl M, von Braun J, Torero M, editors. Cham: Springer International Publishing. 2016. https://doi.org/10.1007/978-3-319-28201-5
19. Wright BD. The economics of grain price volatility. Appl Eco Perspect Pol. 2011;33(1):32–58. https://doi.org/10.1093/aepp/ppq033
20. Chen B, Villoria NB. Climate shocks, food price stability and international trade: Evidence from 76 maize markets in 27 net-importing countries. Environ Res Lett. 2019. https://doi.org/10.1088/1748-9326/aaf07f
21. Ceballos F, Hernandez MA, Minot N, Robles M. Grain price and volatility transmission from international to domestic markets in developing countries. World Develop. 2017;94:305–20. https://doi.org/10.1016/j.worlddev.2017.01.015
22. Santeramo FG, Lamonaca E. On the drivers of global grain price volatility: an empirical investigation. Agric Econ (Czech Republic). 2019;65:31–42. https://doi.org/10.17221/76/2018-AGRICECON
23. Zhang Z, Abdullah MJ, Xu G, Matsubae K, Zeng X. Countries' vulnerability to food supply disruptions caused by the Russia-Ukraine war from a trade dependency perspective. Sci Rep. 2023;13(1):16591. https://doi.org/10.1038/s41598-023-43883-4 PMID: 37789089
24. Liu L, Wang W, Yan X, Shen M, Chen H. The cascade influence of grain trade shocks on countries in the context of the Russia-Ukraine conflict. Humanit Soc Sci Commun. 2023. https://doi.org/10.1057/s41599-023-01944-z
25. Karakoc DB, Konar M. A complex network framework for the efficiency and resilience trade-off in global food trade. Environ Res Lett. 2021;16. https://doi.org/10.1088/1748-9326/ac1a9b
26. Li X, Wang H, Kharrazi A, Fath BD, Liu G, Liu G, et al. A network analysis of external shocks on the dynamics and resilience of the global staple food trade. Food Sec. 2024;16(4):845–65. https://doi.org/10.1007/s12571-024-01462-z
27. Puma MJ, Bose S, Chon SY, Cook BI. Assessing the evolving fragility of the global food system. Environ Res Lett. 2015;10:24007. https://doi.org/10.1088/1748-9326/10/2/024007
28. Bertassello L, Winters P, Müller MF. Access to global wheat reserves determines country-level vulnerability to conflict-induced Ukrainian wheat supply disruption. Nat Food. 2023;4(8):673–6. https://doi.org/10.1038/s43016-023-00806-w PMID: 37537408
29. Hellegers P. Food security vulnerability due to trade dependencies on Russia and Ukraine. Food Secur. 2022;14(6):1503–10. https://doi.org/10.1007/s12571-022-01306-8 PMID: 35891962
30. Heslin A, Puma MJ, Marchand P, Carr JA, Dell'Angelo J, D'Odorico P, et al. Simulating the cascading effects of an extreme agricultural production shock: global implications of a contemporary US dust bowl event. Front Sustain Food Syst. 2020;4. https://doi.org/10.3389/fsufs.2020.00026
31. Kuhla K, Puma M, Schewe J, Kubiczek P, Otto C. International cooperation could help avert a major food crisis due to the Russian invasion of Ukraine. Res Sq. 2022;:1–9.
32. Falkendal T, Otto C, Schewe J, Jägermeyr J, Konar M, Kummu M, et al. Grain export restrictions during COVID-19 risk food insecurity in many low- and middle-income countries. Nat Food. 2021;2(1):11–4. https://doi.org/10.1038/s43016-020-00211-7 PMID: 37117657

33. Carriquiry M, Dumortier J, Elobeid A. Trade scenarios compensating for halted wheat and maize exports from Russia and Ukraine increase carbon emissions without easing food insecurity. Nat Food. 2022;3(10):847–50. https://doi.org/10.1038/s43016-022-00600-0 PMID: 37117877

34. Alexander P, Arneth A, Henry R, Maire J, Rabin S, Rounsevell MDA. High energy and fertilizer prices are more damaging than food export curtailment from Ukraine and Russia for food prices, health and the environment. Nat Food. 2023;4(1):84–95. https://doi.org/10.1038/s43016-022-00659-9 PMID: 37118577

35. Lin F, Li X, Jia N, Feng F, Huang H, Huang J, et al. The impact of Russia-Ukraine conflict on global food security. Glob Food Sec. 2023;36:100661. https://doi.org/10.1016/j.gfs.2022.100661

36. Vittis Y, Folberth C, Bundle SC, Obersteiner M. Restoring nature at lower food production costs. Front Environ Sci. 2021;9:1–14. https://doi.org/10.3389/fenvs.2021.672663

37. Vittis Y, Mosnier A, Navarro J. Global agricultural costing model. Zenodo; 2023. https://doi.org/10.5281/zenodo.7729662

38. Verschuur J, Vittis Y, Obersteiner M, Hall JW. Heterogeneities in landed costs of traded grains and oilseeds contribute to unequal access to food. Nat Food. 2025;6(1):36–46. https://doi.org/10.1038/s43016-024-01087-7 PMID: 39762466

39. FAO. FAO cereal supply and demand brief. 2025. http://www.fao.org/worldfoodsituation/csdb/en/

40. Janssens C, Havlík P, Boere E, Palazzo A, Mosnier A, Leclère D, et al. A sustainable future for Africa through continental free trade and agricultural development. Nat Food. 2022;3(8):608–18. https://doi.org/10.1038/s43016-022-00572-1 PMID: 37118605

41. Takayama T, Judge GG. Spatial and temporal price and allocation models. North-Holland Publishing Company; 1971.

42. Mosnier A. Tracking indirect effects of climate change mitigation and adaptation strategies in agriculture and land use change with a bottom-up global partial equilibrium model. Univ Nat Resour Life; 2014. https://epub.boku.ac.at/obvbokhs/content/titleinfo/1931250/full.pdf

43. Jansson T, Heckelei T. A new estimator for trade costs and its small sample properties. Econ Model. 2009;26:489–98. https://doi.org/10.1016/j.econmod.2008.10.002

44. Tuninetti M, Davis KF. Addressing global hotspots of climate-related crop production losses. Preprint. 2022.

45. OECD. The impacts and policy implications of Russia's aggression against Ukraine on agricultural markets. 2022. https://www.oecd.org/ukraine-hub/policy-responses/the-impacts-and-policy-implications-of-russia-s-aggression-against-ukraine-on-agricultural-markets-0030a4cd/

46. Salin D. Ukraine grain transportation. Washington, DC: US Dep Agric Agric Mark Serv; 2024. https://doi.org/10.9752/TS260.06-2024

47. Evenett S, Fiorini M, Fritz J, Hoekman B, Lukaszuk P, Rocha N, et al. Trade policy responses to the COVID-19 pandemic crisis: evidence from a new data set. World Econ. 2022;45(2):342–64. https://doi.org/10.1111/twec.13119 PMID: 33821084

48. Evenett S, Jakubik A, Martín F, Ruta M. The return of industrial policy in data. World Economy. 2024;47(7):2762–88. https://doi.org/10.1111/twec.13608

49. Karakoc DB, Konar M. Optimization of national grain imports to balance risk and return: a portfolio theory approach. Environ Res Food Syst. 2024;1:011001. https://doi.org/10.1088/2976-601x/ad22d1

50. Laio F, Ridolfi L, D'Odorico P. The past and future of food stocks. Environ Res Lett. 2016;11. https://doi.org/10.1088/1748-9326/11/3/035010

51. Kumar P, Kumar A, Parappurathu S, Raju SS. Estimation of demand elasticity for food commodities in India. Agric Econ Res Rev. 2011;24:1–14. https://doi.org/10.22004/ag.econ.109408

52. Gren I-M, Jonasson L, Andersson H, Knutsson R. Economic impact and food security effects of trade disruptions in agricultural products for Sweden. Agric & Food Secur. 2024;13(1). https://doi.org/10.1186/s40066-024-00483-3

53. Forgenie D, Hutchinson SD, Muhammad A. Welfare implications of rising imported food costs in the Caribbean. J Agricul Food Res. 2024;18:101489. https://doi.org/10.1016/j.jafr.2024.101489

54. Hsiao A, Moscona J, Sastry K. Food policy in a warming world. SSRN J. 2024. https://doi.org/10.2139/ssrn.4859391

55. Nandy S, Thang E. India's wheat export ban pushes Australian FOB price to record high. S&P Global Commodity Insights: Agriculture. 2022. Accessed 2023 December 8. https://www.spglobal.com/commodityinsights/en/market-insights/latest-news/agriculture/051722-indias-wheat-export-ban-pushes-australian-fob-price-to-record-high#:~:text=India%27swheatexportbanpushesAustralianFOBpricetorecordhigh,-AuthorSampadNa

56. Mancombu SR. Domestic white rice prices drop by ₹4,000/tonne after export ban. The Hindu Business Line. 2023. Accessed 2023 December 8. https://www.thehindubusinessline.com/economy/agri-business/domestic-white-rice-prices-drop-by-4000tonne-after-export-ban/article67120396.ece#:~:text=Domesticwhitericeprices(common,ofthecountry'sshipmentsabroad

57. Fair KR, Bauch CT, Anand M. Dynamics of the global wheat trade network and resilience to shocks. Sci Rep. 2017;7(1):7177. https://doi.org/10.1038/s41598-017-07202-y PMID: 28775307

58. Kornhuber K, Lesk C, Schleussner CF, Jägermeyr J, Pfleiderer P, Horton RM. Risks of synchronized low yields are underestimated in climate and crop model projections. Nat Commun. 2023;14(1):3528. https://doi.org/10.1038/s41467-023-38906-7 PMID: 37402712

59. Arndt C, Diao X, Dorosh P, Pauw K, Thurlow J. The Ukraine war and rising commodity prices: implications for developing countries. Glob Food Sec. 2023;36:100680. https://doi.org/10.1016/j.gfs.2023.100680 PMID: 36937378

60. Lawson J, Alam R, Etienne X. Speculation and food-grain prices. Appl Econ. 2021;53:2305–21. https://doi.org/10.1080/00036846.2020.1859451

61. Ianchovichina EI, Loening JL, Wood CA. How vulnerable are Arab countries to global food price shocks?. J Develop Stud. 2014;50:1302–19. https://doi.org/10.1080/00220388.2014.928698

62. Unsal F, Spray J, Okou C. Staple food prices in Sub-Saharan Africa: an empirical assessment. IMF Work Papers. 2022;2022(135):1. https://doi.org/10.5089/9798400216190.001

63. Prifti E, Daidone S, Miguelez B. Impact of increases in food prices on consumer welfare in Lesotho. African J Agric Resour Econ. 2017;12:52–61.

64. Ruvalcaba MA, Prifti E, Daidone S. How do price increases affect vulnerable households in Zambia?. Rome: FAO; 2016. http://www.fao.org/3/a-i6189e.pdf

65. Wiebe K, Lotze-Campen H, Sands R, Tabeau A, van der Mensbrugghe D, Biewald A. Climate change impacts on agriculture in 2050 under a range of plausible socioeconomic and emissions scenarios. Environ Res Lett. 2015;10:085010. https://doi.org/10.1088/1748-9326/10/8/085010

66. Gaulier G, Zignago S. BACI: International trade database at the product-level the 1994-2007 Version. 2010–23. 2010. http://www.cepii.fr/pdf_pub/wp/2010/wp2010-23.pdf

67. Guimbard H, Jean S, Mimouni M, Pichot X. MacMap-HS6 2007, an exhaustive and consistent measure of applied protection in 2007. Int Econ. 2012;(n° 130):99–121. https://doi.org/10.3917/ecoi.130.0099

68. Verschuur J, Murgatroyd A, Vittis Y, Mosnier A, Obersteiner M, Godfray HCJ. Global food shock and trade model. Zenodo; 2024. https://doi.org/10.5281/zenodo.12598597