

The impacts of polycrisis on global grain availability and prices

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Abstract

Recent climatic events and conflict have heightened concern about the vulnerability of the global food system to systemic shocks. Yet it remains unclear what shocks are most pressing for a country's food supply, and whether trade can mediate or amplify negative impacts. Here, using a newly developed global bilateral trade model for 177 countries and four major staple crops (maize, wheat, rice, soybean), we simulate the demand, price and trade impacts of the (i) Ukraine war, (ii) an energy price shock, (iii) imposed trade bans, and (iv) a compound (polycrisis) shock, on top of 54 years of crop production variability. The compound shock results in a 23-52% increase in consumer prices and, consequently, 7.3-16.5% loss to consumers. While the energy price shock is found to be the most important driver of the compound food shock across most regions and crops, the Ukraine war dominates impacts in Eastern Europe and Central Asia. Trade bans can affect certain regions disproportionately, particularly for Sub-Saharan Africa (rice) and Central Asia (rice, wheat). We find that, in many instances, trade adjustments can help cope with both supply and price shocks, although limits to the reliance on trade are found for tail risk events. In the compound shock event, the total negative consumer losses can be over USD600 million for a single year, affecting virtually all countries simultaneously. Managing the risks of such shocks requires a reformed and better coordinated mix of national agricultural and fiscal policies as well as international trade regulations.

Keywords: Food systems, Resilience, Polycrisis, Grains, Climate extremes

Introduction

The global food system is vulnerable to shocks that can impact production, trade and prices (1–4). Disasters cause annual losses worth USD123 billion per year (5), alongside weather variability that is estimated to account for around a third of yield variability (6). Shocks can have a large effect on grain prices. 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 (7). Though droughts have become a recurrent phenomenon in recent years, food price volatility has been dominated by non-climatic factors, including the war in Ukraine and consequent rising fertilizer prices (driven by high energy prices), locust outbreaks, and trade restrictions imposed by various countries (e.g., export bans or quotas) (8–11). These events, along with other factors such as the pandemic and an increasing number of civil and international conflicts, have led to a state of “polycrisis” which has resulted in a doubling of the number of people facing acute food insecurity in 2023 compared to 2019 (12). Countries have responded with a range of interventions including food or fertilizer subsidies and cash transfers or vouchers, often at considerable costs (in some cases over 0.75% of GDP) (9).

Several studies have sought to explore the vulnerability of countries to recent food system shocks, in particular the impacts of the Russian invasion of Ukraine through its effects on wheat and maize supply. One set of studies used trade data to reconstruct the global supply network of crop commodities used both for direct consumption and in the production of processed foods (13–15). Another study combined trade data with information on stocks and food substitution behavior to better characterize different countries’ vulnerabilities (16). These models are typically static, preventing them from incorporating trade adjustments or quantifying the price effects of export reductions. Others have used a more complex dynamic supply-demand model, including stocks, to study the effect of the Ukraine war, fertilizer prices and export restrictions on global wheat prices (17, 18). While better able to represent short-term price spikes and supply/demand adjustments, these models do not explicitly represent bilateral trade flows between countries and so cannot incorporate potential import substitution. A third set of approaches have used global food system models to assess the impact on food prices of a supply disruption from Ukraine alone (19) or combined with fertilizer price increases (20). These models assume a single global market and do not specify bilateral trade flows, so that trade substitution is unconstrained and rapid. General and partial equilibrium models of this type are designed to study long-run price and trade adjustments and their structure and parameterization means that the impacts of short-run shocks are underestimated.

The aforementioned studies have provided important insights into the possible impacts of the Ukraine war and its associated food system shocks, but a number of key considerations remain unaddressed. First, no studies have explicitly included bilateral trade flows in a way that allows dynamic adjustments such as changing trading partners or increasing supply from existing exporters. Second, while attempts have been made to include multiple shocks within a single modelling framework, they are often implemented uniformly across countries (for example, a fertilizer price shock is assumed to affect all countries equally) or explore only a small subset of countries imposing export restrictions. Yet, we know that fertilizer price shocks affect countries unequally because of different fertilizer use and import dependency (21). Similarly, many countries have been known to impose trade bans (import or export), though these were often targeted towards specific countries without affecting the rest of the world. Third, all studies have evaluated the effects of these shocks against a single baseline – for the Ukraine war, the situation in early 2022. This makes sense in trying to understand the historical impact of the war but assessment of risks to the global food system should consider the full range of possible production scenarios, ranging from bad years with major breadbasket failures (22, 23) to good years with bumper harvests (24), and their relative likelihood.

In this study, we use a newly developed bilateral trade model of global grain supply for 177 countries to study the effects of compounding shocks to the world's grain supply. The shocks we model are inspired by the events of 2022-2023: the Ukrainian war and its effects on grain supply, food prices and trade restrictions. We analyze their effects against a background of 54 plausible realizations of crop production variability across regions determined by historic weather variability (25). This allows us to estimate the range of possible consequences for producer and consumer prices, and for patterns of bilateral trade. We demonstrate how countries and regions differ in their exposure to these shocks, and in their capacity to adjust by utilizing stocks, reducing exports, or changing trading partners. Our modelling framework both provide insights into different countries' vulnerability as well as the spread of systemic risks through global grain supply networks. Our results will help efforts to stress-test global supply chains as well as in the design of effective strategies to enhance the resilience of food supply systems.

Results

Overview

We developed a spatial equilibrium price model that simulates demand, supply, producer and consumer prices and trade flows across 177 countries (more fully described in Methods). It is calibrated to reproduce observed trade flows for the period 2017-2021, and relies on recently produced datasets of country-specific crop production costs (26, 27) and detailed bilateral trade costs (28). We consider four crops – maize, wheat, rice, soybeans – as they are strongly affected by the different shocks we model (20) and their importance for global food and feed consumption.

Our baseline model (*Base*) incorporates climate variability information based on 54 years of historic climate data (25) allowing us to estimate the distribution of crop production given realistic patterns of weather-driven yield variability around the world. Against this background, four sets of exogenous shocks are modelled: (i) a supply shock caused by reduced production and restricted exports of Ukrainian grain (*Ukraine*), (ii) an energy price shock of the type associated with the Ukraine war increasing fertilizer, pesticide and diesel prices with knock-on effects on producer prices that are passed on to consumers (*Price*), (iii) imposed trade restrictions (import and export bans) motivated by those observed in 2022-2023 (*Trade*), and (iv) all shocks together, representing our “polycrisis” scenario (*All*). Consumer prices in the model do not include subsidies or marketing mark-ups, and hence should be interpreted as landed cost prices. Supply, demand and trade of food and feedstock quantities are treated in a homogenous commodity setting.

Our model has been specifically designed to explore the short-run impacts of shock scenarios. We study impacts within a single year in which planting decisions have largely been made supporting an inelastic supply assumption. Countries can respond by utilizing grain stocks, adjusting imports from existing suppliers and, at a cost, diversify the scope of trading partners.

Food production variability can drive consumer price fluctuations

The set of weather-related yield variations based on 54 years of climate data (see Methods) were used to simulate production shortages and surpluses in one or more of the four crops, causing price fluctuations across domestic and foreign markets. Consumer price sensitivity to weather variability differs across crops and countries. The average consumer price variability (measured by the coefficient of variation) across countries is lowest for soybean (0.06), followed by rice and wheat (0.07) and highest for wheat (0.09). This is lower than the underlying yield variability (0.07 for rice and soybean, 0.10 for maize and 0.13 for wheat) suggesting an economic risk mitigation function of markets. The global food supply system thus partly buffers the impact of yield variability on consumer prices, mainly through international trade.

In Figure 1 we show price volatility and average consumer prices for the baseline scenario, across all four crops (Figure 1a) and for each crop separately (Figure 1b-e). Some countries face high price variability alongside low consumer prices, while other countries face both high average prices and high price variability. Most of Europe and North Africa have low prices and low volatility, due to the deep and diverse grain markets operating in Europe. Regions with high production serving predominantly domestic markets (Central Asia, Eastern Europe, Australia, South Africa) have low prices but relatively high volatility. In contrast, some large importers (China, Bolivia, Middle-East and Saharan countries) have higher average prices but low volatility. Countries in Sub-Saharan Africa face both high consumer prices and high volatility, caused by high trade costs (28) and risky suppliers.

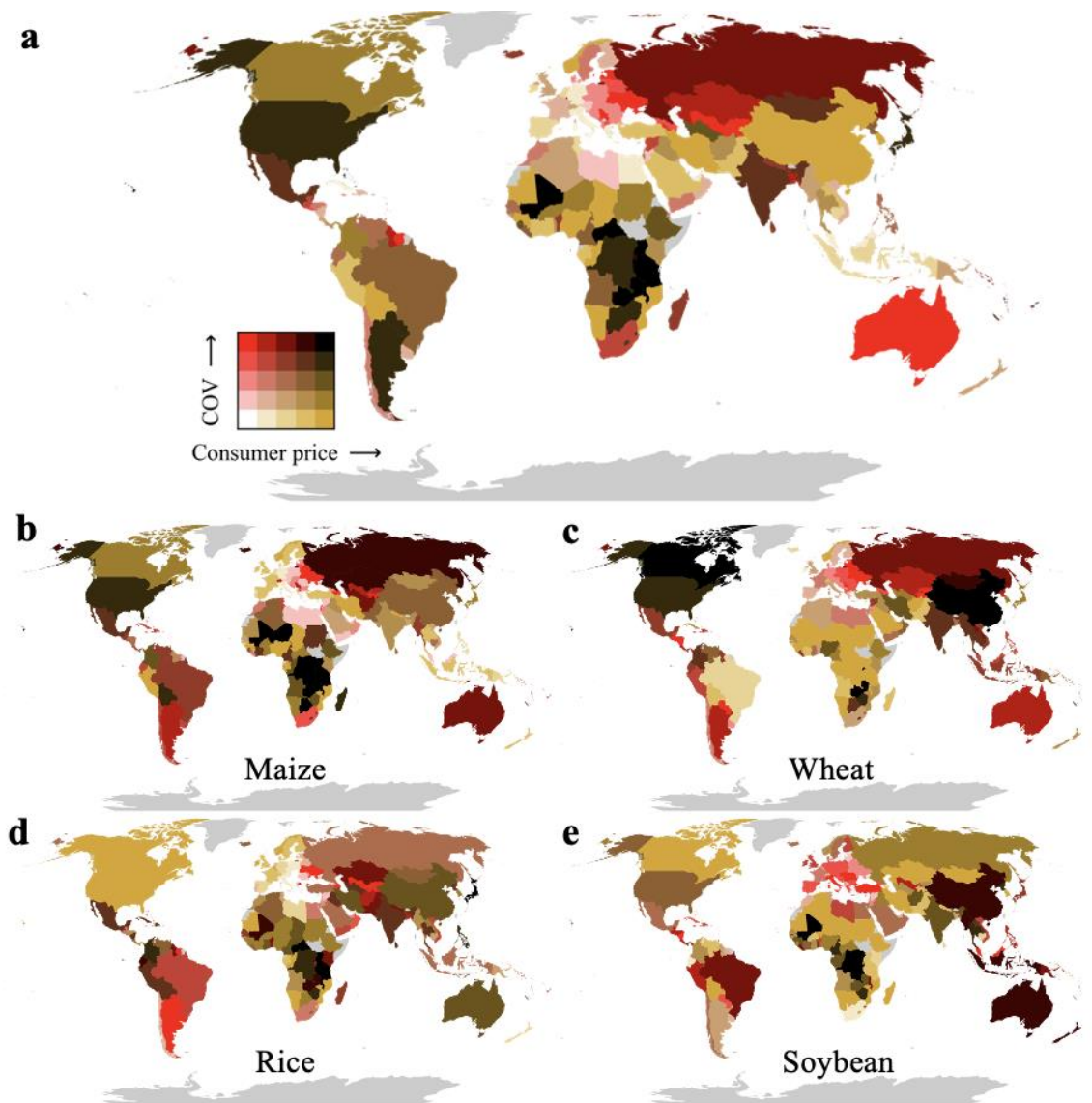


Figure 1. (a) Bivariate plot of the mean consumer price averaged across the 54 counterfactual years, and the coefficient of variation (COV) of consumer prices over the same period across all four crops (weighted average), all under the baseline scenario. (b-e) Show the same as (a) but for Maize (b), Wheat (c), Rice (d) and Soybean (e) specifically.

There are interesting variations across crops (Figure 1b-e). For maize, low consumer prices and price fluctuations are observed in Northern Africa, Eastern and Central Europe, due to their proximity to major maize suppliers in Europe. Contrarily, high transportation costs and reliance on variable production 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 provide relatively stable supplies due to imports from a variety 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 have but high price variability induced by high yield variability (6). For rice, lower consumer prices are experienced in parts of Latin America, Central Asia, and South Asia and South-East Asia, given relatively low cost production for domestic markets. Low price variability is observed in Western Europe and North America, given stable imports from rice producing countries. Soybean patterns are dominated by high price variability and high prices in most of Africa, East and South-East Asia, given their reliance on soybean imports from Latin America, which are susceptible to weather-driven variability.

The impacts of compound shocks

The shocks to the global grain supply system that we model affect producer prices and trade, which impact consumer prices, consumption and consequently consumer surplus (see Supplementary Figure 1). The consumer surplus is the difference between the price a consumer is willing to pay and actually pays (multiplied by the amount they consume), and represents how consumers are impacted by changing prices, both in terms of their expenditure and how much they adjust their consumption. We use consumer surplus as our metric of impact as it simultaneously captures price and demand effects, including country variations in crop-specific short-run demand elasticities. Other metrics, including those more relevant for food security (e.g., people facing hunger), could alternatively be considered in future work.

Across all 54 yield instantiations, the compound shock (A/I) causes an increase in median 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 around 4.4% for soybean, 4.1% for maize, 4.5% for rice, and 8.9% for wheat. This highlights the higher demand elasticities for soybean and wheat compared to rice and maize. This reduces median global consumer surplus by 8.2% for soybean, 7.3% for maize, 7.9% for rice and 16.5% for wheat (Supplementary Figure 1).

The effect of the four shock scenarios on global and regional consumer surpluses are shown in Figure 2, again averaged over the 54 different yield patterns (equivalent plots for consumer prices and consumption are given in Supplementary Figures 2-5 and 6-9 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% (Supplementary Figure 2). For wheat, the energy price shock is also dominant, except for in Eastern Europe (mainly Ukraine and Russia) where the Ukraine war is more important. Trade bans 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 the Indian trade ban). The latter has a knock-on effect on increased demand for wheat from Australia, which raises consumer prices locally, as was observed in 2022 (29). The relative importance of the global energy price shock compared to the trade disruption from the Ukraine war was also found in other studies (17, 20).

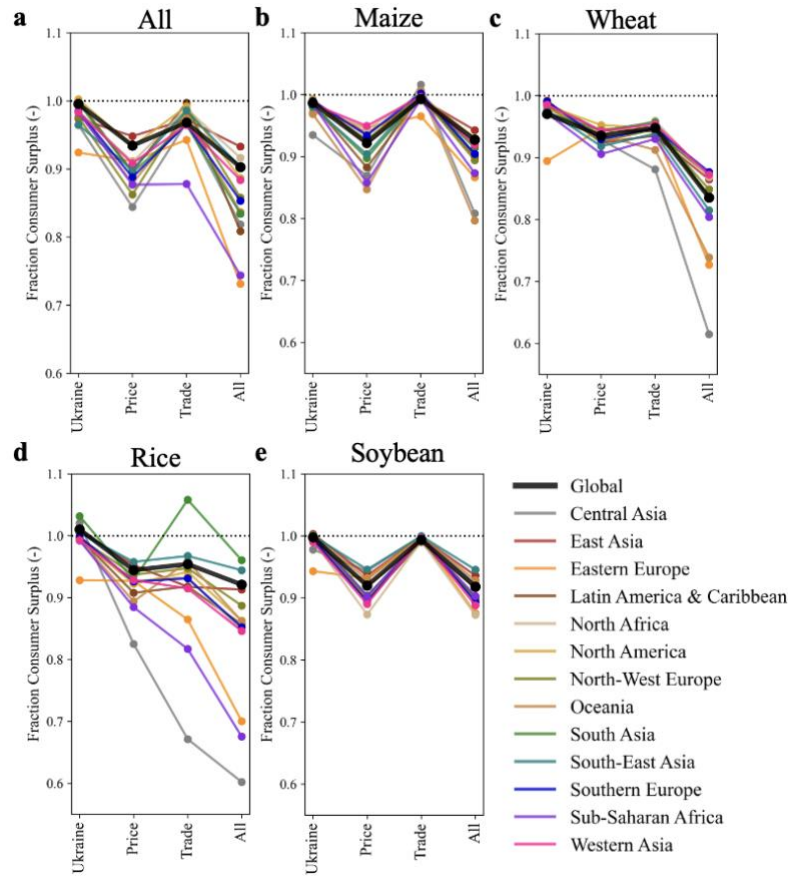


Figure 2. (a) Median deviation (across the 54 events) of the normalized total consumer surplus (CS) under the various shock scenarios compared to the average regional consumer surplus for the baseline scenario (across the 54 events). (b-e) Show the same results but for the crop-specific CS.

For rice, consumer surpluses in Sub-Saharan Africa, East Asia, Central Asia, Western Asia, and Eastern Europe were severely impacted by trade restrictions, particularly the rice export ban imposed by India. This ban led to a reduction in domestic prices and so positively impacted domestic Indian consumer surplus, a response observed after India restricted rice exports in 2023 (30). Consumer surpluses for rice in Central Asia are extremely sensitive to different shocks. This can be explained by a combination of background 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.

Supplementary Figure 10 provides more detail about how different countries are vulnerable to these shocks. Our country-level analysis shows that, especially for wheat and rice, countries within the same region can be affected in quite different ways by shocks, something that could not be studied using a more aggregated model (e.g., regions instead of countries).

Global systemic impact

Within the interconnected global food supply network, even local production shocks can give rise to globally felt systemic impacts. This may happen when local shocks occur simultaneously (e.g., multiple breadbasket failures) or when a local shock is of such magnitude that it has global

ramifications. We measure global systemic impact by the total negative consumer surplus across countries per weather year (i.e., the sum of negative country consumer surplus compared to the mean consumer surplus under the baseline scenario). We quantify the impact of weather-related variation in crop yields (from 54 years of yield data) and overlay the four shock scenarios (*Ukraine*, *Price*, *Trade*, *All*). Ranking the 54 weather years for each shock scenario allows us to empirically estimate the quantiles (quantile being the rank divided by the total number of weather-year, $N = 54$) of the negative consumer surplus, for a given scenario.

Under the baseline scenario (Figure 3a), the worst consumer surplus loss is USD90.8 million/year for maize, USD31.2 million/year for wheat, USD64.4 million for rice, and USD72.3 million for soybean. When this is compounded with the *All* shock scenario the losses rise to USD246.4 million, USD145.6 million, USD135.6 million, and USD78.6 million for maize, wheat, rice, and soybean, respectively. This is 2.3 times greater (USD606.2 million versus USD258.7 million), with the largest relative increase occurring for wheat. The Ukraine war has a minor effect on the systemic risk for wheat, rice and soybean, but shifts the curve up for maize (to a worst case loss of USD125.1 million) (Figure 3a). Comparing *All* with the other three scenarios, 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 consumer surplus in the *All* scenario. What is also apparent is the importance of the weather years for the systemic risk. For instance, the difference between the worst case scenario (tail risk event) and the median event (0.5 quantile) is in most cases larger than the additionality of the shock scenarios. In other words, the occurrence of a bumper harvest or breadbasket failure can be as great or greater than the additional effects of non-climatic shocks, emphasizing the importance of looking at those together.

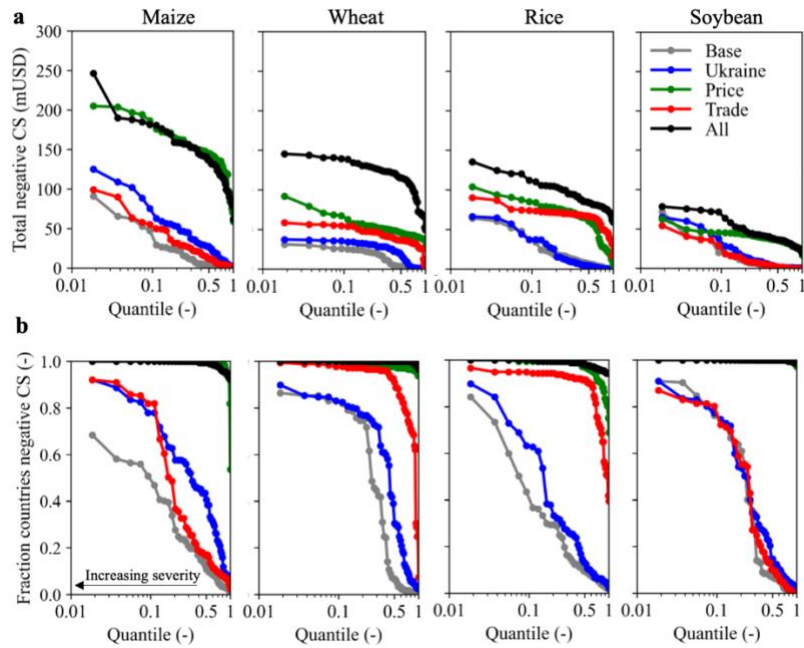


Figure 3 (a) Total amount of a negative consumer surplus (CS) during a single event (sum of all negative CS across countries). (b) The fraction of countries (out of the 177 considered) that experience a negative consumer surplus. The quantiles indicates the rank of the weather year compared to the total number of weather years in our sample ($N = 54$), ordered by severity (rank 1 is worst case).

Under the baseline scenario, the proportion of countries that simultaneously experience negative surplus (Figure 3b) ranges from close to zero to 90% as yield conditions worsen. In most cases, there is a clear transition in the number of countries that experience simultaneous negative CS

between fairly average years (quantile >0.5) and very bad years (quantile <0.5). In particular for wheat and soybean a clear transition is visible, with the food supply system being capable to deal with average years, but with many countries experiencing lower consumer surplus during some breadbasket failures. When this is compounded with the *All* scenario, virtually all countries simultaneously display drops in consumer surpluses. Comparison of *All* with the other scenarios indicates that the energy price shock makes the most significant contribution, while trade restrictions for wheat and rice also cause widespread negative consumer surplus across countries.

Shifting trade patterns

In our model the compound shocks in the *All* scenario led to multiple adjustments to global trade flows (compared to a baseline shown in Supplementary Figure 11). These can be understood by looking how the different shock affect trade. For the *Ukraine* shock, we assumed reduced exports from Ukraine via sea with exports to some countries being stopped (though the scenario does not capture the Black Sea Grain Initiative). The shock led countries relying on Ukraine for imports (mainly wheat and maize) to source grains from elsewhere, while Ukrainian grain that would have been exported by sea was sold on European markets that could be accessed by land (31). The reductions in exports in the *Trade* shock forced import-dependent countries to rely more on domestic markets (from production or stocks) or to source from elsewhere. The *Price* shock has a more systemic effect on trade. Rising input costs meant that producer prices accounted for a higher fraction of total consumer prices, although dependent on how the energy price shock increases producer prices. This effect makes trade costs less of a barrier to establishing new trade partners so that global markets became more competitive as countries competed to source the cheapest supplies.

Changes in regional trade flows for the four grains after the *All* shock are shown in Figure 4. The results illustrated are averages over the observed 54 weather-driven yield patterns. A clear reduction in maize exports from Eastern Europe is visible, in particular to East Asia, North Africa, and Western Asia. North African countries, in turn, have sourced their shortfall from North America. Latin America and the Caribbean have increased interregional trade, at the expense of North American exports, due to improved relative cost competitiveness of local maize. Increases in producer prices in the *All* shock scenario (and similarly for the *Price* shock) reduce maize production by the large amount of 83.0 million tons while trade flows increase by 43.7 million tons as countries seek alternative suppliers and the relative cost of trade reduces.

For wheat, international trade also increases in the *All* shock scenario (by 23.7 million tons) in the face of a global supply reduction of 85.8 million tons. Major shifts in trade flows are associated with the Ukraine war, with lower exports to North Africa, Sub-Saharan Africa and Western Asia. North Africa replaces its losses by increasing imports from NW-Europe and North America, while Sub-Saharan Africa mainly responds with increased imports from NW-Europe. This switch towards imports from NW-Europe was made possible by an abundance of low-cost Ukrainian wheat supply that could not be exported by sea on North-West, Eastern and Southern European markets (32). Western Asia increased supplies from a variety of sources, in particular from Central Asia. The trade imbalance between South-East Asia and East Asia markedly increases with South-East Asia increasing exports to East Asia, while East Asia reduces exports in the opposite direction.

Less extreme shifts are observed for rice, with reductions in both international trade (by 10.3 million tons) and production (by 15.6 million tons). The largest response is the reduction in intraregional rice trade in South Asia and the increased reliance on domestic supplies due to the export restriction of India. A similar response occurs in South-East Asia. Sub-Saharan African countries experience the largest import shock and as a result are forced to source more rice from within the continent. Soybean trade is relatively robust in the *All* shock scenario, except for decreases in Latin America and Caribbean exports to East Asia (which is partly substituted by soybean from North America), alongside a lower domestic supply. This is the result of diminishing global demand for soybean amid rising consumer prices.

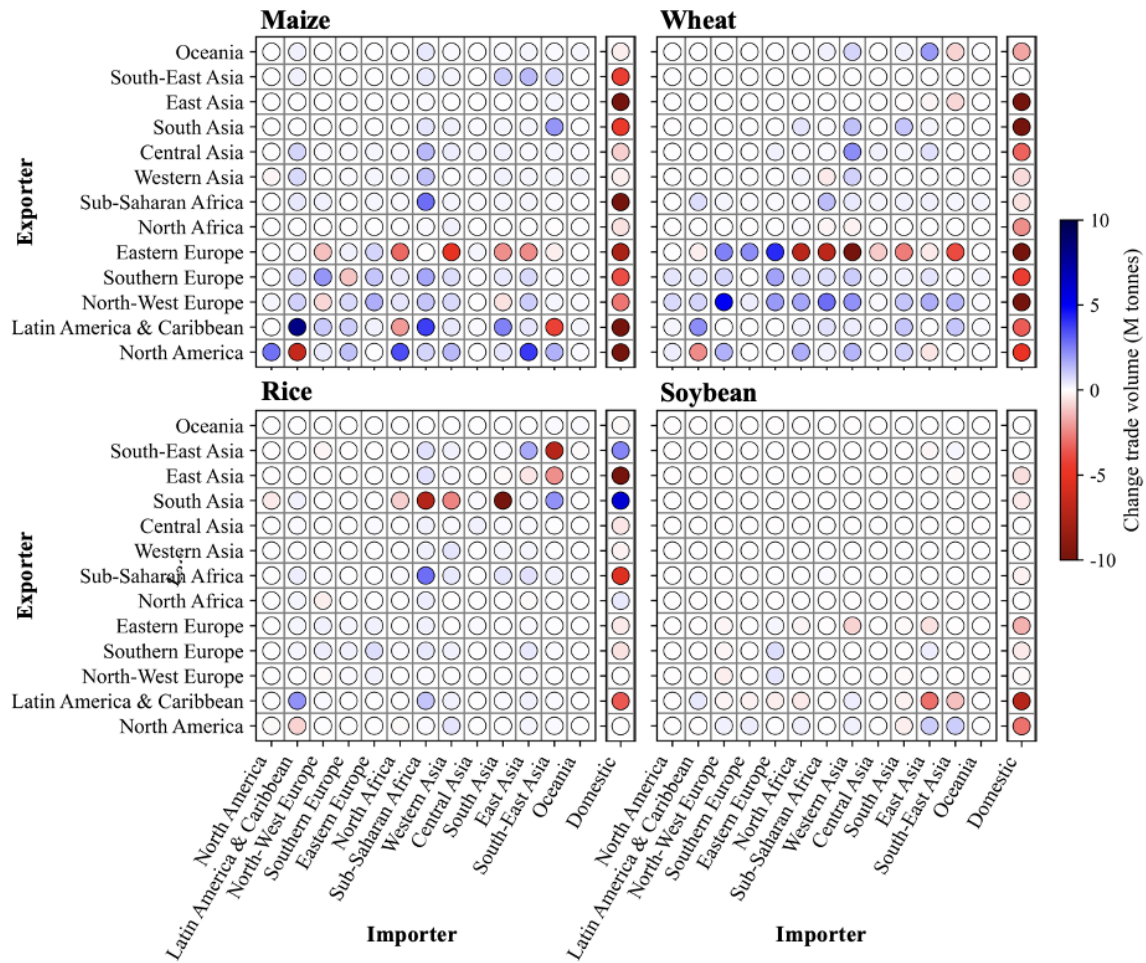


Figure 4. Absolute change in average interregional trade in the 'All shocks' scenario (average over 54 events) compared to the 'Baseline' scenario. The matrix indicates regional international trade, while the last column indicates change in domestic supply for countries within the region. The diagonal indicate the changes of the within region international trade flows.

Trade buffers systemic shocks

There is a long-standing debate about whether high levels of imports are beneficial for countries in allowing them to buffer shocks due to local yield variability and to access markets abroad (33, 34). We test this hypothesis by comparing a country's import dependency (ID, the fraction of a country's supply of a commodity made up of imports) with its average reduction in consumer surplus as yield patterns have increasingly severe effects on production. We ask whether a higher ID leads to a lower sensitivity to changes in consumer surplus, or vice versa, which we test by examining the Spearman rank correlation coefficient between ID and the ranked consumer surplus deviations. We are particular interested how this correlation changes for the average year (quantile 0.5 or above) versus the tail risk events (quantile 0.1 or below).

For maize and rice, a high ID is correlated with lower reductions in consumer surplus under typical yield conditions, but the correlation is reversed in years when weather causes severe effects on

agriculture (Figure 5). Countries with extensive domestic production and low reliance on exports are better able to buffer themselves against more major weather-associated shocks affecting these grains, though in typical years there is an advantage to being able to access multiple international markets. The relationship for soybean is broadly similar but much weaker. The positive effects of high ID during good yield years disappears when the different shock scenarios are implemented. Relatively high levels of domestic production help protect consumers for bad years though do not completely mitigate the effect of the shock. For wheat, the shape of the curve differs between the shock scenarios. This indicates that a higher ID may be beneficial for some combinations of weather years and shocks, but not for others, emphasizing that imports or self-sufficiency does not provide a “one-size-fits-all” solution to build resilience to shocks to wheat supplies.

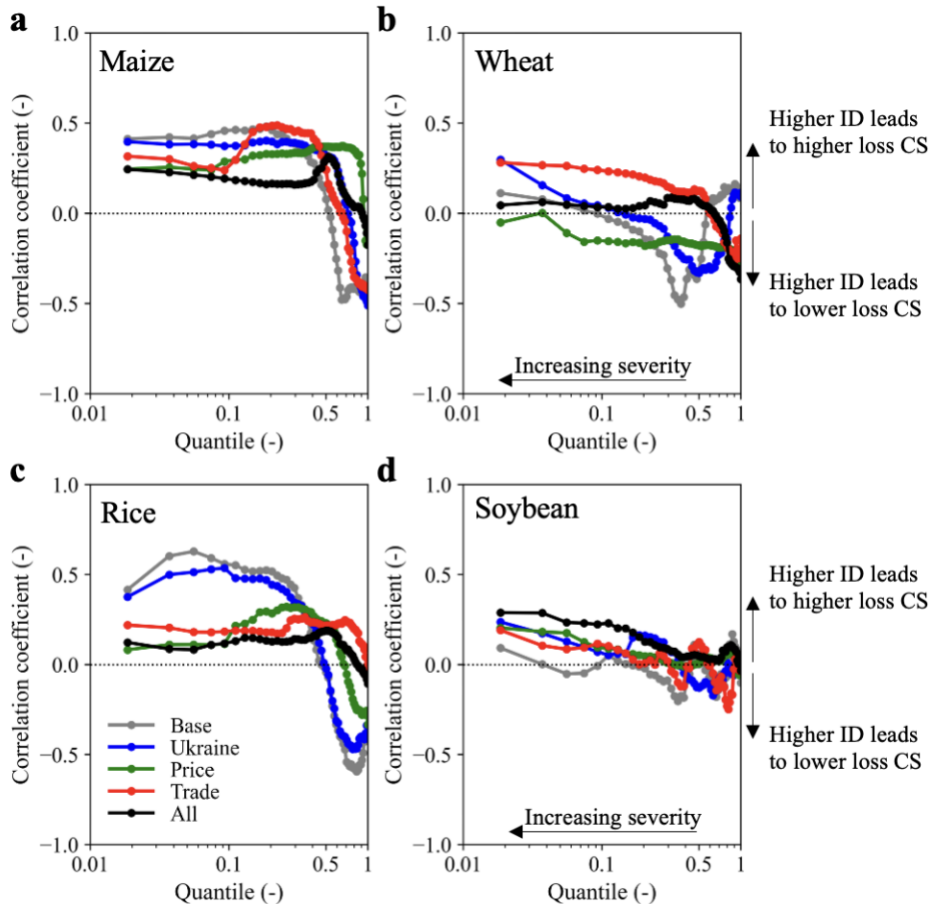


Figure 5. (a) The Spearman rank correlation coefficient between country consumer surplus anomaly and the country import dependency (ID) of a country for maize. This correlation is run per ranked consumer surplus anomaly across countries. (b-d) Show the same figures but for Wheat (b), Rice (c) and Soybean (d). A positive relationship indicates that a lower ID can help buffer CS anomalies while a negative relationship indicates that a higher ID can help buffer the CS anomalies. The quantiles indicate 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).

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. While shocks to food supplies are a growing concern for countries with high levels of food insecurity, food price shocks leading to inflation of food prices is a concern for countries across the world.

Food system modelling can be a helpful way of understanding fluctuations and suggesting how they can be mitigated. Previous analyses have tended to examine a relatively small number of shocks without taking into account year-to-year variation in weather affecting agricultural production. In addition, they have also poorly captured short-term adjustments in food trade and demand which, in practice, effectively buffer shocks. In this study, we estimated variability of food production across 177 countries using 54 years of agricultural yield information subject to weather-driven shocks. We constructed a bilateral trade model to simulate adjustments in food import/export linkages based on detailed bilateral trade costs information, as well as information on stocks. We used a supply-constrained price equilibrium model to incorporate the effects of different supply, price, and trade shocks, and examine how consumer prices respond to supply-side shocks and trade adjustments. It is important to note that consumers in our model cannot switch between grains, hence potentially overestimating impacts on consumer surplus.

The results reveal the sensitivity of the global food system to climate-related supply variability and as well as to further shocks imposed on this background. Across all crops and regions, the impact of rising energy prices (affecting the cost of diesel, pesticides and fertilizer) on crop production was found to have the largest effect on food prices, demand, and consumer surplus. In our model we assume that producers do not adjust their inputs in response to this shock, when in reality, producers may choose to reduce the use of fertilizer and pesticide (or alternatively utilize stocks) in response to rising input prices (as observed across many countries during 2022-2023 (35)), which in turn would reduce yields (21). Were this to happen, producers would reduce supply and increase producer prices that would be passed on to consumers. We hypothesize that the overall effect would be roughly the same, but further analysis of this issue would be needed as we suspect there may be significant differences in the spatial pattern of the response caused by differential use of inputs.

We find that the compound (A//) shock could push global prices up by 22.6%, 40.1%, 47.8% and 51.5% for soybean, maize, rice and wheat respectively. These figures are in line but slightly lower than previous investigations of shocks motivated by the events of 2022-2023 food crisis, which found global market prices to increase by 60-100% (20) and up to 65% (17). The FAO Global Cereals Price Index was around 55% higher in 2022 compared to the long-term average suggesting our model results are of a similar order to observed price shocks. Note that on shorter time spans of days or weeks global price fluctuations may be considerably higher due to aspects of grains markets that are not modelled here, such as speculation (36), derivatives trading, and cross-sectoral interactions with other markets.

The consumer prices modelled here are assumed to be landed costs, without any marketing mark-ups, and without governments interventions to respond to rising food prices. Governments in 2022 responded to rising food prices through a variety of interventions including food and fertilizer subsidies, tariff adjustments and price freezes (9). These interventions determine the actual pass-through of shocks to local market prices, as well as acting counter-cyclically to stabilize demand during price spikes. At the price of increased complexity our modelling framework could be extended to explore these interventions and their first and second-order effects,

The relatively minor impacts of the supply shock of the Ukraine war on global prices and consumption arise because countries are able to source maize and wheat from alternative trading partners, either those that they already traded with before the conflict or by establishing new trading

relationships (at a cost). While in line with anecdotal evidence of trade shifts that did happen over the last two years, there is an ongoing debate about the short-run stickiness of trade flows after a shock (37). Empirical studies of changing trade patterns during shocks, and what factors prevent adjustment, will be important to better calibrate our and similar shock-response trade models.

Whilst our modelling illustrates the potential for trade adjustments to buffer shocks, our results highlight that trade cannot be relied upon to mitigate the most severe and pervasive compound shocks, which can cause systemic risks to the global food supply system. Our results show that trade can allow multiple shocks to combine and propagate to affect consumers throughout the world, especially for the worst, low probability scenarios. The worst-case shock under the baseline scenario (which just includes weather-driven yield variability) can cause a total negative consumer surplus of USD260 million which increases to USD606 million in the *All* shock scenario, with virtually all countries to some degree negatively affected. While having a high import dependency can help buffer against year-to-year weather variability, it is less able to buffer tail-risk events where domestic production capacity is important.

Our results show the importance of considering the effects of non-climate shocks against the background of a realistic range of above or below-average yields determined by global weather patterns. Stress-testing the global food system and assessing strategies to build resilience requires a risk layering (38) approach to deal with the spectrum of shocks. Our results and further modelling may help inform policies around global risk funds, cash transfer programs, agricultural versus other sector investments, and trade. A risk layering approach to mitigating shocks will require a balanced set of agricultural system interventions, fiscal policies, and trade policies.

The world requires a globalized food system so that food surplus countries can provide food for countries with a limited agricultural capacity to feed their population. Global trade in food is 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. The consequence of failure – the inability to feed a large nation for example – could be catastrophic. The relative resilience shown by the global food system to recent shocks including the pandemic and Russia's invasion of Ukraine are grounds for optimism, but not complacency. We believe that the modelling approach we have developed 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 an useful tool to locate food system's strengths and vulnerabilities and identify strategies to increase resilience.

Materials and Methods

Overview

We provided a brief overview of the methodology, split into (i) the derivation of the 54 years of plausible yield variability, (ii) the spatial price equilibrium model, and (iii) the implementation of the various shocks into the model.

Country yield variability

For each country, we derive a set of representative yield anomalies, which are driven by large-scale climate variability (ignoring other factors affecting yield year-to-year). These yield anomalies should be interpreted as plausible deviations from the modern-day yield baseline, and not historical yields.

A dataset of global modelled rainfed and irrigated crop yields (25) is used to calculate country yield anomalies for the four study crops (rice, wheat, maize, sorghum). This dataset was derived from a fused gridded crop model, which takes historical climate (39) and soil data, gridded maps of crop harvested area (40) and a daily process-based crop water model (41) to estimate 10x10km global pixel level crop yields for individual crop growing seasons (42) from 1961 to 2014. The model uses empirical yield-evapotranspiration relationships to estimate changes to crop yields (relative to the year 2010) under 54-years of historical climate conditions. A full description of the model and dataset is provided by ref (25)

Pixel level crop yields from the fused gridded crop model are aggregated to country level and the annual timeseries for the period 1961-2014 and detrended using linear regression. Country level crop yield anomalies for each year in the 54-year period are calculated by dividing the detrended yield by the 54-year country level mean detrended yield.

Global spatial price equilibrium model

We model producer and consumer prices, supply, demand and trade flows using a newly developed global spatial price equilibrium model (SPEM). A SPEM is a multi-regional partial equilibrium model that links producers and consumers across regions (43). Producers and consumers are linked together via domestic or international trade, for which a certain trade cost has to be paid. This includes all costs after leaving the farm, including storage, hinterland transportation, border and custom compliance, maritime transport, intermodal transfers, port fees, and imports tariffs. These have all been separately derived in previous work (28).

Compared to other global food systems models, the benefits of a SPEM is that it explicitly captures bilateral trade flows, which is not standard in many global food systems models. Second, it allows for trade diversion 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, a SPEM allows for embedding different types of shocks, including price shocks, supply shocks, and shocks to bilateral trade costs (e.g., trade bans). Although SPEM are usually set up for longer-term (partial) equilibrium simulations (44, 45), for instance given decreasing trade tariffs or cost, we adjust the standard SPEM formulation to make it suitable for shock simulations in the short-term (e.g., one-off shock). Moreover, we introduce stocks in the modelling framework, which are essential to understand supply shortages in the short-term but are usually omitted for future-orientated model applications.

The SPEM model requires data on trade, transport and trade costs, prices, supply, demand, and information on the shape of the demand and supply curves (e.g., the demand and supply elasticities). At the baseline, the SPEM model assumes that the decision to supply from certain regions is purely based on cost differentials of the total landed cost of goods (that is the cost to

produce crops and ship to the consumer). However, there are non-cost elements which determine where countries source from, and hence, the model need to be calibrated on existing trade data to capture cost and non-cost related factors that determine the supply network of specific countries (44, 46).

In our SPEM model, we consider 177 countries for which we could collect all data required. An overview of the data sources is included in Supplementary Table 1. These countries have interconnected competitive markets that trade a homogenous crop, with trade flows modelled on a directional basis. When referring to trade flows here, we refer to both international trade flows and domestic supply. Producers in each country have a certain amount of supply to provide to the market (either domestic or foreign), which they sell at the highest possible price (following their supply curve). Consumers have a certain amount of demand for the good and buy goods at the lowest possible price (following their demand curve). Each country can trade with any other country, with a corresponding trade cost to source from domestic or foreign markets. In equilibrium, we can find the trade flows between countries that determine the producer and consumer prices. For each country, the total production and imports must match the total consumption and export in equilibrium.

In the Supplementary Methods, we describe the trade cost formulation used, the calibration process, and the model set-up for incorporating different types of shocks. The reference period for the model is the 2017-2021 average trade network, to smooth out intra-year trade fluctuations. A separate SPEM is set-up for each crop considered, without considering any cross-grain substitution effects.

Shock implementation

We implement different types of shocks into the model, including production/yield variability, the Ukraine war, price shock, and trade bans. More details are provided in the Supplementary Methods.

Base: For each country, we have 54 representative years of yield variability, resulting in years of higher or lower than average supply. We implement the yield variability in the model by changing the initial condition of the total supply and shift the supply curve. A positive supply shock moves the curve to the right hand side and a negative supply shock moves it to the left hand side.

Ukraine war: For this scenario we make three adjustments in the model. First, we lower the supply for Ukraine to 60% of its baseline supply, in line with observed supply reduction in 2022/2023 (47). Second, we increase the trade costs to Russia (to cover a surge in insurance costs to trade with Russia). Third, we implement a version of the blockage of the Black Sea ports by increasing the trade costs to and from any country that is not part of the European Union and the United Kingdom, to capture the difficulty of sourcing Ukraine exports via sea.

Price shock: A price shock is introduced to capture the increase in fertilizer, pesticide and diesel costs due to supply issues as well as the energy crisis over the last few years. We follow a similar methodology as in Verschuur et al.(28) and estimate for every country the share of the fertilizer, pesticide and diesel costs to the total crop production cost. We then impose a price shock to these three input, increasing fertilizer and pesticide costs by 200% and diesel costs by 100% (see ref (28) for details). This yields a production price increment, which we assume is being passed through to the consumer

Trade bans. We utilize a global database (<https://www.globaltradealert.org/>) on trade-related interventions taken by countries from 2022 onwards. This database covers which countries impose trade restrictions, which countries are affected by them, and for which commodities these restrictions apply. We extract all import and export trade bans implemented (hereafter trade bans) and encoded this in the model by imposing higher trade costs between these countries.

Compound shock. In the compound shock, or polycrisis, scenario, we include all previously mentioned shocks at the same time to evaluate their compound impacts.

Acknowledgments

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Author Contributions: JV conceptualized the research, performed the analysis and led the writing of the manuscript. AMu. processed the yield anomaly data and contributed to the writing of the manuscript. YV, HCJG and AMo provided input to the analysis and contributed to the writing of the manuscript. MO and JWH conceptualized the research, provided input and contributed to the writing of the manuscript.

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Supplementary Information

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 to it. We refer to regions and countries interchangeably. When reference is made to prices, we should emphasize that subsidies or other support schemes are not included, and consumer prices do not have additional marketing costs added to them (they refer to prices associated with the landed costs of crops, not the retail prices). The reference period (t) for the model is the 2017-2021 average trade network, to smooth out intra-year trade fluctuations, while the previous period referred to throughout is the 2012-2016 average trade network ($t-1$). A separate SPEM is set-up for each crop (c) considered, without considering any cross-grain substitution effects.

Trade cost formulation

Interregional trade is captured through the Enke-Samuelson-Takayama-Judge spatial equilibrium formulation for homogenous goods (1, 2). We can describe the total trade costs (TTC) as the total amount paid for interregional trade flows. The trade costs (C^{trade}) is the sum of different cost components, including the total transport costs ($C^{transport}$), the tariff costs (C^{tariff}), the market entry costs (C^{entry}), and the calibrated trade cost term (C^{calib}). The market entry costs are paid when a new trade flow is set-up between two regions which previously did not have a trade flow. We can distinguish between the total trade cost at the intensive margin (int , for regions that do trade with each other) and at the extensive margin (ext , for countries that do not trade with each other):

$$TTC = \int C_{i,j,t,c}^{trade,int}(T_{i,j,t,c})d(.) = (C_{i,j,t,c}^{tariff} + C_{i,j,t,c}^{calib}) * T_{i,j,t,c} + \frac{\varepsilon}{1 + \varepsilon} * C_{i,j,t,c}^{transport} \left(\frac{T_{i,j,t,c}}{T_{i,j,t-1,c}} \right)^{\frac{1+\varepsilon}{\varepsilon}} * T_{i,j,t,c}$$

$$TTC = \int C_{i,j,t,c}^{trade,ext}(T_{i,j,t,c})d(.) = (C_{i,j,t,c}^{tariff} + C_{i,j,t,c}^{calib} + C_{i,j,t,c}^{transport} + C_{i,j,t,c}^{entry}) * T_{i,j,t,c} + 0.5 * \sigma * T_{i,j,t,c}^2$$

With $T_{i,j,t,c}$ the bilateral trade flow between two regions (i and j). $T_{i,j,t-1,c}$ captures the bilateral trade flows in the previous time step, in our case the average supply network for the period 2012-2016. The variables ε and σ are the non-linear trade expansion costs that reflect the non-linear logistics costs of expanding trade (e.g., due to capacity constraints in existing logistics networks) and enable persistency in existing supply networks, which therefore captures preferences in supply diversification (3). The higher these parameters, the more regions prefer sourcing for existing suppliers, and hence the more costly it becomes to source from elsewhere or increase trade from existing suppliers.

The $C^{transport}$ capture all transport-related costs, including hinterland transport, border compliance costs, charges at intermodal points, port fees, maritime transport, and customs compliance costs. Reference is made to Verschuur et al. (4) for details how these costs are derived. The C^{tariff} costs are estimated using the producer costs ($P^{producer}$), $C^{transport}$ and the ad-valorem tariffs (adv):

$$C_{i,j,t,c}^{tariff} = adv_{i,j,t,c} * (P_{i,t,c}^{producer} + C_{i,j,t,c}^{transport})$$

The C^{entry} are estimated similarly to Janssens et al. (3), and assumed to be a share of the producer cost:

$$C_{i,j,t,c}^{entry} = m_{i,j,t,c} * (P_{i,t,c}^{producer})$$

With m set to 20% across all crops and countries. The (time-invariant) calibration cost term (C^{calib}) reflects the remaining price gap between exporting and importing region in the calibration procedure. This reflect any trade cost component that is not included in the formulation, or capture any non-cost trade frictions (e.g., geopolitics, trade agreements).

A SPEM model has the underlying assumption that trade between regions occurs only when the sum of C^{trade} and the producer price ($P^{producer}$) is equal to the consumer price ($P^{consumer}$) of the destination region, which will become equal to the marginal C^{trade} in equilibrium:

$$\begin{aligned} \text{Intensive margin} \quad & (P_{i,t,c}^{producer} + C_{i,j,t,c}^{tariff} + C_{i,j,c}^{calib}) + C_{i,j,t,c}^{transport} \left(\frac{T_{i,j,t,c}}{T_{i,j,t-1,c}} \right)^{\frac{1}{\varepsilon}} = P_{j,t,c}^{consumer} \\ \text{Extensive margin} \quad & (P_{i,t,c}^{producer} + C_{i,j,t,c}^{tariff} + C_{i,j,c}^{calib} + C_{i,j,t,c}^{transport} + C_{i,j,t,c}^{entry}) + \sigma T_{i,j,t,c} = \\ & P_{j,t,c}^{consumer} \end{aligned}$$

Calibration procedure

The model is calibrated used a bi-level programming calibration procedure, introduced by Jansson and Heckeley (2009) (5) and later advanced by Mosnier (2014) (6).

The initial calibration (*the inner problem*) serves as the input to the second calibration problem. The objective of the inner problem is to minimize the sum of the total trade costs across all interregional trade flows:

$$\text{minimize} \sum_{ij} TTC_{i,j,t,c}$$

Subject to the market equilibrium constraint and positive bilateral trade flows:

$$\begin{aligned} e_{i,t,c} + \sum_j (T_{i,j,t,c} - T_{j,i,t,c}) &= 0 \\ T_{i,j,t,c} &\geq 0 \end{aligned}$$

With e being the excess demand (consumption – domestic production). The output of this optimization is the resulting trade flows associated with the minimum TTC across regions (that is, if there was simply a uniform production price across all regions), which forms the input for the second calibration (*the outer problem*).

The second calibration step consists of a joint minimization of the total deviations from the original producer price, trade, and transport cost values (z) and the total price chain residual penalty (pen). The total deviation can be written as summed squared errors:

$$z = w_t \sum_{ij} (T_{i,j,t,c} - \hat{T}_{i,j,t,c})^2 + w_p \sum_i (P_{i,t,c} - \hat{P}_{i,t,c})^2 + w_{tr} \sum_{ij} (C_{i,j,t,c}^{transport} - \hat{C}_{i,j,t,c}^{transport})^2$$

With the variables with a hat being the observed values or model input and w_t , w_p , and w_{tr} being respective weights on the trade flows, producer prices and transport costs errors. These weights are chosen to provide an equal weight to these error terms at the start of the calibration process. The price chain residual (π) is added to the price chain formula at the intensive and extensive margin:

$$\text{Intensive margin} \quad (P_{i,t,c}^{producer} + C_{i,j,t,c}^{tariff} + C_{i,j,c}^{calib}) + C_{i,j,t,c}^{transport} \left(\frac{T_{i,j,t,c}}{T_{i,j,t-1,c}} \right)^{\frac{1}{\varepsilon}} = P_{j,t,c}^{consumer} + \pi_{i,j,t,c}$$

$$\text{Extensive margin} \quad (P_{i,t,c}^{producer} + C_{i,j,t,c}^{tariff} + C_{i,j,c}^{calib} + C_{i,j,t,c}^{transport} + C_{i,j,t,c}^{entry}) + \sigma T_{i,j,t,c} = P_{j,t,c}^{consumer} + \pi_{i,j,t,c}$$

With the total penalty value being:

$$pen = \mu * \sum_{ij} (\pi_{i,j,t,c} * T_{i,j,t,c})$$

With μ the weight of the penalty. This yields us the objective function to minimize:

$$\text{minimize } zz = z + pen$$

With:

$$\pi_{i,j,t,c} \geq 0$$

We perform the calibration by solving the inner problem, which forms the input for the outer problem, which is solved iteratively by increasing the penalty weight μ to force pen to go towards zero. We stop the calibration if zz converges. This yield calibrated values of producer prices, consumer prices, trade, transport costs and the calibration constant.

Model set-up

We implement different shocks to the model, for which we determine shifts in producer and consumer prices, supply (S), demand (D) and the resulting trade flows. In order to do this, demand and supply curves are introduced to guide these adjustments. At the starting point, each region has S (sum of exports and domestic supply) and D (sum of imports and domestic supply), and the calibrated producer and consumer prices (7).

The country demand price represents the price at which a product will be bought on the markets, which should be lower or equal to the consumer price, and follows the country's demand curve:

$$\alpha_{i,t,c} - h * \beta_{i,t,c} * D_{i,t,c} \leq P_{i,t,c}^{consumer}$$

With $\beta_{i,t,c}$ being the demand elasticity and $\alpha_{i,t,c}$ the intercept of the demand curve. h is the habit persistence factor, which reflect that short-term demand elasticities are smaller than long-term demand elasticities, as regions have a certain persistency in their demand for goods in the short-run (8).

The country supply price in the supply region represents the price at which a product will be sold on the market, which should be greater or equal to producer price, and follows the country's supply curve:

$$\gamma_{i,t,c} + \delta_{i,t,c} * S_{i,t,c} \geq P_{i,t,c}^{producer}$$

With $\delta_{i,t,c}$ the supply elasticity and $\gamma_{i,t,c}$ the intercept of the supply curve.

We assume that regions are supply constrained in the short-run, but regions can utilize their stocks to partly buffer any supply shock they experience (which they can use domestically or export to foreign markets). The total supply (TS) availability is the sum of S plus stocks available (ST) minus the minimum stock requirement of countries (ST^{min}):

$$TS_{i,t,c} = S_{i,t,c} + (ST_{i,t,c} - ST_{i,t,c}^{min})$$

The supply that countries can utilize in the short-run follows the following constraint:

$$S_{i,t,c} \leq TS_{i,t,c}$$

In addition, the price chain relationship at the intensive and extensive margin has to hold:

$$\text{Intensive margin } (P_{o,t,i}^{producer} + C_{o,d,t,i}^{tariff} + C_{o,d,i}^{calib}) + C_{o,d,t,i}^{transport} \left(\frac{T_{o,d,t,i}}{T_{o,d,t-1,i}} \right)^{\frac{1}{\varepsilon}} \geq P_{d,t,i}^{consumer}$$

$$\text{Extensive margin } (P_{o,t,i}^{producer} + C_{o,d,t,i}^{tariff} + C_{o,d,i}^{calib} + C_{o,d,t,i}^{transport} + C_{o,d,t,i}^{entry}) + \sigma T_{o,d,t,i} \geq P_{d,t,i}^{consumer}$$

As well as interregional trade being constrained by supply and demand:

$$S_{i,t,c} = \sum_j T_{i,j,t,c}$$

$$D_{i,t,c} = \sum_j T_{j,i,t,c}$$

Shock implementation

As mentioned, we implement different types of shocks into the model, including production/yield variability, the Ukraine war, price shock, and trade bans. We discuss these one by one.

Production variability. As mentioned, for each country, we have 54 representative years of yield variability, resulting in years of higher or lower than average supply. We implement the yield

variability in the model by changing the initial condition of the total supply ($\tilde{S}_{i,t,c}$), and shift the supply curve:

$$\gamma_{i,t,c} + \delta_{i,t,c} * (S_{i,t,c}^{initial} - \tilde{S}_{i,t,c}) + \delta_{i,t,c} * S_{i,t,c} \geq P_{i,t,c}^{producer}$$

With the initial supply the baseline calibrated supply. A positive supply shock moves the curve to the right hand side and a negative supply shock moves it to the left hand side.

Ukraine war. For the Ukraine war, we make three adjustments in the model. First, we lower the supply for Ukraine to 60% of its baseline supply, in line with observed supply reduction in 2022/2023 (9). Second, we increase the trade costs to Russia (to cover a surge in insurance costs to trade with Russia). Third, we implement a version of the blockage of the Black Sea ports by increase the trade costs to and from any country that is not part of the European Union and the United Kingdom, to capture the difficulty of sourcing Ukraine exports via sea.

Price shock. A price shock is introduced to capture the increase in fertilizer, pesticide and diesel costs due to supply issues as well as the energy crisis over the last few years. We follow a similar methodology as in Verschuur et al. (4) and estimate for every country the share of the fertilizer, pesticide and diesel costs to the total crop production cost. We then impose a price shock to these three input, increasing fertilizer and pesticide costs by 200% and diesel costs by 100% (see ref (4) for details). This yields a production price increment ($P_{o,t,i}^{shock}$), which we assume is being passed through to the consumer:

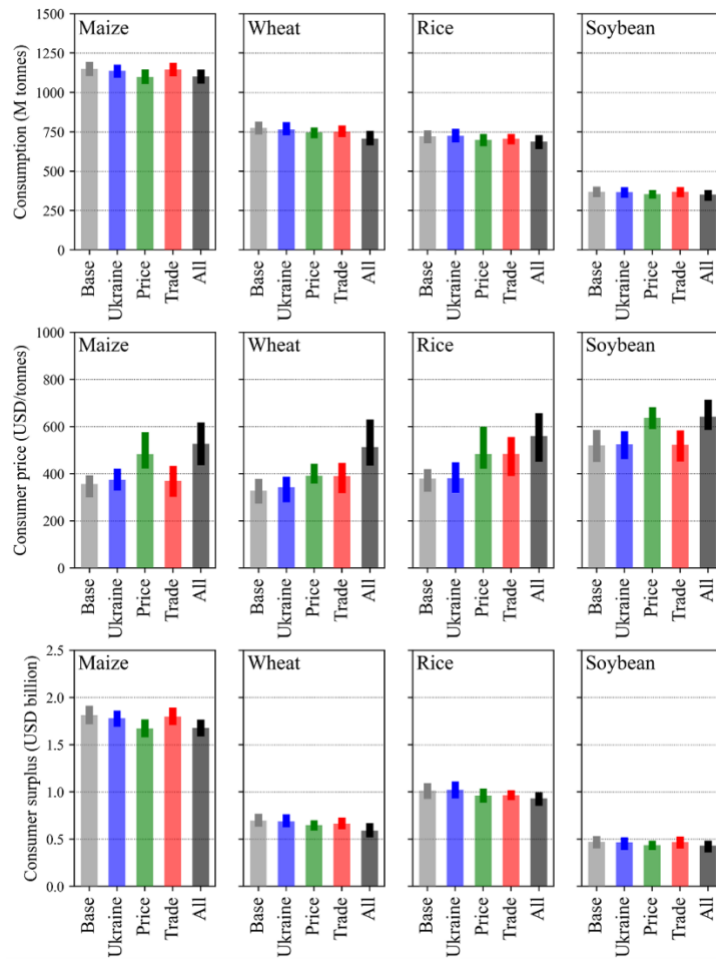
$$\text{Intensive margin} \quad (P_{o,t,i}^{producer} + P_{o,t,i}^{shock} + C_{o,d,t,i}^{tariff} + C_{o,d,i}^{calib}) + C_{o,d,t,i}^{transport} \left(\frac{T_{o,d,t,i}}{T_{o,d,t-1,i}} \right)^{\frac{1}{\epsilon}} = P_{d,t,i}^{consumer}$$

$$\text{Extensive margin} \quad (P_{o,t,i}^{producer} + P_{o,t,i}^{shock} + C_{o,d,t,i}^{tariff} + C_{o,d,i}^{calib} + C_{o,d,t,i}^{transport} + C_{o,d,t,i}^{entry}) + \sigma T_{o,d,t,i} = P_{d,t,i}^{consumer}$$

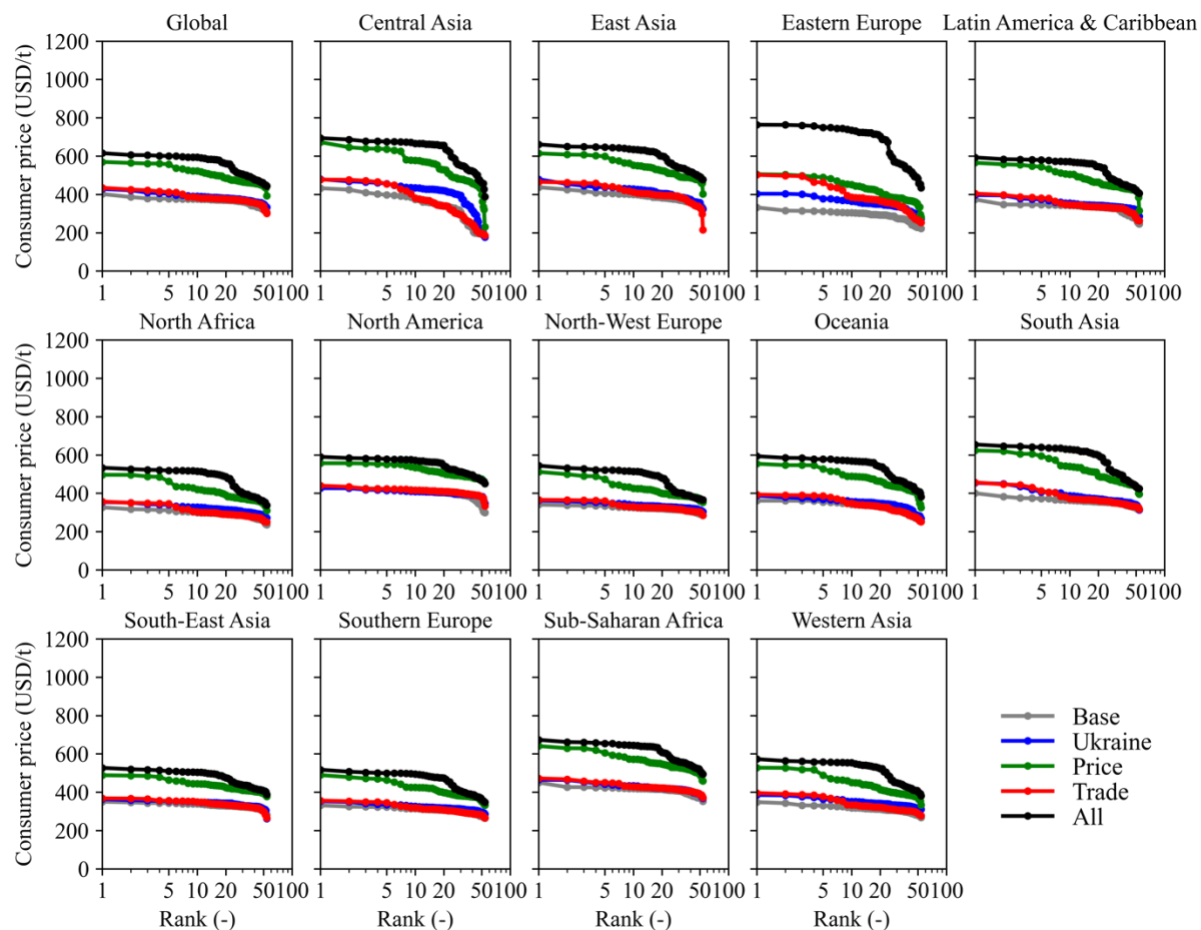
Trade bans. We utilize a global database (<https://www.globaltradealert.org/>) on trade-related interventions taken by countries from 2022 onwards. This database covers which countries impose trade restrictions, which countries are affected by them, and for which commodities these restrictions apply. We extract all import and export trade bans implemented (hereafter trade bans) and encoded this in the model by imposing higher trade costs between these countries.

Compound shock. In the compound shock, or polycrisis, scenario, we include all previously mentioned shocks at the same time to evaluate their compound impacts.

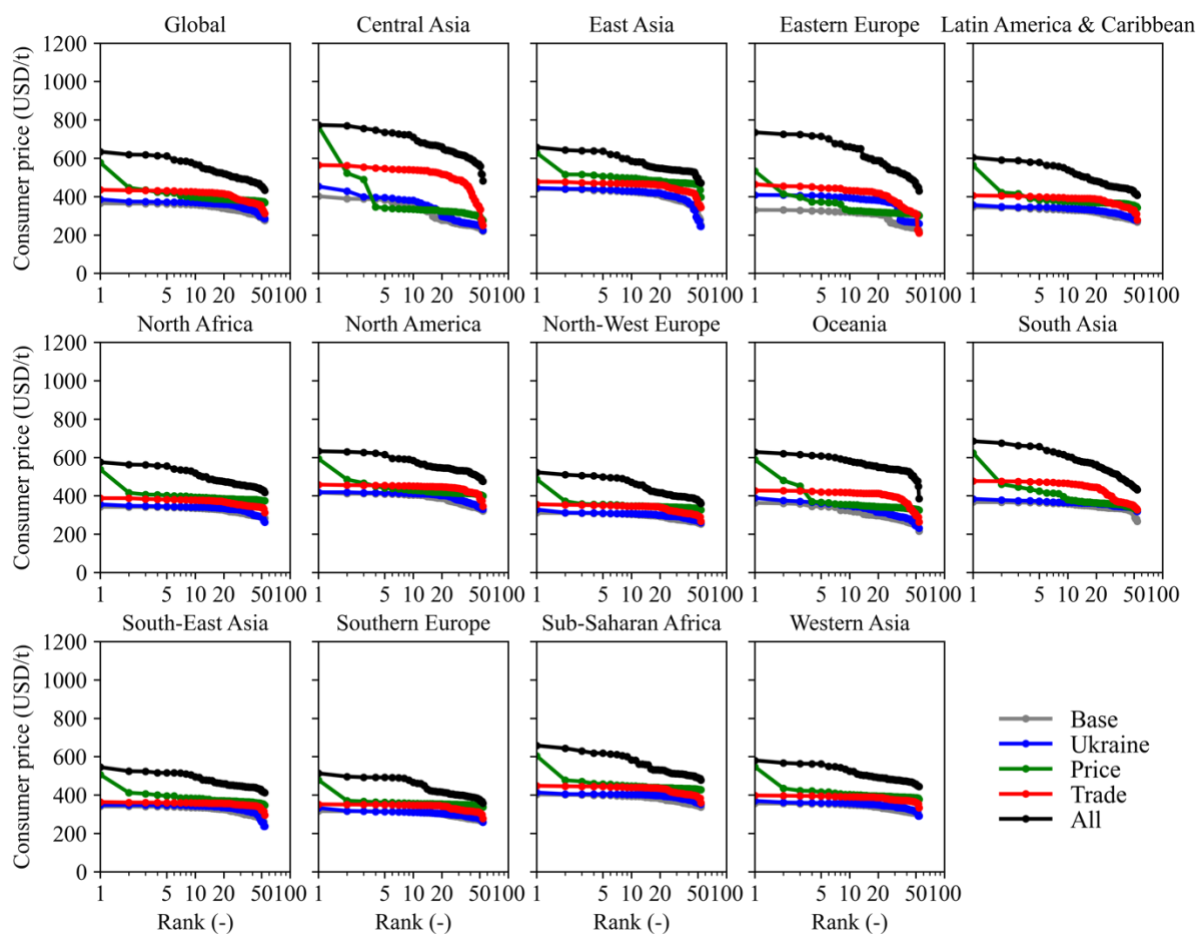
Supplementary Figures



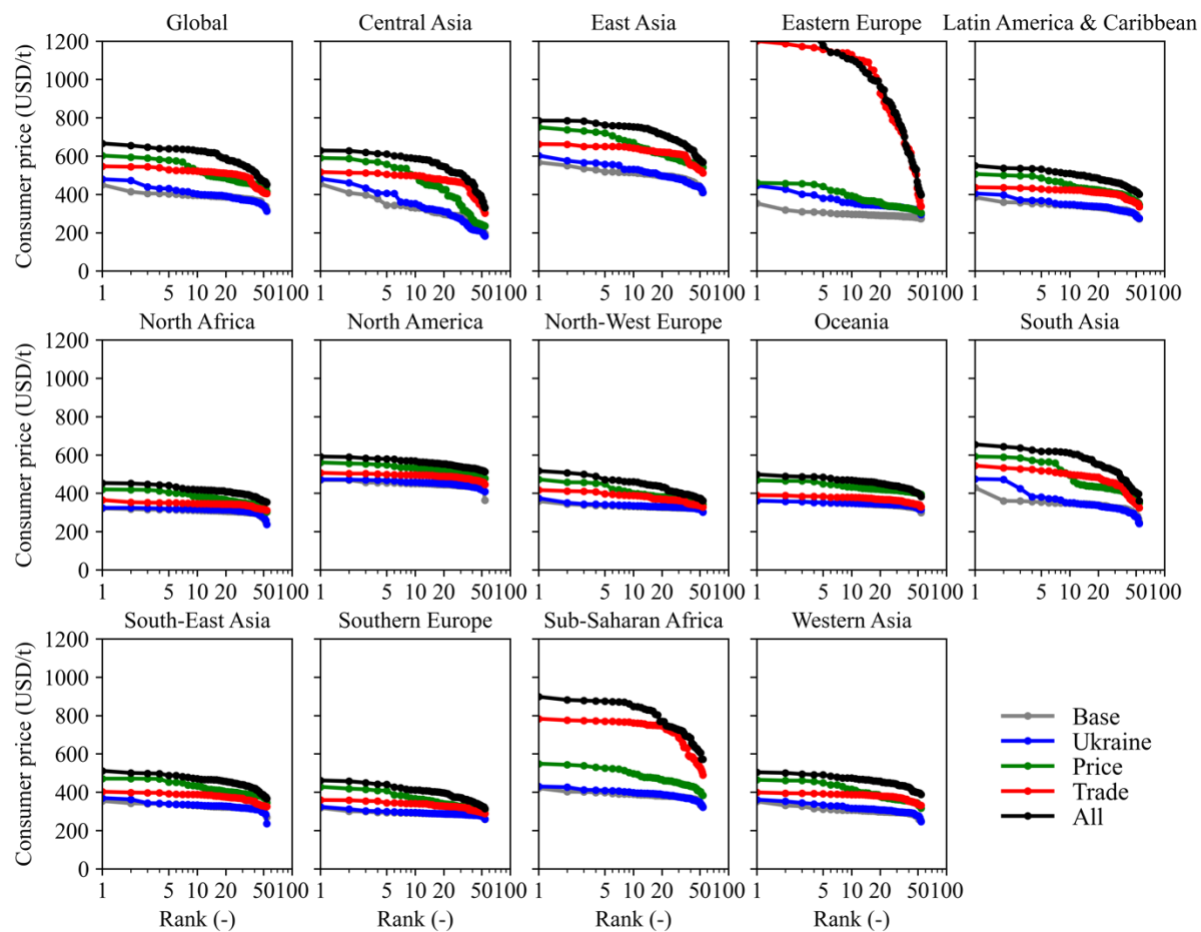
Supplementary Figure 1. Global average consumption, consumer price and consumer surplus across the 54 scenarios. The uncertainty bars indicate the minimum and maximum value across the 54 scenarios.



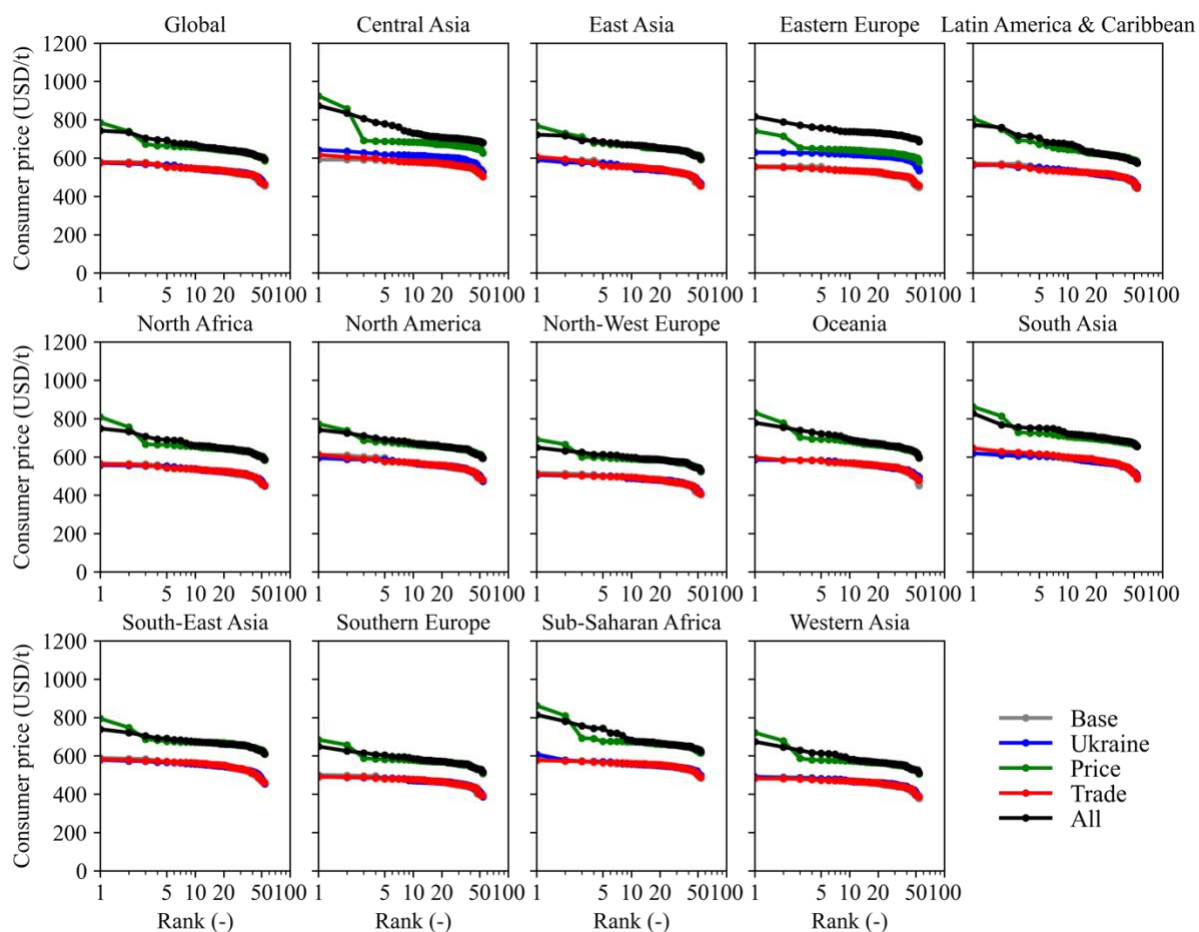
Supplementary Figure 2. Regional weighted average consumer price for each of the 54 counterfactual runs for Maize.



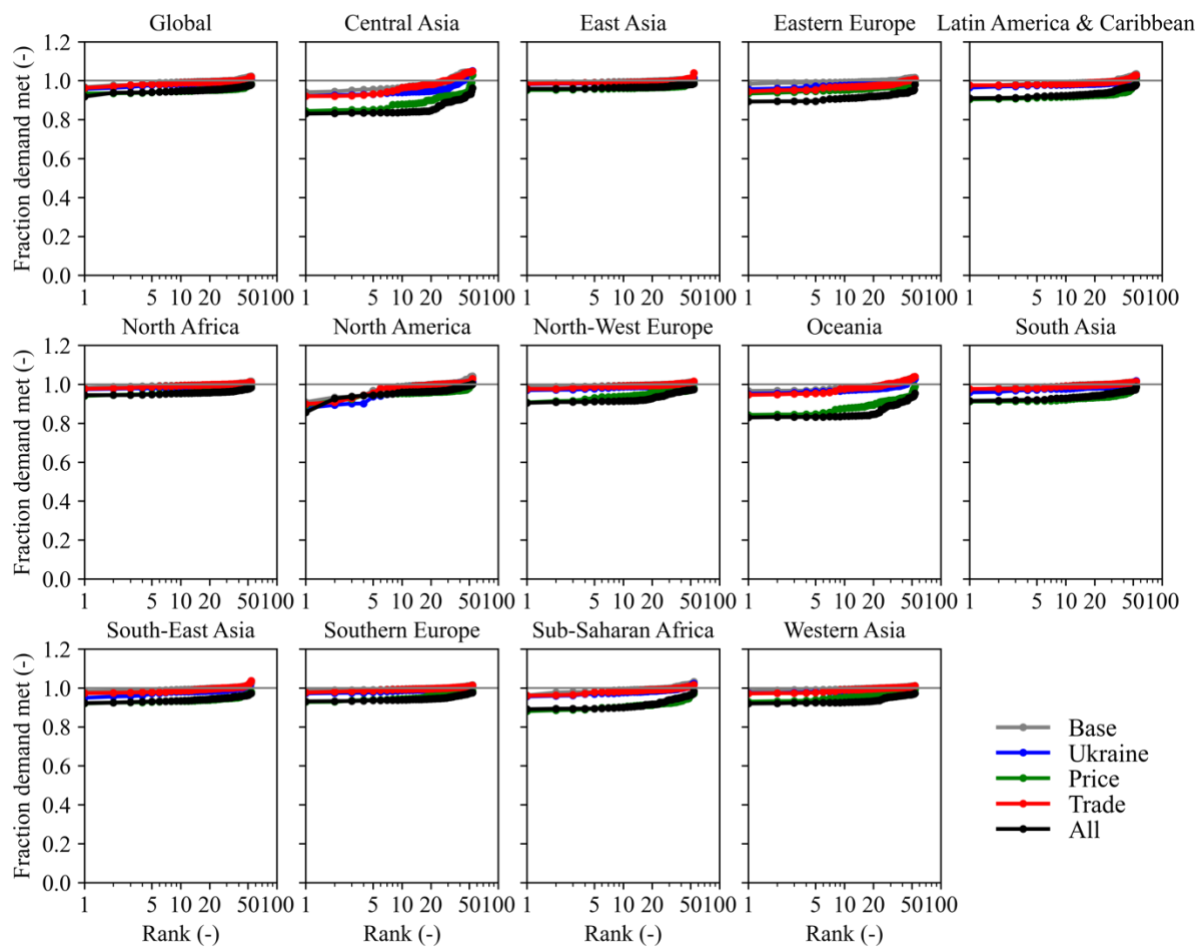
Supplementary Figure 3. Regional weighted average consumer price for each of the 54 counterfactual runs for Wheat.



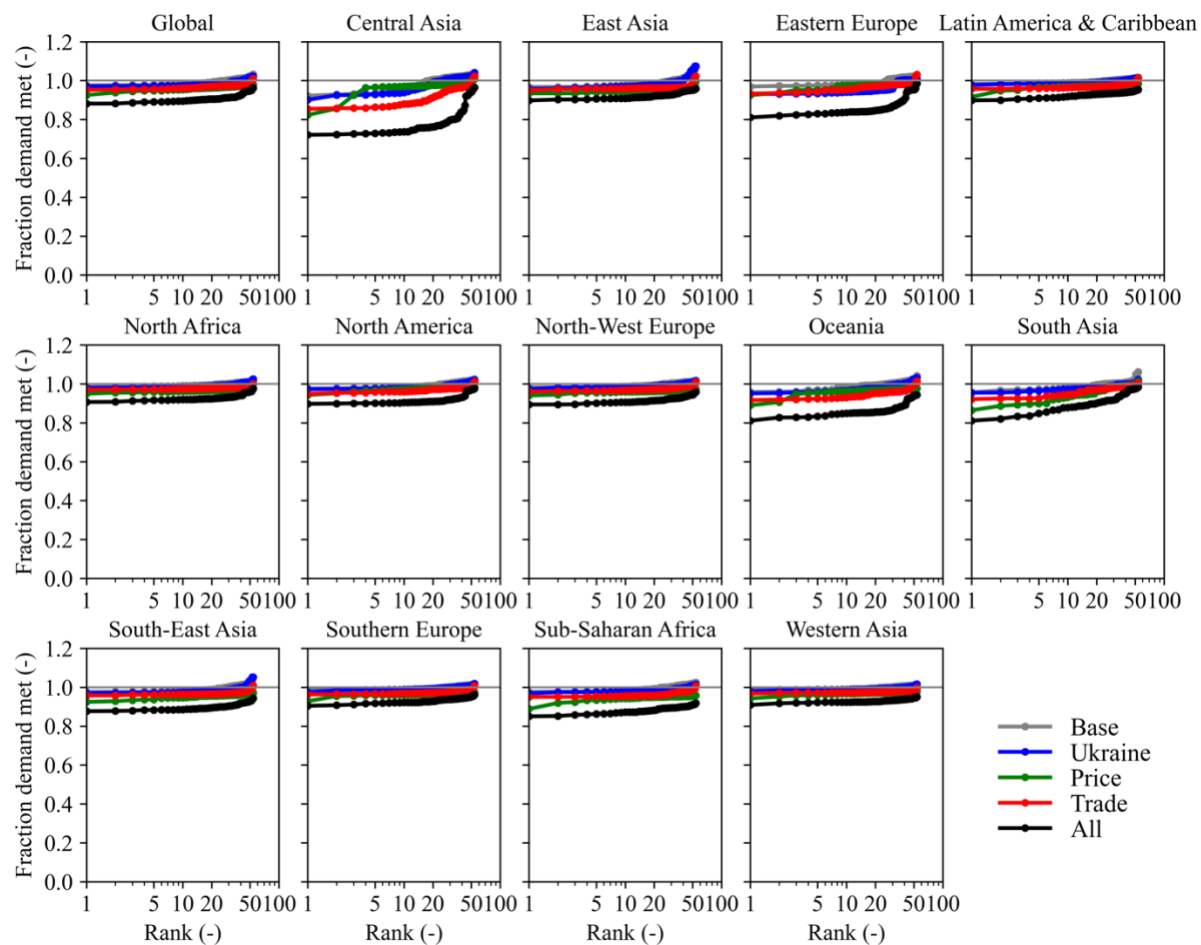
Supplementary Figure 4. Regional weighted average consumer price for each of the 54 counterfactual runs for Rice.



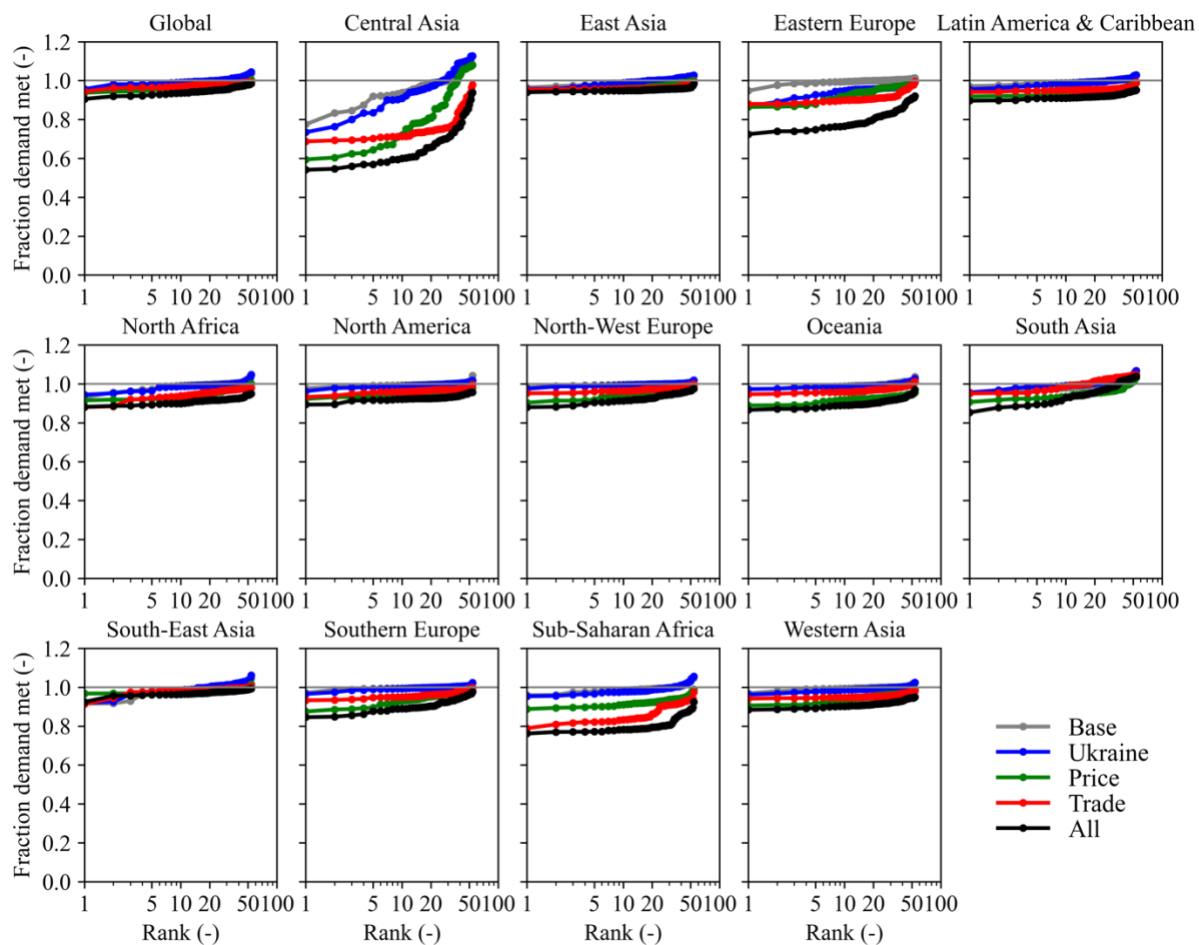
Supplementary Figure 5. Regional weighted average consumer price for each of the 54 counterfactual runs for Soybean.



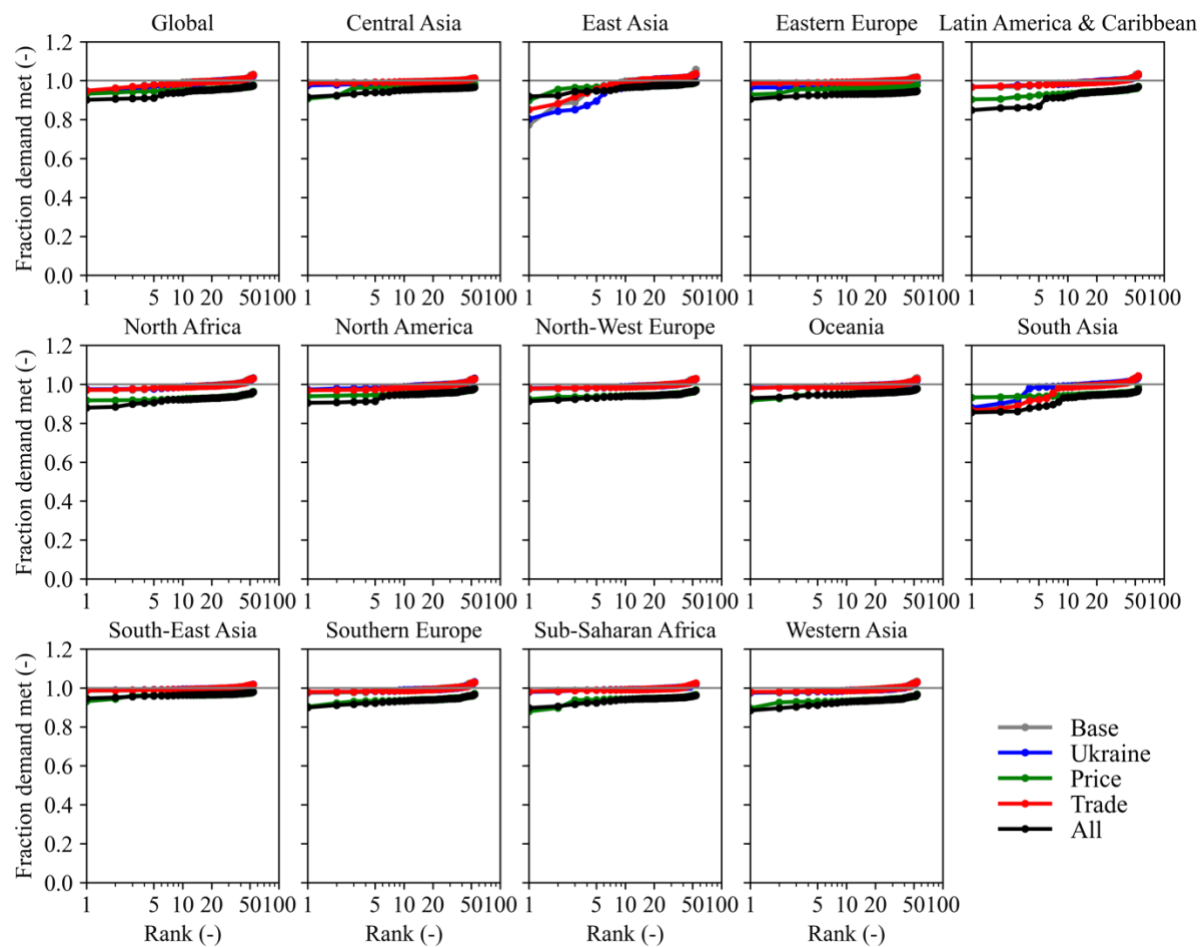
Supplementary Figure 6. Regional change in demand for each of the 54 counterfactual runs compared to the average demand under the baseline scenario for Maize.



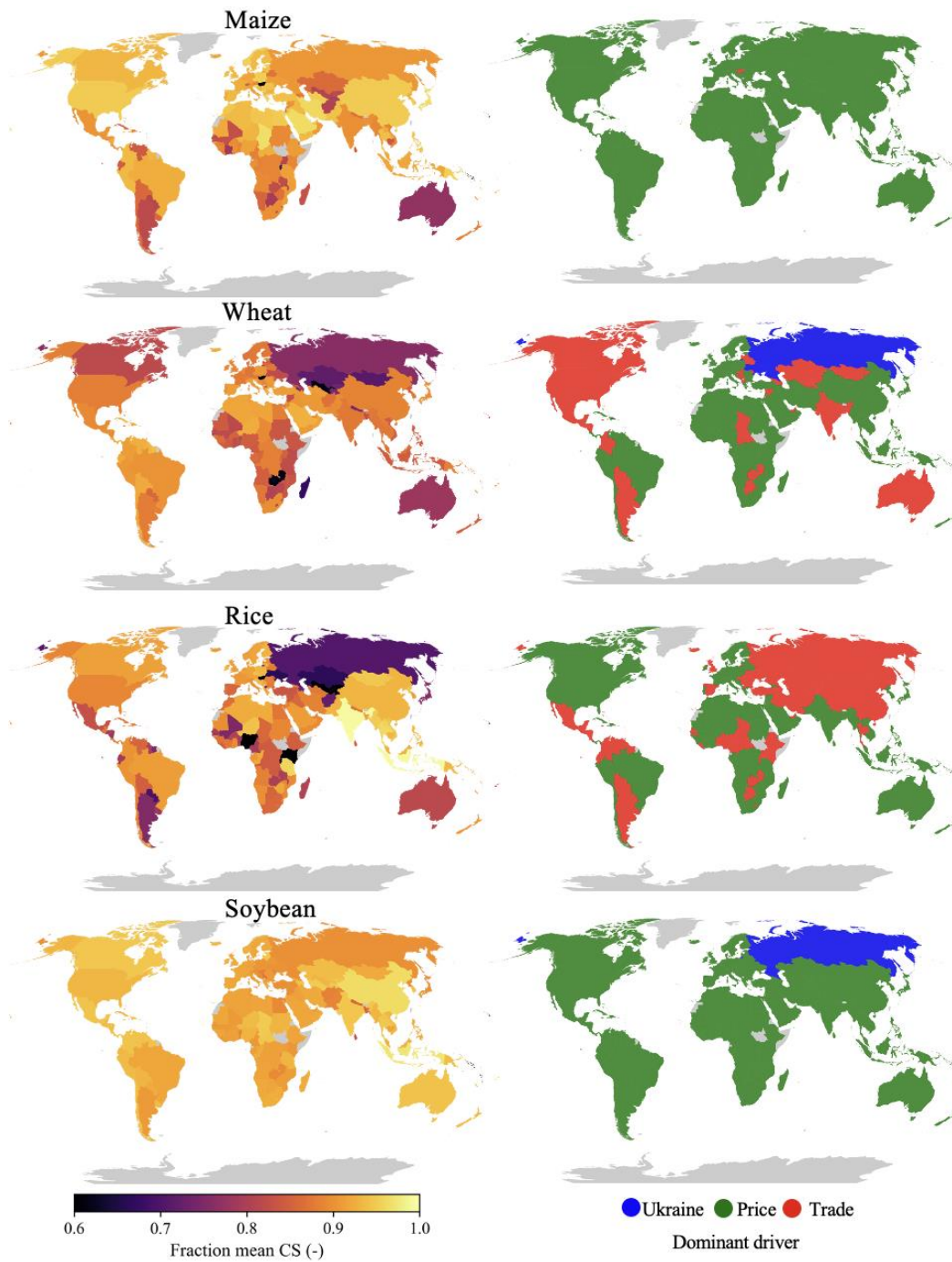
Supplementary Figure 7. Regional change in demand for each of the 54 counterfactual runs compared to the average demand under the baseline scenario for Wheat.



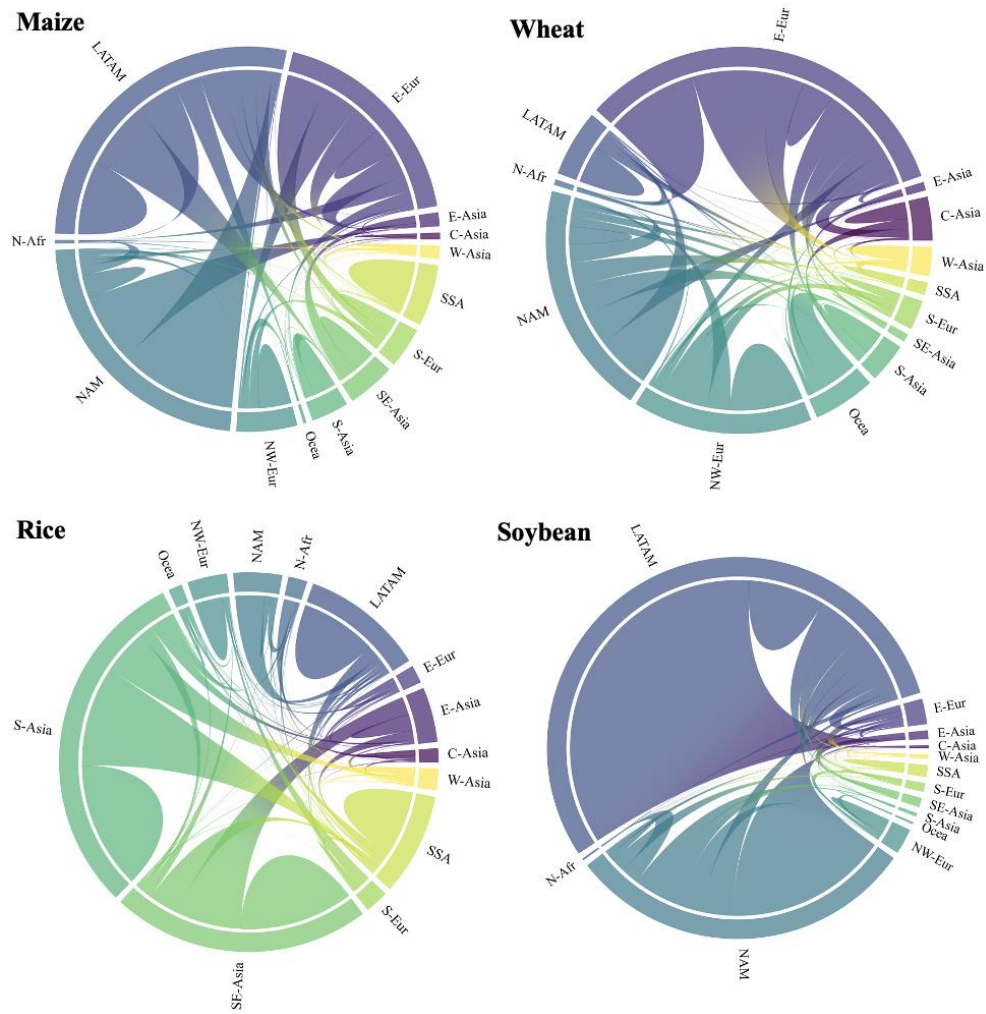
Supplementary Figure 8. Regional change in demand for each of the 54 counterfactual runs compared to the average demand under the baseline scenario for Rice.



Supplementary Figure 9. Regional change in demand for each of the 54 counterfactual runs compared to the average demand under the baseline scenario for Soybean.



Supplementary Figure 10. The left panels indicates the mean change in consumer surplus for across the 54 counterfactual runs compared to the average consumer surplus under the baseline scenario. The right panel shows the dominant shock per country that drive the compound impacts in the All shocks scenario.



Supplementary Figure 11. Chord diagram of global international trade flows between regions under the baseline scenario (average over 54 years). The size of the outer band indicate the export share that regions have with the size of the lines indicate the size of traded volume.

Supplementary Tables

Supplementary Table 1. Overview of the different data sources used in this study.

Variable	Description	Source
Crop yield	Country and crop-specific crop yields in t/ha	FAOSTAT, MAPSPAM (10)
Crop production costs	Country and crop-specific production costs in USD/ha, including the contribution to the production costs from fertilizer, pesticides, labour, machinery and diesel	Vittis et al. (11)
Demand elasticity	Country and crop-specific demand elasticity	IMPACT model (12)
Supply elasticity	Country and crop-specific supply elasticity	IMPACT model (12)
Total supply	Country and crop-specific supply for all productive use	FAO Food Balance Sheets (https://www.fao.org/faostat/en/#data/FBS)
Total demand	Country and crop-specific demand for all productive use	FAO Food Balance Sheets (https://www.fao.org/faostat/en/#data/FBS)
Trade	Bilateral trade data per crop	BACI (13)
Tariffs	Bilateral tariff data per crop for 2019	MAc-MAP-HS6 (14)
Trade costs	Bilateral trade costs from farm-gate to customer, including storage, hinterland transport, intermodal handling cost, port terminal handling, custom and border compliance, and maritime transport cost.	Verschuur et al. (4)
Stocks	Country and crop-specific stocks-to-use ratios. The average stock-to-use level is estimated to be the average between 2017-2021, whereas the minimum stock-to-use requirement is set to the minimum stock-to-use observed between 2000-2021, reflecting the minimum stocks countries desire to keep. In case no data is available, the regional average is taken and assigned to the country.	United States Department of Agriculture – PSD database (https://apps.fas.usda.gov/psdonline/app/index.html#/app/home)

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