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# The Russia-Ukraine war reduced food production and exports with a disparate geographical impact worldwide

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The transboundary impacts of regional war on global food trade remain underexplored, particularly regarding disruptions to production and trade networks. Here we address this gap by developing a rapid assessment framework that integrates remote sensing, policy monitoring, and network analysis to evaluate the effects of the Russia-Ukraine war on global winter cereal production and trade. Using satellite data, we estimated yield reductions for wheat, barley, and oats and analyzed the effects of export-ban policies enacted since February 24, 2022. Our findings indicate that lower- and middle-income countries were disproportionately impacted, as trade networks became fragmented, forming isolated clusters that threatened food accessibility. Geographically distant countries experienced greater disruptions than those near the conflict. This framework provides insights into the cascading effects of conflict on global food systems and offers a predictive tool for policymakers to address food availability challenges during future crises.

As major producers and exporters of agricultural commodities, Russia and Ukraine play critical roles in the global staple food supply. They export more than 54% of globally traded wheat, barley, and oats[1]. A number of countries, including some with vulnerable food availability, heavily rely on imports from these two countries. For instance, the shares of wheat imported from Ukraine by Egypt and Lebanon are 85% and 81% of their total wheat imports[2]. The war between Russia and Ukraine, which began on February 24, 2022, has raised serious concerns about Ukraine's crop production and global food shortages[3]. A series of cascading effects of the war, such as loss of agricultural labor, destruction of infrastructure, and limited access to agricultural inputs, have threatened food production in Ukraine[4–6].

Alongside high energy costs and supply-chain disruptions, the war has further exacerbated the global rise in food prices[7]. International cereals' prices increased by 20% within the first three months after the start of the Russia-Ukraine war[8]. The soaring prices have reduced the purchasing power of food importers and caused hunger, especially in low-income countries in Africa, the Middle East, and South America[9]. The Food and Agriculture Organization (FAO) models suggested that 13 million more people would be undernourished in 2022 due to the Russia-Ukraine war[10]. Furthermore, over 20 nations, including India and Kazakhstan, have declared stringent prohibitions and restrictions on grain exports after the Russia-Ukraine war, worsening the global grain supply and food availability[11]. Quantifying such cross-border impacts is therefore necessary for assessing food availability and making timely responses.

Recent studies have aimed to explore the quantitative impact of the Russia-Ukraine war on global food trade and food availability. Established studies have assessed the direct, indirect, and cascading effects of the Russia-Ukraine war by measuring the resilience, dependence, availability, and stability of other countries[12]. Steinbach used product-level empirical modeling to identify reductions in Ukrainian exports and substantial trade diversions in Russia's favor[13]. Some studies similarly emphasized the increase in global agricultural import prices, quantifying the impact of the war on food prices, trade volumes, and security[14,15]. Some studies have examined the impact of war on trade and supply chains. For example, Arndt et al. used a global trade model to assess the impact of the Russia-Ukraine war on developing food supply chains[16]. The study emphasized the importance of diversifying sources of food supply. The study by Zhou et al. examined the economic impact of the war on agricultural markets,

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highlighting trade disruptions and food price increases[17]. Structural general equilibrium trade models have been used to illustrate how a reduction in Ukraine's wheat production would affect global food security[15]. Van Meijl et al. assessed the impacts of the conflict on global grain markets and food security[18]. The study reveals severe supply disruptions and price increases and argues for policy interventions to stabilize markets. However, these studies still fail to integrate rapid export ban policy data into exploring the impact of the war on countries with different income levels, and it is not clear whether the impacts vary among countries at different spatial distances. This knowledge gap may result in some of the most affected countries being overlooked.

Also, some studies attempted to examine changes in food production in Ukraine and the war's transboundary effects but are based on qualitative analysis or untested quantitative analyses[5,7,19]. While existing studies provide valuable insights into the economic impacts of the Russia-Ukraine war on grain-importing countries, a complementary approach is needed to conceptualize the trading system as a dynamic, interconnected network (Fig. 1). This allows us to assess the structural changes within global trade relationships and explore the resilience of the global trade network in response to external shocks. Collecting ground data in conflict zones is dangerous and challenging. Previous studies have demonstrated the efficacy of remote sensing in assessing the socioeconomic and environmental impacts of war in countries such as Uganda, Iraq, Syria, South Sudan, and Yemen[20–26]. While a few studies have applied remote sensing to monitor agricultural production in Ukraine, they lack systematicity and often focus on specific aspects such as changes in land cover or yields of a single crop[15,27]. Furthermore, the impact of the Russia-Ukraine war on food availability in countries at different distances remains underexplored. To summarize, the impact of the Russia-Ukraine war on adjacent and distant national food systems in different income levels is not well understood in a metacoupled world (e.g., socioeconomic-environmental interactions within and across national borders)[28,29].

Considering the above gaps, we developed a rapid quantitative predicting framework integrating remote sensing and export ban policies with network analysis to build a trade network simulation. The simulation aims to assess the impact of the Russia-Ukraine war on food production in Ukraine. Since winter crops in Ukraine are dominated by canola and cereal, we used climatic algorithms to differentiate the acreage of winter cereals (wheat, barley, and oats) by analyzing seasonal growth differences using the widely used radar satellite images, Sentinel-1[30]. The method is still limited by some of the inherent shortcomings of remotely sensed imagery. For example, the spatial and temporal resolutions of the Sentinel-1 data are not suitable enough for accurately distinguishing morphological changes in crop plots at small scales over short periods of time[30]. While other satellite-based sensors with higher spatial resolution ground sampling distances and/or daily revisits may be better suited to detecting such changes, these options currently require the use of commercial solutions, which can increase survey costs. Considering several advantages, such as not being limited by weather, and timing of visits (which may be obscured by cloud cover in fall and winter), low cost (compared to commercial solutions), and secure access (despite the ongoing war in the study area), the Sentinel-1 is a useful source of data for the monitoring effort. Subsequently, we generated a 10-m resolution map of annual winter cereal farmland extents at the state level within Ukraine. After obtaining a spatial distribution map of annual winter cereals, we estimated the winter cereal yield using a random forest regression model, with model inputs such as the normalized difference vegetation index (NDVI), climate variables, and reference crop yield statistics. Given that staple crops affect food availability, we focused on three major staple crops in Ukraine—wheat, barley, and oats—to assess changes in food production. The planting area and yields of the three cereals account for more than 80% of all cereals[31].

The complex and interdependent nature of the global food system underscores the imperative for a rigorous and comprehensive approach to quantifying the effects of the armed conflict[12]. Network analysis is a method of studying the relationships between the nodes in a network and understanding how the network functions as a whole. It has been widely used for systematic analysis in sociology, medicine, sustainable development, and ecosystems[32–37]. Network analysis allows us to understand how changes in one part of the system can ripple through the entire network, affecting everything from production to distribution to consumption. Additionally, network analysis enables us to identify which countries and regions are most vulnerable to global food-system disruptions and target interventions in those areas[38]. Overall, network analysis is a valuable tool for understanding the complex dynamics of the global food system[39] and developing effective strategies to enhance its resilience and sustainability. Here we constructed a correlation network in which a network node is a country in the global trade

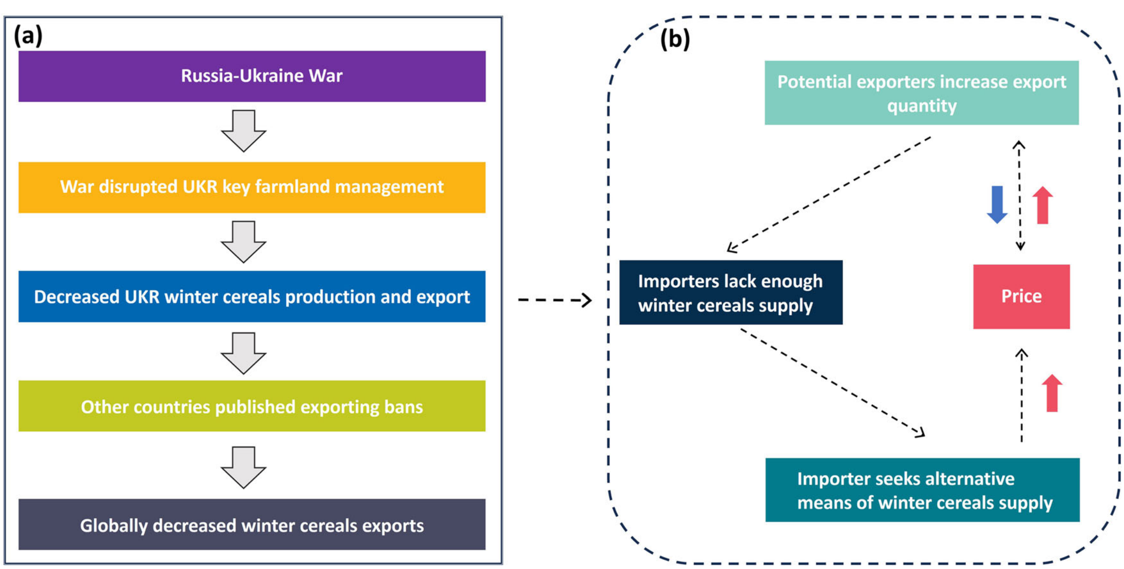



**Fig. 1 | Cascading mechanism by which war affects the global winter cereal network by decreasing production and prompting other exporting countries to publish export policies.** **a** is the shock of the Russia-Ukraine war on the volume of food trade exports, while **b** shows the resilience of the trading system, mitigating the shock through price changes. The gray arrows refer to the quantified impacts covered in this paper. The black dashed arrows are the potential impacts discussed in the qualitative aspects of this paper. The blue arrows in **b** refer to negative impacts on price, i.e., when potential exporters export in large quantities, which reduces cereal prices; the red arrows refer to positive impacts on price, i.e., when import demand increases or there is a shortfall in export volumes, which raises cereal prices.

systems of wheat, barley, and oats, and the strength of each link is the trade quantity between countries. Thus, we built export networks for the three crop trade systems.

Here, we utilized rapid policy data and remotely sensed data in conjunction with trade network analysis and used simulations to gain a comprehensive understanding of global winter cereal trade dynamics affected by the Russia-Ukraine war. Specifically, we aimed to address the following questions:

(1) What is the status of reductions in the production of winter cereal (wheat, barley, and oats) in Ukraine?
(2) How have the structures and interdependencies of the global trade networks of winter cereals changed in the simulated 2022 trade network compared to 2021, taking into account the reduction in winter cereal production in Ukraine as well as the export bans on wheat, barley, and oats in other countries?
(3) How does the war affect countries at different income levels and across distances? Are countries farther from the exporting countries affected differently compared to those near the exporting countries?

## Results

### Winter crop production reduction observed from satellite

Based on the state-level official statistical data, we evaluated the performance of our method at the state level for identifying winter cereals. Supplementary Fig. 1 shows the mapping results of the validation for 2019 to 2021. The $R^2$ values between the satellite-derived area and the official statistical data ranged from 0.80 to 0.94 for 26 states. Meanwhile, the root mean square error (RMSE) ranged from 55.94 $km^2$ to 116.11 $km^2$. Overall, there is good correspondence between official statistical data and identified planted areas. In addition, our state-level yield estimation results compared well against official statistics, with an RMSE of 346 kg/ha and an $R^2$ of 0.70[40,41]. The prediction errors can arise due to the inherent noise in historical data, inaccuracies in model assumptions, or the unpredictability of future conditions not captured in historical observations[42–44]. To account for these uncertainties, we have calculated a 95% confidence interval, depicted in Supplementary Fig. 1. This interval reflects our best estimate of the expected range of predicted values, accounting for possible variations inherent in our modeling framework.

The monitoring results of remote sensing satellites and official statistical data show that the winter crop was mainly distributed in the central and southern parts of Ukraine in 2022 (Fig. 2b). After the war's outbreak, winter crops' main production areas shifted from Odessa, Zaporizhzhya, and Mykolayiv states to Zaporizhzhya, Dnipropetrovs'k, and Kherson states. Meanwhile, war in the eastern region threatened the crops in the war-affected areas and affected the growth and development of winter crops in the entire region (NDVI < 0). From the NDVI changes in the longitude (Fig. 2a) and latitude (Fig. 2c) directions, the NDVI values in the central part of the study area were higher than those in the surrounding areas, and the winter crop yields were higher. The yield estimation results (Fig. 2d–g) show that the war threatened agricultural production and food availability in Ukraine. If war losses are not considered, compared to 2021, winter crop yield reduced by 5.42 million tons (95% CI range: (−0.05, 10.88)) in Ukraine, including 4.72 million tons (95% CI range: (−0.22, 9.67)) of winter wheat and 0.86 million tons (95% *CI* range: (−0.43, 2.15)) of winter barley. But, if we consider 30% of war losses, compared to 2021, winter crop yield would be reduced by 15.04 million tons (95% CI range: (8.68, 21.40)), including 12.89 million tons (95% CI range: (7.72, 18.05)) of winter wheat, 2.09 million tons (95% CI range: (0.29, 3.89)) of winter barley, and 0.07 million tons (95% *CI* range: (0.02, 0.12)) of winter oats[15]. As the main battlefields of the war, the food-producing croplands of the states near the eastern and southern parts of Ukraine have been affected. The total yields of winter cereal in Odessa, Donets'k, Kharkiv, Zaporizhzhya, and Mykolayiv states decreased by over 7.68 million tons. This decline was also observed in the total yield of winter wheat within these states, with a decrease exceeding 6.29 million tons. Similarly, the total yield of winter barley exhibited a reduction, surpassing 1.38 million tons, particularly in Odessa, Zaporizhzhya, Mykolayiv, and Kherson states. In addition, the yield of winter oats also decreased.

### Winter cereal trade networks in 2021

We visualized the global trade networks for wheat, barley, and oats in 2021 (Fig. 3a–c, three letters represent abbreviations of country names; for specific names of countries, see Supplementary Table 1). Ukraine is one of the major exporters in the world's network of wheat, along with the USA, Russia, Canada, Australia, and France. These major exporting countries have very different structures of cooperation partners. For example, the United States, Russia, and Canada export mainly to countries with upper-middle-income levels. The United States exports mainly to Mexico, the Philippines, China, Japan, Korea, Colombia, and Thailand. Russia exports mainly to Turkey, Egypt, Azerbaijan, Kazakhstan, Nigeria, Bangladesh, and Thailand. In contrast, Canada exports mainly to China, Japan, Indonesia, Peru, Colombia, and France's main partners are mostly high-income countries. Australia and Ukraine are the main exporters to lower-middle-income countries. Among them, Ukraine is the only one of these major exporters in the lower-income (lower-middle-income and low-income) level category. It mainly exports to countries with lower-middle-income levels, such as Egypt, Indonesia, Pakistan, Morocco, Bangladesh, and the Philippines, and low-income countries, such as Ethiopia, Yemen, Mozambique, Madagascar, and Indonesia. A number of countries with upper-middle-income or high-income are the major wheat-importing countries in this trade network: China, Turkey, Italy, and Brazil. The reasons for this are closely related to these countries' population sizes, cultivated patterns, and dietary habits.

In the global trade network for barley, the top exporters are very similar to those for wheat and include Australia, Ukraine, Russia, France, Canada, Argentina, and Germany. Ukraine remains the main exporting country with the lowest overall income level among them, and it exports large quantities of barley to China, Turkey, Saudi Arabia, Libya, Tunisia, and other countries. In this trade network, China, Saudi Arabia, Netherlands, Turkey, and Belgium are the most important importers of barley. In the global trade network of oats, Canada's export to the United States is the largest trade flow, making Canada and the United States the largest oats exporter and importer in the world, respectively. Australia, Poland, Russia, and Sweden are also major exporters, while the USA, Germany, China, Netherlands, Belgium, and Spain are the main importers of oats.

In summary, Ukraine is one of the leading exporters of winter grains, with the highest total exports of wheat and barley, and trades mainly with lower- and upper-middle-income countries. As the only lower-middle-income exporting country, the Ukrainian population may be having difficulty affording its own grain production investments during the war, and its reduced production may impact food availability for populations in more vulnerable middle-income countries.

### Affected winter cereal trade networks

The winter cereals (wheat, barley, and oats) for 2021–2022 are used as an example to visualize the predicted dynamics in each country in the trade networks under war effects. We simulated and analyzed the 2022 trade networks based on the fact that Ukraine's reduced production led to a drop in exports to other countries and a ban on exports by other countries.

The validation results, shown in Supplementary Fig. 3, demonstrate a strong correlation between the simulated 2022 trade networks and actual trade data for wheat, barley, oats, and total winter cereals. Although some variations exist, particularly for lower-middle- and low-income countries, where greater deviations in trade quantities are observed due to higher vulnerability to market shocks, the overall distribution patterns remain consistent across income levels. The regression analysis further supports the reliability of the simulation. The $R^2$ value of total winter cereals is 0.72, the $R^2$ value of wheat is 0.76, the $R^2$ value of barley is 0.73 while the $R^2$ value of oats is 0.59. The validation results indicate that our simulation effectively captures the general trends in global trade volumes.

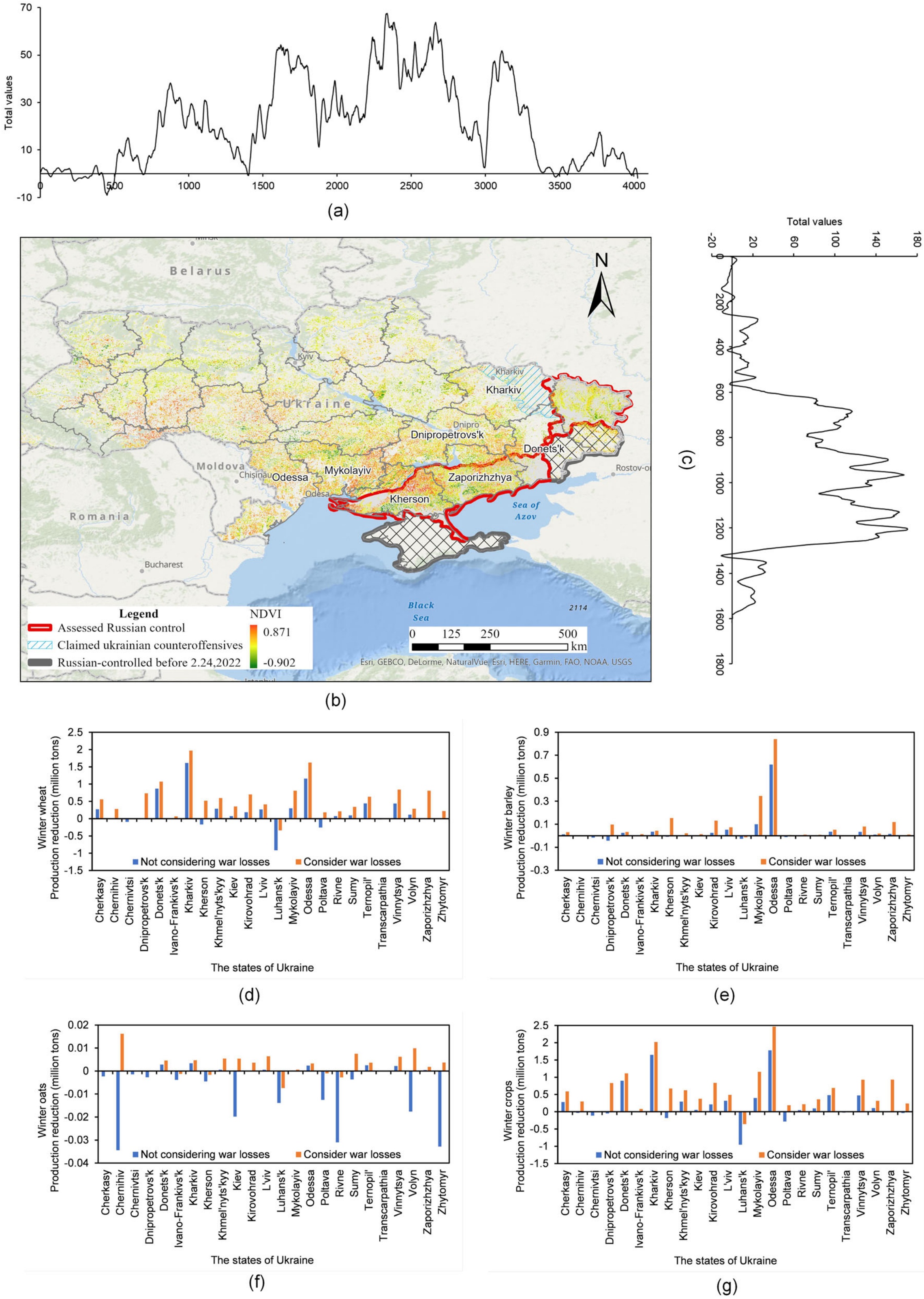



**Fig. 2 | Satellite observations reveal that winter crop yield in Ukraine decreased in 2022. a** NDVI change in longitude direction; the *x*-axis is the pixel number while the *y*-axis is the sum of total NDVI change value. **b** Schematic diagram of NDVI and war areas. **c** NDVI change in latitude direction. **d** The reduction in winter wheat yield in each state. **e** The reduction of winter barley yield in each state. **f** The reduction of winter oats yield in each state. **g** The reduction of winter crop yields in each state. Due to Russia's control, crop yields in the Crimea and Sevastopol regions were not considered in this study; the *y*-axis is the pixel number, while the *x*-axis is the sum of the total NDVI change value.

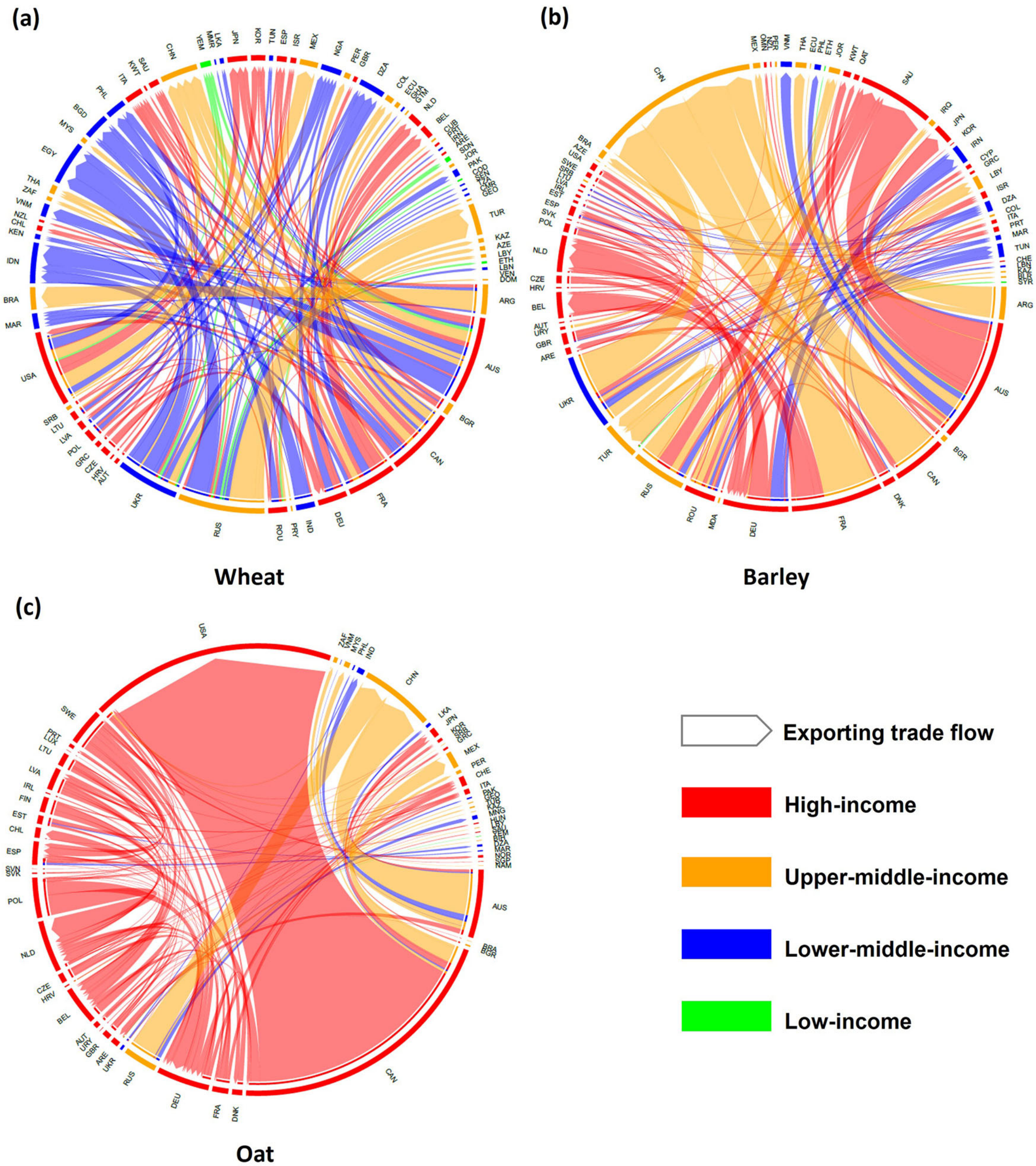



**Fig. 3 | Global trade flows (top 25%) of winter cereals among income groups in 2021.** (for trade flows among all countries, see Supplementary Fig. 2). Networks for winter cereals—wheat (**a**), barley (**b**), and oats (**c**)—are classified by income levels. Trade flows are depicted using chord diagrams, with the direction and volume of trade represented by the connecting bands between countries. The color coding distinguishes the income levels of countries, with high-income countries in red, upper-middle-income countries in yellow, lower-middle-income countries in blue, and low-income countries in green. Thicker bands indicate higher volumes of trade between the respective countries.

Based on the simulation results, we analyzed the percentage impact of each country in the three winter cereal trade networks for the 2021–2022 season. The visualizations (Fig. 4; for specific decreasing rates, see Supplementary Table 2) reveal that countries in Africa and Asia were the most affected, with reductions in imports ranging from 75% to 100%. Specifically, countries such as Guinea-Bissau, Sierra Leone, the Democratic Republic of Congo, Somalia, and Eritrea in Africa, as well as Montenegro, Albania, the former Yugoslav Republic of Macedonia, and Belarus in Europe, were among the most heavily impacted. Additionally, the European countries Macedonia and Belarus were expected to experience reductions in imports, while in Asia, affected countries included Turkey, the Syrian Arab Republic, Georgia, Armenia, Azerbaijan, Kazakhstan, Uzbekistan, Kyrgyzstan, Mongolia, Nepal, and Bhutan. A noteworthy observation is that among the countries most heavily impacted by the reductions in winter cereal exports, only Antigua and Barbuda belongs to the high-income group. Six affected countries are classified as low-income, seven as lower-middle-income, and eight as higher-middle-income. The disparities in the impacts of the export reductions between high-income and low-income countries underline the importance of targeted policies and programs to support vulnerable populations during times of conflict. By recognizing and addressing different groups' unique needs and challenges, we can work toward building more resilient and equitable societies.

Nine countries in the highly impacted category (more than 50%) are classified as lower-middle-income: Egypt, Bangladesh, Senegal, Pakistan, Lebanon, Congo, Cameroon, Benin, and the United Republic of Tanzania. Five countries at the low-income level and nine lower-middle-income

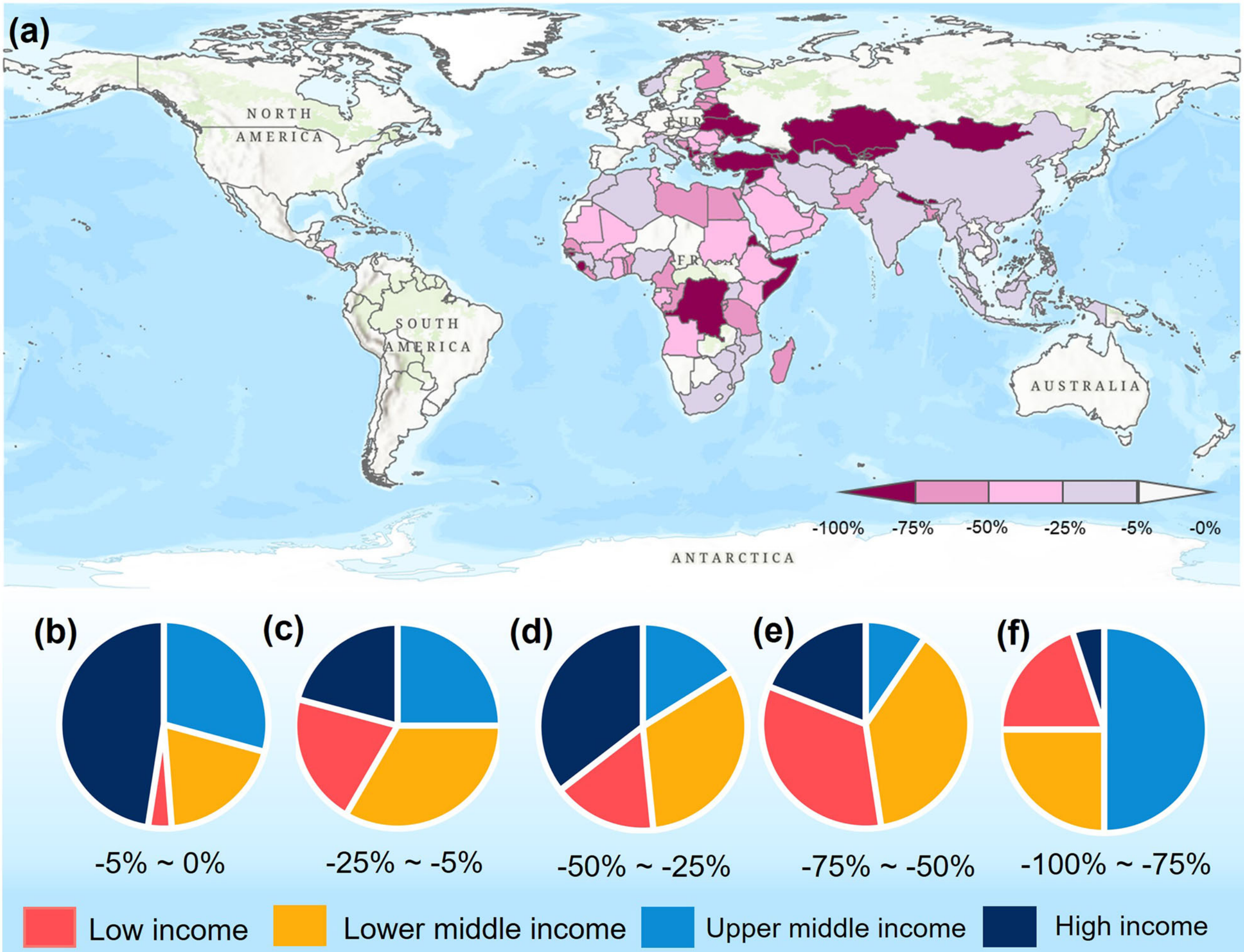



**Fig. 4 | Percentage reductions in projected imports in 2022 for each country. a** Absolute value and rate of change of total import volume by country from 2021 to 2022; contents of **b**–**f** are the shares of countries with different income levels in different affected percentage intervals.

countries were highly impacted, along with four upper-middle-income level countries and five high-income countries. In the countries less impacted (25%–50% reduction in imports), most are in the high-income category, which indicates that high-income countries are more resilient and have a greater diversity of import providers.

Based on remotely sensed yield estimates and information on export ban policies, we simulated the winter cereals trade networks of 2022 to reflect the effects of these conditions (Fig. 5). We considered the global trade networks to remain consistent with 2021 in terms of export volumes and trade parties, except for the impacts of reduced production and policy measures. To analyze these changes, we employed network analysis to model the trade network dynamics, focusing on key metrics—connectance, evenness, and modularity—to capture the war's impact on the global food trade system. The 2021 network was built using data from the UN Comtrade database, which provides detailed trade statistics. For 2022, we simulated the network by integrating remote sensing–based yield forecasts and export policy data. We maintained the 2021 ratio of Ukraine's exports to its production, projecting the total exports for 2022, and allocated exports proportionally to countries. For those countries with export bans, trade was assumed to cease, allowing us to construct simulated 2022 trade networks reflecting the expected shifts. According to the simulated results, the most affected importers in the wheat trade network were mainly Turkey at the upper-middle-income level, Egypt, Bangladesh, Indonesia, and Nigeria at the lower-middle-income level, and Yemen at the low-income level. Overall, the most affected group of countries was the upper-middle-income countries, which were expected to lose more than 46.58 million tons of wheat imports, followed by the lower-middle-income countries, which would see a reduction of 38.92 million tons of imports compared to 2021 imports. The low-income countries were estimated to face a shortfall of 25.59 million tons of grain imports, while high-income countries were the least affected, facing only 20 million tons of import reduction.

For the worldwide barley trade network, reducing production in Ukraine and national trade protectionism in Russia were the most influencing factors. Turkey, China, and Libya at the upper-middle-income level, Tunisia at the lower-middle-income level, and Saudi Arabia at the high-income level are the most affected countries. In the oats trade network, despite the ban on oats exports published by Hungary, Kyrgyzstan, Kuwait, and Turkey, the reduction in production in Ukraine still had the most impactful role due to the volume of trade. The most affected countries were India and Pakistan at the lower-middle-income level, Libya, Serbia, Bosnia Herzegovina at the upper-middle-income level, and Hungary, Switzerland, and Germany at the high-income level.

Production reduction in Ukraine and the introduction of protectionist bans on the trade of winter cereals in various countries as a result of the Russia-Ukraine war have reduced the connectance of the global trade networks for the three cereals, with the wheat trade network being the most affected (Fig. 6). The modularity of the three networks has also increased, which illustrates the impact of the war on the network, causing elevated national protectionism and reduced trade between countries. Specifically, in 2021, wheat, barley, and oats trade networks displayed high connectance and global integration, signifying

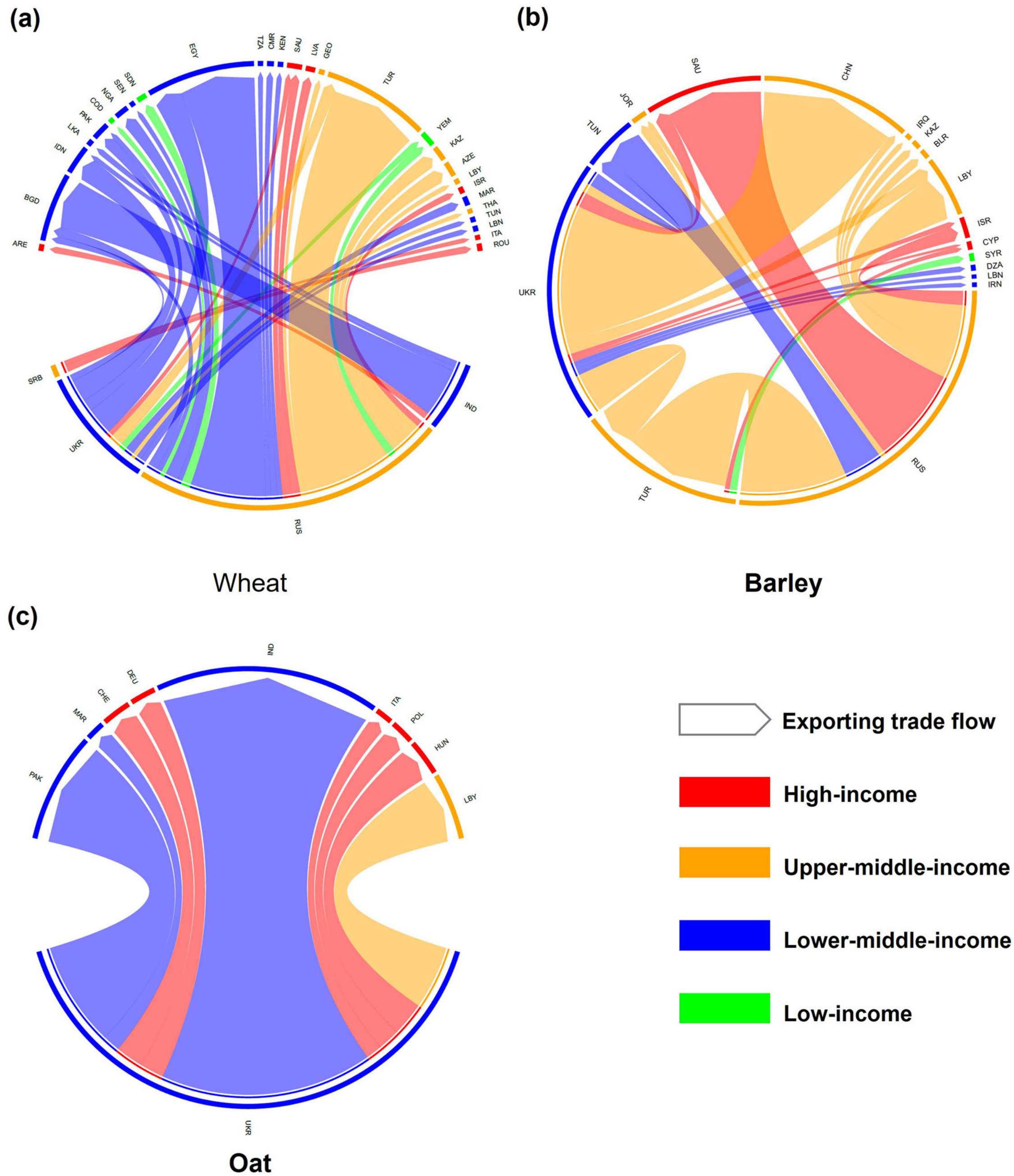



**Fig. 5 | Trade networks affected by production cuts in Ukraine and external cereals export bans in 2022 (top 25%).** (for trade flows among all countries, see Supplementary Fig. 4). Global trade networks for winter cereals—wheat (**a**), barley (**b**), and oats (**c**)—across various countries are classified by income levels. Trade flows are depicted using chord diagrams, with the direction and volume of trade represented by the connecting bands between countries. The color coding distinguishes the income levels of countries, with high-income countries in red, upper-middle-income countries in yellow, lower-middle-income countries in blue, and low-income countries in green. Thicker bands indicate higher volumes of trade between the respective countries.

well-established supply chains. In 2022, the geopolitical disruptions due to the Russia-Ukraine war caused disruptions manifested as a pronounced fragmentation in the trade networks of all three cereals, leading to smaller, regionally concentrated clusters.

For wheat, the trade network's fragmentation was particularly evident (Fig. 6a1, a2). In 2021, the dense connections between countries reflected a high level of global trade, corroborating findings by the FAO that highlight the importance of Ukraine and Russia as wheat exporters[45]. However, the 2022 data indicate a decline in connectivity, signaling the urgent search for alternative suppliers due to Ukraine's diminished production and export restrictions by other nations. This shift resulted in isolated regional clusters, showing a decline in global trade interconnectedness.

Similarly, the barley network faced reorganization (Fig. 6b1, b2). As per the International Grains Council (2022)[46], Ukraine was one of the world's leading barley exporters, and the decrease in its production due to conflict had cascading effects. The 2022 network reflects fewer trade connections, and regional clusters emphasize countries relying more on local or nearby suppliers.

The oats network, comparatively smaller and less globally connected, also underwent a noticeable shift (Fig. 6c1, c2). While its 2021 network showed less connectivity than wheat or barley, the 2022 data further highlight fragmentation, emphasizing regional clusters more pronouncedly. The shift to localized trade reflects broader trends observed in supply-chain research during crises[47].

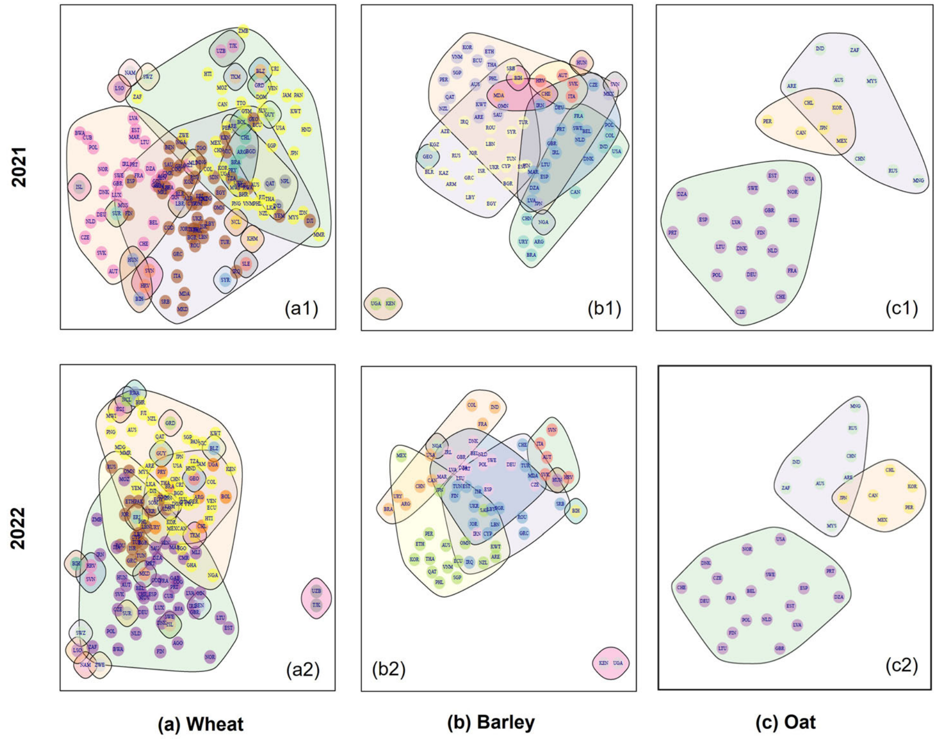



**Fig. 6 | Effect of war on the network structure of winter cereals.** For 2021 and 2022, respectively, **a1**, **a2** indicate the wheat network, **b1**, **b2** indicate the barley network, and **c1**, **c2** indicate the oats network. These figures show the effects of the Russia-Ukraine war on (i) connectance, (ii) modularity, and (iii) evenness in different years. Each colored connecting piece in the figure represents a small trade group with strong trade links. The connectance values exceed the typical [0,1] interval because they are derived from trade volumes, which measure the strength and economic impact of trade connections. This method allows us to capture the intensity of trade flows, offering a more detailed understanding of the network's structure and the potential impact of disruptions on global food security.

| | | Wheat | Barley | Oat |
|---|---|---|---|---|
| Modularity | 2021 | 0.4047 | 0.4988 | 0.5477 |
| | 2022 | 0.4119 | 0.5160 | 0.5481 |
| Connectance | 2021 | 13724029.0830 | 8345134.0850 | 1225087.8494 |
| | 2022 | 12486018.4511 | 8115596.3616 | 1223601.2806 |
| Evenness | 2021 | 0.8088 | 0.7174 | 0.8159 |
| | 2022 | 0.8044 | 0.7085 | 0.8166 |

Our results indicate that war reduces the homogeneity of wheat and barley trade networks, suggesting that trade between countries was more isolated than before. Interestingly, the conflict caused a slight increase in the evenness of the oats network, which may be because the decrease in trade in the oats network is mainly driven by a single country, Ukraine, thus making the overall network more even as Ukraine's importing countries chose other import channels.

These observations underscore the global grain trade's vulnerability to geopolitical events and the imperative need to diversify supply sources to bolster resilience. As witnessed during the COVID-19 pandemic[47], this fragmentation and regionalization of trade networks, driven by geopolitical factors, necessitate a rethink in supply-chain strategies to ensure global food security.

## War affects adjacent and distant countries differently

Generally speaking, in a metacoupled world, war or other shocking events can have internal, peripheral, and distant effects. The impact on adjacent countries due to local wars is often referred to as a pericoupling effect, while the impact on distant countries is a telecoupling effect[48].

To quantify how the Russia-Ukraine war has differentially affected adjacent and distant countries in the winter cereals network, we accounted for all affected exporters and their neighboring and distant importers. We found that, to the extent that wheat, barley, and oats were affected, the war had a much greater impact on distant countries than on adjacent countries, which means a larger trade difference (see Table 1).

Wheat exports to distant countries curtailed a total of 189,658.72 tons in 2022, while exports to adjacent countries shrank by only 50,334.19 tons. A similar phenomenon was observed for barley, where imports in distant countries shrank by 6000.82 tons, while imports in adjacent countries shrank by only 431.21 tons. In the least affected oats trade network, the distant importing countries experienced a total reduction of 1.91 tons, while the adjacent countries had a total reduction of 0.36 tons.

Ukraine and other exporting countries had different levels of impact on distant and adjacent places (Fig. 7). Ukraine showed a clear tendency to have a higher degree of influence on distant places in all trade networks of wheat, barley, and oats, while other exporters showed a tendency to have a higher degree of influence on distant places in wheat

**Table 1 | Trade quantity differences between adjacent and distant countries of Ukraine and other countries (Unit: ton) from 2021 to 2022**

| Country | Type | Wheat | Barley | Oats |
|---|---|---|---|---|
| Ukraine | Distant | 7828.89 | 2252.23 | 1.75 |
| | Adjacent | 41.82 | 0.19 | 0.19 |
| Other countries | Distant | 181,829.83 | 3748.59 | 0.16 |
| | Adjacent | 50,292.37 | 431.02 | 0.17 |

Note: The values in the table are the sums of differences in the countries trade with adjacent and distant countries.

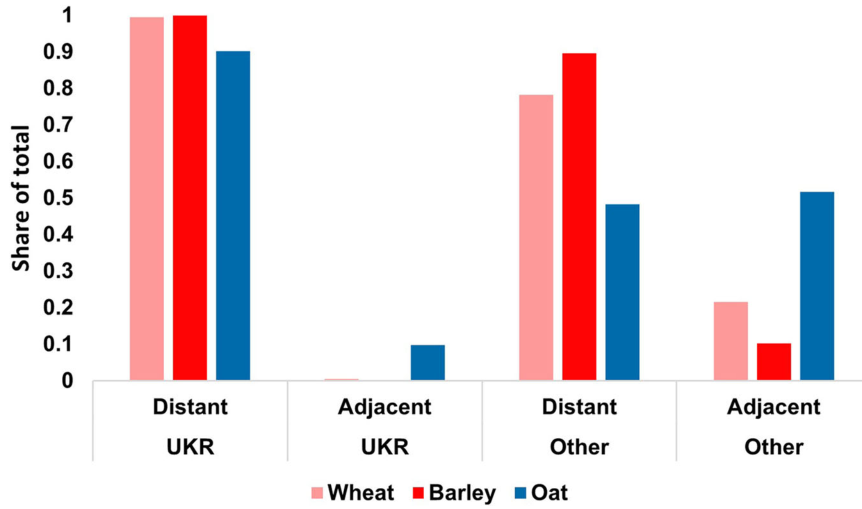



**Fig. 7 | Comparison of the degree of impact of Ukraine and other exporting countries on distant and adjacent importing countries.** Share of total wheat, barley, and oats exports by geographic proximity and exporter type. The bars represent the proportion of winter cereal exports (wheat in light red, barley in red, and oats in blue) to distant and adjacent countries relative to Ukraine (UKR) and other major exporters in 2022. "Distant UKR" represents countries geographically distant from Ukraine, while "Adjacent UKR" refers to neighboring countries. Similarly, "Distant Other" and "Adjacent Other" indicate non-Ukraine exporters, categorized by their proximity to major importing regions.

and barley networks. In the trade networks of other countries' exports of oats, there is no significant difference in the degree of influence between distant and adjacent partners.

## Discussion

To quantify the impact of war on winter crop production in Ukraine, we used remote sensing algorithms to map the distribution of winter cereal and predict the production of winter cereals[49]. Considering 30% of war losses, results indicate that compared to 2021, winter crop production in Ukraine decreased by 15.04 million tons (95% CI range: (8.68, 21.40)), with the main war zones in the eastern and southern regions severely affected, which shows production distribution trends similar to the research findings of Jagtap et al., Deininger et al., and Lin et al. However, the resolution in our study is 30-m, which is much higher than in other studies[4,15,19]. It indicates that our results had a more accurate estimation of the specific amount of production decrease. As a net exporter of grain, Ukraine has always been an important granary for Europe and even the world[50,51]. The ongoing war has directly damaged arable land and agricultural infrastructure, leading to direct losses of crops in the war zones and difficulties in cultivating some arable land[2,6,52]. Ukraine's lost production of three winter cereals in 2021 could have met the caloric needs of 76 million adults for a year[53,54]. At the same time, the war brought huge labor losses, with at least 6.5 million refugees from Ukraine recorded globally, leading to a shortage of agricultural labor and the abandonment of arable land[12,55]. The ongoing Russia-Ukraine war has impacted Ukraine's winter crop production, as the war disrupted key stages of farmland management such as fertilization and irrigation, leading to a large reduction in grain production[4,15]. This reduction could exacerbate an already precarious global food supply, particularly given the potential for further disruption caused by extended heatwaves in the northern hemisphere in 2022 and the sanctions imposed on Russia. The war has also led to a surge in global fertilizer and energy prices, which has created disruptions in the fertilizer market and reduced farmers' willingness to use energy and fertilizers, potentially leading to worldwide crop reduction and food crisis[5,56]. The complex interplay between geopolitical war and global food availability underscores the need for proactive measures to address the vulnerabilities of global food supply chains, particularly in regions that are prone to instability or war.

Fortunately, potential remains for mitigating an impending food crisis that could be triggered by the simulated results in this study. Notably, some major grain-exporting countries boosted their exports to compensate for the absence of Ukraine and other countries that have enacted trade bans from the market[57]. The results of a 2023 network analysis reveal important shifts in the global trade dynamics for wheat, barley, and oats following the disruptions caused by the Russia-Ukraine war and export bans in 2022 (Supplementary Fig. 5). Several major grain-exporting countries have stepped in to mitigate the decline in Ukrainian exports, ensuring a relatively stable global supply. Notably, the United States, Australia, Canada, and Argentina have increased their wheat exports, helping to balance the shortfall. As the 2023 wheat network analysis indicates, the connectance value has increased (14871835.6793), and the evenness metric (0.8283) suggests a more balanced distribution of trade flows, reflecting the successful redistribution of supply routes among key exporters. In the barley trade network, countries such as Australia, France, and Germany have emerged as crucial exporters, alongside Argentina and Canada, filling the void left by the disrupted Ukrainian supply chains. The 2023 analysis shows a connectance value of 14549313.9751 and an evenness of 0.7727, indicating that the barley trade system has also adapted to the disruptions, with more countries sharing the export burden. The oats trade network has seen similar adjustments, with Poland, Australia, and Brazil playing pivotal roles in stabilizing the global supply chain. The 2023 network analysis highlights a connectance of 3071156.198 and an evenness of 0.888, signifying a relatively equal distribution of trade volumes among key exporters.

However, it is also important to note that many of the exporters stepping in to fill these gaps are from high-income or upper-middle-income countries. These countries are typically better equipped to respond to sudden increases in global demand due to their established infrastructure, robust agricultural sectors, and the ability to quickly scale production and have a strong motivation to increase their export quantity with a rapidly increasing price. Although these countries can bridge the gap caused by Ukraine's absence in terms of total exports, several challenges need to be addressed. Negative factors, such as panic surrounding food availability and port blockades resulting from the Russia-Ukraine war, have rapidly increased agricultural commodity prices in a short period. Ukraine's primary trading partners include lower-middle-income and upper-middle-income countries, with fewer high-income and low-income countries. Regions such as low-income European and African countries that rely on food imports from Ukraine to meet domestic needs face a huge challenge because their populations cannot afford the rapidly rising food prices. Consequently, while major exporting countries may close the export gap, reduced affordability continues to pose a threat to global food availability. Some countries have tried to create new cropland from forests or other lands to increase food production, but this may further affect environmental sustainability. Using the metacoupling framework, we quantitatively estimated the negative impact of the Russia-Ukraine war on the winter cereals trade and in interlinked countries worldwide[28]. While reducing imports from countries adjacent to the focal system, the war also has a much larger impact on distant importers[58]. This finding reveals the urgency and need for attention to potentially vulnerable countries. In the face of these challenges, the international community needs to improve its overall understanding of the countries affected. The regions where imports will be most affected may not be those bordering these countries, but rather the distant regions. Policies and subsidies for these countries, which may be underrecognized, will be essential for achieving sustainable development goals.

The current food crisis resulting from the Russia-Ukraine war poses many challenges, including rapidly escalating global commodity prices, declining affordability in less developed countries, and geopolitical tensions. In order to achieve food availability, the international community must focus on the seemingly localized impacts that transcend regions. We recommend calling for a highly resilient agenda, led by international organizations such as the FAO, that focuses on distant places of high vulnerability and fosters intercountry cooperation. This agenda should prioritize countries with low levels of development and high dependence on food imports in order to guarantee food availability for vulnerable groups. By working together under a harmonized and resilient framework, the international community could take decisive steps toward achieving Sustainable Development Goal 2 and ensuring a world free from hunger for all.

It is important to note that inherent uncertainties in trade dynamics data and satellite imagery may influence the reliability of our results. Nationally reported export data might contain inaccuracies due to reporting errors or political and economic motives. Some exporters with large winter cereals storage capacity might have increased their exports driven by increasing prices, creating differences between the true trade network and the simulated results (Supplementary Fig. 5). Similarly, satellite imagery, while effective in monitoring large-scale agricultural changes, has limitations in spatial and temporal resolution that might affect the accuracy of yield estimates. The Sentinel-1 data, while offering advantages like cost-effectiveness and all-weather imaging, still pose challenges in distinguishing crop changes at small scales over short periods. These factors, along with model assumptions and unpredictable future conditions, necessitate caution when interpreting our findings. To address these uncertainties, we calculated confidence intervals for our yield predictions, reflecting possible variations in our modeling framework. In addition, because the simulation setup considers changes based on the 2021 trade system and may ignore the elasticity of the markets, i.e., changing prices, some exporters may increase their exports to compensate for deficiencies. Our simulation setup may result in simulated network exports that differ from the real market situation.

## Conclusion

In this study, we developed a comprehensive and rapid assessment framework that integrates remote sensing, policy monitoring, and network analysis to quantify the impact of the Russia-Ukraine war on global food systems. Our methodology involved using remote sensing–based algorithms to extract and map winter cereal crop areas and a random forest regression model to estimate yield reductions in Ukraine. We also collected global trade and policy data to model the impacts on the global trade networks of wheat, barley, and oats.

Our findings reveal that winter cereal production in Ukraine decreased due to the conflict, with yield reductions primarily affecting regions such as Odessa, Donetsk, Kharkiv, Zaporizhzhya, and Mykolayiv. These reductions, coupled with protectionist policies enacted by a number of exporting nations, impacted the global trade network. The study shows that countries with lower- and middle-income levels were more affected than high-income nations. Furthermore, countries that are geographically distant from exporting regions experienced greater disruptions than neighboring nations. Our analysis suggests that these changes in the trade network structure can exacerbate food shortages in vulnerable countries.

The holistic framework developed in this study allows for a nuanced understanding of the intricate dynamics of the global food system in times of conflict, offering valuable insights into which countries are most vulnerable to disruptions in trade. The research highlights the cascading effects of regional conflicts on the global food system (Fig. 1), emphasizing the need for international cooperation and targeted policies to safeguard food availability.

## Methods and materials

### War-affected areas in Ukraine

There is an ongoing geopolitical dispute between Russia and Ukraine[59]. The main battleground of the armed conflict is primarily located in the eastern part of Ukraine, and the conflict has spread to multiple states, including Kherson, Luhansk, Zaporizhzhya, Mykolayiv, Donetsk, Kharkiv, Crimea, and Sevastopol[60]. These states have all been impacted to varying degrees by the war, which has directly affected agricultural production by causing crop losses and damage to agricultural infrastructure[4,6]. The regions directly affected by the war are the main agricultural states of Ukraine. The winter production of wheat, barley, and oats accounted for 30% of the total production of these three crops in Ukraine in 2021. Among them, the production of winter wheat was 42.08% of the total production in Ukraine, and barley production was 41.32% of the total winter cereals production. When these major agricultural states were hit by the war, their reduced production may have had a ripple effect. In addition to the yield losses caused by the war, in other regions of Ukraine, panic may also have caused yield reductions due to the untimely management of farmland.

### Materials

**Satellite data and processing**. We collected Sentinel-2 and Sentinel-1 images from 2019 to 2022 as the main model input (Fig. 8). These data were produced by the European Space Agency (ESA) and are freely available on the Google Earth Engine (GEE) platform. Sentinel-1 images were acquired in Interferometric Wideswath mode, which provides a dual polarization (vertical-horizontal [VH] and vertical-vertical [VV]) at 10-m spatial resolution. The Sentinel-1 images on the GEE platform were processed using the Sentinel-1 SNAP7 Toolbox to generate Ground Range Detected images[61]. Sentinel-2 satellites provide optical images in 13 spectral bands at 10-m, 20-m, and 60-m spatial resolutions. We used the atmospherically corrected Sentinel-2 surface reflectance product and eliminated the cloud-covered pixels via the Sentinel-2 cloud probability dataset. Then, the red and near-infrared bands from Sentinel-2 images were used to derive the NDVI time series characterizing crop phenology.

**Agricultural map and official statistical data**. The cropland distribution data were derived from the 10-m global land-cover map produced by ESA[62]. In addition, the RapeseedMap10 dataset with a spatial resolution of 10 m was used to assist in the extraction of the annual spatial distribution of rapeseed planting areas in Ukraine[63]. However, the dataset lacks spatial information on winter rapeseed after 2019. We obtained data on planted areas and yield statistics for winter crops (wheat, barley, rye, and rapeseed) at the state level between 2019 and 2021 from the State Statistics Committee of Ukraine. These data were used to train yield models and to validate the derived winter cereal maps and yield forecasts.

**Meteorological data**. Temperature and precipitation data were utilized as important inputs to the yield model to explore the relationship between climate and yield[64]. The temperature data were derived from the remotely sensed thermal product (MYD11A2.006) from the Aqua MODIS sensor at 1-km resolution. The precipitation data were acquired from the CHIRPS dataset, corresponding to a resolution of $0.05 \times 0.05$ degrees[65].

**Trade data**. The overall global trade data were collected from the United Nations Commodity Trade Statistics Database (UN Comtrade database, see "Data availability" section), which is the original and probably the most widely used data source to support physical trade analysis from 2020 to 2021. Comtrade has been considered a reliable source of data by previous studies for purposes such as establishing trade networks, building trade-related databases, and conducting logistics analysis. Since the primary source of Comtrade data is the country itself as a reporter,

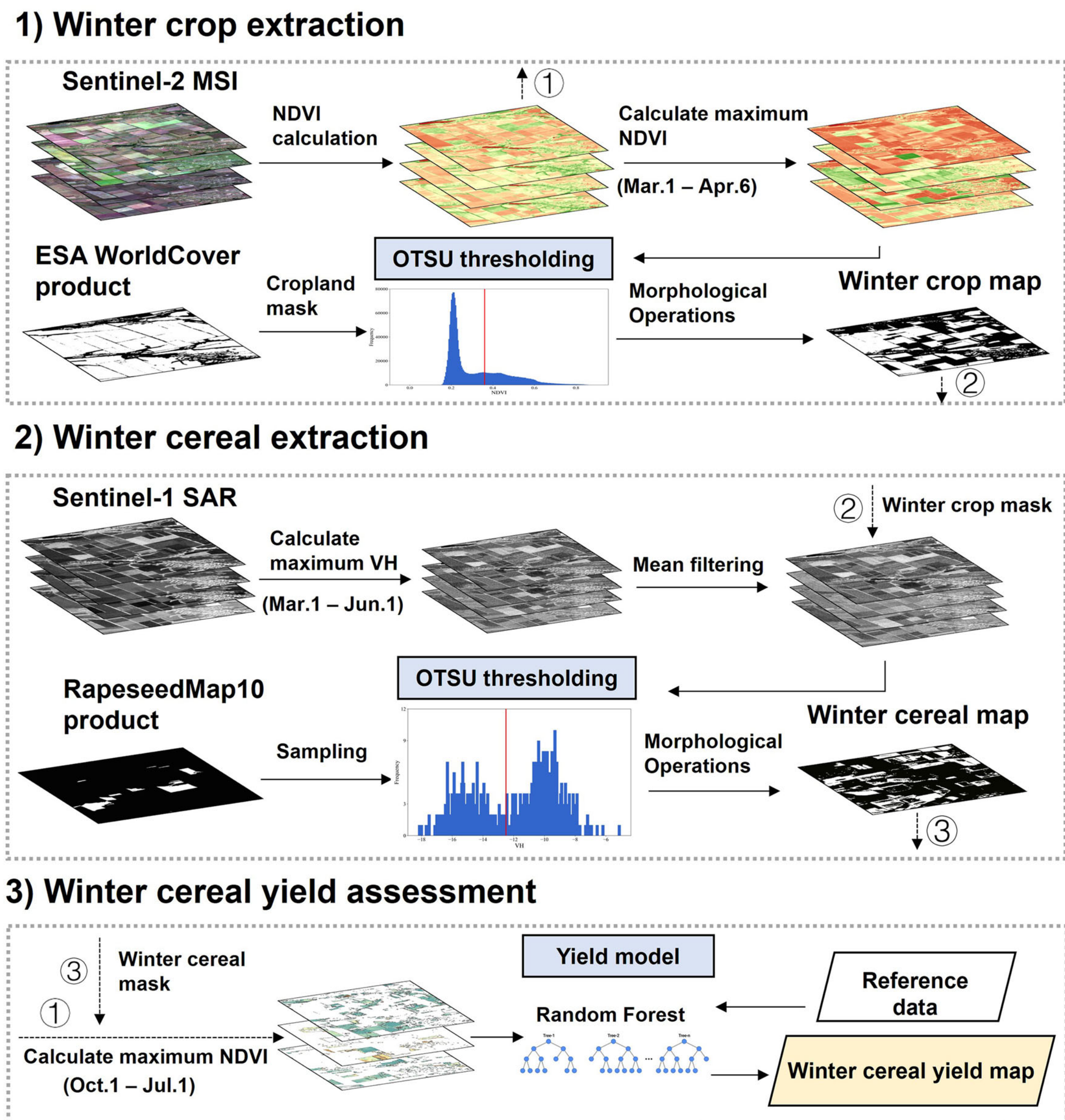



**Fig. 8 | Winter cereal yield map generation flow.** (1) Extraction of winter full crop maps was based on Sentinel-2 MSI data and ESA WorldCover products to determine NDVI thresholding values through OTSU. (2) Maximum VH data were calculated based on Sentinel-1 SAR data, and after the mean filtering process, the winter cereal map was obtained by OTSU thresholding based on the winter crop mask and RapeseedMap 10 product. (3) Yield estimation was based on NDVI and real yield data of previous years combined with the winter cereal map.

there may be political motivations to keep information confidential and cause errors. Previous studies have indicated that UN Comtrade data have three main quality issues: outliers, missing values, and bilateral asymmetries. We compared imports and exports for the crops we used and found that both were missing data, with imports missing 15.27% more than exports. Thus, we believe the export volume data can better reflect the country's agricultural trade[66]. Global wheat, barley, and oats trade data were collected for 2020–2021. We also fitted the export and import data (as shown in Supplementary Fig. 6 and Supplementary Table 3) and found that they are similar, and all of their $p$-values are less than 0.05, which indicates the results obtained by using the export data are reliable.

We planned to introduce some pre-hints to predict the impacts of war on global food trade, thus we collected export restriction acts through tracking websites that had monitored relevant news and policies since the beginning of the war to assess the change in the volatility of exports of 218 countries and regions. Since Ukraine has many battlefields, there is a reduction in production due to negative effects such as a lack of agricultural management and unavailability of harvest. After using NDVI to estimate the yield, we set 30% as the unavailability of harvest based on the FAO report[67]. We used the pixel- and phenology-based model to estimate the yield reduction of winter crops in Ukraine. Second, considering that Ukraine will not export all its winter crops, we calculated the proportion of exports by total production in 2021 and exports in 2021 and used the proportion of grain exports in 2021 as the proportional distribution of exports to countries in 2022. From these calculations, we constructed the trade networks for 2022.

**Trade ban data.** The trade policy ban data were mainly from the food availability portal—food and fertilizer export restrictions tracker—collected in the press and provided by the International Food Policy Research Institute, which the European Commission financially supports. The rest of the ban data was mainly from government websites and news. We collected relevant data for a total of 20 countries that issued export bans related to winter grains and their products, and the specific data can be viewed in the "Data availability" section.

### Assessment of total reductions

The whole predicting framework consists of two main parts: the assessment of reductions in Ukraine, and the simulation of the next year's trade networks through tracking export bans. The summary and workflow of the remote sensing part are shown in Fig. 8 with more details reported in the text. The workflow consists of the following steps: (1) Winter Crop Extraction, (2) Winter Cereal Extraction, and (3) Winter Cereal Yield Assessment.

**Winter crop extraction**. To obtain maps of three annual winter cereals (wheat, barley, and oats), we implemented an automatic winter crop extraction approach proposed by Skakun et al., which was previously applied to map winter crops in Ukraine for 2016–2018[68]. The approach uses a phenological metric known as the maximum NDVI during the green-up stage of winter crop development to differentiate winter crops from summer crops. A cropland map was used as input data to generate a binary cropland mask to eliminate the non-cropland area. For the remaining areas, we extracted the maximum NDVI from March 1 to April 6, which is considered the best informative period for early differentiation between summer and winter crops[68,69]. Since the NDVI was higher for winter crops and lower for summer crops during this period, we applied the maximum between-class variance method (OTSU thresholding) to automatically select appropriate thresholds for differentiating winter and summer crops[70]. Taking into account the effect of regional differences, we chose a threshold that best fit each state. Finally, the binary mathematical morphological operations of erosion and dilation with a radius of 6 pixels were applied to the winter crop maps to reduce the salt-and-pepper noise presented as image speckles.

**Winter cereal extraction**. In the previous step, we extracted winter crop distributions. To obtain the distribution of winter cereal, it is also necessary to remove the disturbance of winter rapeseed, which has a similar crop calendar to winter cereal. According to previous studies, the VH backscatter of winter rapeseed has significant differences from winter cereal in terms of its taller plants and randomly oriented branches at late growth stages in May[71]. Thus, the maximum VH backscatter in May was employed as a specific characteristic to distinguish winter rapeseed from winter cereal[72]. After that, a mean filter with a kernel radius of 1 pixel was applied to reduce speckle noise in VH-intensity images[73]. Once again, we used OTSU thresholding and winter crops mask to select thresholds for each state that would more accurately identify winter rapeseed and winter cereal. For most of the Ukrainian states, the area of winter rapeseed is much smaller than that of winter cereal. In this case, the VH-VH-intensity image histogram was dominated by winter cereal. It no longer exhibited bimodality, which results in the OTSU thresholding method selecting an inappropriate threshold value. To address this issue, we collected winter rapeseed samples from the RapeseedMap10 dataset and the same number of winter cereal samples from winter crop maps after excluding winter rapeseed. We used these samples as input to the OTSU thresholding method and mapped winter cereal from 2019 to 2021 with the output threshold. As before, we implemented binary mathematical morphology operations to reduce the salt-and-pepper noise resulting from the classification. Considering the general decline in crop NDVI due to the war, we anticipated that our method might not perform well in extracting winter cereals for 2022. Therefore, for the 2022 winter cereal distribution, we used the 2021 winter cereal data to represent it. Moreover, at the time of planting the winter crop in 2021, farmers did not anticipate the war and, therefore, would not have reduced the planted area. This estimation method was validated as feasible in previous studies due to the low inter-annual fluctuations in crops[15]. There was a negligible difference in the winter cereal distribution between 2021 and 2022.

**Winter cereal yield assessment**. Winter cereal yield assessment was done by developing a random forest regression model combining NDVI, climate records, and reference crop yield statistics (Fig. 9). With the winter cereal mask, we extracted the maximum NDVI, cumulative precipitation, and average temperature during the growing season at the state level as inputs. These variables were considered to be associated with crop yields[15,64]. We randomly selected 80% of the samples for training and reserved the remaining 20% for evaluating model accuracy.

**Confidence intervals calculation for the prediction**. To compensate for the fact that the prediction results may include uncertainties such as randomness and assumptions based on historical data, we calculated 95% confidence intervals for the predicted data to improve the robustness of the data. These assumptions, including changing environmental factors, such as soil conditions and climatic factors, are considered consistent across the dataset. The steps for calculating the confidence intervals were as follows.

First, the mean of the dataset was calculated:

$$\mu = \frac{\sum x_i}{n} \tag{1}$$

where $\mu$ is the mean value of data points, $x_i$ represents each individual data point value, and $n$ represents the total number of data points.

Second, we calculated the standard deviation ($s$):

$$s = \sqrt{\frac{\sum (x_i - \mu)^2}{n - 1}} \tag{2}$$

Third, we calculated the standard error (SE). This step was used to calculate the margin of the error:

$$SE = \frac{s}{\sqrt{n}} \tag{3}$$

Fourth, we calculated the confidence interval (CI):

$$CI = \mu \pm (Z \times SE) \tag{4}$$

where $Z = 1.96$ for a 95% confidence level.

Finally, the sum range based on the confidence interval was calculated by multiplying the bounds of the confidence interval by the number of data points:

$$SumRange = CI \times n \tag{5}$$

### Network analyses

Network analysis is a widely accepted approach. It has been used to examine the relationships within and between networks of nodes and the connections, or edges, that link them. The nodes of network analysis are usually entities (including individuals, organizations, and countries), while the edges represent the relationships or interactions between these entities. Network analysis has been extensively applied in multidisciplinary studies to reveal the underlying patterns and dynamics of complex systems. It has been essential to sociology's understanding of social interactions and community structures, illuminating the connections between people and groups[74]. Network analysis has also contributed to the field of biology, where it has been used to study gene interactions and protein function, thus contributing to the development of genomics and systems biology[34]. Previous work also demonstrates a solid foundation for examining the complexities of global trade systems by network analysis. Kim and Shin applied a social network approach to examine how regionalization and globalization impact international trade patterns. They provided a longitudinal view of the evolution of trade networks toward denser and more decentralized forms, which validates the use of network analysis to comprehend global

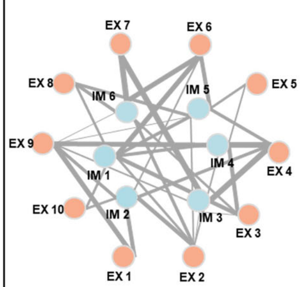
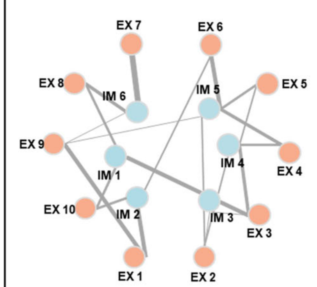
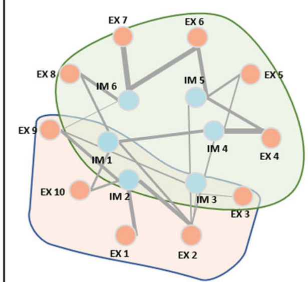
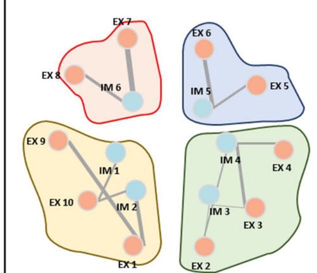
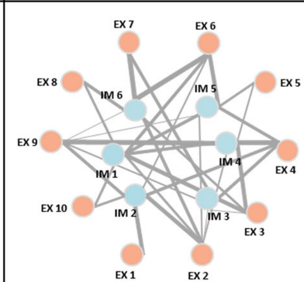
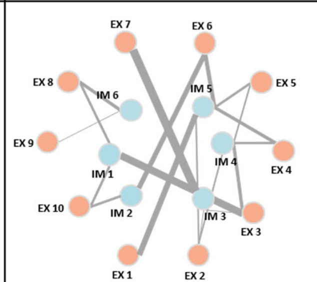
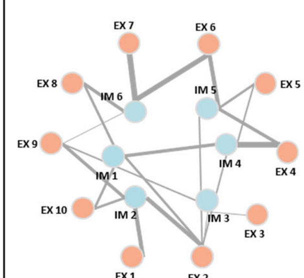
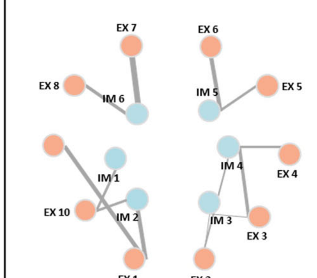
| Network metric | Predicted changes with time and war | Potential effect of war on winter cereal trade network metrics | |
|---|---|---|---|
| | | Before war | After war |
| **Connectance** | Decline if wars happened or affected trade supply chain. It represents the trade intensity of importer and exporter, and we normalize the annual trade volume as an indicator of connetance. When before the war, thanks to the trend of trade globalization, the network had a high connectance value, representing a trade boom between countries. After the war, the connectedance value is lower due to reduced production and reduced exports due to shocks to the supply chain of trade caused by wars, extreme weather events, etc., or due to trade ban policies. |  |  |
| **Module** | A module represents a group of nodes that are highly connected among them and loosely connected to others. More decentralized modules from countries are more likely to emerge when war occurs. |  |  |
| **Evenness** | The diversity of both exporting and importing countries representing cereals is relatively rich and importers have a low dependence on the choice of importers. However, when war occurs, the selection becomes less, making these importers more dependent on a fixed number of exporters, causing the nodes to change from being even connected to having strong links. |  |  |
| **Modularity** | Modularity represents the strength of the partition of a network into modules. In highly modular networks, grain trade links between countries are divided into isolated groups, while in less modular networks, the interconnection of trade networks between countries is higher. |  |  |

**Fig. 9 | Network metrics in global winter cereal trade network analysis.** Connectance, modularity, evenness, and modularity from top to bottom.

economic integration[75]. Mahutga explored how globalization and the "new international division of labor" affect structural inequality in the world economy through a network analysis[76]. Notably, other research further discussed the trade structure. For instance, Fagiolo et al. provided a detailed examination of the World Trade Web using a weighted network analysis, highlighting the structural properties of trade relationships and their evolutions over time, which revealed insights into trade interdependencies and clustering behaviors of nations based on trade intensity[77]. In addition, Smith and White explored how countries interacted in the global trading system and the changing nature of their economic exchanges, thereby revealing structural changes in trade networks[44]. The analysis of specific food trade networks has also been conducted, with Chung et al. discussing the dynamics of trade networks in space and exploring food trade networks in the context of human health, which are influenced by a variety of factors in health, agricultural, and trade policies[78,79]. Previous studies have also examined global seafood trade networks from 1994 to 2012, highlighting the trend of increasing globalization of seafood trade. Through network analysis, the authors identified changes in trade patterns, centrality, and partnerships, indicating increased regionalization[78,80,81]. The studies also discussed the implications of these changes for food availability and environmental impacts. Useful attempts have also taken place in the trading system of crops. For example, a complex network analysis was used to study the international wheat trade network from 2009 to 2013. The authors assessed the network's resilience and vulnerability to supply shocks, noting that while the network's resilience has improved slightly, some developing countries have become more vulnerable. The study simulated the impact of supply disruptions on food availability and analyzed how COVID-19 might affect global wheat trade dynamics. These foundational studies underscore the suitability of network analysis for exploring the complex dynamics of interactions and dependencies among countries that characterize global trade[38].

Thus, in this study, we used network analysis to build a real-world crop trade network and simulated crop trade networks affected by war production cuts and trade ban policies enacted by global exporters. We focused on the dynamics of three key network metrics: connectance, evenness, and modularity, which reflect the impacts of war on the food trade system. We used the 2021 UN Commodity Trade Statistics Database (Comtrade) to build the 2021 real-world trade network. Comtrade provides information on the year of trade, commodity type, volume of goods, amount of trade, exporting country, and importing country, and has been verified as a reliable source of data for constructing trade networks for commodities[82]. The network data for 2022 were constructed as a simulation combining the results of remote sensing forecasts—production data after the Ukraine production cuts—and policy data. First, the ratio between total Ukraine exports and production in 2021 was obtained, and the total amount of exports in 2022 was projected. Second, keeping the ratio between Ukraine's exports to other countries in 2021, data on Ukraine's exports to other countries in 2022 were allocated using the total amount of predicted exports. The countries that had enacted export bans were considered "no trade" in 2022. Then, we constructed simulated trade networks for 2022. To validate the accuracy of the simulated 2022 trade network, we compared the predicted trade quantities for wheat, barley, oats, and total winter cereals against actual trade data obtained from the 2022 Comtrade dataset. We conducted a comparative analysis by plotting the predicted and actual trade quantities across income groups (high, upper-middle-, lower-middle-, and low-income) to assess how well the simulation aligned with real-world outcomes. We further conducted linear regression analyses between the predicted and actual trade values, calculating $R^2$ values to measure the strength of the correlation.

For each network, we calculated the connectance, evenness, and modularity indices of the global trade networks for wheat, barley, and oats by year for 2021 and 2022 through R package igraph. Connectance was calculated as the proportion of present links to all possible links in the network, weighted by the absolute value of the correlation coefficient in previous studies[83]. Here, we adapted the traditional concept of connectance by using trade volumes as proxies. This approach allowed us to quantify not only the existence of trade relationships between countries but also the intensity and economic significance of these connections. As a result, the connectance values reported reflect the absolute magnitudes of trades, rather than a normalized proportion of possible connections, which is particularly valuable for analyzing the resilience and vulnerabilities of global trade networks in the context of disruptions like the Russia-Ukraine war. Evenness was referred to as the homogeneity of the link strengths in the network. In the context of this research, where understanding the complex interdependencies of international trade networks is essential, igraph offers a range of community detection algorithms[83]. However, many of these algorithms have limitations for this specific application. The edge betweenness algorithm, which identifies clusters by removing high betweenness edges, can be too computationally intensive for large trade networks. The fast greedy algorithm, while efficient in modularity optimization, may struggle with the complex, overlapping relationships of global crop trade. The InfoMap method, which relies on information theory to reveal communities, may not accurately capture the nuanced trade flows. The Louvain algorithm is efficient for large networks but might miss subtler community structures. The optimal algorithm offers the best modularity but is computationally impractical for such vast datasets. Spinglass uses simulated annealing for modular networks but can be sensitive to parameter selection, and the Leiden algorithm improves on Louvain but still might not capture the trade networks' intricate patterns as effectively. In contrast, the walktrap algorithm is best suited for capturing the nuanced and overlapping communities within global crop trade networks, providing more meaningful insights into complex trade relationships. Thus, modularity was calculated by using walktrap in igraph, which separates densely connected subgraphs via random walks using correlation coefficients as weights.

First, the volume of food trade is one of the hallmarks of globalization. As globalization becomes more advanced, developed supply chains facilitate food trade between countries, providing food availability to more people in food crises and increasing internal connectance. Conversely, counter-globalization trends can reduce the volume of trade and cause decoupling between countries. Moreover, reduced production caused by, for example, natural disasters and wars, can increase demand in food-importing countries yet weaken the exports and capacities of food-exporting countries. Second, suppose the evenness of food trade networks among countries decreases by restricting or banning certain food exports through export policies. In that case, the dependence on food-importing countries increases globally for a few major exporting countries and reduces the resilience of the network. A reduction in production in the remaining exporting countries, for any reason, could trigger a dramatic food availability risk. Third, a decrease in modularity (i.e., the emergence of an oligarchy of food exporters) may breed new hegemonies. The pricing power for food would be in the hands of a few countries, and the number of people who cannot afford to buy food will increase. Therefore, determining how diverse shocks alter these different network metrics can provide a more integrated view of war impacts on global food availability.

The trade volume between countries was converted to a network graph object and analyzed by the R package igraph[83]. In the network, the nodes represent the individual countries that interact, and the trade quantity between the nodes represents the directed food flows and their weights. Specifically, in 2021, we used the export data reported by countries with their partners to construct a directed trade network, using the absolute trade quantity, or trade quantity, as the connection weight between nodes. For 2022, we assumed that the trade network of countries would have remained unchanged, except for the decline in exports due to reduced production in Ukraine and the bans on exports by other countries to protect their domestic food availability. Thus, the network for 2022 was calculated based on 2021, and the trade volumes of countries that had enacted export bans were zeroed based on 2021, meaning that these countries would not export wheat, barley, or oats to any country in 2022. In contrast, 2022 imports from Ukraine were recalculated for importing countries based on remotely estimated production. First, we calculated the ratio between total exports and total production of wheat, barley, and oats in 2021, which was used to calculate the ratio of exports of these three winter cereals in 2022. Then, this ratio was applied to the production estimated by remote sensing for 2022 to obtain the total exports of the three cereals in 2022. Next, by calculating the ratio of exports to each country to total exports, we simulated the exports from Ukraine to other countries in 2022 and used these export volumes as weights for the network. Besides the network metrics, we used the weighted node degree (the average strength of connection to other nodes, calculated as the product of the degree of a node and the mean of the absolute correlation coefficients of all connections) to calculate the connectance of countries in the interaction networks. We calculated this value for each node in the networks to identify the most connected node and the change in connectance of each node along the winter crop trade network. We compared the composition of the network modules from 2021 to 2022. Note that the existence and composition of the modules in a network are independent of the network's modularity value, which means that modules can be identified even if the modularity value is low.

## Data availability

All data are available in the manuscript or Supplementary Materials, or available at https://doi.org/10.5281/zenodo.13822382; https://comtrade.

un.org/; https://developers.google.com/earth-engine/datasets/catalog/COPERNICUS_S2_CLOUD_PROBABILITY; http://www.ukrstat.gov.ua/ [in Ukraine].

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## Author contributions
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## Competing interests
The authors declare no competing interests.

## Additional information

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