Food trade disruption after global catastrophes

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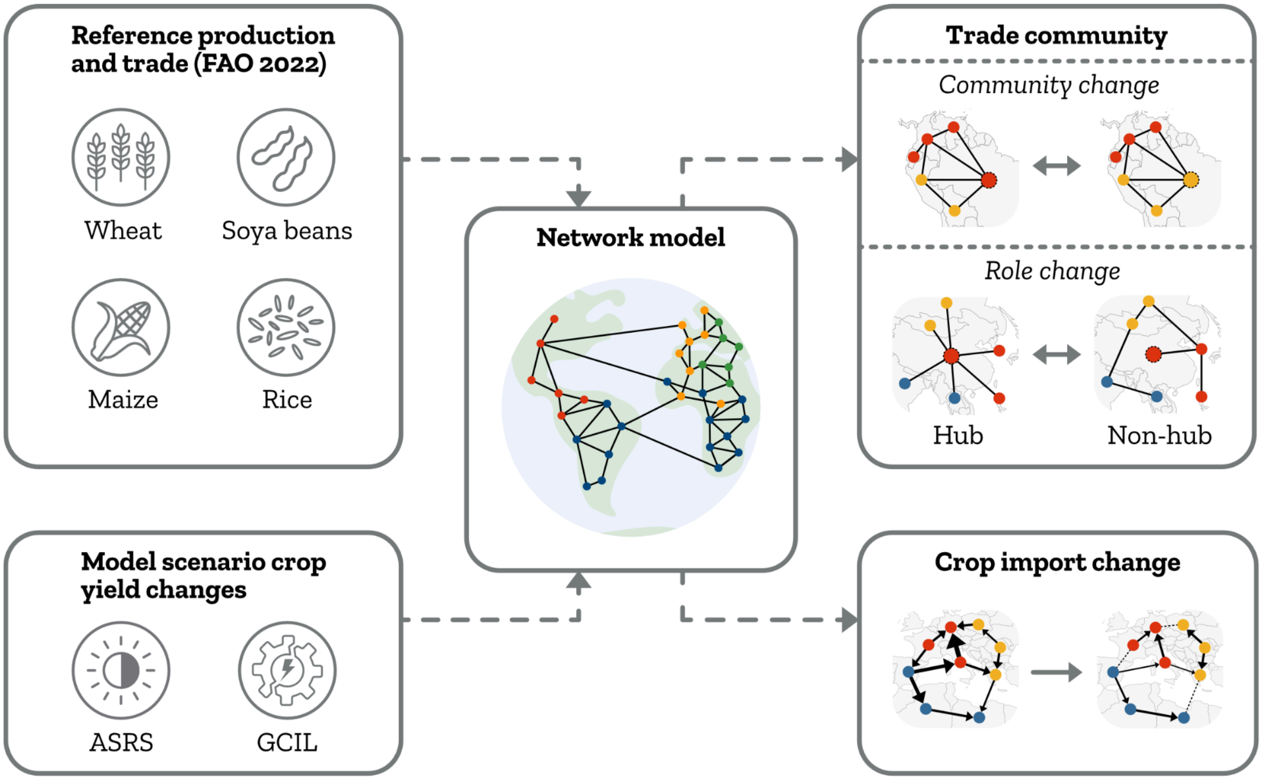
Abstract. The global food trade system is resilient to minor disruptions but vulnerable to major ones. Major shocks can arise from global catastrophic risks, such as abrupt sunlight reduction scenarios (e.g., nuclear war) or global catastrophic infrastructure loss (e.g., due to severe geomagnetic storms or a global pandemic). We use a network model to examine how these two scenarios could impact global food trade, focusing on wheat, maize, soybeans, and rice, accounting for about 60% of global calorie intake. Our findings indicate that an abrupt sunlight reduction scenario, with soot emissions equivalent to a major nuclear war between India and Pakistan (37 Tg), could severely disrupt trade, causing most countries to lose the vast majority of their food imports (50-100 % decrease), primarily due to the main exporting countries being heavily affected. Global catastrophic infrastructure loss with a comparable impact on yields as the abrupt sunlight reduction has a more homogeneous distribution of yield declines, resulting in most countries losing up to half of their food imports (25-50 % decrease). Thus, our analysis shows that both scenarios could significantly impact the food trade. However, the abrupt sunlight reduction scenario is likely more disruptive than global catastrophic infrastructure loss regarding the effects of yield reductions on food trade. This study underscores the vulnerabilities of the global food trade network to catastrophic risks and the need for enhanced preparedness.

Visual Abstract.



Results

Both scenarios show major trade disruptions, due to a strong dependency on key producers and exporters.

- **Global Catastrophic Infrastructure Loss (GCIL)**: Yield and import losses are more evenly spread globally, with little changes in trade communities.
- **Abrupt Sunlight Reduction Scenario (ASRS)**: High yield change variability, especially in the Northern Hemisphere, leading to significant trade community shifts and import losses.

Decreasing vulnerabilities

Combine preventative and adaptive strategies:

- Diversify crops and production sites, including resilient food.
- Integrate contingency plans into infrastructure planning.
- Include catastrophe scenarios in political and trade agreements.

1 Introduction

Humanity receives much of its food via the global trade network (D'Odorico et al., 2014; Janssens et al., 2020). However, with such interconnectedness comes the potential for large-scale systemic risk (Bernard de Raymond et al., 2021), where local failures can have cascading effects throughout the broader system. A significant component of the system's vulnerability is its lack of diversity on all levels, ranging from seed varieties to the number of companies trading food and few but dominant exporters (Clapp, 2023; Hamilton et al., 2020; Nyström et al., 2019). Global trade has been described as "robust, yet fragile," capable of weathering more minor shocks but increasingly vulnerable to major ones (Foti et al., 2013; Ma et al., 2023; Wang et al., 2023). Such major shocks could come in the form of "tipping points", and involve cascading interactions with other processes such as conflict and migration in a globally interconnected world (Centeno et al., 2023; Spaiser et al., 2023) or by multiple separate shocks happening at once (Baum et al., 2024). In this context, the World Economic Forum's Global Risk Report 2023 highlights food supply crises as one of the most severe risks in the coming years and decades (World Economic Forum, 2023).

A key vulnerability in the food trade network lies in the potential disruption of the biggest food exporters (Clapp, 2023; Puma et al., 2015), and this vulnerability appears to be increasing over time (Ji et al., 2024; Ma et al., 2023). Currently, only five countries (China, United States, India, Russia and Brazil) are responsible for producing the majority of wheat, maize, rice and soya beans (Caparas et al., 2021), and these producers are especially vulnerable to disruptions of agricultural inputs (Ahvo et al., 2023). A stop of trade by, e.g., the United States could trigger cascading failures (Goldin and Vogel, 2010; Helbing, 2013; Ma et al., 2023), plausibly endangering the entire system. One possible reason for large yield shocks is synchronised multiple breadbasket failure, which means the simultaneous collapse of multiple major agricultural regions (Anderson et al., 2023; Gaupp et al., 2020; Kornhuber et al., 2023). Beyond this, there are various global catastrophic risk (GCR) scenarios which could involve large-scale food system disruption.

GCR has been defined as the risk of "serious damage to human well-being on a global scale" (Bostrom and Cirkovic, 2008), and could occur due to a wide range of possible hazards. Here, we consider two specific scenarios particularly relevant to the food system. The first is global catastrophic infrastructure loss (GCIL), which could be triggered by High Altitude Electromagnetic Pulses (HEMPs) (Cooper and Sovacool, 2011; Wilson, 2008), geomagnetic storms (Baum, 2023; Cliver et al., 2022; Isobe et al., 2022), globally coordinated cyber attacks (Ogie, 2017), and extreme pandemics causing people to be unable or unwilling to work in critical industries (Denkenberger et al., 2021). These events, disrupting the electrical grid on a global scale and thus the production of inputs for the food system, like fertilisers, pesticides or fuel, could lead to a substantial reduction in global food yields (Moersdorf et al., 2024) and would thus further influence food trade.

The second is that of abrupt sunlight reduction scenarios (ASRSs), which could result from nuclear war (Coupe et al., 2019; Toon et al., 2008), asteroid/comet/meteor (bolide) impacts (Chapman and Morrison, 1994; Tabor et al., 2020), or large volcanic eruptions (Rampino, 2002; Rougier et al., 2018). Such events could inject aerosol particles into the upper atmosphere, causing a significant drop in temperature and disrupting global agriculture (Coupe et al., 2019; White, 2013). A recent analysis of Xia et al. (2022) suggests that a nuclear war between Russia and the United States could lead to global yield reductions of up to 90% in the worst year following the war. Even a smaller nuclear war could disrupt global trade due to a massive spike in food prices (Hochman et al., 2022).

The likelihood of large yield shocks may be substantial. For example, Rivington et al. (2015) estimate an 80% likelihood of a 10% or greater global yield shock due to multiple breadbasket failure within this century. This probability combined with the probability of the abovementioned catastrophes, based on current estimates and preparations, moves to over 90% for this century at least one of them happening (Barrett et al., 2013; Denkenberger et al., 2021, 2022; Karger et al., 2023), with the majority of the probability mass coming from multiple breadbasket failures. While these numbers are highly uncertain, they highlight that there is the need to understand better what might happen if yield shocks on such a scale occur.

While the impacts of climate change and extreme events on trade have been studied more in recent years (Hedlund et al., 2022; Thang, 2024), only limited research has been conducted regarding the effects of GCIL and ASRS on food production and trade. The research that does exist assumes that trade will continue as it is now or cease completely (Hochman et al., 2022; Rivers et al., 2024a; Xia et al., 2022). These simplifications reduce the enormous complexity of how our food system might react to global catastrophic risks. While some preliminary economic research on smaller nuclear conflicts has been conducted (Hochman et al., 2022), broader insight, especially into the consequences of a wider range of scenarios, is needed.

For an initial assessment of how global trade might evolve after such global catastrophes, we study the shifts of trade communities and trade flows caused by GCIL and ASRS in a global food trade network model (Hedlund et al., 2022). In this context, trade communities refer to groups of countries that trade extensively with one another. Understanding them and their changes allows a more targeted assessment of the disruptions caused by changes in yield. The model is intentionally simple, focusing on the direct effects of yield changes on trade without considering second-order economic aspects. Our initial analysis can serve as a foundation for future, more detailed economic assessments, while the model itself offers policymakers and scientists a practical tool to analyse the direct effects of food production shocks on global trade. Such assessments are important because they advance our understanding of how global catastrophes impact food trade, revealing the different implications of various shocks to the system. By modelling these shocks under different scenarios, we can better understand and predict changes in the global food trade system after major disruptions.

2 Methods

2.1 Model setup

The model we used was introduced by Hedlund et al., (2022); for the present analysis, we have re-implemented it in Python (Jehn and Gajewski, 2024) (https://github.com/allfed/pytradeshifts). The global trade network is described as a weighted directed graph with the countries as nodes and trade volumes between two countries as the weight of the edges connecting the nodes. In the model, we accounted for re-exports to represent point-of-origin-to-point-of-destination trade movements, meaning that the resulting data only contain the direct trade between countries without intermediaries (more information about this is in the Section 2.2 of the supplement and in Hedlund et al. (2022). The model determines post-catastrophe trade by applying country-specific yield changes directly to export volumes. For example, if a country experiences a 30% yield reduction, all its exports decrease proportionally – by 30%. We do not introduce new connections, though trade connections can become 0 if the yield is reduced by 100%. Compared to the original model, we have added the option to remove countries from the analysis to simulate an overall inability to take part in trade (e.g. due to destruction after a nuclear war). Other additional functionality is described in the Supplement (Section 1).

To detect the communities in the trade network, we used the Louvain algorithm (Blondel et al., 2008), as implemented in NetworkX (Hagberg et al., 2008). It assigns every country a trade community, i.e., a group of other countries with which said country has the closest trade ties. As the Louvain algorithm is not deterministic, our model can be provided with a random seed parameter to ensure the reproducibility of the results.

The Louvain algorithm identifies communities by optimizing modularity, which measures the density of connections within communities versus connections between communities. The algorithm works iteratively:

1. It assigns each country to its own community
2. For each country, it evaluates whether moving it to a neighbor's community would increase modularity
3. After all possible improvements, it aggregates each community into a single node
4. It repeats the process until modularity cannot be further improved

This approach allows us to detect natural trading blocs based on connection patterns without imposing geographical constraints.

2.2 Production and trade data

The Food and Agriculture Organization of the United Nations (FAO) supplies annual data on crop production and bilateral trade for agricultural commodities. Our study utilised the most recent data available (2022), adjusting for re-exports and relies on crop production and trade matrix information in tonnes.

While research suggests a notable 'stickiness' in the trading system (Reis et al., 2020) and that countries tend to remain in the same trade communities for long periods (Ma et al., 2023), there can still be considerable changes over time, especially after major disrupting events like COVID-19 (Clapp and Moseley, 2020) or the Russian invasion of Ukraine (Jagtap et al., 2022; Zhang et al., 2024). We, therefore, used the most recent data (2022) to most accurately represent the current global food trade network. Our analysis focuses on wheat, rice, soya beans and maize. We used primary commodity data for wheat, maize and soya beans, and for rice, given that paddy rice is predominantly traded in processed forms, we used the milled equivalent in the FAO data. We focus on those crops because they are the most important staple crops, accounting for roughly two-thirds of calories and proteins consumed globally (D'Odorico et al., 2014).

We excluded bilateral trade flows falling below the 75th percentile in trade volume to concentrate on the main trade movements, following Hedlund et al. (2022). This maintained the majority of countries in the network. However, the results are robust across a wide range of percentile cut-offs, as trade is dominated by a small number of large exchanges (Figure S1).

2.3 The impact of global catastrophic risk scenarios on yields

We focus on two main GCR scenarios: GCIL and ASRS (see introduction). We obtained yield losses for GCIL scenarios from Moersdorf et al. (2024). Moersdorf et. al (2024) assumed that if a GCIL happens, this will result in a global stop in the production of agricultural inputs like fuel, pesticides and fertilisers. Based on this they split their simulations into two phases. Phase 1 is the first year after GCIL with some stocks for fuel, pesticides and fertilisers remaining, while phase 2 simulates all following years, where all stocks are depleted. For our analysis, we used the phase 2 data to focus on the lowest yields. Since it is only available on a global (with a 5 arcmin resolution) and continental scale, we averaged the yield losses from global data for all points in each country. The resulting mean values of yield reduction differ slightly from the ones stated in Moersdorf et al. (2024) because: 1) Moersdorf et al., assigned weights using pre-catastrophe productivity, but as the nuclear war data is not productivity weighted, we used Moersdorf et al's unweighted data to ensure comparability between the two scenarios. The wider yield change distribution under ASRS compared to GCIL thus reflects genuine scenario differences rather than methodological artifacts. 2) In our model, the connections between countries are based on the actual amount traded (corrected for re-exports). Weighting the yield changes by their productivity would thus skew the results. Also, we aggregate on country level first instead of taking a global average. The scenario by Moersdorf et al. likely would have wide ranging consequences for society beyond yield impacts, as it assumes a disruption of the industrial base. These further disruptions are not modelled here.

For ASRSs we used the country-level nuclear war crop modelling data from Xia et al., (2022). We used nuclear war as a proxy for all ASRSs because nuclear war has the best climate model data available (Coupe et al., 2019), and the global impact on climate is possibly similar across different ASRS scenarios with similar magnitude. We used data for the third year after the nuclear war, as this represents the year with the lowest yields. To make the scenario more comparable with the GCIL scenario, we used the 37 teragram (Tg) scenario from Xia et al. (2022) as the main comparison. This is meant to simulate a nuclear war between India and Pakistan with 250 nuclear weapons of 100 kt explosive yield each and would thus equal a total of 25 megatons of TNT.. In this scenario, some of the smaller and hotter countries experience increases in yield due to a better climate, and the climate model used with a horizontal resolution of 2 degrees cannot resolve such small countries correctly. Thus, we limit this effect to a maximum value compared to current yields to avoid unrealistically high values (Wheat: 100 %, Rice: 132 %, Soya Beans: 79 %, Maize: 129 %). Since more accurate crop growing models are not available for nuclear war, we determine this upper limit as the Q3+1.5(Q3-Q1), where Q1 and Q3 are the 1st and 3rd quartile respectively (Tukey, 1977), of the data presented in Xia et al. (2022). Xia et al. (2022) did only model spring wheat. We are assuming here that spring wheat can be used as a proxy for wheat in general.

The ASRS with 37 Tg soot emissions has a median wheat yield decline similar to GCIL (Figure 1). Soya beans, maize and rice have more dissimilar ranges (Figure 1). This makes wheat the most comparable crop across the two scenarios, while also being the most traded and, therefore, our main focus; however, we also discuss the other crops and provide the figures for them in the supplement.

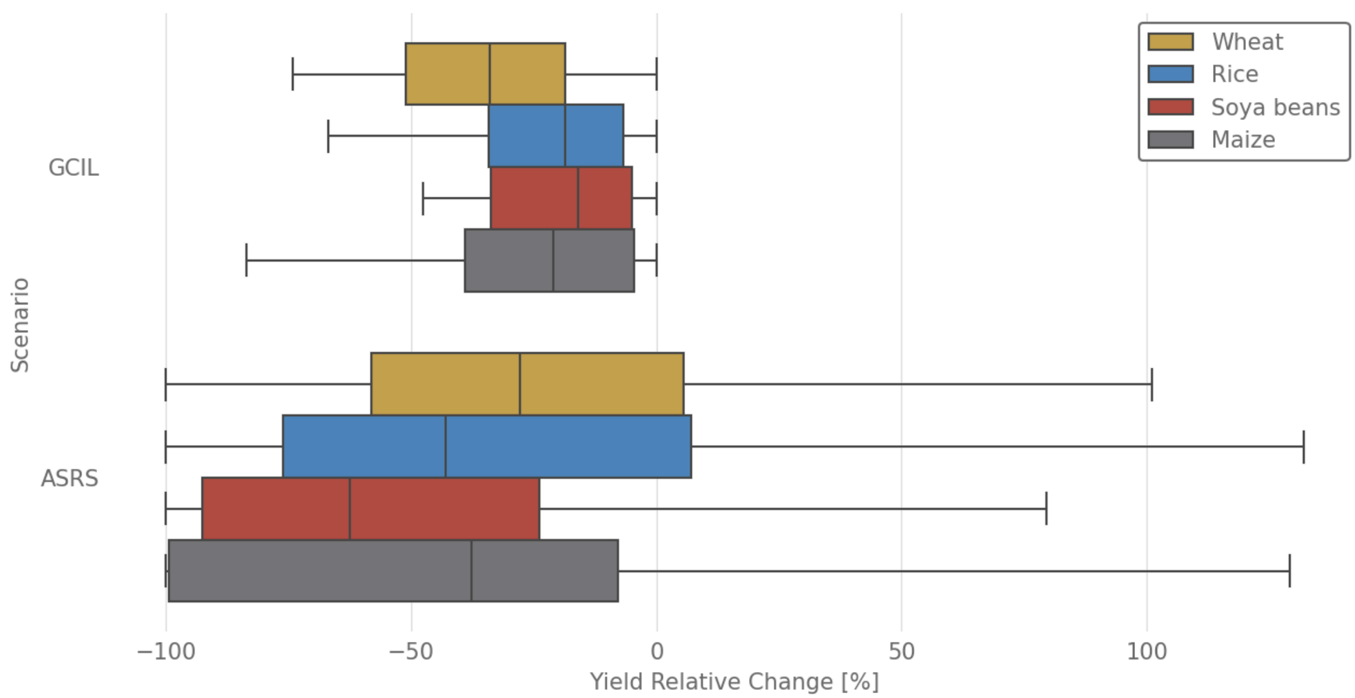


Figure 1: Relative yield change (%) in all affected countries (combined) for both the global catastrophic infrastructure loss (GCIL) and the abrupt sunlight reduction scenario (ASRS), by crop (colour). The values for GCIL yield changes are taken from Moersdorf et al. (2024), and those for ASRS yield changes from Xia et al. (2022) (see Section 2.3 for details). The boxplot displays data distribution using five key summary points: the minimum, first quartile, median, third quartile, and maximum. The box spans from the first to the third quartile, with a line at the median. Whiskers extend to the smallest and largest values within 1.5 times the interquartile range from the quartiles. Outliers are circles beyond the whiskers. This is the same for all boxplots shown in this article.

2.4 Trade communities before and after global catastrophes

The model allows a qualitative analysis of the changes by comparing the trade communities before and after the catastrophic event. To allow for a more quantitative comparison as well, we used a variety of measures (described below and in supplement section 1 and 2) for changes in trade communities alongside the overall complexity and robustness of the resulting trade networks.

2.4.1 Change

Jaccard distance

To assess how much the trade communities of all countries have changed before and after global catastrophes we used the Jaccard distance. This measure allows us to compare how similar/different two trade communities are. It finds the percentage of common countries between trade communities divided by the total number of elements between them. The Jaccard *similarity* (also called Jaccard index) is typically defined as the size of the intersection of two sets divided by the size of the union of these sets, and has a range from zero to one (Jaccard, 1901). The Jaccard distance (d_J) is one minus the Jaccard similarity. Therefore, for any given country, we can look at the set of countries that are in the same community before and after the catastrophe and compute the Jaccard distance (dissimilarity score) for these sets.

Let *A* denote the set of community members of some country before a catastrophe and *A'* the set of community members of the same country after the catastrophe. We can then define the Jaccard distance d_J as:

$$d_J(A, A') = 1 - \frac{A \cap A'}{A \cup A'}. \qquad (1)$$

In the context of this study, the Jaccard distance indicates how similar two trade communities are. A value of zero indicates that the trade community did not change, while a value of one indicates that the trade community has changed completely. The assumption here is that a larger change is bad, as countries build their infrastructure to accommodate their current trading partners and cannot be easily changed without preparation (Jagtap et al., 2022).

Within-community degree and participant coefficient

The functional cartography approach (Guimerà and Nunes Amaral, 2005) assumes that nodes within a network serve specific roles based on their connections within and across communities. A node's role is determined using two indices: one measuring its connectivity within its community (z) and another assessing how its links are distributed among different communities (P). The first index (the z-score) is defined as

$$z_i = \frac{K_i - \overline{K}_{s_i}}{\delta_{K s_i}}, \qquad (2)$$

where K_i is the number of links of country i within its trade community s_i, $\overline{K}_{s_i}$ is the average number of links across all countries in s_i , and δ_{Ks_i} is the standard deviation of the number of links s_i. The trade communities are delineated with the Louvain algorithm (see section 2.1) The second index (the participation coefficient) is defined as

$$P_i = 1 - \sum_{s=1}^{N} \left(\frac{K_{is}}{k_i}\right)^2, \qquad (3)$$

where K_{is} is the number of links of node i to nodes in community *s*, k_i is the total number of links of node *i*, and *N* is the number of communities.

These indices define a parameter space where different regions correspond to specific roles based on threshold values. Guimerà and Nunes Amaral identified seven node roles:

1. **Hubs** (if $z \geq 2.5$) and **non-hubs** (if $z < 2.5$).
2. **Non-hubs** are further classified based on the P-dimension:
   - **Ultra-peripheral** (all or almost all links within their own community, $P \leq 0.05$),
   - **Peripheral** (most links within their own community, $0.05 < P \leq 0.62$),
   - **Connectors** (many links across different communities, $0.62 < P \leq 0.80$),
   - **Kinless** (evenly distributed links across all trade communities, P>0.80).
3. **Hubs** are categorised as:
   - **Provincial hubs** (vast majority of links within their own community, $P \leq 0.30$),
   - **Connector hubs** (many links to most other communities, $0.30 < P \leq 0.75$),
   - **Kinless hubs** (evenly distributed links across all communities, $P > 0.75$).

These roles represent different types of traders within the network, with provincial hubs being crucial for community cohesion, kinless hubs for global network cohesion, and connector hubs playing important roles in both aspects (see Figure 4).

2.4.2 Centrality

Centrality is a measure of the importance of a node in the whole network. This metric allows us to identify the main importers and exporters of food in our trade network. Here, we consider weighted degree centrality, which is calculated by dividing the sum of all incoming/outgoing edge weights (the amount of food traded) for a given node by the sum of all incoming/outgoing edge weights in the entire graph.

3 Results

3.1 Changes in wheat trade

3.1.1 Shifts in trade communities

According to our modelling, the wheat trading communities (based on the Louvain algorithm, section 2.1) would evolve differently during GCIL and ASRS. This can be seen in the distribution of the trade communities globally (Figure 2), but especially in the amount of change that countries could undergo in their trade communities (Figure 3). For this part of the analysis, we assume that all countries still participate in trade, even if they were involved in a nuclear exchange in the ASRS scenario. We separately look at the impacts of a complete removal of countries from the trade network in section 3.3.1..

Under GCIL, most trade communities could remain relatively unchanged from the present configuration. Only a handful of countries, such as the United Kingdom, Ireland, Iran, Senegal, and the Democratic Republic of Congo, may experience a complete reconfiguration of their trade partnerships compared to the current state.

In contrast, the changes might be far more substantial in ASRSs. Nearly half of all countries could experience a shift in their trading partners, with eleven countries undergoing a complete or near-complete overhaul of their trade connections. Some countries affected are consistent with the GCIL scenario, like Iran and the Democratic Republic of Congo, while others, such as Peru or Finland, could be part of the transformed trade landscape.

The global distribution of trading communities (Figure 2) reveals that this significant shift is primarily due to the expansion of the trading community containing Russia. Today, this community comprises mainly Russia, Eastern Europe, and a portion of North Africa. In the ASRS, however, it extends across the Balkans and most of North Africa.

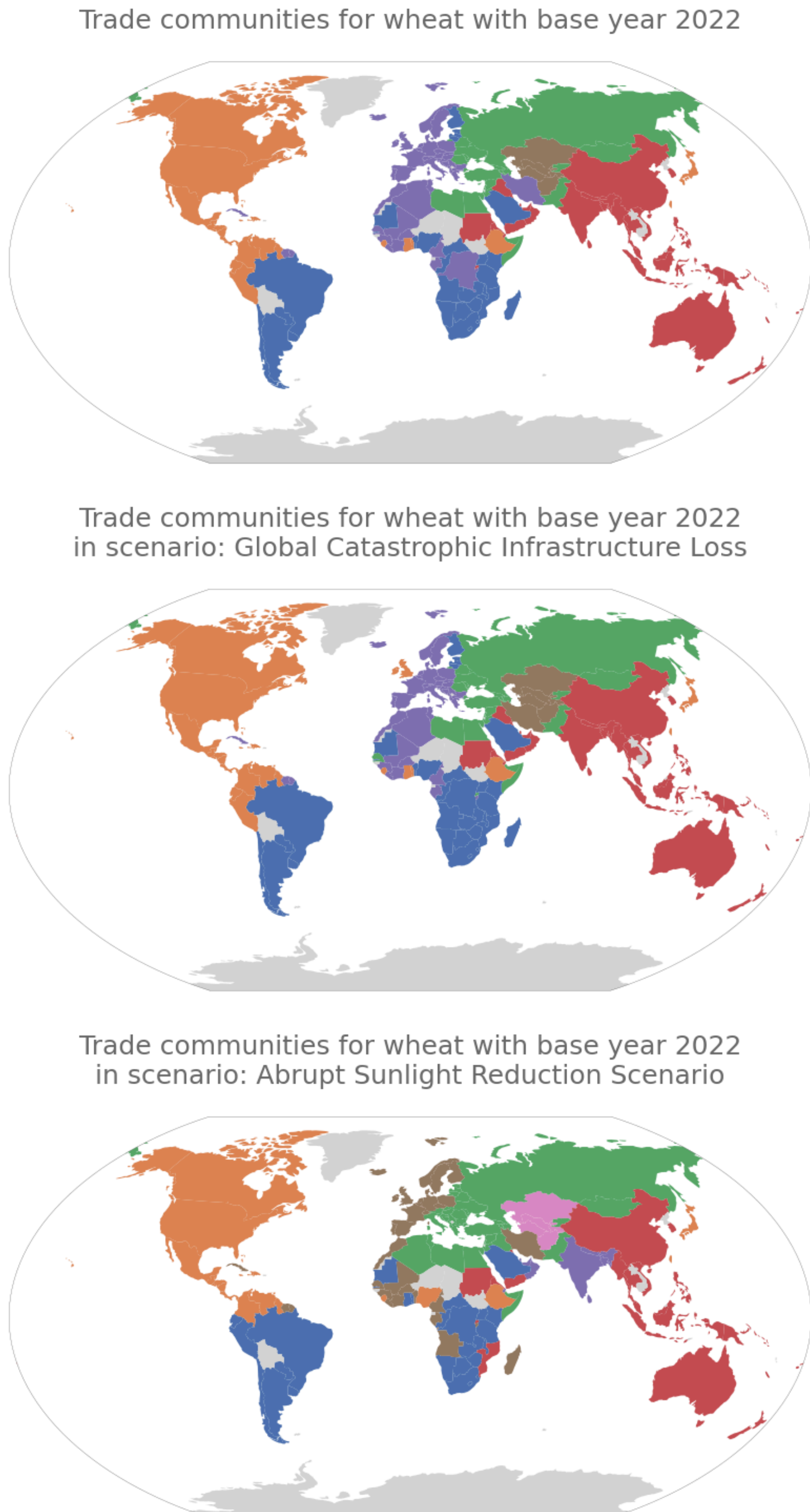


Figure 2: Trade communities for wheat in 2022 after yield reduction due to global catastrophic infrastructure loss as well as abrupt sunlight reduction. The colours indicate trade communities. In the GCIL scenario, despite large drops in yields, global trade communities remain relatively unchanged. However, in the ASRS, the changes are more substantial.

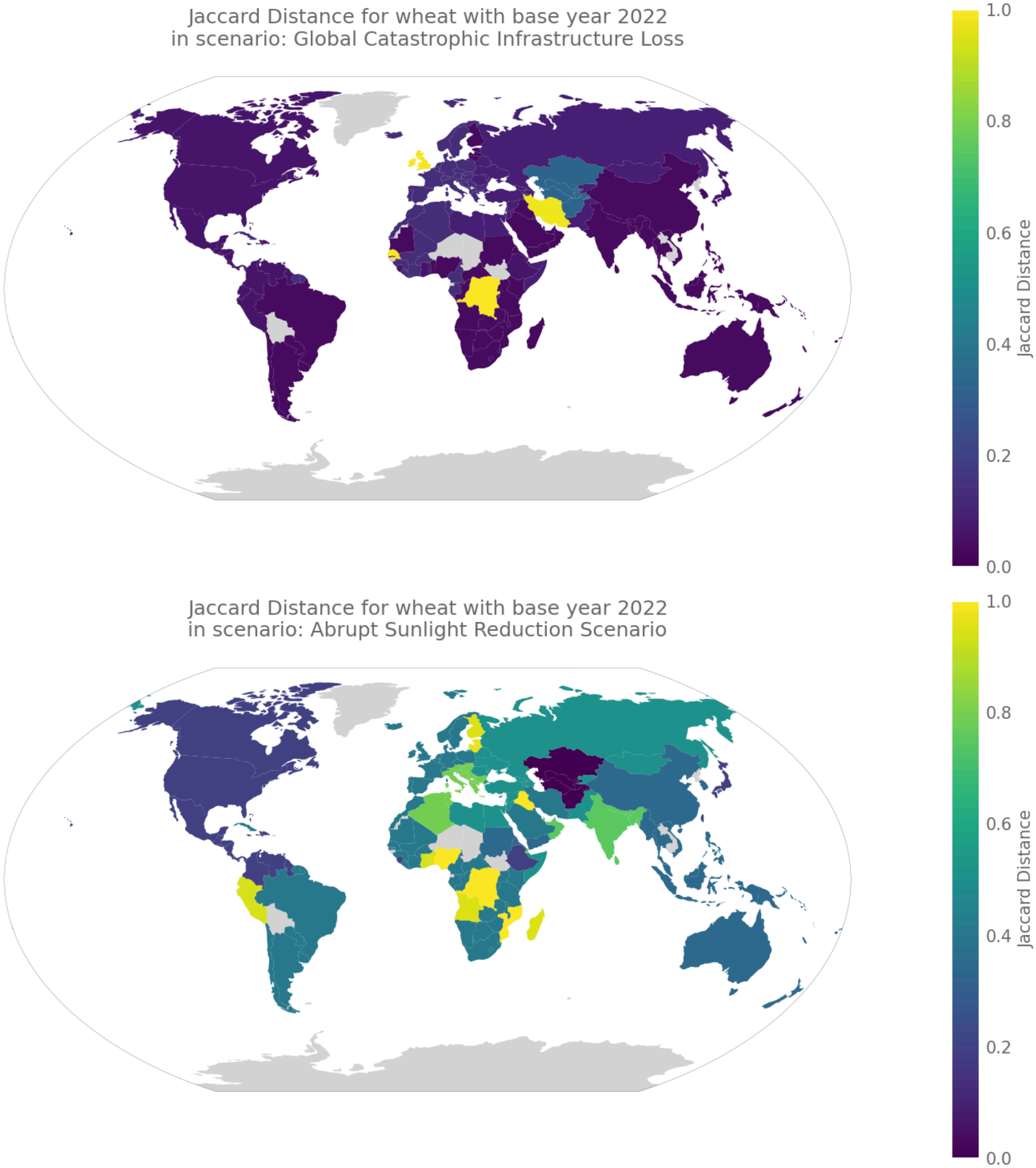


Figure 3: Changes in wheat trade communities after yield reduction due to global catastrophic infrastructure loss as well as abrupt sunlight reduction, in comparison to the communities in 2022. Colours indicate the magnitude of change as the Jaccard distance. Yellow means the trade community of a country has changed completely, and dark blue that the country remains in the same trade community. Again, we see that changes in trade communities are much more pronounced in the ASRS.

3.1.2 Community roles of countries

In contrast to the impact we can see in the trade communities, there are no significant shifts in community roles in the GCIL scenario and the default 37 Tg ASRS (Figure 4). However, we note that in larger ASRSs, country roles within trade networks do shift significantly. The 47 Tg scenario (Figure S2) reveals distinct transitions: some countries shift from non-hub connectors to peripheral non-hubs, while others become provincial hubs. This suggests countries lose connections both within and beyond their trade communities, with external connections most affected. Countries maintain fewer imports overall, but those remaining imports come primarily from within their trade community. These patterns indicate a potential tipping point between 37 Tg and 47 Tg, where the system shifts from minimal change to substantial reorganization.

Another way to assess country roles in the global trade network is through in- and out-degree centrality, which identifies key importing and exporting countries (Figure S3). In-centrality remains stable across all scenarios, reflecting the overall trade volume, although total imports decrease due to reduced yields. Out-centrality experiences more significant changes. Presently, Australia has the highest out-centrality, followed by the United States, France, Canada and Russia. This order remains largely unchanged after GCIL, though Russia's out-centrality slightly surpasses that of the United States and Canada. Likely because of its reduced use of agricultural inputs in comparison with the other countries. The most substantial shifts occur in the ASRS, however, where Russia, Canada, and the United States experience considerable yield losses, resulting in significantly reduced out-centrality. Meanwhile, Australia maintains its top position, with France and Argentina rising to second and third place, respectively.

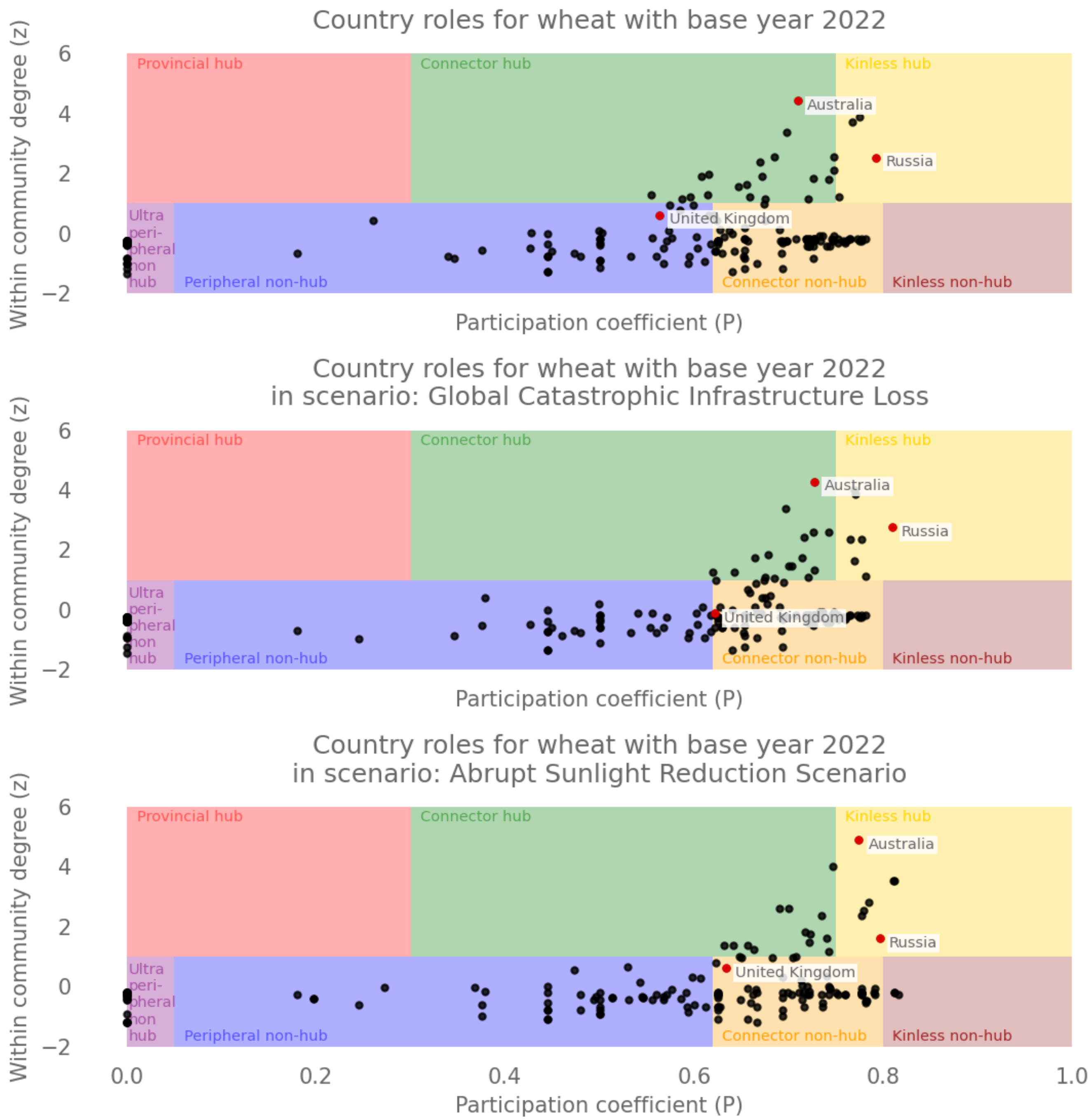


Figure 4: Country roles in the global wheat trade network in 2022 and after yield reduction due to global catastrophic infrastructure loss, as well as, abrupt sunlight reduction; based on within community degree and participant coefficient (see Section 2.4.1).

3.1.3 Changes in trade flows

When examining the decline in imports by country, we observe greater impacts under ASRSs compared to GCIL (Figure 5). Ukraine and Argentina, which only export wheat, remain mostly unaffected in both scenarios. Under GCIL, most countries see a 20-30% reduction in imports, with some African and European nations experiencing up to a 40-60% decrease in imports.

In contrast to GCIL, ASRSs result in a broader range of import changes. Nations such as the United States, Norway, and Mongolia lose up to 100% of their wheat imports, primarily due to reduced yields in major wheat-exporting countries like Canada, the United States, Russia, and Ukraine. These changes are mirrored in both degree-centrality measures, indicating a significant loss of centrality for these previously major exporting countries (Figure S3). This leaves Australia as the only remaining major exporter of wheat.

We can also study the absolute changes in wheat imports (Figure S4). This highlights similar patterns across both GCIL and ASRS, albeit still with a higher impact in the ASRS. The strongest effects in both scenarios can be seen in China, Turkey, Indonesia and Egypt. All these countries import large amounts of wheat from Russia and Central Asian countries like Kazakhstan, which experience major yield losses in both scenarios. In particular, Turkey would experience a massive loss of wheat imports in absolute terms in an ASRS, with around 8 million tonnes of wheat imports lost.

The impact to the trade network is also visible when examining remaining wheat production (Figure S5, S6). The scenarios differ markedly. The GCIL scenario (Figure S5) preserves more wheat production, particularly in Russia, where farming depends less on fertilizer than in Central Europe or the US. However, in ASRS, Russian production drops severely as lower temperatures make wheat growing nearly impossible. Australia, a major wheat exporter, continues production but at reduced levels. India produces the most wheat in ASRS, but primarily grows it for domestic use and may not become a major exporter.

Additionally, we performed robustness checks of our results with different metrics. The shifts in trade patterns and the heightened impact of ASRSs are also evident in other metrics, like community satisfaction and node stability. Community satisfaction gauges the proportion of a country's trade within its trade community, while node stability indicates a country's ability to replace lost trade partners. Both metrics highlight the challenges faced by nations reliant on Russia and the United States. More information on those measures is provided in the supplement (section 3.6).

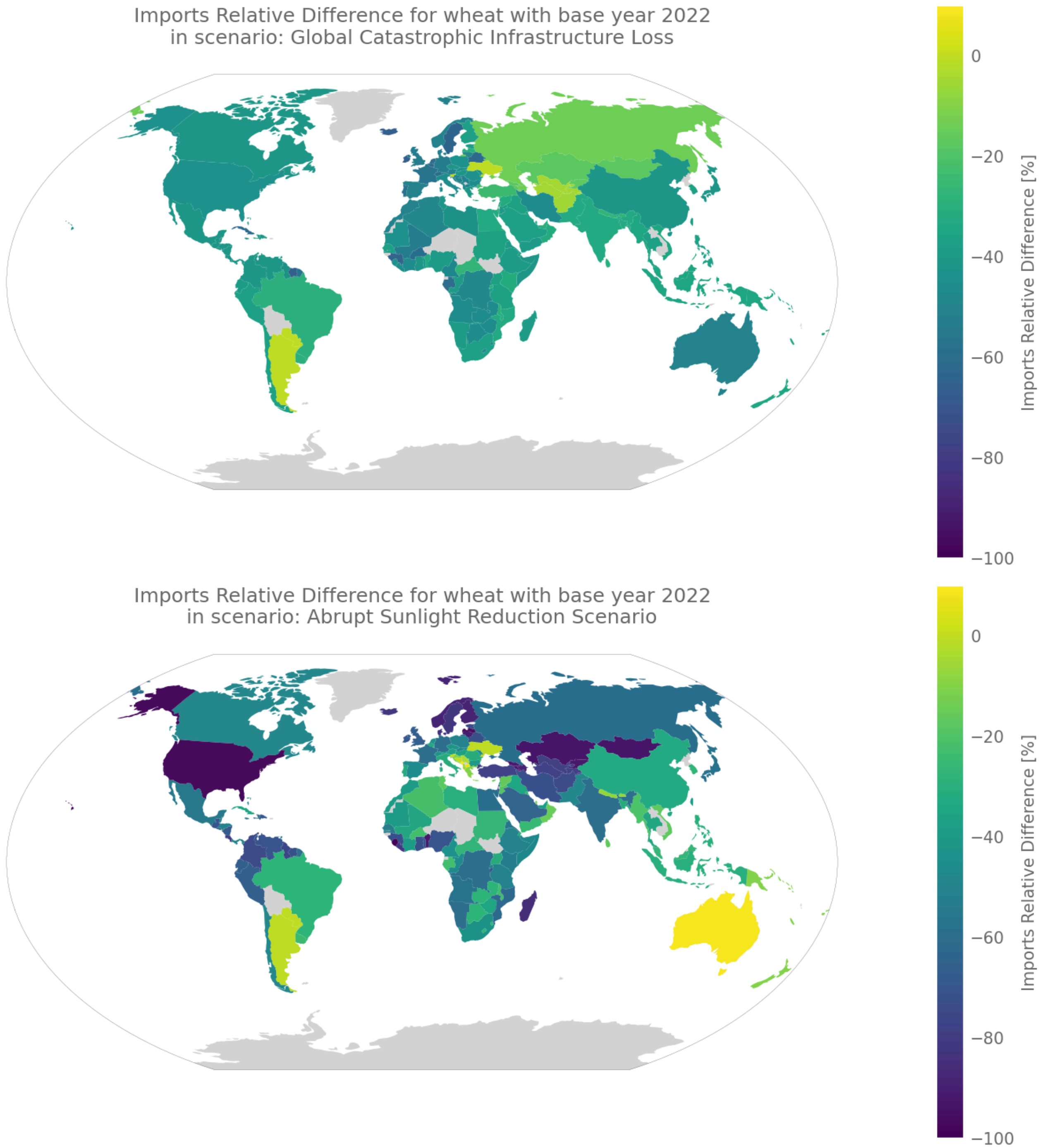


Figure 5: Relative changes in wheat imports after global catastrophic infrastructure loss and abrupt sunlight reduction scenarios in comparison to today.

3.2 Trends in rice, maize and soya beans

3.2.1 Overall pattern and comparison across scenarios

The patterns observed in the wheat data are also evident in rice, maize, and soya beans (Figure 6). Across all crops, the impact of ASRSs is larger than GCIL. This is especially true for the outliers in the distribution. In the case of wheat, for instance, while the median remains similar across scenarios, certain countries experience a complete loss of imports under abrupt sunlight reduction, which does not happen in GCIL. Considering the variations in yield reduction (Figure 1), it becomes clear that at 37 Tg of soot emissions, the effects are generally comparable for both scenarios when it comes to yield reductions. However, the range of impacts and change in trade communities would be much more extensive in ASRSs. Additionally, the most affected countries vary between crops due to differing trade volumes across world regions.

Combining the effects of ASRS and GCIL, which could occur during a nuclear war that influences climate and disables industry due to direct destruction and HEMP, has a very severe impact on food trade. However, the overall impact is less than the sum of their individual effects. Many countries severely affected by ASRS have already experienced significant yield losses and the additional disruption due to GCIL has thus little effect. Nonetheless, this combined catastrophe would severely impact yields and food trade.

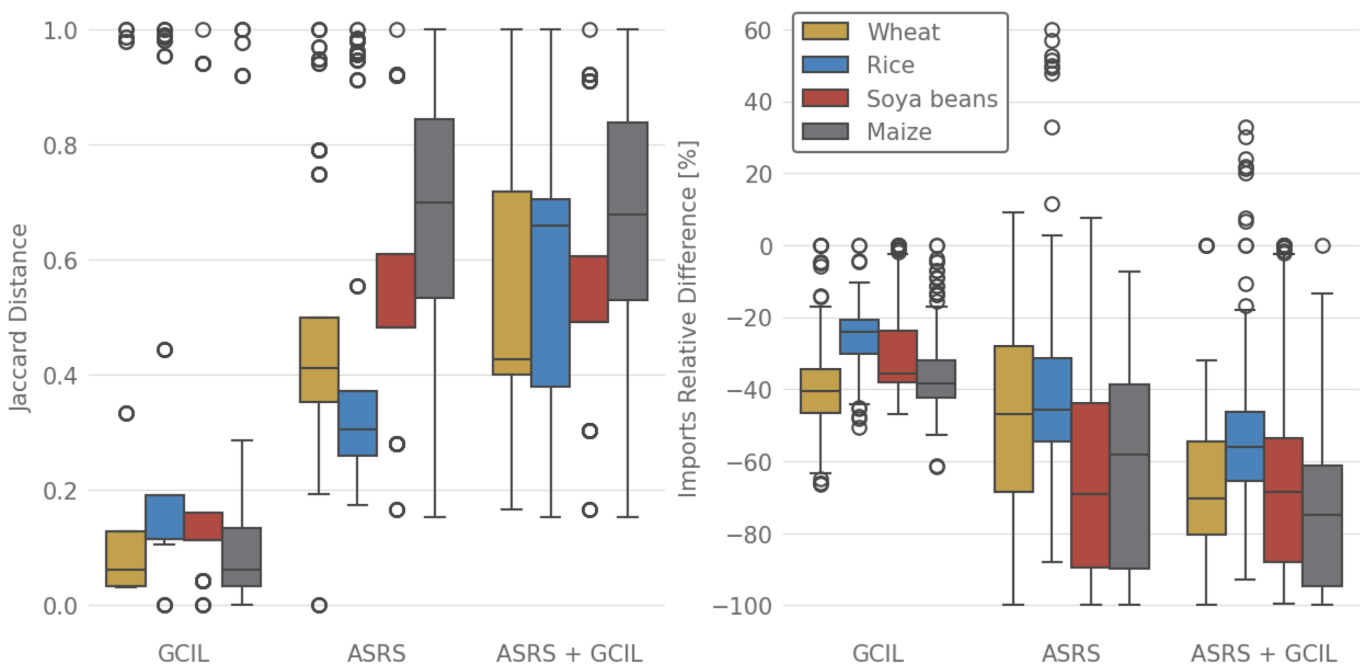


Figure 6: Jaccard Distance and reduction in imports, for each country and crop, for Global Catastrophic Infrastructure Loss (GCIL), and the Abrupt Sunlight Reduction Scenario (ASRS).

3.2.2 Rice

For rice, the import reduction and trade community disruptions are similar between abrupt sunlight reduction and GCIL, differing mainly in magnitude. Under GCIL, most countries typically lose around 20-30% of their rice imports, whereas it ranges from 30-50% under ASRSs. Most countries also maintain much of their pre-catastrophe trading community, with exceptions including Russia, Ukraine, and Indonesia. However, a majority of the countries experience at least some shift. This more limited degree of change in comparison to wheat is also evident in community roles, which remain largely consistent across all scenarios. This stability can be attributed to India's prominent role as the leading rice exporter, its relatively low reliance on agricultural inputs compared to other countries, and it is still relatively high temperatures during ASRSs, thereby stabilising the rice trade network even during catastrophes. See supplement section 4.1 for the figures showing the trends described here.

3.2.3 Maize

In GCIL, the impact on maize is evenly spread worldwide. However, under ASRSs, there's a stark contrast between the Northern and Southern Hemispheres. Nearly all Northern Hemisphere countries lose most or all of their maize imports, while in the Southern Hemisphere, South America, much of Africa, and Southeast Asia maintain some imports, mainly from less affected regions like South America. Many countries switch to the connector non-hub role, likely as most countries experience low trade volumes overall. The maize trade network in ASRSs exhibits low stability and is heavily affected by the removal of the other major exporters, after the United States' decline in importance due to yield reductions. See supplement section 4.2 for the figures showing the trends.

3.2.4 Soya beans

Regarding soya beans, there is a shift in the distribution of affected countries compared to wheat. Many African countries remain relatively unaffected, primarily due to their low trade volumes. Under GCIL, most countries face a similar reduction, roughly 20-40%, in imports. In ASRSs, the patterns resemble those of wheat, except for South-East Asia and Oceania. These regions still receive wheat imports from Australia and each other, but their soya bean imports mainly come from the United States, resulting in a decline. This trend is reflected in trade communities, which remain mostly stable for GCIL but converge into two primary and one minor communities for ASRSs. Soya bean export is heavily concentrated in the United States, so a sharp yield decline there disrupts trade communities significantly. Only countries importing soya beans from Brazil maintain higher import levels, and the trade community with Brazil stays very stable. Similarly to wheat, the role of countries in their communities shifts, with most staying the same for GCIL but losing much connectivity in ASRSs. Another notable deviation from wheat patterns lies in network vulnerability to node removal. With only two major exporters, the United States and Brazil, if the United States is already affected by yield reduction, the network becomes less stable, experiencing another shock when Brazil is removed. See supplement section 4.3 for the figures showing these trends.

3.3 Comparison of nuclear war scenarios

3.3.1 Impact of removing countries

The ASRS data is based on nuclear war simulations. To explore these further, we simulated the removal of Russia/United States and Pakistan/India from the 37 Tg scenario (Figure 7). We compared these scenarios with the ASRS that includes all countries and the wheat trade of today. The findings reveal that while removing these countries affects both trade communities and overall imports (Figure 7), the effect of the yield reduction due to abrupt sunlight reduction is already so big that the removal of those countries is negligible. Thus, if countries involved in a nuclear conflict were to cease as trading partners due to the destruction of their territories, it would cause additional disruptions to the global trade network beyond those due to the yield reductions, but only marginally and for a subset of countries.

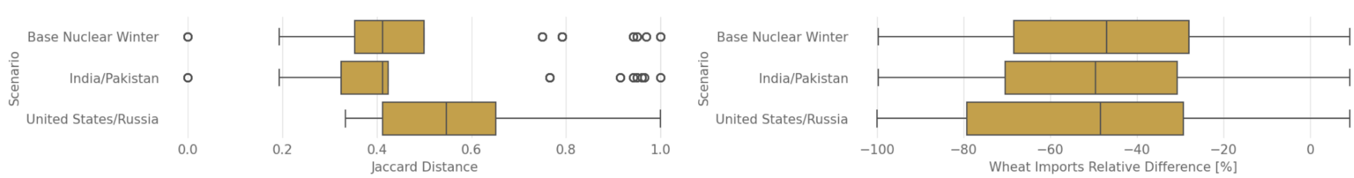


Figure 7: Country removal impact on wheat imports in nuclear war scenarios.

When simulating the gradual removal of nodes, the results indicate that removing random nodes causes a slow but steady decline in network stability. In contrast, specifically targeting the most active exporting nodes results in a rapid decline in stability, leading to network collapse after removing 10-20% of these crucial nodes. Further details can be found in Supplement Section 3.7.

3.3.2 Impact of soot emission magnitude after nuclear exchange

Assessments of the impacts for nuclear war scenarios of different magnitudes (Figure 8) show a consistent pattern across all crops analysed. While the most significant impacts can be seen in the worst nuclear war with 150 Tg of soot emitted (nuclear winter), the effects would already be quite severe at 37 Tg (nuclear fall). The 37 Tg scenario engenders a substantial of about 60 % import loss, suggesting that trade would be massively impacted in the 37 Tg case. However, for most countries, food imports would have ceased almost entirely in a 150 Tg scenario. In addition, even at merely 5 Tg, some countries could experience a 50 % loss of maize, and at 16 Tg, a considerable number of countries have import reductions from 40 % to almost 100 % across all crops.

While trends remain comparable across all crops, including major import changes, wheat seems to be the least affected. Soya beans experience a stark shift in trade communities at as low a magnitude as 5 Tg. However, the change then stays relatively constant for all other magnitudes.

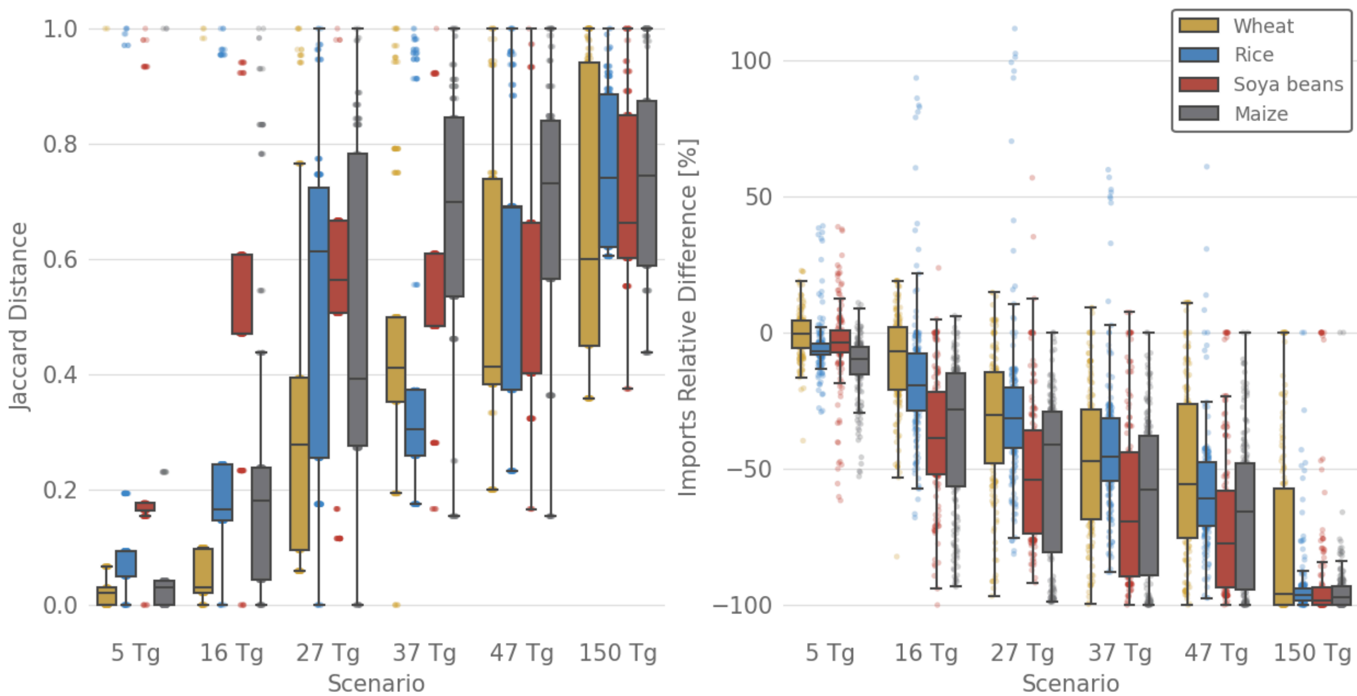


Figure 8: Relative change in imports and Jaccard distance for the four primary crops and nuclear war climate changes resulting from the emission of 5, 16, 27, 37, 47, and 150 teragrams (Tg) of soot across all countries. Coloured points represent individual countries.

4 Discussion

Overall, the main finding of this study is that the two food-system relevant GCR scenarios we have considered may affect agriculture quite differently in both the magnitude of their effects as well as the spatial distribution, suggesting that they will need different mitigation strategies to increase societal resilience against them. ASRS will be challenging as it will hit a fraction of countries very hard, while leaving others mostly unaffected. GCIL on the other hand would affect all countries, but on a similar magnitude.

Our results show clear differences between the effects of ASRSs and GCIL on food trade. The scenarios have different effects on how much trade communities are disrupted, the decrease in overall imports, and the roles of countries within their trade communities. Across all these measures, ASRSs lead to much larger disruption than GCIL, even for a similar net global yield loss. This is due to the way these global catastrophes play out and the spatial distribution of their effects.

When both scenarios are combined to simulate the co-occurence of both kinds of catastrophes, the impacts increase and result in food import losses in the range of 70-100 % for many countries. The impact on yields (Figure 1) and trade (Figure 6) change for both catastrophes in a similar way. We can see that the median losses are similar for both trade and production. However, while there are still countries that will likely see little impact on their food production by direct effects of the catastrophes, almost all countries experience a major loss in their food imports. This is due to the countries that are least affected are usually not major exporters. For GCIL the least affected countries are those that have very low input agriculture, which is usually also not very productive, while for ASRS the positive effects are mostly in countries which are too warm now for most agriculture.

As Moersdorf et al. (2024) have shown, in a GCIL scenario, the countries hit the hardest are those doing the most intense agriculture when it comes to industrial input like fertilisers. This is also in line with other research studying the impact of losing these inputs (Ahvo et al., 2023). These highly productive countries are also typically the countries that export the most food. Also, the effects are felt in all countries globally with no exceptions, as industrial inputs are in use worldwide. This results in a very homogenous impact on food trade, where most countries experience a relatively similar level of trade disruption.

On the other hand, for ASRSs, we see a much larger split between which countries are more or less affected. Generally, the higher the country's latitude, the more it is affected (Coupe et al., 2019). In addition, countries in the Northern Hemisphere are affected more overall. This is partly because nuclear war would most likely occur in the Northern Hemisphere (Coupe et al., 2019), resulting in somewhat lower soot concentrations in the Southern Hemisphere. In addition, the Southern Hemisphere has more land closer to the equator and more ocean (which acts as a temperature buffer), suggesting that the Northern Hemisphere may still be more affected even for ASRSs that do not involve nuclear war. These factors may lead to an especially large yield decline in the United States, Canada, Central and Northern Europe and Russia. These are all major food exporters, particularly for wheat or, in the case of the United States, for all major crops. This loss of exports from the major exporting countries cascades across the whole system. For all crops we can see significant changes in trade communities and large declines in the amount of imported food. This is especially true for maize, as maize is not very cold tolerant and, therefore, especially vulnerable to drops in temperature.

Focusing more specifically on the nuclear war scenario, we can see that the main effects of these disruptions are due to the yield decline. The complete removal of the countries involved in a war only introduces little additional shifts in the overall imports. However, removing Russia and the United States brings additional disruptions to the trade communities, as both countries are the anchors in their respective trade communities. We can also observe that the effects of the nuclear war increase considerably with rising amounts of soot ejected into the atmosphere. While a 5 Tg emission has relatively minor effects, except in soya bean trade communities, the effects quickly grow with higher soot emissions.. This emphasises that even if nuclear weapons were used, it is extremely important to limit further escalation in order to prevent additional disruption to the global food system.

4.1 Implications for the food system

Clapp (2023) identifies three primary vulnerabilities in the food system: 1) dependence on a limited number of staple crops, 2) domination by a small group of major exporters, and 3) concentration of food trade among a few companies. While we did not explore the role of companies, the issues of reliance on a few staple crops and dominance by major exporters are also evident here. The main vulnerability is the extremely central role of the United States in the food trade network. Every scenario resulting in yield reduction in the United States or even its complete removal from the system will result in massive cascading disruptions, both in the overall communities and the amount of food traded. The vulnerability would decrease considerably if the food system were less concentrated in the United States. Other studies of the current trade network show a high dependency on other major exporters, such as Brazil and Russia (Ji et al., 2024). Our results also indicate that a disturbance of these nodes is very significant. For instance, Australia would be the last remaining major exporter of wheat during an ASRS (Figure S3). Therefore, if this country were to stop exporting, the wheat trade would effectively end globally.

We know that complex networks become more susceptible to perturbations as they get more centralised (Wiliński et al., 2013), and the food system is getting increasingly centralised and concentrated (Clapp, 2023). This means that if we do not alter our approaches to food trading, we will get more and more vulnerable to major shocks and the kinds of scenarios we have described. There are some indications that this global concentration of trade might be beginning to change (Kang et al., 2024; Mamonova et al., 2023), as more countries rethink how they handle food and trade more generally. Whether these trends continue depends on how the geopolitical situation develops in the coming years and decades.

Our research also shows that the ASRS has a much wider range of effects. Some countries could even increase imports, as their neighbouring countries profit from the changed climate (e.g. more precipitation and cooler temperatures in some semi-arid regions), while others could lose all of their incoming food products. This means that recommendations to tackle these scenarios have to be tailored to specific countries, as there can be no approach that applies to all countries. For GCIL, more general recommendations might be possible, as all countries are affected similarly.

Recent studies have compiled lists of countries that have experienced substantial food import shocks in the past (Zhang et al., 2023b). While there is some overlap between these countries and the ones affected the most here, it also becomes clear that especially the Central European countries, as well as the major exporting countries, have not experienced large food import shocks on that scale in modern history. This indicates that these countries have no experience with import shocks and are possibly less prepared to handle the scenarios described in this study.

Shifting dietary patterns could also help decrease vulnerability to trade disruptions. A move toward plant-based diets with more locally-produced fruits, vegetables, and legumes could reduce dependence on international grain trade, as much of the currently traded grain (especially soya beans and maize) is used for animal feed rather than direct human consumption. This conversion of grain to animal products is inefficient from an energy perspective. However, this strategy presents a trade-off: while reducing animal feed imports would decrease trade dependencies, it might also reduce the system's overall flexibility. Current livestock systems, despite their inefficiencies, create a buffer by maintaining large stores of grain that could be redirected to human consumption during crises. Additionally, ruminants can digest cellulose that humans cannot, potentially providing an additional food source during catastrophes. Therefore, while dietary shifts toward plant-based foods could improve local food security under normal conditions, maintaining some animal agriculture may provide valuable system redundancy for extreme scenarios. The optimal balance likely varies by region based on local agricultural conditions and trade relationships.

Similarly, more strategic use of agricultural land could enhance resilience. Currently, significant agricultural capacity is devoted to non-food purposes – particularly biofuel production and crops like tobacco. While biofuel crops are often heavily subsidized, transitioning to electric vehicles would be more energy efficient and free up land for food production. The land used for tobacco cultivation could be repurposed for food crops, providing dual benefits of improved food security and public health. Additionally, reducing food waste, which accounts for approximately one-third of food production in many developed countries, represents a readily available opportunity to build resilience (Alexander et al., 2017). However, as with dietary shifts, these changes present trade-offs. Some biofuel infrastructure could potentially be repurposed to produce food during crises, similar to how breweries can be converted to produce sugar from cellulose (Throup et al., 2022). Moreover, maintaining diverse agricultural systems and processing capabilities, even for non-food crops, helps preserve farming knowledge and infrastructure that could be valuable during catastrophes. The key is finding a balance between efficient land use under normal conditions and maintaining adaptable agricultural systems that can respond to major disruptions.

4.2 Study Limitations

The research presented is, to our knowledge, the first to take a more nuanced look into what might happen to the food trade system after global catastrophe, meaning that there is much room for improvement in future work. We consider the main limitations of our study to be:

- We only looked at the direct effects of yield reduction on trade flows and did not consider any additional adaptations. For example, it seems likely that many countries would introduce export bans if their own yields dropped significantly, worsening the overall situation. This means that our study can be seen as the minimal amount of change that one can expect to happen after global catastrophes by the yield changes alone, barring the introduction of resilient food adaptations to counter the loss of yields (Pham et al., 2022). Further research is needed to understand how societies might react to the effects explained here.
- GCIL also includes the assumption that we lose the majority of our mechanisation and transportation. This is not modelled in this study, but plausibly could have major implications beyond the impact on yields and make it more catastrophic then ASRSs. A GCIL would disrupt fossil fuel production, hampering international trade. However, possible interventions include retrofitting ships to be wind powered (Abdelkhaliq et al., 2016) or wood gasification to replace fossil fuels (Nelson et al., 2024).
- We studied the four major food crops in isolation to understand what effects might play out on that level. However, the food system also consists of other parts like fisheries or livestock. While those are also predicted to decline after a global catastrophe (Scherrer et al., 2020; Xia et al., 2022), it remains unclear how the totality of all food trade might be affected by global catastrophes. Livestock would be more strongly affected than major crops because it mostly depends on them; whereas fisheries, while less affected than crops, make up a small percentage of global caloric requirements (<2%).
- Additional layers of interaction from non-food products through social dynamics to economic policies could be considered in a multi-layer network model, which has been shown to be impactful and effective in other scientific disciplines (De Domenico, 2023; Kivelä et al., 2014; Paluch et al., 2021).
- We treated nuclear war simulations as a proxy for large size impact over the land and super volcanic eruptions. While this is a reasonable assumption, the results might end up very different, especially if the impact/eruption happens in the Southern Hemisphere, as nuclear war scenarios usually only involve the Northern Hemisphere, as there are no nuclear weapon states in the Southern Hemisphere. Although these extreme events all produce large amounts of aerosols in the upper atmosphere, which block sunlight and cause significant cooling, the compositions of the aerosols differ. This results in variations in the duration of the cooling and some climate impacts. Recent research indicates that a simulated volcanic winter shows similar trends (Enger et al., 2024) to previous studies on nuclear winter (Coupe et al., 2019), although volcanic winters are likely to be shorter in duration. Additionally, there is a possibility that multiple mid-sized volcanic eruptions could occur simultaneously, releasing enough sulphate aerosol to cool the Earth significantly.
- Even for such a relatively well-studied global catastrophe as nuclear winter, there is still much we do not understand. For example, the work of Coupe et al., (2023) suggests that nuclear winter can paradoxically lead to a decrease in Antarctic sea ice despite global cooling. As our understanding of global catastrophic risks increases, we may see shifts in our expected effects on the food system.

- Trade is only a part of the global value chain, and if we look at the whole value chain, we can expect many more disruptions (Ibrahim et al., 2021).
- The modeling of Xia et al. (2022), which we use to calculate yield reductions during a nuclear war, assumes the usage of spring wheat. However, during an ASRS, wheat producers could switch to winter wheat, which is more resistant to cooler temperatures and frost and generally has slightly higher yields than spring wheat. Therefore, the wheat yields in this study are potentially underestimated.
- We only consider the global aspects of the catastrophes. However, there are a variety of plausible scenarios where regional effects could have global repercussions. For example, the food system has several so-called choke points (Bailey and Wellesley, 2017; Key et al., 2024; Wellesley et al., 2017), where much food trade is funnelled through a small geographic area. Some of these choke points are near volcanoes and could be severely affected by eruptions (Mani et al., 2021). Should these choke points close in the aftermath of a global catastrophe, the disruption of the food system would further increase.

4.3 Comparison to climate change

The model employed in this study was originally developed to study the effects of climate change on food trade (Hedlund et al., 2022). We can see that the impact of a rather severe climate change scenario based on RCP 8.5 has considerably lower effects than the catastrophes explored here and even results in an increase in imports for almost all countries (Figure S25). For all crops the trade communities stay mostly the same, while they would be much more disrupted in our scenarios. A similar pattern holds up for all crops considered. These differences are likely due to the different magnitudes of the catastrophes considered. For RCP 8.5, a land surface air mean temperature increase of around 5°C is expected by 2100 (Zhang et al., 2023a), while for a 37 Tg nuclear fall scenario, a land surface air mean temperature drop of up to 8 °C is predicted in the 3rd and 4th year after the nuclear war. (Xia et al., 2022). Therefore, the ASRS considered here not only has the larger temperature change, but also in a much shorter time period. Also, in the case of climate change, the countries that will be more affected are those closer to the equator (Frame et al., 2017). Since the main exporting countries are mostly at higher latitudes, they will be less affected by climate change, contributing to a more stable food trade in comparison to the scenarios we explored.

4.4 Gaining a deeper understanding of how global catastrophes impact the food system.

4.4.1 Research gaps

The research presented here is a first step in understanding what might happen to food trade after global catastrophes. However, there are still a wide range of factors we do not understand. With the introduction of terms like multiple-breadbasket failures, food system research has increased in scope (Clapp, 2023; Jahn, 2021; Nyström et al., 2019; Savary et al., 2020). Still, this kind of research does not consider events where all countries are affected simultaneously and on a scale not seen in modern history, leaving the effects of global catastrophic risks unexplored. This means that global food system research should also include global catastrophic risk in order to have all angles covered. Due to this general lack of focus on global catastrophes, we outline specific topics that warrant further attention:

- Understanding how global catastrophic risk might affect different parts of the global population by socio-demographic metrics. We know that climate impacts are felt differently depending on how rich the country is (Quante et al., 2024) and also increase wealth inequality (Méjean et al., 2024). Therefore, it is likely that these differences also exist as a consequence of global catastrophes.
- While there is little research on the effects of the dependency on very few food trading companies (Clapp, 2023), there is none when it comes to the question of how this might affect the outcomes of global catastrophic risk scenarios.

- There exists some research that acknowledges the potential cascading effects and systemic risk of an ASRS, like nuclear war, for instance, recent summaries by Green (2024) or Glomseth (2024), but for many of the events that could cause GCIL, we know only very little about the potential cascading effects. Beyond this, even sophisticated modeling efforts like Xia et al. (2022) have limitations - they did not account for several factors that could further impact agriculture after nuclear war, such as changes in irrigation water availability, increased surface ozone levels, ultraviolet light damage, effects on pollinators, and killing frost risk. For many of the events that could cause GCIL, we know even less about the potential cascading effects and systemic risks.
- We need more understanding of the effects of catastrophes like geomagnetic storms and how the loss of industrial inputs might affect agriculture. There is some global research on the direct effects (Cliver et al., 2022; Isobe et al., 2022; Rivers et al., 2024b) but less on the indirect effects, especially on agriculture (Moersdorf et al., 2024). There are some recent research studies which explore similar effects yet do not frame it in regards to global catastrophic risk but instead as a general disruption in the trade of industrial inputs for agriculture (Ahvo et al., 2023; Sandström et al., 2024).
- There is a good chance that catastrophes will not happen in isolation but interact with each other and existing vulnerabilities. An example is the possible interaction between nuclear winter and planetary boundaries (Jehn, 2023) or termination shock caused by civilization collapse (Baum et al., 2013). These are only two of the possible interactions, and many others are entirely unexplored (for example, having a major geomagnetic storm during a pandemic). .
- Our food system is not reliant on the food trade network alone but on a highly complex supply chain with many interacting goods and services (Ibrahim et al., 2021), also consisting of many non-food items. It would be valuable to understand how these might react to the scenarios described in this manuscript. There has been some work to study this for current conditions (Deteix et al., 2024), but not with a focus on global catastrophes.
- We do not know what might happen after the initial effects play out, as this paper only describes the minimal amount of change that is expected to happen due to the yield changes alone. However, if we look into history, we can see that such disruptions of trade networks can have massive consequences. If they unravel the whole network, countries lose access to many goods they need, leading to internal problems and possibly collapse, as happened in the Late Bronze Age (Linkov et al., 2024). Important insights could be gained here by applying insights from quantitative history to the last 100 years, as proposed by Hoyer et al. (2024). This could be built upon by using historical worst cases and using them as downward counterfactuals to create more realistic and comprehensive scenarios (Woo, 2019).

Furthermore, all those research topics that need further exploration and studies like ours should be regularly re-assessed. As the Russian invasion of Ukraine has shown, major disruptions in the food network can and are likely to happen again (Miller et al., 2024). They reshuffle existing trade connections, making research like this less accurate as time passes.

4.4.2 Decreasing vulnerability to global hazards

Since the global food system is vulnerable to major disruptions, it is of high priority to decrease these vulnerabilities. Myers et al. (2022) suggest a list of interventions that could decrease the vulnerability of agriculture to climate change. Some of these suggestions would also help here, like having more diverse crops to ensure flexibility with respect to climate conditions or strengthening international trade agreements to ensure that the flow of food is stable. This also ties in with the criticism of concentration in the food system by Clapp (2023). These concentrations on all levels of the food system increase the risks of collapse and need to be decreased, especially for the safety of people in net food importing countries (Yıldırım and Önen, 2024).

4.4.3 Increasing resilience after a global catastrophe

It is not only important to decrease the risk of a hazard spiralling into a catastrophe, but also to prepare if it happens despite precautions (Cotton-Barratt et al., 2020). The complex events following the described catastrophes would constitute major crises, but historical evidence suggests societies can withstand such a polycrisis by building resilient infrastructure, maintaining the ability to respond effectively at scale, and having high social cohesion (Hoyer et al., 2023). We should increase the overall resilience of the food system and see the resilience of our food supply chains not as something that aims to bring back a system to the status before the catastrophe but as a system that is able to persist, adapt and transform even under intense pressure (Wieland and Durach, 2021). This can be accomplished by a variety of strategies concerning infrastructure, politics and technology (Jagtap et al., 2024). One way is to incorporate contingency plans into our infrastructure. The Russian invasion of Ukraine has shown that it is very difficult to change your trading partners on short notice without a plan or infrastructure (Jagtap et al., 2022) in place and that countries usually rather try to strengthen existing trade connections instead of establishing new ones (Baum et al., 2024). If plans are drawn up that highlight what is needed for different scenarios, this could be taken into account when new infrastructure is built. Also, our food system is very dependent on large amounts of industrial inputs like fertilisers or water use. This has been identified as one the main problems in agriculture right now (Foley et al., 2011). If we could reduce the need for inputs now, this would both increase sustainability, but also make it easier to cope after catastrophe when fewer inputs are available. Another important avenue is to ensure there is a variety of resilient foods that could be scaled up massively if other parts of the food system fail. Examples for ASRSs include seaweed (Jehn et al., 2024), protein from natural gas (García Martínez et al., 2022) hydrogen (García Martínez et al., 2021), sugar from fibre (Throup et al., 2022), and greenhouses (Alvarado et al., 2020). The crops we use are also adapted to current climate conditions and show very little diversity (Clapp, 2023). This low diversity in crops has recently also been highlighted as an inhibiting factor in maintaining crop production during ASRS (McLaughlin et al., 2024). Finally, establishing political agreements (for example trade agreements that also consider global catastrophes) before catastrophes could reduce the need to negotiate in the aftermath of a global catastrophe. For example, Wellesley et al. (2017) discuss this in the context of choke points that critical food corridors could be agreed upon in collaboration with the United Nations and the World Food Programme to offer alternative routes should the choke points become blocked.

5 Conclusion

Our research highlights the substantial impact of global catastrophic risks on the food system, both directly through yield reductions and indirectly via trade disruptions. Among the scenarios we studied, abrupt sunlight reduction scenarios disrupt trade communities more than global catastrophic infrastructure loss due to their uneven spatial distribution, particularly affecting higher-latitude countries that are key food exporters. Our analysis focuses solely on yield reduction effects and does not consider second-order economic effects and political events. Even so, the impacts are already substantial. If second-order effects would be taken into account, it is plausible that GCIL could lead to a larger disruption, as it directly impacts the industrial base that is needed to cope with catastrophes.

The results show that in both kinds of scenarios, the food system would be massively disrupted, underscoring the urgent need for better preparation. The food system's reliance on a few major exporters, especially the United States, amplifies its vulnerability. This concentration means that any yield reduction or removal of these countries from the trade network results in major disruptions. We suggest diversifying crop production, securing trade agreements, and developing resilient food sources that can be rapidly scaled in crisis scenarios.

We need both preventive and adaptive strategies to safeguard the global food system. Future research should continue to explore these dynamics, incorporating broader aspects of the food supply chain and potential cascading effects. Such efforts are crucial, especially in light of recent global disruptions like COVID-19 and the Russian invasion of Ukraine, which have highlighted the food system's vulnerabilities. Successfully navigating global catastrophes requires understanding and preparation, necessitating both research efforts and policy interventions.

Author contributions

Conceptualization: FUJ, JH
Data curation: FUJ, LGG
Formal analysis: FUJ, LGG
Funding acquisition: DD
Investigation: FUJ, LGG
Methodology: FUJ, LGG
Project administration: FUJ
Software: FUJ, LGG
Supervision: FUJ
Validation: FUJ, LGG, CWA
Visualization: FUJ, LGG
Writing-original draft: FUJ
Writing-review & editing: FUJ, LGG, JH, CWA, LX, NW, DD

Data and code availability

The most recent data can be directly downloaded from the Food and Agriculture Organization:

1) Trade: http://www.fao.org/faostat/en/#data/TM
2) Production: http://www.fao.org/faostat/en/#data/QC

The model code (with additional documentation) can be found at: https://github.com/allfed/pytradeshifts (Jehn and Gajewski, 2024).

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Competing interest

The authors declare no competing interest.

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Supplemental information for

“Food trade disruption after global catastrophes”

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1 Additional features of the model

During development of the model additional features were implemented to study the changes of the trade communities in more detail. For the main text we used the most intuitive measures. However, the additional features can be used to explore the disruptions in more detail. Below, we provide an overview of select features we believe could aid other researchers using the model outlined in this study. For a comprehensive understanding of the model's capabilities, see the repository: https://github.com/allfed/pytradeshifts (Jehn and Gajewski, 2024).

1.1 Measuring changes in the trade flows

1.1.1 Frobenius measure

The Frobenius measure computes the distance between graphs G1 and G2 as the distance between their adjacency matrices:

$$r(G1,\ G2) = \sqrt{\sum_{ij}\left(a_{ij}^{\ G1} - a_{ij}^{\ G2}\right)^2} \qquad (1)$$

Where a_{ij}^{G} represents the element i,j of an adjacency matrix of a graph G (Shvydun, 2023). In the context of the food trade system the Frobenius measure represents how much the network has changed between the compared scenarios/graphs.

1.2 Measuring the status of the network before and after disturbance

1.2.1 Community satisfaction

The sum of imports to a country from within its community divided by the sum of all imports to said country. This allows us to identify how much of a country's food demand is met by their current trade community (Ji et al., 2014; Wang et al., 2023).

1.2.2 Node stability

Node stability is a measure of how easily each country can replace their import partners, based on their political stability, trade volume and geographical distance. For this index, we gather data from The World Bank's governance indicator and calculate the mean of all distinct indicator values. Given that the values typically fall within the range of [-2.5, 2.5], we standardise the data to ensure the outcome lies within the range [0, 1] (Ji et al., 2014; Wang et al., 2023). Node stability S of node j is given by:

$$S(j) = \sum_{i} P_i d_i^{out} r_{ij}^{-1} \qquad (2)$$

where the sum is over all other nodes (countries). P_i is the stability index of country i. The variable d_i^{out} denotes the normalised out-degree centrality, indicating the proportion of total exports attributed to country i. Additionally, r_{ij} signifies the distance between countries i and j. A larger value signifies a higher capacity to ensure consistent trade.

1.2.3 Network stability

Stemming from node stability it is:

$$\sum_{j} d_j^{in} S(j) \qquad (3)$$

Where S(j) is the stability of node j, and dj^{in} is the (normalised) in-degree of node j representing the fraction of all imports that the country j is responsible for. This therefore represents the weighted stability of all nodes in the network and thus the overall stability of the network.

1.2.4 Betweenness

The betweenness centrality of a node is determined by adding up the proportion of all possible shortest paths that go through that particular node. When calculating the overall betweenness for the entire graph, it involves taking the average across all nodes. As a trade graph falls under the category of flow graphs, when calculating the shortest paths, we treat the edge weights as the inverses of trade volumes.

1.2.5 Clustering

The clustering coefficient of a node gauges the proximity of its neighbours to forming a clique, or complete graph. In the context of directed and weighted graphs, clustering is determined by the geometric average of the edge weights within the (directed) subgraph (Fagiolo, 2007). To assess the overall graph clustering, we calculate the average clustering coefficient across all nodes.

1.3 Simulating the more difficult trading conditions after catastrophe

The model is now also capable of simulating the challenges of long distance trade after global catastrophes. To represent this we used a gravity based model of trade, which scales the exports downward with increasing distance. The gravity model of trade is an empirical model in economics, in which, similar to Newtonian gravity, trade between countries is attracted by their economic size (like mass) and hampered by distance (like dispersion of the field). In short, bigger economies trade more, and distance makes trade more expensive (Karpiarz et al., 2014). It relates trade volume, T_{ij} , between two countries, i and j, to the product of their GDP's, i.e. Q_iQ_j , and to the geographic distance (country centroid to country centroid in km), r_{ij} , between them. The simplest form of the gravity equation for the bilateral trade volume is (Karpiarz et al., 2014):

$$T_{ij} = G \frac{Q_i Q_j}{r_{ij}^{a}} \qquad (4)$$

Where a is the distance coefficient obtained from data and G is a constant scaling parameter. To simulate more/less difficult trading conditions we can modify the trade volumes by changing the coefficient a such that it is larger/smaller. Thus, in our model we multiply the trade matrix by r_{ij}^{-b}, changing (1) into

$$T_{ij} = G \frac{Q_i Q_j}{r_{ij}^{a+b}} \qquad (5)$$

Where b is our control parameter. When b > 0 the trade volume is decreased with distance, when b=0 nothing changes, and b < 0 trading becomes easier. For both global catastrophic infrastructure loss and abrupt sunlight reduction scenarios we explored a variety of values for b, based on the historical range (see repository for calculation of past values).

2 Additional information for the methodology

2.1 Choice of community detection algorithm

We acknowledge that the Louvain algorithm, being a modularity-based method, may not be the most accurate approach (Fortunato and Hric, 2016); however, due to its prevalence in previous studies and simplicity of operation, we find it to be the most adequate choice. This choice is further justified because we do not need to consider ourselves with the "ground truth" labelling of community memberships since we are interested in changes in the community structure. That said, the model implementation allows the use of more advanced approaches like the Leiden algorithm (Traag et al., 2019) or Infomap algorithm (Rosvall et al., 2009).

2.2 Explanation of re-export algorithm

Should we use the trading data directly for inferring the trade network structure, in some instances, the calculated domestic supply of domestically produced goods would turn out negative which is, of course, erroneous (Croft et al., 2018). This error happens because the trade data do not differentiate if something was genuinely produced in a country or just passed through it (re-exported). The re-export algorithm aims to work around this by estimating the actual trade amounts. Therefore, yield reductions due to the scenarios can be directly applied to the trade flows in the model. For example, if the yield of the United States drops by 30 %, all outgoing trade flows from the US would reduce by 30 % as well. In global catastrophes, states would likely decrease their exports further to protect their own population. However, this model tries to estimate the changes implied by the yield reduction alone to isolate this effect and does not consider additional policies that might change exports.

2.3 Network resilience

After a global catastrophe, it seems likely that further instability will follow. This could result in the complete removal of countries from the network (e.g. by destruction through war or import/export restrictions and bans). To simulate such events, we assessed how resilient the network is against random and structured removal of nodes by using the methodology from Restrepo et al. (2008).

The objective is to anticipate when the network crosses the percolation threshold, which means the point where it loses the majority of its connectedness. Our approach involves constructing an attack vector W, where $W_i = 1$ signifies the removal of node i, and 0 denotes its retention. Subsequently, we compute a matrix, $F = R(1-W)$, where R represents the adjacency matrix of the graph. The indicator for network percolation is the largest eigenvalue of matrix F. If it surpasses 1, the network percolates; if it falls below 1, the network collapses, leading to the disappearance of the giant connected component (Newman, 2018).

We consider two attack strategies:

- Export-Weighted: We remove nodes in order highest to lowest by their out-degree (fraction of total export)
- Random: We remove nodes at random and average the results over several realisations.

Initially, we also considered more advanced attack strategies, such as entropic degree used in power transmission grid vulnerability assessments (Bompard et al., 2009), but preliminary results showed them to not be much more effective than the simple “highest export first” approach. We thus opted not to include them here, for the sake of methodological simplicity without losing generality of our results.

3 Supplementary data and plots for wheat analysis

3.1 Shifts in trade communities after excluding different percentiles

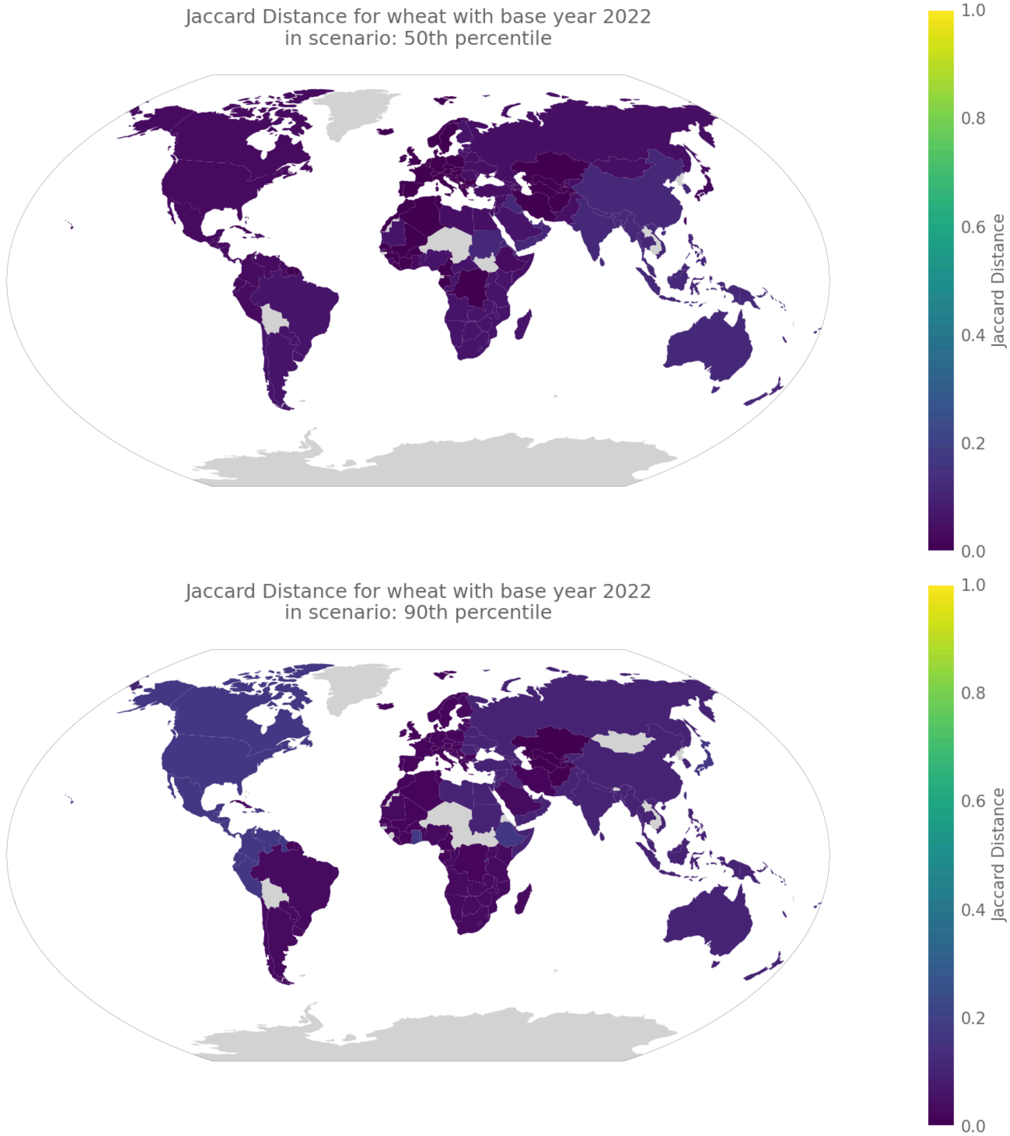


Figure S1: Changes in wheat trade communities after excluding the 50th percentile or 90th percentiles of trade flows, in comparison to the communities in 2022. Colours indicate the magnitude of change as the Jaccard distance. Yellow means the trade community of a country has changed completely, and dark blue that the country remains in the same trade community. Again, we see that changes in trade communities are much more pronounced in the ASRS.

3.2 Shift in community roles in larger nuclear exchanges

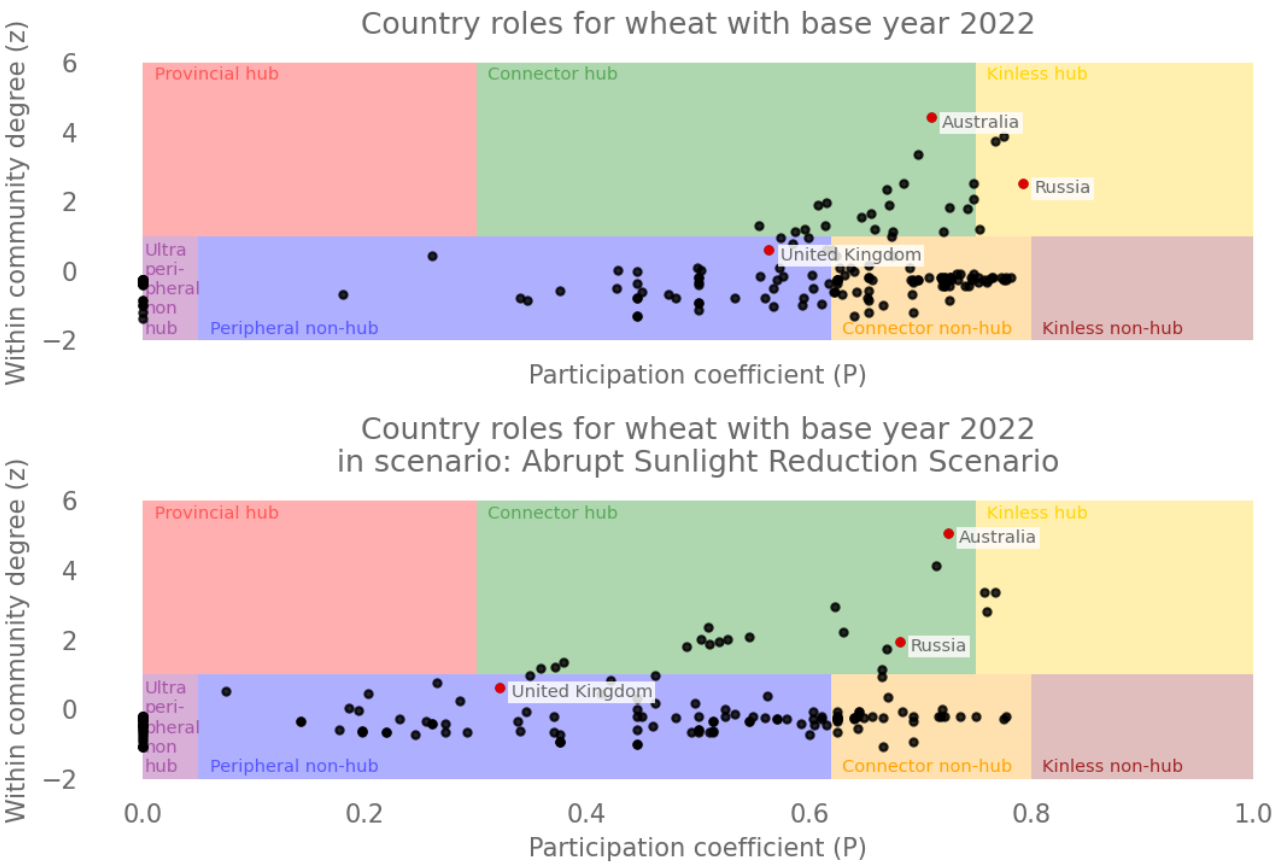
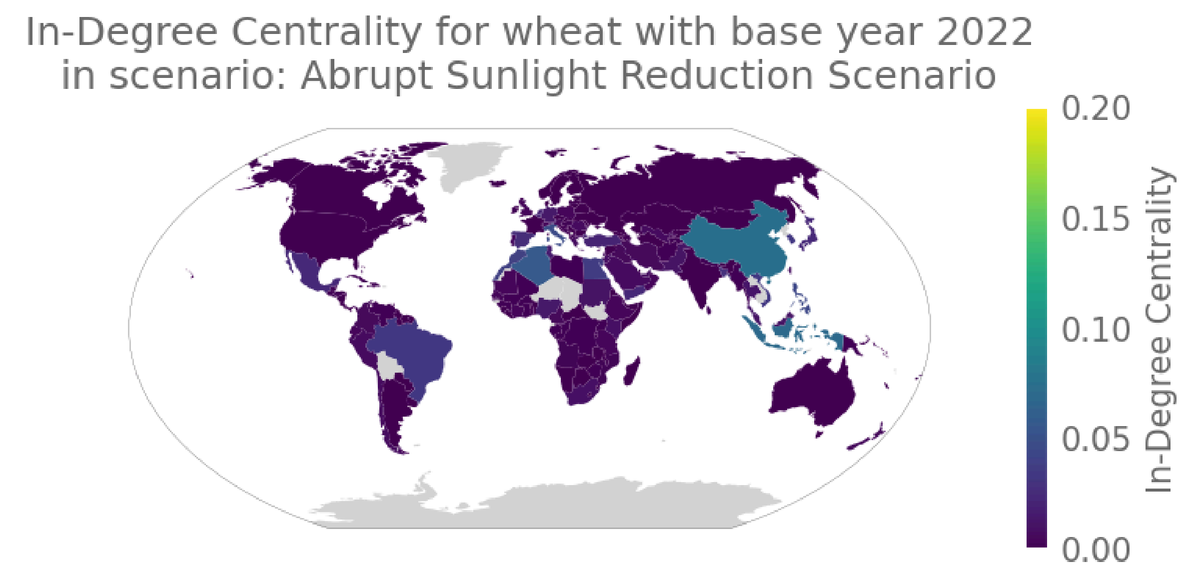


Figure S2: Community role shifts for the wheat trading community after a nuclear war emitting 47 Tg of soot; based on within community degree and participant coefficient (see Section 2.4.1).

3.3 Centrality



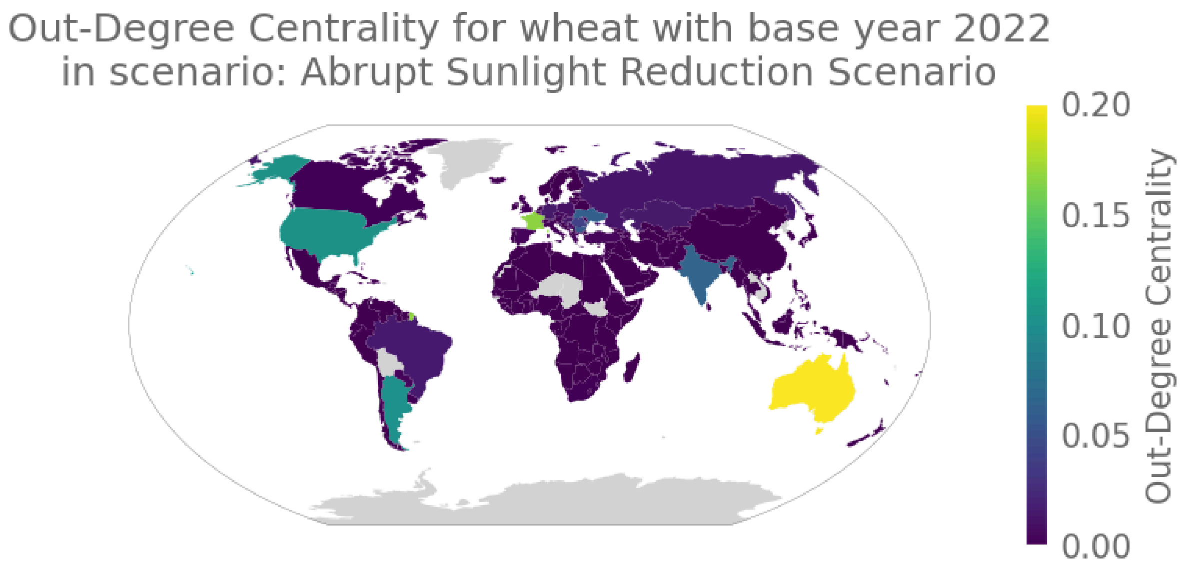


Figure S3: In and out centrality for the abrupt sunlight reduction scenario.

3.4 Absolute wheat import changes

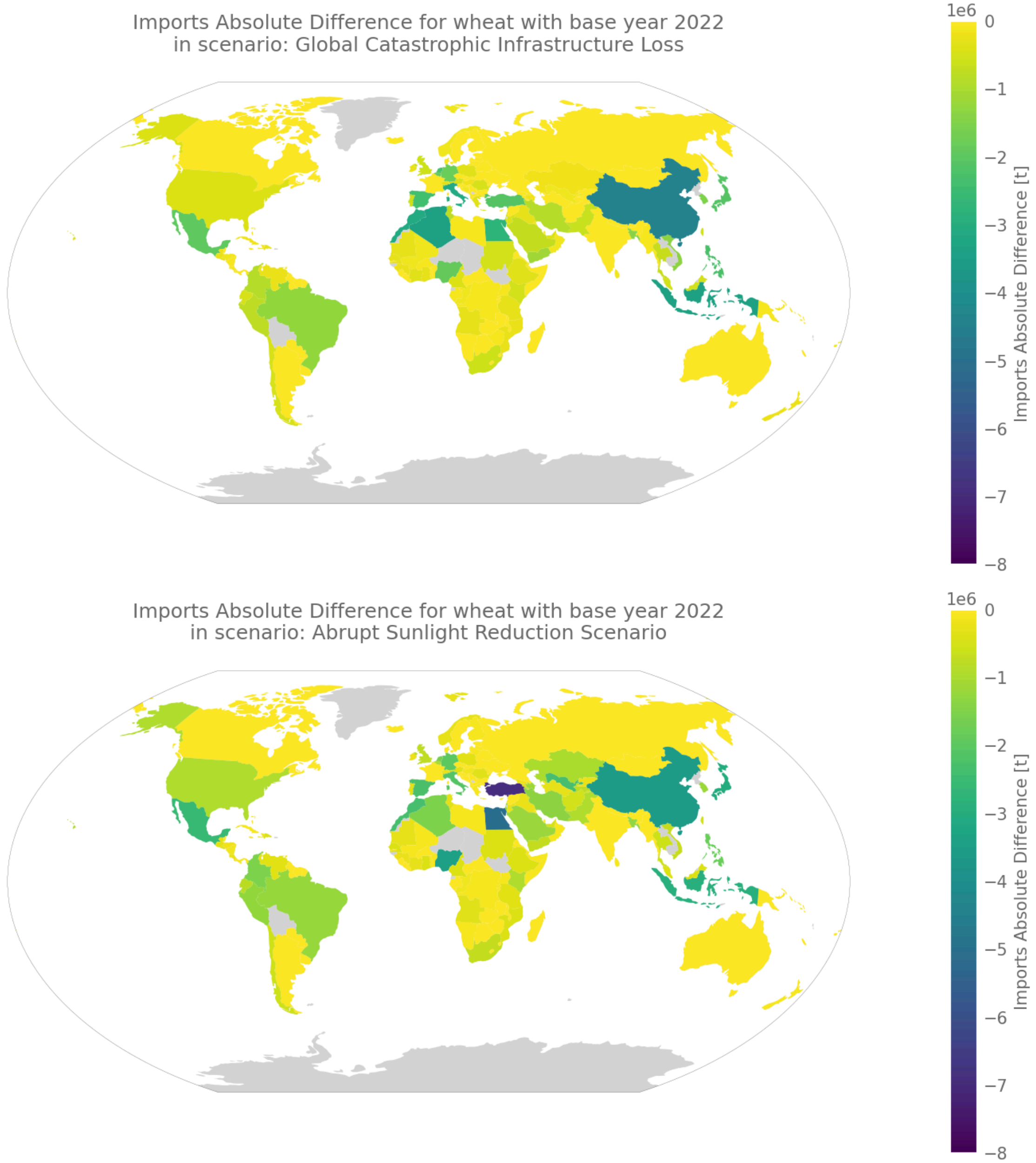


Figure S4: Absolute changes in wheat imports for ASRS and GCIL (in tonnes per year).

3.5 Remaining wheat production after catastrophe

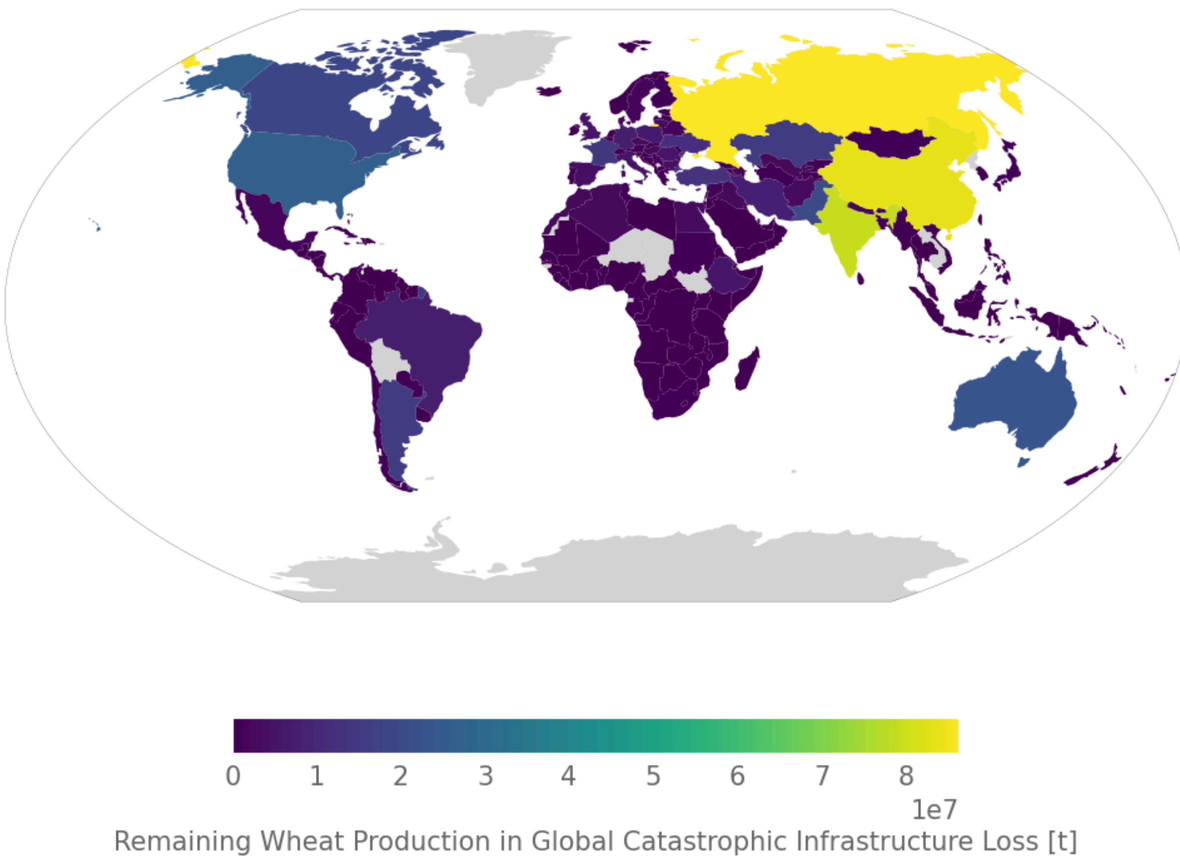


Figure S5: Remaining wheat production after global catastrophic infrastructure loss (in tonnes per year).

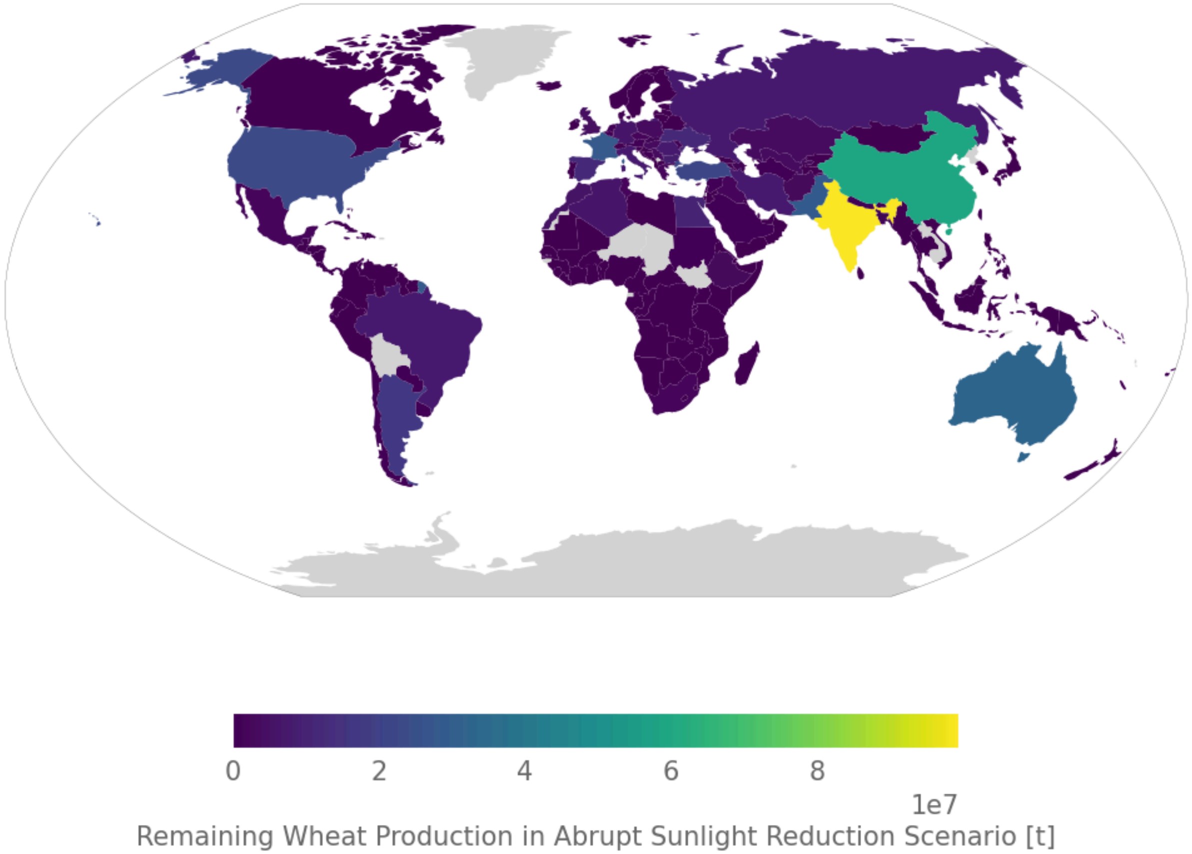


Figure S6: Remaining wheat production in an abrupt sunlight reduction scenario (in tonnes per year).

3.6 Node stability and community satisfaction for wheat

3.6.1 Changes in community satisfaction

Community satisfaction indicates the fraction of a country's imports that come from within its (detected) trade community. During global catastrophic infrastructure loss, overall satisfaction remains relatively stable across countries due to similar global yield reductions (Figure S2). Consequently, nations cannot increasingly depend on external trade partners, as these partners also experience reduced export capacity.

During abrupt sunlight reduction scenarios, the impact is more pronounced (Figure S2). The United States and Somalia are severely affected. The United States, a major food exporter, typically sources wheat from Canada. However, Canada's export capability is significantly hindered in these scenarios, leaving the U.S. reliant on non-community imports. Similarly, Somalia, which imports most of its wheat from Ukraine, faces challenges as Ukraine's exports decline sharply. This trend is observed to a lesser degree in other regions like North America and Central Asia as well.

Surprisingly, we also have some countries which have an improved community satisfaction after abrupt sunlight reduction scenarios (e.g. Belarus). This is caused by the large extension of the trade community with Russia as its centre. This results in many countries having the majority of their trade partners suddenly in their trade community, which increases the satisfaction.

Notes that these numbers are scaled by the overall imports and not the actual amount of food that a country needs. If this was the measure, the values would also be worse for global catastrophic infrastructure loss, but likely still very uniformly worse globally. There also would not be any positive changes in abrupt sunlight reduction scenarios.

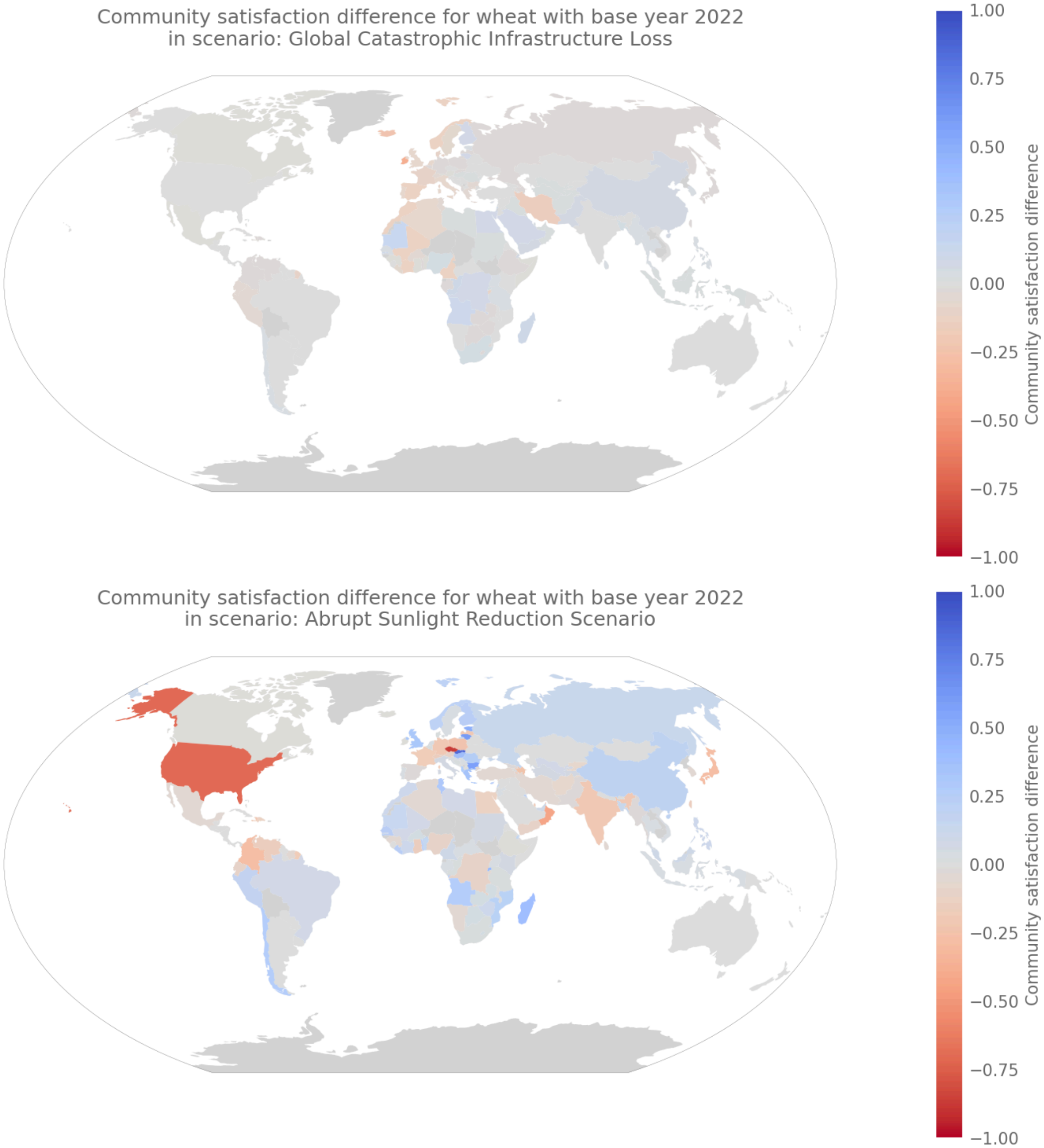


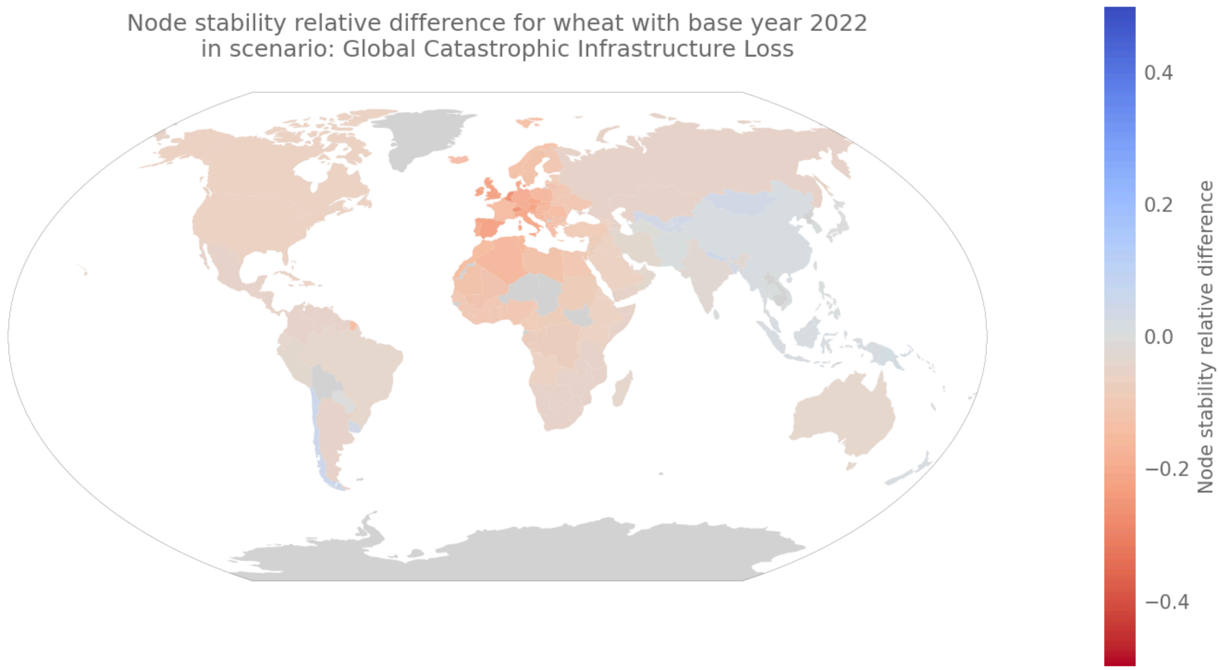
Figure S7: Differences (alternative scenario minus base scenario) in community satisfaction in comparison to the 2022 wheat trade network for global catastrophic infrastructure loss and abrupt sunlight reduction scenarios. Community satisfaction has a range of 1 (all needs satisfied from within the community) to 0 (no needs satisfied from within the community). Therefore, a value of 1 for the relative change would be a country whose needs were not satisfied from their community before, but all needs are satisfied in the alternative scenario. Grey indicates no change in community satisfaction, blue increased community satisfaction and red decreased community satisfaction.

3.6.2 Changes in node stability

Node stability is a measure of how easily a country can replace its trade partners, based on proximity, trade volume and political stability. The values show that for global catastrophic infrastructure loss the node stability is relatively unchanged in comparison to the situation in 2022 (Figure 5). Only Central Europe and North Africa have clearly negative values, meaning that those countries will have more difficulties replacing their trade partners. The most severely affected countries are Belgium, the Netherlands and Austria. A few countries also have slightly positive values. These are mostly concentrated in South-East Asia and the neighbouring countries of Argentina (Chile, Paraguay and Uruguay). These positive values are shaped by the proximity to Australia and Argentina, both major wheat exporters, which also do not use as much inputs like European countries and are therefore less affected by global catastrophic infrastructure loss.

We can see considerably larger changes of the node stability for abrupt sunlight reduction scenarios, but the overall trend is similar (Figure 5). Central an Northern European countries have difficulties replacing their trade partners, as all countries around them have considerably lower yields as well. In this scenario the same is true for the United States, which does not have any close countries which could replace the loss of imports from Canada. In addition, Australia has a much decreased node stability here, as it has no countries it could replace its import losses with. However, the countries close to Australia can replace their import losses from elsewhere by importing from Australia. To a lesser extent this is also true for Argentina and its neighbouring countries.

The results show that most countries globally will have difficulties in finding new trading partners, with the exception of the countries who are close to Australia and Argentina, as those countries are less affected by global catastrophes due to their lower use of inputs like fertilisers and their more stable climate.



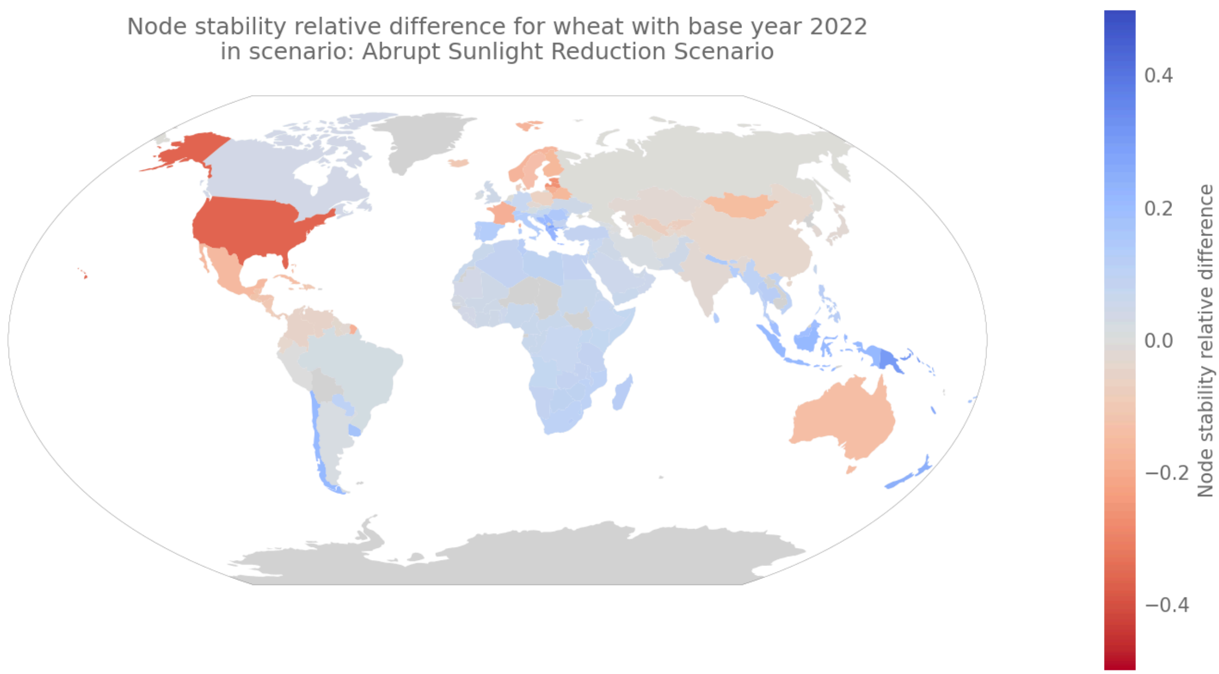


Figure S8: Relative changes in node stability in comparison to the 2022 wheat trade network for global catastrophic infrastructure loss and abrupt sunlight reduction scenarios. Relative change was used to make the values more easily comparable between scenarios. A value > 0 here means that the stability has increased (blue), while a value < 0 means that the stability has decreased (red). Grey indicates no change.

3.7 Vulnerability against loss of nodes

The scenarios vary in how vulnerable the network is to node removal, but the distinctions are minor (Figure S4). The GCIL network (shown in orange lines) behaves similarly to the current network (grey lines). In the ASRS (yellow lines), initial stability is lower compared to the others and reaches the collapse threshold slightly sooner, although not by much, implying that the yield reduction changes the trade communities, but the underlying structure of the network stays very similar. All three networks collapse much faster when the most exporting nations are removed first.

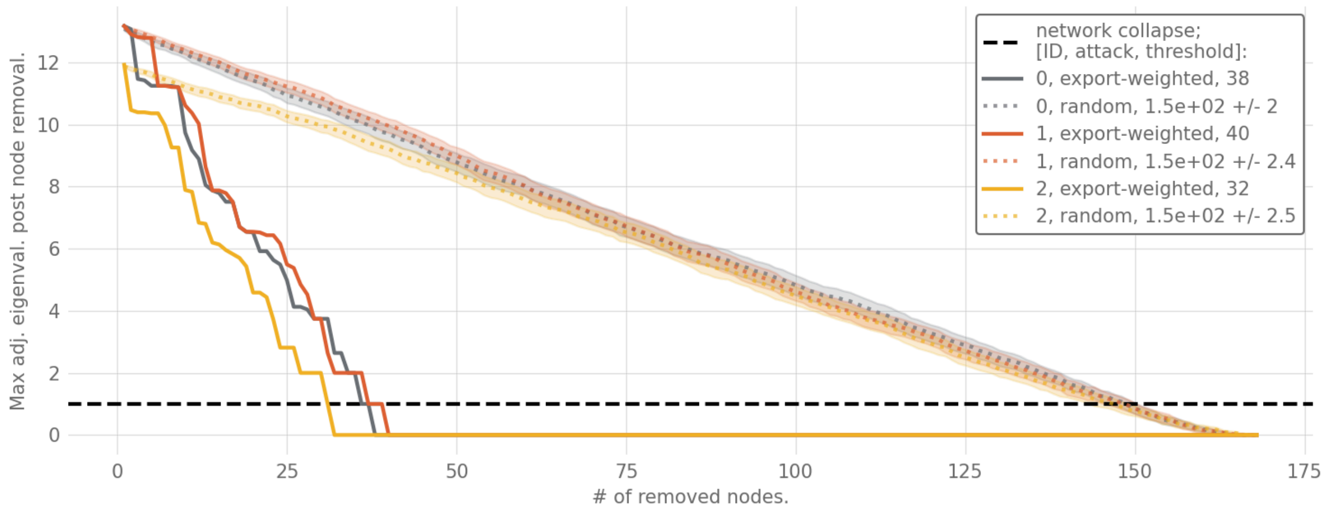


Figure S9: Vulnerability of the different scenarios for wheat to the removal of nodes. ID 0 = wheat trade today, ID 1 = global catastrophic infrastructure loss, ID 2 = abrupt sunlight reduction scenario. Dotted line marks the collapse threshold of the network.

4 Supplementary data and plots for rice, maize and soya beans

4.1 Rice

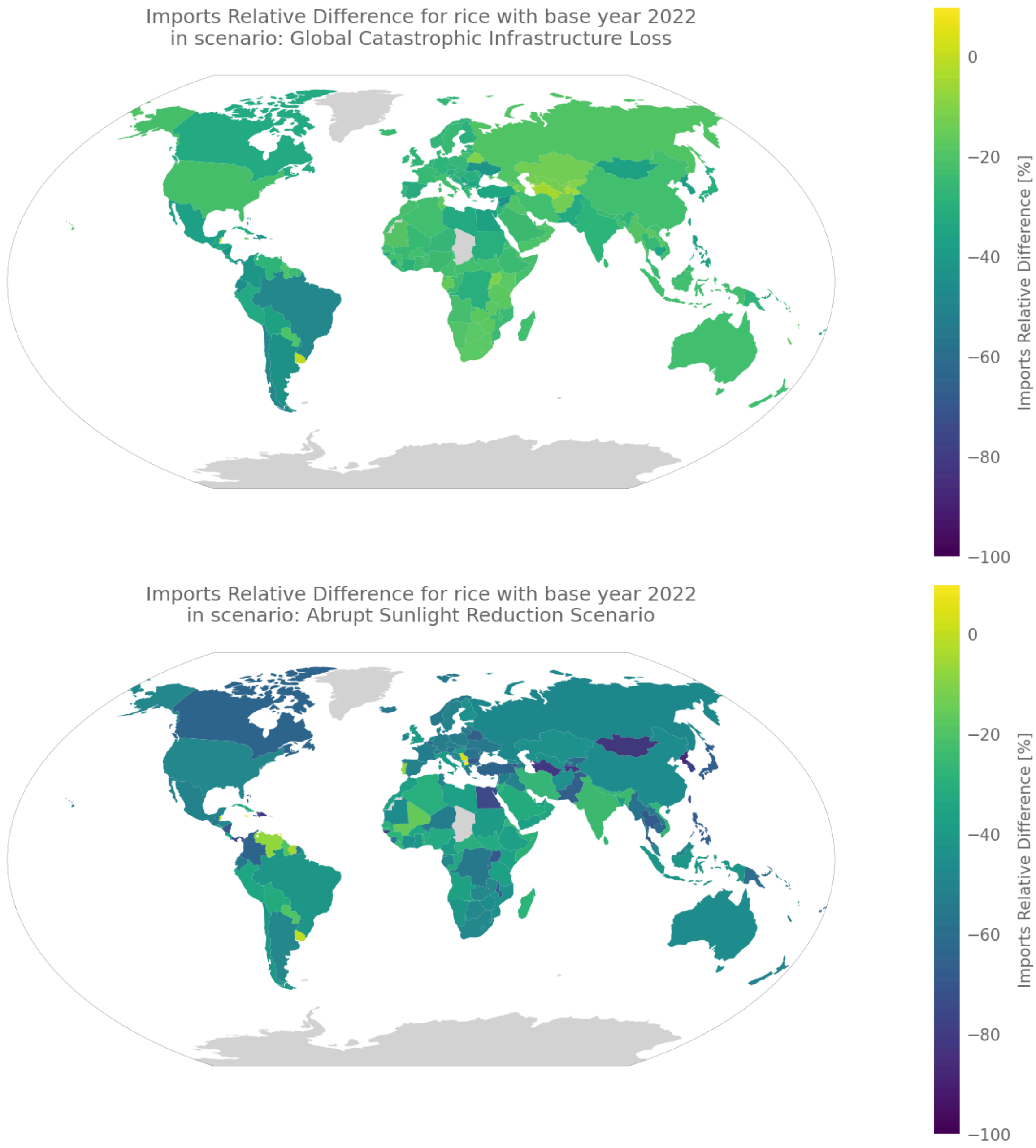


Figure S10: Relative changes in rice imports after global catastrophic infrastructure loss and abrupt sunlight reduction scenarios in comparison to today.

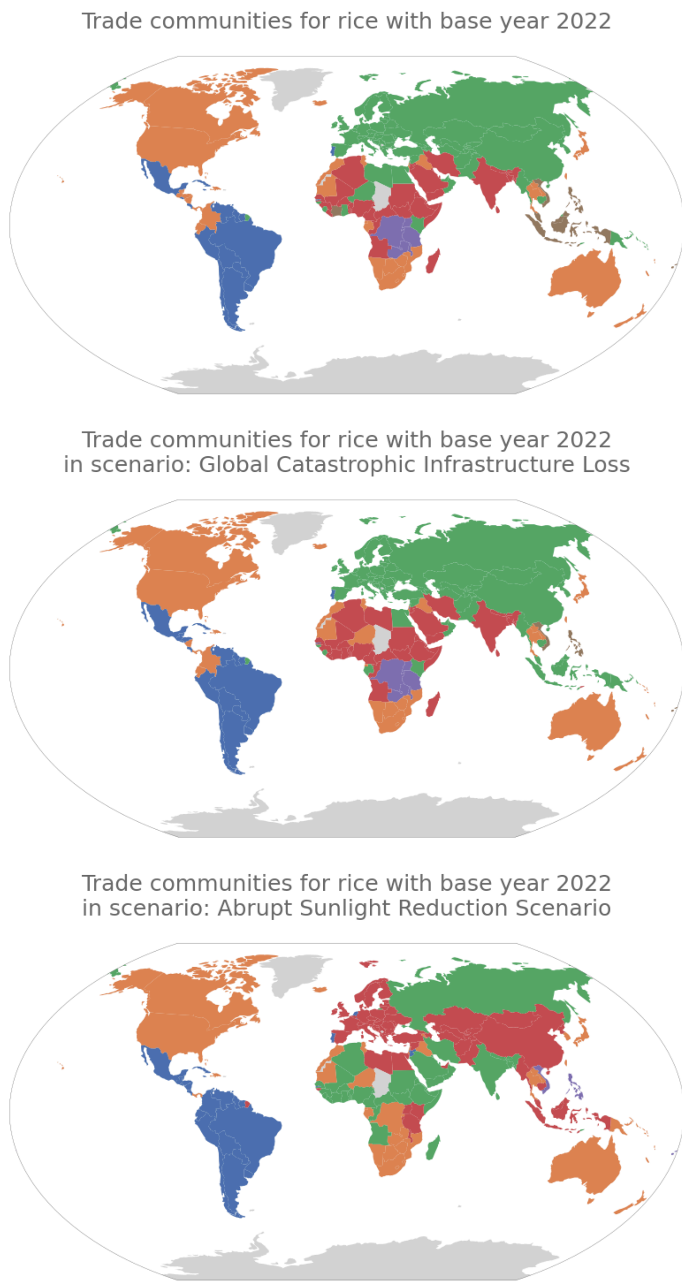


Figure S11: Trade communities for rice in 2022 and after yield reduction due to global catastrophic infrastructure loss as well as abrupt sunlight reduction. The colours show which countries belong in which trade communities.

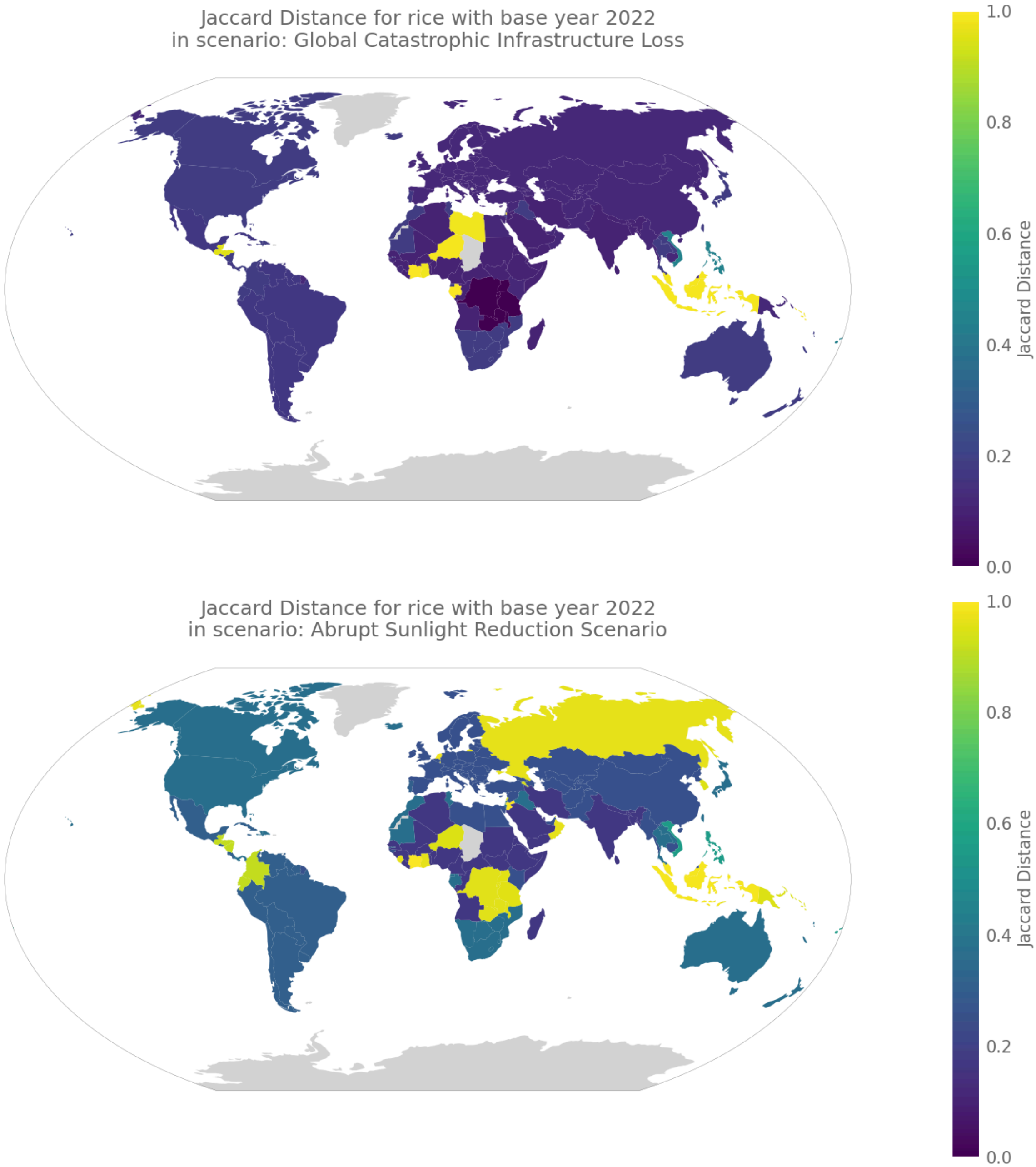


Figure S12: Changes in rice trade communities are plotted in comparison to the communities in 2022 after yield reduction due to global catastrophic infrastructure loss as well as abrupt sunlight reduction. Colours indicate how much the trade community of a country has changed. Yellow means the trade community of a country has changed completely, and dark blue means the trade community has not changed.

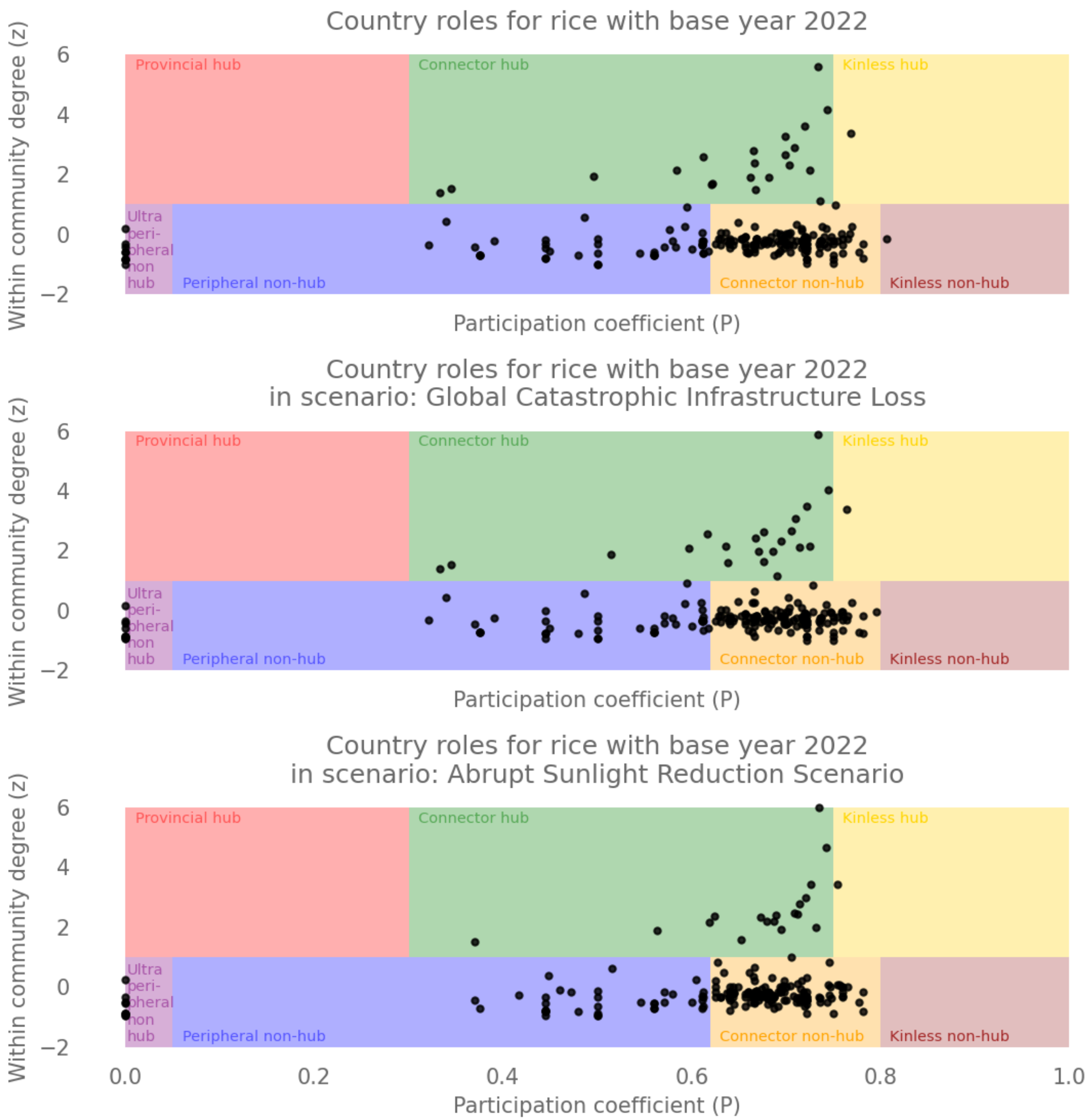


Figure S13: Distribution of country roles in the global rice trade network in 2022 and after yield reduction due to global catastrophic infrastructure loss as well as abrupt sunlight reduction based on within community degree and participant coefficient (see 2.4.1 in main manuscript).

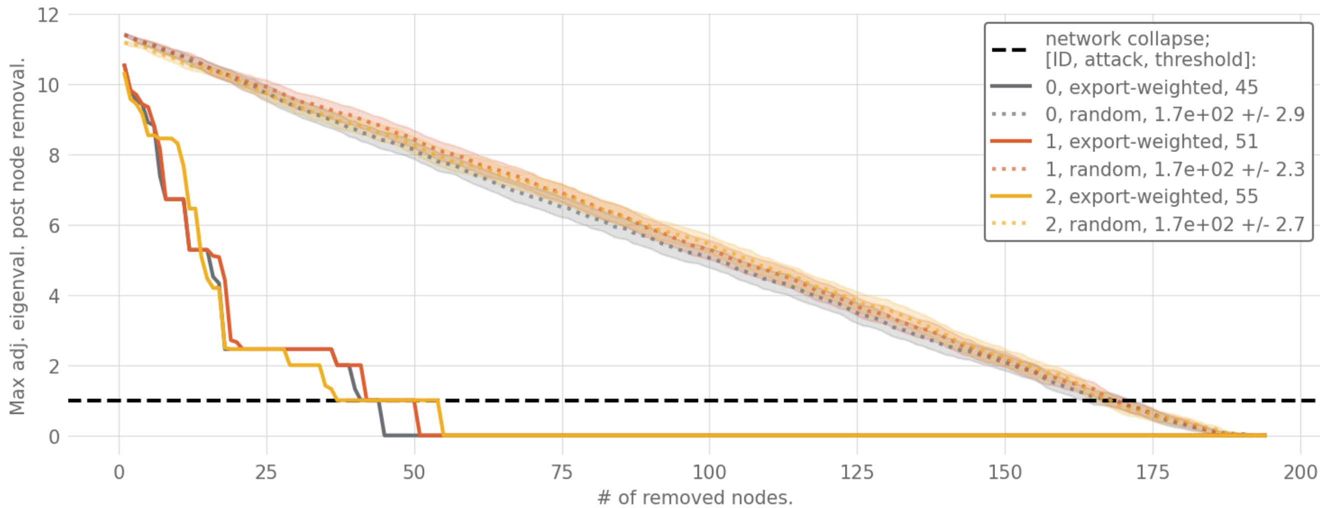
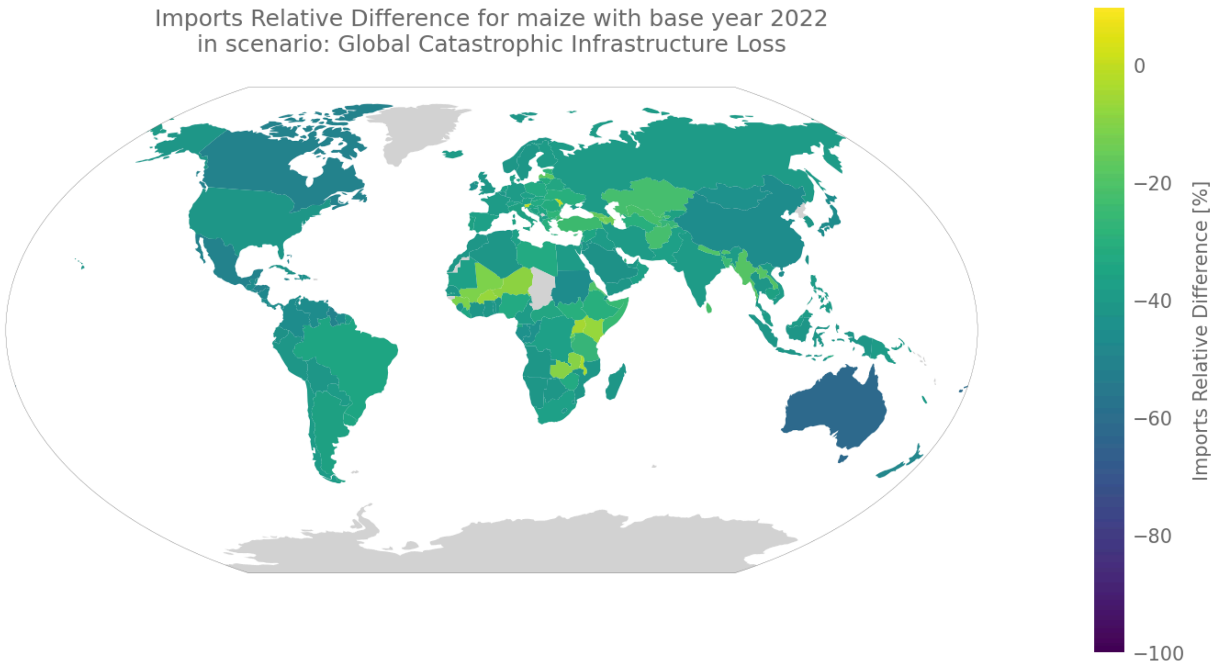


Figure S14: Vulnerability of the different scenarios for rice to the removal of nodes. ID 0 = rice trade today, ID 1 = global catastrophic infrastructure loss, ID 2 = abrupt sunlight reduction scenario. Dotted line marks the collapse threshold of the network.

4.2 Maize



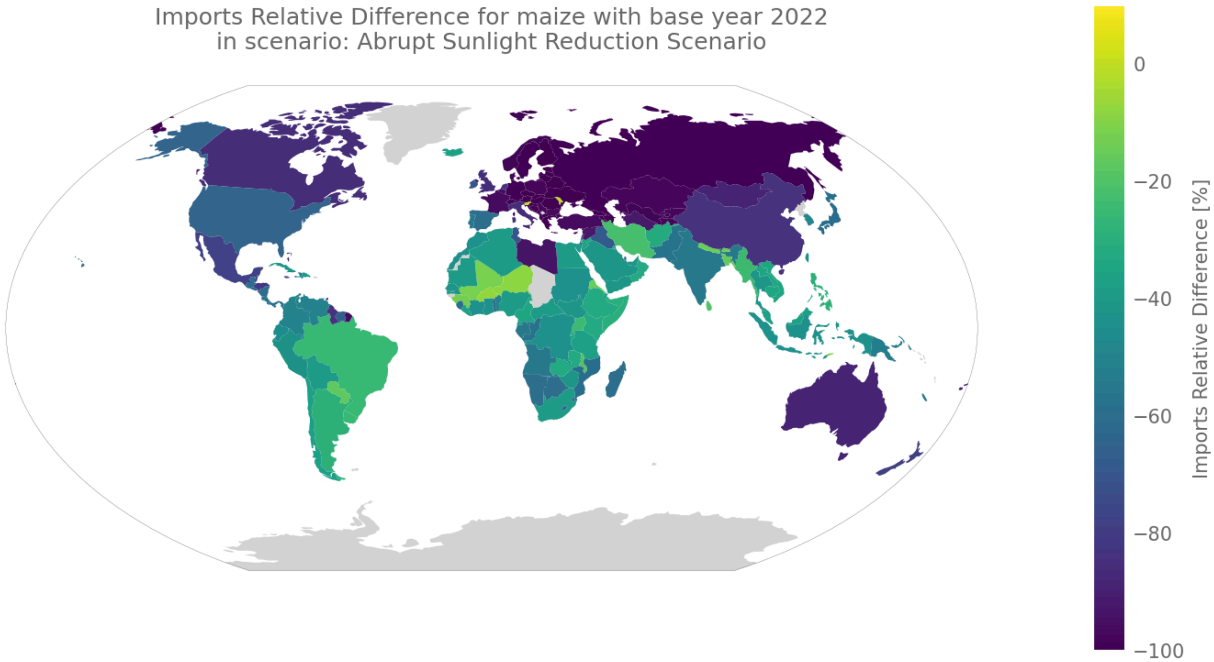


Figure S15: Relative changes in maize imports after global catastrophic infrastructure loss and abrupt sunlight reduction scenarios in comparison to today.

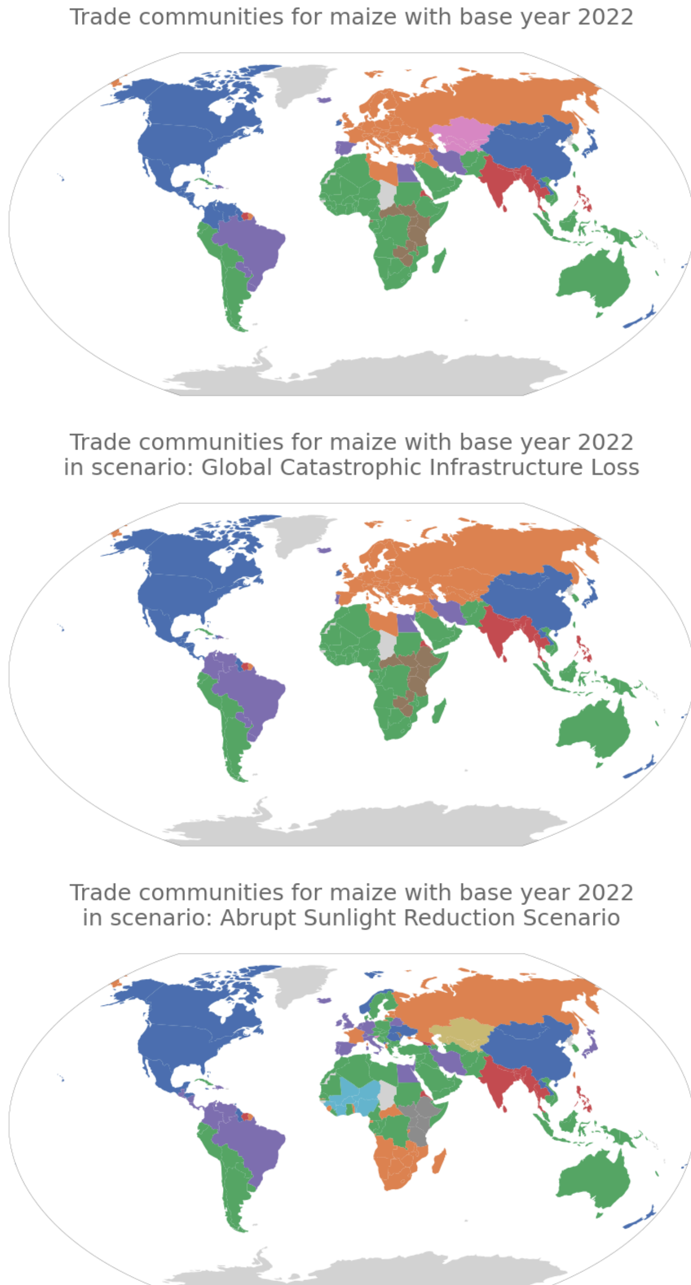


Figure S16: Trade communities for maize in 2022 and after yield reduction due to global catastrophic infrastructure loss as well as abrupt sunlight reduction. The colours show which countries belong in which trade communities.

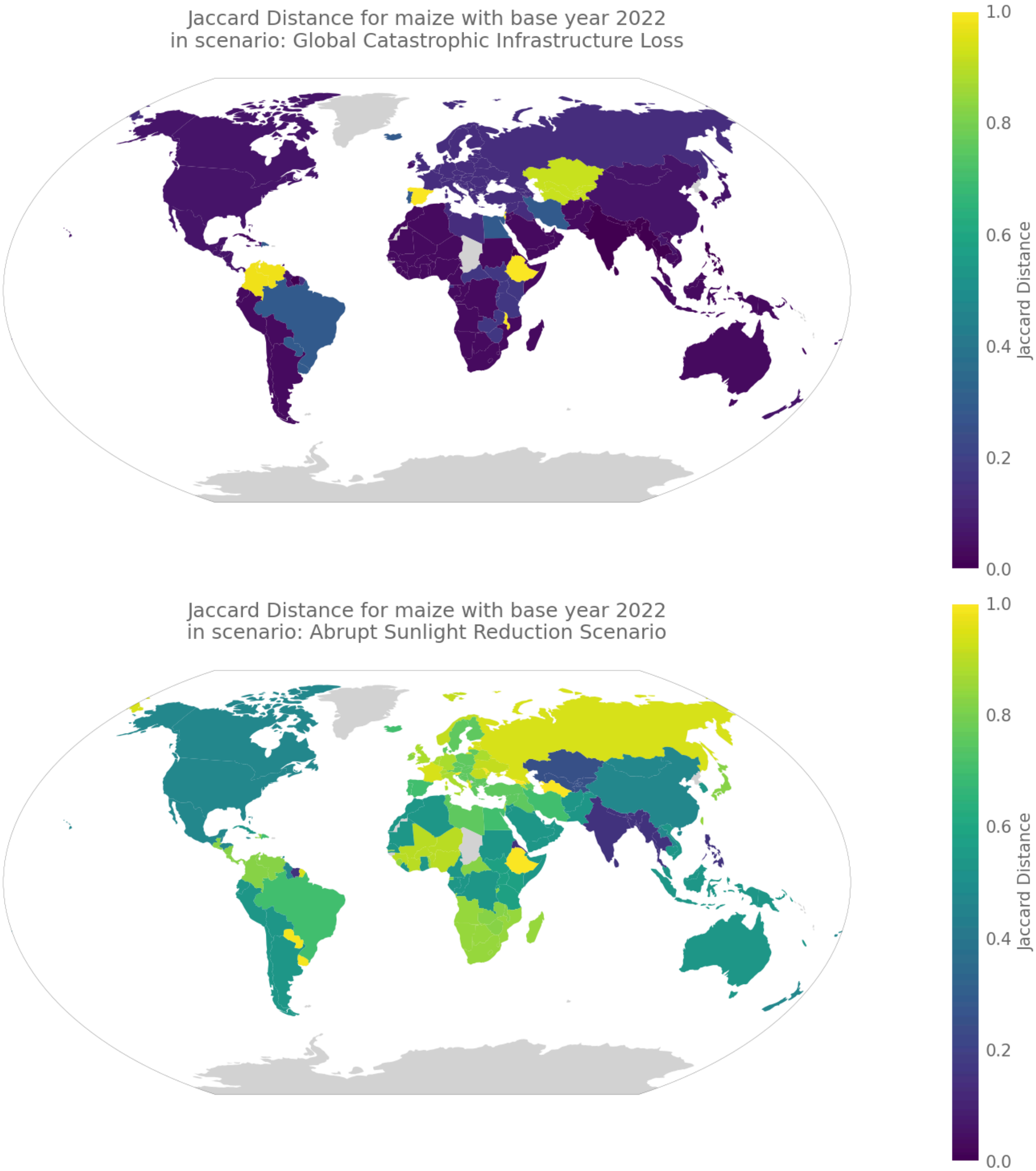


Figure S17: Changes in maize trade communities in comparison to the communities in 2022 after yield reduction due to global catastrophic infrastructure loss as well as abrupt sunlight reduction. Colours indicate how much the trade community of a country has changed. Yellow meaning the trade community of a country has changed completely, dark blue meaning the trade community has not changed.

Figure S18: Distribution of country roles in the global maize trade network in 2022 and after yield reduction due to global catastrophic infrastructure loss as well as abrupt sunlight reduction based on within community degree and participant coefficient (see 2.4.1 in main manuscript).

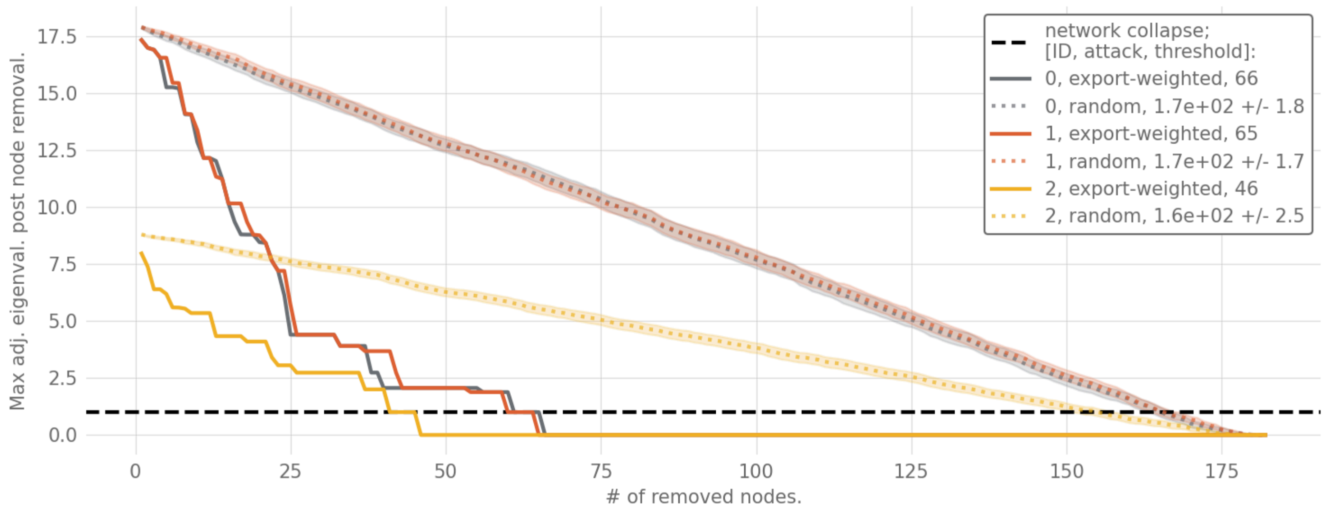


Figure S19: Vulnerability of the different scenarios for rice to the removal of nodes. ID 0 = maize trade today, ID 1 = global catastrophic infrastructure loss, ID 2 = abrupt sunlight reduction scenario. Dotted line marks the collapse threshold of the network.

4.3 Soya beans

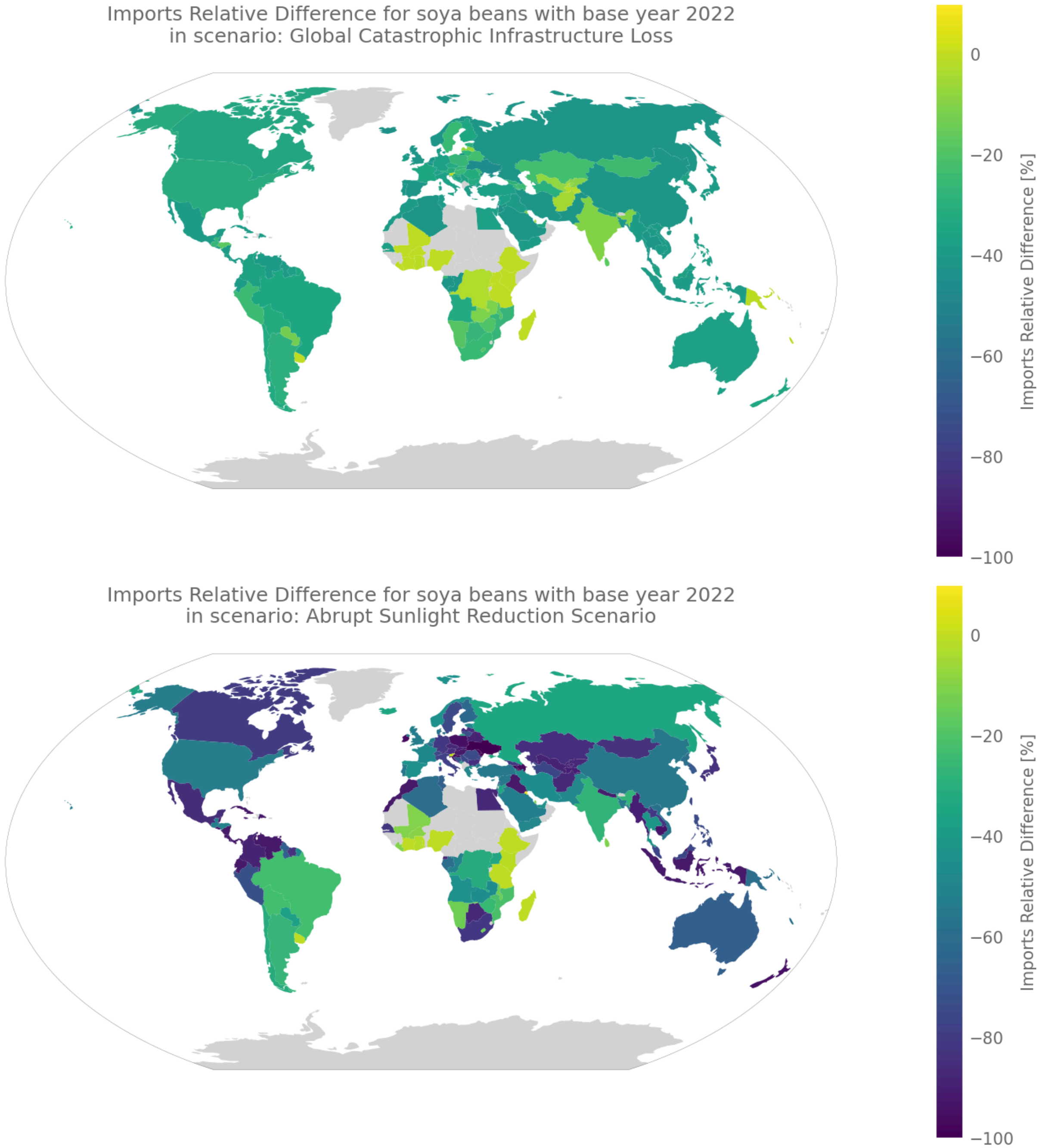


Figure S20: Relative changes in soya beans imports after global catastrophic infrastructure loss and abrupt sunlight reduction scenarios in comparison to today.

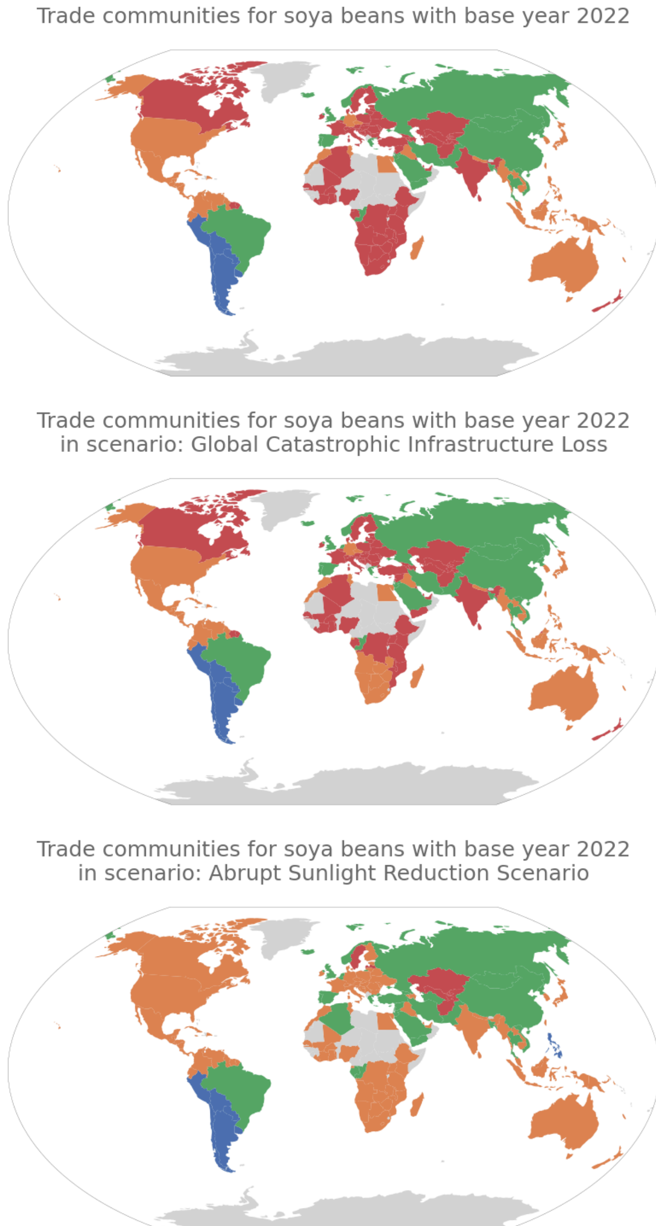
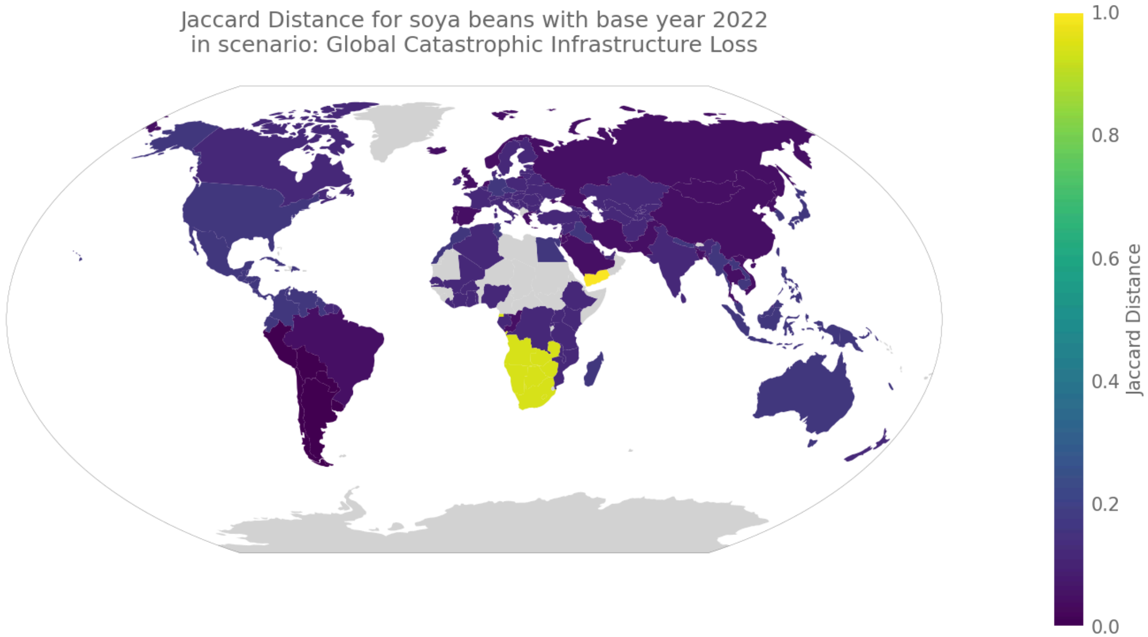


Figure S21: Trade communities for soya beans in 2022 and after yield reduction due to global catastrophic infrastructure loss as well as abrupt sunlight reduction. The colours show which countries belong in which trade communities.



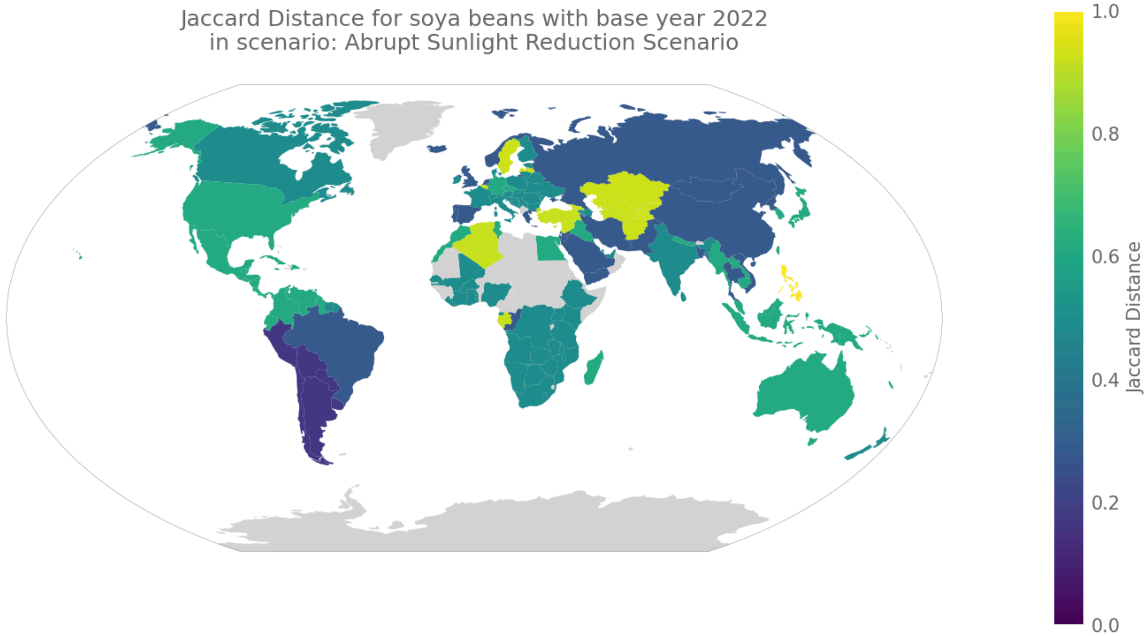


Figure S22: Changes in soya beans trade communities in comparison to the communities in 2022 after yield reduction due to global catastrophic infrastructure loss as well as abrupt sunlight reduction. Colours indicate how much the trade community of a country has changed. Yellow meaning the trade community of a country has changed completely, dark blue meaning the trade community has not changed.

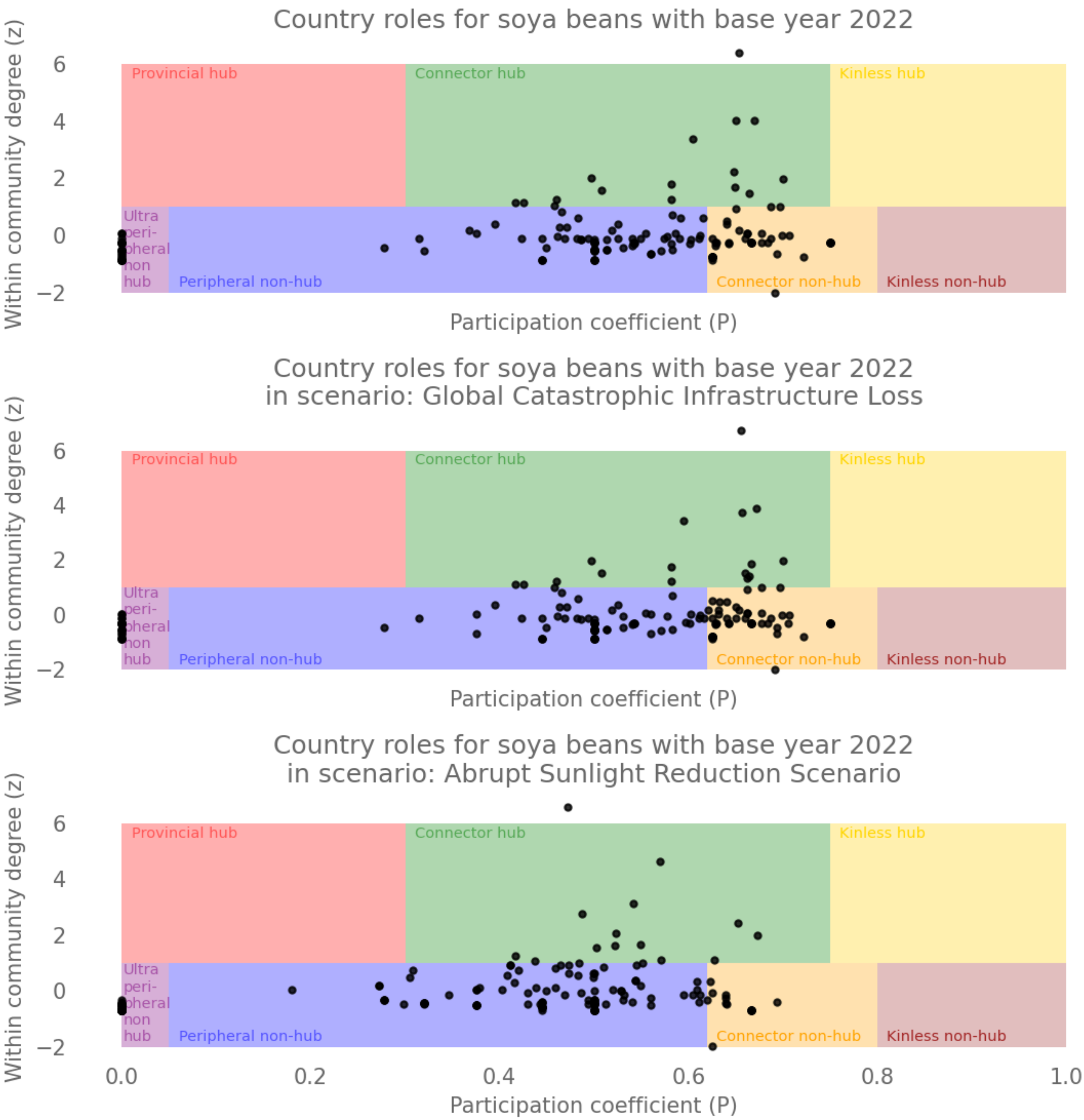


Figure S23: Distribution of country roles in the global soya bean trade network in 2022 and after yield reduction due to global catastrophic infrastructure loss as well as abrupt sunlight reduction based on within community degree and participant coefficient (see 2.4.1 in main manuscript).

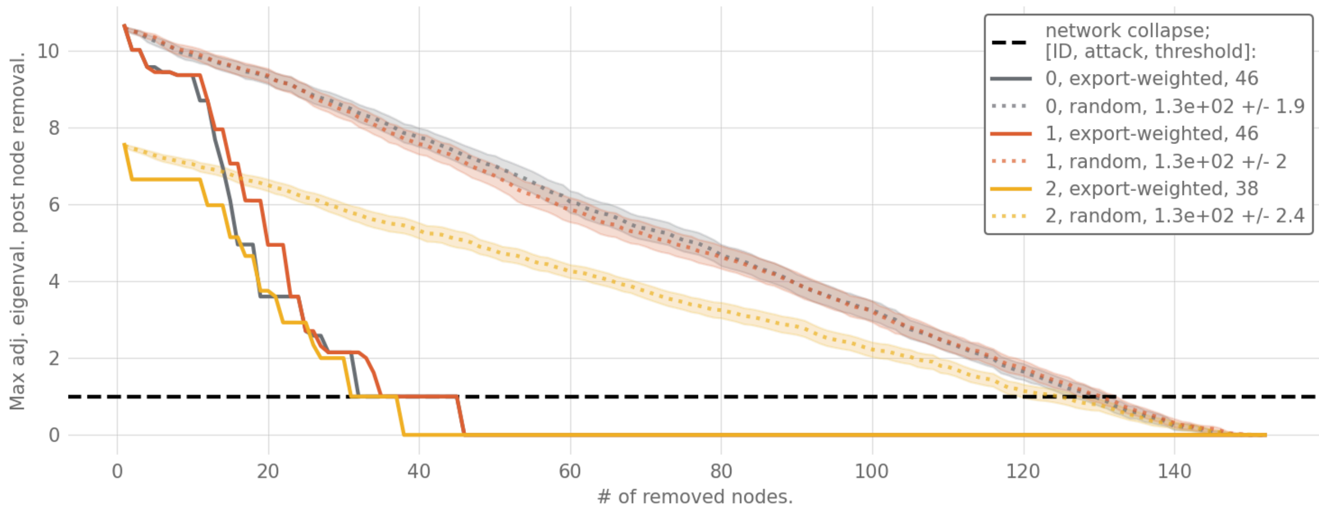


Figure S24: Vulnerability of the different scenarios for soya beans to the removal of nodes. ID 0 = soya bean trade today, ID 1 = global catastrophic infrastructure loss, ID 2 = abrupt sunlight reduction scenario. Dotted line marks the collapse threshold of the network.

5 Further supplemental analysis

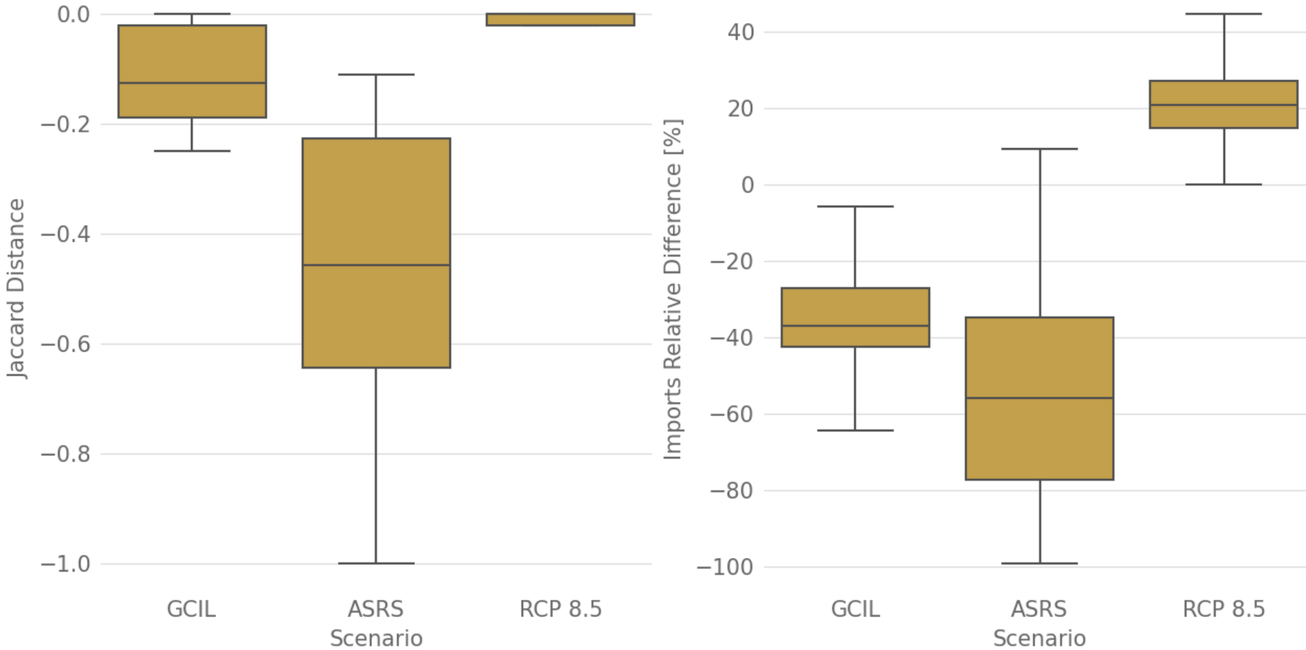


Figure S25: Relative change in wheat imports and Jaccard distance to compare the effects of global catastrophic infrastructure loss (GCIL), abrupt sunlight reduction scenarios (ASRS) and extreme climate change (RCP 8.5). The base year is 2018 to reflect that this comparison is to Hedlund et al. (2022) who based their analysis on that year.

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