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International crop trade networks: the impact of shocks and cascades

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Abstract

Analyzing available FAO data from 176 countries over 21 years, we observe an increase of complexity in the international trade of maize, rice, soy, and wheat. A larger number of countries play a role as producers or intermediaries, either for trade or food processing. In consequence, we find that the trade networks become more prone to failure cascades caused by exogenous shocks. In our model, countries compensate for demand deficits by imposing export restrictions. To capture these, we construct higher-order trade dependency networks for the different crops and years. These networks reveal hidden dependencies between countries and provide an estimate of necessary stock reserves to protect countries from cascading export restrictions. They differ substantially from first-order networks that do not take cascading effects into account. We find rice trade most prone to cascading export restrictions. A great number of Asian and African countries are most exposed to cascades. Noticeably, the main suppliers are similar for most of the crops: USA, Canada, Argentina, Brazil, and India. While shocks in the USA mainly affect South America and several Asian countries, the south of Africa is primarily dependent on American and Asian exporters. The north of Africa depends strongly on Europe, in particular via wheat imports.

1. Introduction

The production and trade of food involves almost all countries in the world, this way forming a global network of dependencies. This network is reconstructed and analyzed in our paper. It reflects *direct* import and export relations between countries and further serves as a basis to estimate how shocks of food production in one country can impact other countries in an *indirect* manner. We focus on the international trade network of staple food, in particular maize, rice, soy and wheat, as the most important sources of calories for human consumption [1]. The amount traded internationally has vastly increased over the past two decades [1] in the course of globalization. This is facilitated by an enhanced globally widespread production to meet the demand of a growing world population [2], increasing meat and feed consumption linked to economic growth [3], or demand for biofuels [4]. This has several advantages and disadvantages for the resilience of the world food system. Countries can specialize in the production of the food they have the appropriate resources for and assume roles within increasingly complex value chains [5]. A larger number of countries can benefit from food trade and added value to food products by means of additional processing. Yet, longer global transportation distances impose higher environmental costs [6], while more transshipment points increase food loss and facilitate the spreading of pests [7]. Still, they provide means to respond to shocks due to climate trends, large-scale pollution events, or soil degradation [8] or short term harvest losses due to weather anomalies, droughts, or pests [9]. Thus, on the one hand, global markets facilitate risk diversification [10] to better mitigate supply shocks. On the other hand, countries become more exposed to shocks through these global markets [11] either directly or indirectly [9, 12, 13]. The complexity of international trade makes it difficult to assess the resulting dependence of countries.

Our aim is to (i) reveal such direct and indirect dependencies using data from 176 countries over 22 years and (ii) to model the impact of different shock scenarios on the international food trade network. This is challenging for several reasons.

First, the roles of countries cannot be easily reduced to *producers*, *importers* and *exporters*. Some countries produce a given crop mainly for export (e.g. Brazil exports 50% of its soy production in 2013), whereas other countries obviously rely on the import of their staple food (e.g. Saudi Arabia imports all of its rice and 77.4% of its wheat in 2013). But many countries are important as intermediaries, either because of their role as traders or because they produce intermediate or final products from these staple foods. Our data does not allow to distinguish theses cases. We simply call countries that import and export a relevant amount of the same grain intermediaries. Furthermore, countries that produce a given staple food can appear as importers, while countries that do not produce a given staple food can appear as exporters.

Second, many factors that influence the generation of the international food trade networks are (partially) unobserved. Examples include subsidies, taxes, tariffs, multi- and bilateral trade agreements, harvest times of crops or food prices that might be influenced by speculation, demand for fuel, the quality of the offered products, price elasticities, etc [14, 15].

Third, many agents following different incentives influence international trade flows [14]. For instance, producers are interested to sell their products at the highest bidding prize, while consumers demand affordable, high quality food. Governments might want to ensure food security of their population but also facilitate trade benefits and maintain good international relations. All have different options to respond to shocks or system changes. For instance, governments can impose export bans, subsidize imports, use stocks, promote local markets by employing protective tariffs at harvest times, or, long term, build up reserves for later shocks and negotiate different trade agreements. Different decisions are made in the course of a year.

Fourth, our data is aggregated over one year. Yet, we can expect that the timing of events has a considerable impact on international trade. For instance, if a country decides to impose an export ban in the middle of a year, it only applies to future trade but not already exported products.

Some of these challenges are addressed by problem simplification. Instead of a realistic generative model of international food trade or the economy, the focus is shifted towards modeling *changes* of an observed international food trade network (which aggregates all trade within a year) in response to a shock as, e.g. a lower production in a specific country. While the mechanisms of this change are not fully understood, it is acknowledged that they contribute to the fragility of international trade [9, 12] and some disaster or climate impact studies try to estimate their effect [16, 17]. Several modeling approaches have a component that assumes that a shock propagates locally through the trade network, i.e. a shocked country influences first its direct trade partners, then, these trade partners impact their trade partners, etc. This way, a *cascade* builds up that can encompass a significant share of the whole network. Termed as multiplier effect, such cascades can also be observed empirically and are found to influence food prices [18–21]. In particular, the food crisis in 2008/2009 is linked to yield losses due to a drought in China [22, 23] and export restrictions in Russia [24]. The resulting increased wheat market price has also affected countries in North Africa and the Middle-East and are conjectured to have contributed to the Arab Spring [25].

Apart from international food trade [9, 20, 26, 27], cascade processes have been encountered in different fields. The financial crisis in 2008/2009 has triggered the development of diverse models for financial contagion [10, 28–30], which mainly serve the estimation of systemic risk, i.e. the risk of a system's break-down. Such cascade models are characterized by predefined possible losses that are independent of the cascade history. Another related approach are input–output models that are, for instance, used for the assessment of costs after a disaster [11, 16, 17, 31, 32] and take also higher-order effects into account. They are often used to model intersectorial dependencies, seldom on the international level. In particular the production of complex products is captured well, but data on input–output tables needs to be available.

In contrast, we focus on a threshold model with accumulating load that is more similar to fiber bundle models in Physics [33, 34] and is also captured by the framework introduced by [35]. It focuses on countries imposing export restrictions as cascade propagation mechanism. To our knowledge, such a model is not yet implemented in stress tests that analyze the resilience of international grain trade [9, 2, 36] with one exception: [27] considers an aggregated grain trade network and more complicated dynamics that assume that the cascade process actually models the time evolution of the network formation. This, however, conflicts with having only information about aggregated trade between countries over one year.

Here, we follow a different philosophy and propose a simple model that assumes minimal change to the observed trade network, which we account as most realistic. For the same reason, we assume that the rules of global food trade do not change within a year and countries keep their preferences for trade partners. Specifically, the shock of a given country reduces its production or supply of a given crop. If this results in an unmet demand, this country can reduce this trade flow by imposing export restrictions. Such restrictions might motivate affected countries to do the same, which can trigger *cascades of export restrictions*. A similar model has been developed recently [26] to study the vulnerability of global seafood trade with respect to shocks that are proportional to a shocked country's seafood exports. Different to that model, we focus on the trade of maize, rice, soy, and wheat and consider shock scenarios that depend on the production and demand of countries. This acknowledges the nature of most possible shocks and allows to study a country's exposure to local shocks in comparison to cascades that started in far distant countries.

Our model is simple (but useful), as it considers only export restrictions as response to supply shocks and does not incorporate price dynamics. Yet, this is also a feature. Our model is not biased by additional assumptions about the network generation mechanism. We identify indirect trade flows between countries solely based on an observed trade network and production data on the country level. On their basis, we propose the construction of a *higher-order trade dependence network*. While a first-order network only captures the impact of shocks on direct export partners, higher-order networks consider all indirect effects resulting from cascades of export restrictions. This alters the analysis considerably. For instance, ca. 50% of links in the first-order trade dependency network for maize in 2013 vanish considering higher-order effects, i.e. they are present in the first-order network, but not in the higher-order network, because countries compensate for demand deficits by export restrictions. Meanwhile, 80% of links in the higher-order network are not captured in a first-order approach. Our visualizations of the higher-order trade dependency network can be compared with other studies about international food trade. For instance, the international rice and wheat trade networks from 1992 to 2009 are discussed by [9] where also their vulnerability to export restrictions (without considering cascade effects) is analyzed in a first-order approach. Considering poverty levels in addition, a first-order analysis of wheat, maize, and rice trade has identified 200 million people below the poverty line at risk [22]. Further, the authors of [36] identify the main actors in the international trade of maize and the trade structure from 2000 to 2009, while [37] focus on clusters. Also related is the analysis of caloric and monetary trade flows [38] aggregating different food types and the development of a dynamic flux model to measure the countries' vulnerability to food contamination [39].

In the following, we use the available data to (i) reconstruct the international food trade network, which then is used to (ii) evaluate the global impact of different shock scenarios on such networks (which are different for every crop and for every year).

2. Data analysis and network construction

2.1. Available data on the country level

Food imported into a country can either be consumed by the population or further exported, either directly or after value is added, e.g. bread is produced from flour. The available data provided by the Food and Agricultural Organization of the United Nations [40] at a resolution of *one year* only gives total numbers about food production, import and export with respect to different countries. For our analysis, we consider data for $N = 176$ countries over a period of 22 years, from 1992 to 2013. This period is particularly interesting because, after the dissolution of the Soviet Union, from 1992 onwards geographic territories have been rather stable and an on-going globalization has shaped also the international food trade.

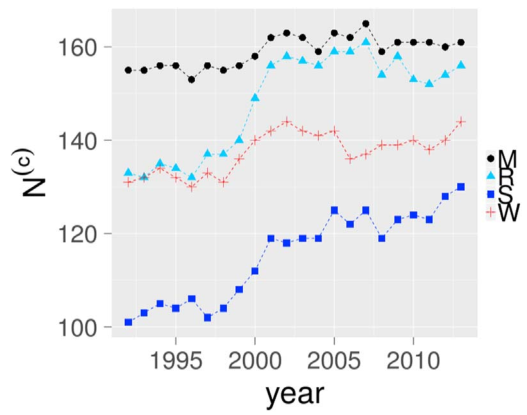

Figure 1. Number of countries $N^{(c)}(y)$ that engage in trade or production of staple food $c \in M, R, S, W$ in a year y. M: maize, R: rice, S: soy, W: wheat.

We consider four different crops, *maize*, *rice*, *wheat* and *soy*, because these are the main internationally traded crops and denote them with the index $c \in \{M, R, S, W\}$. $N^{(c)}(y)$ is the number of countries that engage in trade or production of crop c in year y. It is plotted in figure 1 over time and tend to increase for all crops over the years. However, since 2001/2002, $N^{(c)}(y)$ seems to stagnate for maize, rice, and wheat.

Our data set contains information about the annual *production*, $\mathrm{prod}_i^{(c)}(y)$, of countries $i = 1,\ldots,N$ with respect to a given crop c, their exports, $\exp_i^{(c)}(y)$, and their imports, $\mathrm{imp}_i^{(c)}(y)$, measured in tons. From this, we can already calculate a country's demand for a given crop in a given year as:

$$\mathrm{dem}_i^{(c)}(y) = \mathrm{prod}_i^{(c)}(y) + \mathrm{imp}_i^{(c)}(y) - \exp_i^{(c)}(y). \tag{1}$$

These numbers change over time and vastly differ across countries as figure 2 shows. For instance, the combined harvest of only the five biggest producers in 2013 amounts to ca. 89% of the global soy, 79% of the rice, 71% of the maize, and 52% of the wheat production. Interestingly, as figure 2 demonstrates, most countries are producers, importers and exporters of the same crop at the same time. This already points to the complexity of worldwide food trade, because production shocks in a given country involve almost every other country via import and export.

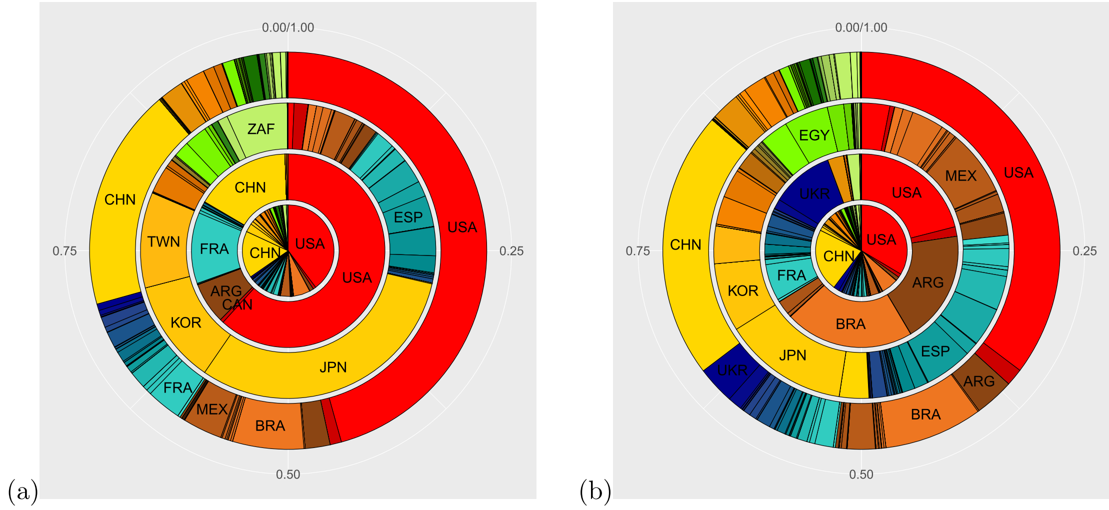

Figure 2. Fractions of maize *production* $\mathrm{prod}_i^{(M)}(y)$ (outer circle), *import* $\mathrm{imp}_i^{(M)}(y)$ (second outer circle), *export* $\exp_i^{(M)}(y)$ (second inner circle) and *demand* $\mathrm{dem}_i^{(M)}(y)$ (inner circle) per country in $y = 1992$ (left) and $y = 2013$ (right). Each figure should be read as the superposition of four separate pie charts. This allows a direct comparison of the respective quantities. Different colors indicate countries according to the world map shown in figure 4. Abbreviations follow the name convention given in table A1. The corresponding figures for rice, soy and wheat are shown in figures B1–B3 (appendix).

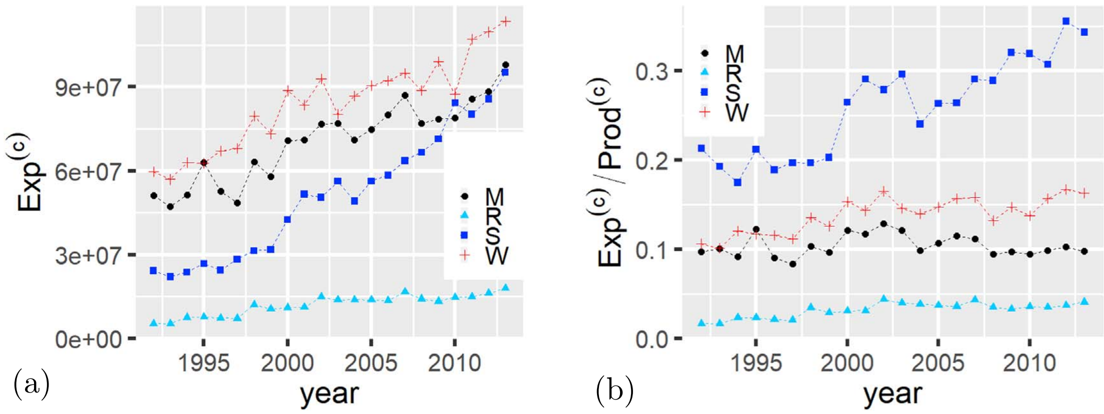

Figure 3. (a) Global exports $\mathrm{Exp}^{(c)}(y)$ in tons over time. (b) Global exports as a fraction of the total production, $\mathrm{Exp}^{(c)}(y)/\mathrm{Prod}^{(c)}(y)$, over time.

Eventually, we can obtain the global exports, $\mathrm{Exp}^{(c)}(y)$, and the global production, $\mathrm{Prod}^{(c)}(y)$, as:

$$\mathrm{Exp}^{(c)}(y) = \sum_{i=1}^{N^{(c)}(y)} \exp_i^{(c)}(y)$$
$$\mathrm{Prod}^{(c)}(y) = \sum_{i=1}^{N^{(c)}(y)} \mathrm{prod}_i^{(c)}(y), \tag{2}$$

where $N^{(c)}(y)$ denotes the number of countries. $\mathrm{Exp}^{(c)}(y)$ is plotted in figure 3(a). While the respective quantities steadily increase, it is more interesting to compare them with the annual global production, $\mathrm{Prod}^{(c)}(y)$, of a given crop in the same year. Figure 3(b) shows that total exports keep up to, or increase even faster, than the global production. This fact should be valued against the observation in figure 1 that the number of countries involved in production or trade of maize and rice is almost constant after the year 2000. Especially soy is traded internationally to a large extent, although the least number of countries participate in trade or production. Accordingly, soy trade is characterized by very high trade volumes.

2.2. Constructing the trade networks

In the following we construct from the available data the trade networks with respect to the different crops and the different years. Each country is represented by a node i in a network $G^{(c)}(y) = (V^{(c)}(y), W^{(c)}(y))$. The set of all nodes is denoted by $V^{(c)}(y)$ with $N^{(c)}(y)$ elements. In total, we consider $N = 176$ countries. However, not all engage in trade or harvest crops in every year. So, usually $N^{(c)}(y) < 176$.

Exports of crop c from country i to j are represented by directed and weighted links, $w_{ij}^{(c)}(y) \geqslant 0$. The set of all weighted links is denoted by $W^{(c)}(y)$. On

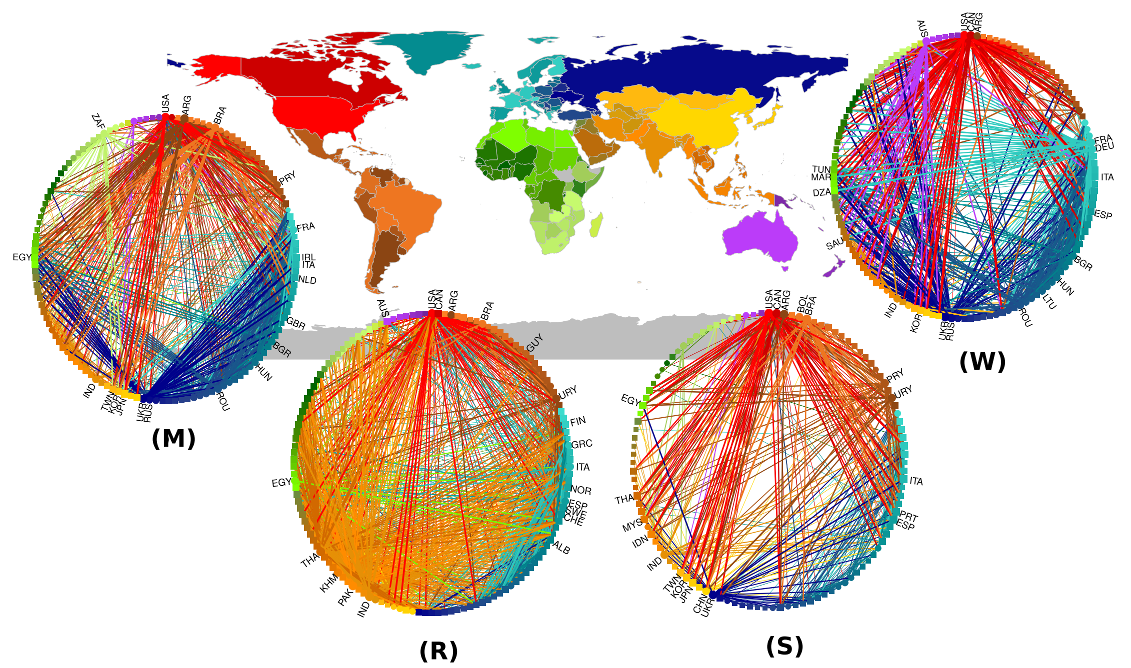

Figure 4. International trade networks in 2013 for maize (*M*), rice (*R*), soy (*S*), and wheat (*W*). Each *node* is colored according to the world map. The color of a *link* (i, j) corresponds to the exporting country i, with a link weight proportional to a logarithmic transformation of the export quantity: $\log(1 + w_{ij})$. Links with larger weights are plotted on top of smaller ones. Square node shapes indicate that the respective country is a net importer, while circles refer to net exporters. The node size is proportional to a log transformation of their net imports or net exports. More detailed information is provided in figure 2. The twenty biggest nodes have their ISO-3 country code assigned (see table A1). Isolated nodes (i.e. without connections) are omitted in a network plot.

the basis of the weights $w_{ij}^{(c)}(y)$, we can express the total exports and imports of a given country i as:

$$\exp_i^{(c)}(y) = \sum_{j=1}^{N} w_{ij}^{(c)}(y); \quad \mathrm{imp}_i^{(c)}(y) = \sum_{j=1}^{N} w_{ji}^{(c)}(y). \tag{3}$$

We do not regard self-loops and, thus, set $w_{ii}^{(c)}(y) = 0$. The difference $\Delta_i^{(c)}(y) = \exp_i^{(c)}(y) - \mathrm{imp}_i^{(c)}(y)$ is used in figure 4 to indicate net importers and net exporters.

The trade networks $G^{(c)}(2013) = (V^{(c)}(2013), W^{(c)}(2013))$ for the four different crops are visualized in figure 4. We observe that the soy trade network has the lowest number of links. However, the single trade volumes are comparatively large and, compared to the other three crops, the highest fraction of the total production is traded internationally (ca. 34%). In contrast, the rice trade network has the highest number of links, while its total trade volume sums up only to ca. 4% of the total rice production, which is the smallest observed fraction.

We have also studied how the global trade networks of maize, rice, soy and wheat have evolved between 1992 and 2013. The plots of the empirical networks are shown in figures D1, E1, F1, G1 in the appendix and show clearly an increase in trade and network complexity. At the same time, the dominant role of a few hubs, i.e. big exporters, is compensated by the many countries that enter the network, of which some emerge as new hubs.

2.3. Change of network properties

The trade relationships between countries evolve over time, as illustrated in the following. Figure 5(a) depicts the change of the link density $\rho^{(c)}(y) = L^{(c)}(y)/(N^{(c)}(y)(N^{(c)}(y) - 1))$, where $L^{(c)}(y)$ denotes the number of all trade links in a network in year y. The normalization is with respect to a fully connected network with $N(N-1)$ directed links. As shown, $\rho^{(c)}(y)$ clearly increases over time, but not always at the same growth rate as the global exports shown in figure 3.

Considering the weight of the links, we can also calculate the average link weight, $\langle w^{(c)}(y)\rangle = (1/L^{(c)}(y))\sum_{i,j}^{N^{(c)}(y)} w_{ij}^{(c)}(y) = N^{(c)}(y)/L^{(c)}(y)\langle \exp^{(c)}(y)\rangle$, which is proportional to the average export per country. Figure 5(b) shows that the average total export in fact decreases for maize and wheat trade and increases for soy trade, while there is no clear trend for rice trade. However, the average export is not a suitable measure to describe such trends, because the weight distributions are highly skewed. This is shown in figure 6 for two different years, 1992 and 2013, to also allow a comparison of the changes over time.

We note that in all cases the weights are much smaller in 1992, but the distribution is always very broad. While the distributions for maize, rice and soy export are right skewed, i.e. have mostly smaller weights, for wheat trade there is a larger fraction of links with big export volumes. If we recast the total trade volumes of the different crop in terms of caloric values, we find that the highest amount of calories is

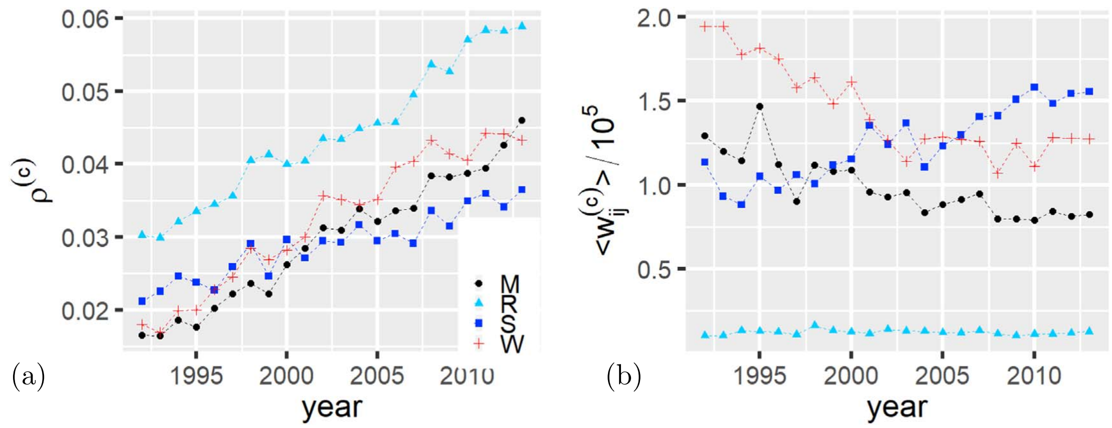

Figure 5. Network density. (a) Link density: fraction of links in comparison to fully connected network. (b) Average positive trade volume.

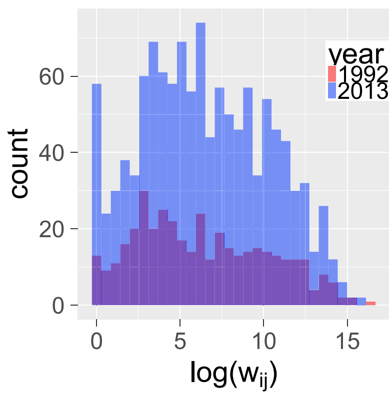

Figure 6. Histogram of the logarithm of the positive trade volumes in the years 1992 (red or purple if behind the blue) and 2013 (blue) for maize. The corresponding figures C1(a)–(c) for rice, soy and wheat are provided in the appendix.

traded in form of wheat. Still, the most calories are *produced* in form of maize in 2013.

3. Modeling the impact of shocks

3.1. Dynamics of cascades

The main goal of our model is to determine how shocks in the production of one crop in a given country k will affect its availability in other countries $i \in N^{(c)}(y)$. Such shocks can have different origin as discussed in the Introduction, but we model them here consistently as a *one time exogenous reduction* shock_k^c of the available crop in *one* country. Because of the *annual* data, we cannot observe how a country responds to such shocks on a shorter time scale t, e.g. within days or weeks, and how such responses affect other countries. Here, our model comes into play to proxy such dynamics on the food trade network on the discrete time scale $t = 1, 2, \ldots, T$, where the maximum time T is less than one year.

$t = 0$ refers to the reported data at the end of year y, i.e. we know for each country $\mathrm{dem}_i^{(c)}(t=0) = \mathrm{dem}_i^c$, $\mathrm{prod}_i^{(c)}(t=0) = \mathrm{prod}_i^c$, $\mathrm{imp}_i^{(c)}(t=0)$, $\exp_i^{(c)}(t=0)$. But theses initial conditions change for every year. Within one year, we assume that demand and production are fixed to dem_i^c, prod_i^c, whereas imports and exports can change on a time scale t, i.e. $\mathrm{imp}_i^{(c)}(t)$, $\exp_i^{(c)}(t)$. If country k is shocked at $t = 1$ by a $\mathrm{shock}_k^{(c)}$, a *demand deficit* $\mathrm{dd}_k^{(c)}(t=1) = \mathrm{shock}_k^{(c)}$ will result. To compensate for that, k reduces its export in the next time step, if possible, such that $\mathrm{dd}_k^{(c)}(t=2) = 0$. This reduction, however, will affect all countries that import the given crop from k. At $t = 2$, these countries will face a demand deficit $\mathrm{dd}_i(t=2)$ which they try to reduce, this way affecting all other countries that import from them. Therefore, a cascade resulting from export restrictions evolves in the food trade network on time scale t, which involves more and more countries. This is illustrated in figure 7.

To formalize the model, we have to express the demand deficit of each country that was not shocked initially:

$$\mathrm{dd}_i(t) = \mathrm{dem}_i - \mathrm{prod}_i - \mathrm{imp}_i(t) + \exp_i(t). \quad (4)$$

If $\mathrm{dd}_i(t) > 0$, i reduces its exports if possible:

$$\exp_i(t+1) = \exp_i(t) - \min\{\mathrm{dd}_i(t), \exp_i(t)\}. \quad (5)$$

Hence, either its deficit vanishes in the next time step, $\mathrm{dd}_i(t+1) = 0$, or at least all current exports are stopped.

To complete equation (4), we have to specify how $\mathrm{imp}_i(t)$ is affected by the export reductions of other countries. According to equation (3), imports are defined through the weights $w_{ji}^{(c)}(t)$ which will change on time scale t if export restrictions occurred. We assume that exporting countries do not change their preference for specific countries at the short time scale t. I.e. in case of an export reduction every of their importers is proportionally affected. This implies that the ratio $w_{ji}(t)/\exp_j(t) = w_{ji}(0)/\exp_j(0)$ is constant

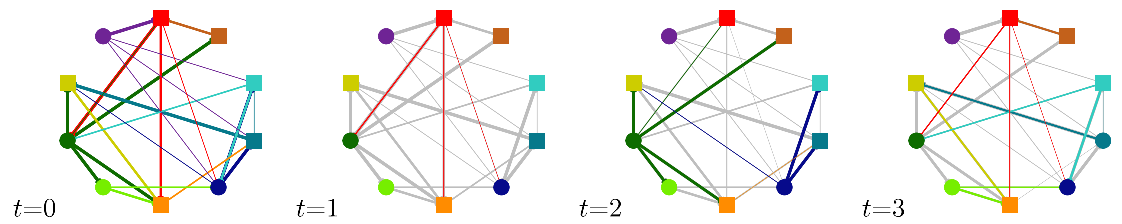

Figure 7. Exemplary cascade process. The previous network is colored in gray, while changing links are colored according to the exporting node. ($t = 0$) Initial trade network. ($t = 1$) The red node is shocked and reduces its exports. ($t = 2$) Importers from the red node compensate for their loss by reducing their own exports. ($t = 3$) Further nodes face a demand deficit because of decreased imports and reduce their exports.

over t and can be set to the initial value, where the initial trades $w_{ji}(0)$ are entries of the trade matrix W for a given year. This gives for the dynamics of the trade weights

$$w_{ji}(t) = \exp_j(t)\frac{w_{ji}(0)}{\exp_j(0)};\quad \mathrm{imp}_i^{(c)}(t) = \sum_{j=1}^{N} w_{ji}^{(c)}(t). \tag{6}$$

Given an initial shock shock_k, the combined equations (4)–(6) determine the dynamics of the cascade. Note that a country can be affected more than once in the course of a cascade because of loops in the network. The reduction of a country's exports can cause a reduction of its imports again at a later time. The final step of the cascade at time $t = T$, which is always smaller than one year, is reached if no country with a demand deficit can further reduce its export. This usually applies to more than one country because the cascade has evolved along various paths, determined by the number of importers. How many countries are eventually left with a non-reducible demand deficit depends on the initial country that could be an important producer, the size of the shock, but also on the sequence in which countries are involved. Hence, in order to systematically study such effects, we need an approach that does not just consider a single event. This is developed in the following.

3.2. Shock scenarios

To assess the vulnerability of the trade network, we consider two different types of shocks that each represent a different limit case: An *equal shock* generates a *fixed* demand deficit of the shocked country, no matter whether this is a small or a large country. This allows us to study how the *same* deficit would affect different countries. To define the size of the shock, we set this to 25% of the production of an average country, $\mathrm{shock}_k^{(c)} = 0.25\langle \mathrm{prod}^{(c)}(y)\rangle$ in a given year y. Only if the size of the shock exceeds the shocked country's production $\mathrm{prod}_k^{(c)}(y)$ and demand $\mathrm{dem}_k^{(c)}(y)$, we limit $\mathrm{shock}_k^{(c)}(y)$ to the maximum of both: $\mathrm{shock}_k^{(c)} = \max(\mathrm{prod}_k^{(c)}(y), \mathrm{dem}_k^{(c)}(y))$.

The second type of shock, at difference with the first one, is not equal for all countries but proportional to the production or demand of the shocked country, i.e. $\mathrm{shock}_k^{(c)} = 0.25\max(\mathrm{prod}_k^{(c)}(y), \mathrm{dem}_k^{(c)}(y))$. Therefore, we call this a *proportional shock*. It allows us to study how countries with very different production impact the size of the cascades. Proportional shocks of 25% can be seen as quite large. However, our data shows that they have happened in more than 5% of all changes of production and demand for all countries and years. I.e. proportional shocks of this size are *not* negligible, but realistic.

If we apply a shock to a given country k, we will observe cascades of export restrictions as illustrated in figure 7. The outcome characterizes the influence only of country k, thus, we have to run the model with every possible country $k = 1,\ldots,N^{(c)}(y)$ as the target of a shock. In order to visualize the influence of all countries together, we generate a *higher-order trade dependency network* as explained in the following.

4. Results

Our aim is to visualize the final outcome for the collection of cascade processes starting in *all* countries. We focus mainly on the impact of a shock on countries at the end of value chains, where the final product is consumed. Figure 8 explains this procedure for the one-time exogenous shock of a *single* country, the USA, in 2013, only for maize trade. All links start in the shocked country, the US, and end in different countries which all face a demand deficit at the end of a cascade. The link strength is proportional to this deficit. We do not show the intermediate steps, only the final outcome, i.e. each link connects the origin of a cascade with a number of finally affected countries. Figure 8 allows to compare the influence of an equal shock (a) with that of a proportional shock (b) of the main producer of maize. Because of the large production, the *proportional* shock of the US (i.e. 88 424 860 tons) is larger than for the *equal* shock (1423 653 tons). Therefore, it inflicts higher demand deficits also in more countries. The difference, however, does not scale linearly with the shock size due to threshold effects during a cascade. For instance, Mexico (MEX) is significantly affected by the proportional shock (with a demand deficit of 6145 784 tons), but not at all by the equal shock (no demand deficit). Japan (JPN),

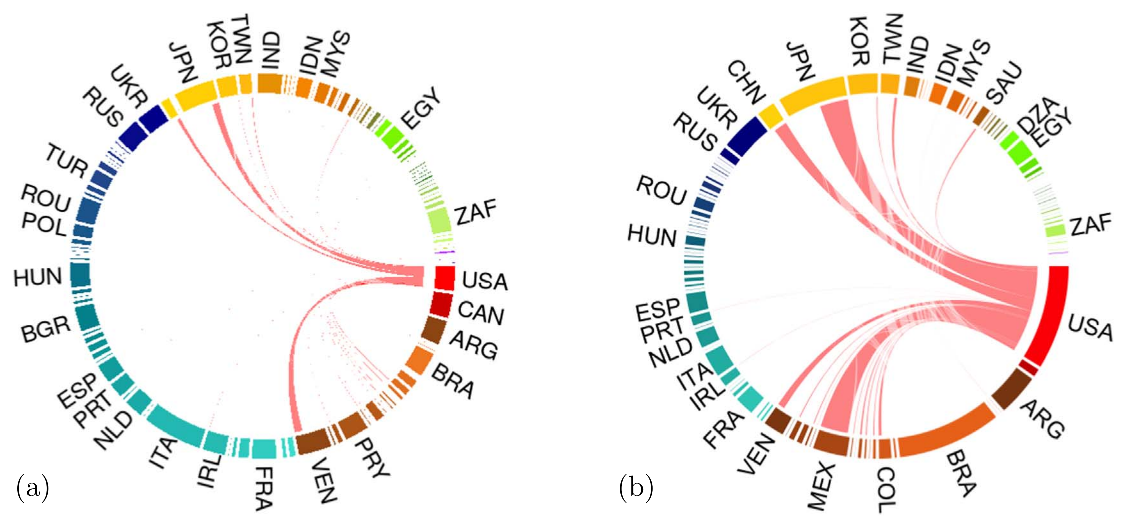

Figure 8. An initial shock of the production of maize in the USA in 2013 causes a cascade (not shown) that eventually leads to demand deficit in countries with whom the USA is connected in the plot. The link strength is proportional to the size of the encountered demand deficit. We do not show the intermediate steps, only the final outcome, i.e. each link connects the origin of a cascade with a finally affected country. (a) Equal shock, (b) proportional shock scenario.

on the other hand, faces a high demand deficit even for smaller shocks of the USA, i.e. 6332 099 tons for proportional shocks and 447 629.7 tons for equal shocks.

In order to visualize the influence of all countries together, we generate a *higher-order trade dependency network* by combining the final outcomes of cascades for all possible countries $k = 1,\ldots,N^{(c)}(y)$ as starting points. A zero-order network would simply be the empirically observed trade network shown in figure 4. The first-order network would show the impact of shocks on direct export partners. The second-order network the impact on the export partners of those direct partners. The highest order is given by the maximum number of steps in all cascades. Hence, higher-order dependency networks reflect the ability of countries to compensate demand deficits by export restrictions.

We explain the construction with our example about the impact of a shock of the USA on Mexico with respect to maize trade in 2013. The USA exports 0.32 of its total exports, i.e. 6579 107 tons, to Mexico in 2013. Thus, in a first-order network, we would draw a link between the USA and Mexico. The link weight is $0.32 * \text{shock}_{\text{USA}}^{(M)}$, i.e. $0.32 * 88\,424\,860 = 28\,295\,955$ tons for proportional shocks and $0.32 * 1423\,653 = 455\,569$ tons for equal shocks. In a second order network, Mexico can try to compensate for the encountered demand deficit, i.e. 28 295 955 tons or 455 569 tons respectively, by reducing its own exports, i.e. in total 581 777 tons. This way, Mexico can only reduce its demand deficit in the proportional shock scenario, since its demand deficit exceeds its total exports. Yet, it can fully compensate for the demand deficit in the equal shock scenario. Thus, in the second order network, there remains a link between the USA and Mexico (with weight $28\,295\,955 - 581\,777 = 27\,714\,178$ tons, i.e. demand deficit of Mexico minus the exports of Mexico) in the proportional shock scenario while there is no link between them in the equal shock scenario. In both shock scenarios, we further have links between the USA and countries that import from Mexico. For instance, Venezuela imports 0.92 of Mexico's exports. Thus, it faces a demand deficit of $0.92 * 581777 = 535\,234.8$ (proportional shocks) or $0.92 * 455\,569 = 419\;\;123.5$ (equal shocks) tons after two cascade steps ($t = 2$). Finally, the higher-order trade network shows only links between the USA and countries that cannot compensate for a demand deficit in the course of a cascade that starts in the USA.

The higher-order trade dependency network for maize is shown in figures 9(a), (b) for equal shocks and for proportional shocks. A sensitivity analysis of the impact of different shock sizes is provided in appendix H. With equal and proportional shock scenarios, we span the range of most shocks. We note that proportional shocks emphasize the impact of the biggest producers, in particular USA, Brazil, and Argentina. Interestingly, shocks in the USA finally impact many countries in South America, while shocks in Brazil mostly impact Asia, but also Africa. Equal shocks, on the other hand, highlight dependencies in general, not just on the biggest producers. Shocks of European countries mostly impact other European countries, with Italy as the most affected country. With respect to Africa, a shock of South Africa generates the highest demand deficit not in Africa, but in Japan and in South America.

Furthermore, figure A1 shows what insights we gain by a higher-order analysis in comparison with a first-order approach. In the proportional shock scenario, 53.9% of links in the first-order network are spurious, i.e. they are not present in the higher-order trade network, while 86.8% of all links of the higher-

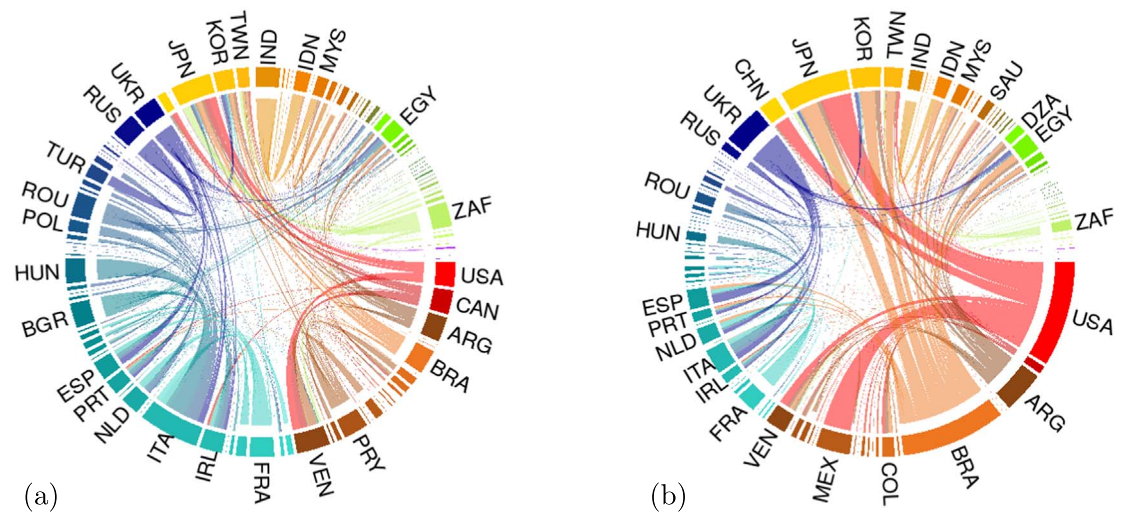

Figure 9. The higher-order trade dependency network for maize in 2013. The bar size of each country represents its weighted degree, i.e. the sum of all in-coming and out-going link weights. Links are defined as in figure 8. (a) Equal shock, (b) proportional shock scenario. For the visualizations, we use the circlize package in R [47]. Smaller links that cannot not be visualized in relation to the large ones are not shown.

order trade dependency network are new, i.e. not regarded in a first-order approach. In the equal shock scenario, we have 55.4% versus 87.6% respectively. In general, the higher-order trade dependency network has ca. four (or 3.6) times more links than the first-order trade dependency network. Interestingly, we underestimate the impact of a shock of the USA, Canada, or Brazil on Asian countries like Japan, Korea, China, and Taiwan and on Venezuela in a first-order approach. Yet, we overestimate the vulnerability of Mexico, for instance, as it can compensate shocks by reducing its own exports.

The higher-order trade dependency network of maize can be also compared with the respective networks for rice, soy and wheat shown in figures A2(a)–(c) both for equal (top) and proportional shock (bottom) scenarios. It is apparent that shocks of the US, for all crops and all scenarios, have a major impact on the demand deficit of other countries, even for *rice*. Equal shock scenarios highlight the importance of European countries as intermediaries. I.e. they import, potentially add value, and export. In particular, shocks of wheat production and demand in European countries affect the whole world as shown by the rather homogeneous link distribution.

Looking at the impact of the biggest producers of *soy*, we find that the strongest dependencies are between the US, Brazil and Argentina on the one hand, and China on the other hand. The higher-order trade dependency network appears to be similar to the one of maize (figure 9(b)) as both maize and soy share the main producers. On the other hand, both the zero-order (figure 4) and the higher-order trade dependency network of soy are less dense than the ones for maize. In consequence, the impact of shocks is more concentrated on a few countries.

Regarding rice, we observe the prominent role of Asian countries. Shocks of India or Thailand appear to have the most critical impact on other countries, in particular in Africa. Surprisingly, also shocks of the USA are relevant for a few Asian countries like Japan and Korea.

Africa mainly depends on rice and wheat imports from Asian and European countries, as illustrated by the fact that the incoming links in the higher-order trade dependency network have a color different from the African countries.

5. Discussion

In this paper, we provide a quantitative analysis of the global food trade of the four major internationally traded crops, maize, rice, soy, and wheat. This analysis makes two major contributions. First, from the available data we have reconstructed the global trade network between 176 countries for 21 years and have evaluated network properties such as link density and distribution of link weights over time. This is complemented by an empirical analysis of the production, import, export and resulting demand of each country for each year. We show that the roles of countries in the global food trade cannot be separated, i.e. many countries are producers, importers and exporters of the same crop at the same time. This highlights the importance of countries as intermediaries, either for trade or food processing, and points to the increasing complexity of global value chains [12].

This insight has motivated our second major contribution, a model to reveal the indirect dependencies between countries if the the production or demand for food in a specific country was shocked exogeneously (e.g. by natural disasters). The model reflects that countries can compensate for shortages in the supply of a given staple food by imposing *export restrictions*. These impact their direct trade partners, which try to compensate supply deficits as well by export restrictions. This way, cascades emerge on the given trade network which involve many countries. They only stop if all countries cannot further compensate their demand deficit by export restrictions. Our cascade model captures a process that cannot be observed given the available data. That means, it allows to relate the country shocked originally with the country that eventually suffers the most from this shock, at the end of a cascade. These indirect relations are neither obvious, nor have they been revealed in the existing literature.

To reflect these dependencies on the global level, we have developed *higher-order trade dependency networks*. They visualize the impact of an initial shock in *any* country on those countries that eventually get a demand deficit from this shock. We have created these visualizations for two different shock scenarios. Proportional shocks highlight the impact of big producers, while equal shocks highlight general dependencies. The value of these higher-order trade dependency networks is in revealing indirect dependencies between countries. As food trade becomes more complex and more countries become involved (see figure 1), disentangling a country's impact on the globalized food trade gives valuable information also for policy makers. They are enabled to anticipate how shocks of different sizes in a given country impact other countries directly *and* indirectly, via export restrictions.

In summary, we could quantify that a great number of Asian and African countries are most exposed to cascades. Noticeably, the main suppliers are similar for most of the crops: USA, Canada, Argentina, Brazil, and India. While shocks in the USA mainly affect South America and several Asian countries, the south of Africa is primarily dependent on American and Asian exporters. The north of Africa depends strongly on Europe, in particular via wheat imports. Remarkably, a great number of European countries appear frequently among the main trade intermediaries. According to our analysis, especially rice trade is prone to cascading export restrictions. Cascades of similar nature, i.e. based on export restrictions, have been observed also empirically [20], but also other crop trade is vulnerable to cascading export restrictions. At the same time, cascades can provide means for good shock diversification. To which extent food losses are critical for specific countries is decided by the amount of national stocks available for compensation.

Our modeling approach provides a way to proxy the necessary size of such stocks. These can serve as relevant input for policy makers. An alternative to reserves would be to reduce a country's import dependence, either by increased domestic production or by incentives for a diversification of diets (to reduce the dependence on specific crops). It might also be worthwhile to consider the assessment of the impact of changes to the trade network, for instance, by import subsidies, a diversification of the supplier base, or the formation of additional trade agreements.

Yet, it is important to keep in mind that our modeling approach is limited to small changes of the international trade network. The reason is that we do not model many of the network's constituting factors explicitly, but indirectly by distortions starting from a realistic observed network.

We do not consider substitution effects. For instance, in our model, demand deficits are considered as independent across the considered crops maize, rice, soy, wheat, whereas in practical situations a shortage of one food may be compensated, at least partially, by other food. Such couplings have to also include prices which are currently left out in our model.

Price dynamics could affect the dynamics and the outcome of cascades because both supply and demand depend on price [20, 41]. Therefore, studies on seafood trade [26] have considered decreasing demand due to price increases. Yet, these are not based on data, data on price elasticity of countries with respect to the studied crops are not readily available. We argue that they are also less relevant for staple foods. While increasing market prices translate into increasing consumer prices [42, 43], the *price elasticity* of staple food is relatively small [44], i.e. the demand does not change substantially despite increasing prices. This reflects that staple food is a basic need for most of the population to exist. Nevertheless, food imports in general could respond more strongly to price changes. Substitution of one crop by other (cheaper) crops may be an alternative for less processed products. This leads to joined price movements of the alternatives so that the overall demand for one crop should not change drastically. Eventually, for highly processed products the price of raw ingredients constitute only a smaller share thus price changes do not alter the consumer price significantly. Still, particularly low income countries reduce the consumption of staple food if prices become too high [44]. Exactly this leads to hunger and might be the motivation for a country to implement an export ban.

Yet, countries have alternative response options that imposing export bans. They could increase their imports or use available stocks to compensate for shocks [27]. So far, we do not consider these. Those could reduce cascading export reductions and thus the need for stocks. Some countries could thus free-ride on the stocks of others. A country with stocks might still not use them to keep them as reserve for more severe circumstances. Thus, a country with less stocks still depends on the choice of a country with higher stocks.

We emphasize that integrating alternative shock responses in a cascade model that alters an observed trade network is a challenge, as we cannot observe the effect of different choices directly in the data. The reason for that is that an international trade network is just an aggregation of all international trade activities within a year. Prices change over time—in particular close to harvest times [45]. A country comprises many agents with different utilities. Consumers might have an interest in export bans to keep food prices lower, while exporters have an interest to sell at higher prices internationally. Governments try to create policies for both sides. None of the agents base their decisions on the trade network as we observe it. The state of the system when such agents make decisions determines the aggregate network that we study here.

With our model of cascading export restrictions we offer a description of this network. We identify effective trade flows between countries and thus an analysis of dependency with respect to the observations. In future, our work can be extended to estimate the likelihood of adverse events and their consequences for specific countries taking also poverty levels of the population [22] and resilience indicators [12] into account. Furthermore, our model can be used to study intermediaries. In this work, we have focused on the impact that a cascade has on countries at the end of a value chain, where the final products are consumed and assumed that countries that can compensate for lost imports are not at risk. Yet, a country that imports grains and exports a considerable proportion usually adds value in between those two steps. Thus, the country's economy might depend crucially on the imports. This dependence can be analyzed by regarding the whole cascade process and is left for future work.

Acknowledgments

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Data availability statement

The data that support the findings of this study are openly available at FAOSTAT [40].

Appendix A. Available data and inconsistencies

The data on each regarded country in the years from 1992–2013 has been provided by by the Food and Agricultural Organization of the United Nations (FAO) [40]. The crop production data is taken from the production section of FAOSTAT, while the detailed trade matrix dataset defines the trades. The FAO distinguishes between reported exports and imports. In some cases, the reports of a trade as export and as import are not consistent. We take a conservative approach by regarding only the minimum of both trades. This way, we underestimate the total international trade. According to the rule of thumb that a high network connectivity and thus high international trade support long cascades, we usually tend to underestimate the severity of cascades, but also their possible shock diversification effect. An alternative approach would be to take the average between the reported export and import, as for instance implemented by [9]. In this case, we could not guaranty that we over- or underestimate the international trade connectivity. However, both network construction approaches lead to qualitatively similar results.

In consequence of the minimal trade approach, we only consider reporting countries by the FAO. A full list of all countries that engage at least once in the trade or production of a crop between 1992 and 2013 and their ISO-3 code is given by table A1. Although the international borders have been rather stable from 1992–2013, we still have to handle a few changes. Since Belgium and Luxembourg form an economic union and their trade statistics are only available for the combination of both till 1999, we merge their data in our whole analysis to provide consistency and acknowledge their economic union. Czechoslovakia was divided into Czech Republic and Slovakia in 1993, so rather in the beginning of our observation period. So, we keep both countries separated in our analysis (and simply assign the 1992 value to one of the countries without any consequence). Yugoslavia (1992–2003) and the state union of Serbia and Montenegro (2003–2006) was split into Montenegro and Serbia. We regard them as one entity till 2005, and afterwards as separate.

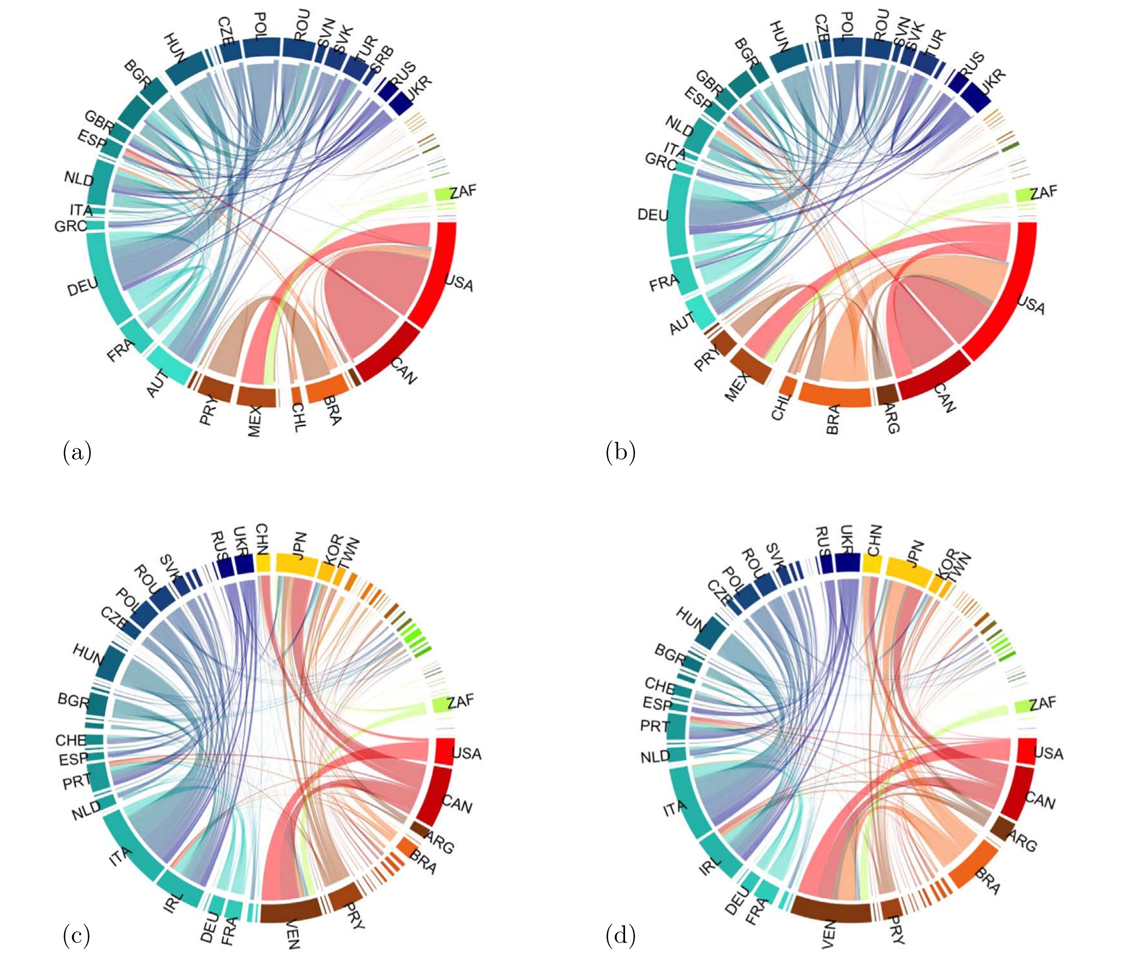

Figure A1. Difference between the higher-order and first-order trade dependency network for maize in 2013. The first row shows links that are larger in the first-order network than in the higher-order network, while the second row shows links that are larger in the higher-order network than in the first-order. Both plot the excess weight, i.e. the difference between the first-order and higher-order network. (a) Equal shock, first-order links, (b) proportional shock, first-order links, (c) equal shocks, higher-order links, (d) proportional shocks, higher-order links.

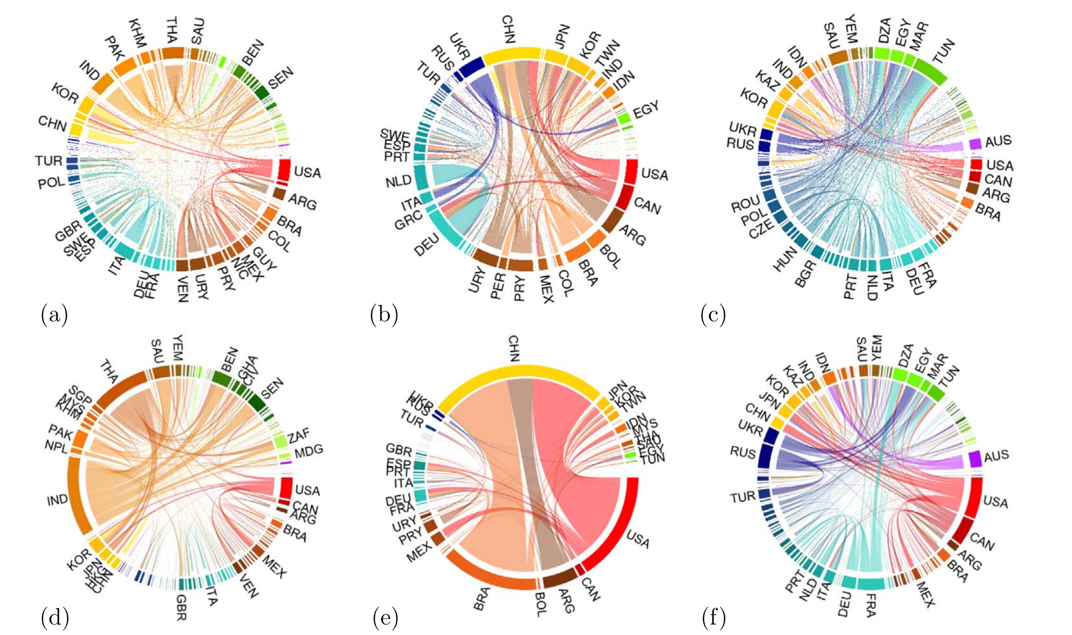

Figure A2. Cascade dependencies in 2013 for (a)/(d) rice, (b)/(e) soy, and (c)/(f) wheat trade. (Top row) Equal shock, (bottom row) proportional shock scenario.

Table A1. List of countries considered in our analysis.

ISO 3166-1 alpha-3 codes	Official country name	ISO 3166-1 alpha-3 codes	Official country name
USA	United States of America	TWN	Taiwan, the Republic of China
CAN	Canada	KAZ	Republic of Kazakhstan
ATG	Antigua and Barbuda	KGZ	Kyrgyz Republic
ARG	Argentine Republic	AFG	Islamic State of Afghanistan
BHS	Commonwealth of the Bahamas	BGD	People's Republic of Bangladesh
BRB	Barbados	BTN	Kingdom of Bhutan
BMU	Bermuda	LKA	Democratic Socialist Republic of Sri Lanka
BOL	Republic of Bolivia	IND	Republic of India
BRA	Federative Republic of Brazil	IRN	Islamic Republic of Iran
ABW	Aruba	MDV	Republic of Maldives
BLZ	Belize	NPL	Kingdom of Nepal
CHL	Republic of Chile	PAK	Islamic Republic of Pakistan
COL	Republic of Colombia	BRN	Negara Brunei Darussalam
CRI	Republic of Costa Rica	IDN	Republic of Indonesia
CUB	Republic of Cuba	KHM	Kingdom of Cambodia
DMA	Commonwealth of Dominica	MYS	Malaysia
ECU	Republic of Ecuador	PHL	Republic of the Philippines
SLV	Republic of El Salvador	SGP	Republic of Singapore
GRD	Grenada	THA	Kingdom of Thailand
GTM	Republic of Guatemala	BHR	State of Bahrain
GUY	Cooperative Republic of Guyana	QAT	State of Qatar
HND	Republic of Honduras	SAU	Kingdom of Saudi Arabia
JAM	Jamaica	OMN	Sultanate of Oman
MEX	United Mexican States	ARE	the United Arab Emirates
MSR	Montserrat	YEM	Republic of Yemen

Table A1. (Continued.)

ISO 3166-1 alpha-3 codes	Official country name	ISO 3166-1 alpha-3 codes	Official country name
NIC	Republic of Nicaragua	JOR	Hashemite Kingdom of Jordan
PAN	Republic of Panama	KWT	State of Kuwait
PRY	Republic of Paraguay	LBN	Lebanese Republic
PER	Republic of Peru	SYR	Syrian Arab Republic
KNA	Federation of Saint Kitts and Nevis	ISR	State of Israel
LCA	Saint Lucia	DZA	People's Democratic Republic of Algeria
VCT	Saint Vincent and the Grenadines	EGY	Arab Republic of Egypt
SUR	Republic of Suriname	LBY	Great Socialist People's Libyan Arab Jamahiriya
TTO	Republic of Trinidad and Tobago	MAR	Kingdom of Morocco
URY	Oriental Republic of Uruguay	SDN	Republic of the Sudan
VEN	Bolivarian Republic of Venezuela	TUN	Republic of Tunisia
AUT	Republic of Austria	CMR	Republic of Cameroon
DNK	Kingdom of Denmark	CPV	Republic of Cape Verde
FRO	Fxoroyar (Faroe Is.)	CAF	Central African Republic
FIN	Republic of Finland	COG	Republic of the Congo
FRA	French Republic	GAB	Gabonese Republic
DEU	Federal Republic of Germany	STP	Democratic Republic of Sao Tome and Principe
GRC	Hellenic Republic	COD	Democratic Republic of the Congo
ISL	Republic of Iceland	BEN	Republic of Benin
IRL	Ireland	GMB	Republic of the Gambia
ITA	Italian Republic	GHA	Republic of Ghana
MLT	Republic of Malta	GIN	Republic of Guinea
NLD	Kingdom of the Netherlands	CIV	

Table A1. (Continued.)

ISO 3166-1 alpha-3 codes	Official country name	ISO 3166-1 alpha-3 codes	Official country name
			Republic of Cote D'Ivoire
NOR	Kingdom of Norway	MLI	Republic of Mali
PRT	Portuguese Republic	MRT	Islamic Republic of Mauritania
ESP	Kingdom of Spain	NER	Republic of Niger
SWE	Kingdom of Sweden	NGA	Federal Republic of Nigeria
CHE	Swiss Confederation	SEN	Republic of Senegal
GBR	United Kingdom of Great Britain and Northern Ireland	SLE	Republic of Sierra Leone
GRL	Greenland	TGO	Togolese Republic
BELLUX	the Kingdom of Belgium and the Grand Duchy of Luxembourg combined	BFA	Burkina Faso
REU	Réunion	BDI	Republic of Burundi
ALB	Republic of Albania	KEN	Republic of Kenya
BGR	the Republic of Bulgaria	RWA	Rwandese Republic
CYP	Republic of Cyprus	UGA	the Republic of Uganda
EST	Republic of Estonia	ETH	Federal Democratic Republic of Ethiopia
BIH	Bosnia and Herzegovina	BWA	Republic of Botswana
HUN	Republic of Hungary	MWI	Republic of Malawi
HRV	Republic of Croatia	NAM	Republic of Namibia
LVA	Republic of Latvia	ZWE	Republic of Zimbabwe
LTU	Republic of Lithuania	ZAF	Republic of South Africa
MKD	Republic of Macedonia	SWZ	Kingdom of Swaziland
CZE	Czech Republic	TZA	United Republic of Tanzania
POL	Republic of Poland	ZMB	Republic of Zambia
ROU	Romania	COM	Federal Islamic Republic of the Comoros
SVN	Republic of Slovenia	MDG	Republic of Madagascar
SVK	Slovak Republic	MUS	Republic of Mauritius

Table A1. (Continued.)

ISO 3166-1 alpha-3 codes	Official country name	ISO 3166-1 alpha-3 codes	Official country name
TUR	Republic of Turkey	SYC	Republic of Seychelles
SRB	Republic of Serbia	AUS	Commonwealth of Australia
MNE	Montenegro	SLB	Solomon Islands
ARM	Republic of Armenia	COK	the Cook Islands
AZE	Republic of Azerbaijan	FJI	Republic of the Fiji Islands
BLR	Republic of Belarus	PYF	Territory of French Polynesia
GEO	Georgia	KIR	Republic of Kiribati
MDA	Republic of Moldova	NCL	Territory of New Caledonia and Dependencies
RUS	Russian Federation	VUT	Republic of Vanuatu
UKR	Ukraine	NZL	New Zealand
CHN	People's Republic of China	PNG	Independent State of Papua New Guinea
HKG	Hong Kong Special Administrative Region	TON	Kingdom of Tonga
JPN	Japan	TUV	Tuvalu
KOR	Republic of Korea	GUF	French Guiana
MAC	Macau Special Administrative Region	GLP	Guadeloupe
MNG	Mongolia	MTQ	Martinique

Appendix B. Production, import, export and demand of rice, soy and wheat across countries

The figures B1–B3 complement figure 2 for maize. They also refer to the years 1992 (left) and 2013 (right).

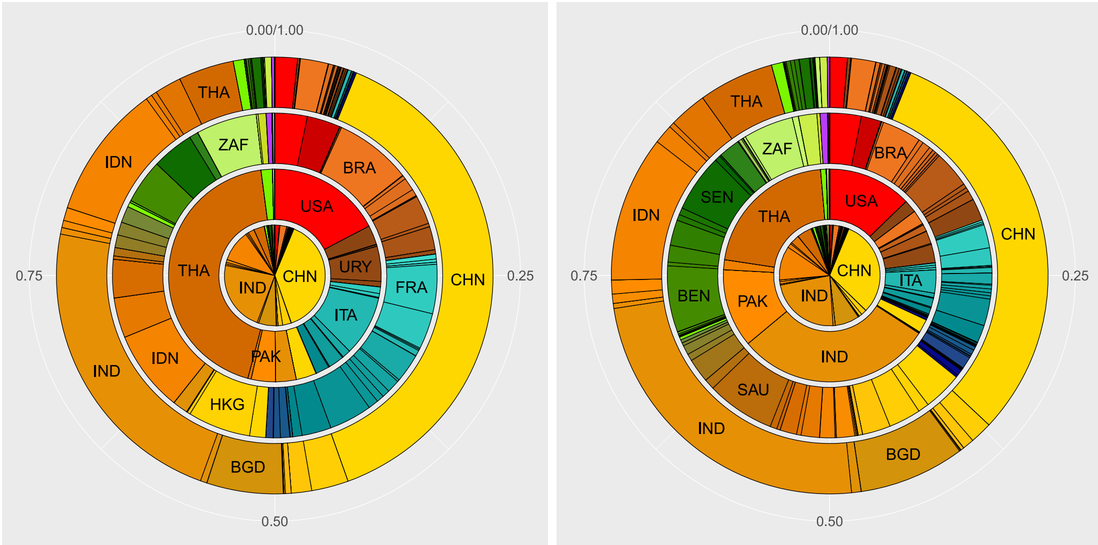

Figure B1. Fractions of rice *production* $\mathrm{prod}_i^{(R)}(y)$ (outer circle), *import* $\mathrm{imp}_i^{(R)}(y)$ (second outer circle), *export* $\exp_i^{(R)}(y)$ (second inner circle) and *demand* $\mathrm{dem}_i^{(R)}(y)$ (inner circle) per country in $y = 1992$ (left) and $y = 2013$ (right).

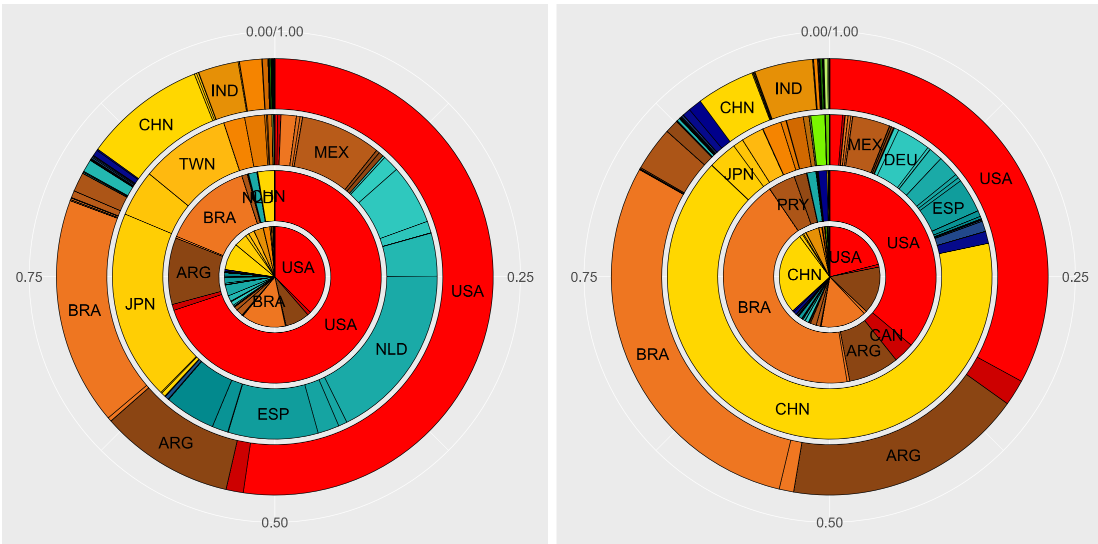

Figure B2. Fractions of soy *production* $\mathrm{prod}_i^{(S)}(y)$ (outer circle), *import* $\mathrm{imp}_i^{(S)}(y)$ (second outer circle), *export* $\exp_i^{(S)}(y)$ (second inner circle) and *demand* $\mathrm{dem}_i^{(S)}(y)$ (inner circle) per country in $y = 1992$ (left) and $y = 2013$ (right).

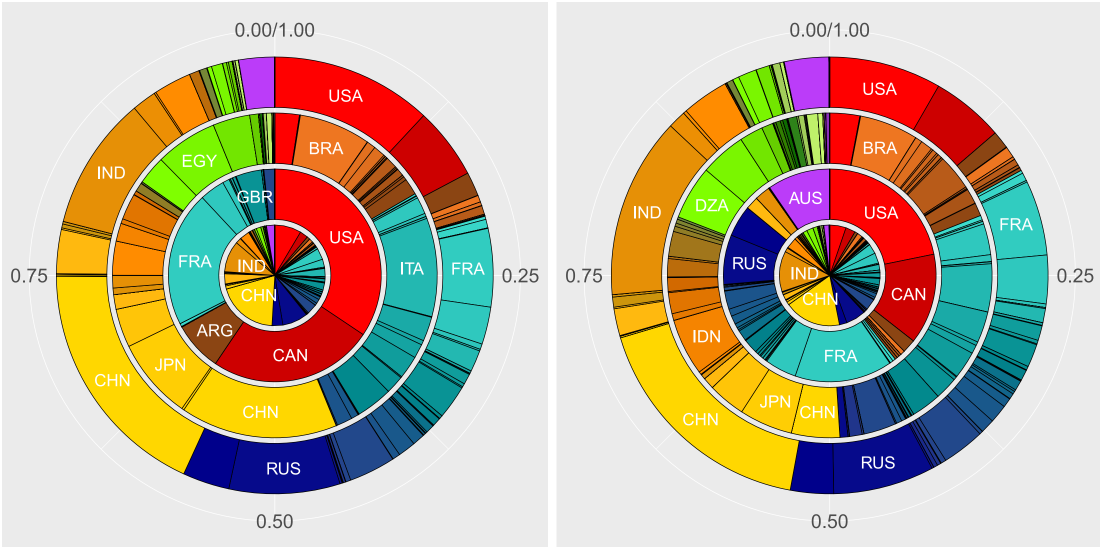

Figure B3. Fractions of wheat *production* $\mathrm{prod}_i^{(W)}(y)$ (outer circle), *import* $\mathrm{imp}_i^{(W)}(y)$ (second outer circle), *export* $\exp_i^{(W)}(y)$ (second inner circle) and *demand* $\mathrm{dem}_i^{(W)}(y)$ (inner circle) per country in $y = 1992$ (left) and $y = 2013$ (right).

Appendix C. Inequalities in the trade dependency networks

The figures C1(a)–(c) complement figure 6 for maize. Also for rice, soy and wheat we find that the weight distributions are highly right skewed, indicating that over time the trade volumes along a link are very different. To emphasize this, figure C1(d) shows the evolution of the Gini coefficient [46], which serves as measure for the dissimilarity between positive trade volumes. We note the rather high values of the Gini coefficient, which do not change much over time.

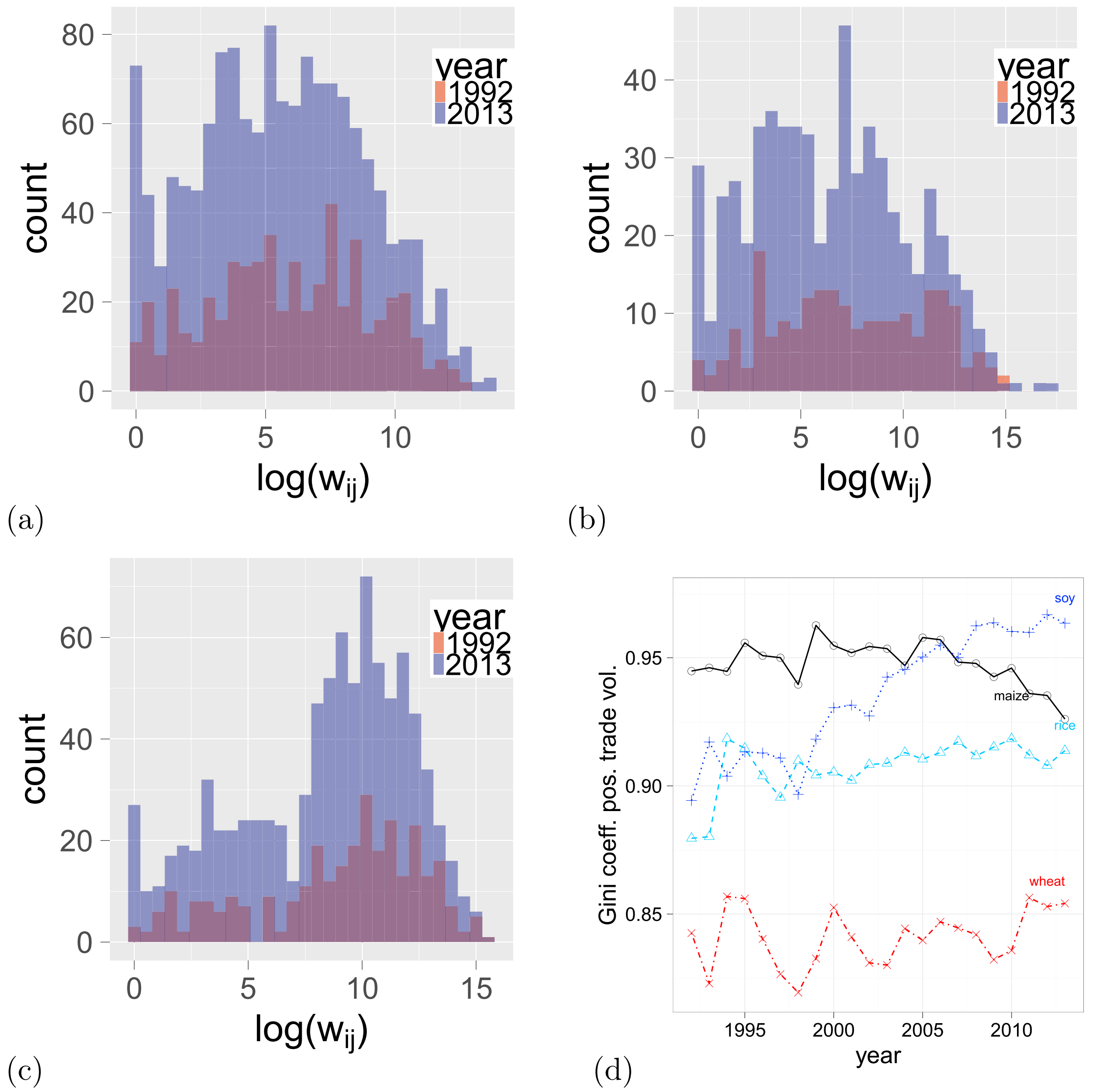

Figure C1. Histogram of the logarithm of the positive trade volumes in the years 1992 (red or purple if behind the blue) and 2013 (blue) for (a) rice, (b) soy, (c) wheat. (d) Gini coefficient of the distribution of positive trade volumes over time.

Appendix D. Evolution of the global maize trade network

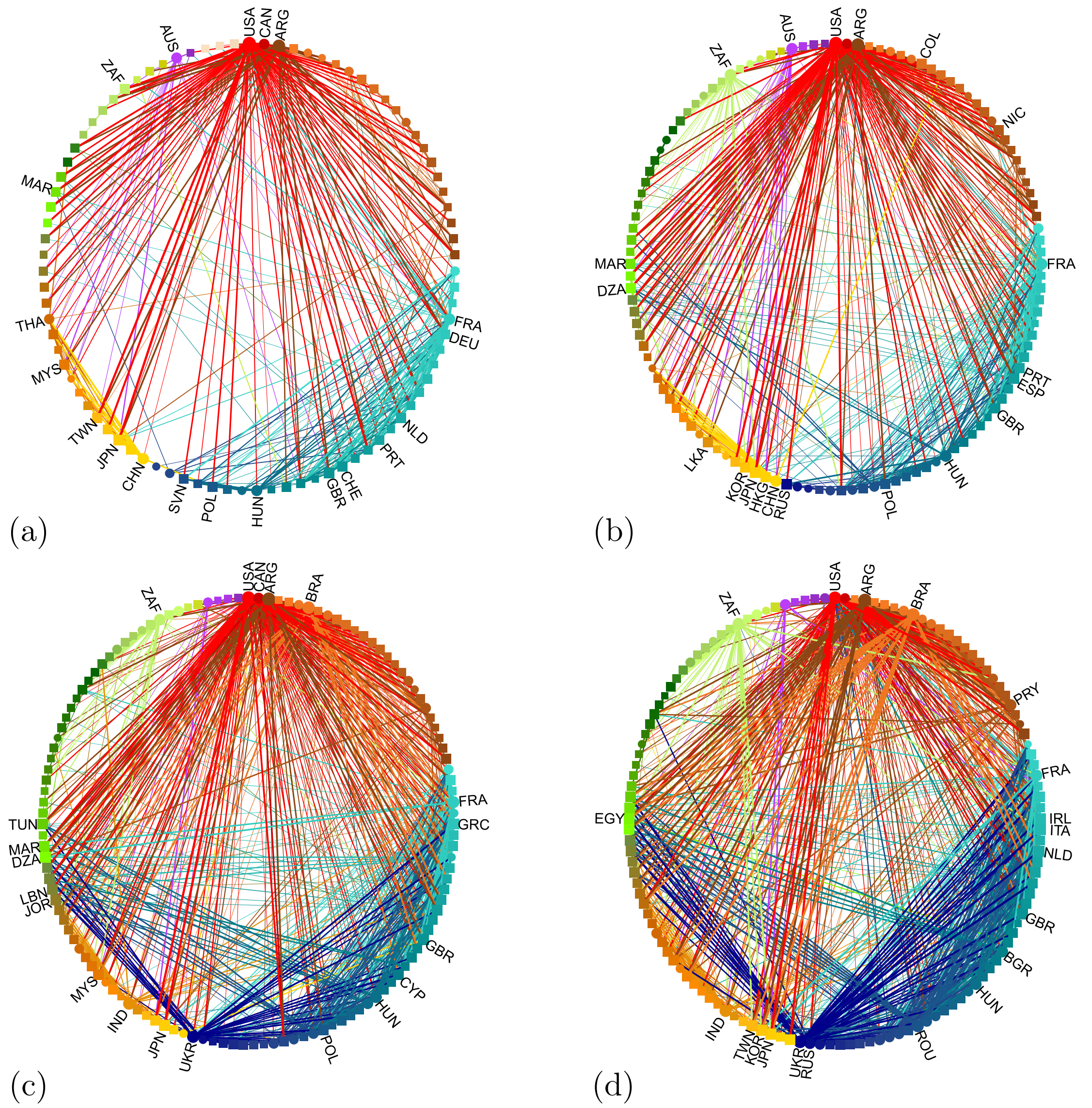

Figure D1. Maize trade. Snapshots of the years: (a) 1992, (b) 2000, (c) 2008 and (d) 2013. For further information about the color code, etc, see the caption of figure 4. We observe a clear increase in the number of market participants and in interconnectivity. In 1992, the USA dominated the international market with almost 46% of the world wide maize production. ARG, CAN and AUS are additional bigger exporters that serve other continents, while CHN mainly serves the Asian market, and FRA and HUN export primarily within Europe. Over the years, further countries cultivate maize so that the share of the production by the USA declines to 35% in 2013. Accordingly, additional exporters and importers enter the market.

Appendix E. Evolution of the global rice trade network

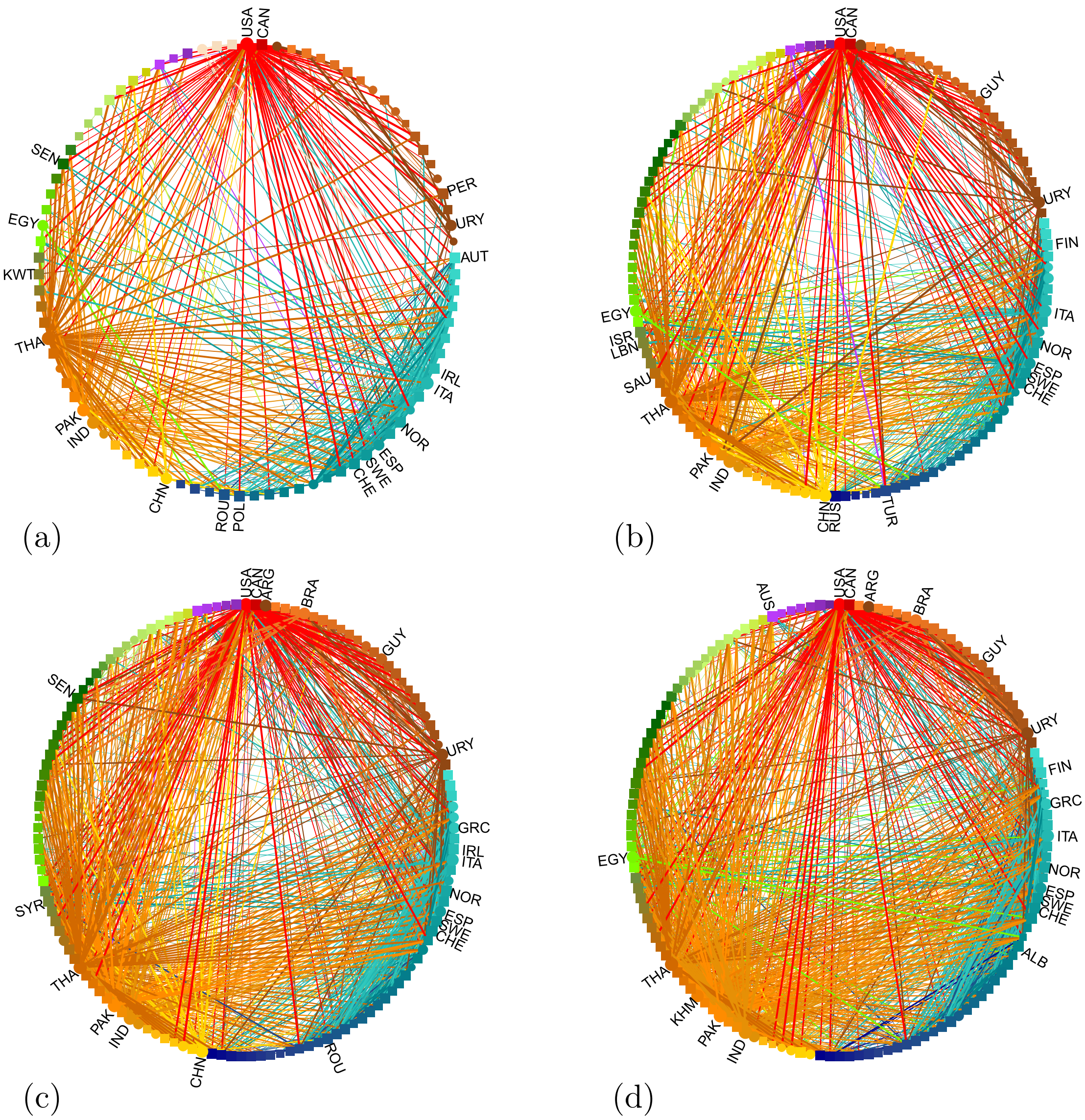

Figure E1. Rice trade. Evolution of the international rice trade network. Snapshots of the years: (a) 1992, (b) 2000, (c) 2008 and (d) 2013. For further information about the color code, etc, see the caption of figure 4. As for maize, we observe an increasing interconnectivity in the global trade of rice over the years. Still, only about 4% of the total production is traded in 2013 because national production is often subject to export (or even import) restrictions or other protective policies. In Asia, rice is primarily produced for national consumption, while overproduction is traded.

Appendix F. Evolution of the global soy trade network

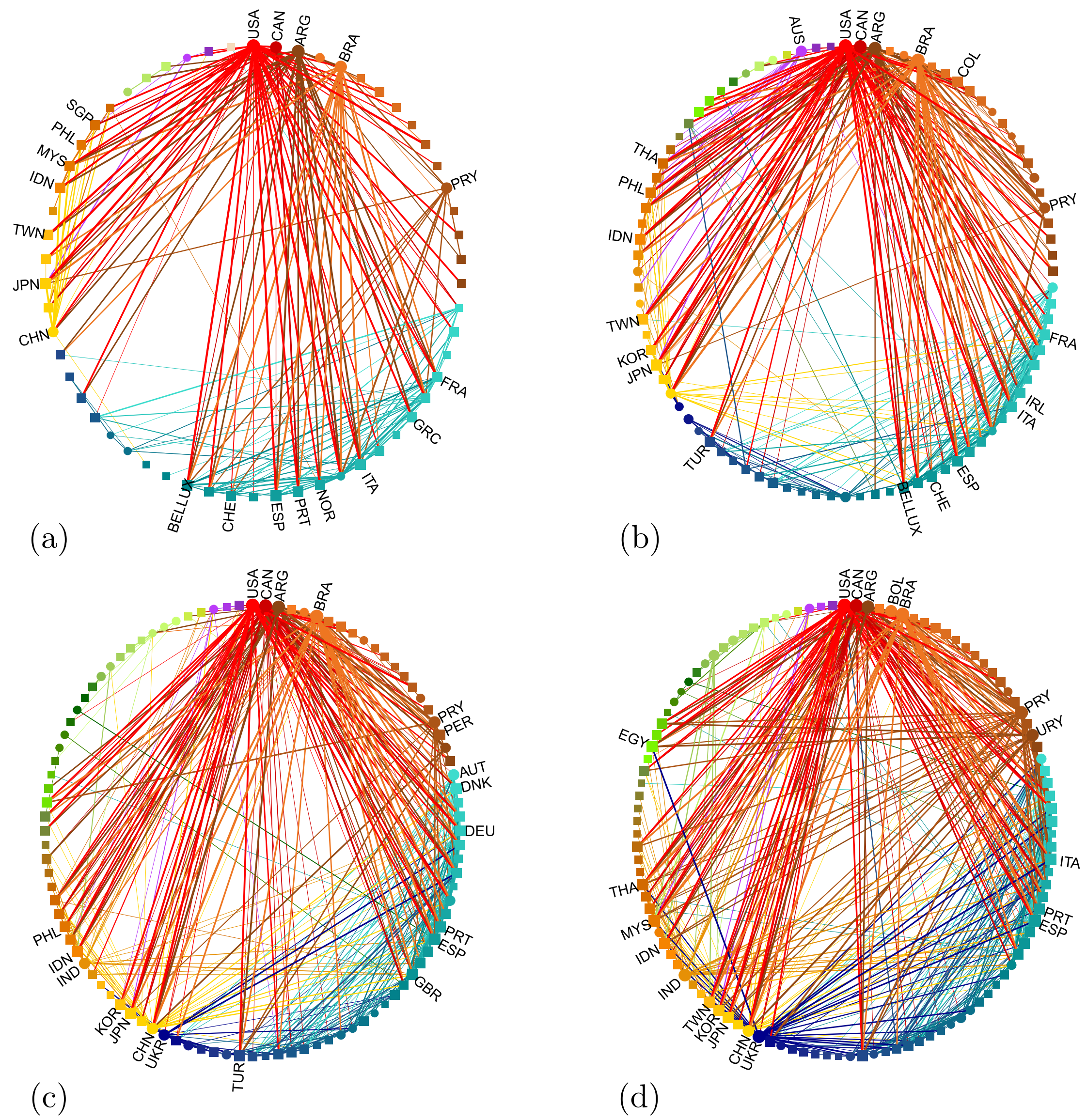

Figure F1. Soybean trade. Snapshots of the years: (a) 1992, (b) 2000, (c) 2008 and (d) 2013. For further information about the color code, etc, see the caption of figure 4. This global trade network seems to be less dense than the ones for maize, rice, or wheat, although we observe growing interconnectivity. With an increasing number of market participants, also a diversification of production and trade links is associated. While in 1992 the USA produces 52% of the total production, this share decreases to 33% in 2013 and BRA produces a similar amount of soy. Whereas CHN is a net exporter in 1992, it imports far more than it produces in 2013.

Appendix G. Evolution of the global wheat trade network

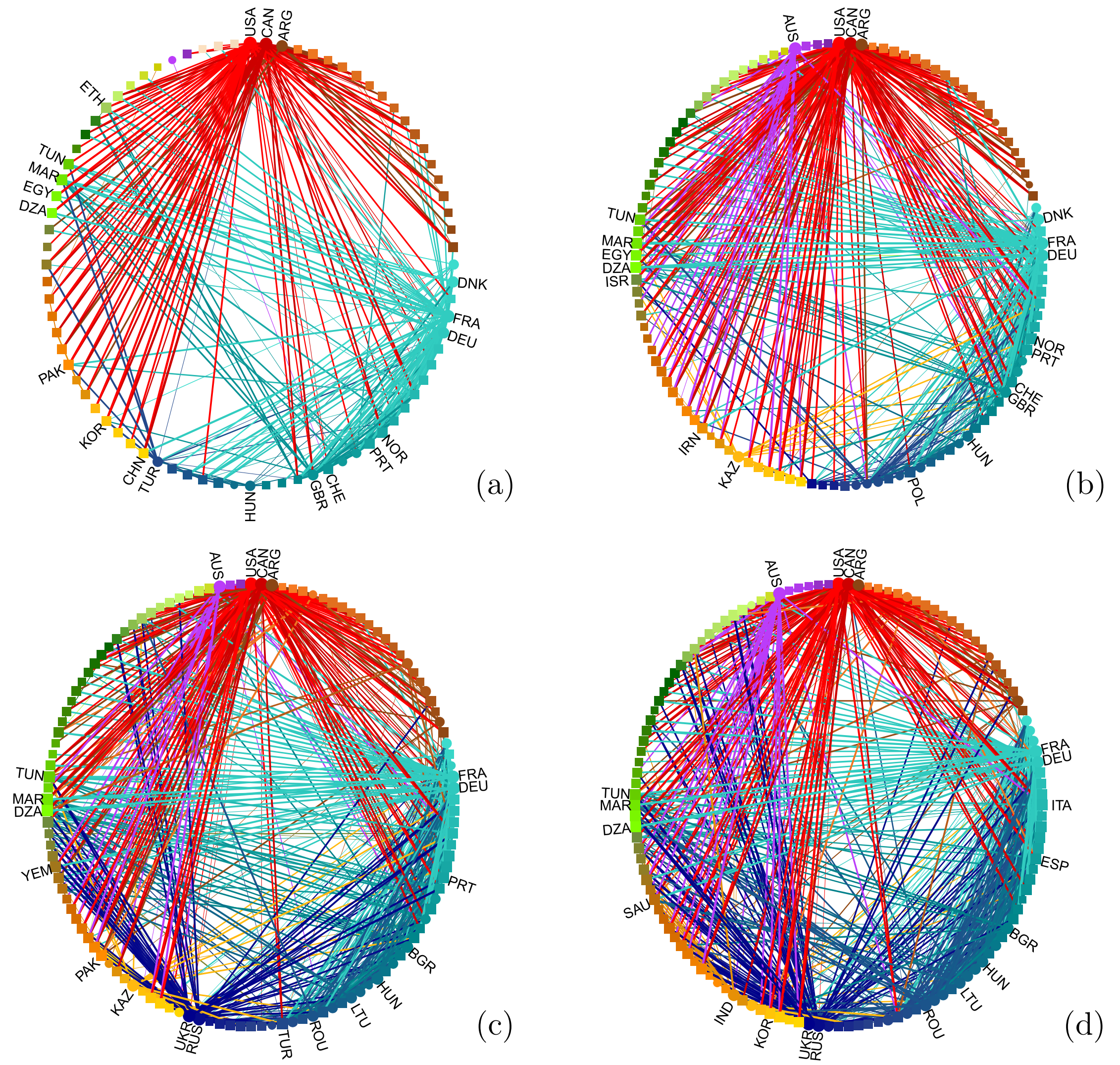

Figure G1. Wheat trade. Snapshots of the years: (a) 1992, (b) 2000, (c) 2008 and (d) 2013. For further information about the color code, etc, see the caption of figure 4. The USA, CAN, and ARG, as well as several European countries, for instance, FRA, DEU, and HUN, together with AUS are the main exporting nations. Especially since 2000, UKR and RUS as big producers and exporters add several links to the network and increase interconnectivity.

Appendix H. Sensitivity to shock sizes

To give an idea of the effect of different shock sizes and the nonlinear response by the cascade process, we take a closer look at different initial shocks of the USA with respect to maize trade in 2013 as also discussed with figure 8. We vary the initial shock size from $0.001\ \exp^{(M)}_{\mathrm{USA}}(2013)$ to $\exp^{(M)}_{\mathrm{USA}}(2013)$ in 0.001 points of the maize exports by the USA in 2013. The equal shock scenario translates in a shock of ca. 0.07 of the maize exports by the USA, while the proportional shock scenario results in a shock of the complete exports by the USA. We therefore capture quite well the relevant range of shocks with our analysis of equal and proportional shock scenarios. Figure H1(a) visualizes the threshold effects, where we define the state of a country as $s_i(T) = 1$ if $\mathrm{dd}_i(T) > 0$ and $s_i(T) = 0$ otherwise. Higher shocks do not necessarily increase the number of countries with demand deficit at the end of a cascade, as long as countries can still compensate for the shock. Yet, they usually lead to longer cascades.

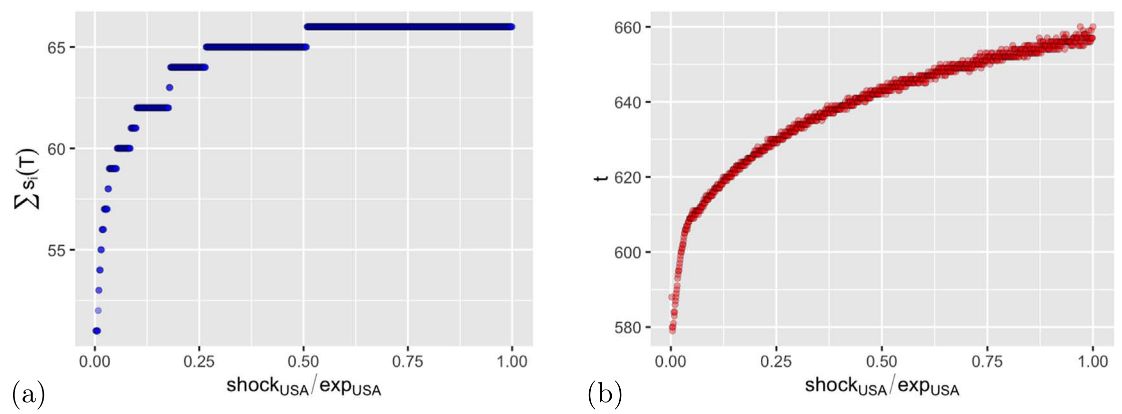

Figure H1. Sensitivity to different shock sizes of the USA in 2013 with respect to maize trade. (a) The number of countries with demand deficit at the end of a cascade when the USA is shocked initially. (b) Number of cascade steps (i.e. cascade process time) until a cascade reaches an equilibrium.

Appendix I. Differences between higher-order and first-order dependency networks

The differences between first-order and higher-order trade networks of rice, soy, and wheat are provided in figures [I1-I3].

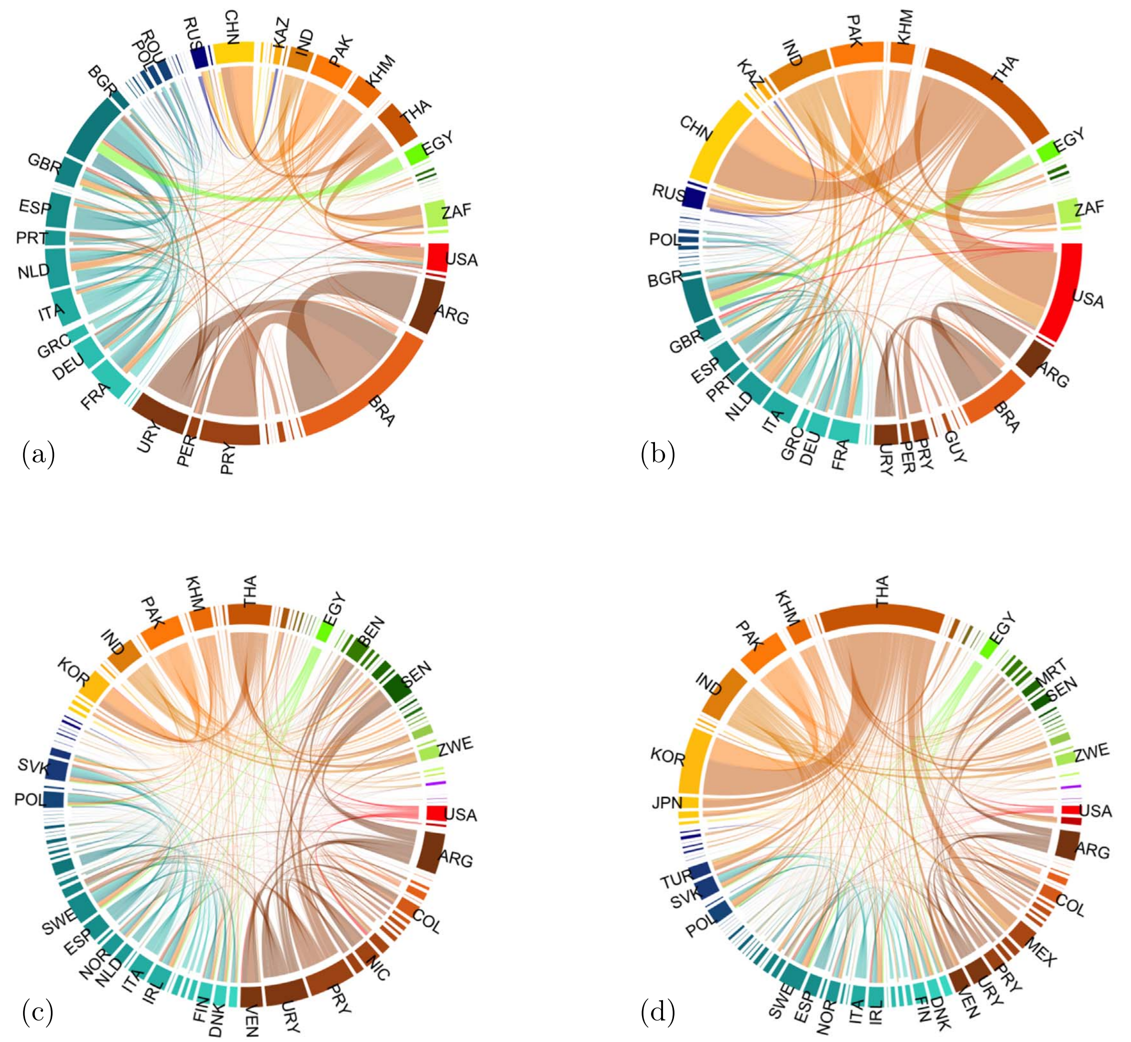

Figure I1. Difference between the higher-order and first-order trade dependency network for rice in 2013. The first row shows links that are larger in the first-order network than in the higher-order network, while the second row shows links that are larger in the higher-order network than in the first-order. Both plot the excess weight, i.e. the difference between the first-order and higher-order network. (a) Equal shock, first-order links, (b) proportional shock, first-order links, (c) equal shocks, higher-order links, (d) proportional shocks, higher-order links.

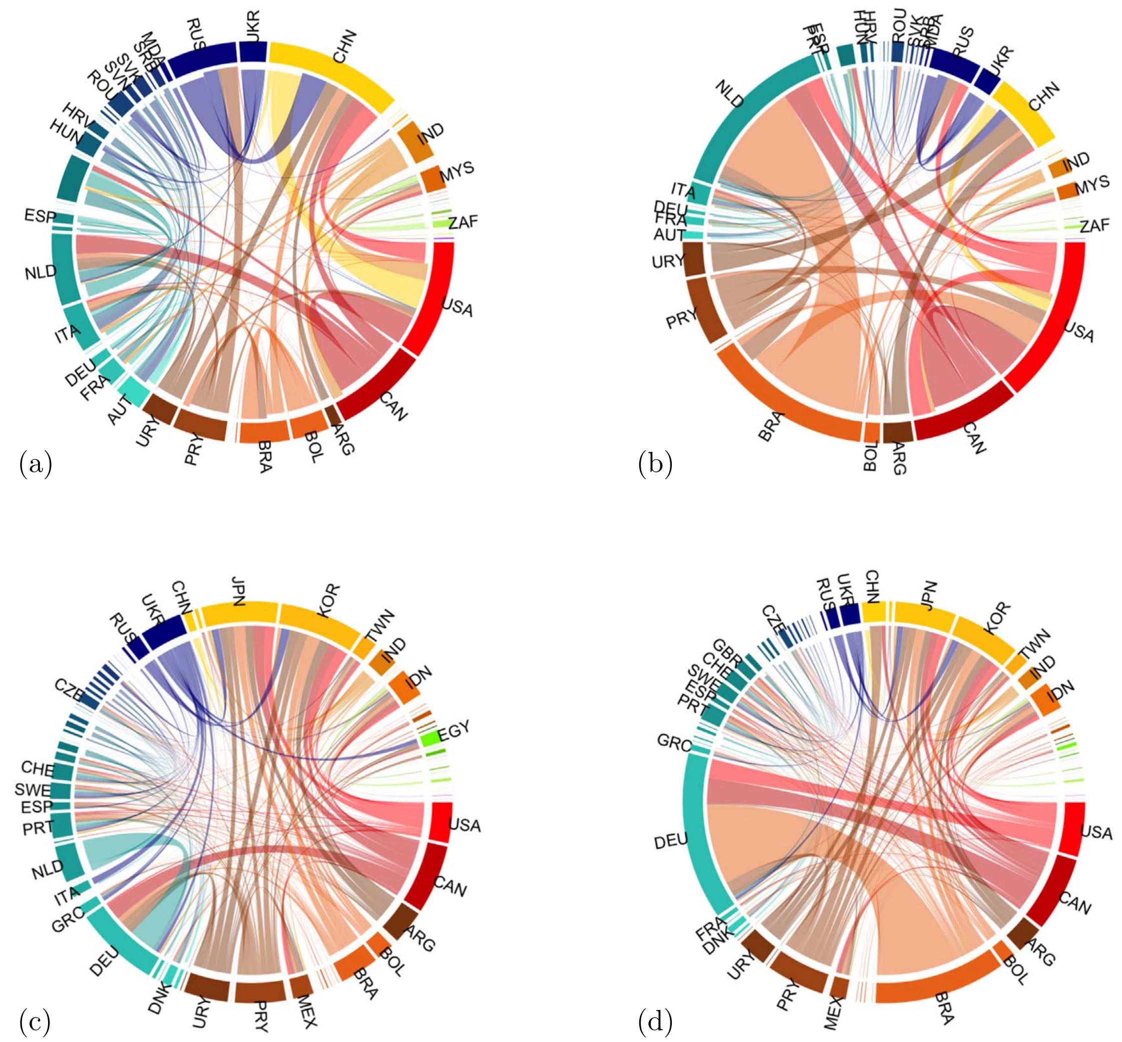

Figure I2. Difference between the higher-order and first-order trade dependency network for soy in 2013. The first row shows links that are larger in the first-order network than in the higher-order network, while the second row shows links that are larger in the higher-order network than in the first-order. Both plot the excess weight, i.e. the difference between the first-order and higher-order network. (a) Equal shock, first-order links, (b) proportional shock, first-order links, (c) equal shocks, higher-order links, (d) proportional shocks, higher-order links.

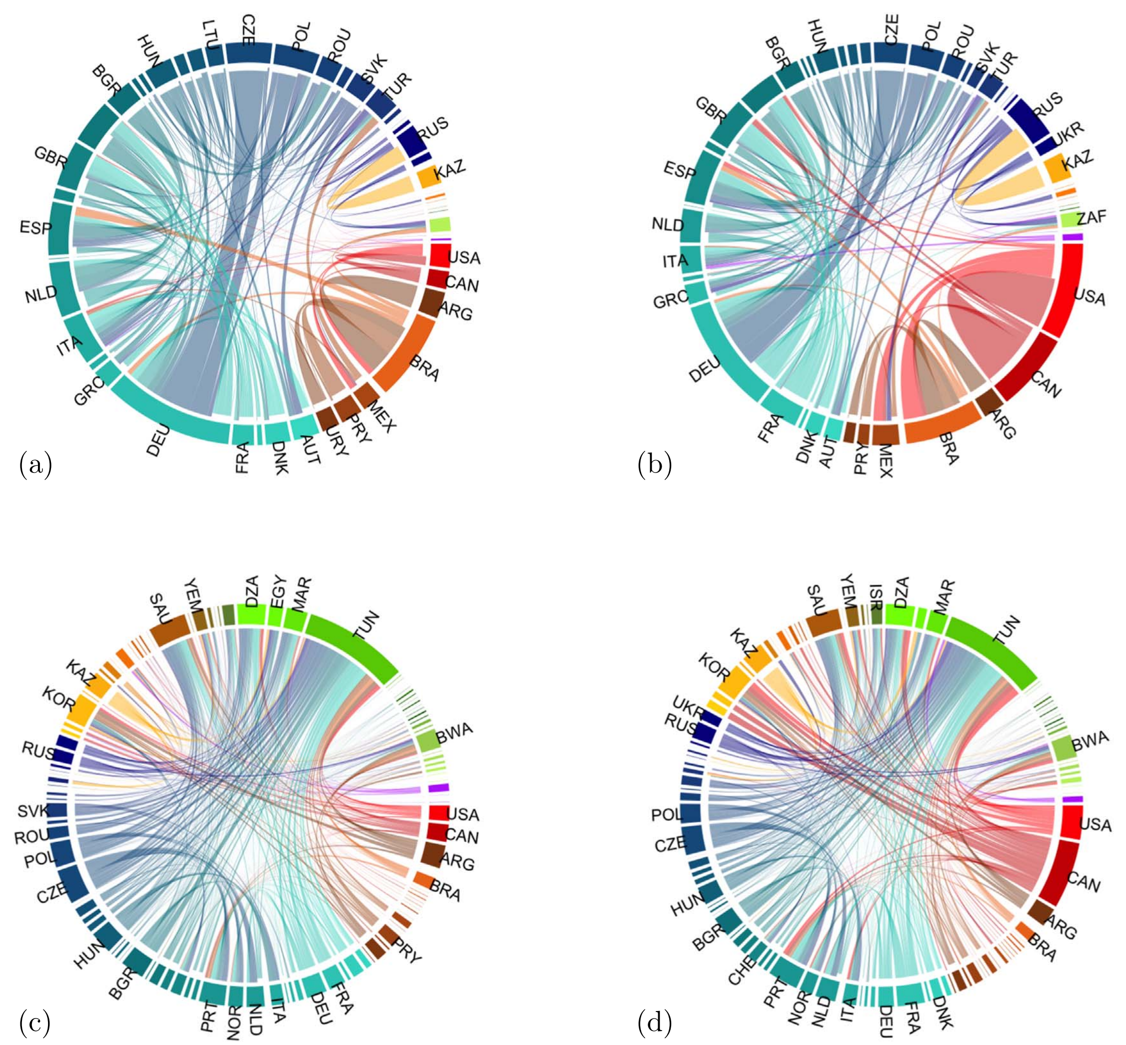

Figure I3. Difference between the higher-order and first-order trade dependency network for wheat in 2013. The first row shows links that are larger in the first-order network than in the higher-order network, while the second row shows links that are larger in the higher-order network than in the first-order. Both plot the excess weight, i.e. the difference between the first-order and higher-order network. (a) Equal shock, first-order links, (b) proportional shock, first-order links, (c) equal shocks, higher-order links, (d) proportional shocks, higher-order links.

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