Heliyon 9 (2023) e21076

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Evolving community structure in the international pesticide trade networks

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ARTICLE INFO

Dataset link: https://comtrade.un.org

Keywords:
Econophysics
International pesticide trade network
Community structure
Regional pattern
Intrinsic community block
Temporal network

ABSTRACT

The statistical properties of the international trade networks of all commodities as a whole have been extensively studied. However, the international trade networks of individual commodities often behave differently. Due to the importance of pesticides in agricultural production and food security, we investigated the evolving community structure in the international pesticide trade networks (iPTNs) of five categories from 2007 to 2018. We reveal that the community structures in the undirected and directed iPTNs exhibit regional patterns. However, the regional patterns are very different for undirected and directed networks and for different categories of pesticides. Moreover, the community structure is more stable in the directed iPTNs than in the undirected iPTNs. We also extract the intrinsic community blocks for the directed international trade networks of each pesticide category. It is found that the largest intrinsic community block is the most stable, appears in every pesticide category, and contains important economies (Belgium, Germany, Spain, France, the United Kingdom, Italy, the Netherlands, and Portugal) in Europe. Other important and stable intrinsic community blocks are Canada and the United States in North America, Argentina and Brazil in South America, and Australia and New Zealand in Oceania. These results suggest that, in the international trade of pesticides, geographic distance and the complementarity of important and adjacent economies are significant factors.

1. Introduction

Food crises have accompanied human history. According to the fifth edition of the Global Report on Food Crises released by the Food Security Information Network of the United Nations, there were around 155 million people in food crises or worse in 55 countries/territories globally in 2020 [1]. Conflicts, climate disruption, and economic shocks are the main reasons causing food crises, which have been aggravated by the COVID-19 pandemic in recent years. Ensuring and increasing agricultural production are important means to relieve food shortages [1]. The use of chemical pesticides can effectively control crop diseases, insects, and grass damage, which can save 30%–40% of the total crop loss in the world every year. Pesticides are crucial in maintaining global crop yields as refraining from pesticide use would result in a loss of 78% fruit production, 54% vegetable production, and 32% cereal production [2]. In this sense, pesticides, as a main agricultural input, play an important role. Hence, investigating the global pesticide

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https://doi.org/10.1016/j.heliyon.2023.e21076
Received 10 November 2022; Received in revised form 4 October 2023; Accepted 15 October 2023

Available online 20 October 2023
2405-8440/

flows from supplying economies to demanding economies from the perspective of international trade networks (ITNs) would deepen our understanding of pesticides reallocation all over the world.

The evolving structure and dynamics of the international trade networks or world trade webs (WTWs) with aggregated goods have been investigated extensively at macro-, meso- and micro-scales, be they undirected or directed, unweighted or weighted [3–12]. There are quite a few studies focusing on the structure and evolution of international food trade networks, including aggregate food [13–16], individual food commodities [17–19], cereals [20], rice [19], maize [19,21], wheat [19,22–24], soybean [19,25], seafood [26–28], and meat [29]. The ITNs of agricultural inputs are relatively rare [30]. Different types of models have been proposed to understand the formation of the international trade networks [31–36]. Studies of risk transmission and the Vulnerability of international food trade networks to shocks are also important to food security [16,21,27,37].

At the meso-scale, the community structure in the international trade networks is of particular interest, as it is often related to the important function of node groups [38,39]. Tzekina, Danthi and Rockmore investigated the ITNs of 186 economies from 1948 to 2005 and revealed trade "islands", which is interpreted as mixed evidence of globalization [40]. Barigozzi, Fagiolo and Mangioni identified the aggregate and commodity-specific community structures of the directed ITNs of 97 commodities traded among 162 economies from 1992 to 2003 by optimizing the modularity using taboo search and found them to be much more correlated with geographic communities than partitions induced by regional trade agreements [41,42]. Estrada obtained three communities using the N-ComBa K-means method for the undirected international miscellaneous metal manufactures network [43]. Fan et al. introduced the weighted extremal optimization algorithm for community detection in the ITN in 2010 and also identified three communities [44]. Applying the modularity optimization method to the undirected ITN during the period from 1995 to 2011, Zhu et al. identified three main communities (the America community, the Europe community, and the Asia-Oceania community) [45]. Reyes, Wooster and Shirrell detected the community structure of the undirected ITN for each year between 1970 and 2000 and found that regional trade agreements have a strengthening effect over time with cyclical components on the formation of the community structure of the world trade network [46]. Bartesaghi, Clemente and Grassi used the communicability distance approach to investigate the community structure of the undirected international trade network in 2016 and the optimal partitioning yields 19 non-trivial communities [47]. Dong et al. investigated the undirected international copper trade networks from 2007 to 2015 and identified three to five communities in different years [48]. Torreggiani et al. investigated the undirected international food trade networks of 16 commodities from 1992 to 2011 and found about 5-6 communities in each commodity-specific network [17]. We note that Piccardi and Tajoli used four approaches (modularity optimization, cluster analysis, stability functions, and persistence probabilities) to analyze communities in the ITNs from 1962 to 2008 and found no agreed evidence of significant partitions but a few weak communities suggesting a truly globalizing trading system [49].

The community structure of a complex network reflects underlying higher-order interactions among different nodes [50,51], which shape the dynamics of complex networks. In this work, we aim at identifying the evolving community structure of five categories of iPTNs. There are numerous community detection methods [38,39], which often provide distinct partitioning results. Since the iPTNs are directed and weighted, we utilize the Infomap algorithm [52]. Certainly, there are other algorithms capable of coping with such graphs, for example, the Order Statistics Local Optimization Method (OSLOM) [53]. However, there are stable clusters identified in temporal networks that we call intrinsic community blocks, which is the main contribution of this work. The detected communities are found to have evident regional patterns and vary over different pesticide categories. The largest and stablest intrinsic community block contains a few developed economies in Europe. Specifically, the largest and stablest intrinsic community block in every pesticide category contains important economies including Belgium, Germany, Spain, France, the United Kingdom, Italy, the Netherlands, and Portugal in Europe. Other important and stable intrinsic community blocks contain Canada and the United States in North America, Argentina and Brazil in South America, and Australia and New Zealand in Oceania.

2. Materials and methods

2.1. Data description

The data sets we analyze were extracted from the UN Comtrade Database (https://comtrade.un.org), under Heading 3808. We consider the international trade flows of five categories of pesticides, including insecticides (380891), fungicides (380892), herbicides (380893), disinfectants (380894), and rodenticides and other similar products (380899). Since the trade data earlier than 2007 are not available for at least one pesticide category and the data for 2019 are still incomplete [30], the sample period considered in this work is from 2007 to 2018.

Simple preprocessing of the data is necessary before we use them [30]. In the UN Comtrade Database, the information of an international trade might be reported by both exporting and importing economies i and j, and the reported values might be different. We use the large value for the trade. There are also missing trade partners and non-economy partners (such as "WLD" and "EU2"), which are not individual economies and thus removed from further analysis.

2.2. Network construction

Denoting the category of pesticide by $cmd \in \{380891, 380892, 380893, 380894, 380899\}$ and the trade value (in units of US$) of pesticide cmd exported from economy i to economy j in year t by $w_{ij}^{cmd}(t)$, we express the temporary international pesticide trade network as follows,

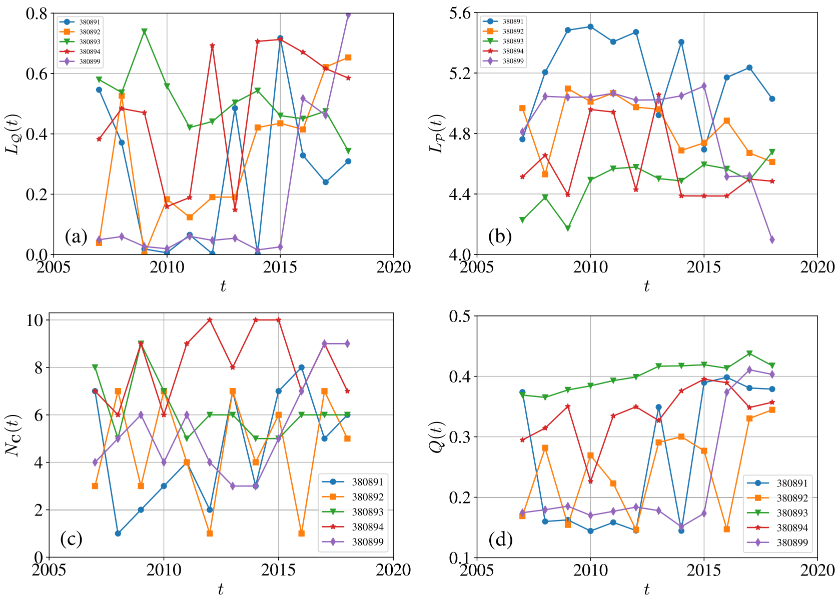

Fig. 1. Yearly evolution of the per level codelengths for modules (a) and leaf nodes (b) for the undirected international trade networks of insecticides (380891), fungicides (380892), herbicides (380893), disinfectants (380894), and rodenticides and other similar products (380899) from 2007 to 2018. (c)Evolution of the number of communities for the undirected international trade networks of insecticides (380891), fungicides (380892), herbicides (380893), disinfectants (380894), and rodenticides and other similar products (380899) from 2007 to 2018. (d) Evolution of the modularity for the undirected international trade networks of insecticides (380891), fungicides (380892), herbicides (380893), disinfectants (380894), and rodenticides and other similar products (380899) from 2007 to 2018.

$$\mathbf{W}^{cmd}(t) = \left[w_{ij}^{cmd}(t)\right],$$

which contains all the information about the set of nodes and links between them of the temporal network. Since national pesticide trade is not considered, we have $w_{ii}^{cmd}(t) = 0$ for all pesticide categories in all years and there are no self-loops in the iPTNs. The main statistical properties have been investigated in Ref. [30], including number of nodes, number of links, numbers of importing and exporting economies, trade value, node metrics, link metrics, and so on.

3. Results

3.1. Community structure of the undirected iPTNs

For the five undirected and weighted iPTNs, we adopt the two-level Infomap algorithm to identify the community partitioning [52]. The Infomap algorithm obtains the community partitioning **C** when the expected description length of a random walk reaches its minimum and the per step average description length is given by a map equation:

$$L(\mathbf{C}) = L_Q(\mathbf{C}) + L_{\mathcal{P}}(\mathbf{C}),$$

where $L_Q(\mathbf{C})$ is the per level codelength for communities, describing the inter-community movements of random walkers, and $L_{\mathcal{P}}(\mathbf{C})$ is the per level codelength for leaf nodes, describing the intra-community movements of random walkers.

For each undirected and weighted international pesticide trade network, we obtain the community partitioning $\mathbf{C}^{cmd}(t)$. We illustrate the evolution of the per level codelength for communities (L_Q) in Fig. 1(a) and the per level codelength for leaf nodes ($L_{\mathcal{P}}$) in Fig. 1(b). Most of the per level codelength curves fluctuate remarkably. It is interesting to see that, for a given category of pesticides, when L_Q increases, $L_{\mathcal{P}}$ decreases, and vice versa. Actually, the $L(t)$ curves fluctuate much less and do not show evident trends.

In Fig. 1(c), we show the evolution of the number $N_{\mathbf{C}}$ of communities for the five categories of iPTNs. It is found that the number of identified communities changes over different years. There are three networks with only one community, that is, insecticides in 2008, fungicides in 2012, and fungicides in 2016. There are also two networks (insecticides in 2009 and 2012) having two communities. All other networks have at least three communities. The international trade networks of disinfectants have relatively more communities than other pesticides, with the largest number 10 of communities. We also find that the curves of the networks of herbicides and disinfectants are relatively stable compared to other pesticides. We note that the fluctuations and different behavior of the per level codelengths for some pesticides in Fig. 1(a) and Fig. 1(b) are caused by the different partitioning of communities for different networks shown in Fig. 1(c).

The most popular measure for the goodness of community partitioning of a network is the modularity [38,54]. The modularity of an undirected but weighted network is

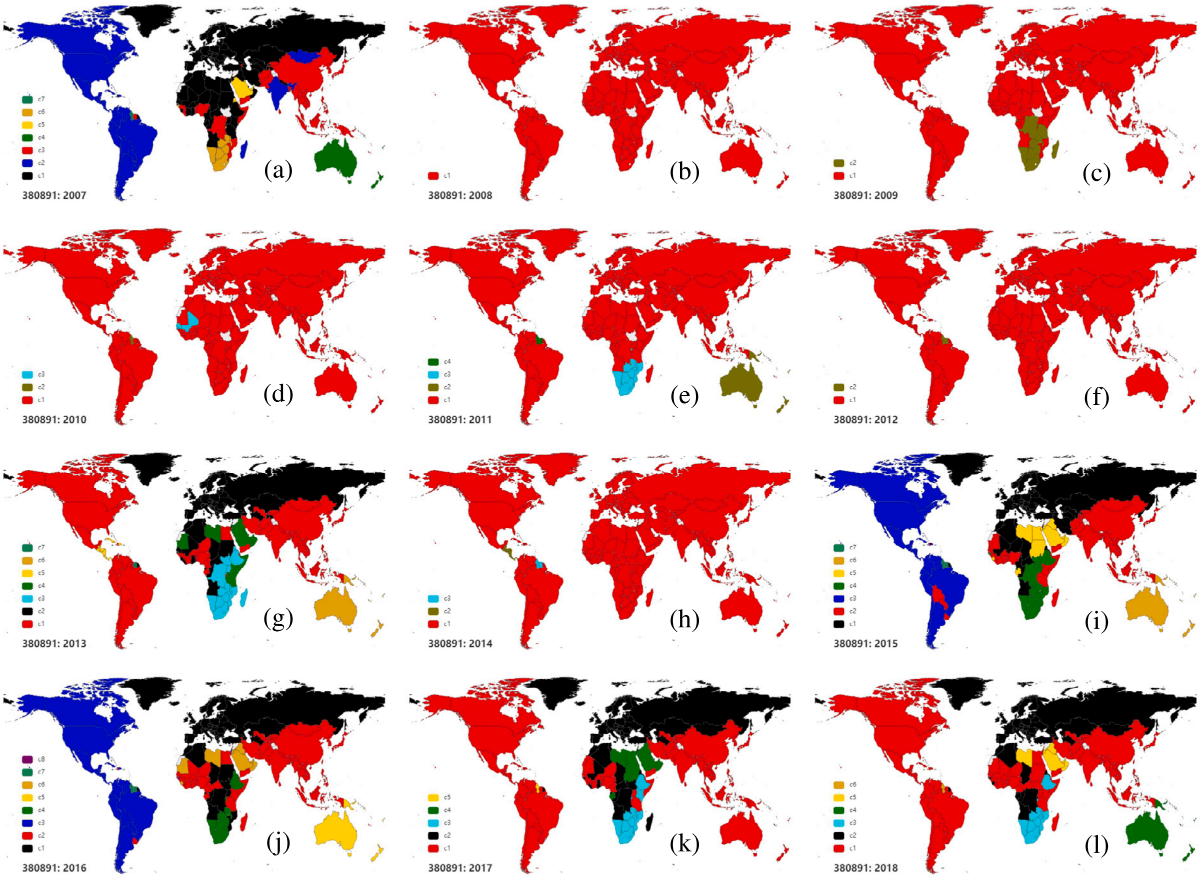

Fig. 2. Community evolution of the undirected iPTNs of insecticides (380891) from 2007 (Panel (a)) to 2018 (Panel (l)).

$$Q = \frac{1}{2w} \sum_i \sum_j \left(w_{ij} - \frac{w_i w_j}{2w} \right) \delta(C_i, C_j)$$

where $\delta(C_i, C_j)$ is the Kronecker delta function such that

$$\delta(C_i, C_j) = \begin{cases} 1, & \text{if } C_i = C_j \\ 0, & \text{otherwise} \end{cases},$$

w_i is the strength of node i

$$w_i = \sum_j w_{ij},$$

and $2w$ is the total strength

$$2w = \sum_i w_i = \sum_i \sum_j w_{ij}.$$

Fig. 1(d) illustrates the evolution of modularity for the undirected iPTNs from 2007 to 2018. We find that the modularity curve of herbicides (380893) has the least fluctuations and largest values and shows a stably increasing trend. The modularity curve of disinfectants (380894) has also relatively large values and mild fluctuations and shows roughly an increasing trend. Correspondingly, their curves of community number are relatively stable. The modularity curve of rodenticides and other similar products (380899) has been stable before 2015 and increases sharply since 2016. The modularities of the three networks with only one community are all very low.

Fig. 2 illustrates the evolution of communities of the undirected iPTNs of insecticides (380891) from 2007 to 2018. It is striking to observe that there are 6 years when one community dominates, that are 2008, 2009, 2010, 2011, 2012, and 2014. In 2008, all the economies formed a community. In 2009, we obtain two communities. The smaller community C_2 contains 18 economies, 16 in southern Africa (Botswana, The Democratic Republic of the Congo, Equatorial Guinea, Madagascar, Malawi, Mauritius, Namibia, Rwanda, Saint Helena, Seychelles, Solomon Islands, South Africa, Swaziland, Tanzania, Zambia, and Zimbabwe, where 11 economies belong to the Southern African Development Community) and two in the Middle East (Palestine and Kuwait). In 2010, we have three communities. The second community C_2 contains 12 economies, including Barbados, Dominica, Grenada, Guyana, Jamaica, Montserrat, Saint Kitts and Nevis, Anguilla, Saint Lucia, Saint Vincent and the Grenadines, and Trinidad and Tobago, which are located around the Eastern Caribbean Sea. The third community C_3 contains two economies, Mali and Senegal in northwest Africa. In 2011, we identify four communities. The second community C_2 contains 15 economies (Australia, Solomon Islands, Cook Islands, Fiji, Kiribati, Nauru, Vanuatu, New Zealand, Niue, Norfolk Island, Papua New Guinea, Tonga, Tuvalu, Wallis and Futuna, and Samoa), located in the Oceania and around. The third community C_3 contains 14 economies (Botswana, Comoros, Lesotho, Malawi, Mauritius, Mozambique, Namibia, Timor-Leste, Rwanda, Saint Helena, South Africa, Zimbabwe, Swaziland, and Zambia) in southern Africa. The fourth community C_4 contains 11 economies (Barbados, Dominica, Grenada, Guyana, Jamaica, Montserrat, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and the Grenadines, Suriname, and Trinidad and Tobago) in Latin-America. In 2012, we find two communities. The second community C_2 contains 12 economies (Antigua and Barbuda, Barbados, Dominica, Grenada, Guyana, Jamaica, Montserrat, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and the Grenadines, Suriname, and Trinidad and Tobago), which are located around the eastern Caribbean Sea. In 2014, there were three communities. The second community C_2 contains seven economies (Belize, Costa Rica, El Salvador, Guatemala, Honduras, Nicaragua, and Panama) located along the western Caribbean Sea, while the third community C_3 contains 13 economies (Antigua and Barbuda, Barbados, Dominica, French Southern and Antarctic Territories, Grenada, Guyana, Jamaica, Montserrat, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and the Grenadines, Suriname, and Trinidad and Tobago), located along the eastern Caribbean Sea.

The other six networks in 2007, 2013, 2015, 2016, 2017, and 2018 have more communities than networks in other years and the communities occupy relatively comparable areas. Comparing these community maps in different years, we see four main regions: American continent, European continent, Asia, and Oceania. In contrast, economies in Africa and Middle East are clustered into smaller communities or belong to other big communities. It shows the importance of geographical distance in international pesticide trade.

Fig. A.1 illustrates the evolution of communities of the undirected iPTNs of fungicides (380892) from 2007 to 2018. There are two networks, respectively in 2012 and 2016, which have only one community. The two networks in 2007 and 2009 had three communities. However, the first community C_1 contains most economies. In 2007, the second community C_2 contains 13 economies (Belize, Colombia, Costa Rica, The Dominican Republic, Ecuador, El Salvador, Guatemala, Haiti, Honduras, Jamaica, Panama, Peru, and Venezuela), while the third community C_3 contains 10 economies (Antigua and Barbuda, Barbados, Grenada, Guyana, Montserrat, Aruba, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and the Grenadines, and Trinidad and Tobago). The economies in these two communities are located around the Caribbean Sea. In 2009, the second community C_2 contains two economies (Palestine in the Middle East and Swaziland in southern Africa), while the third community C_3 also contains two economies (Niger and Burkina Faso), both in northern Africa.

The other eight networks in 2008, 2010, 2011, 2013, 2014, 2015, 2017, and 2018 have at least four communities. We observe several clustered regions, including the three economies of the North American Free Trade Area (NAFTA) together with a few small economies in the east Caribbean, Guyana and smaller economies in the east Caribbean, economies around the Caribbean, Asia, Oceania, Europe, and fragmented regions in Africa. These regions are identified communities in some years, or a few regions form a community in other years. For the economies in the Economic Commission for Latin America and the Caribbean, we mainly observe one, two, or three communities in different years, and some small economies may belong to the NAFTA-based community. Economies in the Oceania may be clustered with Europe (2008, 2010, 2011), the NAFTA (2013, 2014, 2018), or Asia (2010, 2011, 2017). This suggests that geographic distance and trade organizations play important roles in the formation of international fungicide trade communities.

Fig. A.2 illustrates the evolution of communities of the undirected iPTNs of herbicides (380893) from 2007 to 2018. It is found that there are at least five communities in each year. The three economies of NAFTA always belong to the same community, which often contains a few small economies in the Caribbean. In contrast, other economies in Latin America and the Caribbean usually form or belong to other communities, showing a similar regional pattern as in the international fungicide trade networks. In 2018, most of the economies on the American continent formed a unique community. In all the years, most economies in Europe have belonged to a community, and most economies in Asia also belong to a community. Japan and South Korea sometimes belong to the North American community or the European community. Economies in the Middle East are more likely to belong to the European community before 2012 and form their own community afterwards. Economies in Oceania belong to the Asia community in most years, except that they form a separate community in 2007 and belong to the South America community in 2009.

There are about 60 economies in Africa that belong to three or more communities. The economies in each of these communities are not randomly distributed in Africa; rather, they are clustered in a localized way, suggesting that geographical closeness is the dominant determining force in the formation of trade communities. Some economies are more likely to belong to the Asia community, while some other economies tend to join the Europe community. This pattern reflects their stable economic relationship. In most years, the Southern African Development Community and other geographically close economies often belong to the same, separate community.

Fig. A.3 illustrates the evolution of communities of the undirected iPTNs of disinfectants (380894) from 2007 to 2018. These networks contain 6 to 10 communities and the division of communities in different years is quite similar except for the network in 2010. The first community C_1 has 166 economies and contains most economies in North America, Europe, Asia and Oceania. The only exception is Papua New Guinea, the second largest country in Oceania, which belongs to the fifth community C_5. The second community C_2 has 9 economies (Argentina, Bolivia, Brazil, Chile, Haiti, Paraguay, Uruguay, and Venezuela in South America, and Mauritania in Northwest Africa). The third community C_3 has 13 economies (Ethiopia, Kenya, Rwanda, Somalia, Sudan,

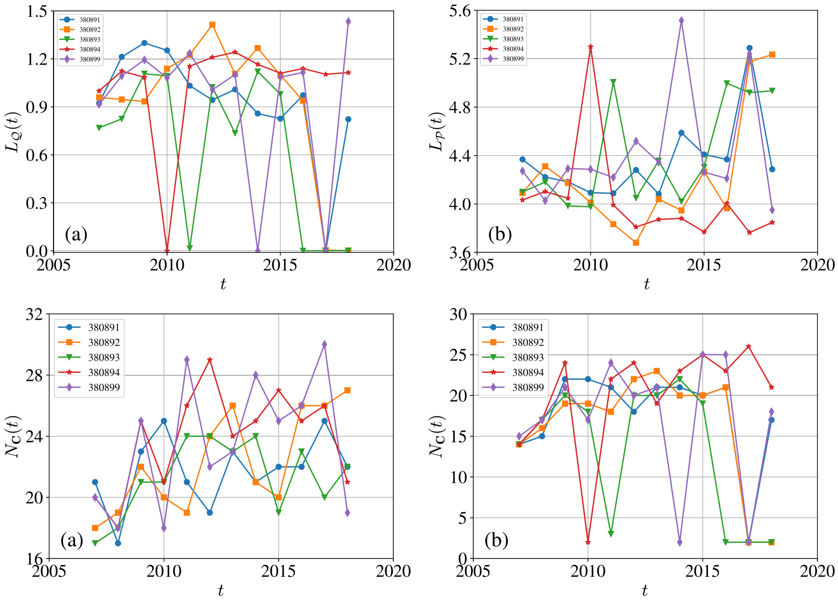

Fig. 3. Yearly evolution of the per level codelengths for modules (a) and leaf nodes (b) in the directed international trade networks of insecticides (380891), fungicides (380892), herbicides (380893), disinfectants (380894), and rodenticides and other similar products (380899) from 2007 to 2018. Evolution of the number of communities (a) and non-trivial top communities (b) for the directed international trade networks of insecticides (380891), fungicides (380892), herbicides (380893), disinfectants (380894), and rodenticides and other similar products (380899) from 2007 to 2018.

Uganda, and Tanzania in Eastern Africa, Bahrain, Kuwait, Lebanon, Syria, and the United Arab Emirates within the Middle East region, and Anguilla in the Eastern Caribbean). The fourth community C_4 has 8 economies (Costa Rica, El Salvador, Guatemala, Honduras, Nicaragua, and Panama in the Western Caribbean, The Dominican Republic in the Eastern Caribbean, and Suriname in South America). The fifth community has 13 economies (Botswana, Lesotho, Malawi, Mali, Mauritius, Mozambique, Namibia, Saint Helena, South Africa, Zimbabwe, Swaziland, Zambia in Africa and Papua New Guinea in Oceania). The sixth community C_6 has three economies (Antigua and Barbuda in the Eastern Caribbean and Liberia and Nigeria in the Western Africa). The African economies are distributed in five communities (except the fourth community C_4), showing that they are less integrated in economic development.

The patterns of community maps of the Other 12 networks look quite similar. It is found that the economies in North America and South America never unite to form a big community in all years including 2010. Economies in the Caribbean and around may belong to different communities rather than the main part of South America. Most economies in Oceania, East Asia, South Asia and Southeast Asia fall in the same community in most years, except that in 2008 most economies in Southeast Asia form a separate community C_5. The relatively large numbers of identified communities in the international disinfectant trade networks are mainly attributed to African economies, which belong to several communities in all years.

Fig. A.4 illustrates the evolution of communities of the undirected iPTNs of rodenticides and other similar products (380899) from 2007 to 2018. In the nine networks from 2007 to 2015, we obtain three to five communities, and each map is dominated by the biggest community and decorated with other communities. South America belongs to the biggest community in all years but 2007. In addition, quite a few economies in the Middle East and Africa do not belong to the largest community. This observation is consistent with other iPTNs.

The three recent networks in 2016, 2017, and 2018 exhibit different community patterns. These networks have seven or nine communities. The majority of economies in Southern Africa and Europe have become two separate communities. In 2016, we observe three separate communities in Southeast Asia, the Caribbean, and the Middle East. In 2017 and 2018, we find a united community in Southeast Asia and the Middle East and a new community in Oceania.

3.2. Community structure of the directed iPTNs

We adopt the multi-level Infomap algorithm [52] to identify the community partitioning of the five categories of iPTNs that are directed and weighted. We show below the community maps of the iPTNs on a yearly basis.

For each directed international pesticide trade network, we obtain the community partitioning $\mathbf{C}^{cmd}(t)$. We illustrate the evolution of the per level codelength for communities (L_Q) in Fig. 3(a). While most of the L_Q values fluctuate around 1, there are 10 points close to 0. Since L_Q represents the codelength of inter-community walks, a small value shows that there are very few identified communities. The evolution of the per level codelength for leaf nodes ($L_{\mathcal{P}}$) is shown in Fig. 3(b). Despite the fact that most of the $L_{\mathcal{P}}$ values fluctuate around 4.2, we again observe 10 points above $L_{\mathcal{P}} = 4.9$, which correspond to the 10 outlier networks identified in Fig. 3(a). Since $L_{\mathcal{P}}$ represents the codelength of intra-community walks, larger communities usually have greater $L_{\mathcal{P}}$ values. Comparing Fig. 1 and Fig. 3, we find that

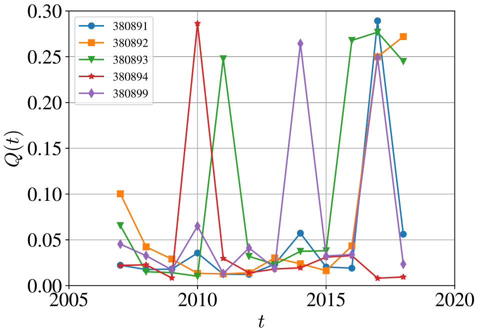

Fig. 4. Evolution of the modularity for the directed international trade networks of insecticides (380891), fungicides (380892), herbicides (380893), disinfectants (380894), and rodenticides and other similar products (380899) from 2007 to 2018.

$$L_{\mathcal{P}}^{\rm dir} > L_{\mathcal{P}}^{\rm undir} \quad \text{and} \quad L_{\mathcal{Q}}^{\rm dir} < L_{\mathcal{Q}}^{\rm undir}$$

for most of the corresponding pairs of direct iPTNs and undirected iPTNs, where the superscripts "dir" and "undir" stand respectively for the directed and undirected international trade networks for the same category of pesticides in the same year.

In Fig. 3(c), we show the evolution of the number $N_{\mathbf{C}}^{\rm dir}$ of communities for the five categories of directed iPTNs. We observe a mildly increasing trend in the first years. In Fig. 3(d), we show the evolution of the number $N_{\mathbf{C}>1}^{\rm dir} = N_{\mathbf{C}}^{\rm dir} - N_{\mathbf{C}1}^{\rm dir}$ of non-trivial top communities for the five categories of directed iPTNs, where $N_{\mathbf{C}1}^{\rm dir}$ is the number of trivial communities. A trivial community is a module with either one or all nodes within it. In the networks we analyzed, there are one-node communities, but not all-node communities.

As shown in Fig. 3(d), after removing trivial communities, we obtain nine networks with $N_{\mathbf{C}>1}^{\rm dir} = 2$ and one network with $N_{\mathbf{C}>1}^{\rm dir} = 3$, which are the same outlier networks recognized from Fig. 3 and hard to be recognized from Fig. 3(c). Excluding these 10 networks, other networks each has at least 14 communities. Comparing Fig. 3(c), and Fig. 1(c), we find that there are more communities identified in the directed networks than in the undirected networks such that

$$N_{\mathbf{C}}^{\rm dir} \geq N_{\mathbf{C}>1}^{\rm dir} > N_{\mathbf{C}}^{\rm undir}$$

for most cases (year and pesticide).

The modularity of a directed and weighted network is defined as follows [55]:

$$Q = \frac{1}{2W} \sum_i \sum_j \left(w_{ij} - \frac{s_i^{\rm out} s_j^{\rm in}}{2W} \right) \delta(C_i, C_j),$$

where $s_i^{\rm out}$ is the total export of economy i

$$s_i^{\rm out} = \sum_j w_{ij},$$

$s_j^{\rm in}$ is the total import of economy j

$$s_j^{\rm in} = \sum_i w_{ij},$$

and W is the total trade volume all over the world

$$W = \sum_i s_i^{\rm out} = \sum_j s_j^{\rm in} = \sum_i \sum_j w_{ij}.$$

Fig. 4 illustrates the evolution of the modularity for the directed iPTNs from 2007 to 2018. We find that the 10 outlier networks have much larger modularity than the rest networks. The rest of the networks have very small modularities, which are much less than the modularities of the undirected networks. Hence, for most cases (year and pesticide), a directed network usually has more communities but lower modularity than its counterpart undirected network.

Fig. 5 illustrates the evolution of communities of the directed iPTNs of insecticides (380891) from 2007 to 2018. For better visibility, the non-trivial communities containing less than 5 economies and trivial communities are merged to C_0. For instance, in the community map of 2007, the merged cluster C_0 contains 3 non-trivial communities (C_{10} with Belarus, Estonia, Latvia, and Lithuania, C_{13} with Azerbaijan and Georgia, and C_{14} with Tunisia and Mayotte) and 7 trivial communities (C_{15} Tanzania, C_{16} Gambia, C_{17} Liberia, C_{18} Suriname, C_{19} Congo, C_{20} Somalia, and C_{21} Equatorial Guinea). In Fig. 5, only the network in 2017 does not have cluster C_0, which contains two communities. The second community C_2 contains six economies (Virgin Islands (British), Saint Kitts and Nevis, Saint Vincent and the Grenadines, Curaçao, Aruba, and The Turks and Caicos Islands), all located in the eastern Caribbean Sea.

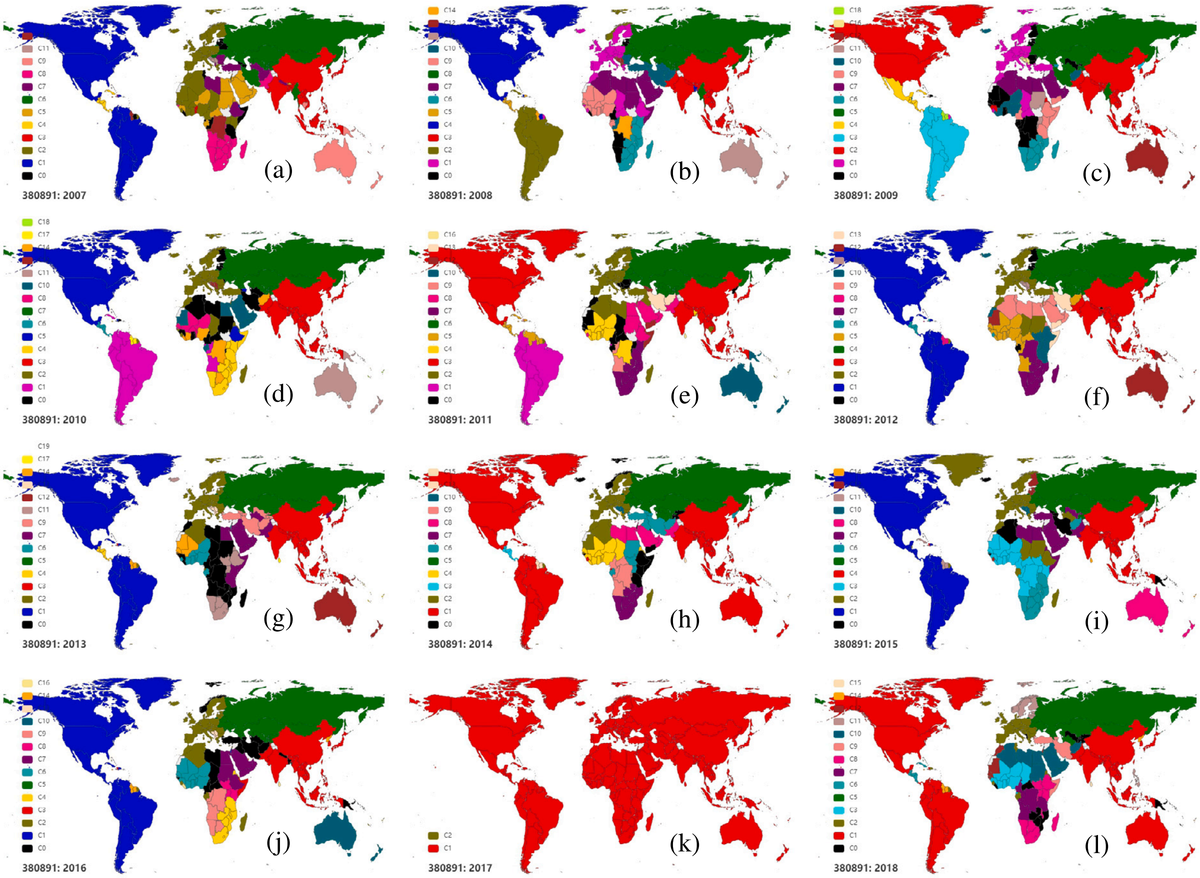

Fig. 5. Community evolution of the directed iPTNs of insecticides (380891) from 2007 (Panel (a)) to 2018 (Panel (l)). For better visibility, the non-trivial communities containing less than 5 economies and trivial communities are merged to C_0.

We now investigate the community structure of the 11 networks (except 2017). Most of the communities exhibit regional clustering or are combinations of regionally clustered areas. The community in green appears in all 11 networks, which mainly contain Russia and several economies geographically close to Russia. China, India, Japan, Korea, and the main economies in South Asia and Southeast Asia usually belong to a community. For instance, in 2007, this Asia community contained 24 economies, including Indonesia, Japan, the Philippines, Thailand, Togo, China, Hong Kong, Korea, India, Singapore, Bangladesh, Sri Lanka, Benin, Macao, Malaysia, Vietnam, Kiribati, the Maldives, Micronesia, the Marshall Islands, Guam, The Northern Mariana Islands, Lao PDR, and Brunei. Australia, New Zealand, and other economies in Oceania form a community. In 2007, the Oceania community contained 17 economies, including Australia, New Zealand, Solomon Islands, Cook Islands, Fiji, French Polynesia, New Caledonia, Vanuatu, Palau, Papua New Guinea, Timor-Leste, Tonga, Samoa, Cambodia, Niue, Norfolk Island, and Swaziland. The Asia community and the Oceania community merged into one community in 2014 and 2018.

Economies in West Europe and sometimes in North Africa and the Middle East form a community. This West European community is often the largest community in the sense of the number of economies it contains. In 2007, it contained 47 economies, including Algeria, France, Germany, Denmark, Ghana, Greece, Israel, Nigeria, Senegal, Spain, Italy, Kenya, Mali, Mauritius, the Netherlands, Poland, Slovakia, Switzerland, the United Kingdom, Austria, Belgium, Cameroon, Cyprus, Czech, Ireland, Côte d'Ivoire, Luxembourg, Norway, Portugal, Sweden, Chad, Comoros, Finland, Iceland, Malta, Morocco, Sierra Leone, Uganda, Burkina Faso, Mauritania, Faroe Islands, Andorra, Cabo Verde, São Tomé and Principe, Wallis and Futuna, Palestine, and Gibraltar.

In the North and South American continents, Canada, Greenland (except 2015), Mexico, and the USA always belong to a community, most economies in South America also form a community, and other economies (especially those in the Caribbean) may belong to the North America community or the South America community or form separate communities. From 2008 to 2011, the North America community and the South America community were separate; otherwise, they formed the biggest community in the sense of area. In 2009 and 2011, the North American community and the Asian community united into one community. In 2014 and 2018, the North American community, the Asian community, and the Oceanian community united to belong to the same community. The community structure of the economies in Africa is quite complex and changes frequently.

Fig. B.1 illustrates the evolution of communities of the directed iPTNs of fungicides (380892) from 2007 to 2018. For better visibility, the non-trivial communities containing less than 5 economies and trivial communities are merged to C_0. We find that the community structure of the two networks in 2017 and 2018 is dominated by a big community and very different from other networks. In 2017, there are three communities, in which C_2 contains 13 economies (Tanzania, Zambia, Kenya, Ethiopia, Uganda, Namibia, Burundi, Rwanda, Malawi, Zimbabwe, South Sudan, Comoros, and The Turks and Caicos Islands) and C_3 (or C_0) contains three economies (Angola, The Democratic Republic of the Congo, and Mozambique), mainly in Africa. In 2018, C_3 contains Solomon Islands, Fiji, Papua New Guinea, Samoa, Kiribati, and Tuvalu in the South Pacific Ocean, while C_0 contains two communities C_2 (Tunisia and Congo) and C_4 (Gambia, Guinea, and Senegal), all in Africa.

Fig. B.2 illustrates the evolution of communities of the directed iPTNs of herbicides (380893) from 2007 to 2018. For better visibility, the non-trivial communities containing less than 5 economies and trivial communities are merged into C_0. We observe that the most evident feature of the community maps is that the four networks in 2011, 2016, 2017 and 2018 are dominated by a big community. In 2011, we identify three communities, in which C_2 contains 16 economies (Antigua and Barbuda, Nigeria, Côte d'Ivoire, Senegal, Sri Lanka, Ghana, Liberia, Mali, Burkina Faso, Bouvet Island, Maldives, Benin, Guinea, Mauritania, Niger, and Togo) and C_3 contains 7 economies (United Arab Emirates, Kenya, Burundi, Rwanda, Uganda, Tanzania, and Malawi). In 2016, we find two economies, in which C_2 (or C_0) contains Angola, São Tomé and Principe, Namibia, and Botswana. In 2017, we find two economies, in which C_2 contains Andorra, Nigeria, Cameroon, Ghana, Côte d'Ivoire, Liberia, Mali, Senegal, Congo, Benin, Gambia, Mauritania, Niger, Sierra Leone, and Burkina Faso. In 2018, we also find two economies, in which C_2: Azerbaijan, Georgia, Senegal, Tunisia, Côte d'Ivoire, Mali, Nigeria, Benin, Gambia, Guinea, Liberia, Madagascar, Togo, Burkina Faso, and Guinea-Bissau. A common feature is that almost all the economies of the five small communities in the four networks are located in Africa.

We now turn to investigate the rest eight networks. Firstly, the main economies in North America and South America do not form a united community. Secondly, most European economies belong to the same community in 2007, 2008, 2013, and 2015 and divide into two communities in other years. Thirdly, India does not belong to the Asia community, except in 2008 and 2012. Fourthly, the Oceania cluster formed a separate community from 2007 to 2010, fell into the same community as North America in 2012, 2013, and 2014, and joined the Asia community in 2015. Fifth, China, Dem. Rep. Korea, and most economies in South Asia and Southeast Asia form the Asia community. In contrast, Japan and Korea belong to the Asia community in 2009, 2010, 2012, and 2014, and to the Russia community in 2007, 2008, and 2013.

Fig. B.3 illustrates the evolution of communities of the directed iPTNs of disinfectants (380894) from 2007 to 2018. For better visibility, the non-trivial communities containing less than 5 economies and trivial communities are merged into C_0. All networks but the one in 2010 have more than 13 non-trivial communities. The network in 2010 has two communities, with the small one C_2 containing five economies in Africa (Algeria, Nigeria, Ghana, Liberia, and Morocco), one economy in the North Caribbean (Antigua and Barbuda), and one economy in West Asia (Qatar).

The other 11 networks share some common features in their community structures. We describe below several big, stable communities. Most economies in East Asia, South Asia, Southeast Asia, and Oceania form a community. Russia and several economies in East Europe and Middle Asia belong to a community, most of which were former members of the Soviet Union. Most Western European economies form a community, often combining several economies in Africa. Most Northern European economies belonged to the Western Europe community from 2007 to 2011 and formed a separate community from 2012 to 2018. On the American continent, we observe two main communities, respectively, in North America and South America. Except for these communities, the economies in the Caribbean, Middle East, and Africa often form different communities that are less stable over time.

Fig. B.4 illustrates the evolution of communities of the directed iPTNs of rodenticides and other similar products (380899) from 2007 to 2018. For better visibility, the non-trivial communities containing less than 5 economies and trivial communities are merged into cluster C_0. The networks usually have more than 14 non-trivial communities, except that the two networks in 2014 and 2017 have only two communities. The small community C_2 in 2014 contains 4 African economies (Ghana, Mali, Guinea, Togo, Burkina Faso, and Côte d'Ivoire) and the Bahamas. The small community C_2 in 2017 contains 19 economies in Africa (Mali, Kenya, Uganda, Burkina Faso, Central African Republic, Benin, Ethiopia, Gabon, Ghana, Côte d'Ivoire, Madagascar, Nigeria, South Sudan, Togo, Niger, Rwanda, Liberia, Burundi, and Somalia) and 2 in South Asia (Maldives and Sri Lanka).

In the rest 10 networks, the main part of the Russia community is quite stable, while the Oceania economies form a separate community. China, Japan, Korea, and several other Asian economies form the main Asian community, while economies in Southeast Asia may form a separate community. The Western European economies formed a separate community in 2009, 2010, 2011, 2015, and 2018, and merged with the main Asia community in 2007, 2008, 2012, 2013, and 2016. On the American continent, there are at least two big communities (except in 2009), one in North America and the other in South America or in Latin America and the Caribbean, and the main economies in Central America around the Caribbean Sea may form a separate community. The North American community and the Asian community also merged from 2009 to 2017.

3.3. Temporal similarity of community structure

In the previous subsections, we have found that the community structure of the iPTNs is more or less stable over different years. In order to quantify how stable the community structure is, we calculate the similarity between the partitions in two successive years using the *normalized mutual information* (NMI) measure, which was originally designed for comparing the performance of community structure detection methods when the "true value" of the community structure of the network under investigation is known [56]. The NMI measure is based on the definition of a confusion matrix $\mathbf{N}$, whose rows correspond to the detected communities of network $\mathscr{G}_{t-1}$ and columns correspond to the identified communities of network $\mathscr{G}_t$. The element N_{ij} of the confusion matrix $\mathbf{N}$ is the number of nodes in community i of network $\mathscr{G}_{t-1}$ that appear in community j of network $\mathscr{G}_t$. The normalized mutual information (NMI) measure between the community partitioning of two successive networks is calculated as follows:

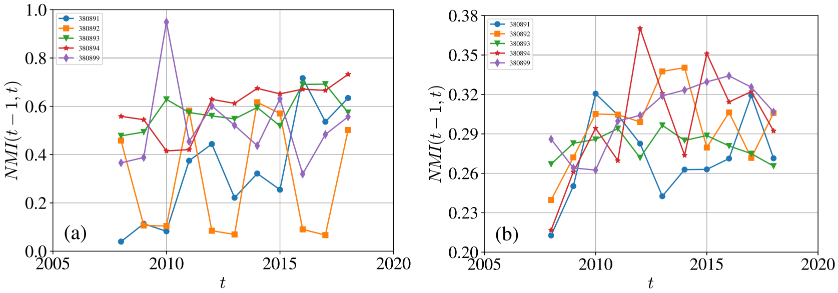

Fig. 6. Normalized mutual information $NMI(t-1,t)$ between the partitions of two successive iPTNs. (a) undirected iPTNs, (b) directed iPTNs.

$$NMI(t-1,t)=\frac{-2\sum_{i=1}^{n_{t-1}^c}\sum_{j=1}^{n_t^c}N_{ij}\log\left(\frac{N_{ij}N}{N_{i.}N_{.j}}\right)}{\sum_{i=1}^{n_{t-1}^c}N_{i.}\log\left(\frac{N_{i.}}{N}\right)+\sum_{j=1}^{n_t^c}N_{.j}\log\left(\frac{N_{.j}}{N}\right)},$$

where n_{t-1}^c is the number of communities in network $\mathscr{G}_{t-1}$, n_t^c is the number of communities in network $\mathscr{G}_t$, $N_{i.}=\sum_j N_{ij}$ is the sum over row i of confusion matrix $\mathbf{N}$, and $N_{.j}=\sum_i N_{ij}$ is the sum over column j. If the two partitions are identical, then $NMI(t-1,t)$ takes its maximum value of 1. If the two partitions are totally independent, we have $NMI(t-1,t)=0$.

Fig. 6 shows the normalized mutual information $NMI(t-1,t)$ between the partitions of two successive iPTNs. For the undirected networks in Fig. 6(a), the NMI curve for fungicides (380892) fluctuates largely, while the other four curves exhibit an increasing trend. For the directed networks in Fig. 6(b), the NMI curves exhibit an increasing trend in early years and become trend-free afterwards. For herbicides (380893), disinfectants (380894), and rodenticides and other similar products (380899), the NMI value for an undirected network is larger than that for the corresponding directed network:

$$NMI^{\rm undir}(t-1,t)>NMI^{\rm dir}(t-1,t).$$

For insecticides (380891) and fungicides (380892), we do not observe any evident relationship between undirected and directed networks.

We also calculate the normalized mutual information $NMI^{\rm undir}(t_i,t_j)$ and $NMI^{\rm dir}(t_i,t_j)$ between any two different years t_i and t_j for the undirected and directed iPTNs. For each category of pesticides, we obtain the average and its standard deviation. For the undirected networks, the average normalized mutual information is 0.30 ± 0.19 for insecticides (380891), 0.33 ± 0.20 for fungicides (380892), 0.50 ± 0.09 for herbicides (380893), 0.55 ± 0.09 for disinfectants (380894), and 0.32 ± 0.15 for rodenticides and other similar products (380899), For the undirected networks, the average normalized mutual information is 0.27 ± 0.02 for insecticides (380891), 0.29 ± 0.03 for fungicides (380892), 0.27 ± 0.02 for herbicides (380893), 0.30 ± 0.03 for disinfectants (380894), and 0.30 ± 0.03 for rodenticides and other similar products (380899). It is found that the average normalized mutual information is comparable between the undirected and directed iPTNs of insecticides (380891), fungicides (380892), and rodenticides and other similar products (380899), while the undirected iPTNs of herbicides (380893) and disinfectants (380894) have significantly larger average normalized mutual information than the directed iPTNs. The most significant feature is that the directed iPTNs have much smaller standard deviations than the undirected iPTNs, showing that the community structure of the directed iPTNs is much stabler than the undirected iPTNs, which implies that the community structure of the directed iPTNs captures better the underlying economic contents of international pesticide trade.

3.4. Community blocks in the directed iPTNs

The results in Sec. 3.2 and Sec. 3.3 have shown that the community structure of the directed iPTNs has evolved stably, which suggests that there are intrinsic community blocks that are common to all communities and form the backbone of the identified communities. An intrinsic community block B_i is a maximum set of nodes in which all the nodes belong to the same community in each iPTN. Hence, starting from an arbitrary node u, if node v belongs to the same community of the iPTN in every year, then u and v belong to the same intrinsic community block; otherwise, u and v belong to two different intrinsic community blocks. We identify the intrinsic community blocks of the temporal directed iPTNs for the five categories of pesticides.

For the temporal iPTN of insecticides (380891), we obtain 18 intrinsic community blocks containing 78 economies in total, including B_1 (United Arab Emirates, Egypt, Jordan, Oman, Saudi Arabia), B_2 (Argentina, Brazil, Chile, Colombia, Ecuador, Peru, Paraguay), B_3 (Australia, Norfolk Island, New Zealand), B_4 (Austria, Belgium, Switzerland, Czech, Germany, Denmark, Spain, France, the United Kingdom, Greece, Ireland, Italy, Luxembourg, the Netherlands, Poland, Portugal, Slovakia), B_5 (Bulgaria, Romania), B_6 (Bosnia and Herzegovina, Macedonia, Serbia), B_7 (Bolivia, Uruguay), B_8 (Barbados, Guyana, Trinidad and Tobago), B_9 (Canada, United States), B_{10} (China, Hong Kong, Indonesia, India, Japan, Korea, Lao PDR, Malaysia, Singapore, Thailand, Vietnam), B_{11} (Côte d'Ivoire, Nigeria), B_{12} (Costa Rica, Guatemala, Honduras, Nicaragua, El Salvador), B_{13} (Estonia, Lithuania, Latvia), B_{14} (Israel, Palestine), B_{15} (Kazakhstan, Mongolia, Russia, Ukraine), B_{16} (Lebanon, San Marino), B_{17} (Mozambique, Zambia, Zimbabwe), and B_{18} (Saint Helena, South Africa). The map of intrinsic community blocks is shown in the first row of Fig. 7, distinguished by different colors, which also shows the networks of the intrinsic community blocks. The intrinsic community block B_4 has the largest size with

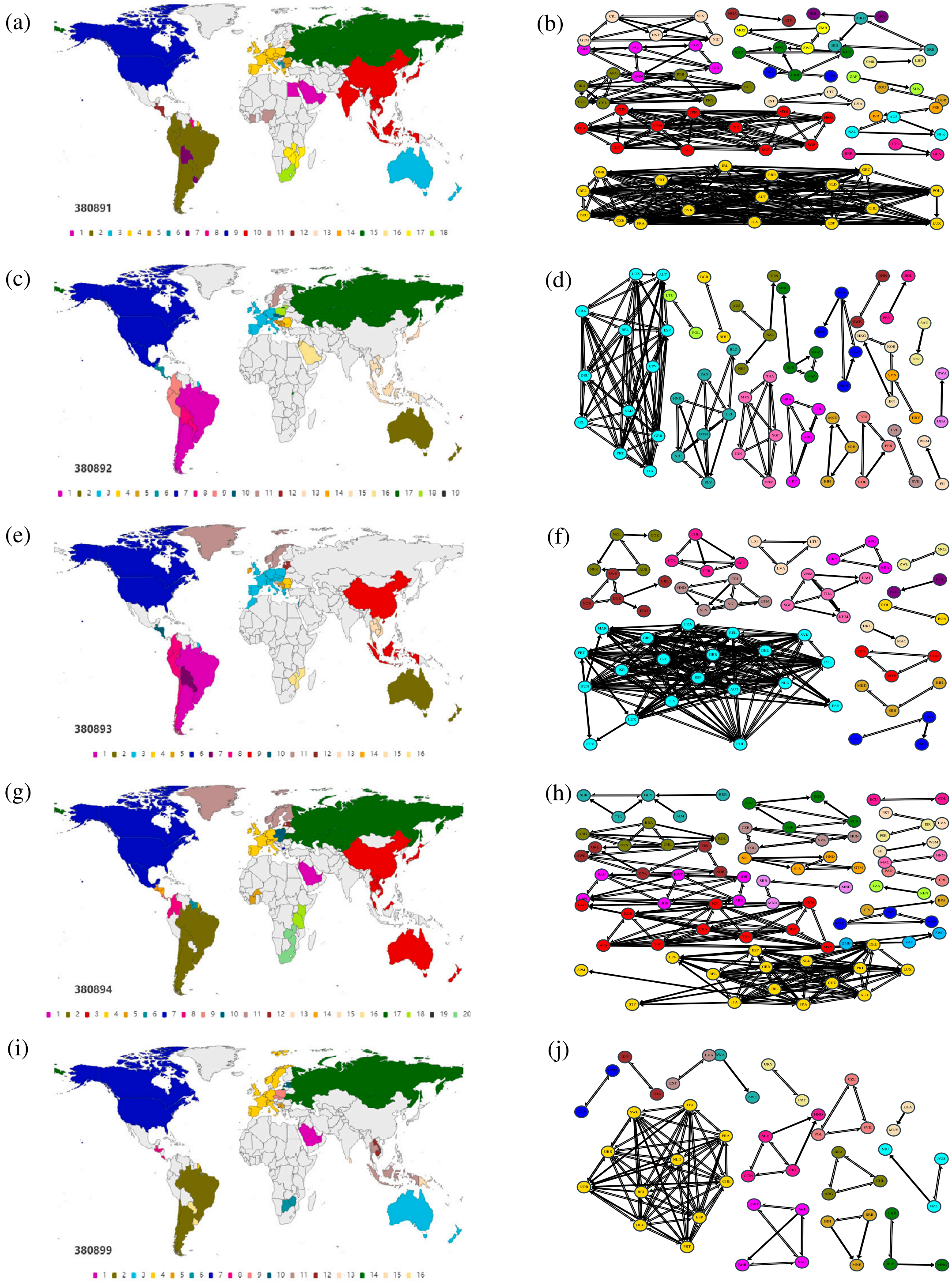

Fig. 7. Intrinsic community blocks in the temporal directed iPTNs from 2007 to 2018 of insecticides (380891, a and b), fungicides (380892, c and d), herbicides (380893, e and f), disinfectants (380894, g and h), and rodenticides and other similar products (380899, i and j) in the colored map (left panel) and in colored networks (right panel). The node color of an intrinsic community block is the same in both panels.

17 economies in Europe, while the second largest block B_{10} contains 11 economies in East and South Asia. Most of the economies that are not included in any intrinsic community blocks are in Africa, the Caribbean, and Central and West Asia.

For the temporal iPTN of fungicides (380892), we obtain 19 intrinsic community blocks containing 67 economies in total, including B_1 (Argentina, Brazil, Chile, Uruguay), B_2 (Australia, Niue, New Zealand, Tonga), B_3 (Austria, Belgium, Cabo Verde, Germany, Spain, France, the United Kingdom, Ireland, Italy, Luxembourg, the Netherlands, Portugal), B_4 (Bulgaria, Romania), B_5 (Bosnia and Herzegovina, Montenegro, Serbia), B_6 (Belize, Costa Rica, Guatemala, Honduras, Nicaragua, Panama, El Salvador), B_7 (Bermuda, Canada, Mexico, United States), B_8 (Bolivia, Paraguay), B_9 (Colombia, Ecuador, Peru), B_{10} (Czech, Slovakia), B_{11} (Denmark, Sweden), B_{12} (Fiji, Samoa), B_{13} (Hong Kong, Japan, Korea), B_{14} (Croatia, Slovenia), B_{15} (Indonesia, Malaysia, Singapore, Thailand, Vietnam), B_{16} (Jordan, Saudi Arabia), B_{17} (Kazakhstan, Kyrgyzstan, Mongolia, Russia), B_{18} (Lithuania, Poland), and B_{19} (Rwanda, Uganda). The second row of Fig. 7 shows the map and the networks of the intrinsic community blocks. The largest intrinsic community block B_3 contains 12 economies mainly in Europe, while the second largest intrinsic community block B_6 contains 7 economies in the Western Caribbean. Most economies in Africa and many economies in Asia (including China and India) do not belong to any intrinsic community blocks.

For the temporal iPTN of herbicides (380893), we obtain 16 intrinsic community blocks containing 66 economies in total, including B_1 (Argentina, Brazil, Uruguay), B_2 (Australia, Cook Islands, Norfolk Island, New Zealand), B_3 (Austria, Belgium, Switzerland, Cabo Verde, Czech, Germany, Spain, France, the United Kingdom, Greece, Hungary, Israel, Italy, Luxembourg, Morocco, the Netherlands, Poland, Portugal, Palestine, Slovakia), B_4 (Bulgaria, Romania), B_5 (Bosnia and Herzegovina, Macedonia, Serbia), B_6 (Bermuda, Canada, United States), B_7 (Bolivia, Paraguay), B_8 (Chile, Colombia, Ecuador, Peru), B_9 (China, Indonesia, Malaysia), B_{10} (Costa Rica, Guatemala, Honduras, Nicaragua, El Salvador), B_{11} (Denmark, Faroe Islands, Greenland, Norway, Sweden), B_{12} (Estonia, Lithuania, Latvia), B_{13} (Hong Kong, Macao), B_{14} (Ireland, Malta), B_{15} (Cambodia, Lao PDR, Singapore, Thailand, Vietnam), and B_{16} (Mozambique, Zimbabwe). The third row of Fig. 7 shows the map and the networks of the intrinsic community blocks. The largest intrinsic community block B_3 contains 20 economies, mainly in Europe. Most economies in Africa, many economies in Asia (including India, Japan, and Korea), and Russia do not belong to any intrinsic community blocks. We find that block B_{14} (Ireland, Malta) does not appear in the network plot since Ireland and Malta always belong to the same community in each year but do not have direct international trade of herbicides.

For the temporal iPTN of disinfectants (380894), we obtain 20 intrinsic community blocks containing 83 economies in total, including B_1 (United Arab Emirates, Bahrain, Jordan, Kuwait, Lebanon, Saudi Arabia), B_2 (Argentina, Bolivia, Brazil, Chile, Uruguay), B_3 (Australia, China, Japan, Korea, Lao PDR, Malaysia, New Zealand, Singapore, Thailand, Vietnam), B_4 (Austria, Belgium, Switzerland, Cabo Verde, Germany, Spain, France, the United Kingdom, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Saint-Pierre and Miquelon, São Tomé and Principe), B_5 (Burkina Faso, Côte d'Ivoire), B_6 (Barbados, Guyana, Jamaica, Suriname, Trinidad and Tobago), B_7 (Canada, Mexico, United States), B_8 (Colombia, Ecuador), B_9 (Costa Rica, Panama), B_{10} (Czech, Hungary, Poland, Slovakia), B_{11} (Denmark, Finland, Greenland, Norway, Sweden), B_{12} (Estonia, Latvia), B_{13} (Fiji, Samoa), B_{14} (Guatemala, Honduras, Nicaragua, El Salvador), B_{15} (Hong Kong, Macao), B_{16} (Israel, Palestine), B_{17} (Kazakhstan, Kyrgyzstan, Russia, Ukraine), B_{18} (Kenya, Tanzania), B_{19} (Macedonia, Montenegro, Serbia), and B_{20} (South Africa, Zambia, Zimbabwe) The fourth row of Fig. 7 shows the map and the networks of the intrinsic community blocks. The largest intrinsic community block B_4 contains 16 economies mainly in Europe, while the second largest intrinsic community block B_3 contains 10 economies in Asia and Oceania.

For the temporal iPTN of rodenticides and other similar products (380899), we obtain 16 intrinsic community blocks containing 46 economies in total, including B_1 (United Arab Emirates, Bahrain, Kuwait, Saudi Arabia), B_2 (Argentina, Brazil, Chile), B_3 (Australia, Niue, New Zealand), B_4 (Belgium, Switzerland, Germany, Spain, France, the United Kingdom, Italy, the Netherlands, Norway, Portugal, Sweden), B_5 (Bosnia and Herzegovina, Montenegro, Serbia), B_6 (Botswana, Zimbabwe), B_7 (Canada, United States), B_8 (Costa Rica, Guatemala, Honduras, El Salvador), B_9 (Czech, Poland, Slovakia), B_{10} (Estonia, Latvia), B_{11} (Indonesia, Thailand), B_{12} (Cambodia, Lao PDR), B_{13} (Sri Lanka, Maldives), B_{14} (Mongolia, Russia, Ukraine), B_{15} (Papua New Guinea, Vanuatu), and B_{16} (Paraguay, Uruguay). The fifth row of Fig. 7 shows the map and the networks of the intrinsic community blocks. The largest intrinsic community block B_3 contains 11 economies in Europe. There are two second largest communities B_1 and B_8, each containing four economies, respectively, in the Middle East and Western Caribbean. Most economies in Africa and Asia do not belong to any intrinsic community blocks. There are two intrinsic community blocks B_{12} (Cambodia, Lao PDR) and B_{15} (Papua New Guinea, Vanuatu), whose two members do not have direct international trade in rodenticides and other similar products and thus do not appear in the network plot.

Comparing the intrinsic community blocks of different pesticides, we find that the largest block is always mainly based in Europe and contains Belgium, Germany, Spain, France, the United Kingdom, Italy, the Netherlands, and Portugal, the intrinsic community block in North America always contains Canada and the United States, the intrinsic community block in South America always contains Argentina and Brazil, and Australia and New Zealand also appear together. In all the iPTNs, the identified intrinsic blocks act as the core of communities.

4. Discussion

There are limitations to the study. Firstly, due to the fact that many economies report their trade data to the UN with time lags, the trade data in the UN Comtrade Database is not complete, especially in recent years. We are thus not able to investigate the international trade networks that have been impacted by the COVID-19 pandemic and the Russia-Ukraine conflict. Secondly, the formation of the communities is only partially interpreted through geographical proximity and trade-agreement co-membership. Other factors, such as food production shocks, are not investigated. Thirdly, there is much work to do to understand the dynamics of the detected community structures and intrinsic community blocks. Although we observed the persistence of community structures over time, as indicated by the normalized mutual information, there are also slow or abrupt changes.

Furthermore, the detected community structures and intrinsic community blocks in the iPTNs form the starting point for further research. Firstly, it is crucial to uncover influencing factors in the formation of bilateral trade and communities. For instance, the seminal work of Torreggiani et al. found that, besides geographical proximity, trade-agreement co-membership is another determinant that promotes the co-presence of economies in communities [17]. Secondly, one can use these findings to validate network growth models specific to international pesticide trade or, alternatively, to develop network growth models integrating the determinants of community formation. Thirdly, the communities and their intrinsic blocks reveal the underlying higher-order interactions among economies and can be used to design attack strategies in the study of network vulnerability. Most previous studies concerned attacks on nodes and/or links [57–59], and attacks based on higher-order interactions were much less considered. Fourthly, it is interesting to investigate the role of higher-order interactions embedded in the community structure in shock propagation between pesticide and food trade networks, linking pesticide trade patterns and food security. Finally, in contrast to the fact that most community detection methods use information about the links and link weights, it would be interesting to use the multi-attribute community detection method that takes into consideration nodes' centrality metrics [60] or the multilayer community detection method by combining the individual trade networks of different pesticides into a multilayer network [61].

5. Conclusion

In summary, we have investigated the evolving community structure in five categories of iPTNs from 2007 to 2018. We reveal that geographic distance plays an important role, and the community structures in the undirected and directed iPTNs exhibit regional patterns. These regional patterns are very different for undirected and directed networks and for different categories of pesticides. Using the normalized mutual information between successive communities to quantify the stability of community structures in undirected and directed networks, we found that the community structure is stabler in the directed iPTNs.

We further extracted the intrinsic community blocks for the directed international trade networks of each pesticide category. We found that the largest and stablest intrinsic community block in every pesticide category contains important economies (Belgium, Germany, Spain, France, the United Kingdom, Italy, the Netherlands, and Portugal) in Europe. Other important and stable intrinsic community blocks are found to be Canada and the United States in North America, Argentina and Brazil in South America, and Australia and New Zealand in Oceania. These findings also indicate the important role played by geographic distance and imply the importance of the pesticide supply and demand complementarity of important adjacent economies in the international trade of pesticides.

Ethics statement

Informed consent was not required for this study because there are no participants/patients involved in this study.

CRediT authorship contribution statement

Jian-An Li: Writing – original draft, Investigation. **Li Wang:** Writing – review & editing, Investigation. **Wen-Jie Xie:** Methodology, Investigation. **Wei-Xing Zhou:** Writing – review & editing, Supervision, Methodology, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data associated with this study has not been deposited into a publicly available repository. Data has been included in article/supplementary material/referenced in article. Data can be retrieved freely from the UN Comtrade Database (https://comtrade.un.org).

Acknowledgements

This work was partly supported by the National Natural Science Foundation of China (72171083), the Shanghai Outstanding Academic Leaders Plan, and the Fundamental Research Funds for the Central Universities.

Appendix A. Community evolution of the undirected iPTNs

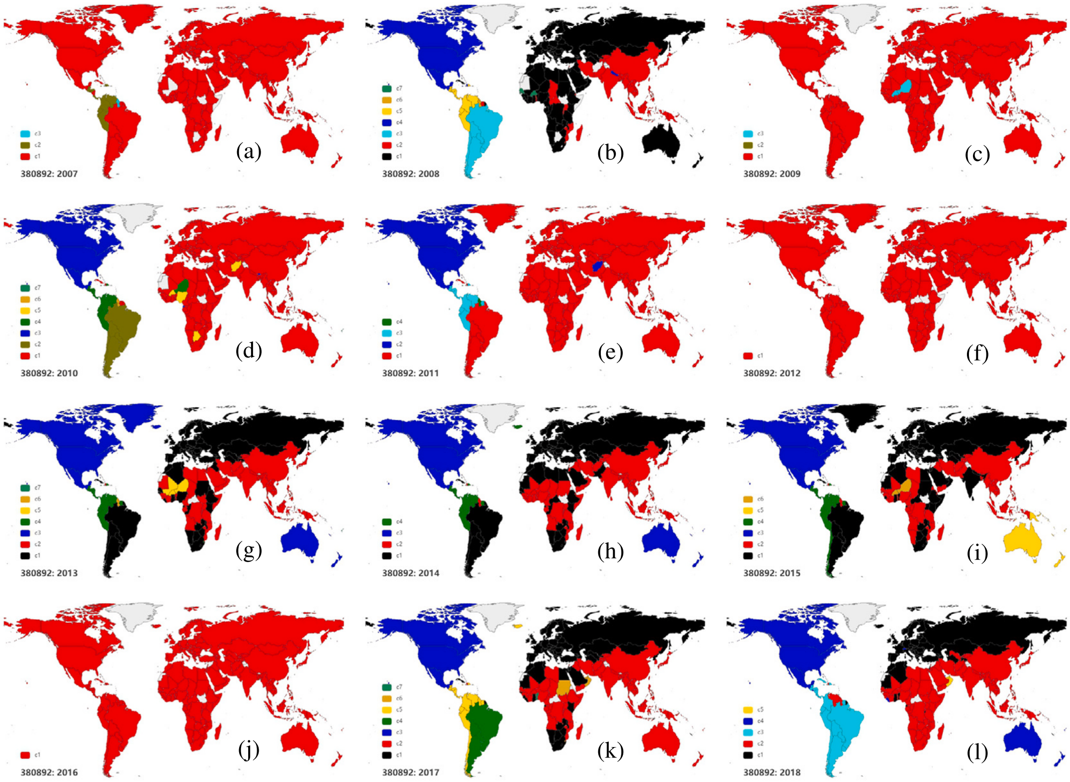

Fig. A.1. Community evolution of the undirected iPTNs of fungicides (380892) from 2007 (Panel (a)) to 2018 (Panel (l)).

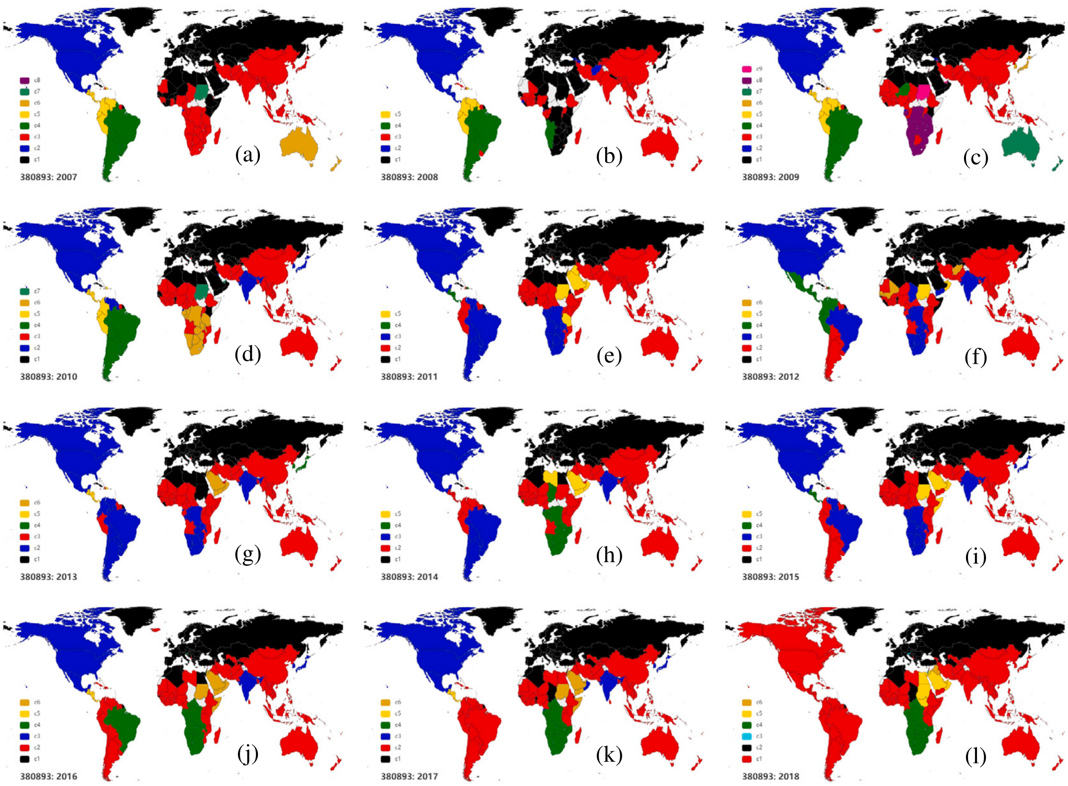

Fig. A.2. Community evolution of the undirected iPTNs of herbicides (380893) from 2007 (Panel (a)) to 2018 (Panel (l)).

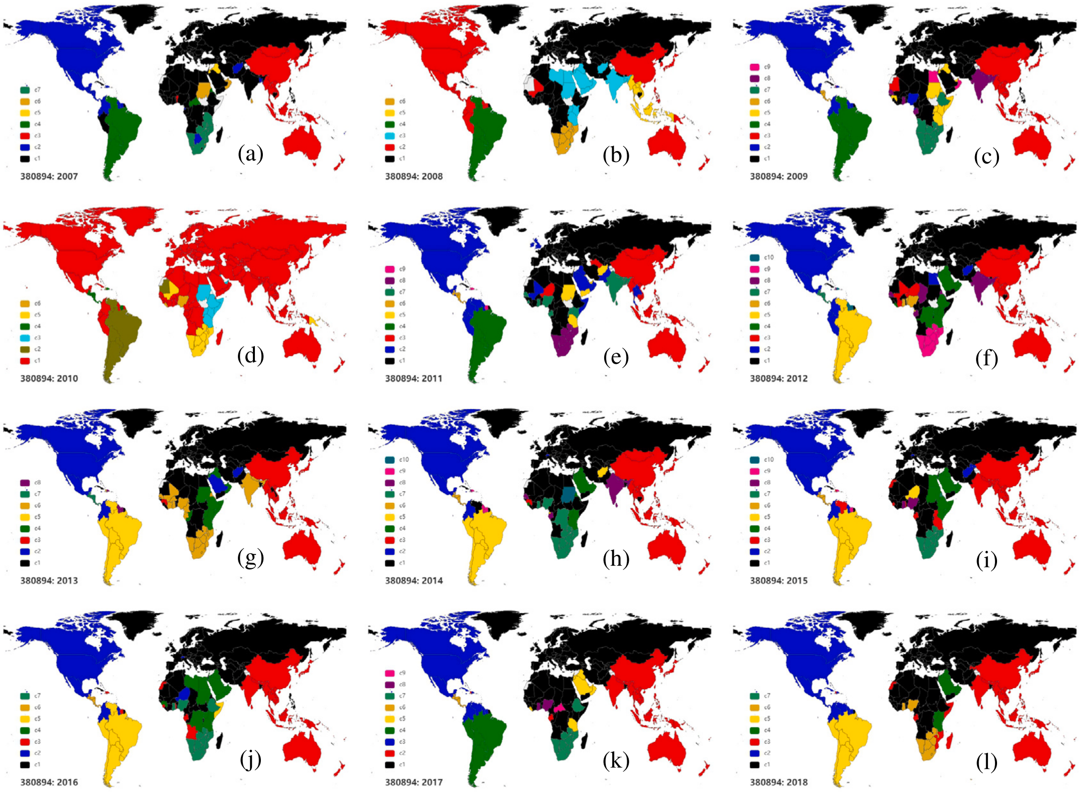

Fig. A.3. Community evolution of the undirected iPTNs of disinfectants (380894) from 2007 (Panel (a)) to 2018 (Panel (l)).

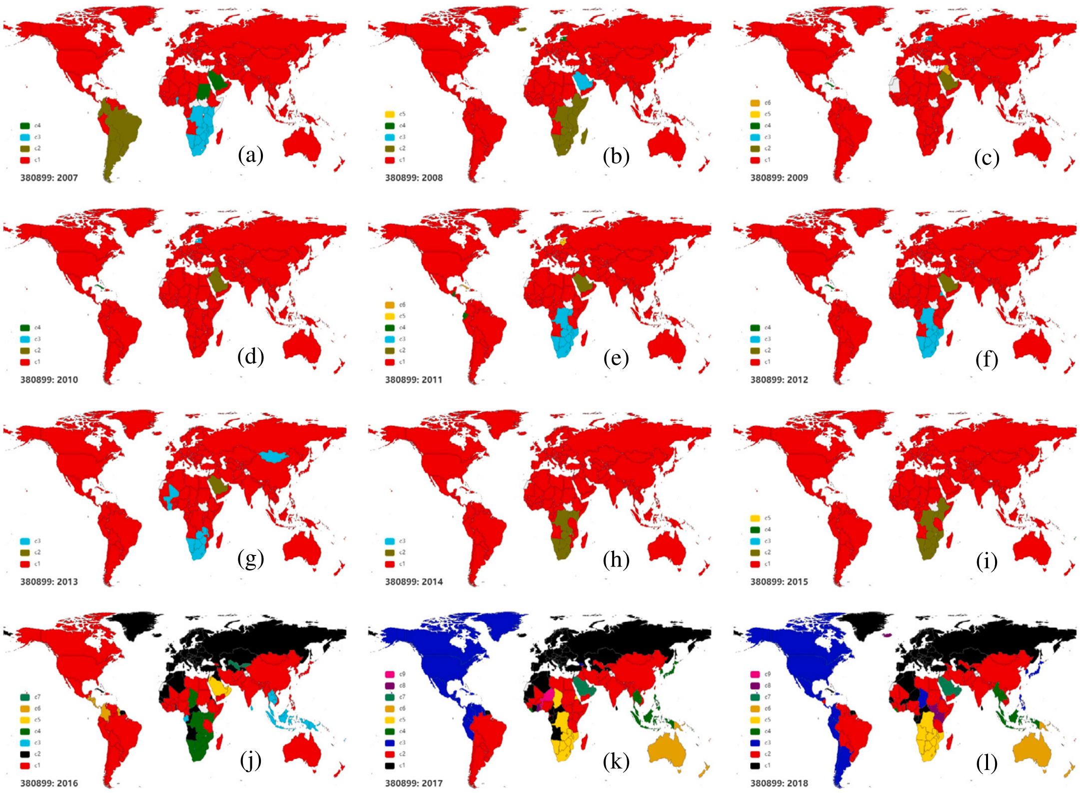

Fig. A.4. Community evolution of the undirected iPTNs of rodenticides and other similar products (380899) from 2007 (Panel (a)) to 2018 (Panel (l)).

Appendix B. Community evolution of the directed iPTNs

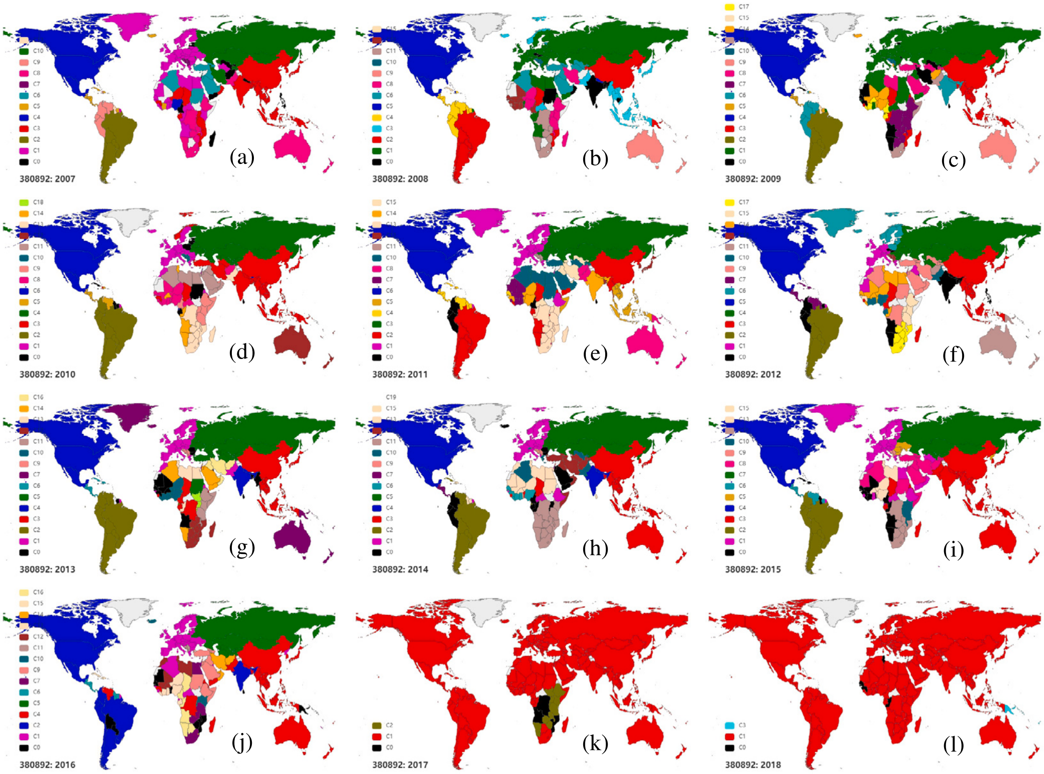

Fig. B.1. Community evolution of the directed iPTNs of fungicides (380892) from 2007 (Pane (a)) to 2018 (Panel (l)). For better visibility, the non-trivial communities containing less than 5 economies and trivial communities are merged to C_0.

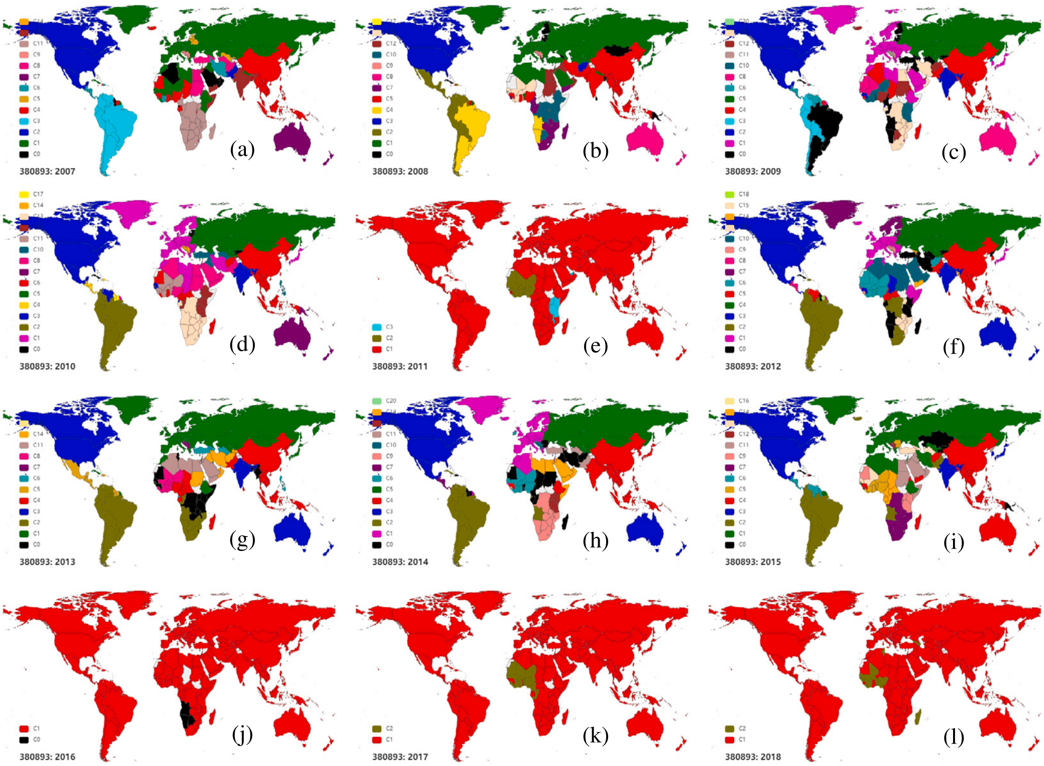

Fig. B.2. Community evolution of the directed iPTNs of herbicides (380893) from 2007 (Pane (a)) to 2018 (Panel (l)). For better visibility, the non-trivial communities containing less than 5 economies and trivial communities are merged to C_0.

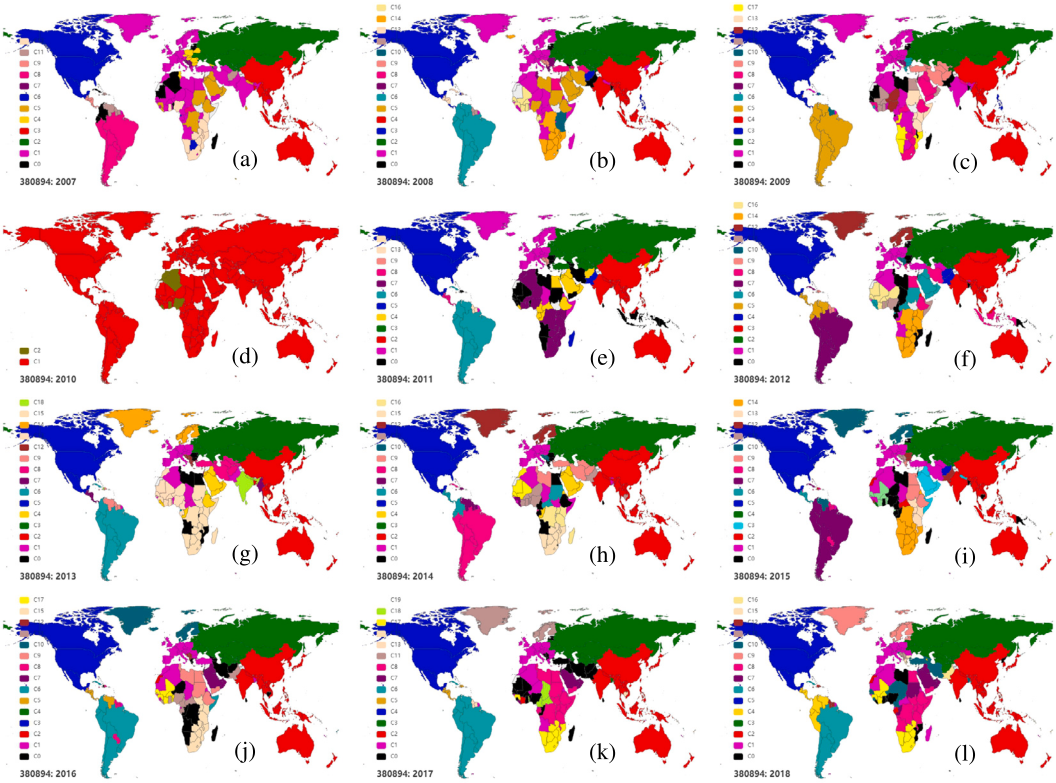

Fig. B.3. Community evolution of the directed iPTNs of disinfectants (380894) from 2007 (Pane (a)) to 2018 (Panel (l)). For better visibility, the non-trivial communities containing less than 5 economies and trivial communities are merged to C_0.

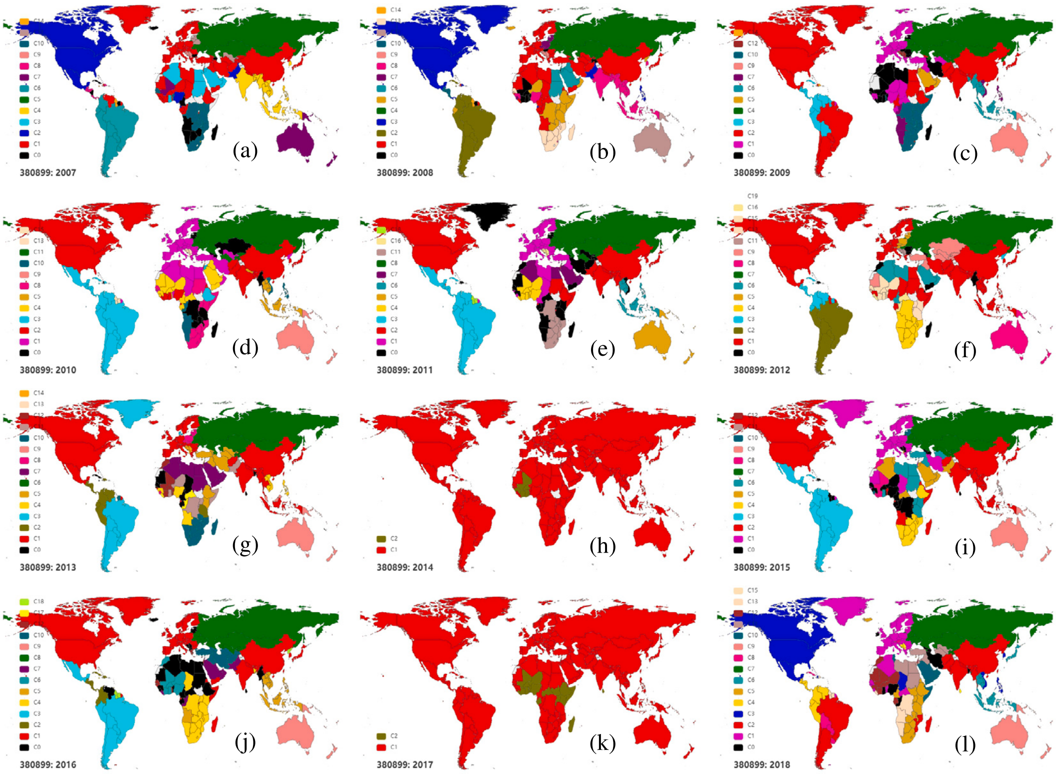

Fig. B.4. Community evolution of the iPTNs of rodenticides and other similar products (380899) from 2007 (Pane (a)) to 2018 (Panel (l)). For better visibility, the non-trivial communities containing less than 5 economies and trivial communities are merged to C_0.

References

[1] Food Security Information Network, Global Report on Food Crises 2021, May 2021, https://www.wfp.org/publications/global-report-food-crises-2021.
[2] M. Tudi, H.D. Ruan, L. Wang, J. Lyu, R. Sadler, D. Connell, C. Chu, D.T. Phung, Agriculture development, pesticide application and its impact on the environment, Int. J. Environ. Res. Public Health 18 (3) (2021) 1112, https://doi.org/10.3390/ijerph18031112.
[3] M.A. Serrano, M. Boguñá, Topology of the world trade web, Phys. Rev. E 68 (2003), https://doi.org/10.1103/PhysRevE.68.015101 015101(R).
[4] D. Garlaschelli, M.I. Loffredo, Structure and evolution of the world trade network, Physica A 355 (2005) 138–144, https://doi.org/10.1016/j.physa.2005.02.075.
[5] D. Garlaschelli, T. Di Matteo, T. Aste, G. Caldarelli, M.I. Loffredo, Interplay between topology and dynamics in the world trade web, Eur. Phys. J. B 57 (2007) 159–164, https://doi.org/10.1140/epjb/e2007-00131-6.
[6] G. Fagiolo, J. Reyes, S. Schiavo, On the topological properties of the world trade web: a weighted network analysis, Physica A 387 (2008) 3868–3873, https://doi.org/10.1016/j.physa.2008.01.050.
[7] G. Fagiolo, J. Reyes, S. Schiavo, World-trade web: topological properties, dynamics, and evolution, Phys. Rev. E 79 (2009) 036115, https://doi.org/10.1103/PhysRevE.79.036115.
[8] G. Fagiolo, J. Reyes, S. Schiavo, The evolution of the world trade web: a weighted-network analysis, J. Evol. Econ. 20 (2010) 479–514, https://doi.org/10.1007/s00191-009-0160-x.
[9] T. Squartini, G. Fagiolo, D. Garlaschelli, Randomizing world trade. I. A binary network analysis, Phys. Rev. E 84 (4) (2011) 046117, https://doi.org/10.1103/PhysRevE.84.046117.
[10] T. Squartini, G. Fagiolo, D. Garlaschelli, Randomizing world trade. II. A weighted network analysis, Phys. Rev. E 84 (4) (2011) 046118, https://doi.org/10.1103/PhysRevE.84.046118.
[11] M. Karpiarz, P. Fronczak, A. Fronczak, International trade network: fractal properties and globalization puzzle, Phys. Rev. Lett. 113 (24) (2014) 248701, https://doi.org/10.1103/PhysRevLett.113.248701.
[12] M. Campi, M. Duenas, G. Fagiolo, How do countries specialize in agricultural production? A complex network analysis of the global agricultural product space, Environ. Res. Lett. 15 (12) (2020) 124006, https://doi.org/10.1088/1748-9326/abc2f6.
[13] L.T. Raynolds, The globalization of organic agro-food networks, World Dev. 32 (5) (2004) 725–743, https://doi.org/10.1016/j.worlddev.2003.11.008.
[14] M. Ercsey-Ravasz, Z. Toroczkai, Z. Lakner, J. Baranyi, Complexity of the international agro-food trade network and its impact on food safety, PLoS ONE 7 (5) (2012) e37810, https://doi.org/10.1371/journal.pone.0037810.
[15] S. Suweis, J.A. Carr, A. Maritan, A. Rinaldo, P. D'Odorico, Resilience and reactivity of global food security, Proc. Natl. Acad. Sci. USA 112 (34) (2015) 4811, https://doi.org/10.1073/pnas.1512971112.
[16] P. Marchand, J.A. Carr, J. Dell'Angelo, M. Fader, J.A. Gephart, M. Kummu, N.R. Magliocca, M. Porkka, M.J. Puma, Z. Ratajczak, M.C. Rulli, D.A. Seekell, S. Suweis, A. Tavoni, P. D'Odorico, Reserves and trade jointly determine exposure to food supply shocks, Environ. Res. Lett. 11 (9) (2016) 095009, https://doi.org/10.1088/1748-9326/11/9/095009.
[17] S. Torreggiani, G. Mangioni, M.J. Puma, G. Fagiolo, Identifying the community structure of the food-trade international multi-network, Environ. Res. Lett. 13 (5) (2018) 054026, https://doi.org/10.1088/1748-9326/aabf23.
[18] W. Qiang, S. Niu, X. Wang, C. Zhang, A. Liu, S. Cheng, Evolution of the global agricultural trade network and policy implications for China, Sustainability 12 (1) (2020) 192, https://doi.org/10.3390/su12010192.
[19] Y.-T. Zhang, W.-X. Zhou, Microstructural characteristics of the weighted and directed international crop trade networks, Entropy 23 (10) (2021) 1250, https://doi.org/10.3390/e23101250.
[20] M.-C. Dupas, J. Halloy, P. Chatzimpiros, Time dynamics and invariant subnetwork structures in the world cereals trade network, PLoS ONE 14 (5) (2019) e0216318, https://doi.org/10.1371/journal.pone.0216318.
[21] F. Wu, H. Guclu, Global maize trade and food security: implications from a social network model, Risk Anal. 33 (12) (2013) 2168–2178, https://doi.org/10.1111/risa.12064.
[22] M.J. Puma, S. Bose, S.Y. Chon, B.I. Cook, Assessing the evolving fragility of the global food system, Environ. Res. Lett. 10 (2) (2015) 024007, https://doi.org/10.1088/1748-9326/10/2/024007.
[23] K.R. Fair, C.T. Bauch, M. Anand, Dynamics of the global wheat trade network and resilience to shocks, Sci. Rep. 7 (2017) 7177, https://doi.org/10.1038/s41598-017-07202-y.
[24] E. Gutierrez-Moya, B. Adenso-Diaz, S. Lozano, Analysis and vulnerability of the international wheat trade network, Food Secur. 13 (1) (2021) 113–128, https://doi.org/10.1007/s12571-020-01117-9.
[25] D. Schaffer-Smith, S.A. Tomscha, K.J. Jarvis, D.Y. Maguire, M.L. Treglia, J. Liu, Network analysis as a tool for quantifying the dynamics of metacoupled systems: an example using global soybean trade, Ecol. Soc. 23 (4) (2018) 3, https://doi.org/10.5751/ES-10460-230403.
[26] J.A. Gephart, M.L. Pace, Structure and evolution of the global seafood trade network, Environ. Res. Lett. 10 (12) (2015) 125014, https://doi.org/10.1088/1748-9326/10/12/125014.
[27] J.A. Gephart, E. Rovenskaya, U. Dieckmann, M.L. Pace, A. Braennstroem, Vulnerability to shocks in the global seafood trade network, Environ. Res. Lett. 11 (3) (2016) 035008, https://doi.org/10.1088/1748-9326/11/3/035008.
[28] J.S. Stoll, I. Crona Beatrice, M. Fabinyi, E.R. Farr, Seafood trade routes for lobster obscure teleconnected vulnerabilities, Front. Mar. Sci. 5 (2018) 239, https://doi.org/10.3389/fmars.2018.00239.
[29] M.G. Chung, K. Kapsar, K.A. Frank, J.-G. Liu, The spatial and temporal dynamics of global meat trade networks, Sci. Rep. 10 (1) (2020) 16657, https://doi.org/10.1038/s41598-020-73591-2.
[30] J.-A. Li, W.-J. Xie, W.-X. Zhou, Structure and evolution of the international pesticide trade networks, Front. Phys. 9 (2021) 681788, https://doi.org/10.3389/fphy.2021.681788.
[31] D. Garlaschelli, M. Loffredo, Patterns of link reciprocity in directed networks, Phys. Rev. Lett. 93 (26) (2004) 268701, https://doi.org/10.1103/PhysRevLett.93.268701.
[32] K. Bhattacharya, G. Mukherjee, J. Saramäki, K. Kaski, S.S. Manna, The international trade network: weighted network analysis and modelling, J. Stat. Mech. 2008 (2) (2008) P02002, https://doi.org/10.1088/1742-5468/2008/02/P02002.
[33] G. Fagiolo, The international-trade network: gravity equations and topological properties, J. Econ. Interact. Coord. 5 (1) (2010) 1–25, https://doi.org/10.1007/s11403-010-0061-y.
[34] M. Duenas, G. Fagiolo, Modeling the international-trade network: a gravity approach, J. Econ. Interact. Coord. 8 (1) (2013) 155–178, https://doi.org/10.1007/s11403-013-0108-y.
[35] R. Mastrandrea, T. Squartini, G. Fagiolo, D. Garlaschelli, Reconstructing the world trade multiplex: the role of intensive and extensive biases, Phys. Rev. E 90 (6) (2014) 062804, https://doi.org/10.1103/PhysRevE.90.062804.
[36] A. Almog, R. Bird, D. Garlaschelli, Enhanced gravity model of trade: reconciling macroeconomic and network models, Front. Phys. 7 (2019) 55, https://doi.org/10.3389/fphy.2019.00055.
[37] T. Distefano, F. Laio, L. Ridolfi, S. Schiavo, Shock transmission in the international food trade network, PLoS ONE 13 (8) (2018) e0200639, https://doi.org/10.1371/journal.pone.0200639.
[38] S. Fortunato, Community detection in graphs, Phys. Rep. 486 (3–5) (2010) 75–174, https://doi.org/10.1016/j.physrep.2009.11.002.

[39] F.D. Malliaros, M. Vazirgiannis, Clustering and community detection in directed networks: a survey, Phys. Rep. 533 (4) (2013) 95–142, https://doi.org/10.1016/j.physrep.2013.08.002.
[40] I. Tzekina, K. Danthi, D.N. Rockmore, Evolution of community structure in the world trade web, Eur. Phys. J. B 63 (4) (2008) 541–545, https://doi.org/10.1140/epjb/e2008-00181-2.
[41] M. Barigozzi, G. Fagiolo, G. Mangioni, Identifying the community structure of the international-trade multi-network, Physica A 390 (11) (2011) 2051–2066, https://doi.org/10.1016/j.physa.2011.02.004.
[42] M. Barigozzi, G. Fagiolo, G. Mangioni, Community structure in the multi-network of international trade, in: L. da F. Costa, A. Evsukoff, G. Mangioni, R. Menezes (Eds.), Complex Networks, Springer, Berlin, 2011, pp. 163–175.
[43] E. Estrada, Community detection based on network communicability, Chaos 21 (1) (2011) 016103, https://doi.org/10.1063/1.3552144.
[44] Y. Fan, S. Ren, H. Cai, X. Cui, The state's role and position in international trade: a complex network perspective, Econ. Model. 39 (2014) 71–81, https://doi.org/10.1016/j.econmod.2014.02.027.
[45] Z. Zhu, F. Cerina, A. Chessa, G. Caldarelli, M. Riccaboni, The rise of China in the international trade network: a community core detection approach, PLoS ONE 9 (8) (2014) e105496, https://doi.org/10.1371/journal.pone.0105496.
[46] J. Reyes, R. Wooster, S. Shirrell, Regional trade agreements and the pattern of trade: a networks approach, World Econ. 37 (8) (2014) 1128–1151, https://doi.org/10.1111/twec.12121.
[47] P. Bartesaghi, G.P. Clemente, R. Grassi, Community structure in the world trade network based on communicability distances, J. Econ. Interact. Coord. 17 (2) (2022) 405–441, https://doi.org/10.1007/s11403-020-00309-y.
[48] D. Dong, X.Y. Gao, X.Q. Sun, X.X. Liu, Factors affecting the formation of copper international trade community: based on resource dependence and network theory, Resour. Policy 57 (2018) 167–185, https://doi.org/10.1016/j.resourpol.2018.03.002.
[49] C. Piccardi, L. Tajoli, Existence and significance of communities in the world trade web, Phys. Rev. E 85 (6) (2012) 066119, https://doi.org/10.1103/PhysRevE.85.066119.
[50] J. Grilli, G. Barabas, M.J. Michalska-Smith, S. Allesina, Higher-order interactions stabilize dynamics in competitive network models, Nature 548 (7666) (2017) 210, https://doi.org/10.1038/nature23273.
[51] F. Battiston, E. Amico, A. Barrat, G. Bianconi, G. Ferraz de Arruda, B. Franceschiello, I. Iacopini, S. Kefi, V. Latora, Y. Moreno, M.M. Murray, T.P. Peixoto, F. Vaccarino, G. Petri, The physics of higher-order interactions in complex systems, Nat. Phys. 17 (10) (2021) 1093–1098, https://doi.org/10.1038/s41567-021-01371-4.
[52] M. Rosvall, C.T. Bergstrom, Maps of random walks on complex networks reveal community structure, Proc. Natl. Acad. Sci. USA 105 (4) (2008) 1118–1123, https://doi.org/10.1073/pnas.0706851105.
[53] A. Lancichinetti, F. Radicchi, J.J. Ramasco, S. Fortunato, Finding statistically significant communities in networks, PLoS ONE 6 (4) (2011) e18961, https://doi.org/10.1371/journal.pone.0018961.
[54] M.E.J. Newman, M. Girvan, Finding and evaluating community structure in networks, Phys. Rev. E 69 (2004) 026113, https://doi.org/10.1103/PhysRevE.69.026113.
[55] A. Arenas, J. Duch, A. Fernandez, S. Gomez, Size reduction of complex networks preserving modularity, New J. Phys. 9 (6) (2007) 176, https://doi.org/10.1088/1367-2630/9/6/176.
[56] L. Danon, A. Diaz-Guilera, J. Duch, A. Arenas, Comparing community structure identification, J. Stat. Mech. 2005 (9) (2005) P09008, https://doi.org/10.1088/1742-5468/2005/09/P09008.
[57] M. Bellingeri, D. Bevacqua, F. Scotognella, R. Alfieri, Q. Nguyen, D. Montepietra, D. Cassi, Link and node removal in real social networks: a review, Front. Phys. 8 (2020) 228, https://doi.org/10.3389/fphy.2020.00228.
[58] M. Oehlers, B. Fabian, Graph metrics for network robustness-a survey, Mathematics 9 (8) (2021) 895, https://doi.org/10.3390/math9080895.
[59] S.E. Schaeffer, V. Valdes, J. Figols, I. Bachmann, F. Morales, J. Bustos-Jimenez, Characterization of robustness and resilience in graphs: a mini-review, J. Complex Netw. 9 (2) (2021) cnab018, https://doi.org/10.1093/comnet/cnab018.
[60] R. Grassi, P. Bartesaghi, S. Benati, G.P. Clemente, Multi-attribute community detection in international trade network, Netw. Spat. Econ. 21 (3) (2021) 707–733, https://doi.org/10.1007/s11067-021-09547-4.
[61] P. Bartesaghi, G.P. Clemente, R. Grassi, D.T. Luu, The multilayer architecture of the global input-output network and its properties, J. Econ. Behav. Organ. 204 (2022) 304–341, https://doi.org/10.1016/j.jebo.2022.10.029.