Structure and Evolution of the International Pesticide Trade Networks

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To meet the increasing demand for food around the world, pesticides are widely used and will continue to be widely used in agricultural production to reduce yield losses and maintain product quality. International pesticide trade serves to reallocate the distribution of pesticides around the world. We investigate the statistical properties of the international trade networks of five categories of pesticides from the view angle of temporal directed and weighted networks. We observed an overall increasing trend in network size, network density, average in- and out-degrees, average in- and out-strengths, temporal similarity, and link reciprocity, indicating that the rising globalization of pesticides trade is driving the networks denser. However, the distributions of link weights remain unchanged along time for the five categories of pesticides. In addition, all the networks are disassortatively mixed because large importers or exporters are more likely to trade with small exporters or importers. We also observed positive correlations between in-degree and out-degree, in-strength and out-strength, link reciprocity and in-degree, out-degree, in-strength, and out-strength, while node's local clustering coefficient is negatively related to in-degree, out-degree, in-strength, and out-strength. We show that some structural and dynamic properties of the international pesticide trade networks are different from those of the international trade networks, highlighting the presence of idiosyncratic features of different goods and products in the international trade.

Keywords: econophysics, directed networks, weighted networks, network metrics, international pesticide trade networks

1 INTRODUCTION

The past decades after the World War II have witnessed a marked growth in food production and the total population of the world, together with a dramatic decrease in the proportion of the world's people that are hungry, and the global demand for food will continuously increase in the coming decades [1, 2]. Seeds, fertilizers, and pesticides, as major agricultural inputs, will continue to play a central role in raising agricultural yields and product quality to meet the challenge of feeding billions of people. Pesticides are widely used in agricultural production around the world to reduce yield losses and maintain product quality by controlling pests, weeds, and other plant pathogens, which has long raised serious concerns about risks to human health and the environment [3–8]. Nevertheless, the current need to increase food production to feed a rapidly growing population puts pressure on the intensive use of pesticides and thus drives the international trade of pesticides.

International pesticide trade serves to reallocate the distribution of pesticides around the world and forms complex networks. Indeed, the structure and dynamics of the international trade networks as a whole have been extensively studied [9–19], and researchers have proposed dynamic models to understand the formation of the international trade networks [20, 21], such as the fitness model [22], the gravity model [23, 24], and the enhanced gravity model [25]. There are also studies on the international trade networks of agricultural goods and products. For instance, Gephart and Pace investigated the structure and evolution of the global seafood trade network [26], and Qiang et al studied the evolution of the global agricultural trade network of eight groups of agricultural products [27], and Dupas, Halloy, and Chatzimpiros focused on the dynamics and invariant sub-network structures in the world cereals trade [28]. Furthermore, Wu and Guclu developed a social network model of the global trade of maize to analyze the network patterns and to determine the vulnerable exporters in food security [29], Gephart et al. investigated the vulnerability to shocks in the global seafood trade network [30], and Distefano et al. unveiled shock transmission in the international food trade network [31]. The international trade of food goods and products are associated with a virtual transfer of water resources from production to consumption regions through a network of trade, and the international virtual water networks have also been studied extensively [32–40].

However, the international trade networks of agricultural inputs (seeds, fertilizers, and pesticides) are rarely studied. In this work, we investigate the structure and evolution of the international pesticide trade networks (iPTNs) from the view angle of temporal directed and weighted networks. We take into consideration the directions and weights of the links, which are crucial traits of the iPTNs. Specifically, we investigate the evolution of total trade value, network size, network density, overall in- and out-degrees of nodes, overall in- and out-strengths of nodes, four measures of assortativity, network structure stability, reciprocity, and clustering coefficient, as well as the relationships between some pairs of these network metrics. We find that, although most of the structural properties of the international pesticide trade networks are qualitatively similar to those of the whole international trade network, there are also qualitative and quantitative differences, indicating the presence of idiosyncratic features of different goods and products in the international trade. It is thus necessary to explore such disaggregated networks to uncover idiosyncratic properties and dynamics of the international trade networks of specific goods and products.

The remainder of study is organized as follows. **Section 2** describes the data sets used in our analysis and the construction of the international pesticide trade networks. **Section 3** presents the evolution of total trade value, network size, and network density. **Section 4** studies the properties of node degrees, link weights, and node strengths. **Section 5** investigates the structural patterns of the iPTNs by looking into the similarity of temporal directed networks, the mixing patterns, the reciprocity, and the clustering coefficients. We conclude in **Section 6**.

2 DATA SETS AND NETWORK CONSTRUCTION

2.1 Data Description

The data sets analyzed in this work were retrieved from the UN Comtrade database[1]. The goods about pesticides are under Heading 3808, which contains insecticides, rodenticides, fungicides, herbicides, anti-sprouting products, plant growth regulators, disinfectants, and the like, being put up in forms or packings for retail sale or as preparations or articles. We do not consider the goods with the HS codes being 380852, 380859, 380861, 380862, and 380869 since they have a rather short history. We analyze five categories of pesticides including insecticides (380891), fungicides (380892), herbicides (380893), disinfectants (380894), and rodenticides and other similar products (380899). The data sets available span from 2007 to 2018. Since the data for the year 2019 are incomplete, we use the data from 2007 to 2018.

2.2 Network Construction

Since the trade quantities or net weights of some trades are missing in the UN Comtrade database and are not comparable, we use trade values (US$) of the goods in our investigation. If the trade value of pesticide goods (with HS Code $code$) exported from economy i to economy j in year t is $w_{ij}^{code}(t)$, the temporal international pesticide trade network is

$$\mathcal{W}^{code}(t) = \left[w_{ij}^{code}(t) \right], \tag{1}$$

where $code \in \{380891, 380892, 380893, 380894, 380899\}$ is the HS codes of the pesticide under investigation and $w_{ii}^{code}(t) = 0$ for all goods in all years. Since a trade might be reported by both exporting and importing economies i and j usually with different values, we use the large value as $w_{ij}^{code}(t)$. There are missing partners and non-economy partners (WLD and EU2), which are not considered in our analysis except noted otherwise. We stress that isolated nodes that do not have any trades with other nodes are not included in the networks. Hence, the economies involved are nodes of the trade network, and a directed link e_{ij} is formed if economy i exports to economy j whose weight is w_{ij}.

Figure 1 illustrates the international pesticide trade networks for the five goods with codes 380891, 380892, 380893, 380894, and 380899 from top to bottom. For each good, we plot the links with high (98–100%), medium (49–51%), and low (0–2%) trade values of 2% and compare the two networks in 2007 and in 2018. It is observed that the network for each good shows persistence and structural changes.

3 GLOBAL NETWORK FEATURES

3.1 Network Size and Number of Links

The size of a network is usually quantified by the number of nodes in the network, $N_{\mathcal{V}}$, where $\mathcal{V}$ is the set of nodes. **Figure 2A** shows the evolution of $N_{\mathcal{V}}$ for the five networks. It is observed that the network sizes exhibit an increasing trend decorated with local

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[1]https://comtrade.un.org/data/
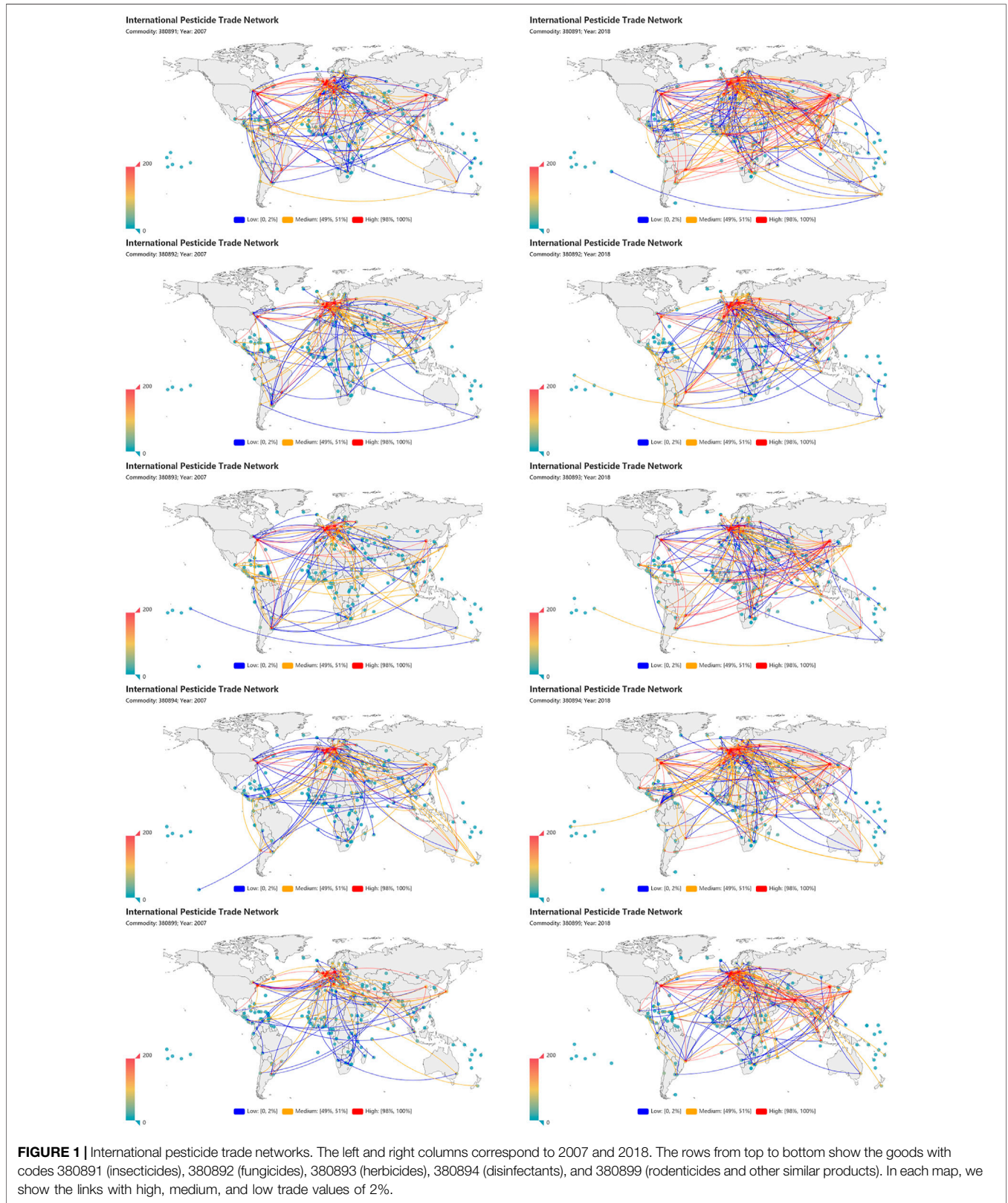
FIGURE 1 | International pesticide trade networks. The left and right columns correspond to 2007 and 2018. The rows from top to bottom show the goods with codes 380891 (insecticides), 380892 (fungicides), 380893 (herbicides), 380894 (disinfectants), and 380899 (rodenticides and other similar products). In each map, we show the links with high, medium, and low trade values of 2%.

fluctuations. We can also use the number of links, $N_{\mathcal{E}}$, as the size metric for the network, where $\mathcal{E} = \{e_{ij}\}$ is the set of links. **Figure 2B** shows the evolution of $N_{\mathcal{E}}$ for the five networks. It

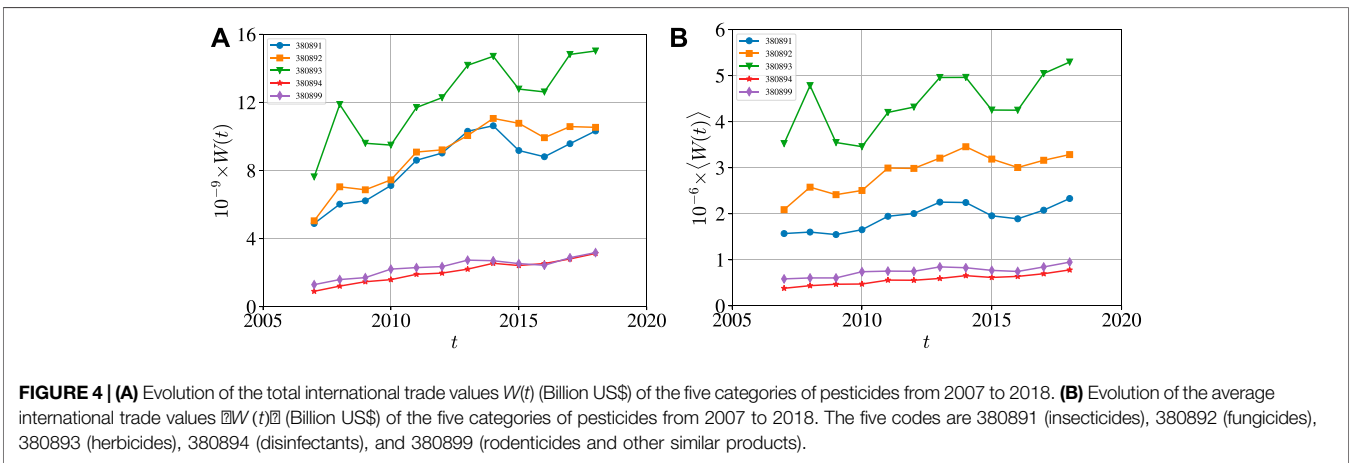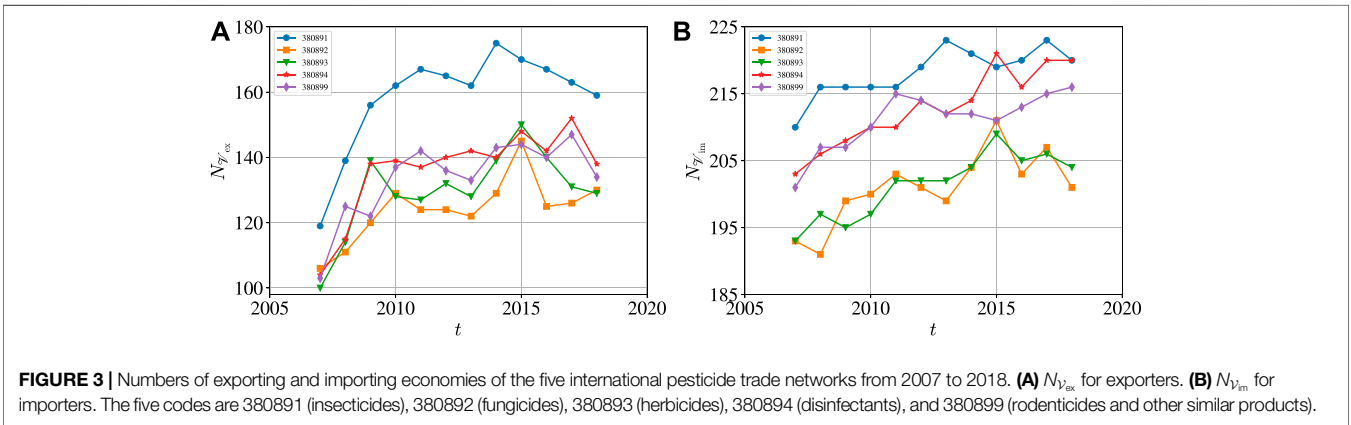is observed that the network sizes increased first and then decreased. In the increasing stage, the increasing trend of the network size flattened along time.

FIGURE 2 | Evolution of network size and number of links of the five international pesticide trade networks with the codes being 380891 (insecticides), 380892 (fungicides), 380893 (herbicides), 380894 (disinfectants), and 380899 (rodenticides and other similar products) from 2007 to 2018. The network size is quantified by the number of nodes $N_{\mathcal{V}}$ in **(A)** or the number of links $N_{\mathcal{E}}$ in **(B)**.

FIGURE 3 | Numbers of exporting and importing economies of the five international pesticide trade networks from 2007 to 2018. **(A)** $N_{\mathcal{V}_{ex}}$ for exporters. **(B)** $N_{\mathcal{V}_{im}}$ for importers. The five codes are 380891 (insecticides), 380892 (fungicides), 380893 (herbicides), 380894 (disinfectants), and 380899 (rodenticides and other similar products).

FIGURE 4 | (A) Evolution of the total international trade values $W(t)$ (Billion US$) of the five categories of pesticides from 2007 to 2018. **(B)** Evolution of the average international trade values $\langle W(t) \rangle$ (Billion US$) of the five categories of pesticides from 2007 to 2018. The five codes are 380891 (insecticides), 380892 (fungicides), 380893 (herbicides), 380894 (disinfectants), and 380899 (rodenticides and other similar products).

In **Figure 3**, we also investigate the numbers of exporting and importing economies of the five international pesticide trade networks from 2007 to 2018, denoted by $N_{\mathcal{V}_{ex}}$ and $N_{\mathcal{V}_{im}}$, respectively. Comparing $N_{\mathcal{V}_{ex}}$ and $N_{\mathcal{V}_{im}}$ in **Figure 3** with $N_{\mathcal{V}}$ in **Figure 2A**, we find that

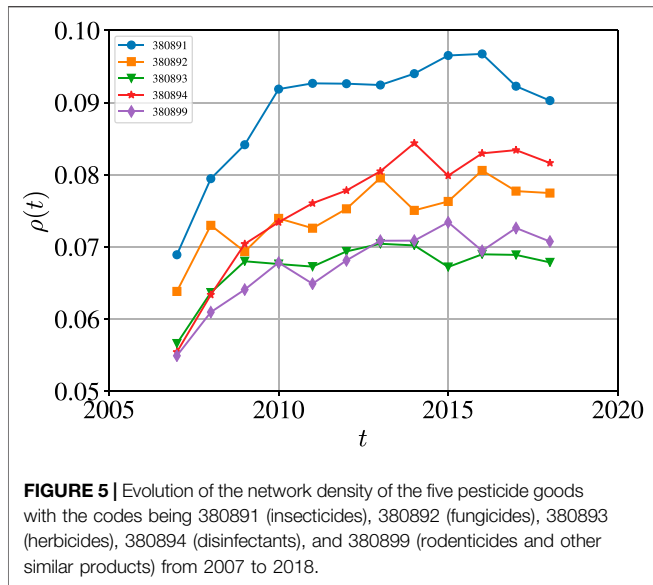$$N_{\mathcal{V}_{ex}} < N_{\mathcal{V}_{im}} < N_{\mathcal{V}}. \tag{2}$$

Hence, there are much more importing economies than exporting economies. On average, the numbers of importing

and exporting economies increased along time, but the increasing speed slowed down especially for exporting economies.

3.2 Total Trade Value

The total trade value of a given goods *code* is

$$W^{code}(t) = \sum_{i=1}^{N_{\mathcal{V}}} \sum_{j=1}^{N_{\mathcal{V}}} w_{ij}^{code}(t), \tag{3}$$

FIGURE 5 | Evolution of the network density of the five pesticide goods with the codes being 380891 (insecticides), 380892 (fungicides), 380893 (herbicides), 380894 (disinfectants), and 380899 (rodenticides and other similar products) from 2007 to 2018.

which is a value less than the actual value since we do not consider the trade data whose importing or exporting economies are not labeled in the UN Comtrade database. **Figure 4A** presents the evolution of the international trade values $W(t)$ of the five pesticides from 2007 to 2018. We find that the $W(t)$ curves show an overall rising trend and experienced a fall after rise in 2015. In each year, herbicides (380893) have the largest international trade value, while disinfectants (380894) and rodenticides (380899) have the much lower international trade values.

The average international trade value of a given goods *code* with respect to the number of links is calculated as follows:

$$\langle W^{code}(t) \rangle = \frac{W^{code}(t)}{N_{\mathcal{E}}^{code}(t)}, \tag{4}$$

which is illustrated in **Figure 4B**. The average international trade value for each pesticide category also shows a rising trend, with a local drop since 2015.

3.3 Network Density
The density of a directed network is the ratio of the number of existing links to the number of links of the complete directed network

$$\rho = \frac{N_{\mathcal{E}}}{N_{\mathcal{V}}(N_{\mathcal{V}} - 1)}, \tag{5}$$

where the complete directed network has $N_{\mathcal{V}}(N_{\mathcal{V}} - 1)$ directed links since there are two reciprocal links between each pair of nodes. The evolution of network density ρ is shown in **Figure 5**. It is found that the shapes of the density curves are similar to the $N_{\mathcal{E}}$ curves in **Figure 2B**, which is rational because $N_{\mathcal{V}}$ varies slowly and thus according to **Eq. 5**, the density ρ is approximately proportional to $N_{\mathcal{E}}$. However, the order of network densities is different from that of the number of links. The insecticides (380891) networks are the most dense, and the disinfectants

(380894) networks are also relatively dense. This discrepancy is due to the fact that we do not include in the networks the "inactive" economies that do not have a trade relationship with any other economies, and thus, the number of nodes $N_{\mathcal{V}}^{code}(t)$ is different for different goods in different years. The densities of the pesticides networks are much smaller than those of the international trade networks (around 0.6) [14], which are natural since the international trade networks contain many more goods and thus more links.

4 FEATURES OF NODES AND LINKS

In this section, we investigate the features of nodes and links, including node in-degree and out-degree, link strength or link weight, and node in-strength and out-strength.

4.1 Node In-Degree and Out-Degree
The in-degree of node $j \in \mathcal{V}$ is defined as follows:

$$k_j^{in} = \sum_{i \in \mathcal{V} - \{j\}} \left(w_{ij} \right)^0 = \sum_{i=1}^{N_{\mathcal{V}}} \left(w_{ij} \right)^0, \tag{6}$$

where we pose $0^0 = 0$. Similarly, the out-degree of node $i \in \mathcal{V}$ is defined as follows:

$$k_i^{out} = \sum_{j \in \mathcal{V} - \{i\}} \left(w_{ij} \right)^0 = \sum_{i=1}^{N_{\mathcal{V}}} \left(w_{ij} \right)^0. \tag{7}$$

The average in-degree of nodes ($i \in \mathcal{V}$) is expressed as follows:

$$\langle k^{in} \rangle_{\mathcal{V}} = \frac{1}{N_{\mathcal{V}}} \sum_{j=1}^{N_{\mathcal{V}}} k_j^{in} = \frac{1}{N_{\mathcal{V}}} \sum_{i=1}^{N_{\mathcal{V}}} \sum_{j=1}^{N_{\mathcal{V}}} \left(w_{ij} \right)^0, \tag{8}$$

The average out-degree of nodes ($i \in \mathcal{V}$) is expressed as follows:

$$\langle k^{out} \rangle_{\mathcal{V}} = \frac{1}{N_{\mathcal{V}}} \sum_{i=1}^{N_{\mathcal{V}}} k_i^{out} = \frac{1}{N_{\mathcal{V}}} \sum_{i=1}^{N_{\mathcal{V}}} \sum_{j=1}^{N_{\mathcal{V}}} \left(w_{ij} \right)^0. \tag{9}$$

Since

$$N_{\mathcal{E}} = \sum_{i=1}^{N_{\mathcal{V}}} \sum_{j=1}^{N_{\mathcal{V}}} \left(w_{ij} \right)^0, \tag{10}$$
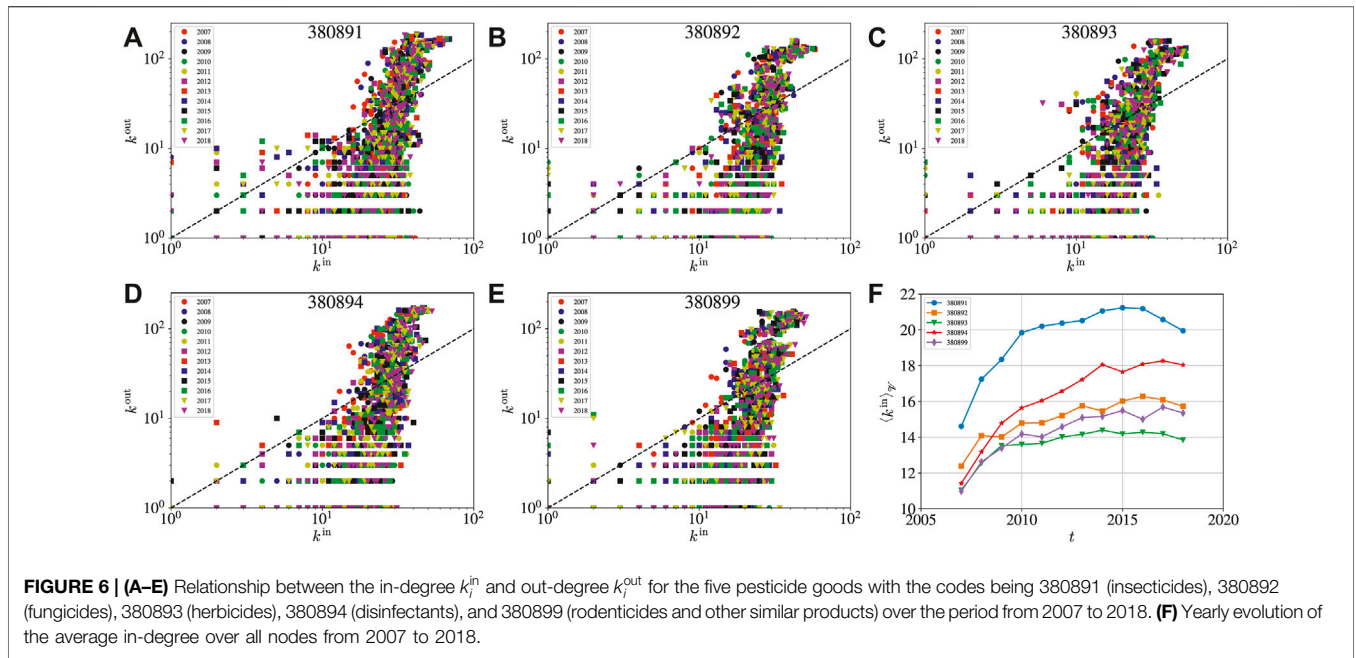
we have

$$\langle k^{in} \rangle_{\mathcal{V}} = \langle k^{out} \rangle_{\mathcal{V}} = \frac{N_{\mathcal{E}}}{N_{\mathcal{V}}} \tag{11}$$

and

$$\langle k_{\mathcal{V}} \rangle = \langle k^{in} + k^{out} \rangle_{\mathcal{V}} = \frac{2N_{\mathcal{E}}}{N_{\mathcal{V}}}. \tag{12}$$

In **Figures 6A–E**, we plot in loglog scales the in-degree k_i^{in} and out-degree k_i^{out} for the five pesticide goods over the period from 2007 to 2018. An economy i has more export partners than import partners if $k_i^{out} > k_i^{in}$, which locates above the dashed diagonal in the plots. There is a positive

FIGURE 6 | (A–E) Relationship between the in-degree k_i^{in} and out-degree k_i^{out} for the five pesticide goods with the codes being 380891 (insecticides), 380892 (fungicides), 380893 (herbicides), 380894 (disinfectants), and 380899 (rodenticides and other similar products) over the period from 2007 to 2018. **(F)** Yearly evolution of the average in-degree over all nodes from 2007 to 2018.

correlation between in-degree and out-degree, which means that an economy that has many (or few) importing partners is more likely to have many (or few) exporting partners. In addition, for each category of pesticides, we can observe the presence of a power law, especially when the number of importing economies (k^{in}) is not too small.

In **Figure 6F**, we digest the evolution of the average in-degree $\langle k^{in} \rangle_{\mathcal{V}}$ from 2007 to 2018. We observe that the average in-degree increased first and then experienced a decline. We also find that the shapes of the average in-degree curves are similar to the $N_{\mathcal{E}}$ curves in **Figure 2B** and to the density curves in **Figure 5**, which is rational because $N_{\mathcal{V}}$ varies slowly, and thus, according to **Eq. 11**, the average in-degree $\langle k^{in} \rangle_{\mathcal{V}}$ is approximately proportional to $N_{\mathcal{E}}$.

4.2 Weight Distribution

In order to obtain the empirical distribution density $f(w)$ of link weights w, we use logarithmic binning. Equivalently, we determine the empirical distribution $g(\log_{10} w)$ of $\log_{10} w$ through linear binning. The two distributions are related as follows [41].

$$f(w)dw = g(\ln w)d\ln w. \tag{13}$$

It follows that

$$f(w) = \frac{1}{w} g(\ln w). \tag{14}$$

Hence, we first obtain the distribution density $g(\ln w)$ of $\ln w$. We show in **Figure 7** the distributions of link weights for the five pesticide goods. The most intriguing feature is that, for each pesticide goods, the 12 empirical distributions for the 12 years collapse on the same curve. The distributions for the insecticides (380891) networks in **Figure 7A**, the fungicides (380892)

networks in **Figure 7B**, and the herbicides (380893) networks in **Figure 7C** exhibit a power-law scaling when the weights are not large, followed by a faster decay when the weights become larger. There is also a bimodal pattern for the fungicides (380892) networks in **Figure 7B** and the herbicides (380893) networks in **Figure 7C**, reminiscent of the bimodal distribution of some social networks [42–44]. The distributions for the disinfectants (380894) networks in **Figure 7D** and the rodenticides (380899) networks in **Figure 7E** do not show an evident power law. These distributions also exhibit differences from that for the international trade network [45].

4.3 Node In-Strength and Out-Strength

The total import value of an economy $i \in \mathcal{V}$ is known as the in-strength of node i in network science, which is defined as follows:

$$s_i^{in} = \sum_{j \in \mathcal{V}-\{i\}} \left(w_{ji}\right)^1 = \sum_{j=1}^{N_{\mathcal{V}}} \left(w_{ji}\right)^1, \tag{15}$$

where we note that $w_{jj} = 0$. Similarly, the export value of an economy $i \in \mathcal{V}$ is known as the out-strength of node $i \in \mathcal{V}$ is defined as follows:

$$s_i^{out} = \sum_{j \in \mathcal{V}-\{i\}} \left(w_{ij}\right)^1 = \sum_{i=1}^{N_{\mathcal{V}}} \left(w_{ij}\right)^1, \tag{16}$$

The average in-strength of nodes ($i \in \mathcal{V}$) is expressed as follows:

$$\langle s^{in} \rangle_{\mathcal{V}} = \frac{1}{N_{\mathcal{V}}} \sum_{j=1}^{N_{\mathcal{V}}} s_j^{in} = \frac{1}{N_{\mathcal{V}}} \sum_{i=1}^{N_{\mathcal{V}}} \sum_{j=1}^{N_{\mathcal{V}}} \left(w_{ij}\right)^1 = \frac{W}{N_{\mathcal{V}}}, \tag{17}$$

where the last equality is obtained according to **Eq. 3**. Similarly, the average out-strength of nodes is expressed as follows:
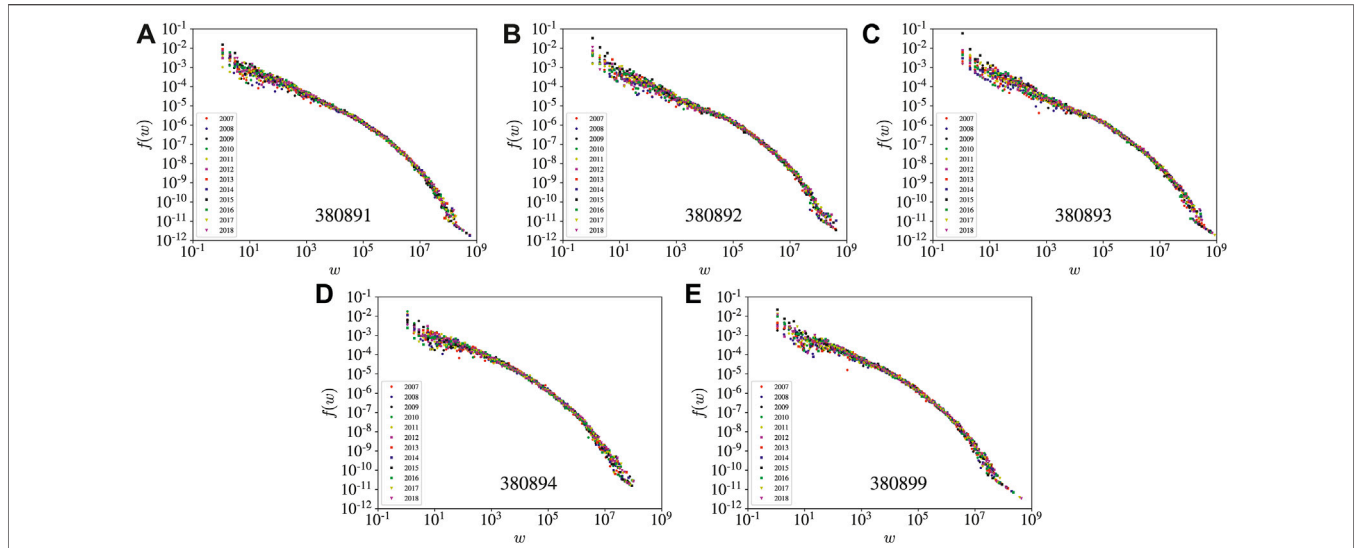
FIGURE 7 | Empirical distributions of link weights for the five pesticides trade networks: **(A)** 380891 for insecticides **(A)**, 380892 for fungicides **(B)**, 380893 for herbicides **(C)**, 380894 for disinfectants **(D)**, and 380899 for rodenticides and other similar products **(E)**. In each plot, there are 13 distributions corresponding to the 13 years.
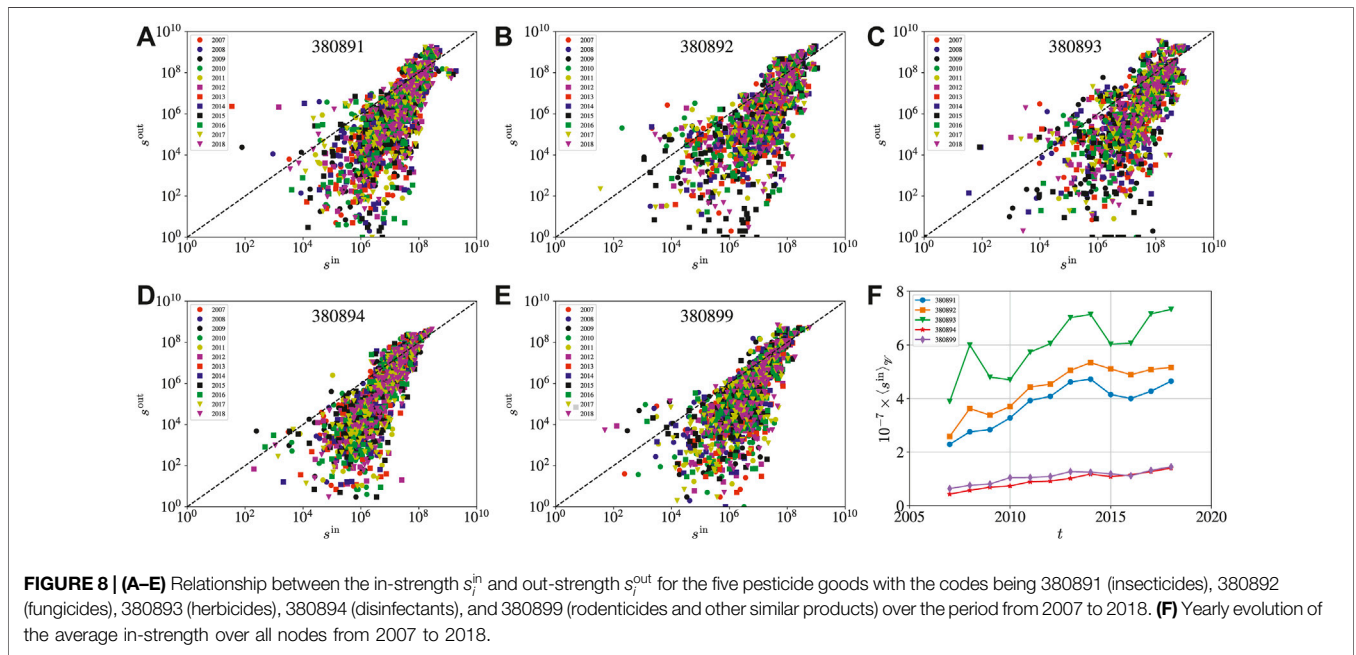

FIGURE 8 | (A–E) Relationship between the in-strength s_i^{in} and out-strength s_i^{out} for the five pesticide goods with the codes being 380891 (insecticides), 380892 (fungicides), 380893 (herbicides), 380894 (disinfectants), and 380899 (rodenticides and other similar products) over the period from 2007 to 2018. **(F)** Yearly evolution of the average in-strength over all nodes from 2007 to 2018.

$$\langle s^{\text{out}} \rangle_{\mathcal{V}} = \frac{1}{N_{\mathcal{V}}} \sum_{i=1}^{N_{\mathcal{V}}} s_i^{\text{out}} = \frac{1}{N_{\mathcal{V}}} \sum_{i=1}^{N_{\mathcal{V}}} \sum_{j=1}^{N_{\mathcal{V}}} \left(w_{ij} \right)^1 = \frac{W}{N_{\mathcal{V}}}. \quad (18)$$

Therefore, we have

$$\langle s^{\text{in}} \rangle_{\mathcal{V}} = \langle s^{\text{out}} \rangle_{\mathcal{V}} = \frac{W}{N_{\mathcal{V}}} \quad (19)$$

and

$$\langle s_{\mathcal{V}} \rangle = \langle s^{\text{in}} + s^{\text{out}} \rangle_{\mathcal{V}} = \frac{2W}{N_{\mathcal{V}}}. \quad (20)$$

In **Figures 8A–E**, we plot in loglog scales the in-strength s_i^{in} and out-strength s_i^{out} for the five pesticide goods over the period from 2007 to 2018. We observe that there is a powerlaw relationship

$$s^{\text{out}} \sim \left(s^{\text{in}} \right)^{\alpha_s} \quad (21)$$

with $\alpha_s \approx 2.5$. An economy i has more exports than imports if $s_i^{\text{out}} > s_i^{\text{in}}$, which locates above the dashed diagonal in the plots. We find that most economies locate below the diagonal, which are import-oriented. It means that the in-strength and out-strength of the pesticide networks are positively correlated. It is

FIGURE 9 | Evolution of the temporal similarity coefficient $S(t)$ between two successive networks of the five pesticide goods with the codes being 380891 (insecticides), 380892 (fungicides), 380893 (herbicides), 380894 (disinfectants), and 380899 (rodenticides and other similar products) from 2007 to 2018. **(A)** All links. **(B)** Small links with the weights less than the 20% percentile. **(C)** Medium links with the weights between the 40 and 60% percentiles. **(D)** Large links with the weights greater than the 80% percentile.

different from the case of the whole international trade network, where the in- and out-strengths are almost not correlated with a correlation coefficient of 0.09 being not significantly different from zero [45]. **Figure 8F** shows the evolution of the average in-degree over all nodes from 2007 to 2018.

5 STRUCTURAL PATTERNS

5.1 Similarity of Temporal Networks
In order to compare the structural stability of two successive networks at t and $t + 1$, we calculate the similarity coefficient of temporal networks. Let $\mathcal{E}_{(t-1) \cup t} = \mathcal{E}(t-1) \cup \mathcal{E}(t)$ be the union set of directed links and $\mathcal{E}_{(t-1) \cap t} = \mathcal{E}(t-1) \cap \mathcal{E}(t)$ be the intersection of directed links in two successive networks $\mathcal{G}(t-1)$ and $\mathcal{G}(t)$. The similarity coefficient between two successive networks $\mathcal{G}(t-1)$ and $\mathcal{G}(t)$ is defined as the ratio of the number of overlapping directed links in the two networks, and the number of all directed links appeared in the two networks:

$$S(t) = \frac{\sharp(\mathcal{E}_{(t-1) \cap t})}{\sharp(\mathcal{E}_{(t-1) \cup t})}. \quad (22)$$

where $\sharp(\mathbf{X})$ represents the cardinal number of set $\mathbf{X}$. The similarity coefficient $S(t)$ takes a value in $[0, 1]$. When the two networks have exactly the same set of directed links, that is, $\mathcal{E}(t-1) = \mathcal{E}(t)$, we have $S(t) = 1$. When the two networks have no directed links in common, that is, $\mathcal{E}_{(t-1) \cap t} = \varnothing$, we have $S(t) = 0$. The similarity coefficient defined here is not the same as the

temporal correlation coefficient [46–48], which is an average of temporal correlation coefficients of nodes in successive networks.

Figure 9A shows the evolution of the temporal similarity coefficient $S(t)$ between two successive networks of the five pesticide goods from 2007 to 2018. We find that the temporal similarity increased first and reached a relatively stable level. The fungicides (380892) trade networks have the highest temporal similarity. Intuitively, we conjecture that links with large weights are more temporally stable. We calculate the similarity coefficients of sub-networks containing small links with the weights less than the 20% percentile, medium links with the weights between the 40 and 60% percentiles, and large links with the weights greater than the 80% percentile. The results are shown in **Figures 9B–D**, respectively, which verify that the large international trade relationships are more stable than the small international trade relationships.

5.2 Mixing Pattern
Mixing patterns of links in undirected networks have been introduced and widely studied to quantify the correlation relationship (assortative or disassortative) between node degrees [49, 50], which can be extended to direct networks [51]. From the perspective of trade relationship from exporting economy i to importing economy j, described by link e_{ij}, the exporting economy i has an in-degree k_i^{in} and an out-degree k_i^{out}, and the importing economy j has an in-degree k_j^{in} and an out-degree k_j^{out}. Hence, associated with the link set $\mathcal{E}$, we
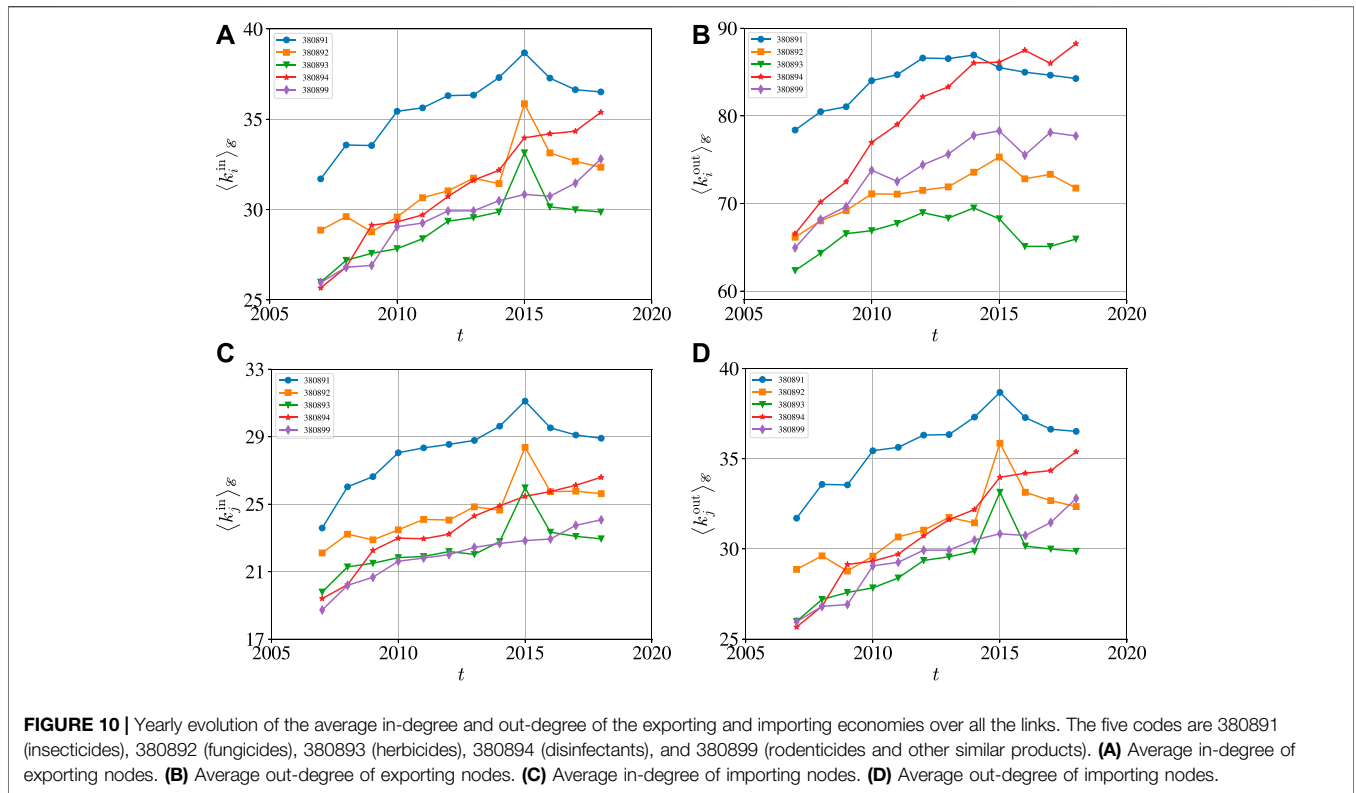
FIGURE 10 | Yearly evolution of the average in-degree and out-degree of the exporting and importing economies over all the links. The five codes are 380891 (insecticides), 380892 (fungicides), 380893 (herbicides), 380894 (disinfectants), and 380899 (rodenticides and other similar products). **(A)** Average in-degree of exporting nodes. **(B)** Average out-degree of exporting nodes. **(C)** Average in-degree of importing nodes. **(D)** Average out-degree of importing nodes.

have four sequences of the same length $N_{\mathcal{E}}$: in-degree sequence of exporting economies $\{k_i^{in}\}$, out-degree sequence of exporting economies $\{k_i^{out}\}$, in-degree sequence of importing economies $\{k_j^{in}\}$, and out-degree sequence of importing economies $\{k_j^{out}\}$. Note that, the in-degree sequences $\{k_i^{in}\}$ and $\{k_j^{in}\}$ of exporting and importing economies are not necessarily identical, and out-degree sequences $\{k_i^{out}\}$ and $\{k_j^{out}\}$ of exporting and importing economies are not necessarily identical either. The mean in-degree of exporting economies is

$$\langle k_i^{in} \rangle_{\mathcal{E}} = \frac{1}{N_{\mathcal{E}}} \sum_{e_{ij} \in \mathcal{E}} k_i^{in}, \tag{23}$$

with the variance being

$$\left(\sigma_{i,\mathcal{E}}^{in} \right)^2 = \frac{1}{N_{\mathcal{E}}} \sum_{e_{ij} \in \mathcal{E}} \left(k_i^{in} - \langle k_i^{in} \rangle_{\mathcal{E}} \right)^2, \tag{24}$$

The mean in-degree of importing economies is

$$\langle k_j^{in} \rangle_{\mathcal{E}} = \frac{1}{N_{\mathcal{E}}} \sum_{e_{ij} \in \mathcal{E}} k_j^{in} \tag{25}$$

with the variance being

$$\left(\sigma_{j,\mathcal{E}}^{in} \right)^2 = \frac{1}{N_{\mathcal{E}}} \sum_{e_{ij} \in \mathcal{E}} \left(k_j^{in} - \langle k_j^{in} \rangle_{\mathcal{E}} \right)^2, \tag{26}$$

The mean out-degree of exporting economies is

$$\langle k_i^{out} \rangle_{\mathcal{E}} = \frac{1}{N_{\mathcal{E}}} \sum_{e_{ij} \in \mathcal{E}} k_i^{out} \tag{27}$$

with the variance being

$$\left(\sigma_{i,\mathcal{E}}^{out} \right)^2 = \frac{1}{N_{\mathcal{E}}} \sum_{e_{ij} \in \mathcal{E}} \left(k_i^{out} - \langle k_i^{out} \rangle_{\mathcal{E}} \right)^2, \tag{28}$$

and the mean out-degree of importing economies is

$$\langle k_j^{out} \rangle_{\mathcal{E}} = \frac{1}{N_{\mathcal{E}}} \sum_{e_{ij} \in \mathcal{E}} k_j^{out} \tag{29}$$

with the variance being

$$\left(\sigma_{j,\mathcal{E}}^{out} \right)^2 = \frac{1}{N_{\mathcal{E}}} \sum_{e_{ij} \in \mathcal{E}} \left(k_j^{out} - \langle k_j^{out} \rangle_{\mathcal{E}} \right)^2. \tag{30}$$
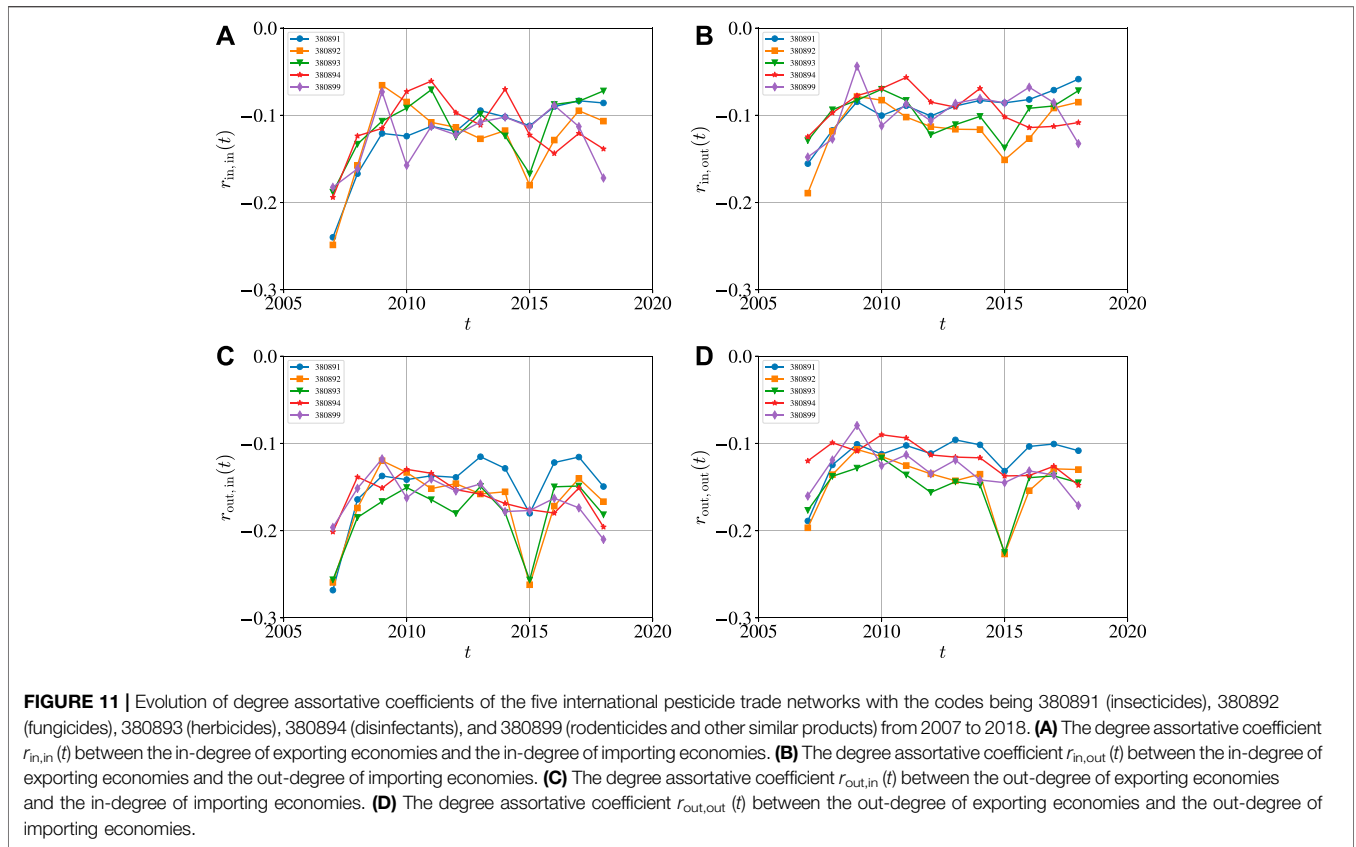
Figure 10 shows the yearly evolution of the average in-degree and out-degree of the exporting and importing economies over all the links. Comparing **Figure 10A** and **Figure 10D**, we find that

$$\langle k_i^{in} \rangle_{\mathcal{E}} = \langle k_j^{out} \rangle_{\mathcal{E}}, \tag{31}$$

which can be proved. For each exporting economy i, it has k_i^{out} out-links such that

$$\langle k_i^{in} \rangle_{\mathcal{E}} = \frac{1}{N_{\mathcal{E}}} \sum_{e_{ij} \in \mathcal{E}} k_i^{in} = \frac{1}{N_{\mathcal{E}}} \sum_{i \in \mathcal{V}_{ex}} k_i^{out} k_i^{in} = \frac{1}{N_{\mathcal{E}}} \sum_{v \in \mathcal{V}} k_v^{out} k_v^{in}, \tag{32}$$

where $\mathcal{V}_{ex}$ is the set of all exporting economies. The last equality holds since non-exporting economies do not have out-links, that

FIGURE 11 | Evolution of degree assortative coefficients of the five international pesticide trade networks with the codes being 380891 (insecticides), 380892 (fungicides), 380893 (herbicides), 380894 (disinfectants), and 380899 (rodenticides and other similar products) from 2007 to 2018. **(A)** The degree assortative coefficient $r_{in,in}$ (t) between the in-degree of exporting economies and the in-degree of importing economies. **(B)** The degree assortative coefficient $r_{in,out}$ (t) between the in-degree of exporting economies and the out-degree of importing economies. **(C)** The degree assortative coefficient $r_{out,in}$ (t) between the out-degree of exporting economies and the in-degree of importing economies. **(D)** The degree assortative coefficient $r_{out,out}$ (t) between the out-degree of exporting economies and the out-degree of importing economies.

is, $k_v^{out} = 0$ for $v \notin \mathcal{V}_{ex}$. Similarly, for each importing economy j, it has k_j^{in} any in-links such that

$$\langle k_j^{out} \rangle_{\mathcal{E}} = \frac{1}{N_{\mathcal{E}}} \sum_{e_{ij} \in \mathcal{E}} k_j^{out} = \frac{1}{N_{\mathcal{E}}} \sum_{j \in \mathcal{V}_{im}} k_j^{out} k_j^{in} = \frac{1}{N_{\mathcal{E}}} \sum_{v \in \mathcal{V}} k_v^{out} k_v^{in}, \quad (33)$$

where $\mathcal{V}_{im}$ is the set of all importing economies. The last equality holds since non-importing economies do not have any in-links, that is, $k_v^{in} = 0$ for $v \notin \mathcal{V}_{im}$.

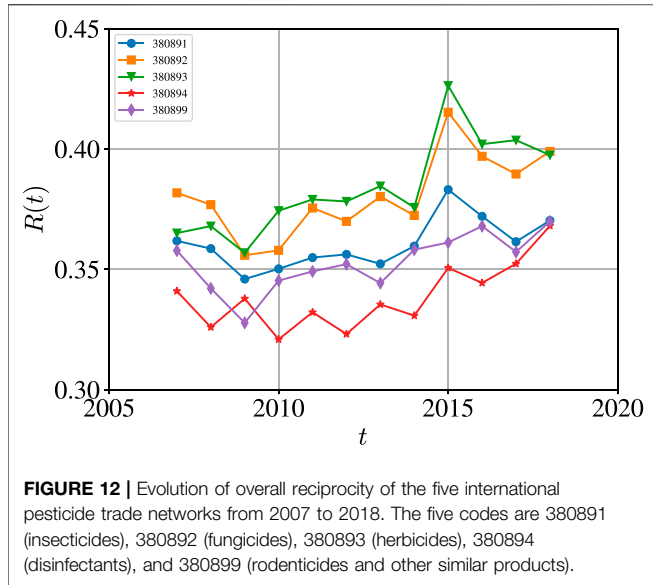One can define the set of assortativity measures using the Pearson correlation [51]. Specifically, the degree assortative coefficient $r_{in,in}(t)$ between the in-degree of exporting economies and the in-degree of importing economies is

$$r_{in,in}(t) = \frac{1}{N_{\mathcal{E}}} \sum_{e_{ij} \in \mathcal{E}} \frac{\left[\left(k_i^{in} - \langle k_i^{in} \rangle_{\mathcal{E}} \right) \left(k_j^{in} - \langle k_j^{in} \rangle_{\mathcal{E}} \right) \right]}{\sigma_{i,\mathcal{E}}^{in} \sigma_{j,\mathcal{E}}^{in}}, \quad (34)$$

The degree assortative coefficient $r_{in,out}$ (t) between the in-degree of exporting economies and the out-degree of importing economies is

$$r_{in,out}(t) = \frac{1}{N_{\mathcal{E}}} \sum_{e_{ij} \in \mathcal{E}} \frac{\left[\left(k_i^{in} - \langle k_i^{in} \rangle_{\mathcal{E}} \right) \left(k_j^{out} - \langle k_j^{out} \rangle_{\mathcal{E}} \right) \right]}{\sigma_{i,\mathcal{E}}^{in} \sigma_{j,\mathcal{E}}^{out}}, \quad (35)$$

The degree assortative coefficient $r_{out,in}$ (t) between the out-degree of exporting economies and the in-degree of importing economies is

$$r_{out,in}(t) = \frac{1}{N_{\mathcal{E}}} \sum_{e_{ij} \in \mathcal{E}} \frac{\left[\left(k_i^{out} - \langle k_i^{out} \rangle_{\mathcal{E}} \right) \left(k_j^{in} - \langle k_j^{in} \rangle_{\mathcal{E}} \right) \right]}{\sigma_{i,\mathcal{E}}^{out} \sigma_{j,\mathcal{E}}^{in}}, \quad (36)$$

and the degree assortative coefficient $r_{out,out}$ (t) between the out-degree of exporting economies and the out-degree of importing economies is

$$r_{out,out}(t) = \frac{1}{N_{\mathcal{E}}} \sum_{e_{ij} \in \mathcal{E}} \frac{\left[\left(k_i^{out} - \langle k_i^{out} \rangle_{\mathcal{E}} \right) \left(k_j^{out} - \langle k_j^{out} \rangle_{\mathcal{E}} \right) \right]}{\sigma_{i,\mathcal{E}}^{out} \sigma_{j,\mathcal{E}}^{out}}. \quad (37)$$

Figure 11 illustrates the evolution of the degree assortative coefficients of the five international pesticide trade networks from 2007 to 2018. It is found that all the correlation coefficients are negative, showing that the networks are disassortatively mixed. In disassortative international pesticide trade networks, high-degree nodes tend to connect to low-degree nodes, which limit the effects of node failure and relieve the propagation of shocks because important nodes (with many links) are isolated from each other [52]. On average, the degree assortative coefficient $r_{out,in}$ (t) between the out-degree of exporting economies and the in-degree of importing economies is the most negative. We also find that the four-degree assortative coefficients seem more negative in the years 2007 and 2015, compared to the coefficients in other years. We note that the international trade network is also disassortative and the assortativity coefficient (about -0.4) is smaller [14], where the link directions are not considered.

FIGURE 12 | Evolution of overall reciprocity of the five international pesticide trade networks from 2007 to 2018. The five codes are 380891 (insecticides), 380892 (fungicides), 380893 (herbicides), 380894 (disinfectants), and 380899 (rodenticides and other similar products).

5.3 Reciprocity

The reciprocity of a directed network is defined as the ratio of the number of bilateral links (i.e., links pointing in both directions) to the total number of links in the network [9, 22], that is,

$$R = \frac{\#\left(\left\{(i, j) : e_{ij} \in \mathcal{E} \ \& \ e_{ji} \in \mathcal{E}\right\}\right)}{\#\left(\left\{(i, j) : e_{ij} \in \mathcal{E}\right\}\right)} = \frac{1}{N_{\mathcal{E}}} \sum_{i \in \mathcal{V}} k_i^R, \quad (38)$$

where

$$k_i^R = \#\left(\left\{j : e_{ij} \in \mathcal{E} \ \& \ e_{ji} \in \mathcal{E}\right\}\right) = \sum_{j \neq i} \left(w_{ij} w_{ji}\right)^0 \quad (39)$$

is the reciprocal degree of node i so that

$$\#\left(\left\{(i, j): e_{ij} \in \mathcal{E} \ \& \ e_{ji} \in \mathcal{E}\right\}\right) = \sum_{i \in \mathcal{V}} k_i^R. \quad (40)$$

The reciprocity coefficient is also known as the percentage of bilateral links [14].

Figure 12 shows the evolution of overall reciprocity of the five international pesticide trade networks from 2007 to 2018. It is found that the overall reciprocity coefficients are all greater than 0.32. It is found that the overall reciprocity was stable before 2014 and increased slightly afterward. In addition, the overall reciprocity coefficients are abnormally greater than its neighbor years, especially for pesticide goods 380891, 380892, and 380893. The reciprocity coefficients of the pesticides networks are much smaller than those of the international trade networks (around 0.9) [14], which are natural since the international trade networks contain many more goods and thus more reciprocal links.

The reciprocity of a single node i is defined similarly, and it is the ratio of the number of links in both directions to the total number of links attached to node i:

$$R_i = \frac{\#\left(\left\{j : e_{ij} \in \mathcal{E} \ \& \ e_{ji} \in \mathcal{E}\right\}\right)}{\#\left(\left\{j : e_{ij} \in \mathcal{E} \ \text{or} \ e_{ji} \in \mathcal{E}\right\}\right)} = \frac{k_i^R}{k_i}. \quad (41)$$

We calculate the reciprocity coefficients R_i of economies in each network and compare them with the in-degree k_i^{in} and out-degree k_i^{out} as well as the in-strength s_i^{in} and out-strength s_i^{out} of the corresponding economies. The results for the international insecticides (380891) networks are shown in **Figure 13**. The results are similar for other four categories of pesticides. We find that for each network, the node reciprocity coefficients are distributed broadly, spanning from 0 (pure import or export economies) to 1 (economies that have both import and export relationships with each trade partner). The economies with $R_i = 1$ are leaf nodes with a pair of reciprocal links because they have $k_i^{\text{in}} = 1$ and $k_i^{\text{out}} = 1$ as shown in **Figures 13A,B** while their import and export values are not large as shown in **Figure 13C** and **Figure 13D**. Excluding data points with $R = 0$ or $R = 1$, we observe an linearly increasing relationship between reciprocity R_i and logarithmic trade values s_i^{in} and s_i^{out}. In other words, an economy with a large import or/and export value will have a large reciprocity coefficient. In addition, the slope is larger for k_i^{in} in **Figure 13A** and s_i^{in} in **Figure 13C** than k_i^{out} in **Figure 13B** and s_i^{out} in **Figure 13D**.

5.4 Clustering Coefficient

For unweighted graphs, the clustering of a node i is the fraction of possible triangles through that node that exist,

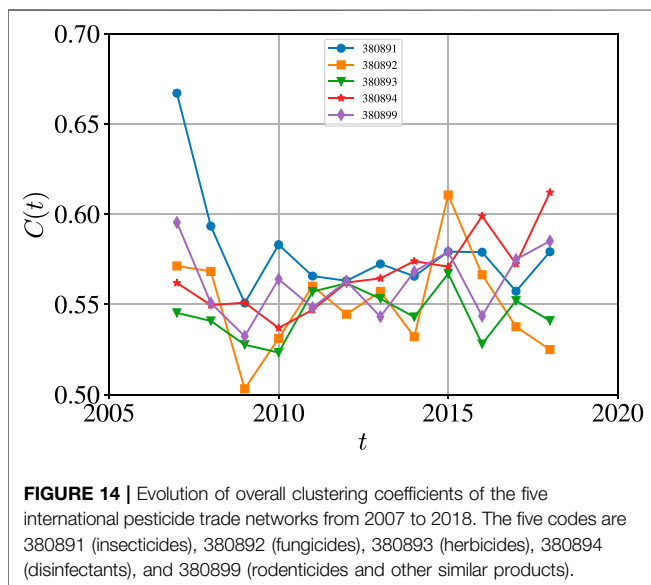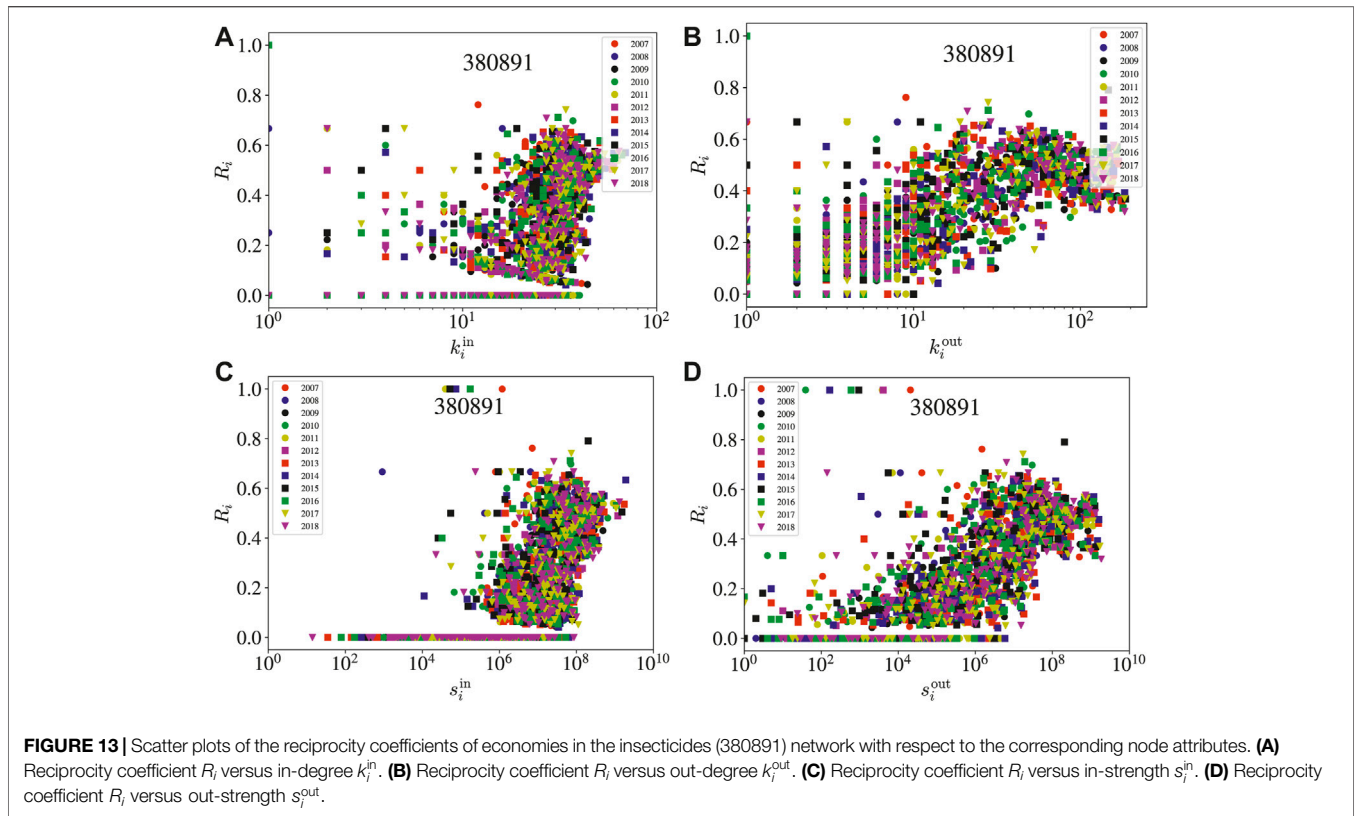$$c_i = \frac{2T_i}{k_i(k_i - 1)}, \quad (42)$$

where T_i is the number of triangles through node u and k_i is the degree of i. For weighted networks, there are several ways to define the clustering coefficient [53, 54]. For directed graphs, the clustering is similarly defined as the fraction of all possible directed triangles or geometric average of the subgraph link weights for unweighted and weighted directed network, respectively [45]:

$$c_i = \frac{2T_i}{k_i(k_i - 1) - 2k_i^R}, \quad (43)$$

where T_i is the number of directed triangles through node i, $k_i = k_i^{\text{in}} + k_i^{\text{in}}$ is the sum of in-degree and out-degree of i, and k_i^R is the reciprocal degree of i. The overall clustering coefficient of a network is the average of the clustering coefficients of all nodes, that is,

$$C = \frac{1}{N_{\mathcal{V}}} \sum_{i=1}^{N_{\mathcal{V}}} c_i. \quad (44)$$

Figure 14 shows the evolution of the overall clustering coefficients of the five international pesticide trade networks from 2007 to 2018. For the insecticides (380891) network and the rodenticides (380899) network, the overall clustering coefficient $C(t)$ curves exhibit a U-shape. For the disinfectants (380894) network, the $C(t)$ curve has an increasing trend. For the rest two networks, the $C(t)$ curves fluctuate stably, and the curve for the fungicides (380892) network has an evident local maximum at the year 2015. It is not surprising that the international

FIGURE 13 | Scatter plots of the reciprocity coefficients of economies in the insecticides (380891) network with respect to the corresponding node attributes. **(A)** Reciprocity coefficient R_i versus in-degree k_i^{in}. **(B)** Reciprocity coefficient R_i versus out-degree k_i^{out}. **(C)** Reciprocity coefficient R_i versus in-strength s_i^{in}. **(D)** Reciprocity coefficient R_i versus out-strength s_i^{out}.

FIGURE 14 | Evolution of overall clustering coefficients of the five international pesticide trade networks from 2007 to 2018. The five codes are 380891 (insecticides), 380892 (fungicides), 380893 (herbicides), 380894 (disinfectants), and 380899 (rodenticides and other similar products).

trade networks have higher clustering coefficients close to 0.82 [14].

We show the scatter plots of the clustering coefficients c_i of nodes in the insecticides (380891) network with respect to the in-degree k_i^{in} in **Figure 15A** and the out-degree k_i^{out} in **Figure 15B**. The results for other pesticide networks are similar. When the degrees (k_i^{in} and k_i^{out}) are not too small, the clustering coefficient

c_i shows a decreasing trend, indicating that economies with less trade partners are more likely to form local denser clusters. In addition, we observe a more evident decreasing trend in **Figure 15B** than in **Figure 15A**. These patterns are similar to the whole international trade network, where the correlation between the clustering coefficient and node degree is negative [14].

We also show the scatter plots of the clustering coefficients c_i of nodes in the insecticide (380891) network with respect to the in-strength s_i^{in} in **Figure 15C** and the out-strength s_i^{out} in **Figure 15D**. The results for other pesticide networks are similar. It is observed that the economies with a zero clustering coefficient have not too large import and export values ($s_i^{in} < 2 \times 10^6$ or $s_i^{out} < 10^6$), while the economies with $c_i = 1$ usually have medium import and export values. Excluding the points with $c_i = 0$, we can observe a decreasing trend, which is more evident for s_i^{out} in **Figure 15D**. It indicates that economies with smaller trade values are more likely to form local denser clusters.

6 CONCLUSION

In this study, we have investigated the structure and evolution of the international trade networks of five categories of pesticides including insecticides (380891), fungicides (380892), herbicides (380893), disinfectants (380894), and rodenticides and other similar products (380899) retrieved from the UN Comtrade database. The yearly sampled data sets cover the time period from 2007 to 2018. Specifically, we

FIGURE 15 | Scatter plots of the clustering coefficients of economies in the insecticides (380891) network with respect to the corresponding node attributes. **(A)** Clustering coefficient c_i versus in-degree k_i^{in}. **(B)** Clustering coefficient c_i versus out-degree k_i^{out}. **(C)** Clustering coefficient c_i versus in-strength s_i^{in}. **(D)** Clustering coefficient c_i versus out-strength s_i^{out}.

have explored the global properties including total trade value, network size, and network density, the first-order properties of nodes and links including node degrees, link weights and node strengths, and the structural patterns including temporal similarity, mixing patterns, reciprocity, and the clustering coefficients. Our analyses were carried out from the perspective of temporal weighted and directed network. In particular, taking link directions into consideration allows us to better understand the structure and behavior of international pesticide trade. Certainly, other topics about complex networks like node centrality, group formation, community detection, and link prediction may be useful for future research on the temporal international pesticide trade networks [55–60].

We observed an overall increasing trend in almost all global network metrics quantifying the growth and densification of networks, including network size, network density, average in- and out-degrees, average in- and out-strengths, temporal similarity, and link reciprocity. It means that the international pesticide trade networks are becoming more connected. These findings show the continuous integration and globalization of international pesticide trade. However, we also observed that the trend of integration and globalization of international pesticide trade have slowed down in the last decade. Interestingly, we found that the distributions of link weights remain unchanged along time for the five categories of pesticides.

From the directed network perspective, we found that all the networks are disassortatively mixed. It means that large importers or exporters are more likely to trade with small exporters or importers, while the probability of trades between large importers or exporters and between small importers or exporters is relatively low. We also observed positive correlations between in-degree and out-degree, between in-strength and out-strength, between link reciprocity and in-degree, out-degree, and in-strength and out-strength. In contrast, node's local clustering coefficient is negatively related to in-degree, out-degree, in-strength, and out-strength. It suggests that exporting economies usually produce only some pesticides with an excess volume of production due to their comparative advantages of technology or labor and need to import other pesticides.

Our preliminary analysis shows that, although most of the structural properties of the international pesticide trade networks are qualitatively similar to those of the whole international trade network, we uncovered qualitative and quantitative differences. The quantitative differences mainly come from the fact that the international pesticides networks are only part of the whole international trade network. However, the qualitative differences show the presence of idiosyncratic features of different goods and products in the international trade. Exploration of such disaggregated networks will uncover idiosyncratic properties and dynamics of the international trade networks of specific goods and products.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: https://comtrade.un.org/data.

AUTHOR CONTRIBUTIONS

W-JX and W-XZ conceived the research. J-AL analyzed the data and prepared the figures. J-AL and W-XZ analyzed the results and wrote the paper. All authors discussed and reviewed the manuscript.

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