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A pre-pandemic analysis of the global fertiliser trade network

Ester Gutiérrez-Moya [a,*], Sebastián Lozano [a], Belarmino Adenso-Díaz [b]

[a] Department of Industrial Management, Universidad de Sevilla, Spain
[b] Department of Industrial Engineering, University of Oviedo, Spain

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ABSTRACT

In this paper a complex network analysis of global fertiliser trade during the period 2014–2018 has been carried out. The goal is to study its structure both at the global and local level, identifying communities and main players, motifs, structural holes and brokerage roles. The persistency and variability of trade links have also been analysed. The Global Fertiliser Trade Network is characterised as a small-world network with scale-free properties, revealing a high level of reciprocity and centralisation. The network has a core-periphery structure consisting of five core countries (namely EU, USA, China, Brazil, and the Russian Federation) which trade among themselves and with most periphery countries, which have sparse connections between them. The interregional and community analyses indicate a moderate level of heterophily and a geographical component in the trade communities. The network also exhibits an overall tendency toward intransitivity which implies a strategic advantage for countries that act as brokers. This study provides a clear picture of the situation prior to the COVID pandemic and the Ukraine military conflict. Those events have affected global fertiliser trade in a way that has yet to be fully ascertained. The purpose of this paper is to firmly establish a reference against which to gauge the direction and magnitude of those changes.

1. Introduction

The increase in the world population and the economic development resulting from globalisation has caused an increase in the demand for agricultural products. In the last 25 years the world population has grown by 35%, while the area of cultivated land has remained almost constant (USGS, 1999).

In order to meet this challenge, fertilisers have been key to help cope with the growth in demand of food. Nitrogen, phosphorus and potassium (NPK) are the three major nutrients used in fertilisers. Industry can easily produce ammonia for agricultural use. Potash is extracted from underground mines located throughout the world, Canada being by far the major producer (USGS, 2022). In the case of phosphorus, phosphate rock is the economic source for this element, and it is mined from the Earth, although prior to being used it must be treated with sulphuric acid to make it soluble for plants. Another important environmental concern associated with fertilisers is the aquatic eutrophication due to erosion from fertilised soils which is causing severe problems in lakes and seas around the globe (Nesme et al., 2018). That is, fertilisers have indeed provided an increase in productivity but at the cost of a significant environmental impact, without many alternatives being available. Due to that concern, the European Union passed, in 2019, a new regulation harmonising safety, quality and labelling, limiting values for contaminants in fertilisers, and promoting circular economy (EUR-Lex, 2019).

Traditionally the fertiliser industry has been ruled by some cartels that maintained market prices well above marginal production costs, by regulating production to match demand. This oligopolistic market is due to production concentration in a few countries and companies (Dmitrieva et al., 2017). In 2013 Canada's major potash exporters were accused of forcing prices up and agreed to pay a huge fine to settle lawsuits (Jordan and Gray, 2013). In addition, some countries like China (with a 20% of the global population but only 10% of arable lands) have strong interests in access to fertilisers at a reasonable price (Yu et al., 2020).

According to different reports from Graphical Research (graphicalresearch.com), the rising population rate mentioned above implies an increase in the demand of fresh produce, which is accelerating the growth of the fertilisers market worldwide. FAO (2019) states that in the period 2017–2022 the global demand for nitrogen, phosphorus and potassium for fertiliser use has increased a 6.23%, 8.73% and 10.68% respectively. The International Fertilizer Association (IFA, 2020) states that South Asia will be for years to come the driver of the expansion of global

* Corresponding author.
E-mail addresses: egm@us.es (E. Gutiérrez-Moya), slozano@us.es (S. Lozano), adenso@uniovi.es (B. Adenso-Díaz).

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fertiliser use, followed by EECA, Latin America and Africa.

Organic fertilisers (manure, guano, compost, etc.) are in greater demand as the population is more concerned (mainly after COVID19 pandemic) about healthier food, fresh produce and eco-friendliness. In addition to having a minimal negative impact on soil quality, they provide a beneficial option to address the challenge of rising costs. This encouraged the USA government to start a programme in 2022 to aid the production of fertilisers by farmers (USDA, 2022).

The fact is that the number of people affected by hunger in the world in 2021 was above 800 million (FAO, 2022), 150 million of them joining that list due to the last pandemic outbreak and its impact on logistics networks. Making the situation worse, some of the most important countries exporting agricultural commodities, and the leading producer of NPK fertilisers, became involved in February 2022 in a conflict that threatens to disrupt the supply chain of these products (although, at least during the first half of 2022, Russian fertiliser exports have not decreased, see FAO, 2022), increasing food and energy prices. Thus, N-urea prices rose more than threefold due to the high price of natural gas, P-fertilisers also suffer a high price increase, with potash being the least affected (FAO, 2022).

All this creates increasing difficulty for farmers to produce profitably, increasing food security risks especially in countries that are net importers such as those in Africa. In addition, African countries have greater difficulty to buy fertilisers by themselves as their currencies are devalued against the dollar, the prices of the products and transportation are increasing, and there is so much uncertainty in the market with regard to disruptions and volatility. Furthermore, some major food exporter countries are net fertiliser importers, which again represents another threat to global food security.

Against this background, The World Bank (Voegele, 2022) recommends taking some liberalising measures that de-stress the markets: removing export restrictions, facilitating financing for manufacturers and importers, and rationalising the use of fertilisers by farmers, and investing in innovation to improve its efficiency. However, it is unlikely that these measures will be implemented in the short-term.

All this signifies the necessity to understand the structure of the global fertilizers market to guarantee global food security. To achieve this, several scientific approaches are possible. In our case, given the networked character of global trade relationships, a quantitative approach based on complex networks analysis methodology is proposed. This methodology allows for the identification of hidden patterns in the data that a more superficial analysis may overlook, enabling a scientific understanding of the collected data (Herman, 2022). Actually, as indicated in the literature review, this is the approach used by many other authors to study the global trade of various raw materials and commodities.

As regards the scientific significance of the paper, it does not come so much from the methodology used, which is more or less standard, but from the thoroughness of the analysis carried out, which provides a complete characterisation of the global fertiliser trade (up to 2018). Thus, apart from the basic characterisation measures of the network, node centrality indexes and motifs, the geographic homophily, the trade communities and the existence of a core-periphery structure have also been studied. The latter is an important finding, not only because it is not a frequent feature of global trade networks but also because it has significant effects on the degree distribution and the degree-degree correlation, among others. Other methodological aspects that are innovative for this type of studies is the analysis of the persistence and variability of fertiliser trade relationships (again, up to 2018) and the study of structural holes and brokerage opportunities.

The structure of the papers follows. Section 2 presents the literature review regarding international trade analysis based on complex networks, focusing on two aspects: the use of complex networks analysis to interpret the structure of global commodity trade, and the work done for the analysis of fertiliser flows and their components. Section 3 presents the results obtained after analysing the corresponding complex networks. It also includes the description of the data source, the period under study and the established hypotheses. Finally, Sections 4 and 5 present the discussion of the results and the conclusions of the study, respectively.

2. Literature review

Since global trade involves a network of trading relationships it is natural to use the network paradigm and tools to study the problem. This applies to trade in all kinds of goods and services. Hence, the complex network analysis methodology has been extensively used to study global trade in general and with regard to specific sectors. Thus, for example, Kim and Shin (2002) studied and compared the international trade network in the years 1959, 1975 and 1996, observing a small world character (i.e., average geodesic distance) and increasing density (i.e., increasing trade relationships among countries). They found that during that period world trade became globalised in the sense that the overall network density significantly increased, and, at the same time, regionalised in the sense that intraregional density also increased significantly. They claimed that the two processes can be complementary rather than incompatible. Serrano and Boguñá (2003) analysed the topology of the World Trade Web using the data for year 2000. They built a directed, unweighted network and found that it showed small world and scale free characteristics as well as high clustering, high reciprocity and positive in-degree/out-degree correlation. Considering the undirected network that results from keeping only the bidirectional links, the network showed a decreasing average nearest neighbour degree (i.e. disassortativity).

Garlaschelli and Loffredo (2005) also studied the structure and evolution of the World Trade Web during the period 1950–1996. They built an unweighted, undirected network and found that the degree distribution followed a power law with cut-off and that the network was disassortative (i.e., countries with many trade partners are on average connected with countries with few partners). They proposed a fitness model and showed that some important topological properties are tightly related to the Gross Domestic Product (GDP) of the countries.

Similarly, De Benedictis and Tajoli (2011) analysed the evolution World Trade Network from 1960 to 2000, computing in- and out-closeness centralities as well as betweenness centralities. They found that, with the exception of Africa, there is more overall trade within continents than between continents. They built and analysed intensive and extensive margins networks. They also proposed a gravity model. Zhou et al. (2016) proposed simplifying international trade networks by considering only top trade relations, revealing a tree-like hierarchical structure organised around key countries (USA, China, and Germany). They also proposed a network formation model based on countries' behaviour in triads. Cepeda-López et al. (2019) also found that the world trade network increased its density, its reciprocity and its average clustering, while the average geodesic distance decreased during the period 1995–2014. They also found that the degree-degree correlation was positive (i.e., assortativity) and that the node strength (but not the node degree) followed a power law distribution. They did not find a scale free character nor a core-periphery structure for the world trade network. They propose using the minimum spanning tree to determine the network backbone and thus reveal its hierarchical structure.

The above is just a sample of studies of the overall world trade network and have been considered to illustrate the type of concepts that are generally used in this type of studies and the findings that may be obtained. Apart from those studies of the overall global trade there are complex network analyses of the international trade of oil and fossil fuel (e.g., Zhong et al., 2016; Du et al., 2017), agricultural products and virtual water (e.g., Konar et al., 2011; Gutiérrez-Moya et al., 2020), digital services (e.g., Riccaboni et al., 2013), metals and rare earths (e.g., Qi et al., 2014; Ge et al., 2016), electricity (e.g., Ji et al., 2016), photovoltaic panels (e.g., Guan et al., 2016), medical devices (e.g., Bai et al., 2022), etc.

Having established the applicability of complex network tools to analyse global trade and the existence of many such studies and that, apart from the overall global trade, there is a broad number of sectors whose global trade flows can be analysed using this type of tools, let us consider some existing fertiliser flows studies, none of which uses the complex network analysis methodology successfully used in all other sectors previously mentioned. Thus, regarding the fertiliser trade, a number of studies focus on Nitrogen (N), Phosphorus (P) and Potassium (K) flows generally at the global level (Nesme et al., 2018), national level (e.g., Zheng et al., 2021) and local level (e.g., Bellarby et al., 2018). Most of these flows are embedded in the trade of agricultural products. By analogy with the Virtual Water concept, they are sometimes called Virtual P flows (e.g., Lun et al., 2021; Wang et al., 2022). Generally, all these studies are interested in mass balances, nutrient footprints and nutrient use efficiency and the regional distribution and trade aspects are important, the methodology used does not involve complex network analysis tools and concepts. Recently, Li et al. (2023) has carried out a complex network analysis of the global trade networks of three types of phosphorus materials, namely phosphate rock, phosphorus fertilisers and phosphoric acids. They compute basic characterisation measures and node centrality indexes and monitor its evolution over the period 2000–2020, using Principal Component Analysis (PCA) to identify the factors driving the structural change of the network over time. They also compute a supply risk index using the normalized betweenness centrality index and the Herfindahl-Hirschman import concentration index.

In summary, although complex network analysis has been used to study trade flows of numerous products, to the best of our knowledge it has not yet been used to analyse the global fertiliser trade. The aim of this paper of this paper is to fill this research gap using up to the most recent reliable data, which is the year 2018. In this regard, note that due to trade data being reported with a one-year lag, the data for years 2019 and 2020 were incomplete, as during the corresponding period most countries were preoccupied with the COVID19 pandemic and many did not see this type of reporting as a priority. Also, the data for year 2021 were not yet normalized (i.e., complete) plus they seemed to show the distorting effects of the COVID19 pandemic and associated disruptions.

3. The global fertiliser trade network

3.1. Data source and pre-processing

Data on bilateral cross-border fertiliser trade volumes (measured in current US dollars, $US) for years 2014–2018 were extracted from the Statistics Division of the World Trade Organisation (WTO, http://stats.wto.org) under the Harmonised System (HS) code 31, which includes animal, vegetable, mineral and chemical fertilisers. Subsequently, the data were transformed into millions $US and deflated using the 2018 GDP deflator (https://data.worldbank.org). These data were used to model fertiliser trade flows as a directed network in which nodes (i.e., countries) are connected by directed edges whose weights represent the corresponding trade volumes (in value). Specifically, five yearly Fertiliser Trade Networks (FTN) and a global accumulated FTN for entire period (GFTN) are constructed. All these networks are weighted and directed. FTN arcs involving fertiliser trade flows below a threshold of 0.5 million $US and GFTN arcs involving accumulated trade flows below a threshold of 2.5 million $US are removed from the corresponding networks.

It can be noted that international fertiliser trade data published by WTO refer to the sum of the import and export activities of mainly private companies that compete inside and outside their domestic market based on business strategies; hence they do not necessarily work together. In the present study, we refer to the import and export activity of a country, which do not necessarily imply a deliberate move by a country's government. However, the fertiliser industry is extremely regulated and monitored by authorities in several countries, where the price at which the fertiliser traded by the beneficiary is compensated by the government in the form of a subsidy.

In this study, data analysis was performed using the *igraph* library (Csardi and Nepusz, 2006), *qgraph* library (Epskamp et al., 2012) and *UCINET* software (Bogartti et al., 2002). Data were analysed using R programming language (R Core Team, 2022). Also, Alpha-3 (three letter) ISO code is used to name each country, and a Table incorporating the full name of each country is included in the supplementary material section (see Table S1, in the Supplementary material file).

3.2. Basic FTN and GFTN characterisation measures

Table 1 shows some characterisation measures of the yearly FTN and the aggregated GFTN. As it can be seen, they involve 126 countries and a number of arcs ranging from 868 in 2018 to 1044 in 2014. Each of these fertiliser trade networks is weakly connected but the FTN density, i.e., the likelihood that two countries are connected through cross-border fertiliser trade flows, steadily declined during the period, from 0.066 percent in 2014 to 0.055 in 2018. The GFTN density is slightly higher (0.10). In any case, most countries do not trade with all other countries but have their preferred partners, so that the fertiliser trade flows tend to be concentrated along a fraction of exporter and importer pairs. Note also that the reciprocity is relatively high for FTN (around 0.25) and even higher (0.73) for GFTN. Regarding the latter, the number of mutual, asymmetric and null dyads is 612, 444 and 6819 respectively, i.e., there are 6819 instances of pairs of countries that have not traded with each other in the period 2014–2018, 444 instances in which one of the partners has exported to the other and 612 instances in which the partners have traded bidirectionally.

3.3. Small world character of FTN and GFTN

In spite of the relatively low density, the shortest distance between countries (i.e., the number of edges of the corresponding geodesic paths) is small, with a slight decline over the years, from 2.16 countries in 2014 to 2.08 countries in 2018. Similarly, the largest geodesic distance between countries (i.e., the diameter of the network) is also small, (around 5 in FTN, 4 in GFTN). These features are characteristic of small world networks. This is also reflected in the global network efficiency, which is higher (0.44) for GFTN than for FTN (around 0.2).

In respect of local cliquishness, it is interesting to note that the average local efficiency is relatively high (around 0.20) for FTN but much lower (0.08) in the case of GFTN. This is due to the fact that GFTN includes a number of arcs that correspond to volatile trading partnerships that occur in just one year, for example. In the corresponding FTN such arcs would also appear but in GFTN there are more of these. The Small World Index proposed by Humphries and Gurney (2008), which takes into account the transitivity and the average path length, is rather high for FTN (above 7.0 and with an upward trend), somewhat lower for GFTN (3.96), but in both cases point to small world structure in the classical sense of Watts and Strogatz (1998). This could be expected from other global trade studies (Wilhite, 2001; Fan et al., 2014; Zhang et al., 2016). In particular, for the phosphorus fertiliser network, Li et al. (2023) reported a low average path length and a large average clustering coefficient, typical of small world networks. This small world character signifies that most trading is done locally in logical terms, although the commodity is physically distributed worldwide. This pattern of decentralised structure has intensified over the years, based on the benefits that the small-world character offers related to the reduction of exchange costs (mainly searching and negotiation costs). Hence, if actions regarding fertiliser trading were taken by several economies in collaboration (regional cooperation), the effect could easily spread to other partners of the network.

Table 1
Basic characterization measures of the yearly FTN and aggregated GFTN (2014–2018).

	FTN (2014)	FTN (2015)	FTN (2016)	FTN (2017)	FTN (2018)	GFTN (2014–2018)
# nodes	126	126	126	126	126	126
# arcs	1044	1007	981	969	868	1668
Density	0.066	0.063	0.062	0.061	0.055	0.10
Average path length (APL)	2.16	2.14	2.12	2.09	2.08	2.11
Diameter [country pair]	6 [HND/TGO]	5 [BHR/URY]	5 [KGZ/URY]	5 [KGZ/MOZ]	5 [BEN/CRI]	4 [BHR/KEN]
Av. total/in-/out-degree (standard deviations)	16.57/8.28/8.28 (19.03/8.93/13.50)	15.98/7.99/7.99 (18.88/12.86/9.18)	15.57/7.78/7.78 (18.99/12.51/9.39)	15.38/7.69/7.69 (18.78/12.18/9.65)	13.77/6.88/6.88 (17.37/10.88/9.64)	26.47/13.23/13.23 (29.40/15.03/14.81)
In/Out-degree centralisation	0.53/0.29	0.51/0.30	0.50/0.31	0.46/0.29	0.41/0.30	0.61/0.60
Av. total/in-/out-strength (standard deviations)	846.0/423.0/423.0 (2153.7/1268.7/1356.4)	890.0/445.5/445.5 (2300.3/1462.5/1314.0)	673.0/336.5/336.5 (1683.5/1045.8/989.4)	724.8/362.4/362.4 (1786.4/1114.5/1077.2)	748.6/374.3/374.3 (1918.1/1147.3/1246.0)	3873.2/1936.6/1936.6 (9780.3/5308.5/5209.9)
#mutual/#asymm/#null dyads	122/800/6953	128/751/6996	131/719/7029	120/729/7026	98/672/7105	612/444/6819
Arc/Dyad reciprocity	0.23	0.25	0.27	0.25	0.22	0.73
Global network efficiency	0.22	0.21	0.20	0.19	0.17	0.44
Average local efficiency	0.20	0.20	0.23	0.22	0.19	0.08
Small World Index[a]	6.98	7.58	8.28	9.02	9.87	3.96
Assortativity coefficient	−0.224	−0.231	−0.239	−0.250	−0.259	−0.274

Notes:
[a] A network can be said to be “small world” if its Small World Index is higher than 3 (Humphries and Gurney, 2008).

3.4. Degree, strength and weight distribution of FTN and GFTN

With regard to the in-degree, on average each country has imported from around 15 other countries (16.57 in 2014, 13.77 in 2018) of the total potential partners. The in-degree centralisation index is high, although it has decreased from 0.53 in 2014 to 0.41 in 2018. It is even larger for GFTN (0.61). The out-degree centralisation index is similar for the GFTN (0.60) but lower for FTN (around 0.30). These high degree centralisations point to some centralisation of power within the network, both on the import and export sides. This is consistent with the existence of a small number of core countries trading with a large number of periphery countries. Following the decrease in the network density, the average total degree has slightly decreased along the period (from 16.57 in 2014 to 13.77 in 2018). Similarly, the same as the GFTN density is much larger than that of FTN, the GFTN average total degree (26.47) is much higher than those of FTN.

The total strength has ranged between a maximum of 890.0 million $US (in 2015) and a minimum of 673.0 million $US (in 2016) with a high dispersion between the different countries. The corresponding values for the GFTN are naturally around 5 times larger (3873.22 million $US).

An analysis of degree-degree correlation shows that all the yearly FTN and the GFTN are disassortative, i.e., countries with high degree (i.e., that export/import to/from many countries) generally trade with countries with a low degree. Periphery countries usually have low degrees and trade mostly with core countries, which have high degrees.

The trading relationship with the largest weights, i.e., the largest fertiliser trade flows each year, corresponds to the internal North American trade between the USA and Canada, the main primary fertiliser producers worldwide, reaching an average yearly amount of 2991.02 (million $US), with the largest flow (3118.35 million $US) occurring in 2014 and descending in the following years. Table 2 shows the distribution of the edge weights, i.e. the trade volumes in millions $US, for the yearly FTN and the GFTN. Note that the minimum is 0.5 million $US for FTN and 2.5 for GFTN because the threshold uses to build these networks were set to those values. More importantly, the distribution of the weights is fairly stable throughout the years, with a mean value several times above the third quartile and a standard deviation several times the mean.

A comparative analysis of the empirical distributions of the in- and out-degree and strength for the yearly FTN using Kolmogorov-Smirnov tests is reported in Table S2 in the Supplementary material file. The null hypothesis implies that the observed empirical distributions (for each pair of years) are drawn from the same data-generating process cannot be rejected. The empirical distributions of the out-degree and strength are steadier than those of the in-degree and strength. The year 2014 seems to have been an unusual year from the import side in the fertiliser trade, possibly due to the dissolution of the two largest potash fertiliser export cartels in 2013, the remaining effects of the economic global crisis in the advanced economies (public debt adjustment and deflation) and the vulnerability of emerging economies, together with political pressures in the Middle East and Ukraine.

3.5. Persistence and variability of the yearly FTN

Table S3 (in the Supplementary material file) shows a more detailed analysis of the connectivity changes in the yearly FTN using two metrics: *Persistence*, which measures how many of the import (respectively, export) partners of a country have remained so for the whole 2014–2018 period, and, *Variability,* which gauges the dispersion (measured by the corresponding coefficient of variation, CV) of the trade flows between countries during the period 2014–2018, averaged over all import

Table 2
Edge weights distribution for the yearly FTN and aggregated GFTN (2014–2018).

Network	# obs.	Min.	1st Quartile	Median	Mean	3rd Quartile	Max.	Std. Dev.
FTN2014	1044	0.5	1.81	6.31	51.05	26.15	3118.35	184.56
FTN2015	1007	0.5	1.97	7.00	55.74	26.52	3684.32	206.89
FTN2016	981	0.5	1.68	6.02	43.22	23.53	2584.95	140.78
FTN2017	969	0.5	1.80	5.94	47.12	25.39	2720.81	151.35
FTN2018	868	0.5	1.72	7.42	54.33	28.39	2846.69	183.75
GFTN	1668	2.5	4.14	19.49	146.29	47.04	12,763.68	555.02

(respectively, export) partners of a given country. A low standard deviation and a high mean implies a low CV, indicating that annual trade flows are more clustered around the mean. The analysis of these persistence and variability metrics provides information that can be useful to improve trade facilitation, to strengthen trade relationships and to increase trade competitiveness. As it can be seen in Table S3, in absolute terms, most of the countries with the highest persistence are major players in the corresponding export or import side. They are accompanied by other countries like Singapore, Hong Kong or Senegal (with less than three permanent links each from the export side) and Malaysia, Jordan, New Zealand, Sri Lanka, Tunisia or Uruguay (with less than eight permanent links each from the import side). Europe, USA, Japan, Chile and China lead the persistence first positions. Note the high persistence, in relative terms, of Japan and Chile, 47.83% and 41.67% respectively, on the export side, and 42.86% and 32.26%, respectively, on the import side. The correlation between the absolute and percentage persistence is not too high (0.49 for exports, 0.53 for imports). The top five countries with the most variable exports are Botswana, Lesotho, Brazil, Mongolia, and USA, while those whose imports vary most are Seychelles, USA, Swaziland, Japan and Lao. The FTN from one year to the next seem to be highly affected by changes on the import and export policies of these countries. Note that in Table 3 only countries with a Variability index above 0.30 are displayed. The correlation analysis between Degree and Persistence and Strength and Variability has also been explored, both from the exporter and the importer view (see Fig. S1 in the Supplementary material file). A weak positive relationship is detected between the total number of import and export partners of a country and the persistence of those relationships during the period 2014–2018. However, a higher aggregated in- or out-strength is not associated with a higher variability in the corresponding trade flows through the period 2014–2018. This may be due to large exporters and importers of fertilisers not being as exposed to risks related to market, financing, and pricing among others, whereas smaller exporters and importers are more vulnerable to the global economy shocks and fluctuations in foreign currencies. The above indicates that in the global fertiliser market, the size of the monetary value of trade flows matters.

3.6. Scale free character of GFTN

The scale-free character of the GFTN is assessed by performing the Kolmogorov-Smirnoff (KS) test through the in- and out-Degree and in- and out-strength distributions. KS test checks if the Power Law (PL) distribution with maximum-likelihood based estimation parameters and the observed data come from the same distribution. Hence, if the PL distribution is confirmed, and assuming the Preferential Attachment mechanism, the probabilities of capturing trade opportunities at a given level of network complexity and of adding new trade partners are proportional to the number of existing trade links. The results, shown in Fig. S2 of the Supplementary material file, do not reject the hypotheses of the scale-free network character of the in-degree and in- and out-strength distributions. The exponent for the trade volume (i.e., strength) distributions is slightly smaller than that for the number of partners (i.e., degree) distributions, which is reasonable because the traded volume spans a larger scale on the horizontal axis than the number of partners does. Also, interestingly, the in- and out-strength seems to have similar distributions, with small PL exponents (1.47 and 1.50, respectively) while the in- and out-degree distributions differ slightly. These PL distributions may be the result of a Preferential Attachment mechanism so that countries tend to prefer trading with well-established/well-connected countries. In any case, the scale free character of GFTN implies that there are a small number of countries that act as hubs and whose failure/disconnection would cause important disruptions in the network.

3.7. GFTN node centrality indexes

Importer and exporter countries can be ranked via PageRank index (Brin and Page, 1998), providing information on the relevance of countries in the GFTN. Fig. 1 shows the countries with export and import PageRank indexes above the mean. EUR, USA, Russian Federation, China, Canada, Brazil and India rank in the top seven (above 4.0) in both import and export sides, accounting for 51% and 46% of total relevance in each case. It is worth noting that some countries that rank top on the export side, like Japan, Argentina, Colombia, Philippines, Pakistan, and Korea have a below-average PageRank index on the import side. The opposite occurs for Egypt and Jordan. This finding indicates a

Table 3
Top 20 countries of GFTN (2014–2018) as per different centrality indexes.

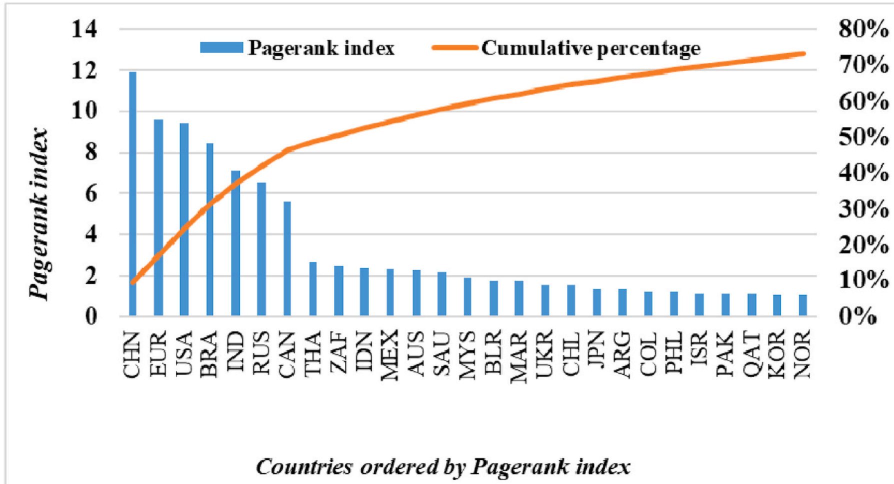
Out-degree centrality (normalized[a])	In-degree centrality (normalized[a])	Out-strength (normalized[b])	In-strength (normalized[b])	Betweenness centrality (normalized[c])
EUR 0.712	**EUR 0.720**	***USA 12.50%***	***RUS 12.71%***	*EUR 0.275*
CHN 0.536	**CHN 0.544**	***BRA 12.19%***	***CHN 12.70%***	*CHN 0.091*
USA 0.464	**RUS 0.536**	***EUR 9.64%***	***CAN 10.40%***	*RUS 0.081*
RUS 0.440	**USA 0.472**	***IND 9.63%***	***USA 8.79%***	*USA 0.073*
CAN 0.360	**CAN 0.360**	***CHN 8.58%***	***EUR 8.56%***	*ZAF 0.065*
IND 0.344	BLR 0.320	***CAN 4.69%***	***BLR 3.92%***	*IND 0.037*
MAR 0.304	NOR 0.288	***RUS 3.53%***	***BRA 3.65%***	*THA 0.030*
AUS 0.296	**SAU 0.288**	THA 2.86%	***MAR 3.46%***	*CAN 0.018*
BRA 0.296	**BRA 0.277**	***MEX 2.53%***	***SAU 3.30%***	*MAR 0.018*
MEX 0.288	**MAR 0.272**	***IDN 2.46%***	***IND 2.65%***	*MYS 0.018*
ZAF 0.280	**AUS 0.256**	AUS 2.35%	ISR 2.13%	*IDN 0.014*
IDN 0.272	CHL 0.248	UKR 1.68%	QAT 2.12%	SAU 0.012
COL 0.256	**IND 0.248**	***MYS 1.51%***	NOR 1.80%	GEO 0.012
MYS 0.256	**MYS 0.248**	ARG 1.37%	EGY 1.44%	*BRA 0.012*
SAU 0.240	**ZAF 0.248**	JPN 1.31%	***CHL 1.30%***	*UKR 0.012*
THA 0.240	EGY 0.240	COL 1.20%	MYS 1.28%	UGA 0.012
UKR 0.232	**THA 0.240**	PAK 1.15%	***IDN 1.18%***	BLR 0.011
ARG 0.224	ARE 0.240	ZAF 1.07%	***MEX 1.14%***	TZA 0.008
KOR 0.216	**IDN 0.224**	***CHL 1.04%***	JOR 1.11%	*AUS 0.008*
PHL 0.208	**UKR 0.216**	MAR 1.04%	OMN 1.09%	LKA 0.008

Notes: Countries that appear in both In- and Out-degree rankings are shown in **bold**. Countries that appear in both In- and Out-strength rankings are shown in ***bold italics***. *Italics* is used for countries that appear in the Betweenness centrality ranking and in any of the other four rankings.

[a] Normalization by total potential export (respectively, import) partners.

[b] Normalization by total trade flows.

[c] Maximum possible betweenness centrality is unity.



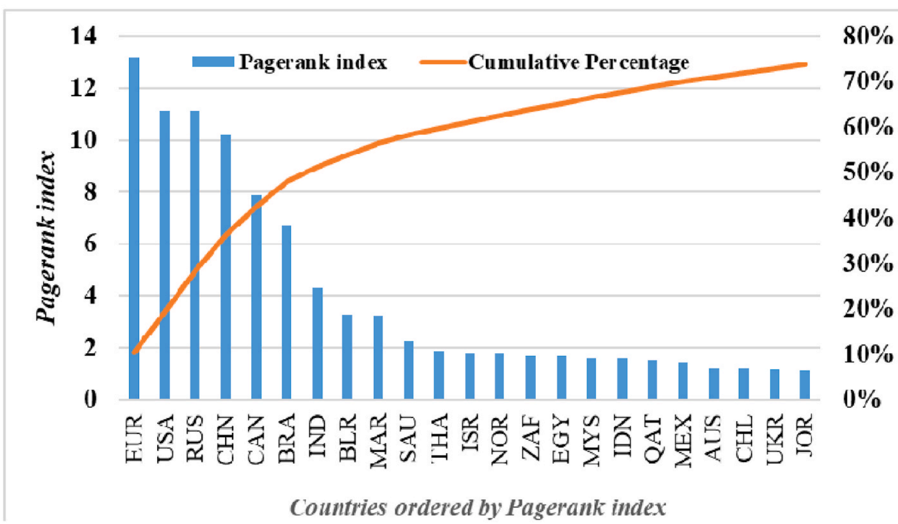


Fig. 1. PageRank index (top: Exports side; bottom: Imports side) for GFTN (2014–2018)
Note: Countries are shown in descending order according to their PageRank index (only countries with a Page Rank above 1.0 index are considered).

differentiated import (respectively export) orientation in these economies. Note that, instead of the PageRank index, Li et al. (2023) computed the Eigenvector centrality although, as with the other node centrality indexes they computed, the values for the individual nodes are not reported.

The number of trade partners is a useful metric to assess the relevance of an economy on the fertiliser world market. The top 20 countries with the highest In- and Out-degree centrality are shown in Table 3. It can be seen that EUR, China, USA, Russian Federation and Canada have the largest number of trade partners with in- and out-degree centralities above 0.36. In particular, EUR (0.712), China (0.536) and USA (0.464) have the highest out-degree centralities, indicating that they can rely on the widest network of partners to export fertiliser products. Similarly, EUR (0.720), China (0.544) and Russia (0.536) have the highest in-degree centralities, indicating that they import from a large number of external sources to meet their commercial agreements (including their domestic demand). In general, they are intensely interconnected with other countries and thus hold a crucial position in the GFTN. Hence, these countries are decisive in the global fertiliser market. The strength analysis shows that the revenues regarding fertilisers transactions of USA, Brazil, EUR, India, and China accounted for more than 50% of the sales in the global fertiliser market. However, only China has a relevant position in the potash, phosphate reserves, as well as nitrogen production. Note that, despite the global importance of Morocco in the production of phosphorus fertilisers, the export revenues of Morocco accounted for just above 1% of total market sales, with EUR and Brazil as its main export partners. On the other hand, the main importers of fertilisers in the period 2014–2018 were the Russian Federation and China, followed by Canada, USA and EU. Notably, Israel has a small number of import partners, but its imports account for a sizeable 2.13% of the total market. Something similar occurs with Qatar (2.12%), Mexico (1.14%), Jordan (1.11%) and Oman (1.09%). The largest fertiliser importers and exporters identified in Table 3 coincide with those with the largest P imports and exports reported Nesme et al. (2018) and Lun et al. (2021). Note also that the concentration of P fertiliser exports reported in Li et al. (2023) (above 50%, 70% and 80% for the top 3, top 5 and top 10 exporters, respectively) is larger than the one observed in our case. These differences are due to their considering physical trade data (measured in tons of elemental phosphorus) and only P fertilisers.

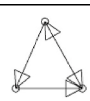
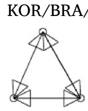
Unlike the centrality measures described above that reflect the direction of the fertilisers trade flows, the betweenness centrality measures the ability of a country to act as an intermediary in the GFTN. As shown in Table 5, EUR (0.275 held the strongest intermediary position in the period 2014–2018, followed by China (0.091), Russian Federation (0.081), USA (0.073) and South Africa (0.065), indicating that they are critical channels in the global fertilisers market.

Table 4
Brokerage between community groups in the GFTN (2014–2018).

Community group	Country	$z_{Coordinator}$ G(a)=>G(b)=>G(c)	$z_{Gatekeeper}$ G(a)=>G(b)=>G(c)	$z_{Representative}$ G(a)=>G(b)=>G(c)	$z_{Consultant}$ G(a)=>G(b)=>G(c)	$z_{Liaison}$ *G(a)*=>G(b)=>G(c)	z_t^c
1	CAN	17.45	19.29	13.82	7.12	12.71	18.34
	COL	4.82	1.96	5.06	−0.40	0.05	2.03
	ARE	−0.94	0.18	0.18	0.81	4.82	2.72
	USA	43.53	30.56	36.75	16.92	26.28	38.78
2	AUS	8.77	6.45	6.75	0.29	1.67	6.68
	CHN	35.64	40.76	45.66	26.74	36.88	55.64
	IND	16.67	9.15	8.82	1.09	4.33	11.20
	IDN	12.62	4.51	4.41	−0.96	−0.70	4.74
	MYS	11.47	7.52	4.35	−0.16	0.86	6.31
	NOR	3.09	6.04	3.43	−0.16	0.95	4.04
	SAU	7.52	8.18	5.99	0.49	3.90	7.65
	THA	12.44	6.60	3.49	−0.36	0.48	5.69
3	BLR	3.46	6.01	6.70	3.46	4.43	7.42
	BRA	6.31	7.43	7.43	3.30	6.45	9.47
	EUR	84.85	79.32	86.80	50.31	68.59	110.78
	MAR	12.90	8.70	10.07	1.04	3.58	11.00
	RUS	38.66	32.39	39.42	15.09	27.09	46.94
	UKR	14.95	3.03	4.60	−0.79	−0.88	5.74
4	MX	0.41	1.42	3.07	2.96	6.65	5.55
	ZAF	24.58	12.18	10.94	1.97	3.51	9.52
Global Brokerage Z test statistic		20.15	16.40	17.78	−4.78	0.86	10.98

Notes: Statistically significant at 0.05 level if $|z| \geq 1.96$ (two tailed z test); Given the size of GFTN, it is assumed that z-statistic is standard normal distributed.
z_t represents a country's overall brokerage level (Gould and Fernandez, 1989).
Community structure identified by Fast greed algorithm (Clauset et al., 2004).
Bold text and *italics* indicate that the importer or exporter belongs to a group different from that of the broker.

Table 5
Significant three-node motifs in the GFTN (2014–2018).

Motif Id.	Subgraph/Examples	F_{real}	$[F_{rand}] \pm sd(F_{rand})$	z-score	p-value	UNIQ	C_{real}
102 (One mutual dyad)	 USA/CIV/NOR UKR/SAU/TUR KOR/BRA/TWN	348	295.8 ± 19.2	2.71	0.007(*)	15	13.76
238 (Clique)	 EUR/BEN/MAR RUS/TWN/NOR CHN/JPN/NOR	1823	1553 ± 26.9	9.99	0.000(*)	15	72.10

Notes: Total number of 3-node subgraphs: 25,283; Number of random networks generated: 1000; Random networks generation method: Switches.
F: Frequency; sd = standard deviation; z-score=$(F_{real}-[F_{rand}]/sd(F_{rand}))$; (*): p-value ≤ 0.01.
UNIQ: Number of times a graph appears in the network with completely disjoint groups of nodes.
C_{real}: Concentration (per thousand), number of motif appearance divided by the total number of 3-node.
Criteria for identifying significant motifs are z-score>2 and UNIQ≥4.

In summary, the central roles in GFTN correspond to some western countries (EUR, USA, Canada and Australia) plus other key players like China, the Russian Federation, South Africa, India, Thailand, Morocco, Malaysia, Indonesia, Brazil, and Ukraine, which not only rank in the top 20 positions of some of the degree and strength metrics but also possess large betweenness centrality in the GFTN. Therefore, given the impact that these nodes can exert on the GFTN, their internal and financial stability as well as their trade policies should be closely monitored.

3.8. Interregional trade in GFTN

The cross-regional GFTN flows are shown in Table S4 of the Supplementary material and depicted in Fig. 2. Fertiliser trade flows within and between each of six regions are considered. These regions are North America (including Central America and the Caribbean), South America, Europe (including Ukraine), Africa, Asia (including Russian Federation), and Oceania. The E-I index (external minus internal links) of the GFTN during the period 2014–2018 is 0.203, indicating a moderate level of heterophily, that is, it is a frequent occurrence for countries to have trade relations with countries in other regions. In particular, although Asian countries (representing 23.6% of the total value of fertiliser trade and 19.6% of trade links) and North American countries (representing 10% of the total value of fertiliser trade and 5.1% of trade links) trade actively within their own regions, most regions have more trade with the rest of the world than within their own region. Note that Asia is the region with the largest exports to other regions. Thus, its exports to EUR represent 7.5% of global fertiliser trade, to South America 7.3%, to North America 6.7%, to Africa 1.7% and to Oceania the 0.4%. This represents close to a quarter (23.6%) of all trade fertiliser trade around the world. Asia is also a major importer. Its imports from EUR represent 6.4%, those from North America 5.6%, those from South America 2.2%, from Africa 1.2% and from Oceania 0.1%, 15.5% in total.

The pairs of regions for which the density of trade links is higher than for the overall network are Asia ↔ Asia, Europe ↔ Asia, Africa ↔ Asia

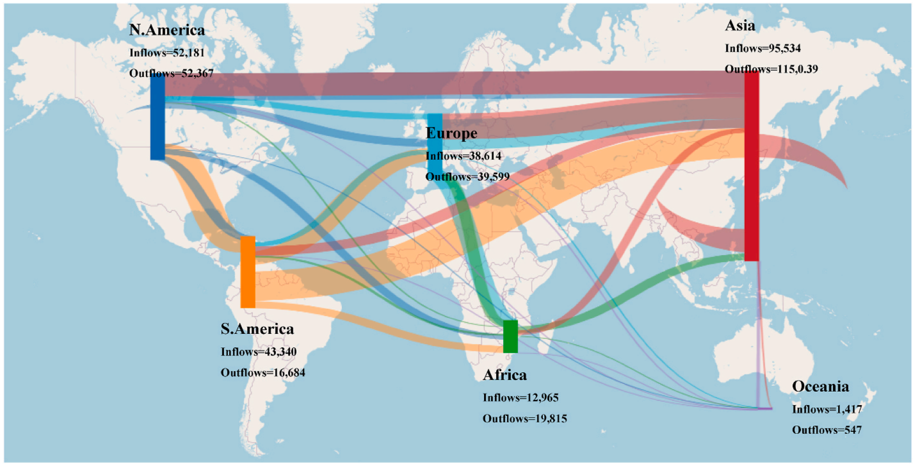


Fig. 2. The exports and imports between regions for GFTN (2014–2018) (only fertilisers trade flows higher than 2.5 million $USD are considered). Flows are coloured according to their destination.
Notes: Fast Greed algorithm (Clauset et al., 2004). Modularity value = 0.24. Number of communities = 4. Community sizes: 1[21]; 2[40]; 3[48]; 4 [17].

and North America ↔ North America. In terms of trade balance (total value of fertiliser exports minus total value of fertilisers imports) for the different regions; South America (−26,656 $USD million) and Oceania (−870 $USD million) have negative trade balances, showing a weak position on the fertiliser's global trade market, while Asia (19,505 $USD million) possesses the largest surplus of all the regions, confirming the important source of competitive advantage of the region.

The interregional fertiliser trade flows in Fig. 2 and Table S4 can be compared with the P flows through trade of mineral P fertilisers in Fig. 5 in Nesme et al. (2018), although note that the latter refers to 2011 and are measured in Tg P/year instead of in US$. Both studies report important fertiliser flows from North America to Asia and South America, from Asia (a net fertiliser exporter) to Europe and South America and from Africa (also a net fertiliser exporter) to Asia, Europe and North and South America.

3.9. Community structure of GFTN

The density of the identified trade communities within the GFTN indicates the extent of the corresponding trade relationships structures and in some sense measures the efficiency of the underlying supply chain network, including the existence of subsidiaries, international business agreement, and storage, production, and distribution centres of the fertiliser industry that enable and support these trade connections. Several community detection approaches, considering agglomerative methods and divisive methods, have been applied. The method that provided the largest modularity (0.240) was the Fast Greedy algorithm (Clauset et al., 2004). The four communities identified (with sizes 48, 40, 21 and 17) are depicted in Fig. 3. For the sake of comparison, the modularity reported by Li et al. (2023) for the phosphorus fertiliser trade network is much lower (with values between 0.044 and 0.104 for the period 2015–2020). Note, however, that Li et al. (2023) do not report neither the number nor the composition of the communities.

As expected, the communities identified exhibit geographic characteristics of SW as with the community formed by 21 members that integrate USA and Canada trade hubs with Central-America (i.e., Panama, Honduras, Belize) and South-America (i.e., Venezuela, Colombia) countries, Caribbean Islands, and most Arab Golf countries (except Saudi Arabia and Oman). For example, CF Industries (a USA manufacturer) has production complexes worldwide with unparalleled storage, transportation, and distribution networks throughout North America. Similarly, Nutrien (a Canadian fertiliser company) has diverse networks of farm centres located across North America, Australia (through its subsidiary Landmark) and South America, and is the largest producer of potash and the third largest producer of nitrogen fertiliser in the world.

Another predictable community, hosting 40 members, integrates the

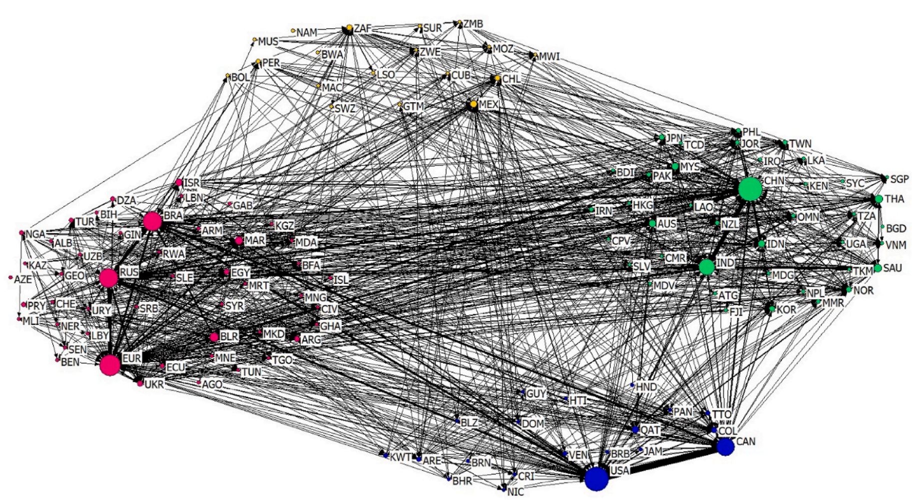


Fig. 3. Community structure of GFTN (2014–2018).

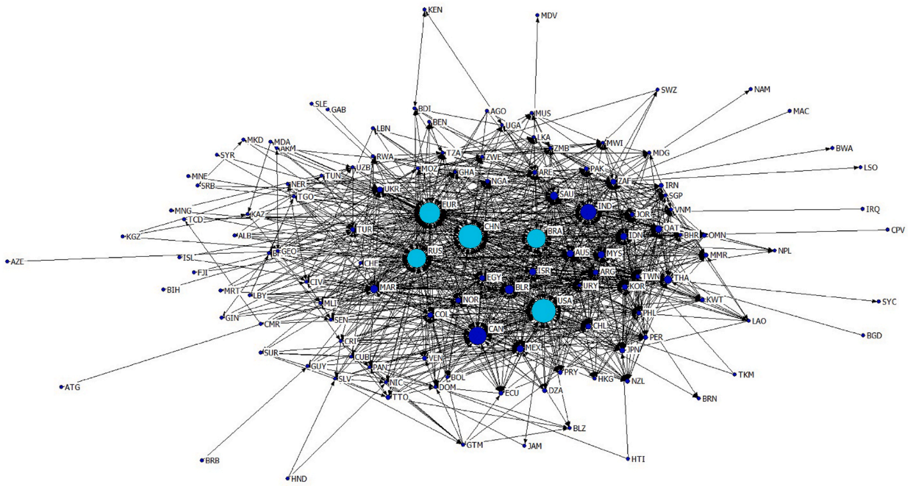


Fig. 4. Core-pheriphery structure of GFTN (2014–2018)
Notes: From top left to bottom right the ego-networks of EUR, USA, CHN, BRA, RUS and UKR are displayed. Structural Hole Measures: Constraint (Const); ES (Efficiency Size); Hierarchy (H); Number of Holes (NH); Density (D).

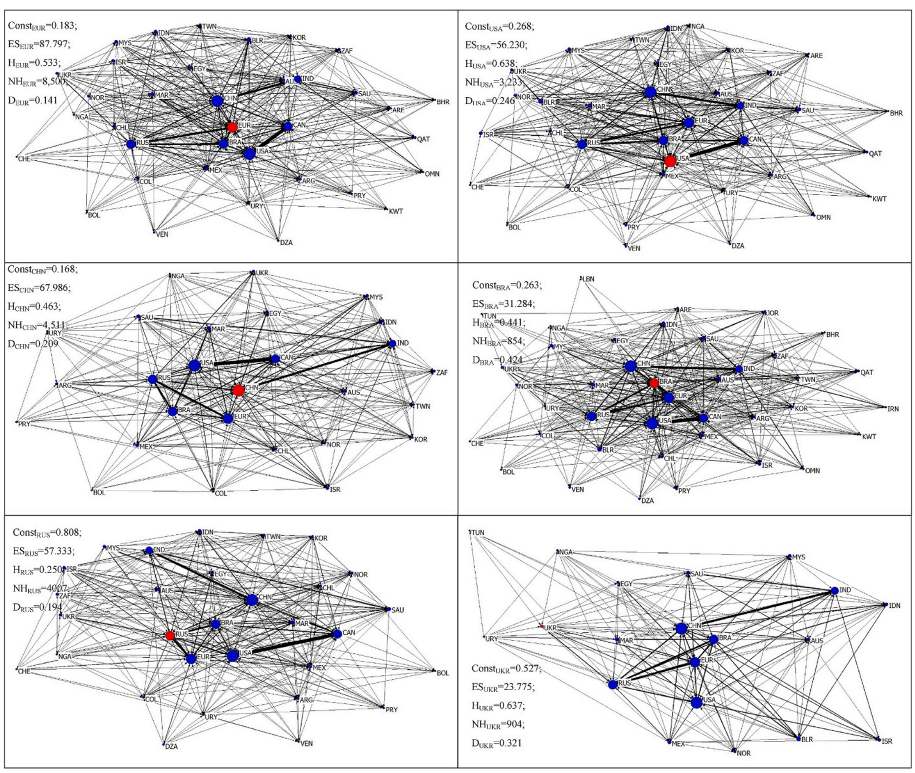


Fig. 5. Ego-networks of major players in GFTN (2014–2018).

China and India hubs with South Asia (i.e., Bangladesh, Nepal, Pakistan), East Asia (i.e., Taiwan, Japan), rest of Arab Gulf countries (Saudi Arabia and Oman), Oceania and East Africa (i.e., Burundi, Comoros, Kenya, Madagascar, Seychelles, Tanzania, Uganda); it also integrates countries like Norway, El Salvador, and some Central and Western Africa countries (Chad, Cape Verde). The presence of Oman and Jordan is explained by their international joint ventures and subsidiaries (such as the Oman India Fertiliser Company and the Jordan India Fertiliser Company) with the Indian multistate cooperative IFF. Also, Norway has its own entity away from EUR countries in the fertiliser trade, Yara International, with a strong international trade presence (it is the world's leading manufacturer and trader of ammonia with one third of the world total).

The largest community is formed around the top exporter and importer hubs of EUR, Russian Federation, and Brazil, that account for around 25% of the total aggregated export and import value of fertilisers during the period 2014–2018. In EUR, the German company K + S has a predominant position in the market for potash and in the production of fertiliser, with production sites all over Europe. Note also that Belarus and the Russian Federation belong to the same community despite the disagreement between the partners that controlled over a third of the global market potash, Belarusian Potash Company (BPC) and Uralkali (Russian Federation) in 2013. The former Soviet republics are also part of this community because of their historical and economic ties. Israel belongs to this community due to the Haifa group ownership of production facilities in France. This EU, Russian Federation, and Brazil community also integrates all countries of North Africa, most of West Africa (i.e., Côte d'Ivore, Ghana, Mali, Senegal) and some countries of East Africa (i.e., Rwanda). Turkey is conjoined to this community due to its relations with Europe, the Baltic countries, and Central Asia.

Finally, the smallest community is formed by all Southern African countries and some Eastern Africa countries (i.e., Zambia, Zimbabwe, Mozambique). Also, some South American countries are present (Mexico, Chile, Peru, Bolivia) together with Cuba. Chile occupies the most relevant position through the SQM company, the world leader in the export of potassium nitrate.

An alternative approach to the above community structure perspective of the GFTN corresponds to a Core-periphery analysis. This identifies a core formed by five major players in the GFTN, namely EU, USA, China, Brazil and the Russian Federation. These core countries are the hubs of the GFTN and their trade relationships with the periphery countries induce disassortativity in the network. This can also account for the high in- and out-degree centralisation indexes observed. Fig. 4 visualises this core-periphery structure of the GFTN.

3.10. Structural holes analysis of main GFTN players

This section is dedicated to identifying structural holes in the GFTN to gain a better understanding of the global fertiliser trade competition. According to Burt (1992) the term structural hole is associated to the non-redundancy of the connection between two nodes (i.e., the lack of a tie between two alters in a given ego-network) and can potentially provide benefits to the network. Fig. 5 shows the ego-networks of the five core countries in the GFTN (EU, USA, China, Brazil and the Russian Federation) in addition to Ukraine. Considering their respective ego-networks, that of EUR has the smallest density ($D_{EUR} = 1.41$), hence the largest number of structural holes ($NH_{EUR} = 8500$), almost double that of China ($NH_{CHN} = 4511$) and more than double that of the Russian Federation ($NH_{RUS} = 4007$). Brazil has the most compact ego-network with the smallest number of structural holes ($D_{BRA} = 0.424$; $NH_{BRA} = 857$).

The Constraint measure (Const) gauges the extent to which the ego's connections are to alter who are connected to one another. The Russian Federation has the highest Constraint ($Const_{RUS} = 0.808$), meaning that most of its alter partners have trade relationships with the other trading partners, thus reducing the Russian Federation's ability to make critical business decisions and increasing its dependency from its export/import partners. Note that the Constraint measure is lower in the Ukraine case ($Const_{UKR} = 0.527$), China has the opposite side trading dependency with its partners ($Const_{CHN} = 0.168$), similar to EUR ($Const_{EUR} = 0.183$), which provides China and Europe greater freedom of business movement. The nature of the constraint is measured by the Hierarchy index (H), which quantifies the dependency/inequality in the distribution of constraints on the ego across the alters in its neighbourhood. If the total constraint on the ego is concentrated in a single other partner, the Hierarchy measure will have a higher value. Thus, the USA has its ego-network Constraint concentrated in a few partners ($H_{USA} = 0.638$), while Russia has its Constraint diffused over a higher number of partners ($H_{RUS} = 0.250$). Effective Size (ES) is a measure of the total size of the ego network (excluding its redundancy); in our case, EUR's total impact is the highest ($ES_{EUR} = 87.797$), followed by China ($ES_{CHN} = 67.986$), Russian Federation ($ES_{RUS} = 57.333$), USA ($ES_{USA} = 56.230$), Brazil ($ES_{BRA} = 31.284$) and Ukraine ($ES_{UKR} = 23.775$).

3.11. Brokerage analysis of GFTN

Brokerage behaviour (Burt, 1992, 2005) refers to those actors connected to weakly connected subgroups, trying to fill a structural hole, i.e., a fissure within the network. In this section, the brokerage opportunities regarding the identified four communities in the GFTN is assessed following the approach of Gould and Fernandez (1989), who proposed five distinct types of brokerage structures (Coordinator, Gatekeeper, Representative, Consultant, and Liaison) based on triads relations between nodes linked with no less than two ties from a partition of actors into no overlapping subgroups. Standardised partial scores (for each country) and global brokerage scores (for the 126 countries) have been calculated for GFTN on the five types of mediation. The countries with significant overall brokerage score are reported in Table 4. Global brokerage properties show a statistically significant positive value of t ($z_t = 10.98$) indicating that GFTN exhibits an overall tendency towards intransitivity; the significant positive values of $z_{coordination}$, $z_{Gatekeeper}$ and $z_{Representative}$, for the partial global measures indicate that countries in the GFTN are prone to participate in brokerage relations in which at least two countries belong to the same group.

The significant relative frequency of the Coordinator, Gatekeeper, and Representative brokerage role implies that, in general, countries try to avoid depending on a small number of brokers when they trade within their own group, when they trade with other groups, and when countries of their own group trade with members of other groups. Similarly, the negative value of $z_{Consultant}$ indicates that countries avoid participating in brokering relationships where the intermediary does not belong to the same group as the exporter and the importer countries (assuming that both belong to the same group). That may be because, in this case, the mediator can be considered an outsider as regards the group trading relationships. Finally, regarding the Liaison brokerage role, i.e., when the importer, the exporter and the broker all belong to different groups, the fact that it is not statistically significant implies that it occurs with a similar frequency as in a random network.

At the country level, the only countries with significant a standardised total measure z_t are Canada, Colombia, United Arab Emirates, and USA in group 1; Australia, China, India, Indonesia, Malaysia, Norway, Saudi Arabia, Thailand in group 2; Belarus, Brazil, Europe, Morocco, Russian Federation and Ukraine in group 3; and Mexico and South Africa in group 4. The null hypothesis of a random network should be rejected as 20 countries (much more than 5% of total of 126 countries) have significant scores. The latter analysis suggests that the fertiliser trade in GFTN flows in a particular way. It can be noted in Table 4 that the five core countries have significant brokerage roles. That is not surprising since core countries frequently trade with periphery countries which, independently of the group they belong to, do not trade with each other.

Note that EUR (with 6607 interconnections) occupies the position with the highest brokerage capacity in GFTN, followed far behind by China (3396 interconnections), Russian Federation (2844 interconnections), the US (2414 interconnections) and Brazil (707 interconnections). Ukraine (490) brokers mainly as Coordinator, and much less as Gatekeeper and Representative. Similar brokerage roles have Colombia (Group 1, 274 interconnections) and Australia (545), Indonesia (808), Malaysia (523), Norway (391), Thailand (487) in Group 2. These countries have a visible propensity to trade within their own group acting as intermediaries with members of other groups. The only brokerage role that Saudi Arabia (602; G2) does not play is Consultant, i.e., mediating between an importer and exporter country that belong to the same group. United Arab Emirates (314; G1) only brokerage role is as a Liaison, i.e., linking different exporter and importer countries each belonging to a different group. As well as a Liaison, Mexico (479; G4) can also act as Representative and Consultant. Morocco (796; G3) and South Africa (710; G4) can play all the brokering roles, but mainly as a Consultant.

It can also be noted that EUR mediates as Gatekeeper between mainly exporter countries of G2 and importer countries of G3 (i.e., $G2 \rightarrow G3_{EUR} \rightarrow G3$) and Representative between mainly exporter countries of G3 and importer countries of G2 (i.e. $G3 \rightarrow G3_{EUR} \rightarrow G2$). The direction of brokerage trade links in China and the Russian Federation coincides with those of EUR (i.e. $G2 \rightarrow G2_{CHN} \rightarrow G3$; $G3 \rightarrow G2_{CHN} \rightarrow G2$, $G3 \rightarrow G3_{RUS} \rightarrow G2$; $G2 \rightarrow G3_{RUS} \rightarrow G3$), however they also have significant roles as Gatekeeper and Representative with G4 countries: $G2 \rightarrow G2_{CHN} \rightarrow G4$ and $G4 \rightarrow G2_{CHN} \rightarrow G2$, in case of China; $G3 \rightarrow G3_{RUS} \rightarrow G4$ and $G4 \rightarrow G3_{RUS} \rightarrow G3$ and in the case of Russian Federation. Finally, Brazil acts as mediator preferably as an importer country of G2 and G1 countries in its role as Gatekeeper (i.e., $[G2,G1] \rightarrow G3_{BRA} \rightarrow G3$) and as an exporter country to G2 and G1 countries playing a Representative role (i. e., $G3 \rightarrow G3_{BRA} \rightarrow [G1,G2]$).

3.12. Motifs analysis

The analysis of recurrent interconnection patterns in the GFTN can be carried out through the frequency of local network topological structures, called motifs. Triadic and tetradic structures in trade relations are more stable than dyadic relations as they represent a set of relationships between three/four countries that is not easy to replace (Yoon et al., 2013). Tables 7 and 8 display the significant three- and four-node motifs detected using the *mfinder* algorithm (Kashtan et al., 2004). The analysis of triadic fertiliser trade motifs reveals that only two regular subgraphs occur much more frequently than in a random network. One is motif Id. 102 which represents a single mutual dyad between two countries in a triadic trade relationship, i.e., two countries (A and B) that export and import to each other, and A (respectively, B) is the exporter (respectively, importer) for the third member of the triad (C). This motif has frequency and concentration indexes $F_{REAL} = 348$; $C_{REAL} = 13.76‰$. The other significant motif ($F_{REAL} = 1823$; $C_{REAL} = 72.10‰$) is the one with Id. 238, which corresponds to a clique, i.e., a fertiliser trade structure where the three countries trade bidirectionally among themselves, implying the ease of importing or exporting fertilisers. Interestingly, this motif has the highest statistical significance. These two triadic patterns show a pattern of interaction and mutual dependence in fertiliser trade between countries that leads to a lack of resilience to fertiliser demand or supply disruptions. Some examples of these two types of configurations are also shown in Table 5.

The analysis of four-node directed motifs reveals a much higher number (fourteen) of statistically significant structures. These are listed in Table S5 in the Supplementary material file. The common feature in tetradic trade relations is the tendency to reciprocity (i.e., bidirectional trade links) in GFTN, which suggests the intensive collaborative relations between countries in the framework of their business strategies, such as the existence of overseas subsidiaries, commercial agreements or joint ventures between companies. Some specific four-nodes connected subgraphs with the greatest concentration are motif Id. 350 ($C_{REAL} = 11.83‰$), motif Id. 862 ($C_{REAL} = 22.22‰$) and motif Id. 4950 ($C_{REAL} = 24.04‰$), involve a common pattern in fertiliser trade relations where three partners trade jointly (bidirectionally in most cases) and a fourth partner that plays a very limited trading role in the sense that only exports to or imports from a single country of the tetradic structure. Finally, consider motif Id. 31710. That this completely bidirectionally connected clique is a significantly frequent trade pattern in GFTN is remarkable and informative.

4. Discussion

The complex network analysis whose results have been presented in detail in the previous section provides many insights into the structure and behaviour of the global fertiliser trade (up to 2018). One is the small world and scale free character of GFTN. The latter is common in global trade networks. The network density (0.10) is similar to the values reported by Li et al. (2023) for the phosphorus fertiliser networks (between 0.090 and 0.098 during the period 2015–2020). Its high reciprocity ratio is rather high (0.73) as are also its in- and out-degree centralisation (around 0.60). A key finding is the existence of a core-periphery structure in which a few core countries (namely EU, USA, China, Brazil and the Russian Federation) trade among themselves and with most of the periphery countries, which have sparse connections between them. Thus, these five core countries act as hubs, increase the in- and out-centralisation and induce disassortativity. Superimposed to this core-periphery structure is a modular structure that involves four communities that follow clear geographic patterns. Thus, one community (formed by 21 members) is centred around USA and Canada and includes different Central-America and South-America countries, the Caribbean Islands, and most Arab Golf countries. A larger community (formed by 40 members) is centred around China and India and includes South and East countries, Oceania, some Arab Gulf countries, and some countries from East and West Africa. The largest community (formed by 40 members) is centred around EUR, the Russian Federation and Brazil and includes all the former Soviet republics, Turkey, Israel and many countries in Africa. The smallest community (formed by 17 members) includes some African and South American countries (e.g., Mexico, Chile, Peru, Bolivia), as well as Cuba.

Concerning cross-regional flows, the E-I index indicates a small degree of heterophily (i.e., more trade between regions than within regions) although the within-Asia trade accounts for 23.6% of global fertiliser trade and the trade between North America countries represents 10% of total trade. Asia is a major exporter region as well as a major importer region. The large weight of Asia in the global fertiliser trade should not be surprising given that it represents 60% of the world population, and that the Russian Federation has been included in this region. Interestingly, South America, a large net exporter of agricultural products, is however a net importer of fertilisers with the geostrategic dependency that this implies.

As regards individual countries centrality indexes, the same countries appear again and again. Thus, EUR, USA, Russian Federation, China, Canada, Brazil and India have the largest PageRank indexes, both as exporters and as importers. EUR, China, USA, Russian Federation and Canada have the largest number of trade partners, with in- and out-degree centralities above 0.36. As regards the in- and out-strength, the main actors are USA, Russian Federation, Brazil, EUR, India, and China accounted for more than 50% of the global fertiliser trade. Finally, using the betweenness centrality index that measures the ability of a country to act as an intermediary in the GFTN, EUR held the strongest position in the period 2014–2018, followed by China, the Russian Federation, USA and South Africa.

Another important piece of information obtained from the analysis of the temporal evolution of the trade flows during the period under study is that the major players have the highest persistency indexes, indicating that most of their trade partners appear in all five FTN. Other countries that also show a high level of persistence, i.e., high levels of loyalty in terms of commercial relationships, are Japan and Chile. The high persistence does not necessarily involve stable trade volumes. Thus, in some cases, like the USA, China, EUR or Japan, the variability of the import and export trade volumes with their trading partners is rather high. The Russian Federation also has a high variability but only as regards import volume. Its exports during this period were much less variable. The opposite occurs in the case of Brazil, whose exports vary far more than its imports. Also, there seems to exist a weak positive relationship between the total number of import and export partners of a country and the persistence of those relationships during the period 2014–2018.

Given the important role of the five core countries in the functioning of the network, their corresponding ego-networks have been analysed and different measures aimed at identifying the number of structural holes present, the ego constraints and the dependency/redundancy of its trading relationships have been computed. Thus, for example, EUR (respectively, Brazil) has the largest (respectively, the smallest) number of structural holes. The Russian Federation has the highest Constraint which indicates a large dependency from its export/import partners, unlike China and EUR, which have a much lower Constraint. The low Hierarchy index of the Russian Federation indicates that this dependency is not concentrated on a few partners but spread over many of them.

In the complex network methodology, brokerage refers to taking advantage of intransitive trade links that act as bridges between communities. We have analysed the brokerage roles of all the countries in the GFTN in terms of the community structure grouping and the results indicate that all the core countries have overall significance brokerage levels. The communities between which these countries play the different brokerage roles have been identified. For the whole GFTN, three particular roles have a positive significance (i.e., they occur more frequently than would be expected by chance), namely Coordinator, Gatekeeper and Representative, while that of Consultant has a negative significance (i.e., they occur less frequently than would be expected by chance).

Motifs (i.e., three and four node local structures whose frequency is significant) have been identified. In particular, the two main three node motifs correspond to a one mutual dyad and to the three mutual dyads (i.e., a 3-clique). In the case of four node structures a total of 14 motifs, most of them with high subgraph density and including the 4-clique, are significant. The motifs present in the GFTN are consistent with the high reciprocity ratio observed. The high relative frequency of the three and four node cliques is very telling as they represent very stable patterns in which all participants trade with each other bidirectionally. This implies and fosters trust, a scarce commodity nowadays.

As regards the political and economic implications of the findings of the study it is difficult to ascertain them in the short term given the current uncertainty but the fragility (i.e., the vulnerability to targeted disruptions) inherent the scale-free nature of the GFTN (see, for example, Foti et al., 2013; Puma et al., 2015) and the polarisation of the members of the core of the GFTN augurs a split of the previously integrated global fertiliser market into two distinct trading blocks, with a reconfiguration of the currently observed trading communities.

5. Conclusions

In this paper a thorough analysis of the yearly FTN and the corresponding GFTN for the period 2014–2018 has been carried out. The aim was to determine the structure and main features of global fertiliser trade previous to the pandemic and the military conflict in Ukraine, which have produced significant disruptions whose effects can be gauged in the future by comparison with the GFTN studied in this paper. Thus, a number of facts about the pre-pandemic structure of the GFTN have been identified in this study. Some of them, like the small world and scale-free character, the high reciprocity ratio, the disassortativity and the aggregated interregional flows, are likely to remain more or less the same. We conjecture that the network motifs will not change much either since this type of structures derive from some basic local behaviours. The existing core-periphery structure and the trade communities, however, are likely to be affected by the re-wiring of trade relationships as a result of the Ukraine conflict. This will run in parallel with the ongoing, far-reaching de-dollarisation process and should lead to a more complex bi-polar core-periphery structure.

Among the limitations of this study are, apart from the lack of more recent data, the use of the monetary value of the trade flows instead of the gross weights of these flows. Also, it does include an analysis, using an Exponential Random Graph Model (ERGM), of the factors that may explain the observed topological features of the GTFN or a cascading failure analysis of the vulnerability of the GTFN. Looking to the continuation of this research, apart from overcoming the above limitations, it will be very interesting to see the changes in the structure and functioning of the GFTN that have occurred due to the COVID19 pandemic and, more importantly, as a result of the conflict between Ukraine and the Russian Federation and its trade, economic and geopolitical consequences. Although some partial preliminary assessments have been presented (e.g., Shahini et al., 2022) we believe that, due to transient and lagged data reporting effects, the definitive study of those changes cannot be done at this moment.

CRediT authorship contribution statement

Ester Gutiérrez-Moya: Data collection, Conceptualization, Methodology, Writing, Visualization. **Sebastián Lozano:** Conceptualization, Methodology, Writing, Visualization. **Belarmino Adenso-Díaz:** Data collection, Methodology, Writing.

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 will be made available on request.

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Appendix A. Supplementary data

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