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Analysing the Structure of the Global Wheat Trade Network: An ERGM Approach

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Abstract: This paper studies the relationship between wheat trading countries using both descriptive and statistical inference methods for complex networks. The global Wheat Trade Network (WTN) and its evolving topological characteristics is analysed for the periods 2009–2013 and 2014–2018, using the Food and Agriculture Organization (FAO) data. The network characterisation measures in both periods are rather stable. There are some differences, however, in the magnitude of some measures (e.g., connectivity or disassortativity), and a higher degree of inequality in the distribution of the number of partners and the distribution of trade volume in the period 2014–2018. An Exponential Random Graph Model (ERGM) has been applied to identify significant determinants associated with the presence/absence of trade links between countries. The results indicate that wheat trade links are driven mainly by country openness, reciprocity (mutual importer-exporter relationship), whether the exporting country is US or Canada and the geographical location of importer and exporter. Other factors, such as the economic size of the importing country, if the importing country is US or Canada and the land surface of the exporting country also contribute less to capture interlinkages of WTN.

Keywords: global wheat trade; complex network analysis; ERGM

1. Introduction

Wheat is one of the most extensively grown and the most traded cereals throughout the world because of its significant contribution to human consumption providing high nutritional value [1]. For most developing and less developed countries wheat constitutes their main staple food, not being completely substitutable for any other type of cereal crop. Table 1 shows the top ten wheat exporting, importing and producing countries during the most recent ten-year period 2009–2018 [2] Regarding exports, the US is ranked in first position, exporting on average 26 MMT/year, accounting for 15.5% of the global volume of total wheat exports; the Russian Federation exporting 22 MMT/year (12.97%) and Canada exporting 20 MMT/year (12.06%) occupy the second and third positions, respectively. The three Central Eurasian countries, Russia, Ukraine and Kazakhstan, together accounted for more than a fifth of total wheat export volume. Most of the top ten wheat exporters also occupy prominent positions as top producers. However, wheat production is dominated by China, which accounts for over 17% of wheat production worldwide on average. Exporter and producer volume distribution are highly concentrated, with the top ten wheat exporting countries accounting for nearly 84% of total export volume and 70% of total production volume. With regard to importing, Egypt is the top importing country (6.17%) with average annual wheat imports of 10 MMT/year, followed by Indonesia, Algeria and Italy, importing around 7 MMT/year (4%) each. Importer volume distribution is more dispersed, with the top ten wheat importers accounting for only 37% of total wheat imports.

Table 1. Top wheat exporter, importer and producer countries (2009–2018).

Country	Average Annual of Exports (Tonnes)	Country	Average Annual of Imports (Tonnes)	Country	Average Annual of Production (Tonnes)
US	26,208,349 (15.50%)	Egypt	10,302,612 (6.17%)	China	12,492,211 (17.51%)
Russian Federation	21,943,252 (12.97%)	Indonesia	7,459,224 (4.47%)	India	9,096,270 (12.75%)
Canada	20,399,502 (12.06%)	Algeria	7,153,240 (4.29%)	Russia Federation	6,022,793 (8.45%)
France	18,713,389 (11.06%)	Italy	7,038,934 (4.22%)	US	5,671,135 (7.95%)
Australia	17,590,152 (10.40%)	Brazil	6,202,215 (3.72%)	France	3,745,670 (5.25%)
Ukraine	11,332,862 (6.70%)	Japan	5,665,702 (3.40%)	Canada	2,913,554 (4.09%)
Germany	8,505,329 (5.03%)	Spain	5,363,981 (3.21%)	Pakistan	2,486,908 (3.49%)
Argentina	7,267,218 (4.30%)	Netherlands	4,683,566 (2.81%)	Australia	2,475,048 (3.47%)
Kazakhstan	4,641,570 (2.74%)	Turkey	4,310,652 (2.58%)	Germany	2,427,295 (3.40%)
Romania	4,296,731 (2.54%)	Philippines	3,624,535 (2.17%)	Ukraine	2,257,099 (3.16%)

The OECD/FAO world wheat outlook 2018–2027 projects an increase in wheat production by 11%, a more modest pace compared to the last decade, with most of the growth in India, European Union, Russian Federation, Pakistan and Turkey. Wheat consumption is expected to increase by 13% compared to 2018 with food consumption accounting for an increase of about two-thirds of total use; an increase in wheat use for animal feed and biofuels is expected mostly in China and the Russian Federation. In addition, the share of global wheat production traded is expected to reach 24% by 2027, compared with 13% for maize and 15% for other coarse grains. This means that wheat exports are expected to grow by 24 MMT (million metric tonnes) to reach 199 MMT by 2027 [3].

Wheat trade allows climatic-related and other supply risks to be shared across countries, resulting in steadier prices and supply volumes. However, vulnerabilities remain due to production shocks as well as geopolitical and global health crises. For example, the current global outbreak of COVID-19 has disrupted agricultural and food systems around the world. The COVID-19 pandemic situation has affected trade volumes and supply chains, raising some concerns about domestic food security. Thus, in the beginning of the pandemic, some small and big producers, namely Kazakhstan, Kyrgyzstan, North Macedonia and Russia, imposed temporary export restrictions. On the other hand, in order to attenuate trade disruptions, several countries (such as Bangladesh, Egypt, India, Mexico, Morocco, Nigeria, among others) have reduced their import barriers, leading to greater global wheat demand [4].

A number of studies have dealt with the robustness of the global food system due to local and global crop shocks like trade restrictions [5], crop supply shocks [6] and crop production shocks [7–9]. In particular, [10], considering the period 2009–2013, show how the production/supply shocks propagate through the trade network and how certain topological features of the network affect this process. Hence, it is important to understand the network structure and to try to find the factors that determine it. The goal of this paper is to analyse and explain the trade network structure. To this end, complex network analysis tools and, in particular, the Exponential Random Graph Model (ERGM), are used. Additionally, the period under study has been extended to 2009–2018.

During recent years, a number of studies have analysed the international agri-food trade through their connections in order to understand the networks' structural characteristics. Given the complexity of the flows and relationships among countries exchanging food commodities, complex network theory has been used as a suitable modelling tool [11–13] Wheat trade and production have been extensively studied in recent decades [14,15]. The existing literature, however, has focussed mainly on the global food network trade where the wheat exchanges were integrated with other agricultural commodities [8,16,17] or from a comparative analysis perspective [5]. However, recent studies have applied the complex network methodology to investigate the international wheat trade specifically. Thus, [18] identified prominent wheat exporters and importers in 1999 and found that wheat prices were established mainly by exporting countries. Ref. [19] developed a preferential attachment network model to study resilience of the wheat trade network based on data of international wheat trade from 1986 to 2011, predicting that the wheat trade network will become less susceptible to outbreaks up till 2050. Ref. [20] conceived the international trade system as a core-periphery structure where the rigidity of competitive links has decreased over the period 2004–2014.

The descriptive analysis of the characteristics of the network is crucial to understand its trade features from a macro and micro-level perspective. ERGMs are probabilistic models and can be used to estimate the patterns of network connections and the interactions between these connections and individual behaviours [21]. Within the realm of trade, existing ERGM studies have focussed on the electricity industry [22], virtual water flows [23], the pork industry [24], cryptomarket [25], the high-tech industry [26], maritime transport [27], the arms industry [28] and free trade agreements formation [29]. However, no research has applied inference network analysis on nodal (i.e., country) and flow-level attributes in the global wheat trade network.

This study aims to fill the existing gap, and the main contribution is to provide insights to the global wheat trade patterns using ERGM as inferential structure methodology, an approach that allows for identifying the processes that affect the interconnectedness between countries and the link formation mechanisms. The database comprises the last ten years, 2009–2018, of available data from the Food and Agriculture Organization (FAO).

2. Materials and Methods

This section describes the dataset, network construction, the network analysis indicators and ERGM methodology.

2.1. Data

To analyse the global wheat trade flows for the period 2009–2018, data on bilateral wheat trade flows between countries were obtained from the Statistics Division of FAO (FAOSTAT, http://faostat.fao.org) and used to build two weighted, directed wheat trade networks (WTN), one network covering the period 2009–2013 and the other network comprising the most recent five-year period 2014–2018. These networks are labelled WTN (2009–2013) and WTN (2014–2018), respectively. Six countries (Andorra, Anguilla, Fakland Islands, Marshall Islands, Pitcairn and South Sudan) in WTN (2009–2013) and five countries (Guam, Isle of Man, Nauru, Turks and Caicos Islands, Mayotte) in WTN (2014–2018), are not included in the WTNs because the corresponding data were not reported for any the periods of the time horizon considered. Despite the different composition of the two WTNs, only 2% of countries are not overlapped. We have kept all the data obtained from FAO to provide a more accurate depiction of the international wheat trade. In addition, in cases where data from a reporting country and from the partner country were not coincident, the maximum of the two values was considered. To smooth out fluctuations in the different years the yearly trade flows were averaged. We focus on data after the latest world food crisis in 2008 that particularly in case of wheat commodity affected developing countries, as in most cases these countries are net importers. Over the 10-year period under study there have been significant changes in world wheat trade flows between the top wheat exporters, importers, growing wheat dependence of low-income countries, wheat price volatility, climate change, changes in yields and fuel prices, among others.

2.2. Network and Node-Related Statistics

Network statistics are descriptive measures of a network that reflects crucial information on network characteristics. The global WTN can be represented by a graph $G = (N, E)$ composed of a set of nodes N (countries) and a set of E edges (trade links) that interconnect them. Each edge has a weight given by a weighted adjacency matrix $W = \{w_{ij}\}$, where w_{ij} represents the weight of the edge from node i to node j, i.e., the average wheat flow from the exporting country i to the importing country j (that coincides with the average imports to country j from country i). The network can be also expressed by its adjacency matrix $A = \{a_{ij}\}$, $i, j = 1, 2, \ldots, n$, dimension $N \times N$, where $a_{ij} = 1$ if there is an edge from node i to node j, and $a_{ij} = 0$ otherwise. Several standard statistics metrics at the network level and the node level can be computed to characterise a weighted directed network like these [30]. They are presented below, distinguishing between global (i.e., network-level) and local (i.e., node-level) measures.

2.2.1. Statistics Measures at Node Level

Export degree of country i indicates the number of export partners:

$$k_i^{out} = \sum_j a_{ij} \tag{1}$$

Import degree of country i indicates the number of import partners:

$$k_i^{in} = \sum_j a_{ji} \tag{2}$$

In-strength of country i indicates the volume of imports:

$$s_i^{in} = \sum_j w_{ji} \tag{3}$$

Out-strength of country i corresponds to the volume of exports:

$$s_i^{out} = \sum_j w_{ij} \tag{4}$$

Total strength of country i indicates the total volume of trade (including both imports and exports):

$$s_i = s_i^{in} + s_i^{out} \tag{5}$$

Betweenness centrality represents the average fraction of shortest paths connecting all countries in the network to all other countries that pass through the country of interest (high-betweenness is akin to being a network broker):

$$\beta_i = \frac{1}{(n-1)(n-2)} \sum_{\substack{j \neq p \\ j \neq i \neq p}} \frac{\varsigma(j,p|i)}{\varsigma(j,p)} \tag{6}$$

where $\varsigma(j,p)$ is the number of geodetic paths from node j to node p and $\varsigma(j,p|r)$ is the number of these paths that pass through r.

2.2.2. Statistics Measures at Network Level

Density describes the proportion of the potential number of connections between two countries in the network, G, $m_{max}(G)$, that are actual connections $m(G)$:

$$\rho = \frac{m(G)}{m_{max}(G)},\ 0 < \rho \leq 1 \tag{7}$$

where $m_{max}(G) = n(n-1)$ in a directed network.

Diameter is the length of the shortest path between the most distanced nodes in the network. For a strongly connected network it can be computed as:

$$D = \max_{j \neq i} \ d_{ij} \tag{8}$$

where d_{ij} is the geodesic distance from node i to node j (calculated using Dijkstra's algorithm)

Average degree is the average number of connections (considering imports and exports) per country in the weighted network:

$$\langle k \rangle = \frac{m}{n} \tag{9}$$

where m is the number of arcs.

Average geodesic distance is path with the minimum sum of wheat trade flows:

$$\langle d \rangle = \frac{1}{n \cdot (n-1)} \sum_{i \neq j} d_{ij} \tag{10}$$

In-degree centralization index is a network measure that informs on how much variance there is in the distribution of the number of incoming connections (i.e., the number of trading partners of an importing viewpoint):

$$CI^{in} = \frac{\sum_i \left(k^{in.\max} - k_i^{in}\right)}{(n-1)^2} \quad (11)$$

Out-degree centralisation index is a network measure that informs on how much variance there is in the distribution of outgoing connections (i.e., the number of trading partners of an exporting viewpoint):

$$CI^{out} = \frac{\sum_i \left(k^{out.\max} - k_i^{out}\right)}{(n-1)^2} \quad (12)$$

Global transitivity index is the overall probability for the network to have adjacent nodes interconnected, thus revealing the existence of tightly connected communities (or clusters, subgroups, cliques):

$$T = \frac{trace(A^3)}{\sum_{ij}(A^2)_{ij}}, 0 \le T \le 1 \quad (13)$$

Assortativity coefficient (degree-degree correlation) computes the tendency for countries to connect to other countries with similar properties in terms of the number of trading partners, within a network:

$$r = \frac{\frac{1}{m}\sum_i j_i k_i - \left[\frac{1}{m}\sum_i \frac{1}{2}(j_i + k_i)\right]^2}{\frac{1}{m}\sum_i \frac{1}{2}\left(j_i^2 + k_i^2\right) - \left[\frac{1}{m}\sum_i \frac{1}{2}(j_i + k_i)\right]^2} \quad (14)$$

where k_i and j_i are the excess degrees (i.e., the number of other trading partners) of the two ends of a given link i. The assortativity index ranges from −1 (low degree nodes often connect high degree nodes) to 1 (nodes of equal or similar degree are frequently connected). If r is significantly positive (negative) the network is called assortative (disassortative).

Degree distribution P_k, corresponds to the fraction of countries that have a given number of partners k. In the case of directed networks, there are three such distributions, one for the in-degree, another for the out-degree and a third for the total degree.

Strength distribution P_s, corresponds to the fraction of countries that have a given total trade volume s. In the case of directed networks, there are three such distributions, one for the in-strength, another for the out- strength and a third for the total strength.

2.3. Exponential Random Graph Models (EGRMs)

ERGMs are a stochastic approach for modelling the associations among interdependent data determining the global structure of a network from local configurations, where each potential instance graph is assigned a probability [30,31]. ERGMs depart from regression frameworks and its independence assumption, considering complex conditional dependence assumptions to model the network. An ERGM define the probability of any network $\boldsymbol{y}$ given a set of n nodes and their network statistics as:

$$P\left(\boldsymbol{Y} = \boldsymbol{y}\middle|n\right) = \left(\frac{1}{c}\right)\cdot \exp\left(\sum_{k=1}^{K} \theta_k z_k(\boldsymbol{y}, \boldsymbol{X})\right) \quad (15)$$

where the $z_k(\boldsymbol{y}, \boldsymbol{X})$ terms represent model network statistics (also referred as covariates) corresponding to the any subgraph configuration k, c is the normalising constant that ensures that the sum of the expression (15) over all possible $\boldsymbol{y}$ (all possible graphs) is equal to 1, θ_k are parameters that estimate the strength of the effect of each covariate. Graph configurations include networks statistics, such as statistics built from ties (e.g., mutual ties, transitive triads, etc.), and statistics based on node attributes. The networks' statistics are generally different in undirected and directed networks. It can be noticed that the selection of the network statistics is crucial for the accurate estimation of the graphs' distribution.

ERGMs consider Markov dependency (also known as conditional dependence), which means that if the value of a tie changes, the probability of the other ties will change (even if the remainder of the ties do not change).

Several methods exist for estimating the parameters of ERGMs. In the pseudo-likelihood estimation method [32], although fitting the model is not difficult, the estimates are not accurate. Markov Chain Monte Carlo (MCMC) maximum likelihood estimation (MLE) [21,32–35] has the advantage of making a more efficient use of MCMC samples. Metropolis-Hastings algorithm is used to control the behaviour of the MCMC for sampling networks. In this paper the simulation-based estimation method MCMC has been used to estimate the θ_k coefficients based on the maximisation of the probability over the observed data:

$$\theta_{ML} = \arg max_{\theta \in \mathbb{R}^p} P(\mathbf{Y}|n) \tag{16}$$

The iteration optimisation process progresses until the value of the approximate likelihood function no longer changes (i.e., the difference between the sufficient statistics of the observed network and the average of the sufficient statistics in the sample of simulated networks are not significant).

3. Results

We assess standard network characteristics to explore the ten years (2009–2018) of trade relations between countries using CNA. In addition, ERGM is used to develop statistical inferences of the wheat trade connections observed during the period 2009–2018.

3.1. The Topology of the WTN

Table 2 summarises some topological metrics of the networks: WTN (2009–2013) and WTN (2014–2018). This updates a previous study carried out by [10] that involved WTN (2009–2013) only. The networks contained 2880 and 3114 trade links (8% increase), respectively. The density values 0.069 and 0.073 are relatively high with respect to other global trade networks that cover several types of commodities [36,37]. This means that, for instance in the last five years (2014–2018), choosing two countries at random the probability that there is wheat trade between them is 7.3%. The fact that the density of the WTN (2014–2018) has increased from WTN (2009–2013) reflects the tendency towards openness of new markets in world wheat trade. Most of the connections are unilateral trade relations, although there is an increase of 14% in bilateral relationships (mutual reciprocity values of 0.206 and 0.235, respectively. The double character, exporter and importer, of a country is motivated by internal and external reasons related to domestic prices stabilisation, an increase in wheat-based products demand, global market volatility, among others.

In general, as regards other network measures, not many differences between 2009–2013 and 2014–2018 are observed. The diameter has increased slightly but the WTN remains a small world, with average geodesic distances of 2.6 and 2.4, respectively. In- and out-degree centralisation have both increased slightly, average degree has increased (as a result of the increase in the number of trade links) and transitivity has remained the same (around 0.384), indicating moderate clustering. A slight increase in disassortativity can be observed though. This is related to countries with a low number of trade links conducting trade with highly connected countries and suggests a hierarchical wheat trade configuration that may affect the connectedness of the network in the case of a major supply shock occurs. These results are consistent with the studies of [12,37–39]. This is also related to the increase in centralisation that has been mentioned above. In particular, the centralisation is rather high in the case of out-degree, indicating a high degree of concentration in exports, i.e., a few countries concentrate most of the export trade links. This concentration is much lower in the import side (in-degree).

The visualisation of WTN (2014–2018) network is displayed in Figure 1 (using NetDraw, a software included within the UCINET 6.0 Package, [40]). To reduce clutter, the arcs have been filtered so that only those with a weight above the third quantile (Q3) have been retained. Importing and exporting are depicted in Figure 1. Thus, in the top panel, to emphasise imports, the sizes of the nodes are proportional to the in-degree, while in the bottom panel exports are emphasised and the node sizes are proportional to their out-degree. ISO 3166-1 alpha-2 country codes are used to designate the countries. Countries with a major importer role, are Iran, Yemen, Morocco, Italy, Spain, Germany, Turkey and United Kingdom, among others. Exporting countries with a large number of trading partners include the US, Canada, Australia, Russia, France and Germany, among others. Note that it is not uncommon for a country to be involved simultaneously in imports and exports. The WTN (2014–2018) shown in Figure 1 can be compared with that of 2009–2013 shown in [10].

Table 2. Some characterisation measures of the WTN (2009–2013) and WTN (2014–2018).

	WTN (2009–2013)	WTN (2014–2018)
Num. of nodes	205	206
Num. of ties	2880	3114
Density	0.069	0.073
Diameter	6	7
Average geodesic distance	2.6	2.4
Average degree	28.09	30.23
In/Out-degree centralization	0.192/0.601	0.209/0.638
Average node strength	1,987,868	2,018,854
Num. of mutual/Num. of asymm/Num.of null dyads	494/1892/18,524	595/1923/18,597
Arc/Dyad reciprocity	0.341/0.206	0.381/0.235
Global transitivity	0.384	0.386
Degree Assortativity	−0.189	−0.231

Imports viewpoint

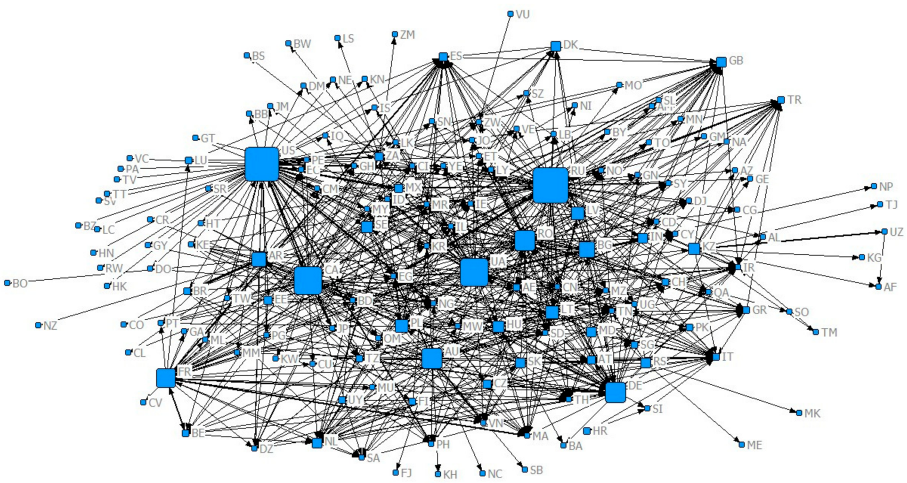


Figure 1. *Cont.*

Exports viewpoint

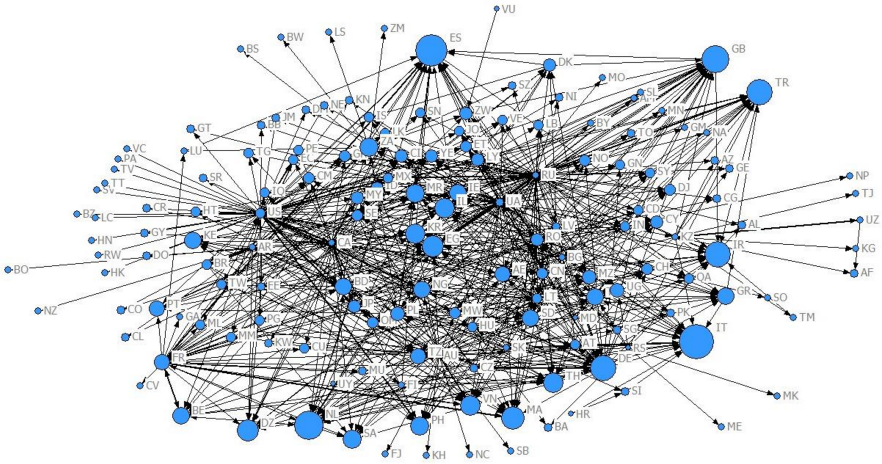


Figure 1. Visualisations of the WTN (2014–2018) (only arcs with weights above Q3 are shown).

The results of a power law (PL) fit of the distribution of the in-, out- and total degrees and of the in-, out- and total strengths are displayed in Table 3. The method used follows the methodology described in [41]. The Kolmogorov–Smirnov (KS) statistic indicates that in all cases, except out-degree, a PL distribution with corresponding exponent can be fitted. This confirms the right-skewed distribution of these variables, with most countries having a small number of trade links and a low trade volume, and a few countries having a large number of trade link and large trade volume. It also implies that the WTN is a scale free network, with all the implications that has in terms of robustness to random failures but fragility to targeted attacks [42].

Table 3. Power law fit of node degrees and strengths distribution.

	Exponent (α)	Cut-off (x_{min})	Parameters' Uncertainty				
			Std α	Std x_{min}	Std Tail	Std KS	p-Value
Total degree	3.34/3.81	52/72	0.06/0.04	2.60/2.31	29.97/25.04	0.07/0.04	0.61/0.76
In-degree	5.15/4.71	29/27	1.21/2.53	5.05/4.63	21.91/19.65	0.09/0.06	0.60/0.56
Out-degree	3.16/2.80	39/35	0.07/0.04	2.61/2.87	29.97/31.25	0.09/0.04	0.01/0.02
Total strength	1.41/1.74	99,002/787,911	0.03/0.04	6564.3/7413.1	6.52/5.64	0.01/0.02	0.56/0.42
In-strength	1.48/1.62	99,374/199,333	0.04/0.01	4,026.1/5289.3	6.63/7.21	0.01/0.03	0.99/0.84
Out-strength	1.36/1.21	93,260/412.4	0.05/	7992.1/9845.6	6.30/5.25	0.01/0.02	0.99/0.10

Notes: Parameters' uncertainty analysis using bootstrap procedure (based on 1000 simulations). The two entries in each cell correspond to WTN (2008–2013)/WTN (2014–2018).

Table 4 shows the (unnormalised) betweenness centrality, which measures the frequency with which a country lies on the shortest path between any pair of countries. This centrality index informs on the countries that have more information on the wheat network because more connections pass through them and can be considered as central, the main ones being Zambia, the UK, US, Switzerland, France, Belgium, United Arab Emirates, New Zealand and Germany. Hence, the network is dominated by a small set of centrally positioned countries (namely, US, France, Germany, Belgium, UK, U. Arab Emirates, Italy, Turkey and Canada) and their trade relationships. This group of countries have high betweenness and also tend to be have the largest degrees (network hubs) in the WTN. However, there are also high degree countries that do not have high betweenness centrality values (e.g., The Netherlands). Note the role of Zambia and Mexico as bridging nodes, with a relatively high betweenness centrality but a low degree.

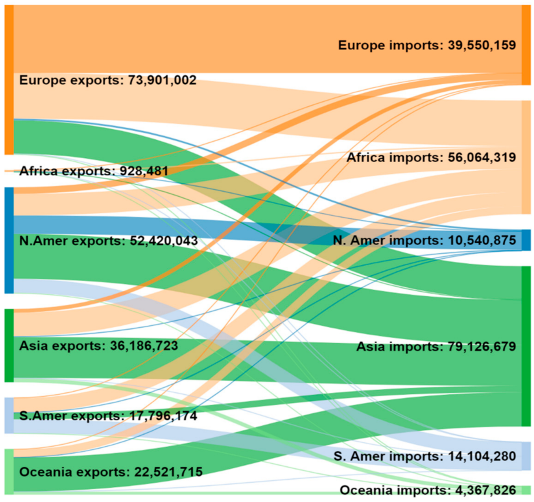
Table 4. Countries with highest betweenness centrality.

Country	WTN (2008–2013)	Country	WTN (2014–2018)
Zambia	9455.35	**Switzerland**	9101.35
U.K.	9230.15	**France**	6377.26
U.S.	7083.67	**U.K.**	6153.92
Mexico	5863.23	Serbia	5042.09
Turkey	5839.08	**Zambia**	4970.08
Switzerland	5732.90	**Belgium**	4777.87
Greece	5301.15	Taiwan	4605.39
Luxembourg	5240.98	Spain	4395.35
Denmark	5045.32	China	4065.25
U.A.E.	4616.40	Slovenia	4050.36
Norway	4336.05	Kazakhstan	4004.39
France	4261.75	Italy	3857.03
India	3964.15	**New Zealand**	3842.50
Bahrain	3943.67	Turkey	3582.12
New Zealand	3607.68	**U.A.E.**	3410.58
Germany	3188.68	Singapore	3319.07
Belgium	2714.72	**U.S.**	3304.45
Finland	2501.10	Canada	3233.08
Brazil	2424.18	**Mexico**	2986.15
Chile	2373.75	**Germany**	2808.13

Note: Countries that appear in both rankings are shown in bold.

Figure 2 shows the wheat trade flows within and between each of the six regions considered, namely North America (including Central America and the Caribbean), South America, Europe (including Ukraine), Africa, Asia (including Russia) and Oceania. The E-I index of WTN (2009–2013) and WTN (2014–2018) are 0.125 and 0.163, respectively, which means within-region trading has increased in the last five years. In particular, although the wheat trade between European countries is significant, most regions have more trade with the rest of the world than within Europe. An extreme case is Africa, whose trade corresponds to imports from Europe, Asia and North America, in that order. In the case of Asia, although its exports are mainly within the region, the imports come mainly from outside the region, in particular from North America and Europe, in that order. The pairs of regions for which the density of arcs is higher than the overall network density are: North-America ⇔ North America, North America ⇒ South America, South America ⇔ South America, South-America ⇒ Africa, South America ⇒ Asia, Europe ⇔ Europe, Europe ⇒ Africa, Europe ⇔ Asia, Asia ⇔ Asia, Oceania ⇒ Asia and Oceania ⇔ Oceania. Note also the trade balance (total exports minus total imports) for the different regions; it is positive, large and with an upward trend through the period 2014–2018 for Europe (an increase of 17% of exports with respect to 2009–2013) and North America (18%), positive and moderate for Oceania and South America (WTN 2009–2013) and negative and large for Africa and Asia, and South America (WTN 2014–2018). The negative trade balance of South America is due to the decline in exports to Europe (a reduction of 86% respect 2009–2013), Oceania (86%) and Africa (77%) during the period 2014–2018.

WTN (2009–2013)



WTN (2014–2018)

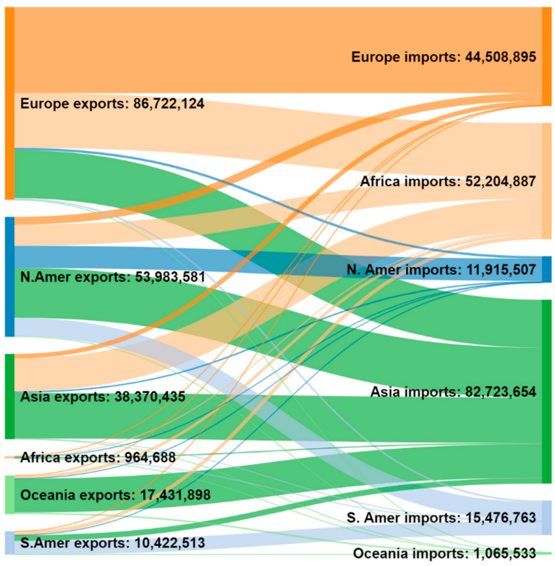


Figure 2. Cross-regional distribution of wheat trade flows (in tonnes) (2009–2013) and (2014–2018).

3.2. *Exponential Random Graph Modelling of Global Wheat Trade Flows Network*

To test the hypothesis that the observed structure of the WTN (2009–2013) and WTN (2014–2018) can be explained by local processes and that is significantly different from random chance, we have carried out an ERGM fit to identify the significant local substructures that are present or absent with more frequency than could be expected by simple randomness using ERGM estimation software [43]. In the ERGM model, the response variable is the log-odds of creating a network tie and the estimated coefficients are considered as log-odds ratios, restricted in the remainder of the network. As the network is directed, the model tests the influence of every attribute for both importing and exporting wheat trading ties. The structural and nodal attributes' parameters considered in the construction of the ERGMs are shown in Table 5. Several control variables are considered in the ERGMs in order to improve the model fit. Edge term is the baseline likelihood of wheat trade tie formation, Mutual term controls the reciprocated wheat trade ties character of a country. Note that [44,45] highlight the presence of reciprocal trade within agricultural trade networks.

Table 5. Statistics variable definitions in the ERGM model.

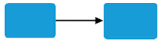
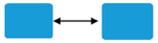
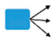
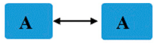
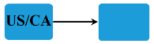
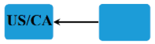
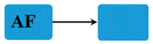
Variable		Configuration	Statistic	Definition (Source) [Measure Unit]
Network structure effects	Edges		$\sum_{i \neq j} y_{i,j}$	A baseline propensity for a country to form a link with another country.
	Mutual		$\sum_{i \neq j} y_{j,i} y_{i,j}$	The network nodes contribute to form interactions.
	# of active import countries: 11		$\sum_j y_{j,i},\ k_j^{in} = 11$	Countries with 11 import partners.
	# of active import countries: 12		$\sum_j y_{j,i},\ k_j^{in} = 12$	Countries with 12 import partners.
	# of active import countries: 13		$\sum_j y_{j,i},\ k_j^{in} = 13$	Countries with 13 import partners.
	# of active import countries: 14		$\sum_j y_{j,i},\ k_j^{in} = 14$	Countries with 14 import partners.
	# of active import countries: 15		$\sum_j y_{j,i},\ k_j^{in} = 15$	Countries with 15 import partners.
	# of active export countries: 2		$\sum_j y_{i,j},\ k_j^{out} = 2$	Countries with two export partners.
	# of active export countries: 3		$\sum_j y_{i,j},\ k_j^{out} = 3$	Countries with three export partners.
	# of active export countries: 4		$\sum_j y_{i,j},\ k_j^{out} = 4$	Countries with four export partners.
	# of active export countries: 5		$\sum_j y_{i,j},\ k_j^{out} = 5$	Countries with five export partners.

Table 5. *Cont.*

Variable		Configuration	Statistic	Definition (Source) [Measure Unit]
Node attribute effects	Homophily (Same region indicator)		$\sum_{i\neq j} y_{i,j}\delta^1{}_{i,j}$	Number of links in which the exporter and importer belongs to the same region, $\delta^1{}_{i,j} = 1$, counted separately for each possible region, $\delta^1{}_{i,j} = 0$ otherwise. Regions: North America; South America; Europa; Africa; Asia; Oceania. if importer and exporter
	Gross Domestic Product (Importer country)		$\sum_{i\neq j} y_{i,j}\mathrm{GDP}_{i,j}$	Gross Domestic Product of importer country, purchasing power parity terms (constant 2017 billion international dollars).
	Exporter's land surface		$\sum_{i\neq j} y_{i,j}\mathrm{LAND}_{i,j}$	The amount of land in the exporter country that is potentially cultivable (in thousand hectares).
	US or Canada source country		$\sum_{i\neq j} y_{i,j}\delta^2{}_{i,j}$	Number of links involving US or Canada as exporter country, $\delta^2{}_{i,j} = 1$, $\delta^2{}_{i,j} = 0$ otherwise.
	US or Canada destination country		$\sum_{i\neq j} y_{i,j}\delta^3{}_{i,j}$	Number of links involving US or Canada as importer country, $\delta^3{}_{i,j} = 1$, $\delta^3{}_{i,j} = 0$ otherwise.
	Origin region: S. America		$\sum_{i\neq j} y_{i,j}\delta^4{}_{i,j}$	If the source of exports comes from a country in the South America region, $\delta^4{}_{i,j} = 1$, $\delta^4{}_{i,j} = 1$ otherwise (reference group: North America).
	Origin region: Europe		$\sum_{i\neq j} y_{i,j}\delta^5{}_{i,j}$	If the source of exports comes from a country in the Europe region, $\delta^5{}_{i,j} = 1$, $\delta^5{}_{i,j} = 0$ otherwise.
	Origin region: Africa		$\sum_{i\neq j} y_{i,j}\delta^6{}_{i,j}$	If the source of exports comes from a country in the Africa region, $\delta^6{}_{i,j} = 1$, $\delta^6{}_{i,j} = 0$ otherwise.
	Origin region: Asia		$\sum_{i\neq j} y_{i,j}\delta^7{}_{i,j}$	If the source of exports comes from a country in the Asia region, $\delta^7{}_{i,j} = 1$, $\delta^7{}_{i,j} = 0$ otherwise.
	Origin region: Oceania		$\sum_{i\neq j} y_{i,j}\delta^8{}_{i,j}$	If the source of exports comes from a country in the Oceania region, $\delta^8{}_{i,j} = 1$, $\delta^8{}_{i,j} = 0$ otherwise.
	Destination region: S. America		$\sum_{i\neq j} y_{i,j}\delta^9{}_{i,j}$	If the exports destination is a country in the South America region, $\delta^9{}_{i,j} = 1$, $\delta^9{}_{i,j} = 0$ otherwise. (Reference group: North America)
	Destination region: Europe		$\sum_{i\neq j} y_{i,j}\delta^{10}{}_{i,j}$	If the exports destination is a country in the Europe region, $\delta^{10}{}_{i,j} = 1$, $\delta^{10}{}_{i,j} = 0$ otherwise.
	Destination region: Africa		$\sum_{i\neq j} y_{i,j}\delta^{11}{}_{i,j}$	If the exports destination is a country in the Africa region, $\delta^{11}{}_{i,j} = 1$, $\delta^{11}{}_{i,j} = 0$ otherwise.
	Destination region: Asia		$\sum_{i\neq j} y_{i,j}\delta^{12}{}_{i,j}$	If the exports destination is a country in the Asia region, $\delta^{12}{}_{i,j} = 1$, $\delta^{12}{}_{i,j} = 0$ otherwise.
	Destination region: Oceania		$\sum_{i\neq j} y_{i,j}\delta^{13}{}_{i,j}$	If the exports destination is a country in the Oceania region, $\delta^{13}{}_{i,j} = 1$, $\delta^{13}{}_{i,j} = 0$ otherwise.

#: Number of.

To check the scale-free structure in the WTN, degree-related terms are included in the model as endogenous structural characteristics. In particular, based on previous network topology analysis, the number of active import countries (11–15) and number of active export countries (2–5) have been considered as covariates, their inclusion will enable the validation of the hypothesis of propensity in exporting partners' concentration and importing partners' diversification, reflecting the asymmetric bilateral relationship in the international wheat trade.

Additional variables that consider exogenous country-level characteristics are included in the proposed ERGM model. Thus, geographic homophily (i.e., whether the wheat trade partner belongs to the same geographical region) is tested in the formation of a trade network as a measure of geographical closeness [46,47]. Gross Domestic Product (GDP) is also incorporated in the model as a measure of the economy size and can capture the country's trade openness to international wheat trade [37,48,49]. Another covariate labelled Exporter's Land Surface is considered to detect if the size of the arable land influences the export capacity of a country [50]. Two other categorical attributes, namely the USA or Canada, exporter countries and the USA or Canada, importer countries, detect trade between the world countries and these two leading wheat exporters [51]. Lastly, the direction of the international wheat trade flows from/to each region was included using two binary variables for each of the five regions considered (using the North America region as the reference region).

The proposed model is based on an extensive exploration process using model selection criteria: the convergence of MCMC-MLE estimates, the minimum Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Table 6 shows the Monte Carlo Maximum Likelihood (ML) estimates ("while controlling" for the other parameters in the model) and standard deviation, and the significance tests performed on each parameter of the ERGM built, together with their AIC and BIC goodness of fit measures. The parameters that are coincident in both network models are unanimous in terms of significance and its direction. Note that first we test the networks with just two basic terms: Edges (which explains density) and mutual (which explains reciprocity). Both network models were estimated and tested for each network, starting with the basic model that incorporates only edges and mutual relations. Both terms are significant. Like most observed networks, the sign of the edge parameter estimates is negative [52], meaning that trade links are not likely to be formed randomly. The latter is also evidence that the tendency to create trade relations between countries is not predominant without the presence of other effects. A strong and significant reciprocity effect, ceteris paribus, is detected, i.e., import-export relations between partners has a positive influence on wheat trade connections tendency for the basic model, and also for the extended model. Estimated coefficients range from 2.149 to 2.484, i.e., in the case of the WTN (2009–2013) proposed model the probability of a wheat trade link between the country i to the country j is 8.58 (exp (2.149)–1) times higher if there is also a wheat trade link between the country j to the country i. The proportionality drops slightly to 8.38 in WTN (2014–2018).

The refined model includes the number of partners as structural variables as well as other exogenous attribute-based variables. The number of importing partners and number of exporting partners of a country have significant effects, but in opposite direction, in wheat networks. The number of importing (exporting) partners of a country has a negative (positive) effect across the proposed models, indicating that a country has 11–15 partners (2–5 partners) decreases (increases) the conditional log-odds of countries wheat links connections. However, the number of exporting partners is a positive. In the case of WTN (2009–2013), the influence is stronger in countries with 11–14 importing partners, and in WTN (2014–2018) the effect is more prominent in countries with 2–4 exporting partners.

Table 6. ERGM fit (Monte Carlo ML method) for WTN (2009–2013) and WTN (2014–2018).

Parameter	ERGM Term	WTN (2009–2013)		WTN (2014–2018)	
		Basic Model	Proposed Model	Basic Model	Proposed Model
Network structure effects	Edges	−2.962 *** (0.023)	−3.335 *** (0.005)	−2.897 *** (0.025)	−3.187 *** (0.005)
	Mutual	2.481 *** (0.065)	2.149 *** (0.005)	2.419 *** (0.063)	2.238 *** (0.005)
	# of active import countries: 11	-	−1.970 *** (0.010)	-	-
	# of active import countries: 12	-	−1.409 *** (0.011)	-	-
	# of active import countries: 13	-	−2.633 *** (0.013)	-	−0.874 *** (0.007)
	# of active import countries: 14	-	−1.799 *** (0.010)	-	−0.615 *** (0.007)
	# of active import countries: 15	-	-	-	−1.416 *** (0.009)
	# of active export countries: 2	-	-	-	5.428 *** (0.025)
	# of active export countries: 3	-	0.310 *** (0.011)	-	3.341 *** (0.023)
	# of active export countries: 4	-	0.081 *** (0.011)	-	2.362 *** (0.021)
	# of active export countries: 5	-	0.038 *** (0.008)	-	0.320 *** (0.016)
Nodal attribute effects	Homophily (Same region indicator)	-	0.144 *** (0.003)	-	0.197 *** (0.003)
	Gross Domestic Product (Importer country)	-	3.611×10^{-5} *** (7.532×10^{-6})	-	2.740×10^{-5} *** (6.777×10^{-6})
	Exporter's land surface	-	2.497×10^{-5} *** (5.747×10^{-7})	-	2.193×10^{-5} *** (5.634×10^{-7})
	USA or Canada source country	-	1.178 *** (0.016)	-	1.482 *** (0.016)
	USA or Canada destination country		0.013 *** (0.015)	-	0.099 *** (0.015)
	Source reg_S. America	-	−0.4755 *** (0.006)	-	−0.378 *** (0.004)
	Source reg._Europe	-	0.0664 *** (0.004)	-	0.593 *** (0.004)
	Source reg._Africa	-	−0.613 *** (0.005)	-	−0.241 *** (0.004)
	Source region_Asia	-	−0.4309 *** (0.004)	-	−0.304 *** (0.005)
	Source reg._Oceania	-	−0.262 *** (0.007)	-	−0.137 *** (0.007)
	Destination reg._S. America	-	−0.408 *** (0.007)	-	−0.341 *** (0.007)
	Destination reg._Europe	-	0.364 *** (0.005)	-	0.352 *** (0.005)
	Destination reg_Africa	-	0.108 *** (0.004)	-	0.107 *** (0.005)
	Destination reg._Asia	-	0.039 *** (0.005)	-	0.091 *** (0.005)
	Destination reg_Oceania	-	−0.383 *** (0.008)	-	−0.475 *** (0.008)

Table 6. *Cont.*

Parameter	ERGM Term	WTN (2009–2013)		WTN (2014–2018)	
		Basic Model	Proposed Model	Basic Model	Proposed Model
Model diagnostics	L (θ_M)	−10,463.4	−8581.40	−10,253	−8773.5
	AIC	20,862	20,173	20,498	17,600
	BIC	20,879	20,311	20,515	17,806
	Goodness of fit	0.01	0.18	0.06	0.19

Note: Estimate (Std. Error); (***): p-value ≤ 0.01; (**): 0.01 < p-value ≤ 0.05; (*): 0.05 < p-value ≤ 0.10 (two-tailed tests). Goodness of fit: {1-[L(θ_M)/ L(θ_0)]}·100, where L(θ_M) is the log-likelihood of the proposed model and L(θ_0) is the log-likelihood of the null model (only the arcs terms). #: Number of.

The effects of nodal attributes are also coincident in significance and sign in both networks. The results also show that the estimated coefficient of wheat trade relationships between countries belong to the same region (i.e., the region-homophily effect), is positive and significant in both WTN's. The log-odds of a within-region tie is 0.197 greater than an across-region tie, which means that in terms of odds ratio, wheat trade between countries that belong to the same region is 1.217 more likely than between countries that do not belong to the same geographical region. This suggests a slight propensity for countries to form ties with others of the same region due to lower transportation costs, language and cultural similarity, more complete market information and free trade agreements [53].

Conversely, economic size of the importing countries and land area of the exporter country have a positive significance but with a poor explanatory power in links formation. In the case of land area of the exporter country, the estimated effect on the log of the odds of a 1 km^2 change in the land surface of 2.497×10^{-5} and 2.197×10^{-5}, respectively. The covariates associated with wheat trade flows where the US or Canada acts as exporter or importer are also positive and significant. In particular, wheat trade flows where the US or Canada act as suppliers were exp (1.178) = 3.248 times and exp (1.482) = 4.402 times, respectively, more likely than other wheat trade flows, and wheat trade flows where the US or Canada acts as clients were exp (0.013) = 1.013 times and exp (0.099) = 1.104 more likely than others. These results reflect that the US and Canada have achieved a position of dominance in global wheat trade and indicates the importance of role as wheat exporter and to a lesser extent as importer.

A more detailed analysis of the geographic features of the WTN reveals that the likelihood of wheat export ties from South American, African, Asian and Oceanian countries were lower (considering as the reference category the North American region) than expected by chance in a random network. The opposite occurs for the effects of wheat exports from Europe, which are positive, indicating a higher likelihood than expected by chance. Regarding importers, the only significant and positive coefficients are for Europe, Asia and Africa, regions where the odds of these attribute effects are exp (0.0664) = 1.068 and exp (0.593) = 1.809, respectively. The importers by region analysis also show significant trade links formation in all the regions, with Europe, Africa and Asia showing a higher likelihood (considering North America as reference region) than expected by chance in a random network. The results confirm that the observed WTNs can be explained as emerging from the superposition of local effects.

The extended model for each network converged at the sixth-WTN (2009–2013) and the 14th WTN (2014–2018) iteration out of 20 iterations. Convergence suggests that wheat trade linkages are not excessively diverse to be captured by the same model. The MCMC sample size was 10,000 and the MCMC interval was also 10,000. The proposed model has the best overall fit (lowest AIC and BIC). Model adequacy and Goodness-of-fit statistics are provided in the supplementary material section (see Figure S1), where the corresponding statistics on the observed networks, namely, in-degree, out-degree, edge-wise shared partners and minimum geodesic distance are not significantly different from the average statistics in a set of networks simulated based on the model parameters. The plots show that the proposed models for WTN (2009–2013) and WTN (2014–2018) are a good representation of the observed networks. The models tend to slightly underestimate the number of countries with one and eight import partners, and also overestimate the trade links of up to six shared partners (WTN-2009–2013) and up to seven shared partners (WTN-2014–2018).

4. Discussion

In the present situation, when food security is facing major challenges due to climate change, abiotic stresses, land degradation and commodity prices volatility, understanding the global wheat market fundamentals and how countries interact may allow producers, consumers and policymakers to plan more efficiently and foresee the changes in the near future. Accordingly, we have analysed and described the characteristics of the WTN, using data for the period 2009–2018. Previous research applied network measures to analyse its network structure but did not use endogenous and exogenous factors to analyse trade formation in the WTN. In this paper, ERGMs have been fitted to test whether the global structure of the WTN can be explained by local patterns and attributes. The characterisation analysis has shown that the WTN corresponds to a small world with moderate reciprocity and a scale-free structure during the period 2009–2018. The ERGM results have revealed that the overall structure of WTN can be explained using some local variables that drive the trade connectedness. In particular, the significant factors include whether the two trading partners belong to the same geographical region (regional homophily), whether the exporter country is the US or Canada and which are the source and destination regions of the trade flow. A lower rate of wheat trade connections can be predicted if the importer country is the US or Canada. Finally, the likelihood of a formation of a trade tie decreases with the land surface of the exporting country and the GDP of importer country.

There are several topics for future research. The inclusion of additional variables in the importer/exporter database, such as greenhouse gas emissions and irrigated water rates per country in order to consider GHG and water footprint of wheat production. The conjoint analysis could provide relevant information for governments, policymakers and companies, and will allow the identification and promotion of effective environmental, social and governance (ESG) practices in the wheat industry. There is also scope to expand the analysis to international organic wheat trade, given the expansion of organic agriculture among farmers and consumers worldwide. The comparison between the conventional and organic wheat trade networks could reveal different topological patterns and different network formation processes. The results could also lead to strategies and policies for reinforcing developing countries' competitive position.

Supplementary Materials: The following are available online at http://www.mdpi.com/2073-4395/10/12/1967/s1, Figure S1. Goodness of fit diagnostics for ERGM-WTN (2009–2013) and ERGM-WTN (2014–2018)

Author Contributions: Conceptualization: E.G.-M., S.L. and B.A.-D.; methodology: E.G.-M., S.L. and B.A.-D.; software: E.G.-M. and S.L.; writing—original draft: E.G.-M., S.L. and B.A.-D.; visualization: E.G.-M., S.L.; funding acquisition: B.A.-D. All authors have read and agreed to the published version of the manuscript.

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