Characterisation and analysis of the international agro-food trade network

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Overview

Overview

A World of Food

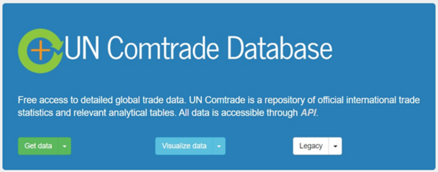
International trade in agro-food products consist of complex relationships between countries. Global food safety and sustainability is a growing concern; understanding the underlying structures at different scales is thus essential to promote well-being. Our aim is to evaluate the states of the world trade from the perspective of networks.

Overview

Data source

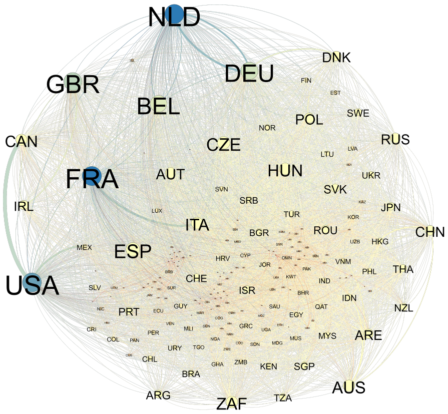
United Nations Comtrade Database (UN Comtrade) offers global trade data on an annual basis. We get import trade data from 2001 to 2020. The fields are the following:

- yr : year
- rt3ISO : reporter country (i.e.: 'USA')
- pt3ISO : partner country (i.e: 'FRA')
- cmdCode : commodity code [1, ... , 23]
- TradeValue : import value in $U\$D$ dollars



Link: https://comtrade.un.org/

Network Topology



- Graph → weighted, directed
- Nodes → Countries
- Edges → Country A imports from country B
- Weight → Trade Values

Agro-Food Trade in livestocks, 2015

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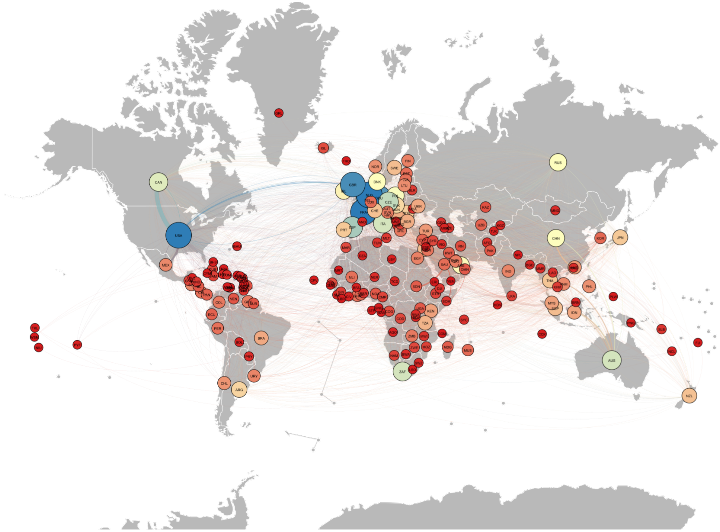


Network topology

Metric	2012	2013	2014	2015
$G_{year}(N, L)$	$G_{2012}(192, 3618)$	$G_{2013}(198, 3835)$	$G_{2014}(198, 3850)$	$G_{2015}(194, 3922)$
Average degree	18, 84	19, 37	19, 44	20, 22
Diameter	5	5	5	5
Density	0, 10	0, 10	0, 10	0, 10
Strongly Cntd Components	44	47	48	37
Weakly Cntd Components	1	1	1	1
In-Degree Centrality	USA-FRA-NLD	USA-FRA-NLD	NLD-USA-DEU	FRA-NLD-CAN
Closeness Centrality	USA-FRA-NLD	USA-FRA-NLD	NLD-USA-DEU	FRA-NLD-USA
Betweenness Centrality	CAN-ARE-LKA	SGP-CAN-ZAF	CAN-THA-SGP	ZAF-THA-IND
Eigenvector Centrality	NLD-USA-FRA	NLD-DEU-FRA	NLD-USA-DEU	NLD-DEU-DNK
PageRank Centrality	DEU-USA-NLD	DEU-NLD-USA	NLD-DEU-USA	DEU-NLD-USA
Total Trade (U$S millions)	20.523	21.192	22.845	20.868

Table: Agro-Food Trade Networks metrics from 2012 to 2015 (livestock commodity).

Degree Distribution

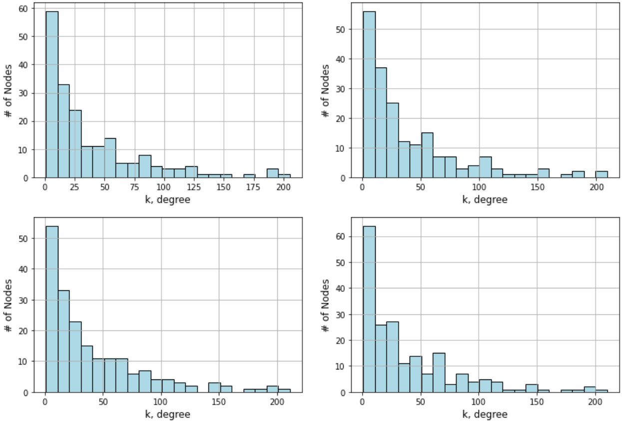


Figure: Livestock commodity WTN from 2012 to 2015, clockwise starting from top left

Scale Free property

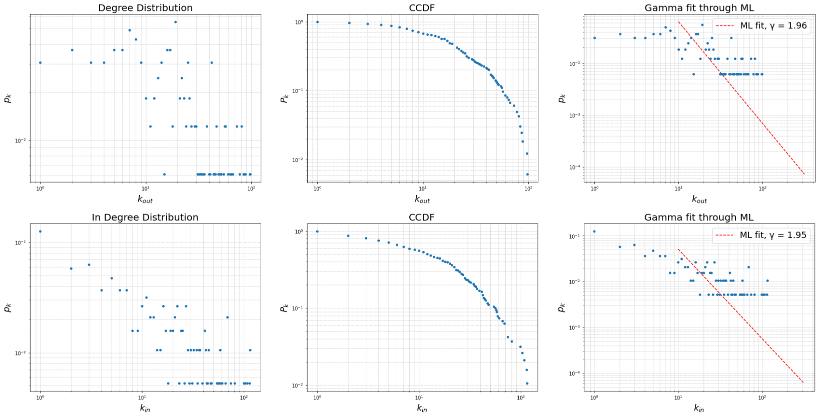


Figure: Degree distribution, CCDF and power-law fits

The Key Players

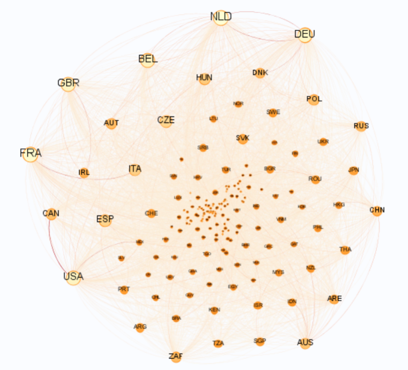


Figure: Authorities on WTN livestock commodity, 2015

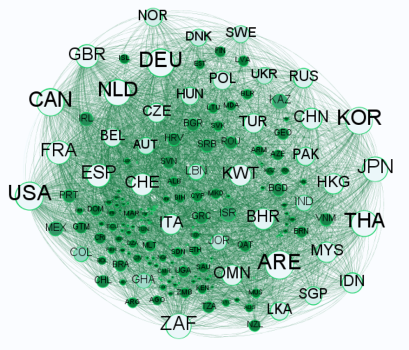


Figure: Hubs on WTN livestock commodity, 2015

Top 5 centralities

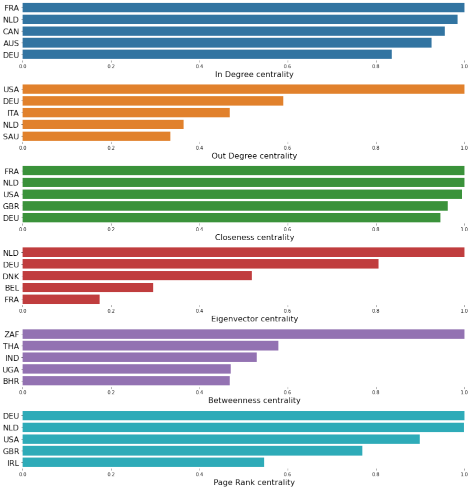
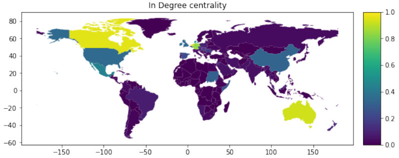
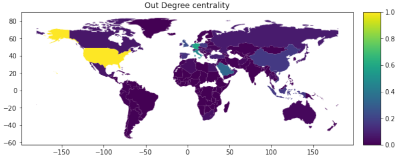
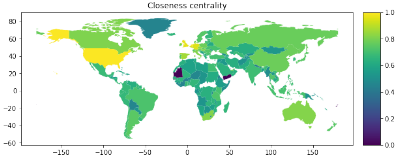


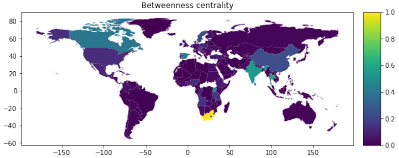
Figure: Top 5 countries by centrality.

Centrality maps









Overview

Community detection algorithms

1. Based on dynamics
   - *Infomap* [Rosvall and Bergstrom, 2008].
   - *Walktrap* [Pons and Latapy, 2005]
   - *Label propagation* [Raghavan et al., 2007].
2. Based on statistical mechanics
   - *Spinglass* [Reichardt and Bornholdt, 2006]
3. Based on optimisation
   - *The Louvain modularity* [Blondel et al., 2008].
   - *Louvain Surprise* [Traag et al., 2015].

Community detection algorithm	Number of clusters	Modularity
Walktrap	34	0.46
Infomap	30	0.54
Label propagation	14	0.49
Spinglass	5	0.18
Louvain Modularity	9	0.11
Louvain Surprise	156	−0.005

Table: Different algorithms results for commodity livestock and year 2015.

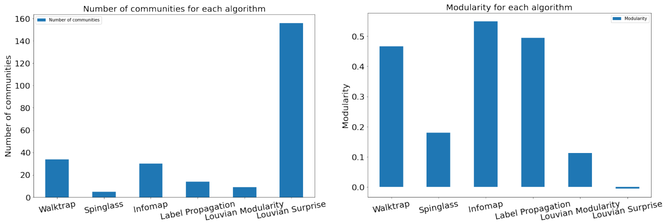


Figure: Number of communities and the modularity found by each algorithm.

Results on livestock commodity year 2015

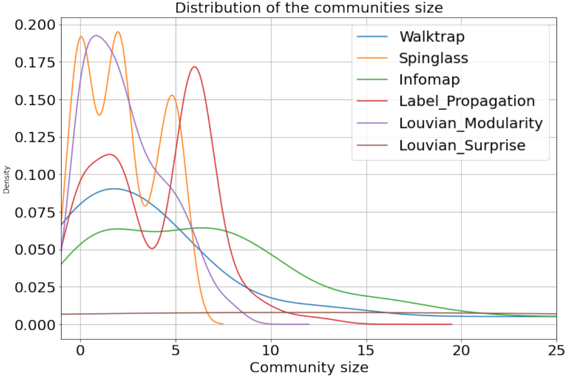


Figure: Size distribution of the communities.

Communities for livestock 2015

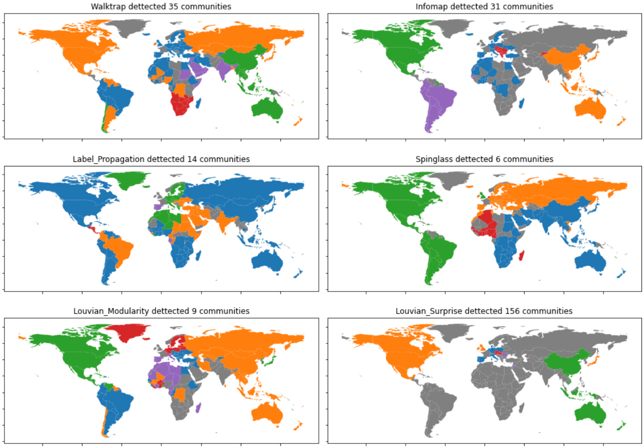
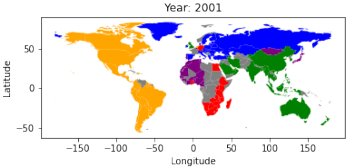
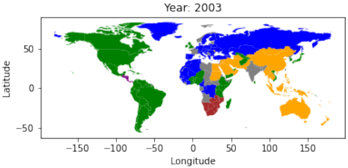


Figure: Geographical visualisation of the 10 biggest communities encountered by each algorithm.

Communities identification

How can we say that the yellow community identified in 2001 is the same as the green community identified in 2003?

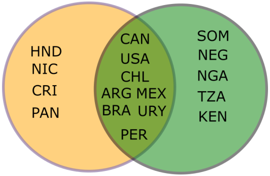


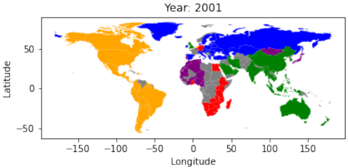


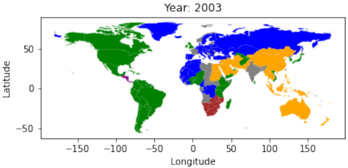
Communities identification

Our proposal is to introduce an index that we call *sharedness* s:

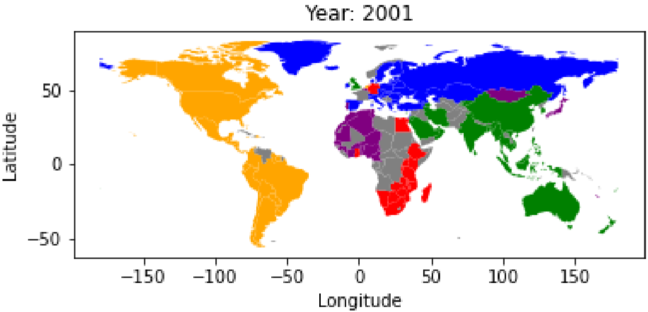
$$s(A,B) = \frac{|A \cap B|}{|A \cup B|} \qquad (1)$$





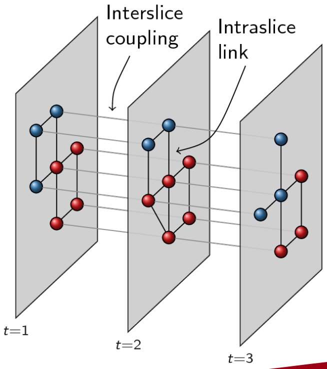


Results



Multilayer networks

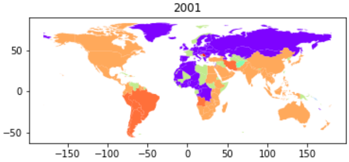
- In order to account for the diversity of commodities in trade, we explor a multilayer model.
- Multilayer networks can model both intralayer and interlayer edges between the nodes
- For the matter at hand, we use a multiplex network, which has fixed nodes across all layers

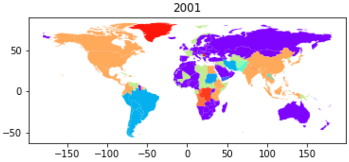


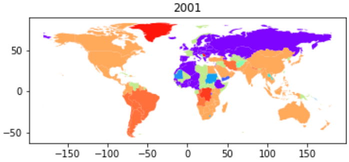
Algorithm 1 MNLPA

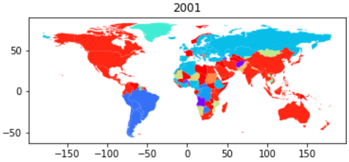
```
labels ← 1 : N_countries
shuffle(nodes)
while condition ≠ true do
    for node in nodes do
        scores[labels] ← 0
        for neighbour in node.filtered_neighbours do
            curr_label ← neighbour.label
            scores[curr_label] ← scores[curr_label] + edges[neighbour, node].weight
        end for
        node.label ← argmax(scores)
    end for
end while
```

Time evolution









Modularity

Using the multiplex modularity $\sum_l \frac{\omega_l}{m_l} \sum_{i,j} \left(A^l_{i,j} - S^{in,l}_i S^{out,l}_j \right) \delta_{c_i,c_j}$, a significative value has yet to be reached

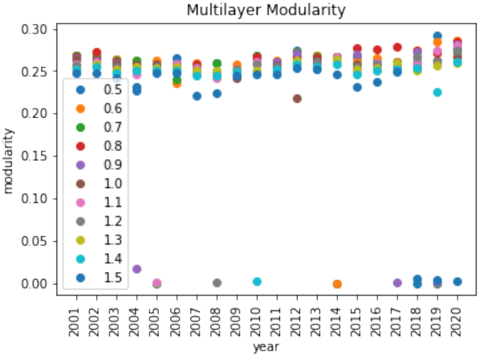


Figure: Modularity for the mnlpa results on different neighbour thresholds

Overview

Definition

The Robustness quantify the ability of the network to withstands failures and perturbations[Barabási and Márton, 2016]. We distinguish two measures to describe the functioning of the network:

Robustness Metrics

1. The *Largest Strongly Connected Cluster (LSCC)* is the natural extension of LCC for directed graph. LSCC is a widely used measure of the network functioning; it is the highest number of (strongly) connected nodes in the network. This value is normalized with respect to the LSCC of the total network (before the attacks).
2. The IMP ratio, which is an *ad hoc* metrics thought to express how changes the percentage volume of a country's imports on average:

$$IMP = \frac{1}{N} \sum_{c}^{N} \frac{\text{tot. import of c after the attack}}{\text{tot. import of c before the attack}}$$

with N the number of countries.

Attack Strategies

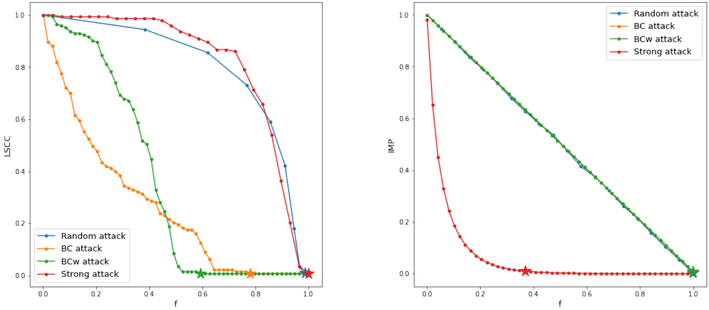
In particular we are interested in the response of the network to the removal of links. The Robustness has been tested for different kinds of attack removal strategies[Bellingeri et al., 2020].

Attack Strategies

- **Rand**: links are randomly removed. This represent the possibility of links failure in the network.
- **Strong**: links are removed in decreasing order of weight, i.e. links with higher weight are removed first and it represents an attack directed to strong links.
- **BC**: links are removed according their betweenness centrality (BC). The betweenness centrality of a link accounts the number of shortest paths from any couple of nodes passing along that link. Links with higher betweenness centrality are deleted first.
- **BCw**: links are removed according to their weighted betweenness centrality (BCw), i.e. links with higher BCw are deleted first.

Robustness analysis

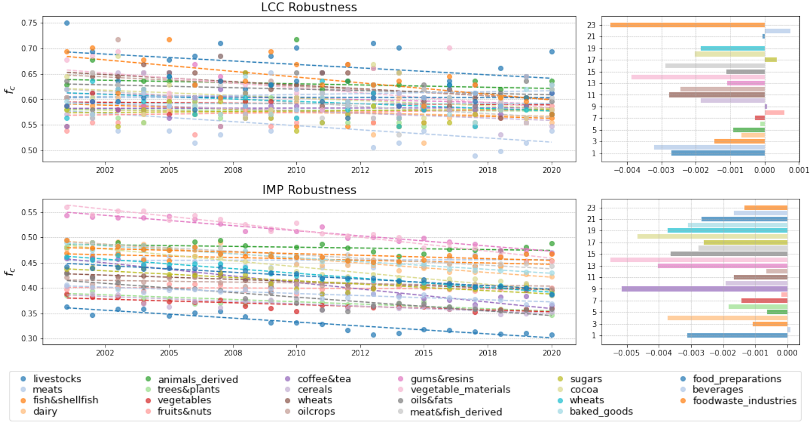
To characterise the evolution of the network's Robustness need a way to compare the response to failures among different networks: we assume that the Robustness of a network is well represented by f_c, the fraction of links to be removed in order to lower the given metrics by 99%.



Time Analysis

For this studies the attacks are performed according to the most effective removal strategy for the given Robustness measure; we consider the best link removal strategy as the one able to produce the faster functioning decrease in the network. In other words, the strategy able to select most important links in the networks[Bellingeri et al., 2020].

Robustness over time



Overview

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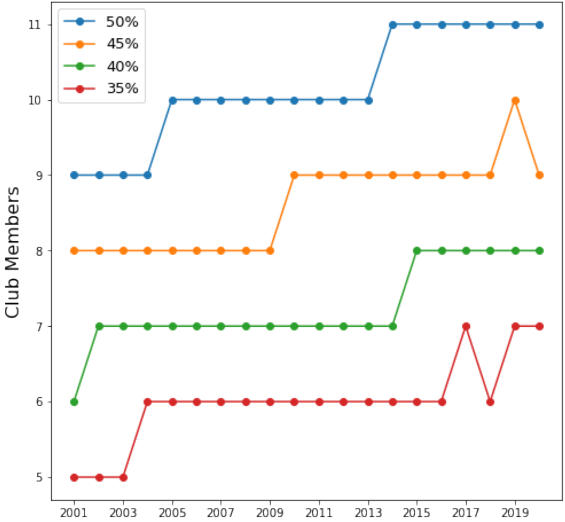
Rich Club

Taking inspiration from the work of Kunal Bhattacharya et al.[Bhattacharya et al., 2007] we tried to investigate the time evolution of the "Rich Club", the lobby of countries controlling half of the world agro-food market. The slice of the market of a given country is assumed to be the total value of its export.

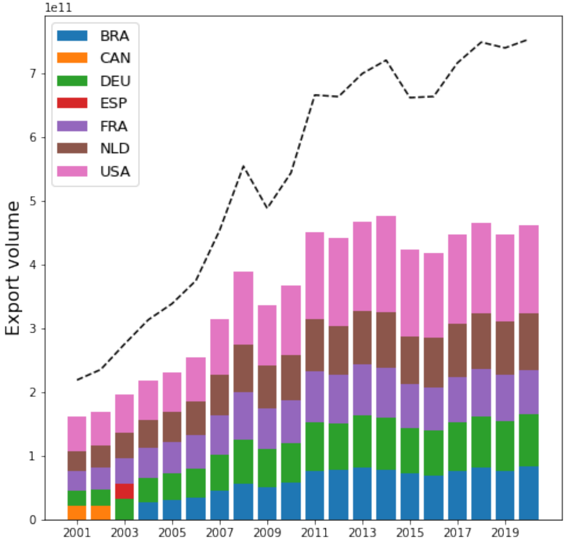
For each year we are considering the aggregated network, consisting of all the different commodities.

For this purpose we first counted the number of countries belonging to the Rich Club year by year. Then we studied how evolves the slice of the market controlled by the top 5 countries.

The Rich Club



The Rich Club



Overview

Conclusions

- We managed to build a network with data from the COMTRADE database and show its general properties.
- The centrality measures prove to be useful to provide insights about the market configuration.
- Only the dynamics based algorithms manage to detect communities with a meaningful modularity measure.
- We manage to identify the communities along the time, which would allow the analysis of their evolution.
- We showed that the multi layer approach can be useful to identify communities along different commodities.
- We managed to show that the network for different commodities tend to be less robust along time.

Author Contributions

- **J. C. Arganaraz:** Network characterization, Centrality measures and other metrics.
- **H. Capettini:** Centrality measures, Community detection, Time evolution of the communities.
- **G. Carmona:** Data collection, multilayer community detection analysis, community mapping heuristics for time evolution.
- **L. Rinaldi:** Robustness Analysis, Robustness evolution over time, Rich Club.

Thanks for your attention!

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