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Spatial organization and drivers of the virtual water trade: a community-structure analysis

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Abstract

The trade of agricultural commodities can be associated with a virtual transfer of the local freshwater resources used for the production of these goods. Thus, trade of food products virtually transfers large amounts of water from areas of food production to far consumption regions, a process termed the 'globalization of water'. We consider the (time-varying) community structure of the virtual water network for the years 1986–2008. The communities are groups of countries with dense internal connections, while the connections are sparser among different communities. Between 1986 and 2008, the ratio between virtual water flows within communities and the total global trade of virtual water has continuously increased, indicating the existence of well defined clusters of virtual water transfers. In some cases (e.g. Central and North America and Europe in recent years) the virtual water communities correspond to geographically coherent regions, suggesting the occurrence of an ongoing process of regionalization of water resources. However, most communities also include countries located on different 'sides' of the world. As such, geographic proximity only partly explains the community structure of virtual water trade. Similarly, the global distribution of people and wealth, whose effect on the virtual water trade is expressed through simple 'gravity models', is unable to explain the strength of virtual water communities observed in the past few decades. A gravity model based on the availability of and demand for virtual water in different countries has higher explanatory power, but the drivers of the virtual water fluxes are yet to be adequately identified.

Keywords: virtual water network, water globalization

1. Introduction

Most of the human appropriation of freshwater resources is for food production, while only a small fraction is spent for

Content from this work may be used under the terms of the Creative Commons Attribution-NonCommercial-ShareAlike 3.0 licence. Any further distribution of this work must maintain attribution to the author(s) and the title of the work, journal citation and DOI. drinking, household or industrial usage (e.g. Falkenmark *et al* 2004, Hanjra and Qureshi 2010). Societies historically relied on local water resources to produce the food they consume, and imported from other regions only a limited amount of agricultural products. In recent years, however, the escalating growth of international trade of food commodities has made societies increasingly reliant on food produced in other parts of the world (Hoekstra and Chapagain 2008, Mekonnen and Hoekstra 2011, Carr *et al* 2012). It has been noted that food

trade may lead to a long distance dependency on foreign water resources and that, by importing or exporting food commodities, we virtually transfer the water required for the production of these goods (Allan 1998).

Virtual water trade has allowed some societies to sustain rates of demographic growth that exceed the limits determined by the local hydrological conditions. Moreover, virtual water transfers may be used for water solidarity towards regions affected by drought and crop failure. By mitigating conditions of water deficit, virtual water trade may prevent social unrest and water wars (Barnaby 2009). However, it has been found that the current patterns of virtual water trade are driven by gross domestic product (Suweis et al 2011) rather than water solidarity (Seekell et al 2011). Overall, virtual water trade plays a crucial role in (virtually) modifying the geographic distribution of freshwater resources, affecting the rates of demographic growth, and creating a disconnection between people and the resources they use (D'Odorico et al 2010, Hoekstra and Mekonnen 2012, Carr et al 2012). It is therefore crucial to investigate the global patterns of virtual water transfers and identify some of the underlying drivers.

Virtual water trade can be represented as a network of fluxes among a number of countries in different regions of the world. For each pair of trading partners (or 'nodes') two fluxes (in opposite directions) may exist. Thus, virtual water trade occurs through a directed network of trade among nodes. In recent years research in complex system analysis has developed a number of theories and methods for the analysis of the structure and function of network systems (Albert and Barabasi 2002, Boccaletti et al 2006, Barrat et al 2008). These methods have been used as a framework for the analysis of the organization underlying the emergence of the virtual water network (Suweis et al 2011, Konar et al 2011) and its temporal evolution (Carr et al 2012, Dalin et al 2012). This research has shown that the virtual water network exhibits 'small world' properties (Milgram 1967), whereby most pairs of vertices are connected through only a small number of links. Moreover the virtual water network is clustered: most vertices (countries, in this case) have only a limited number of links, while only a few countries (or 'hubs') have many connections to other vertices of the network. While these hubs have more options in the selection of partners for virtual water trade, most of the vertices in the network are connected to the global system by only a few links. In the last two decades the number of connections and their strength has almost doubled. This increase in connectivity and in the globalization of virtual water resources did not happen by simply adding new links to an existing network. Many links have been discontinued, reactivated or rewired while the network has maintained only a few permanent links (Carr et al 2012). It is still unclear how this intermittent character of the network configuration translates into changes in the structure of virtual water trade partnerships. The existence of clusters of trading partners within a network is typically investigated by detecting the community structure of the network (e.g. Fortunato 2010). This analysis determines groups (or 'communities') of nodes defined in a way that pairs of nodes belonging to the same community are more likely

to be connected by a link than pairs of nodes from different communities (e.g. Newman 2004). This paper investigates the spatiotemporal dynamics of virtual water trade through changes in the community structure of the virtual water network. In particular, it evaluates and discusses a variety of factors determining the emergence and disappearance of clusters of trading partners and highlights the emergence of some regional patterns embedded in the global network of virtual water trade.

2. Methods

Virtual water trade data were obtained following a two-step procedure (see Carr et al 2012 for details). Firstly, starting from the FAOSTAT database (http://faostat.fao.org/site/406/ default.aspx) we reconstructed 23 years (1986-2008) of international global trade data for 309 crops and animal products, including all the major agricultural commodities. Secondly, food trade data for each commodity were converted into virtual water trade values and added together to obtain for each year the total virtual water transferred between pairs of trading partners. The conversion to virtual water estimates was done using the country-specific average water footprint of each product (Mekonnen and Hoekstra 2011) accounting only for blue and green water consumption associated with the production of each food commodity. The virtual water trade was represented through non-symmetrical matrices, W (one matrix per year), whose elements (i, j) represent the virtual water flux from node *i* to node *j*. The corresponding network is a weighted directed graph. Overall, we considered 253 countries as the network nodes, but their exact number changed from year to year because of political events (e.g. the collapse of the USSR and Yugoslavia in 1992). Each node is characterized by its degree (i.e. the number of export links connected to that node) and strength (i.e. the sum of the fluxes through links connected to that node).

Community detection in graphs has recently drawn the attention of a number of authors (see for example the review by Fortunato 2010). Here, we partition the network into M non-overlapping communities, $\mathbf{C} = \{C_1, C_2, \ldots, C_M\}$, using a method based on the maximization of the modularity Q, proposed by Newman and Girvan 2004 and modified by Newman (2004). This procedure is applied every year to the weighted directed networks of virtual water trade. Modularity is defined as the following sum over all pairs of nodes

$$Q = \frac{1}{S} \sum_{ij} \left(s_{ij} - \frac{s_i^{\text{out}} s_j^{\text{in}}}{S} \right) \delta(C_i, C_j), \tag{1}$$

where *S* is the sum of the fluxes through all the network edges, s_{ij} is the actual flux through the edge connecting node *i* to node *j* (from *i* to *j*), s_i and s_j are the strengths of vertices *i* and *j*, respectively, and the δ -function yields one if vertices *i* and *j* are in the same community (i.e. $C_i = C_j$), and zero, otherwise. Moreover the 'in' and 'out' superscripts indicate that the strength of a node is calculated based only on that node's import or export links, respectively. The underlying

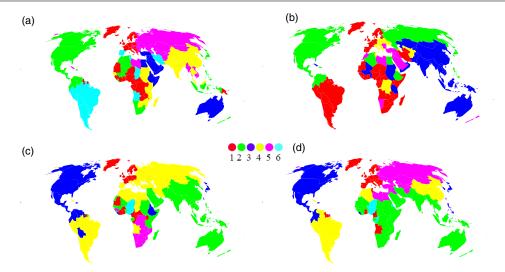


Figure 1. Community structure of VW network in 1986 (a), 1992 (b), 2002 (c) and 2008 (d). The communities are ordered from the highest to lowest modularity and the corresponding community-colour is shown in the centre of the figure.

idea is to assume as the null model, a random graph where nodes have the same strength distribution as the real network, and the edge weights (i.e. fluxes) are those that would be expected to exist only on the basis of the vertex strengths (i.e. $s_i^{\text{out}} s_j^{\text{in}}/S$). The null model is thus expected not to have a community structure, which corresponds to Q = 0; positive values of Q, in contrast, indicate the existence of a community structure in the original network. In particular, the partition $\{C_i\}$ (i = 1, ..., M) that maximizes the value of Q gives the community structure of the network. Notice that different numbers of partitions (i.e. M) are explored in the process of maximization of Q.

To obtain the community structure maximizing Q we use the fast greedy technique proposed by Blondel *et al* (2008). This method has been shown to perform well in applications to benchmark networks (Lancichinetti and Fortunato 2009). The arrangement of the rows and columns in the W matrix (i.e. the manner in which countries are sorted) may have an effect on the detection of the community structure, because the algorithm may be stuck in local maxima instead of identifying the global maximum of Q. In order to avoid possible spurious community partitions due to sensitivity to initial conditions, community detection was repeated one hundred times starting from different random initial arrangements of the nodes. In most cases, the same community structure was obtained; however, sometimes weak differences occurred. In those cases, the partition with the highest modularity was selected.

In order to compare different community structures we adopted the normalized mutual information (Danon *et al* 2005, Fortunato 2010)

$$I(\mathbf{C}, \mathbf{D}) = \frac{2[H(\mathbf{C}) - H(\mathbf{C}|\mathbf{D})]}{H(\mathbf{C}) + H(\mathbf{D})},$$
(2)

where $\mathbf{C} = \{C_i\}$ and $\mathbf{D} = \{D_j\}$ are the two community partitions to be compared, $H(\mathbf{C}|\mathbf{D})$ is the conditional entropy of **C** given **D**, and $H(\mathbf{C})$ and $H(\mathbf{D})$ are the Shannon entropies (e.g. Papoulis 1984) of **C** and **D**, respectively. When I = 1 the partitions are identical, while if I = 0 they are independent.

To assess whether the community structure of virtual water (VW) trade can be explained by external variables (e.g. geographic distances or gross domestic product), we use the mutual information to compare the community of virtual water with the communities defined on the basis of these variables. The geography-based communities (model 1) are obtained using the greedy technique on the (symmetrical) 'proximity matrix', whose elements (i, j) are defined as $(d_{\text{max}} - d_{ii})$, where d_{ii} is the geographical distance between the most populated cities of country i and country j (based on the dataset www.cepii.fr) and d_{max} is the maximum value of all distances between nodes in the network. We also consider other possible driving variables, including human population, gross domestic product, and water demand and availability, all evaluated at the country level. In each case gravity-law-based communities (e.g. Barigozzi et al 2011) are obtained from a matrix whose elements are $W_{ij} = Q_i Q_j / d_{ij}$, where Q_i and Q_j are the populations of the countries *i* and *j*, respectively (model 2); the GDP of *i* and *j* (model 3); the availability of water for food production in country *i* and the VW demand in country j (model 4). Global data set for population (www.gapminder.org/data/documentation/ gd003/) was utilized with GDP from United Nations (http:// unstats.un.org/unsd/snaama/dnllist.asp). Values of in-country water availability for food production and of country-specific VW demand were obtained from Mekonnen and Hoekstra (2011, tables I and VIII, respectively).

3. Results and discussion

The community structure of the virtual water network has undergone substantial changes in the course of the past two to three decades (figure 1). It is possible to recognize some patterns in the course of the study period. For example, The Netherlands, France and Germany have always been the backbone of the community (based mostly in Western Europe) that has the highest modularity, i.e. of the community with the tightest bonds among countries.

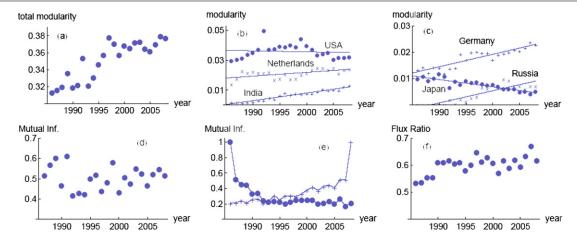


Figure 2. Top row: changes in time of the total network modularity (a) and the modularity of some countries (b) and (c). Bottom row: mutual information between consecutive years (d), or with respect to 1986 (circles) or 2008 (crosses) (e); ratio between fluxes internal to communities and total network fluxes (f).

Here we define the community 'backbone' as the set of countries of a community, which have the highest modularity and—altogether—contribute to at least 50% of the community's modularity. Eastern Europe and Russia were part of this community in the 1993–7 period (not shown), but for the rest of the study period Russia remained in a separate community encompassing Eurasia and (episodically) also countries in North Africa and the Middle East. Southern Europe frequently changed communities, demonstrating connections with eastern European countries and the former Soviet Union. In the last few years, however, all the European countries (except the former USSR) have been in the same community. Interestingly, over time this community has lost most of its non-European (i.e. south American and African) partners.

The USA, Canada, Central America and Japan consistently belonged to the same community. The USA and Canada are currently the backbone of this community but until 1991 Japan was part of this backbone too. The modularity of the USA–Canada community was the second highest until 2001, when it was exceeded by the community located along the Indian Ocean–South Pacific shorelines. The modularity of this Indian Ocean–South Pacific community has been the second highest since 2002 with a backbone that consists of India, Indonesia, Malaysia and Australia. In some years, China, Thailand and Argentina also contributed to the backbone of this community (not shown). Notice that Indochina, Indonesia and Australia were in different communities until 1989, when they switched to the 'Indian Ocean–South Pacific' community.

In 1986 most South American countries were in the same community as Spain and Portugal. In the early 1990s they switched—along with Spain and Portugal—to the community with the highest modularity (mostly western European countries), and in the early 2000s to the Eurasia–Southern Europe community. Starting from 2003 most of South America has been in the same community as China or in the Indian Ocean–South Pacific community (2005–7, not shown), consistent with the intensification of VW transfer from South America to Southeast Asia (e.g. the increase in the importation of soy by China) reported by Carr *et al* (2012). The northern part of Latin America (Venezuela, Colombia and Ecuador), however, is consistently associated with the USA–Canada community, which episodically expands also into Peru and Bolivia. Central America is also always within the USA–Canada community.

Despite its apparent complexity, the community structure of African countries exhibits some well defined patterns. For instance, the influence of the highest modularity community (i.e. with backbone in Germany, France and The Netherlands) has decreased over time, while the connections with the Indian Ocean–South Pacific community have increased and become predominant, at least for East Africa. At the same time, North African countries repeatedly changed their association with virtual water trade communities. However, in recent years the Eurasian community has expanded into part of North Africa, with a belt spanning from Russia to Libya through the Caucasus and the Middle East countries (except for Saudi Arabia, which has consistently remained linked to the Indian Ocean community).

It can be noticed that the community structure of virtual water trade also reflects some of the trade partnerships resulting from political alliances and that some of the changes can be directly associated with political events. For instance, Cuba, which in 1986 was in the same community as the former USSR (along with Eastern Europe, Libya, Cambodia, Vietnam and Burma), has recently switched to the community that contains most of South America. As noted before, the USA has consistently been in the same community with Canada, Central America, Japan and (most of the time) South Korea. Moreover, Namibia's split from South Africa, or the reliance of the former Soviet Union on food imports from the USA right after the collapse of the USSR explain some of the temporary changes in community structure observed in the early 1990s.

The increase over time in the total modularity of the network (figure 2) indicates an enhancement in the clustering of virtual water trade. Thus, despite the intermittent character

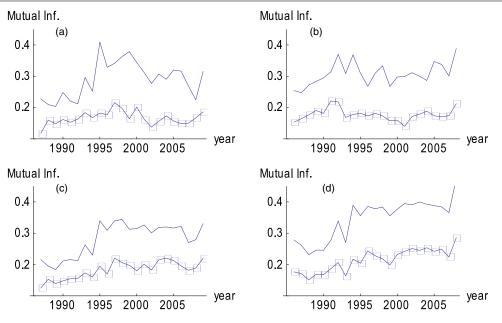


Figure 3. Changes in time of the mutual information between VW trade communities and geographic communities (a) or gravity-law-based communities using population (b), GDP (c) or VW availability and demand (d) as the explanatory variables. The mutual information considering all countries (circles) or countries with population larger than one million (crosses) are shown in the graphs.

of the network, the increase in the number of connections and the increased magnitude of virtual water fluxes (Carr *et al* 2012), trade is becoming more and more organized in communities with an increasing fraction of virtual water flows remaining segregated within each community. Communities have an overall structure that is determined by the major trading countries and tend to behave more like 'closed systems', as evidenced by the fact that the fluxes internal to each community are increasing at a faster rate than the total fluxes in the global virtual water network (figure 2(f)).

However, this increase in the total modularity is not the result of a generalized increase in the modularity of all countries. A closer examination of the modularity of individual countries reveals that, for some countries it is increasing (e.g. The Netherlands, Germany, India and Russia), while for others it is decreasing, demonstrating a relatively weaker connection of these countries with their own communities (e.g. Japan and Italy). Finally, other countries (e.g. China, not shown) maintain an almost constant modularity in spite of their increase in trade (figures 2(b) and (c)). This suggests that these countries are intensifying their trade without preferentially choosing trading partners within their own community.

The one-year mutual information is here used as a measure of the relation and degree of dependence existing between the community structures in two consecutive years. The fact that the one-year mutual information remains relatively high—around 0.5—throughout the study period (figure 2(d)), indicates that changes in the community structure occur on timescales longer than one year. The mutual information calculated using as a reference configuration the first (1986) or the last (2008) year of the study period indicates that community structure has evolved over time. However, the similarity is overall greater with the last year than with the first year of the study period (figure 2(e)).

The relatively low mutual information (when evaluated for all countries) between the community structure of virtual water trade and communities obtained based on distances (figure 3(a)) or using a gravity model for population (figure 3(b)), GDP (figure 3(c)) or VW availability and demand (figure 3(d)) demonstrates that geography and these other variables (at least in the way they are described by these simple reference models) do not play a strong a role in determining the community structure of VW.

However, when only countries with more that one million people are considered (about 160 countries), the mutual information dramatically increases, in particular when one considers VW availability and demand as the driving forces of VW trade (figure 3(d)). The mutual information also exhibits a positive trend in the course of the study period, particularly in the comparison with communities based on the gravity laws. This result indicates that VW trade among medium-to-large countries (in term of population) is becoming increasingly dependent on both the distance between trade partners and their populations or GDP.

4. Conclusions

This paper has developed an analysis of the community structure of the virtual water network and highlighted the existence of well defined communities in which virtual water trade within each community is much stronger than between countries from different communities. In the 1986–2008 period the ratio between virtual water flows within communities and the total global trade of virtual water has continuously increased, indicating the existence of increasingly better defined clusters of virtual water trade. In some cases these communities correspond to geographically coherent regions, suggesting the occurrence of an ongoing process of regionalization of water resources. However, most communities include countries located on different 'sides' of the world; our analysis has shown that geographic proximity only partly explains the community structure of virtual water trade. Similarly, the global distribution of people and wealth (i.e. GDP), as expressed by simple 'gravity models', is unable to explain the strength of virtual water communities observed in the past few decades. A gravity model based on the demand for and availability of virtual water in different countries has higher explanatory power, but the drivers of the virtual water fluxes are yet to be adequately identified.

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