Temporal dynamics of blue and green virtual water trade networks

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[1] Global food security increasingly relies on the trade of food commodities. Freshwater resources are essential to agricultural production and are thus embodied in the trade of food commodities, referred to as "virtual water trade." Agricultural production predominantly relies on rainwater (i.e., "green water"), though irrigation (i.e., "blue water") does play an important role. These different sources of water have distinctly different opportunity costs, which may be reflected in the way these resources are traded. Thus, the temporal dynamics of the virtual water trade networks from these distinct water sources require characterization. We find that 42×10^9 m^3 blue and 310×10^9 m^3 green water was traded in 1986, growing to 78×10^9 m^3 blue and 594×10^9 m^3 green water traded in 2008. Three nations dominate the export of green water resources: the USA, Argentina, and Brazil. As a country increases its export trade partners it tends to export relatively more blue water. However, as a country increases its import trade partners it does not preferentially import water from a specific source. The amount of virtual water that a country imports by increasing its import trade partners has been decreasing over time, with the exception of the soy trade. Both blue and green virtual water networks are efficient: 119×10^9 m^3 blue and 105×10^9 m^3 green water were saved in 2008. Importantly, trade has been increasingly saving water over time, due to the intensification of crop trade on more water-efficient links.

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1. Introduction

[2] The international food trade is essential for food security [*Hanjra and Qureshi*, 2010] and leads to a global redistribution of freshwater resources. This redistribution of water through international food trade is due to the water embodied in the production process of the traded commodities [*Hoekstra and Chapagain*, 2008]. In other words, water resources that are physically utilized in the country of production are "virtually" transferred to the country of consumption, in a "virtual water trade." Thus, globalization in the trade of food commodities has not only alleviated food insecurity, but has also led to a globalization of water resources [*Hoekstra and Chapagain*, 2008], with potential implications for water security [*D'Odorico et al.*, 2010].

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[3] Food production is inextricably linked and reliant upon freshwater resources. For this reason, the vast majority of surface and groundwater (i.e., "blue" water) resources goes toward agricultural production [*Rosegrant et al.*, 2002; *Rost et al.*, 2008]. However, this does not mean that agriculture is primarily produced using irrigation water supplies. In fact, agriculture is predominantly rain-fed (i.e., produced using "green" water). Approximately 60%–70% of the global food supply is produced on rain-fed lands [*Falkenmark and Rockstrom*, 2004]. Green water supplies remain important even on lands with irrigation infrastructure, because blue water is often only applied to crops when the rainfall is insufficient to meet optimal crop growth [*Rost et al.*, 2008]. When water requirements for grazing lands are considered, the dominance of green water in agricultural production becomes even more apparent [*Falkenmark and Rockstrom*, 2004].

[4] It is essential to distinguish between freshwater sources embodied in food trade, because blue and green water use have dramatically different opportunity costs and environmental impacts [*Aldaya et al.*, 2010]. Blue water is water that comes from rivers, lakes, reservoirs, ponds, or aquifers. For this reason, blue water requires conveyance facilities to the point of end use. With this infrastructure, blue water is a highly mobile resource able to be substituted between water users (e.g., municipal, industrial, recreation, or environmental). Blue water has a direct cost associated with it, due to its infrastructure requirement, as well as a high opportunity cost, since there are many potential end users of blue water resources [*Yang et al.*, 2006; *Aldaya et al.*, 2010].

Additionally, excessive irrigation can lead to soil salinization, water logging, and soil degradation, which are indirect costs of blue water, in addition to the environmental impacts associated with dam construction and operation [*Postel*, 1999; *Aldaya et al.*, 2010].

[5] The concept of green water was introduced by *Falkenmark* [1995]. Green water refers to the water that is stored in the unsaturated zone of soil and available for evapotranspiration by crops. Green water is highly immobile, making it difficult to substitute to other water users and leading to it having a low opportunity cost of production. For this reason, green water is primarily utilized either in rainfed agriculture or by natural vegetation [*Yang et al.*, 2006]. However, it should be noted that both blue and green water are components of the hydrological cycle, so they are not completely distinct [*Rockstrom et al.*, 1999]. In this paper we separate blue and green water to explore how the unique attributes of each water source are embodied in trade.

[6] The virtual water literature has focused on the ability of food importing countries to address water scarcity by importing food. However, *Yang et al.* [2006] highlight the importance of the water endowments and resource use efficiency of food exporting countries. Analyzing virtual water trade using the tools of network theory has been presented as a methodology to explicitly quantify both the directed features of trade and the volumes of embodied water resources [*Konar et al.*, 2011]. We argue that the network approach presents a consistent framework within which the global properties of the water and food systems as linked through trade can best be explored. The temporal dynamics of the global virtual water trade network have been established [*Dalin et al.*, 2012; *Carr et al.*, 2012], but the temporal dynamics of the virtual water trade network broken down by water source still require elucidation.

[7] The importance of considering the water source in the virtual water literature has been highlighted [*Hoekstra and Chapagain*, 2008; *Aldaya et al.*, 2010; *Siebert and Döll*, 2010; *Fader et al.*, 2011]. However, the unique characteristics of blue and green virtual water trade have not yet been analyzed using a network approach. In this paper we apply the tools of network theory to blue and green virtual water trade to address the following questions: (1) How has the trade of green and blue virtual water resources changed over time? (2) Do the green and blue virtual water trade networks exhibit different structures? (3) How does the direction of trade impact the flow of blue and green virtual water resources? (4) Is the international trade of green and blue virtual water resources efficient and how is this efficiency changing in time?

2. Network Construction

[8] Here we describe the construction of the blue and green virtual water trade networks associated with the global food trade from 1986 to 2008. The nodes of the networks are countries that participate in international food trade in each year. Links between nodes are directed based on the direction of the food trade and weighted by the volume of virtual water embodied in the traded agricultural commodities in each year. Yearly trade data from the Food and Agricultural Organization (FAO) and yearly blue and green virtual water content estimates from the H08 global hydrological model [*Hanasaki et al.*, 2010] were used to build the networks.

2.1. Virtual Water Content

[9] For a time series analysis, it is essential to estimate the virtual water content (VWC) of each product in each year. This was done for each nation of production by water withdrawal source (i.e., either blue or green water) from 1986 to 2001 using the H08 global hydrological model [*Hanasaki et al.*, 2008a, 2008b, 2010]. The H08 model consists of six modules: land surface hydrology, river routing, crop growth, reservoir operation, environmental flow requirements, and water withdrawal for human use. We do not go into detail on the H08 model here, but instead refer the interested reader to *Hanasaki et al.* [2010].

[10] We calculated the VWC of five unprocessed crops: barley, corn, rice, soy, and wheat; as well as three unprocessed livestock products: beef, pork, and poultry. VWC is defined as the total evapotranspiration ($\overline{ET}$) during a cropping period [kg m^{-2}] divided by the total crop yield (Y) [kg m^{-2}], e.g., $\text{VWC} = \overline{ET}/Y$. The VWC of unprocessed livestock products is defined as the water consumption per head of livestock [kg head^{-1}] divided by the total weight per head of livestock [kg head^{-1}]. From 1986 to 2001 VWC was calculated using the national crop yield time series data from FAOSTAT [*FAOSTAT*, 2011] and yearly estimates of $\overline{ET}$ simulated with the H08 model [*Hanasaki et al.*, 2008a, 2008b, 2010]. Thus, VWC is a country-specific estimate of the volume of water used to produce a unit of agricultural output [*Hanasaki et al.*, 2010].

[11] Importantly, the H08 model tracks $\overline{ET}$ water use by source: green and blue. Since H08 tracks the source of crop water use, the total $\overline{ET}$ of a particular crop in a particular location can be broken down into the fraction of $\overline{ET}$ originating from blue and green water sources. In the H08 model, blue water originates from either streamflow, medium-sized reservoirs, or nonlocal and nonrenewable sources. The model assumes that irrigation supplies are available to meet crop water requirements. In this way, the H08 model may overestimate the blue $\overline{ET}$ fraction. However, the model does not estimate irrigation delivery loss, which may lead to underestimation [*Hanasaki et al.*, 2010]. Thus, using the H08 model, we obtain estimates of the virtual water content of each unprocessed agricultural item indexed by water source.

[12] Two types of input data are used to force the H08 model: land use and meteorological. For land use, the global distribution of cropland [*Ramankutty et al.*, 2008], major crops [*Monfreda et al.*, 2008], irrigated areas [*Siebert et al.*, 2005], and cropping intensity [*Döll and Siebert*, 2002] were used to run the model. These data were fixed to the year 2000 and were regridded for consistency with the spatial resolution of the meteorological forcing data. For meteorological data, the H08 model is forced with WATCH data [*Weedon et al.*, 2011], available at a 0.5° spatial resolution at 6 h intervals from 1901 to 2001. For this reason, H08 estimates of yearly VWC end in 2001. Thus, we only have yearly estimates of VWC from H08 from 1986 to 2001 for this study.

[13] To obtain yearly estimates of VWC for the remainder of our time frame, we utilize national crop yield statistics from the FAO [*FAOSTAT*, 2011]. To do this, the

evapotranspiration component of VWC was fixed to the year 2001, the last year of the H08 model simulation. Crop yield data from 2002 to 2008 was then used to obtain estimates of VWC from 2002 to 2008 according to the equation

$$VWC_{e,c,s,t} = \frac{\overline{ET}_{e,c,s,2001}}{Y_{e,c,t}}, \tag{1}$$

where the subscripts e, c, s, and t correspond to the country of production (and export), the raw crop, the water source, and year, respectively. Note that the total VWC will change yearly according to changes in yield data during the 2002–2008 period. However, the VWC fraction originating from blue and green water sources will remain fixed to 2001 values. Additionally, there is no yield data for livestock products from the FAO, so the VWC of livestock from 2002 to 2008 is kept constant at 2001 values.

2.2. Trade Data

[14] The bilateral trade of staple food commodities from 1986 to 2008 was obtained from the FAO [*FAOSTAT*, 2011]. In particular, we obtained trade data on 58 commodities stemming from the unprocessed crop and livestock products for which we have yearly virtual water content estimates from the H08 model (i.e., barley, corn, rice, soy, wheat, beef, pork, and poultry; refer to Table 1 for the commodity list). Even though we only consider 58 commodities in this analysis, these are the staple food commodities that account for over 60% of global calorie consumption [*FAOSTAT*, 2011] and embody the dominant virtual water flows [*Hoekstra and Hung*, 2005; *Hanjra and Qureshi*, 2010].

[15] We utilize both the import and export trade matrices reported by each country in each year. When one country reports a trade link, but the other country does not, the trade volume is taken as the reported value. In 2008 there are 27,991 times that one country reports a trade link but the other country does not across 58 commodities. However, this is a relatively small percentage (i.e., 1.5%) of the 1,879,200 potential links. When two different values are reported, then the average of the two reported values is used. The mean difference in the reported values between two countries is approximately 10 t. If no data was reported, then we assumed that no trade was occurring.

[16] Note that some countries report the final destination country, while others report the first destination. This makes it difficult to distinguish between export and re-export in the FAO trade matrices, which is significant for some trade hubs, such as the Netherlands and the United Arab Emirates [*U.S. Agricultural Trade Office*, 2010]. Due to this inconsistency in FAO data, the trade of countries that are major trade hubs and those that process commodities for re-export may be overestimated in this analysis. In

Table 1. List of Commodities and the Yield Ratio (r), Price Ratio (p), and Content Ratio (c); Reproduced From *Hanasaki et al.* [2010]

Crop Commodities	r	p	c	Livestock Products	r	p	c
Wheat	1	1	1	Cattle meat	0.6	0.61	1
Flour of wheat	0.78	0.97	1	Offal of cattle, edible	0.32	0.38	1
Bran of wheat	0.22	0.024	1	Fat of cattle	0.04	0.0024	1
Macaroni	0.78	0.97	1	Meat-cattle boneless (beef and veal)	0.6	0.61	1
Germ of wheat	0.025	0.01	1	Cattle, butchered fat	0.04	0.0024	1
Bread	0.78	0.97	0.71	Preparation of beef	0.4	0.61	1
Bulgur	1	1	1	Pig meat	0.7	0.88	1
Rice, paddy	1	1	1	Offal of pigs, edible	0.12	0.12	1
Rice, husked	0.72	1	1	Fat of pigs	0.06	0.006	1
Milled husked rice	0.72	1	1	Pork	0.49	0.88	1
Rice, milled	0.65	0.95	1	Bacon and ham	0.49	0.88	1
Rice, broken	0.65	0.95	1	Pig, butchered fat	0.06	0.006	1
Bran of rice	0.07	0.049	1	Pork sausages	0.49	0.88	1
Rice, bran oil	0.013	0.049	1	Prepared pig meat	0.49	0.88	1
Cake rice bran	0.057	0.049	1	Lard	0.06	0.006	1
Rice, flour	0.65	0.95	1	Chicken meat	0.53	0.95	1
Rice, fermented beverages	0.48	0.95	0.36	Offal and liver of chicken	0.022	0.014	1
Barley	1	1	1	Fat liver prepared (foie gras)	0.022	0.014	1
Pot barley	0.46	0.76	1	Chicken meat canned	0.53	0.95	1
Barley, pearled	0.46	0.76	1	Fat of poultry	0.022	0.013	1
Bran of barley	0.54	0.24	1	Fat of poultry, rendered	0.022	0.013	1
Barley flour and grits	0.46	1	1				
Malt	0.78	1	1				
Malt extract	0.78	1	0.8				
Beer of barley	0.78	1	0.14				
Maize	1	1	1				
Germ of maize	0.115	0.18	1				
Flour of maize	0.8	0.75	1				
Bran of maize	0.085	0.068	1				
Maize oil	0.04	0.18	1				
Cake of maize	0.075	0.18	1				
Soybeans	1	1	1				
Soybean oil	0.19	0.35	1				
Cake of soybeans	0.76	0.65	1				
Soya sauce	0.76	0.65	0.17				
Maize, green	1	1	1				
Maize for forage and silage	1	1	1				

other words, it is impossible to distinguish production and consumption flows in all cases using FAO trade data. However, this problem plagues all studies based on FAO trade flows, of which most virtual water trade studies are based upon.

2.3. Building the Networks

[17] Estimates of VWC by water source and FAO bilateral crop trade data allow us to construct the blue and green virtual water trade networks. In these networks, each nation participating in international food trade is a node, and the links represent the blue and green volume of virtual water flow between nations. This virtual water flow is calculated by multiplying the agricultural trade between nations by the blue and green VWC of that commodity in the country of export in the year of trade.

[18] The virtual water trade between two nations e and i in year t is given by

$$W_{e,i,s,t} = \sum_{a} VWC_{e,a,s,t}\left[\sum_{x\in a}\frac{p_x c_x}{r_x}T_{e,i,x,t}\right], \tag{2}$$

where the subscripts e, i, s, t, a, and x denote the exporting country, importing country, water source (i.e., blue or green), year, agricultural item (i.e., unprocessed crop or livestock item), and commodity, respectively. The notation $x \in a$ indicates the ensemble of commodities that are produced from the raw agricultural item a. $T_{e,i,x,t}$ is the annual trade from exporting country e to importing country i of commodity x in year t. $W_{s,t}$ is the virtual water trade between nations (m^3 yr^{-1}) indexed by water source and time period and aggregated over all commodities considered in the international food trade. For this reason, we will refer to W as the "aggregate" network throughout this paper, as opposed to a particular commodity or combination of commodities.

[19] The VWC of raw crops is transformed into that of a processed commodity by multiplying by the $p_x c_x / r_x$ coefficient, which does not vary in time. Values of r, p, and c are specific to commodity x and are provided for each of the 58 commodities in Table 1. The price ratio (p) is the ratio between the price of the raw crop and the price of the commodity produced from that raw crop. The content ratio (c) indicates the percentage of a particular processed commodity that originates from the raw crop. The yield ratio (r) quantifies the fraction of the raw crop that goes into the processed commodity.

[20] One example of this transformation is that of raw soybeans into the processed soybean oil commodity. The coefficients of soybean oil are $r = 0.19$, $p = 0.35$, and $c = 1$. This indicates that 0.19 kg of soybean oil can be obtained from 1 kg of raw soybeans. The ratio of prices between soybean oil and raw soybeans is 0.35:1. Soybean oil is made exclusively (i.e., 100%) from raw soybeans, so $c = 1$. Thus, the VWC of soybean oil is $0.35 \times 1/0.19 = 1.84$ times that of raw soybeans, indicating that more water is required to process raw soybeans into soybean oil [*Hanasaki et al.*, 2010].

3. Global Flows and Structure by Water Source

[21] We first consider how some of the global characteristics of the green and blue virtual water trade networks change over time. From Figure 1 it is clear that the number of links has gone up significantly, from approximately 3000 links in 1986 to about 6800 links in 2008. Similarly, the mean number of trade partners (k) has increased as well. The mean number of export trade partners (k_{out}) increased from 29 in 1986 to 48 countries in 2008, while the mean number of import trade partners (k_{in}) has increased from 16 in 1986 to 35 countries in 2008. Note that, unsurprisingly, the number of links and mean number of trade partners are very similar for both the blue and green networks (refer to Figure 1). This is what we expect, because these measures do not yet account for the volumes of virtual water traded. Instead, these measures simply count the links and trade relationships with embodied blue or green water.

[22] The distribution of the number of export trade partners was shown to follow an exponential distribution in the year 2000, while the distribution of the number of import trade partners does not follow an exponential distribution in 2000. The tail of the distribution of the data of import trade partners is skinnier than the exponential distribution tail, indicating that countries meet their import requirements with less trade relationships [*Konar et al.*, 2011]. This relationship holds over the 1986–2008 time period [*Dalin et al.*, 2012]. We show that this topology holds for the trade of both blue and green virtual water. Thus, the mean number of export trade partners (circles in Figure 1b) represents the parameter of the exponential distribution in each year.

[23] More green water is traded than blue water. Additionally, the volume of green water traded has grown faster than that of blue (refer to Figure 1c). The volume of blue

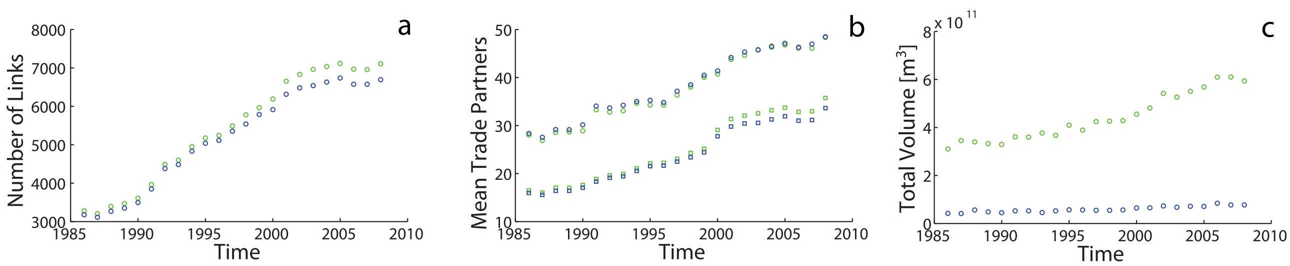

Figure 1. Characteristics of blue and green virtual water trade networks. (a) Number of links over time; (b) mean export trade partners (circles) and mean import trade partners (squares) over time; and (c) total volume of the network over time. In all plots, green points represent virtual water from green sources and blue points represent virtual water from blue sources.

water traded in 1986 was 0.42×10^{11} m^3, growing to 0.78 $\times$ 10^{11} m^3 in 2008. The volume of green water traded, on the other hand, was an order of magnitude higher at 3.10 $\times$ 10^{11} m^3 in 1986, growing to 5.94×10^{11} m^3 in 2008. It makes sense that more green water is embodied in agricultural trade since the majority of agricultural production is rain-fed. Additionally, exporting green water constitutes a low opportunity cost in water use for major exporting countries [*Aldaya et al.*, 2010].

[24] Three countries dominate the export of green water: the USA, Argentina, and Brazil (refer to Table 2). The largest volumes of green virtual water export are associated with the soy, wheat, and corn trades. The USA, Argentina, and Brazil are the top three exporters of green virtual water from corn and soy, but the top three exporters of green virtual water from wheat are the USA, Argentina, and Russia. Note that these values are for the year 2008 and help to explain the significance of Russia's wheat export ban following intense fires in 2010.

[25] From Table 2, note that the ranking of countries in terms of virtual water exported by crop changes when the type of water is considered. For example, the USA, India, and Pakistan are the top three exporters of blue virtual water, while Argentina and Brazil fall to position 6 and 9, respectively. These changes are due to both climatic and technological considerations of the countries of export. Some countries with very inefficient irrigation practices and arid climates are highlighted, such as Iraq and Morocco, both in the top five exporters of blue virtual water for barley and corn, respectively. While these countries do export these crops and associated commodities, it is really their exceptionally high blue VWC (i.e., highly inefficient use of blue water per unit of crop) that drives them to be in the top exporters of blue virtual water. However, note that the volumes of blue water exported by Iraq and Morocco are relatively small, 0.09×10^9 m^3 and 0.11×10^9 m^3, respectively.

[26] Table 2 highlights a major problem with FAO trade data. The FAO does not distinguish between export and re-export, which is evident as the United Arab Emirates features in the top blue virtual water exporters in Table 2, due to the prominent role of Dubai as a major trade hub [*U.S. Agricultural Trade Office*, 2010]. It is unlikely that the UAE is exporting such a large volume of blue water from its own agricultural production. Rather, since the UAE is a major trade hub in the Middle East, many countries likely report their trade as coming from the UAE, when, in fact, trade may simply pass through UAE on the way to the country of final consumption. However, using FAO trade data, we cannot distinguish trade from local production to the end point of consumption. This issue with FAO data is most problematic for major trade hubs, such as the UAE and the Netherlands.

[27] The total volume of virtual water imported (s_{in}) and exported (s_{out}) was shown to follow a stretched exponential distribution in the year 2000, e.g., $P(X > x) = e^{-(\lambda x)^{\alpha}}$ [*Konar et al.*, 2011]. The stretched exponential distribution is a generalization of the exponential distribution with an additional parameter α referred to as the stretching exponent. When $\alpha = 1$ the exponential distribution is recovered, but when $\alpha \in (0,1)$ the exponential distribution is stretched. In Figure 2 we show that the trade of both blue and green

Table 2. Country Rankings in 2008[a]

	Rank	Barley	Country	Corn	Country	Rice	Country	Soy	Country	Wheat	Country	Beef	Country	Pork	Country	Poultry	Country	All	Country
Green	1	4.98	Australia	21.8	USA	13.6	Thailand	81.8	Argentina	26.9	USA	10.5	Australia	5.98	USA	13.8	Brazil	139	USA
	2	3.91	Ukraine	8.47	Argentina	3.22	India	64.1	USA	18.7	Argentina	8.58	USA	4.06	Denmark	8.20	USA	119	Argentina
	3	2.29	Canada	5.66	Brazil	2.37	USA	64.1	Brazil	9.57	Russia	6.75	Canada	2.85	Brazil	1.23	Thailand	92.5	Brazil
	4	2.27	France	3.13	India	1.01	Vietnam	19.7	India	9.36	Canada	4.29	Brazil	2.78	Germany	1.15	Argentina	28.1	India
	5	1.97	Argentina	2.26	Paraguay	0.63	Brazil	15.3	Paraguay	7.08	Australia	3.30	Argentina	1.95	Canada	1.14	Netherlands	22.7	Australia
	6	1.34	Russia	1.33	Ukraine	0.48	Uruguay	8.41	Netherlands	4.62	Ukraine	2.70	Ireland	1.67	Netherlands	0.70	UK	22.0	Canada
	7	0.99	Germany	1.27	France	0.46	China	5.65	Germany	4.24	France	2.60	Germany	0.93	Belgium	0.61	China	19.5	Paraguay
	8	0.68	USA	0.77	Hungary	0.43	Pakistan	4.20	Bolivia	2.03	Germany	2.31	New Zealand	0.92	Spain	0.56	Germany	15.5	Thailand
	9	0.59	Belgium	0.73	South Africa	0.40	Guyana	3.36	China	1.19	Turkey	2.18	Uruguay	0.89	France	0.45	France	15.0	Germany
	10	0.49	Uruguay	0.40	China	0.36	Argentina	1.76	Uruguay	0.17	Brazil	2.03	Netherlands	0.59	Poland	0.41	Belgium	14.3	Netherlands
Blue	1	4.54	Australia	3.17	USA	9.79	Pakistan	13.9	India	5.22	USA	0.95	India	0.95	USA	1.20	USA	22.4	USA
	2	0.94	USA	2.52	India	2.4	Thailand	9.73	USA	0.61	Australia	0.17	Australia	0.62	Denmark	0.60	Thailand	19.0	India
	3	0.18	France	0.92	Argentina	1.64	India	1.73	Argentina	0.58	UAE	0.10	USA	0.23	Netherlands	0.23	Brazil	10.3	Pakistan
	4	0.12	Ukraine	0.14	Thailand	1.12	USA	1.23	Netherlands	0.45	Russia	0.09	Pakistan	0.15	Australia	0.16	Netherlands	5.59	Australia
	5	0.09	Iraq	0.11	Morocco	0.31	Egypt	0.90	Brazil	0.44	Canada	0.07	New Zealand	0.09	Canada	0.13	China	3.23	Thailand
	6	0.07	Canada	0.10	Brazil	0.29	Vietnam	0.88	China	0.35	Mexico	0.06	Netherlands	0.08	China	0.09	Argentina	3.08	Argentina
	7	0.06	Argentina	0.10	UAE	0.20	China	0.21	UAE	0.32	Pakistan	0.03	Denmark	0.08	Italy	0.09	Australia	1.77	Netherlands
	8	0.06	Denmark	0.09	Cambodia	0.16	Uruguay	0.18	Uruguay	0.22	Ukraine	0.02	UAE	0.06	Spain	0.07	UAE	1.42	China
	9	0.04	Turkmenistan	0.08	Oman	0.15	UAE	0.11	Korea	0.16	Argentina	0.02	Italy	0.06	Chile	0.05	Morocco	1.40	Brazil
	10	0.04	Romania	0.07	China	0.12	Argentina	0.09	Germany	0.13	Turkey	0.01	Argentina	0.05	Russia	0.03	Denmark	1.13	UAE

[a]Top ten positions according to volume of virtual water exported by crop and water source. All values are in billions of cubic meters.

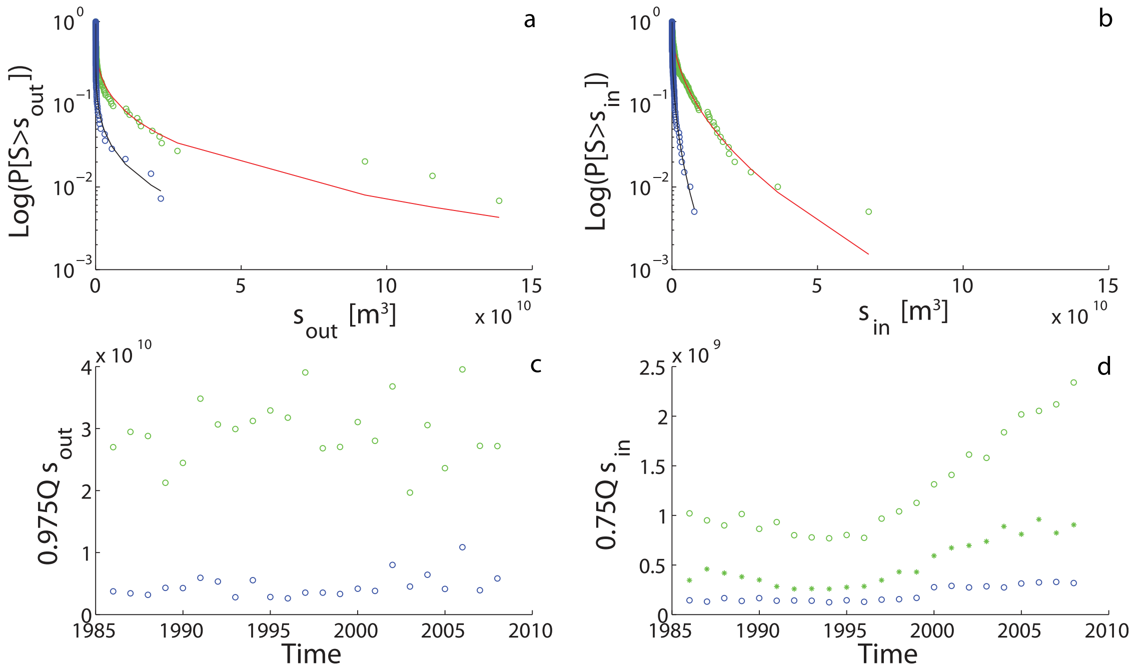

Figure 2. Statistical distributions of the volume of blue and green virtual water traded. (a) Exceedance probability distribution of the volume of virtual water exported (s_{out}) in 2008 with stretched exponential distributions fit ($\alpha^{\mathrm{green}}_{\mathrm{out}} = 0.3$ and $\alpha^{\mathrm{blue}}_{\mathrm{out}} = 0.22$). (b) Exceedance probability distribution of the volume of virtual water imported (s_{in}) in 2008 with stretched exponential distributions fit ($\alpha^{\mathrm{green}}_{\mathrm{in}} = 0.5$ and $\alpha^{\mathrm{blue}}_{\mathrm{in}} = 0.42$). (c) 0.975 quantile for the volumes of virtual water exported from blue and green sources over time. (d) 0.75 quantile for the volumes of virtual water imported from blue and green sources over time. The green stars in (d) represent the 0.75 quantile for the volumes of virtual water imported from green sources associated with the soy trade only. In all plots, green points represent virtual water from green sources and blue points represent virtual water from blue sources. From (a) it is clear that three countries dominate the export of virtual water from green sources: USA, Argentina, and Brazil. For this reason, the 0.975 quantile of virtual water export is presented in (c). Note the steady increase in the 0.75 quantile for the import of virtual water from green sources over time in (d), driven primarily by the soy trade.

virtual water follows a stretched exponential distribution. To fit a stretched exponential distribution to the data, we fixed λ to be the mean of the data to maintain the meaning of the exponential distribution and tuned α to fit the data.

[28] The stretched exponential distribution fits the trade of both blue and green virtual water. However, the parameter that controls the curvature of the distribution (α) is different for the trade of blue and green virtual water, as well as for the trade direction. In particular, for the export of virtual water (s_{out}), $\alpha^{\mathrm{green}}_{\mathrm{out}} = 0.3$ and $\alpha^{\mathrm{blue}}_{\mathrm{out}} = 0.22$, while for the import of virtual water (s_{in}), $\alpha^{\mathrm{green}}_{\mathrm{in}} = 0.5$ and $\alpha^{\mathrm{blue}}_{\mathrm{in}} = 0.42$. In both directions, $\alpha^{\mathrm{green}} > \alpha^{\mathrm{blue}}$, indicating that there is more heterogeneity in the import and export of green water. Note that the tuning parameter α does not have a strong physical interpretation, because the mean of the data was also used to fit the distribution.

[29] From the fat tail of s_{out} in (a) in Figure 2, the dominance of three countries in the export of green virtual water (i.e., the USA, Argentina, and Brazil, refer to Table 2) is evident. This is related to the fact that exporting countries tend to export to more trade partners than importing countries tend to import from (refer to Figure 1b). This is explained by the fact that exporting countries specialize in the production and wide-spread distribution of certain commodities, while countries that import commodities are able to meet their consumption requirements in fewer trade relationships. Note that the distribution of s_{in} does not extend to as large of values along the x axis as does s_{out}. For this reason we examine the 0.975 quantile of s_{out} in Figure 2c, while we differentially examine the 0.75 quantile for s_{in}. Thus the y axis values in Figures 2c–2d are not directly comparable and are not scaled to be.

[30] Interestingly, the volume of green water exported by dominant exporters (i.e., the 0.975 quantile; refer to Figure 2c) varies over time, which may be due to climatic shocks in the country of production or to economic shocks to the world food system, such as price fluctuations. This is in contrast to the smoothly increasing volume of green water imported by major importers (i.e., the 0.75 quantile; displayed in Figure 2d). This illustrates that trade may be able to smooth climatic and economic fluctuations for major importing countries. This increasing trend in green water imports was most evident for the upper quartile, indicating that some countries have been dramatically increasing their access to rainwater resources through food imports over time. In particular, this trend appears to be driven by the redistribution of rainwater resources associated with the soy trade (i.e., the green stars in Figure 2d). This corroborates

and refines the finding of *Dalin et al.* [2012], who demonstrate that China has dramatically increased the volume of virtual water it imports over time after restrictions on soy imports were lifted in 2001.

4. Relationship Between Trade Partners and Volumes by Water Source

[31] It is known that the total volume of virtual water traded follows a power law relationship when compared to the number of trade partners, i.e., $s \propto ak^{\beta}$ [*Konar et al.*, 2011; *Suweis et al.*, 2011]. This power law relationship implies that the more trade connections a country has, the much more it is able to participate in the exchange of virtual water in a highly nonlinear way. We demonstrate that this relationship holds for volumes of both green and blue virtual water, but that the slope (β) differs with the water source and direction of trade. This implies that the volume of virtual water that a country exchanges as a function of its trade connectivity varies by water source.

[32] The power law relationship between the volume of virtual water exported and the number of export trade partners for the year 2008 is shown in Figure 3a ($s_{out}^{green} \propto 12.17k_{out}^{1.99}$ and $s_{out}^{blue} \propto 8.54k_{out}^{2.18}$), while the power law relationship for the volume of virtual water imported and the number of import trade partners in 2008 is presented in Figure 3b ($s_{in}^{green} \propto 10.82k_{in}^{2.69}$ and $s_{in}^{blue} \propto 9.20k_{in}^{2.61}$), both for aggregate crop trade.

[33] In 2008 the slope for the export of green water is 1.99, while the slope for the export of blue water is 2.18 (refer to Table 3). Note that it is possible for the slope of the blue water relationship to be steeper than the green water relationship, but note that the intercept is necessarily larger for the green water relationship (i.e., compare the a values), due to the larger volumes involved in the green water trade. The fact that β_{out}^{blue} is greater than β_{out}^{green} indicates that as a country increases its export trade partners, it tends to export relatively more irrigation water. This is likely due to the fact that as a country increases the number of countries to which it exports agricultural goods its agricultural system becomes more intensive. With increased agricultural intensification, irrigation inputs likely increase in order to obtain higher yields. This relationship shows little trend over time.

[34] However, as a country increases its import trade partners, it does not preferentially import virtual water from a particular source. The slope for the import of green water is 2.69, while the slope for the import of blue water is 2.61. This indicates that as a country increases its number of import trade partners, it does tend to increase its access to rainwater resources more so than for blue water sources, but this gap is smaller than is the export gap. Note from Figure 3d that the gap between the import slope of green and blue water remains small over time. This makes sense since a country does not have a preference for the importation of water from a specific source, just virtual water in

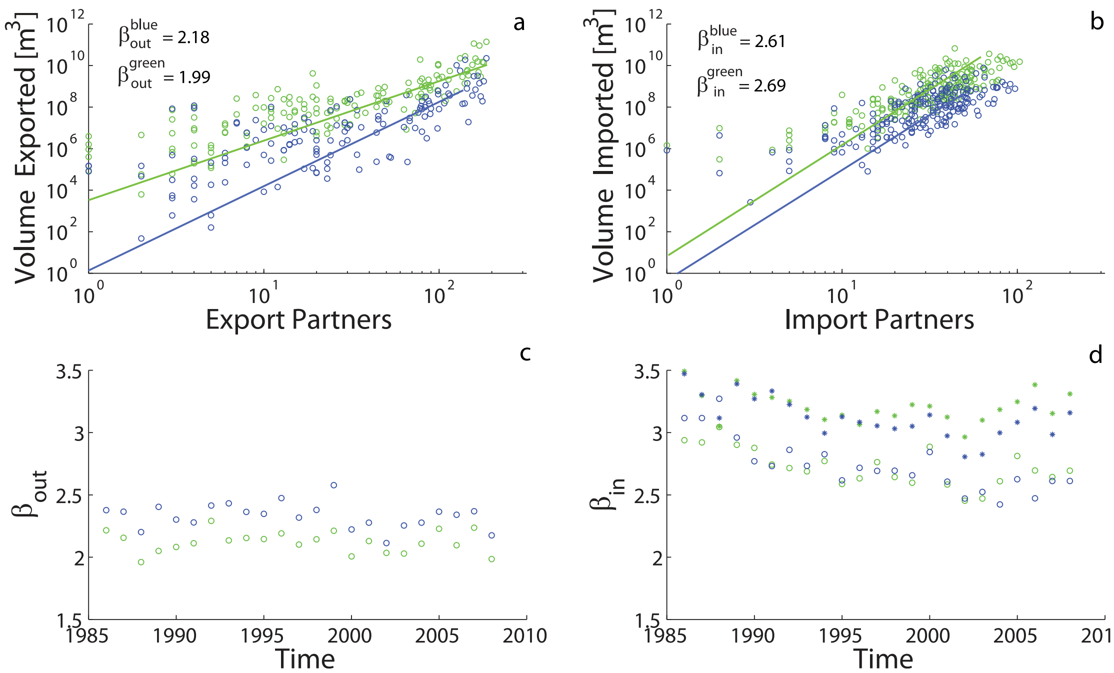

Figure 3. Relationship between the volume of virtual water traded and number of trade partners follows a power law. (a) Volume of virtual water exported versus number of export trade partners in 2008 ($s_{out}^{green} \propto 12.17k_{out}^{1.99}$ and $s_{out}^{blue} \propto 8.54k_{out}^{2.18}$). (b) Volume of virtual water imported versus number of import trade partners in 2008 ($s_{in}^{green} \propto 10.82k_{in}^{2.69}$ and $s_{in}^{blue} \propto 9.20k_{in}^{2.61}$). (c) Slope of the volume of virtual water exported versus number of export trade partners (β_{out}) over time. (d) Slope of the volume of virtual water imported versus number of import trade partners (β_{in}) over time, where circles represent the aggregate virtual water trade network and stars illustrate virtual water trade associated with the soy trade only. In all plots, green points represent virtual water from rainfall sources (i.e., green water) and blue points represent virtual water from irrigation sources (i.e., blue water).

Table 3. Slope of the Relationship Between the Volume of Virtual Water Traded and the Number of Trade Partners by Crop, Water Source, and Direction of Trade in 2008[a]

		Export	Import
Green	Barley	2.38	2.57
	Corn	1.94	2.59
	Rice	1.80	1.86
	Soy	2.24	3.31
	Wheat	1.75	2.28
	Beef	2.26	2.49
	Pork	2.06	2.88
	Poultry	1.78	2.22
	Aggregate	1.99	2.69
Blue	Barley	2.32	2.53
	Corn	2.16	2.51
	Rice	2.25	2.30
	Soy	2.24	3.16
	Wheat	1.97	2.20
	Beef	2.06	2.68
	Pork	1.90	2.82
	Poultry	1.90	2.01
	Aggregate	2.18	2.61

[a]Note that this relationship follows a power law.

general [*Aldaya et al.*, 2010]. Blue and green water resources have different opportunity costs, which present themselves to the country of production. For this reason, different slopes of the different water sources in their country of export present opportunities for water resource management.

[35] The volume of water traded by source as a function of the number of trade partners also varies by crop. For example, rice has the largest gap in $\beta_{\text{out}}^{\text{blue}}$ and $\beta_{\text{out}}^{\text{green}}$ (i.e., $2.25 - 1.80 = 0.45$, refer to Table 3). This indicates that countries that export rice tend to export relatively more irrigation water than rainwater as they increase the number of countries to which they export. Similar to the aggregate network, this relationship can be explained by the fact that countries that increase the number of countries to which they export do so following intensification of their agricultural system. Increased agricultural intensification is typically accompanied by more irrigation, of which rice production is heavily reliant upon.

[36] Over time, both $\beta_{\text{in}}^{\text{green}}$ and $\beta_{\text{in}}^{\text{blue}}$ have been decreasing (i.e., both green and blue circles in Figure 3d have been decreasing over time). This may indicate that trade may be reaching its limits when it comes to increasing access to volumes of virtual water by increasing trade partners. However, note that the importation of virtual water associated with the soy trade exhibits the largest slope and remains relatively steady over time (refer to the stars in Figure 3d). Thus, countries looking to expand their access to virtual water may consider increasing the number of countries from which they import soy, much as China has done [*Dalin et al.*, 2012].

5. Water Savings by Water Source

[37] When food tends to be exported by countries with a higher water productivity than the countries of import there is a trade-based global water savings (GWS). International trade in food commodities has been shown to save water [*Chapagain et al.*, 2006; *Yang et al.*, 2006; *Hoekstra and Chapagain*, 2008; *Aldaya et al.*, 2010; *Hanasaki et al.*, 2010; *Fader et al.*, 2011], increasingly so over the last few decades [*Dalin et al.*, 2012]. However, it is unclear how differences in water efficiencies between countries as a function of water source contribute to GWS. Building on the idea presented by *Aldaya et al.* [2010], we calculate GWS by water source as

$$GWS_{e,i,x,s} = T_{e,i,x} * (VWC_{i,x,s} - VWC_{e,x,s}), \tag{3}$$

where the subscripts e, i, x, and s correspond to the exporting country, importing country, commodity traded, and water source, respectively. T is the volume of commodity x traded from exporting country e to importing country i. The difference in water use efficiency between i and e is $VWC_{i,x,s} - VWC_{e,x,s}$, which is indexed by water source.

[38] The difference in water use efficiency provides a theoretical measure of how much blue or green water would have been used had the commodity been produced in i, rather than produced in e and exported to i. When this difference is positive, it indicates that the trade relationship is saving either blue or green water. When the difference is negative, the trade is inefficient in terms of water resources. Thus, this measure of GWS calculates the water savings associated with agricultural production under the current world where trade exists compared to an autarky world with no trade. This measure assumes that countries would produce to consume what they currently import to consume, without any changes to agricultural water use efficiency.

[39] Importantly, we demonstrate that the global food trade is saving both blue and green water and is increasingly doing so over time. This is significant since international food trade rarely occurs with water resources as the rationale. In Figure 4 and Table 4 it is clear that both the blue and green GWS of aggregate crop trade is positive and increasing over time. The blue water network is more efficient than the green water network, i.e., the blue water network is saving more water and increasingly so over time. In 1986, we calculate 52×10^9 m^3 blue and 39×10^9 m^3 green water were saved through trade, growing to savings of 119×10^9 m^3 blue and 105×10^9 m^3 green water in 2008. It is surprising that the blue water network saves more water than the green water network due to the smaller volume of blue water traded (i.e., 42×10^9 m^3 blue compared with 310×10^9 m^3 green water was traded in 1986; 78×10^9 m^3 blue compared with 594×10^9 m^3 green water was traded in 2008; refer to Table 4). However, it makes sense that the blue water trade, though smaller in volume, would be more efficient, due to the higher opportunity cost of irrigation water supplies within countries of production.

[40] To better understand what is driving this GWS over time, we present three components that affect the calculation of GWS. These components are the number of water-efficient links (i.e., "positive" links, refer to Figure 4b) as a fraction of the total number of links over time, the mean difference between the water efficiencies of the importing and exporting countries (i.e., "VWC gap," refer to Figure 4c) over time, and the volume of crop trade occurring on positive links as a fraction of the total volume of crop trade (refer to Figure 4d). From Figures 4b–4d it is evident that neither component of GWS is increasing as much as GWS over time for the aggregate network (i.e., Figure 4a).

[41] The GWS associated with a specific crop can also be examined (refer to Table 4). Two interesting examples

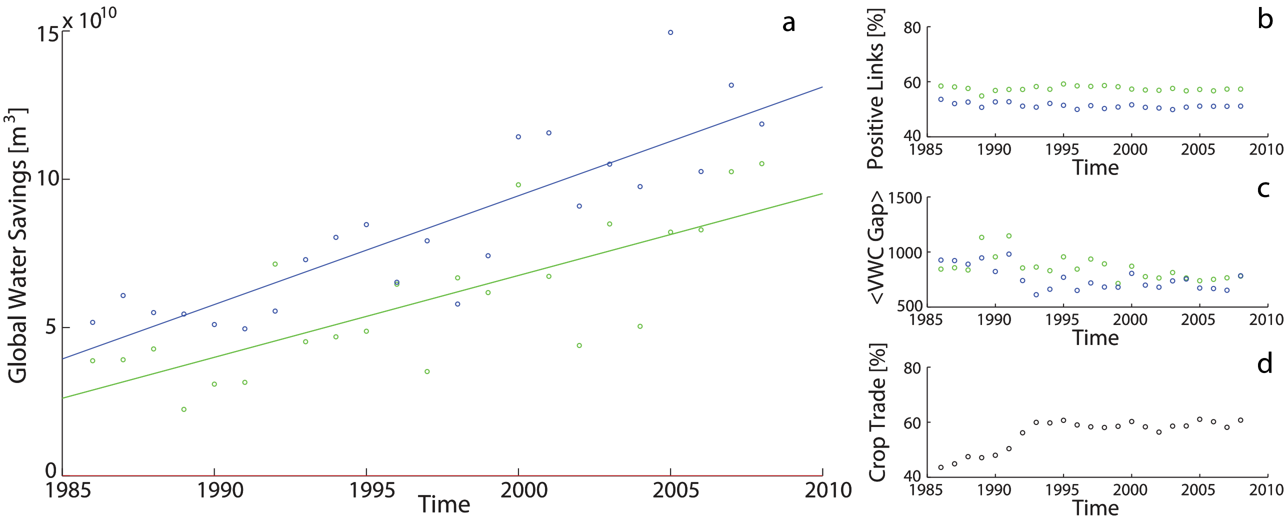

Figure 4. Global water savings of the blue and green virtual water trade networks. (a) Volume of global water savings (GWS) over time for the blue and green water networks; (b) links that save water (i.e., positive from a water-efficiency perspective) as a fraction of total links in the network; (c) mean gap in the virtual water content [dimensionless] of all trade links in the network; and (d) volume of crop trade on positive links as a fraction of total crop trade in the network. Note that (a)–(d) illustrate the components of water savings, but neither illustrates an increase over time comparable to that of GWS in (a). In all plots, green points represent virtual water from green water sources and blue points represent virtual water from blue water sources. The circles in (d) are black because they represent crop trade volumes and not a particular water source.

are presented in Figures 5a and 5b. In Figure 5a the GWS associated with only the soy trade is shown to be increasing from both blue and green sources over time. However, the green water network associated with soy was negative over almost the entire time period and lost 2.35×10^9 m^3 of green water in 2008 (but losing only 1% of total water savings in 2008, compared to losing 24.8% of total water savings in 1986, refer to Table 4). However, in 2007 the soy trade did save 1.59×10^{10} m^3 of green water (see green point above the red horizontal line in Figure 5a). This demonstrates that the soy trade is capable of organizing into a green water-efficient structure. The blue water network associated with the soy trade has been positive since 1986 and has been becoming more efficient in terms of water over time (growing from 11.3% of blue water savings in 1986 to 18.7% of blue water savings in 2008). In Figure 5b the GWS associated with only the rice trade is presented. For rice, the blue water network has been increasingly losing

Table 4. Global Virtual Water Trade and Savings by Crop and Water Source in 1986 and 2008[a]

		1986				2008			
		Trade	% Trade	Savings	% Savings	Trade	% Trade	Savings	% Savings
Green	Barley	20.1	5.7	−0.8	−0.9	24.76	10.9	6.96	3.1
	Corn	36.9	10.5	26.9	31.0	50.36	7.5	25.33	11.1
	Rice	13.9	3.9	2.52	2.9	25	3.7	6.12	2.7
	Soy	115	32.7	−21.5	−24.8	276.3	41.2	−2.35	−1.0
	Wheat	84.4	24.0	28	32.3	99.75	14.9	40.66	17.8
	Beef	31.3	8.9	1.91	2.2	59.78	8.9	7.32	3.2
	Pork	2.92	0.8	1.3	1.5	27.13	4.0	14.07	6.2
	Poultry	5	1.4	0.56	0.6	30.61	4.6	7.13	3.1
	Aggregate	310	88.1	38.8	44.8	593.68	88.5	105.24	46.2
Blue	Barley	6.07	1.7	5.67	6.5	6.4	1.0	7.8	3.4
	Corn	5.7	1.6	16.4	18.9	7.92	1.2	35.97	15.8
	Rice	4.4	1.3	1.6	1.8	16.63	2.5	−3.41	−1.5
	Soy	15.4	4.4	9.84	11.3	29.49	4.4	42.72	18.7
	Wheat	8.63	2.5	12.8	14.8	9.83	1.5	17.82	7.8
	Beef	0.71	0.2	3.1	3.6	1.65	0.2	3.91	2.8
	Pork	0.47	0.1	−0.07	-0.1	2.7	0.4	6.45	2.8
	Poultry	0.58	0.2	2.41	2.8	2.93	0.4	7.4	3.2
	Aggregate	41.9	11.9	51.7	59.6	77.54	11.6	118.63	52.0

[a]All volumes are in billions of cubic meters and percentages are in comparison to the aggregate crop trade from both water sources.

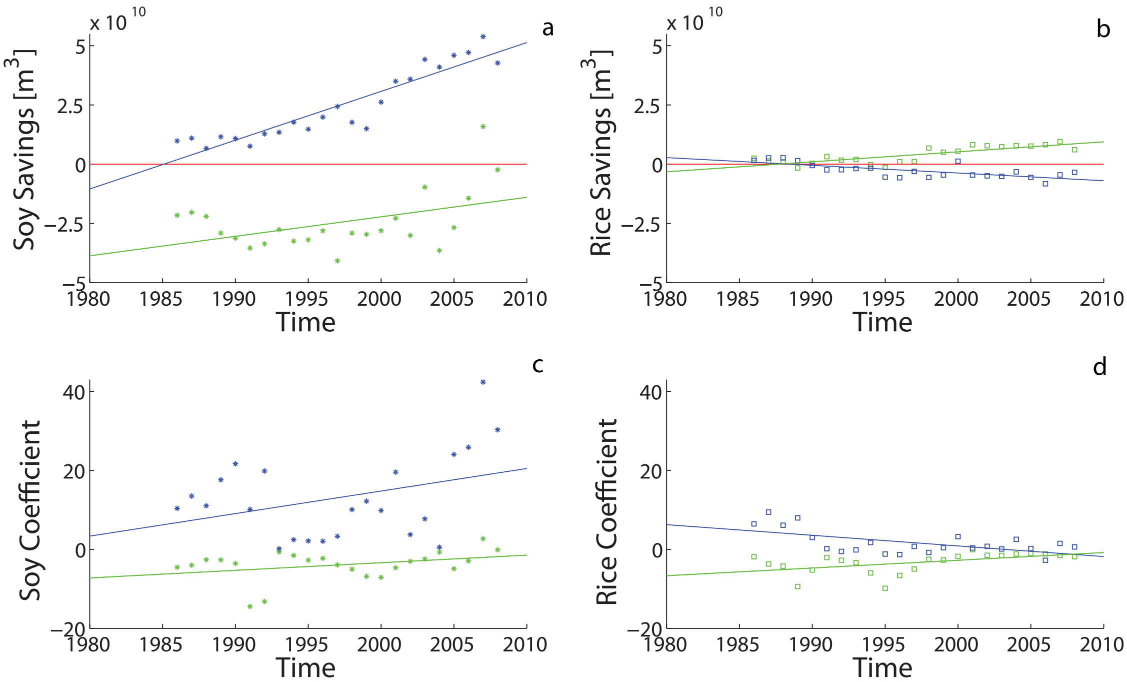

Figure 5. Comparison of the water savings and regression coefficient for two crops: soy and rice. (a) and (b) display the water savings of each crop. A red horizontal line at zero savings is provided. (c) and (d) illustrate the slope coefficient between the crop trade volume and the water efficiency of each link. Note that the water savings associated with each crop trade network mirrors its slope coefficient for both blue and green water [i.e., compare (a) with (c); (b) with (d)]. This indicates that the trade of soy is increasingly occurring on more blue and green water-efficient links, while the trade of rice is increasingly being distributed onto links that lose blue water, albeit with slight gains in green water resources.

water over time, though the change has been relatively slight. On the other hand, the green water network associated with rice has been becoming more water efficient.

[42] To better understand what is driving these networks to become more or less efficient over time, we regress the volume of crop traded on the gap in water use efficiency for each crop over each trade link. The regression coefficient thus indicates whether crop volumes are preferentially distributed on links with high VWC gaps (i.e., large water efficiency) or onto links with negative VWC gaps (i.e., losing water). When the regression coefficient is positive, this indicates that large crop volumes are preferentially occurring on increasingly water-efficient links. When the regression coefficient is negative, it indicates large crop volumes are organized on links that lost water. Note that a similar analysis cannot be performed for the aggregate network, as VWC is a crop-specific measure.

[43] The regression coefficient for soy and rice are plotted in Figures 5c and 5d over time. In Figure 5c it is evident that the trade of soy is increasingly being distributed onto blue water-efficient links over time (since the regression coefficient is positive and increasing). However, the regression coefficient for green water links is negative over most of the time frame, but just becomes positive in 2007. This indicates that the trade of soy was historically losing rainwater, but trade volumes are increasingly being distributed onto green water-efficient links. For rice, the regression coefficient of the blue water trade network has been decreasing with time, while the regression coefficient of the green water coefficient has been increasing (refer to Figure 5d). Thus, the time series of the crop-specific regression coefficient can help to explain why certain crops and water sources are becoming more and less efficient in terms of water over time.

6. Conclusions

[44] There are different physical constraints, opportunity costs, and environmental impacts of blue and green water. Due to these unique features, the virtual water trade of each water source should be considered independently. We utilize the coherent analytical framework of network theory to explore the relationship of each water source with the international food trade. We confirm findings in the literature that green water dominates virtual water trade. However, we also find and present some of the unique ways in which these different water sources are embodied in trade.

[45] As a country increases its export trade partners, it tends to export more irrigation water. This is likely due to the fact that the agricultural system of a country becomes more intensive, typically with increased irrigation inputs, as a country expands the number of countries that it exports to. This relationship shows little trend over time. On the other hand, importing countries do not demonstrate a preference for a particular water source, just improved access to virtual water generally. The different opportunity and environmental costs of blue and green water present themselves in the country of export and should be taken into

consideration when developing trade policy. For instance, subsidies to irrigated agriculture may encourage inefficient use of blue water resources with high opportunity and environmental costs.

[46] Global food trade has been increasingly saving both blue and green water resources over time. However, opportunities remain to make specific crop trade networks more efficient from a water resource perspective. The soy trade has lost green water on a global basis in almost every year from 1986 to 2008, losing 2.35×10^9 m^3 in 2008. However, the soy trade does save blue water, a more expensive resource, and did save 15.88×10^9 m^3 green water in 2007. This demonstrates that the soy trade is capable of organizing in a manner which saves both blue and green water resources.

[47] Intensification of crop trade volumes onto water-efficient or water-inefficient links drives global water savings or loss, respectively, over time. If saving water through trade is the goal, policy makers and water resource managers should calculate the difference in water efficiency between countries and focus on increasing trade on those links with the largest positive gap.

[48] **Acknowledgments.** We acknowledge the Food and Agricultural Organization for making available the global agricultural trade data. M.K. is thankful for support from the Siebel Energy Challenge and the Princeton Environmental Institute's program in Science, Technology, and Environmental Policy (PEI-STEP).

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