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Key Points:
- Internal virtual water flows in the U.S. are 51% as much as global
- The U.S. virtual water flow network is homogeneous, social, and equitable
- A core group of U.S. States highlights potential network vulnerabilities

Supporting Information:
- Supplementary methods and tables

Correspondence to:
M. Konar,
mkonar@illinois.edu

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Agricultural virtual water flows within the United States

Qian Dang[1], Xiaowen Lin[1], and Megan Konar[1]

[1]Department of Civil and Environmental Engineering, University of Illinois at Urbana-Champaign, Urbana, Illinois, USA

Abstract Trade plays an increasingly important role in the global food system, which is projected to be strained by population growth, economic development, and climate change. For this reason, there has been a surge of interest in the water resources embodied in international trade, referred to as "global virtual water trade." In this paper, we present a comprehensive assessment of virtual water flows within the United States (U.S.), a country with global importance as a major agricultural producer and trade power. This is the first study of domestic virtual water flows based upon intranational food transfer empirical data and it provides insight into how the properties of virtual water transfers vary across scales. We find that the volume of virtual water flows within the U.S. is equivalent to 51% of international flows, which is slightly higher than the U.S. food value and mass shares, due to the fact that water-intensive meat commodities comprise a much larger fraction of food transfers within the U.S.. The U.S. virtual water flow network is more social, homogeneous, and equitable than the global virtual water trade network, although it is still not perfectly equitable. Importantly, a core group of U.S. States is central to the network structure, indicating that both domestic and international trade may be vulnerable to disruptive climate or economic shocks in these U.S. States.

1. Introduction

It is increasingly important to understand the role that humans play in transforming the hydrologic cycle [*Sivapalan et al*., 2012, 2014]. In particular, the global food trade system impacts water resources, since the vast majority of water withdrawals goes toward producing food [*Godfray et al*., 2011; *Gleick*, 2011; *Foley et al*., 2011]. In fact, since water is such a crucial factor in the production of food, it influences the trade patterns of nations [*Reimer*, 2012; *Debaere*, 2014]. The water resources used to produce food commodities are "virtually" transferred with these commodities, in a "virtual water trade" [*Hoekstra and Chapagain*, 2008], with important implications for both food and water security [*Porkka et al*., 2013].

Many studies have examined global virtual water trade and yielded important insights. For example, the water footprint of global trade (i.e., the volume of water embodied in the trade of commodities) for both agricultural and industrial products has been estimated to be 2320 billion m^3/yr [*Hoekstra and Mekonnen*, 2012]. The network properties of global virtual water trade have been described [*Konar et al*., 2011; *Dalin et al*., 2012; *Carr et al*., 2012], illuminating some key organizing principles of this global system [*Suweis et al*., 2011; *Tamea et al*., 2014]. Additionally, regional virtual water trade patterns have been described [*Konar and Caylor*, 2013] and the importance of key nations has been highlighted [*Zhang et al*., 2011; *Tamea et al*., 2013], particularly in the United States [*Hoekstra and Chapagain*, 2008]. The importance of the commodities selected to quantify virtual water trade has been established [*Lenzen*, 2009; *Carr et al*., 2013] and aspects of specific water sources embodied in trade highlighted [*Hanasaki et al*., 2010; *Konar et al*., 2012], including scarce water resources [*Lenzen et al*., 2013].

Intranational assessments of virtual water flows have highlighted the importance of domestic food transfers (i.e., intranational food transfers) to national water resources [*Ma et al*., 2006; *Guan and Hubacek*, 2007; *Lenzen*, 2009; *Verma et al*., 2009]. Recent studies indicate that, surprisingly, the water-scarce North of China exports water-intensive goods to the water-rich South of China, which may be exacerbating water scarcity in the North of China [*Guan and Hubacek*, 2007; *Wang et al*., 2014]. For this reason, indirect (virtual) transfers of water resources should be incorporated into the national decision-making process [*Guan and Hubacek*, 2007], particularly as they relate to major infrastructure projects, such as the North-South Water Transfer Project in China [*Ma et al*., 2006], although it is important to realize that many other factors must also be considered for infrastructure projects and national trade and production policies. Similarly, recent research indicates that intranational food transfers in India may be exacerbating water scarcity [*Verma et al*., 2009]. Other subnational studies highlight opportunities to increase water use efficiency in the agricultural sector [*Zhang and Anadon*, 2014; *Dalin et al*., 2014], such as through the redistribution of the production of water-intensive goods to locations that are not water scarce [*Mubako and Lant*, 2013].

For the first time, we quantify and describe intranational virtual water flows using data on commodity transfers. Other studies on intranational virtual water flows model the commodity transfers that underpin estimates of internal virtual water flows [*Ma et al*., 2006; *Guan and Hubacek*, 2007; *Lenzen*, 2009; *Mubako and Lant*, 2013; *Zhang and Anadon*, 2014; *Dalin et al*., 2014]. Our study focuses on the United States, a key nation in the global virtual water trade network [*Konar et al*., 2011], as it is a major agricultural producer, consumer, and economic power, and is projected to remain a major contributor to virtual water exchanges for the foreseeable future [*Konar et al*., 2013]. We present a comprehensive assessment of domestic virtual water flows within the United States, including: quantifying flows, network properties, and metrics of equality. This enables direct comparison with other studies of virtual water transfers at the global scale [*Konar et al*., 2011; *Seekell et al*., 2011; *Dalin et al*., 2012; *Konar et al*., 2012; *Carr et al*., 2012]. Importantly, this study helps us to understand the impact of scale on virtual water transfers, an outstanding question in the literature. Additionally, food transfers in the United States proxy both a free trade and equitable setting [*Lin et al*., 2014], thereby helping us to understand the properties of virtual water flows that we can expect in such a situation.

The key questions that we seek to address in this paper are: (1) what is the volume of virtual water embodied in internal U.S. food transfers and how does it compare with global virtual water trade values? (2) what are the network properties of domestic U.S. virtual water flows and how do they compare with global properties? (3) are intranational U.S. virtual water flows more equitable than global flows? we use intranational food transfer data [*U.S. Department of Transportation*, 2013], agricultural production data [*U.S. Department of Agriculture*, 2014], and estimates of virtual water content for each U.S. States in the literature [*Mekonnen and Hoekstra*, 2011; *Mubako and Lant*, 2013; *Mubako*, 2011] to quantity U.S. virtual water flows.

2. Methods

2.1. Food Transfer Data

Data on food transfers within the United States are provided by the Commodity Flow Survey (CFS). The CFS represents a collaboration between the Bureau of Transportation Statistics and the Census Bureau. The purpose of the CFS data is to inform policy makers and transportation planners about the demand for transportation facilities, as well as various aspects of energy use, safety risks, and environmental concerns. The CFS data help U.S. government agencies to make more informed decisions about improving transportation infrastructure, including how to allocate the billions of dollars needed to maintain and improve the domestic transportation system.

CFS provides information about the movement of commodities within the United States: their value, weight, and mode of transportation. This information is provided for mining, manufacturing, wholesale, and select retail and service sectors. Since 1997, the CFS has been conducted every 5 years as part of the Economic Census. Each survey year, a sample of 100,000 establishments is selected based upon geographic location and industry. Each establishment selected into the CFS is requested to report on its shipment activities during each quarter of the survey year, including information on shipment value, weight, commodity code and description, mode of transportation, and final U.S. destination. Information on transportation mode includes categories of air, deep draft vessel, shallow draft vessel, truck, parcel, pipeline, railroad, and multimode. The information from this sample is used to estimate the total value and weight of goods shipped in each industry [*U.S. Department of Transportation*, 2013].

CFS data on bilateral food transfers are provided only for 2007, so we focus our analysis on this year. Commodities provided in the CFS data are classified according to the Standard Classification of Transported Goods (SCTG) coding system. The full list of SCTG commodity classes and items contained within each commodity class is available from the *U.S. Census Bureau* [2014]. We select State-level data for the movement of food commodity groups. The CFS provides data for seven food commodity groups (listed in Table 1). For the remainder of this paper, we refer to specific commodity groups by the SCTG commodity group number

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Table 1. Food Commodity Groups Provided in the Commodity Flow Survey (CFS) Database [*U.S. Department of Transportation*, 2013][a]

SCTG	Full Commodity Group Name	Short Name
1	Live animals and live fish	Animals
2	Cereal grains	Cereal
3	Other agricultural products	Other
4	Animal feed and products of animal origin, nec	Feed
5	Meat, fish, seafood, and their preparations	Meat
6	Milled grain products and preparations and bakery products	Milled
7	Other prepared foodstuffs and fats and oils	Prepared

[a]There are seven food commodity groups provided. We define "staple" food as SCTG commodity groups 1, 2, 4, 5, and 6. We assign commodity group short names for use in this paper.

or by the short name assigned in Table 1. Despite its name, commodity group 4 is almost entirely comprised of feed items (i.e., cereal straw or husks, inedible flours, bran, sharps, and other residues of cereals, etc) [*U.S. Census Bureau*, 2014]. We define "staple" food commodities to be commodity groups 1, 2, 4, 5, and 6. We do not consider fish in this analysis. To remove fish from commodity groups 1 and 5, we determine the non-fish fraction of production in each State [*U.S. Department of Agriculture*, 2014]. We then multiply the food transfers of commodity groups 1 and 5 by this fraction.

It is important to note that the CFS provides data on the weight of food transfers (e.g., transportation, movements) within the United States. We refer to these intranational food shipments as "transfers," which are different to international food trade employed in studies of international virtual water trade. Food transfers and food trade are conceptually distinct, since international trade is the exchange of capital, goods, and services across international borders [*Krugman and Obstfeld*, 2009]. Thus, we use "food trade" to refer to the exchange of food commodities between countries, while "food transfers," instead, refers to exchanges of food commodities within a single country, here, between U.S. States. A key difference between CFS food transfer data and international food trade data is the spatial and commodity resolution. CFS data present a higher spatial resolution than does international trade data. However, the price for using this higher spatial resolution is a lower commodity resolution, since the SCTG system aggregates items within a commodity group [*U.S. Census Bureau*, 2014].

2.2. Virtual Water Content Estimates

Here, we describe how we estimate the virtual water content (*VWC*) [*Hanasaki et al*., 2010] for each staple food commodity group (i.e., commodity groups 1, 2, 4, 5, and 6). $VWC=\overline{ET}/Y$, where $\overline{ET}$ refers to the total crop evapotranspiration $[\mathrm{m}^3_{water}\mathrm{area}^{-1}]$ and Y indicates crop yield [ton_{crop} area^{-1}]. This definition is equivalent to the water footprint of food [*Hoekstra and Chapagain*, 2008]. Estimates of item-specific *VWC* exist for the spatial resolution of U.S. States [*Mekonnen and Hoekstra*, 2011; *Mubako and Lant*, 2013; *Mubako*, 2011], which we rely upon.

The major methodological challenge in our paper is determining how to combine CFS commodity transfer data with estimates of *VWC* when they are provided at different levels of commodity resolution. We remedy this mismatch in commodity resolution with a production-weighted mean of the VWC of items within a broader SCTG commodity group, based upon U.S. State level agricultural production data [*U.S. Department of Agriculture*, 2014]. In this approach, we assume that the composition of food transfers corresponds to the composition of agricultural production of each State. We believe this is the most reasonable assumption to make in order to disaggregate coarse commodity groups into specific items to match with *VWC* estimates.

We obtain *VWC* data for both cereal and milled grains from *Mekonnen and Hoekstra* [2011]. *Mekonnen and Hoekstra* [2011] provides *VWC* data for crops and derived crop products for individual U.S. States. These data are averaged over the 1996–2005 time period and provide the green, blue, and grey water footprint of crops. We select both green and blue *VWC* and sum these values to arrive at the total crop *VWC*. We do not include the gray *VWC* since we do not consider water pollution in this analysis. For States with no *VWC* data, we use the average across the States with data. To select the appropriate commodities from the database, we use the U.S. Census Bureau definition of cereal grains and milled grains [*U.S. Census Bureau*, 2014].

We use production data for cereals in the year 2007 [*U.S. Department of Agriculture*, 2014] to weight the *VWC* of each item within the cereal and milled grains commodity groups for each State, according to the following equation:

$$VWC_{c,s} = \frac{\sum_{i \in c}^{I} (VWC_{i,s} * Production_{i,s})}{\sum_{i \in c}^{I} Production_{i,S}} \quad (1)$$

where *c* indicates commodity group (i.e., cereal or milled), *i* indicates item, *I* indicates number of items within *c*, $i \in c$ indicates items contained in commodity group *c*, and *s* indicates State of production. Cereal production data were evenly divided between milled items that correspond to each raw cereal crop. For example, "wheat or meslin flour," "dry pasta," "wheat groats and meal," and "wheat pellets" are milled items that correspond to wheat. In this case, each item was assigned a 25% share of the wheat production data to weight the *VWC* data. Production and *VWC* data are provided in supporting information.

Mekonnen and Hoekstra [2011] does not provide data on the *VWC* of livestock products by State, so we use data provided in *Mubako and Lant* [2013] and *Mubako* [2011]. We assume that commodity group 4 is entirely comprised of animal feed products to enable our *VWC* calculation. This is a conservative assumption, since animal feed items are less water intensive than products of animal origin. To estimate the *VWC* of feed, we follow *Mubako and Lant* [2013], which defines $VWC_{feed} = VWC_{livestock} - VWC_{withdrawal}$, where $VWC_{withdrawal}$ represents 1% of the total water footprint of livestock [*Mubako and Lant*, 2013]. Following *Mubako and Lant* [2013], lifetime VWC_{feed} is defined as:

$$VWC_{feed}[a] = \frac{\int_{birth}^{slaughter} \left\{ \sum_{c=1}^{n_c} VWC[c] \times Feed[a, c] \right\} dt}{W[a]} \quad (2)$$

where *Feed*[*a*,*c*] is the quantity of feed crop *c* consumed by the animal over its lifetime, *VWC*[*c*] is the virtual water content of feed crop *c* in the State of production, and *W*[*a*] is the average live weight of the animal at the end of its lifespan [*Mubako and Lant*, 2013].

Note that the above definition of VWC_{feed} is for the lifetime *VWC* of feed. Here, we require the unit *VWC* of feed in order to determine the water embodied in feed transfers. To obtain the unit *VWC* of feed from the lifetime *VWC* of feed, we calculate the ratio $\frac{W}{Feed}$ using data provided in *Mubako* [2011]. $\frac{W}{Feed}$ is determined for each animal by its production system (e.g., according to Table 3.8 in *Mubako* [2011]). Data on the production system of each animal are only provided for the State of Illinois in *Mubako* [2011]. We assume that the $\frac{W}{Feed}$ ratio does not vary across States in order to obtain the unit *VWC* of feed for each State. We use production data for livestock animals to weight the unit *VWC* of feed, such that $P_{feed} = P_{animal} * (W/Feed)^{-1}$, where *P* indicates production data. In this way, we obtain the production-weighted unit *VWC* of feed for each State.

For live animals, we use data provided for the *VWC* of live animals in each State of production in *Mubako* [2011]. We use data for "beef cattle,", "swine," "broiler chickens," "turkey," "sheep," "goats," and "horses." For meat, we also use data provided for the *VWC* of live animals in each State of production in *Mubako* [2011]. This is a conservative approach, since live animals are less water intensive than their corresponding meat products. However, for the meat commodity group, we exclude horses, since they are not consumed as meat. We use production data for livestock animals [*U.S. Department of Agriculture*, 2014] to arrive at a production-weighted *VWC* of live animals and meat for each State.

2.3. Virtual Water Flows

We combine food transfer data and virtual water content estimates to obtain virtual water flows within the United States:

$$VWF_{o,d} = \sum_{c} VWC_{o,c} \cdot CF_{o,d,c} \quad (3)$$

where the subscripts *o*, *d*, and *c* denote State of origin, State of destination, and commodity group, respectively. *VWF* indicates virtual water flows, *CF* indicates commodity transfers between U.S. States, and *VWC* indicates virtual water content of the origination State. Our estimate of *VWF* is thus subject to the uncertainties inherent in the commodity transfer data and in the estimates of *VWC* in the literature. Importantly, estimates of *VWF* assume that the location of the origin of the *CF* is also the production location and that the *VWC* of the origin location applies. This is a major assumption that is also employed in all virtual water accounting studies, including those for international trade [see e.g., *Konar et al.*, 2011, 2012].

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2.4. Network Statistics

Virtual water flows in the United States can be thought of as a network. The nodes of the network are States within the United States. The links are weighted by the volume of water (m^3) embodied in the trade of food and directed by the direction of trade.

We calculate key network statistics for the U.S. virtual water flow network (*W*). Node degree (*k*) is an unweighted property that measures node connectivity. We consider node in-degree and out-degree, corresponding to import and export relationships, respectively. The node in-degree sums links incoming to a node, measured by $k_{in_i}=\sum_j a_{ji}$, where *a* is an element of *A* [*Wasserman and Faust*, 1994], the unweighted adjacency matrix. Similarly, node out-degree counts the number of links emanating from a node and is measured as $k_{out_i}=\sum_j a_{ij}$.

Node strength (*s*) is the weighted corollary to node degree and quantifies the weighted intensity of nodal links. We consider direction with node in-strength and out-strength. Now, node in-strength sums the value of links incoming to a node and is measured by $s_{in_i}=\sum_j w_{ji}$, while node out-strength sums the value of links emanating from a node and is measured with $s_{out_i}=\sum_j w_{ij}$, where *w* is an element of *W* [*Wasserman and Faust*, 1994]. Thus, the volume of water (m^3) embodied in U.S. food transfers provides the weights for the network links.

To better understand the importance of a node to the overall structure of the network, we consider higher-order network properties. Network assortativity (*knn*) is a second-order network property because it describes the relationship between network neighbors. *knn* measures the affinity of a node to connect to high-degree or low-degree neighbors [*Watts*, 1999; *Jackson*, 2008], typically using the Pearson correlation coefficient (τ) [*Newman*, 2002]. Values of $\tau \in (-1, 1)$: $\tau = 1$ indicate perfectly assortative mixing, while values of $\tau = -1$ indicate perfectly disassortative mixing [*Fricke et al.*, 2013]. When direction is accounted for *knn* can be measured with four directional pairs: in-in (ii), out-out (oo), in-out (io), and out-in (oi). For the explicit equations of *knn* refer to the supporting information.

Network clustering *C* is also a second-order network property, since it describes the propensity of nodes in the network to form closed triangles with their neighbors [*Watts*, 1999]. With direction, there are eight possible combinations of *C* that fall into four categories (see [*Fagiolo*, 2007] for a complete description and representation): C_{in}, C_{out}, C_{cyc}, and C_{mid}. Equations for *C* are provided in supporting information.

Betweenness centrality (*B*) is a higher-order network property, as it quantifies the importance of a node in terms of its importance to the overall network architecture [*Jackson*, 2008]. Node *B* counts the fraction of shortest paths that pass through the node of interest, defined as $B=\sum_{i,j}\frac{\sigma(i,u,j)}{\sigma(i,j)}$, where $\sigma(i,u,j)$ is the number of shortest paths between nodes *i* and *j* that pass through node *u*, $\sigma(i,j)$ is the total number of shortest paths between *i* and *j*, and the sum is over all pairs *i*, *j* of nodes [*Costa et al.*, 2007]. *B* is normalized by $1/(N-1)(N-2)$ for directed graphs to ensure it is $\in [0,1]$ [*Barthelemy*, 2004]. Directed paths are used to calculate directed *B* and undirected paths for undirected *B*.

2.5. Measures of Equality

We quantify the equality of virtual water flows between U.S. States with the same measures used for global virtual water trade (e.g., following *Seekell et al.* [2011]). First, we calculate the Gini coefficient (*G*) which measures the inequality among values of a frequency distribution. $G \in [0,1]$ and $G = 0$ indicates perfect equality (i.e., all values equal), while $G = 1$ indicates perfect inequality (i.e., one State has all the resources) [*Gini*, 1909]. Second, we calculate the Lorenz asymmetry coefficient (*S*) [*Damgaard and Weiner*, 2000; *Seekell et al.*, 2011]. *S* values $= 1$ indicate a symmetric distribution of resources, $S > 1$ indicates inequality because a few nodes consume most of the resources, and $S < 1$ indicates inequality due to a large number of nodes with small resources. The Hoover index (*D*) measures the maximum vertical distance between the line of equality and the Lorenz curve and can be interpreted as the proportion of trade by above-average States that would need to be redistributed to below-average States to achieve trade equality. If all trade needs to be redistributed to achieve equitable trade, then $D = 1$ (i.e., 100%); if perfectly equitable trade already exists, then no flows need to be redistributed, so $D = 0$ [*Hoover*, 1941; *Seekell et al.*, 2011].

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Table 2. Comparison Between Food Transfers Within the Unites States and International Food Trade

		United States	Global
Food value (billion (dollar))	Total	475	1,060
	Meat	133	
	Crops	117	
Food mass (billion tons)	Staple	0.18	0.42
	Meat	0.04 (24.0%)	0.03 (7.5%)
	Crops	0.14 (76.0%)	0.39 (92.5%)
Water volume (billion m^3)	Staple	317	625
	Meat	217 (68.4%)	101 (16.1%)
	Crops	100 (31.6%)	524 (83.9%)
Value intensity ((dollar)/ton)	Total	1,301	
	Meat	2,989	
	Crops	837	
Water intensity (m^3/ton)	Staple	1,724	1,490
	Meat	4,915	3,186
	Crops	717	1,351

3. Results and Discussion

3.1. Food Transfers

The total mass of staple food commodity transfers is 0.18 billion tons (refer to Table 2). This bulk weight is the total across all food commodity groups, which is the information that transportation planners find necessary for the planning and maintenance of the transportation infrastructure of the United States. Figure 1 shows the breakdown across commodity groups. Note that the commodity with the largest fraction of trade by weight is feed. Also note that the fraction of trade represented by live animals is small, particularly in comparison to the meat commodity group.

3.2. Virtual Water Content

Table 3 presents statistics on *VWC* by commodity group. A map of *VWC* values for each State in the U.S. is provided by commodity group in Figure 2. Note that the scale of the continuous color bar in the legend varies for each commodity group. White shading for States refers to the lowest value of each color bar and does not indicate missing data. The values and spatial pattern of *VWC* closely follow other estimates in the literature [e.g., *Mekonnen and Hoekstra*, 2011; *Mubako and Lant*, 2013; *Mubako*, 2011], since we rely on these to construct our own. The key difference is that we perform a production-weighted mean to aggregate across items within commodity groups.

3.3. Total Virtual Water Flows

Table 2 presents key characteristics of food transfers using different weighting schemes within the United States and for international trade. Note that the value of food movements within the United States is based on all food commodities presented by the CFS (i.e., SCTG items 1–7; "total" in Table 2). We use all food commodities for value calculations for better comparison with estimates of the value of global food trade, which are based upon all food commodities [*Ercsey-Ravasz et al.*, 2012]. However, calculations of the mass of food transfers and volume of virtual water flows are based on only staple food commodities (i.e., SCTG items 1, 2, 4, 5, and 6; "staple" in Table 2) for better comparison with estimates of international trade. Quantities for international staple food and virtual water trade are taken from *Konar et al.* [2011].

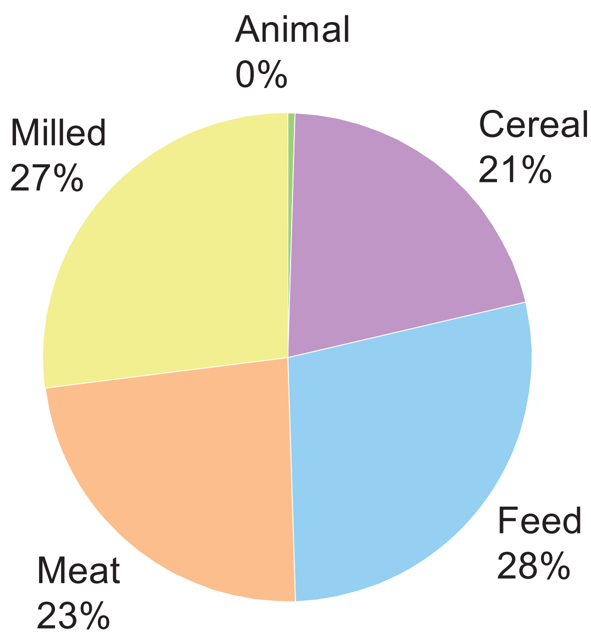

Figure 1. Percentage of staple food transfers by commodity group weight. The total mass of staple food transfers in the United States is 0.18 billion tons.

The value of domestic food transfers is 475 billion (dollar),

Table 3. Virtual Water Content (m^3/ton) of Staple Food Commodity Groups in the United States[a]

	Animal	Cereal	Feed	Meat	Milled
Mean	5,933	970	566	5,950	1,052
Minimum	1,245	394	321	1,243	392
Maximum	12,920	2,486	981	12,962	2,670

[a]Statistics on the mean, minimum, and maximum values are provided.

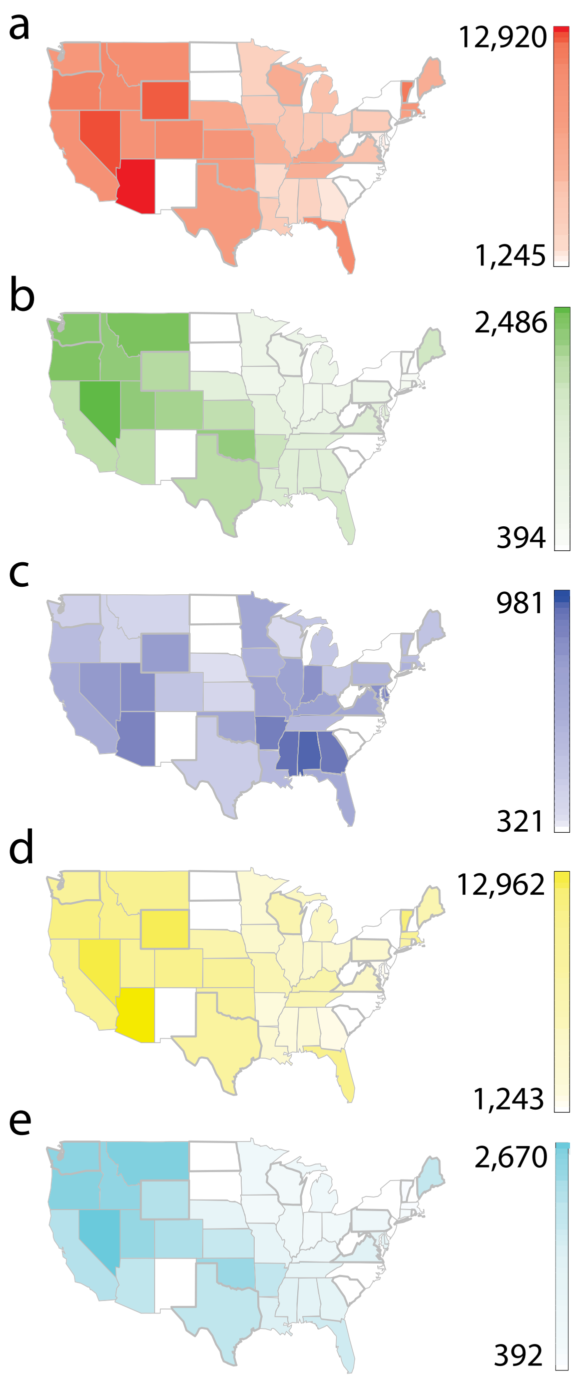

Figure 2. Maps of virtual water content (*VWC*) (m^3/ton) by food commodity groups. *VWC* is mapped for the staple commodity groups: (a) animals, (b) cereal, (c) feed, (d) meat, and (e) milled. Note that all U.S. States have a *VWC* value and white shading does not indicate missing data.

compared with 1060 billion (dollar) for international food trade. Thus, the value of U.S. food transfers represents approximately 45% (= 475/1060) that of international food trade, which scales in roughly the same proportion as the mass of food trade (i.e., 0.18/0.42 = 43%), albeit slightly higher. The volume of water embodied in U.S. food transfers is 317 billion m^3. Thus, the volume of water embodied in the U.S. food trade is approximately 51% that of global virtual water trade (= 317/625), which is a larger share than is food value or mass. This can be explained by the larger share of meat trade within the United States (i.e., 24.0% of food trade by mass is meat in the United States, but only 7.5% of global food trade by mass is meat; refer to Table 2), since meat is more water intensive than crops. It makes sense that more meat is traded within the United States than globally, since relatively heavy items like meat, especially those that require refrigeration in their transport, are more likely to be traded between locations that are close in space [*Tamea et al.*, 2014].

We graph the virtual water flows between U.S. States in Figure 3, using network visualization software [*Krzywinski*, 2009]. Refer to the supporting information for a complete list of the States. We estimate that 317 billion m^3 of virtual water is flowing over 1299 links

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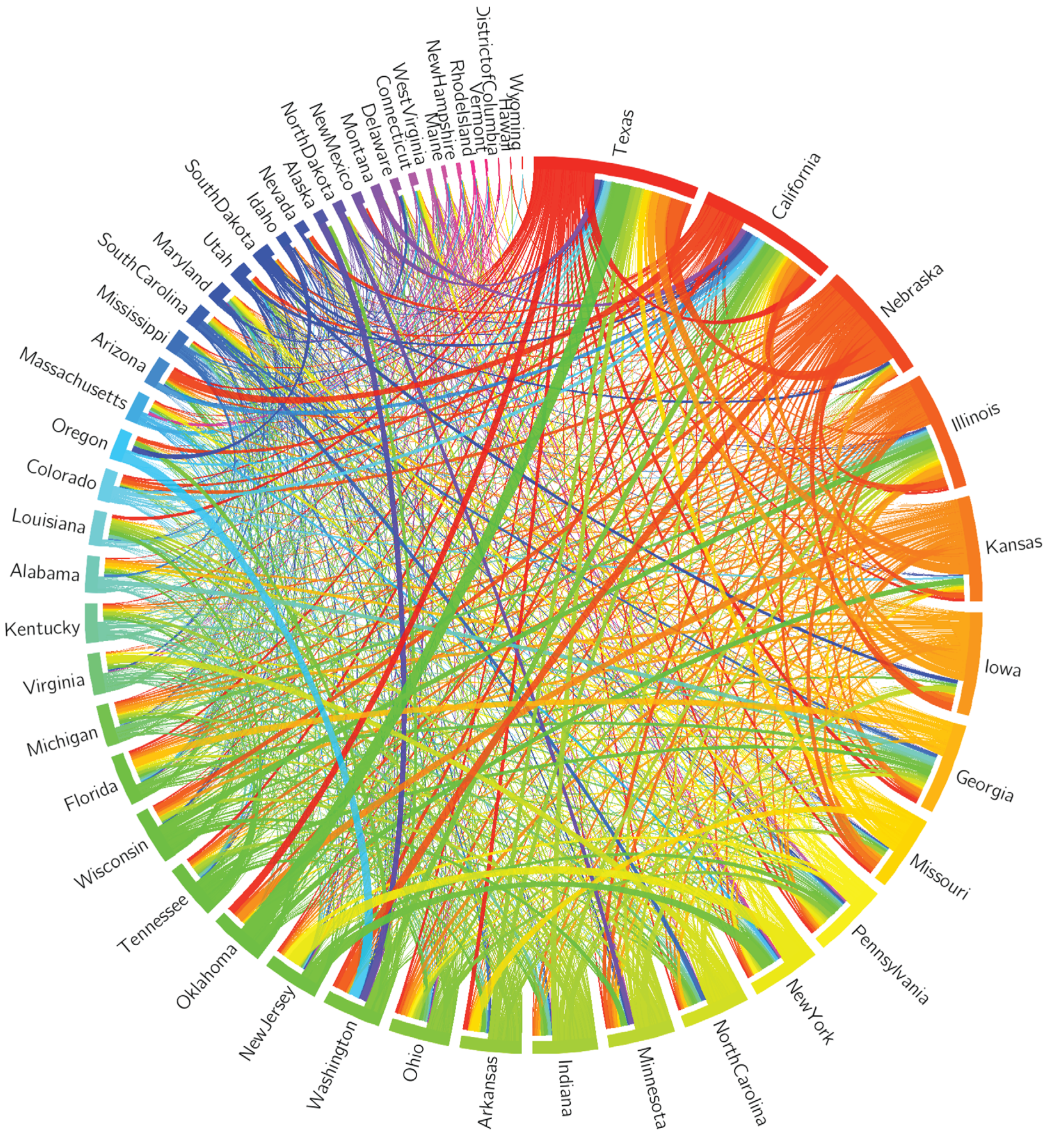

Figure 3. Virtual water flows within the United States. U.S. States are ranked according to the total trade volume and plotted clockwise in descending order. The size of the outer bar indicates the total virtual water trade volume of each State as a percentage of total U.S. trade. Destination volume is indicated with links emanating from the outer bar of the same color. Origin volume is indicated with a white area separating the outer bar from links of a different color. The volume of virtual water flows captured in this graph is 317 billion m^3 yr^{-1}. This figure was created with network visualization software available at http://circos.ca, developed by *Krzywinski* [2009].

(Refer to Table 6), which is what is illustrated in Figure 3. Note that the number of links differs from previous studies of food transfers within the United States (i.e., 4198 links reported in *Lin et al*. [2014]). This is due to the fact that *Lin et al*. [2014] analyze food transfers between CFS areas and a U.S. State-level analysis is presented here. Our estimate of 317 billion m^3 of virtual water transfers within the United States is in line with previous estimates, which suggest that interstate trade in the United States likely exceeds 190 billion m^3 (refer to *Mubako and Lant* [2013]). However, note that *Mubako and Lant* [2013] model commodity transfers using mass balance equations. So, it is reasonable that our estimate is higher, given that there are likely redundant food transfers that a model would not capture.

We calculate the value and water intensity of United States and global flows. We define the value intensity ((dollar)/ton) to be the total value of the food commodity transfers divided by the total weight of the food transfers. We define the water intensity (m^3/ton) to be the total volume of water embodied in the food commodity transfers divided by the total weight of the food transfers. Unfortunately, estimates of the value intensity of global food trade are not available in the literature. Note that the water intensity of meat

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Table 4. Ranking of U.S. States That Exchange the Most Virtual Water[a]

Rank	Destination		Origin	
1	Texas	29.7	Nebraska	28.6
2	California	27.1	Kansas	22.1
3	Illinois	20.0	Iowa	20.0
4	Georgia	15.8	Texas	17.8
5	Pennsylvania	14.0	Illinois	13.8
6	New York	11.5	California	13.0
7	Washington	11.0	Indiana	12.8
8	Ohio	10.1	Missouri	12.2
9	Florida	10.0	North Carolina	10.8
10	New Jersey	9.8	Minnesota	10.6

[a]Note that volume data is provided in billion m^3.

transfers within the United States is higher than at the global scale. This can be partly explained by the underlying CFS food transfer data, in which we do not know the fraction of trade per animal, unlike international trade data which provides trade data for each livestock commodity [*Konar et al*., 2011].

The States that import and export the most virtual water are listed in Table 4. Texas imports the most virtual water (i.e., 29.7 billion m^3), driving this State to be ranked first in terms of total virtual water trade volume (refer to Figure 3). California, Illinois, and Georgia all also import over 15 billion m^3 of virtual water. Nebraska exports the most virtual water, with a volume of 28.6 billion m^3 exported. This is closely followed by other States in the U.S. Midwest. Kansas, Iowa, and Texas all export volumes greater than 15 billion m^3 of water through staple commodities.

3.4. Blue and Green Virtual Water Flows

Here, we present estimates of the volume of green (i.e., rainwater) and blue (i.e., irrigation) water embodied in the transfers of cereal and milled commodity groups (i.e., SCTG commodity group 2 and 6, respectively). We estimate virtual water flows by source for these commodity groups only, because we do not have estimates of blue and green *VWC* for the other commodity groups. The total volume of blue water embodied in cereal and milled commodity transfers is 9.9 billion m^3. The total volume of green water embodied in cereal and milled commodity transfers is 62.0 billion m^3.

Table 5 presents the ranking of the top 10 States that import and export by water source. This table augments our understanding of total virtual water flows with information on virtual water flows by source of water. For example, it is evident that a significant share of Nebraska's virtual water exports are from rainfed

Table 5. Ranking of U.S. States That Exchange the Most Green and Blue Virtual Water[a]

	Rank	Destination	Cereal	Origin	Cereal	Destination	Milled	Origin	Milled
Green	1	Louisiana	4.72	Nebraska	3.77	California	3.21	Illinois	3.07
	2	Texas	3.73	Ohio	3.08	Illinois	2.86	Tennessee	2.49
	3	Oklahoma	1.70	Oklahoma	2.18	Texas	2.86	Minnesota	1.96
	4	California	1.61	Kansas	1.97	Pennsylvania	2.62	Missouri	1.95
	5	Kansas	1.51	Iowa	1.59	Georgia	2.43	Pennsylvania	1.58
	6	Nebraska	1.44	Missouri	1.55	Ohio	1.59	Iowa	1.50
	7	Illinois	1.32	Indiana	1.53	New York	1.19	New York	1.42
	8	Georgia	1.25	Minnesota	1.39	Florida	1.05	Ohio	1.33
	9	Minnesota	1.12	Illinois	1.17	Tennessee	1.03	Utah	1.29
	10	Alabama	1.12	Idaho	1.07	Washington	1.00	Kansas	1.25
Blue	1	Oregon	0.68	Nebraska	1.26	Texas	1.27	California	2.37
	2	Texas	0.59	Idaho	0.79	California	0.73	Arkansas	0.71
	3	Louisiana	0.48	Arkansas	0.38	Washington	0.43	Utah	0.68
	4	California	0.37	Kansas	0.31	Nevada	0.40	New Mexico	0.54
	5	Oklahoma	0.36	Oklahoma	0.15	Arizona	0.37	Texas	0.28
	6	Kansas	0.29	Colorado	0.12	Utah	0.29	Kansas	0.23
	7	Arizona	0.21	Missouri	0.11	Illinois	0.28	Nebraska	0.23
	8	Colorado	0.16	New Mexico	0.11	Florida	0.25	Missouri	0.18
	9	Nebraska	0.09	Mississippi	0.10	Pennsylvania	0.23	Oregon	0.17
	10	Washington	0.07	California	0.07	Oregon	0.23	Georgia	0.11

[a]Note that volume data are provided in billion m^3.

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Table 6. Network Properties of Domestic Virtual Water Flows and International Virtual Water Trade[a]

	United States	Global
Summary		
# Export nodes	50	151
# Import nodes	51	166
# Links	1,299	6,033
Degree		
Mean k	25.5	32.79
Range k_{out}	[0, 44]	[0, 159]
Range k_{in}	[2, 43]	[0, 97]
Strength		
Mean s	6.2	3.4
Range s_{out}	[0, 28.6]	[0, 165]
Range s_{in}	[0.12, 29.8]	[0, 52.1]
Assortativity		
knn_{ii}, knn_{ii}^{W}	−0.39, −0.10	−0.77, 0.00
knn_{io}, knn_{io}^{W}	−0.30, 0.38	−0.85, 0.20
knn_{oo}, knn_{oo}^{W}	−0.06, 0.43	−0.27, 0.35
knn_{oi}, knn_{oi}^{W}	−0.46, −0.02	−0.41, 0.29
Clustering		
C_{out}, C_{out}^{W}	0.83, 0.90	0.51, 0.73
C_{in}, C_{in}^{W}	0.87, 0.93	0.74, 0.94
C_{cyc}, C_{cyc}^{W}	0.34, 0.37	0.09, 0.16
C_{mid}, C_{mid}^{W}	0.36, 0.40	0.13, 0.24

[a]The properties of the U.S. virtual water flow network are presented here for the first time. The network properties of international virtual water trade are taken from *Konar et al.* [2011]. Flow volumes are in billions m^3 yr^{-1}.

cereals (i.e., since Nebraska is the first-ranked State for the export of cereals from green water sources). This table can be used to better understand which virtual water flows may be more vulnerable to climate disruptions, since green water flows highlight rainfed production, which is most susceptible to climate variability and extremes. Similarly, this information is useful in determining the extent to which irrigation infrastructure contributes to food transfers.

3.5. Network Properties

The network properties of the U.S. virtual water flow network are compared with those for global virtual water trade in Table 6. The U.S. network has fewer nodes and links than does global food trade, limiting the node degree (k). Note that mean k and maximum k_{in} and maximum k_{out} are smaller than at the global scale. Similarly, the maximum values of s_{in} and s_{out} are smaller than they are in global trade. However, mean s is larger for U.S. flows, indicating a more homogeneous flow network, in which many nodes participate in the trade of relatively large volumes of embodied water (refer to Table 6). Interestingly, interprovincial flows of virtual water in China were also found to be relatively more homogeneous when compared with global flows [*Dalin et al.*, 2014].

Figure 4 presents some of the key statistical distributions for k and s. Node degree follows a normal distribution for both k_{in} and k_{out}. A normal node degree distribution is indicative of a social network [*Pennock et al.*, 2002]. This is compared with the exponential degree distribution of global virtual water trade [*Konar et al.*, 2011]. The normal node degree distribution likely occurs due to complexities in the social and biophysical aspects of the food system. Climate suitability and local politics likely encourage positive feedbacks on the food production system. However, domestic subsidies and policies encourage nationwide production. Thus, the normal distribution reflects national policies that balance out local reinforcement mechanisms [*Lin et al.*, 2014].

The U.S. strength distribution follows an exponential distribution for both s_{in} and s_{out}, compared with a stretched exponential at the global scale [*Konar et al.*, 2011]. In other words, global virtual water trade volumes exhibit a fatter tail, representing the fact that more countries trade large volumes of virtual water. The exponential distribution of U.S. trade volumes does not have this fat tail, so there is less heterogeneity in the volume of virtual water traded by States. For the U.S. network, node strength versus node degree exhibits a power law relationship, which was also evident at the global scale. However, the power law exponent is smaller for the U.S. network than it is for the global network (i.e., the exponent for s_{in} versus k_{in} equals 1.72 for the U.S. network and equals 3.05 for the global network; s_{out} versus k_{out} equals 1.70 for the U.S. network and equals 1.93 for the global network) (refer to *Konar et al.* [2011] for global exponents). This power law relationship indicates that access to virtual water resources grows supralinearly with more social exchange relationships.

The weighted-rich club phenomenon is not evident for most assortativity structures within the United States, unlike for international virtual water trade [*Konar et al.*, 2011]. For example, the assortativity structure of *knn* moves from disassortative, when weights are not considered (note the strongly negative values of unweighted τ for global knn_{ii}, knn_{io}, knn_{oo}, and knn_{oi}), to assortative when weights and direction are included (note the positive values of weighted global τ for knn_{ii}^{W}, knn_{io}^{W}, knn_{oo}^{W}, and knn_{oi}^{W}). Unlike global trade, this movement from disassortative when unweighted to assortative when weighted is only apparent

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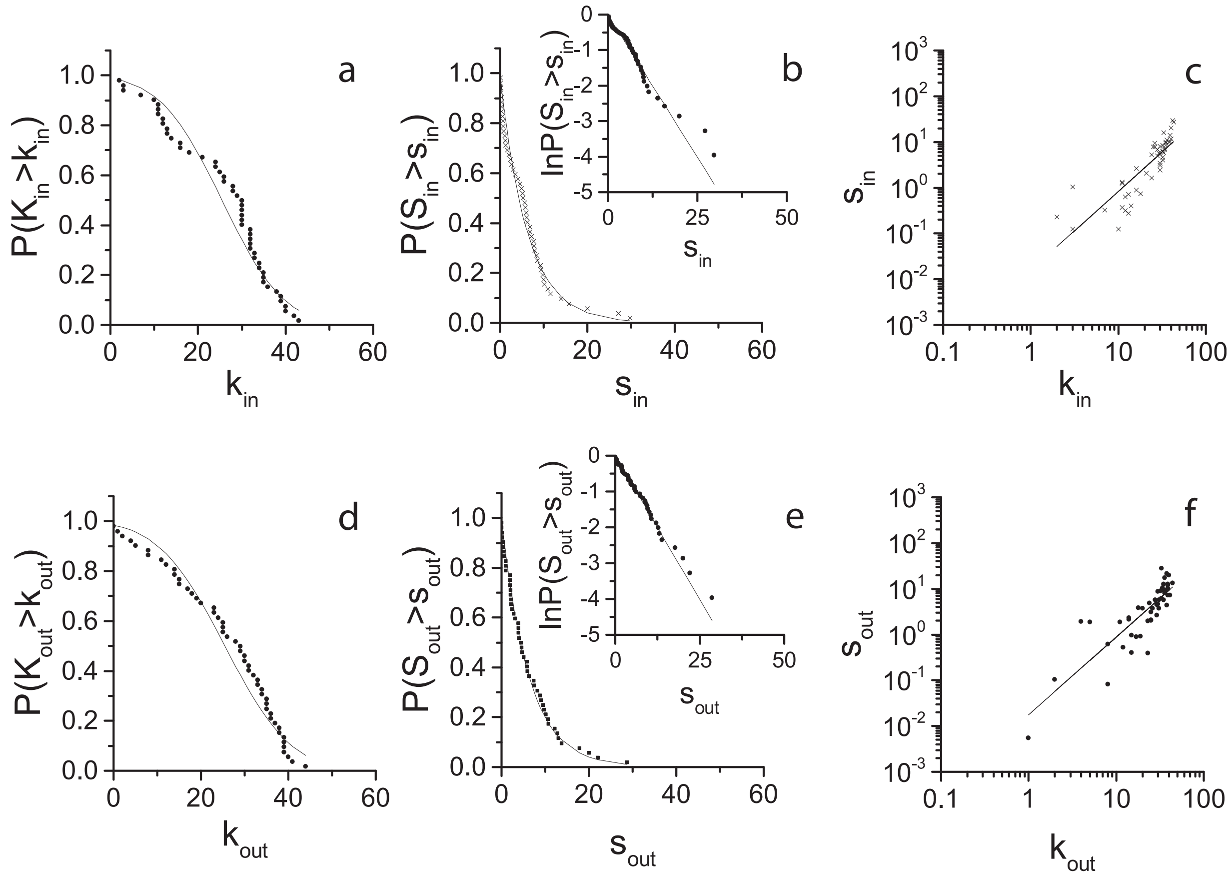

Figure 4. Statistical properties of the United States virtual water flow network. Distributions of node in-degree (plot A; $P(k_{in}) \sim N(25.5, 11.2^2)$) and node out-degree (plot D; $P(k_{out}) \sim N(25.5, 11.9^2)$) follow a normal distribution, indicative of a social network. Distributions of node in-strength (B) and node out-strength (E) follow an exponential distribution ($P(S_{in} > s_{in}) = P(S_{out} > s_{out}) = e^{-\frac{s_{in/out}}{6.2}}$). The relationship between node degree and node strength follows a power law relationship for both directional relationships in (C) and (F) ($s_{in} = 0.0158k_{in}^{1.72}$; $s_{out} = 0.0176k_{out}^{1.70}$). The unit of *s* is billion tons.

for two of the *knn* structures within the United States. However, the import-export relationship does indicate a strongly disassortative structure when only connectivity is considered, moving to a strongly assortative relationship ($\tau > 0.3$) with the inclusion of trade volumes. This indicates that major importing States have a propensity to connect with major exporting States in the United States.

Clustering measures (C) indicate that the U.S. virtual water flow network is more social than is global virtual water trade. Here, we define "social" to be synonymous with how clustered a network is. Values of C are higher across the board for the United States (with the minor exception of C_{in}^{W}). The United States exhibits relatively high C values for patterns of clustering that are very uncommon in global trade, such as C_{cyc} and C_{mid}. These parameters indicate that most States interact with one another.

The relationship between node degree (k) and directed node betweenness centrality (B) in Figure 5a illustrates the presence of a "core" group of nodes. This core group of nodes is central to the global structure and functioning of the virtual water flow network in the United States. The core nodes are listed in Table 7 and are: Illinois (IL), Pennsylvania (PA), California (CA), Massachusetts (MA), Washington (WA), New York (NY), and Texas (TX). Values of directed B are mapped for each State in Figure 5b. The States that play a key role in the network are prominent hubs of transportation for food within the United States (i.e., IL and PA) and major export harbors (i.e., CA, NY, and TX).

Thus, signatures of fragility are present in this empirical network analysis. Since the United States is such a key country in the global trade system, both domestic and international trade networks may be vulnerable to disturbances to these core nodes. It is important to note that we present empirical characteristics of network vulnerability. However, in order to truly understand the vulnerability of the network to the removal of

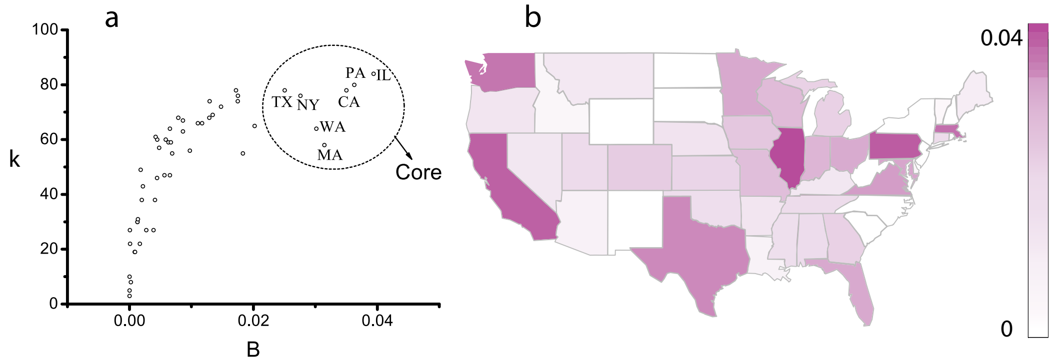

Figure 5. Centrality (*B*) of States to the United States virtual water flow network. (a) Node degree (*k*) plotted against node betweenness centrality (*B*) exhibits a "core" group of nodes. The seven core nodes are: Illinois (IL), Pennsylvania (PA), California (CA), Massachusetts (MA), Washington (WA), New York (NY), and Texas (TX). (b) Map of the betweenness centrality of each State.

these core U.S. States, a model must be developed. For this reason, analytical (e.g., similar to *Buldyrev* [2010]) and process-based (e.g., similar to *Ercsey-Ravasz et al*. [2012]) network models should be employed in the future to fully understand the fragility of the United States and global food transfer systems.

3.6. Equality Analysis

The equality of virtual water transfers is studied in the literature [*Seekell et al*., 2011]. In this section, we compare measures of global virtual water trade equality with those for the United States. Table 8 compares equality statistics for virtual water transfers within the United States with those that occur at the global scale. Virtual water flows within the United States exhibit a smaller Gini coefficient (*G*), indicating that flows within the United States are more equal than they are globally. The Lorenz asymmetry coefficient (*S*) and Hoover index (*D*) further support this finding: higher *S* values indicate greater symmetry, while lower *D* values mean less flows need to be redistributed to achieve equality.

From Table 8, it is clear that virtual water transfers within the United States are more equitable than they are for global trade [*Seekell et al*., 2011]. However, the United States does not exhibit a perfectly equitable virtual water trade system. The United State does not have barriers to trade, has a shared national agricultural policy, a national currency, and is relatively wealthy. For these reasons, food transfers within the United States can be thought to indicate a null model for trade equality [*Lin et al*., 2014]. Thus, it is unlikely—and probably even undesirable—that global trade will achieve perfect equality. Rather than examining if trade is equitable and striving to achieve this goal [*Seekell et al*., 2011], we suggest that future research efforts examine equality in food consumption, and whether or not trade expands access to food, thereby improving equitable food security [*Godfray et al*., 2011].

4. Conclusions

In this paper, we present a comprehensive analysis of virtual water flows in the United States: a key nation for global food trade, as it is a major agricultural producer, consumer, and economic power. This is the first study of intranational virtual water flows based upon food transfer data. Previous studies on intranational virtual water flows model commodity transfers. Thus, this is a first step to quantify domestic virtual water flows in the United States based upon data and we hope that future research efforts will continue to refine upon these estimates and improve their reliability. Additionally, this paper explores how properties of virtual water flows in the United States compare with global values. However, inconsistencies in food transfer data and the multiple water content methodologies employed in the literature make direct comparison across scales difficult. This highlights the need for consistent data and methodologies going forward.

Table 7. Core Group of U.S. States in Terms of Their Centrality (*B*)

State	B
Illinois	0.039
Pennsylvania	0.036
California	0.035
Massachusetts	0.031
Washington	0.030
New York	0.028
Texas	0.025

We find that (1) the value of U.S. food transfers scale in accordance with food weight, but virtual water flow

Table 8. Equality Measures for Virtual Water Trade Within the United States and Globally[a]

	United States	Global
Gini (*G*)	0.51	0.63
Lorenz (*S*)	0.85	0.70
Hoover (*D*)	0.36	0.5

[a]Measures of the equality of virtual water flows in the USA are presented here for the first time. Global values are taken from *Seekell et al.* [2011].

volumes are larger within the United States due to a higher composition of meat transfers; (2) the network properties of the United States indicate a more homogeneous and equitable structure than the global network, with similarities in vulnerability to key nodes; and (3) they are more equitable, although still not perfectly equitable.

We show that U.S. food values are approximately equivalent to 45% of the value of global food trade, while the mass of U.S. food transfers are roughly 43% of international food trade. However, the volume of virtual water flows within the United States is 317 billion m^3, representing 51% as much as global virtual water trade. This value is in line with previous estimates in the literature based upon modeled food transfers, but higher due to redundancies in commodity transfers not captured by idealized models. The virtual water volume represents a higher fraction of global trade than does food value or mass because meat comprises a larger share of the staple food transfers in the United States. Most U.S. States exchange a relatively large amount of virtual water when compared with nations participating in global trade, as evidenced by the higher mean virtual water flow volume in the United States.

The U.S. virtual water flow network is more social, homogeneous, and equal than global virtual water trade. However, the equality metrics indicate that virtual water flows in the United States are not much more equitable than at the global scale. Since even the United States is not perfectly equitable, it is unlikely—and probably undesirable—that global trade ever will be. Trade systems are based upon comparative advantage between countries, in which differences in factor productivity drives exchanges and hopefully enhances system efficiency. The welfare implications of the food trade system are really what is of concern, such as access to affordable, desirable, and nutritious food, rather than homogeneity of the food transfers themselves. We suggest that future research efforts focus on understanding equality in food consumption and security for end users and the role that trade plays in water security objectives.

A core group of States is critical to the structure and functioning of the U.S. virtual water flow network: Illinois, Pennsylvania, California, Massachusetts, Washington, New York, and Texas. Since the United States is such a key country in the global trade system, both domestic and international trade networks may be vulnerable to disturbances to these core nodes. It is important to note that these U.S. States are highlighted with empirical signatures of network fragility; however, we suggest that network models be developed and employed in future research to better understand the fragility of the United States and global food transfer networks. Additionally, we suggest that future research efforts should aim to inform policy on the opportunities for improving the resiliency of these key U.S. States to climate and economic shocks. Future work should seek to understand how to best invest in food production, water resources, and transportation infrastructure in these critical U.S. States.

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