Virtual nitrogen and virtual water transfers embedded in food trade networks across the US

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Abstract
Understanding environmental impacts through embedded resource accounting tools, such as footprints, allows scholars to connect resource demands to consumption choices. To date, considerably less attention has been paid to tracking the flow of goods, particularly at a sub-national level, to relate consumption patterns to the origin where nitrogen pollution may be occurring. We present and analyze the virtual N networks alongside virtual water networks embedded in the internal food trade within the United States. We utilize a Monte Carlo simulation to estimate the associated uncertainty of these values and compare them to existing works on both nitrogen and water footprint flows. Our results indicate that most of the US states exhibit a high nitrogen footprint for meat/seafood and a larger water footprint for cereal grain products. Additionally, we find that both the meat/seafood virtual nitrogen and virtual water networks exhibit high density and larger connectivity properties compared to the cereal grain and fruit/vegetable networks. We also examined the uncertainty associated with the commodity trade across the US and find that sampling errors tend to vary linearly with the footprint values. The sampling uncertainty in the N footprint values indicates greater variability in the cereal grain and fruit/vegetable products. To relate these networks with environmental externalities we also examined virtual N transfers between states based on the percent of assessed water bodies in a state that have nutrient-related impairments. We found that most of the virtual N transfers move from states with high impairments to states with lower rates of impairments. The outcomes from this research could be used to inform eutrophication and water use management across the United States.

1. Introduction
The study of coupled natural-human systems, i.e. complex arrangements of environmental, social, and economic connections and feedbacks, has proved to be an important area of research across recent decades due to the potential of this work to inform effective policies for ecological and socioeconomic sustainability (Liu et al 2007). Both water and nitrogen play important roles in coupled natural-human systems and are at risk of being out of sync with planetary boundaries (Rockström et al 2009, Steffen et al 2015). Methods including environmental footprint assessments (Vanham et al 2019) and ecological network analyses (Zhang et al 2018a) have allowed scholars to evaluate interactions between socio-economic and natural resource system components to investigate questions of sustainability and trade-offs between multiple coupled natural-human system elements (Ruddell et al 2014). The goal of this paper is to advance previous efforts in the study of coupled natural-human system by analyzing embedded nitrogen and water contents for several food commodities within the United States and studying these embedded resources through ecological network analyses of trade across the U.S.

Anthropogenic activities such as food and energy production have greatly influenced the release of reactive nitrogen (Nr; all nitrogen species except N₂) to the environment (Galloway et al 2004, 2008). This
increased release of Nr into the environment has contributed to various environmental challenges including coastal ‘dead zones’, biodiversity loss, and stratospheric ozone depletion (Galloway et al 2003, Diaz and Rosenberg 2008, Zhang et al 2010). Similar to the water footprint (Natzyak et al 2017), the nitrogen (N) footprint framework has been developed to understand the human’s contribution to the release of anthropogenic Nr to the environment (Leach et al 2012, Galloway et al 2014, Castner et al 2017). The food consumption N footprint is the amount of nitrogen contained in the consumed food product and thus enters the wastewater stream, while the food production N footprint (known as virtual N) accounts for all of the nitrogen lost to the environment during the food production process (Leach et al 2012). Nitrogen footprint tools provide a way to allow people to make decisions about their resource consumption and demonstrate how offsets could be combined with behavior change to decrease contributions to N-related problems (Galloway et al 2014).

Commodity trade distances the environmental impacts of Nr loss far away from where a product is consumed since the negative consequences of the production often remains in the producer regions (Lassaletta et al 2014). Several studies have examined Nr flows and trade associated with food production and consumption patterns at different spatial and temporal scale (Galloway et al 2007, Asmala et al 2011, Gu et al 2013, Lassaletta et al 2014, Oita et al 2016, Zhang et al 2018b). Xue and Landis (2010) applied the life-cycle assessment method to examine the nitrogen and phosphorus emissions throughout the food production system including agriculture, processing, packaging, and transportation. They found that high variability in nutrient emissions exist among various food groups where red meat has the largest nutrient footprint and cereal/carbohydrate has the lowest. Leach et al (2012) developed a N-calculator tool to estimate the N footprints in the US and found that the average per capita N footprint is 41 kg N yr$^{-1}$ among which the food production accounts for 25 kg N yr$^{-1}$. Globally, the total amount of N traded through agricultural commodities has increased almost eightfold during the past 50 years (Lassaletta et al 2014). Additionally, although the number of highly net N exporting countries has not increased very much (from 6 to 16 countries between 1961 and 2010), the number of highly net N importing countries has increased notably from ten countries in 1961 to 47 countries in 2010 (Lassaletta et al 2014). According to Oita et al (2016), the United States, India, Brazil, and China account for over 45% of the global emissions of ammonia, nitrogen oxides and nitrous oxide to the atmosphere, and of nitrogen potentially exportable to water bodies. They also concluded that approximately one-fourth of the global nitrogen footprint is from commodities traded across national borders. This highlights the need to study sub-national flows of embedded nitrogen to further understanding around the other three-fourths of the global nitrogen footprint. To our knowledge, the virtual N food trade network at a subnational scale in the US has not yet been investigated thus we lack a comprehensive, quantitative understanding of the role of virtual N transfers within the US.

In other environmental footprint scholarship, network theory has been utilized to understand the strengths and connections of embedded resources within trade (Konar et al 2011, MacDonald et al 2015, Sartori and Schiavo 2015, Vora et al 2017, D’Odorico et al 2018, Garcia and Mejia 2019, Xu et al 2019, Mahjabin et al 2020). While these studies have showcased the usefulness of network-based approaches for understanding virtual water trade, considerably less attention has been paid to network-based approaches for understanding virtual N transfer. In general, compared to the water footprint, there are fewer studies on N footprint, and the sources of Nr used in N footprint calculation are limited (Gu et al 2013, Pierer et al 2014). One recent work which attempted to fill this gap in network-based analyses showcased the evolution and interactions of six kinds of global environmental and socioeconomic networks and found that all of the material flow networks were connected and in each kind of network, distant countries had higher total trade volumes with each other than adjacent countries (Xu et al 2019). Additional network perspectives on how the movement of embedded resources including both nitrogen and water at a sub-national scale have the potential to provide additional insights into sustainable resource management.

In this paper, we develop and analyze the virtual N networks embedded in the internal food trade within the United States. We construct virtual N networks using open-source commodity flow data (Hwang et al 2016), estimate the N footprint by states producing and consuming three different sets of commodities, and examine the network properties of trade flows. We compare these properties to virtual water networks for these same sets of commodities and to other scholars which have utilized network theory to study embedded resources. Finally, we assess the uncertainty in the footprint values due to sampling variability in the commodity trade by utilizing a Monte Carlo simulation approach. Our study expands current research across both virtual water and virtual N flow networks by expanding understanding of the sub-national spatial patterns in the traded products and estimating their associated uncertainty.

2. Materials and methods

2.1. Construction of virtual N and virtual water networks

We constructed the virtual N networks for the interstate food trade by using commodity flow data and their associated virtual N contents for the
year 2012. These networks present virtual N transfers through food commodities among 50 states in the US. The Freight Analysis Framework version 4 data (FAF4) (Hwang et al. 2016) were used to obtain the weight of the commodity flow within 50 states in the US. The FAF4 data present the commodity flow for Standard Classification of Transportation Goods (SCTG) commodity classes. Based on the availability of the virtual N data, we included three SCTG food classes, which are cereal grain, agricultural products (mostly comprised of fruits and vegetables), and meat/seafood. The virtual N content, expressed in g of N per unit weight of food product, is the amount of nitrogen lost to the environment throughout the entire production process of that specific commodity. The virtual N contents for the food commodities are collected from Gephart et al. (2016) and presented in the supplementary file (table S1 (available online at stacks.iop.org/ERL/16/045015/mmedia)). To be consistent with the water footprint, we only considered the food production N footprint where N loss occurred at the upstream of food consumption. We did not include N loss that occurred after food consumption (e.g. as human waste) in the N footprint calculation. Since SCTG classification system aggregates several food products into one single class, we applied the production-weighted averaging approach (equation (1)) using USDA production data (USDA 2012) to calculate the virtual N content for the entire SCTG class (table S2).

\[
VNC_k = \frac{\sum_{i \in k} (VNC_i \times P_i)}{\sum_{i \in k} P_i}
\]  

where VNC indicates the virtual N content, \(k\) indicates a specific SCTG commodity class, \(i\) is the individual product belongs to that commodity class \(k\), and \(P\) indicates the production value for each individual product \(i\).

The constructed virtual N networks are weighted-directed networks where the flows indicate virtual N embedded in food commodities that are produced at the origin state and consumed at the destination state. For example, N footprint by origin state is calculated by aggregating all the outflows from state \(A\) (figure 1) and N footprint by destination state is computed by aggregating all the inflows into state \(A\) (figure 1). We did not include within state transfer in our analysis since we mainly focused on the interstate food trade. For a specific commodity class \(k\), we calculated the nitrogen footprint by origin state, NFO, and by destination state, NFD using equations (2) and (3), respectively

\[
NFO_{x,k} = \sum_{y} (VNC_y \times T_{x,y,k}, x \neq y)
\]

\[
NFD_{x,k} = \sum_{y} (VNC_y \times T_{y,x,k}, x \neq y)
\]

where NFO indicates nitrogen footprint by origin state, NFD indicates nitrogen footprint by destination state, \(x\) indicates different states and \(T_{x\rightarrow y}\) indicates the tonnage of \(k\) by origin state \(x\) and by destination state \(y\).

In this paper, we compared our virtual nitrogen networks with the virtual water networks, which we have presented in two recent publications (Mahjabin et al. 2018, 2020). We considered both blue and green water to construct the virtual water networks. The blue water originates from surface and groundwater sources where green water is available soil moisture from precipitation. Most of the figures related to water footprint and virtual water networks are shown in the supplementary file (figures S1–S4).

To visualize the virtual N and water networks, we used the open source software Gephi (Bastian et al. 2009). We used R packages (Csardi and Nepusz 2006, Wickham 2016) to analyze the weighted-directed networks by applying network statistical approaches from previous literatures (Konar et al. 2011, Lin et al. 2014, Garcia and Mejia 2019). We presented network metrics such as node degree, node strength, clustering coefficient, and network density. The node degree measures the number of incoming (in-degree) and outgoing (out-degree) links to or from a node. The node strength (also known as weighted degree) represents the magnitude of flow which is calculated by aggregating weights for each individual link. We used global clustering coefficient which is a measure of the overall tendency of the nodes to cluster together within the network. The global clustering coefficient is defined as the number of closed triplets over the total number of closed or open triplets, where a triplet comprises three nodes connected by either two (open
triplet) or three (closed triplet) undirected ties. The network density measures the proportion of present edges from all possible edges in the network.

To further explore the environmental and climate change impacts of the food trade, we incorporated the state’s nutrient related impairment and water scarcity (WS) data. According to Environmental Protection Agency (EPA), impaired waters require a total maximum daily load or alternative restoration plan to reduce pollutant loadings and restore the waterbody. In this paper, we used the data indicating percentage of assessed lakes/reservoirs that have a nutrient-related impairment (EPA 2010). We collected WS index from Mekonnen and Hoekstra (2016), where WS is defined as the ratio between local blue water footprint and total blue water availability. Therefore, state with a WS value greater than 1 is defined as the water-scarce state. In addition, we categorize the virtual N transfers by using National Oceanic and Atmospheric Administration (NOAA) climatic regions (Karl and Koss 1984) to understand the geographical impacts on food trade (shown in figure 7).

2.2. Exploring uncertainty
The Commodity Flow Survey (2015) reports sampling variability of the survey estimates as standard error and coefficient of variation. In this study, we explored uncertainty in the footprints by accounting for sampling variability in the commodity flows. To calculate the error in the footprint values, the error due to sampling variability in the commodity flows were propagated to the virtual N and water flows. In order to do so, we perturbed each commodity flow (equation (4)) by adding an error term that was randomly sampled from the t-distribution with 9 degrees of freedom, chosen based on the Commodity Flow Survey sampling variability (CFS 2015). The probability distributions were used as input to Monte Carlo simulations of 1000 runs to obtain output sample distributions of virtual N and virtual water flows

\[ F_e = F_o \pm t \times Se \]  

where \( F_e \) is the estimated commodity flow, \( F_o \) is the original FAF4 commodity flow, \( t \) is a random value sampled from the t-distribution with 9 degrees of freedom, and \( Se \) is the standard error computed as \( Se = CV \times F_o \). The CV is the coefficient of variation obtained from the CFS (2015) report.

3. Results and discussion

3.1. N footprint by origin and destination states
Our results indicate that a total of 8.2 × 10^{12} g of virtual N was transferred through food trade networks. On a per capita basis, utilizing a U.S. population of 328 million, this total footprint is approximately 25 kg N capita^{-1} yr^{-1} which is in line with previous estimates (such as Leach et al 2012, who also reported that 25 kg N yr^{-1} capita^{-1} is lost to the environment during food production). Consistent with national level studies that have found that trade significantly affect the N footprint in countries that rely on imported products (Oita et al 2016, Shibata et al 2017), we showcase that subnational state-level footprints are also strongly influenced by trade. We found that the nitrogen footprint is controlled by the meat and seafood class (figure 2), as opposed to the water footprint which is dominated by the cereal grain products (figure S1). Kansas, Nebraska, Illinois, and Iowa represent the highest N footprint for food production by total value (figure 2(A)). When normalized by population, Nebraska, North Dakota, and Kansas remain on top (figure 2(B)). By computing outflows minus the inflows of virtual N and virtual water, we found net footprint exporters and importers for both nitrogen footprints (figure 3) and water footprints (figure S2). A few differences between water and nitrogen here provide insight into implications of our findings. For example, Louisiana is a high net-water importing state but is not among the top importing states for embedded nitrogen. Texas and California are large importers for nitrogen and water, a trend that is likely driven by their large populations. Iowa, Kansas, and Nebraska remain high exporters for both nitrogen and water and thus represent key states for mitigating N loss based on production. North Carolina exports a high amount of embedded nitrogen representing another key state for mitigating N loss, yet it is a net water importer unlike the Midwest states. Arkansas is also a high N exporting state yet does not export a large volume of embedded water. High consuming states also have a role to play in the mitigation of N losses since a portion of the N embedded in these commodities will also be lost through food waste and human waste during the consumption process. The rank-order correlation between the state’s N and water footprint by origin indicated a Spearman correlation coefficient as 0.90. This strong positive correlation indicates that states with a high N footprint also tend to have a high water footprint.

To understand the environmental impact of N footprint, we examined the states lake and reservoir water quality assessment reports. We collected the data for percent of assessed lakes/reservoirs that have nutrient-related impairments from Environmental Protection Agency (2010). While imperfect due to different data collection and tracking techniques by state, we use this indicator as a proxy indicator to represent the extent of nutrient-related pollution in state surface waters (EPA 2010).

Figure 4 showcases that states with a larger N footprint of production tend to be the states having a larger percentage of lakes/reservoirs with nutrient-related impairment. However, Oregon exhibited a different relationship as it has a larger percentage of nutrient load but comparatively smaller N footprint.
Interestingly, Minnesota and Iowa both share substantial production footprints however they exhibit much lower nutrient related impairments according to this metric. Although we do not know why this trend exists, this may imply that perhaps these states have found ways to balance environmental externalities associated with their production of these commodities in ways that neighboring states such as Nebraska, Illinois, and Kansas have not. This could also be a function of natural processes since factors such as multiyear precipitation patterns can affect nitrate loading in streams (Van Metre et al 2016). Future efforts to discern additional insights into spatial patterns could leverage largescale approaches to map nitrogen concentrations (Bellmore et al 2018) alongside trade analyses across scales.

We also mapped a WS index to further understanding around state water availability and associated water footprint in food production (figure 5). We can see a distinct pattern as all the water scarce states are located in the western US. Some states in the Midwest show large water footprint mainly due to the grain production even though they are in the water scarce regions.

To calculate the percent of interstate virtual nitrogen transfer (figure 6(A)), we used five ranges of percent impairment shown in figure 4. In comparing the water impairment and WS state distributions, for nitrogen content transfers, the majority of transfers move between groups of impairments (i.e. from states with higher impairment to states with lower impairment or vis versa) (figure 6). Contrastingly, the percentage of transfers between scarce to scarce and abundant to abundant states within water footprint transfers indicate that these trade relationships are highly regional. The regional and climactic trends are further analyzed in section 3.2.

3.2. Virtual N flows embedded in food trade
We investigate the interstate transfer of the virtual N embedded in cereal grain, fruit/vegetable, and meat/seafood by nine climatic regions (figure 7). The node size in figure 7 represents the weighted degree (inflows plus outflows) and the link width indicates the flow volume (million g N yr⁻¹) between two nodes. The largest interstate transfer occurred between Kansas and Texas for cereal grain, and between Louisiana and Mississippi for fruit/vegetable.
The meat/seafood network is highly dense and connected with a clustering coefficient of 0.81 and a density of 0.55 compared to the cereal grain and fruit/vegetable networks which have clustering coefficients of 0.52 and 0.78 and densities of 0.21 and 0.49 respectively. Higher network densities indicate dependencies amongst a particular commodity and the state transfers thus meat/seafood represents a network more dependent on state to state transfers while grain represents a network with fewer state to state transfers. This indicates that the cereal grain network is dominated by fewer numbers of interstate connections.
Several of the topological properties (in degree, out degree, clustering coefficient, and density) of both the water and nitrogen networks mirror each other because the network construction is formed based on the same FAF4 database for trade (Mahjabin et al 2020). Strength of these networks however varies between water and virtual N networks since the network strength is tied to the environmental factor associated with that commodity. Among three food classes, average strength for virtual N network is larger for meat/seafood (111 400 million g N yr$^{-1}$) and smaller for cereal grain (22 005 million g N yr$^{-1}$). Similarly, for virtual water network, average network strength is larger for meat/seafood (4844 million m$^3$ yr$^{-1}$) and smaller for cereal grain (3863 million g N yr$^{-1}$). We also examined the relationship between node degree vs node strength and found that virtual N networks for cereal grain and fruit/vegetable can be best fitted by power-law relationship with $R^2$ values as 0.61 and 0.52, respectively. However, virtual N network for meat/seafood showed best fit for exponential relationship with $R^2$ value equal to 0.83. This is indicative of a trend that the greater number of trade partners that a particular state has the much more virtual N it trades which has important implications for states looking to increase or decrease their virtual N impact. Power-law fit is the property of a scale free network and power law relationships have been found in a number of real network analyses including in water footprint studies (Konar et al 2011, Dalin et al 2012, Chini et al 2018, Garcia and Mejia 2019).
3.3. Uncertainty in footprints

The spatial distribution of coefficient of variation associated with the N footprint by origin state is presented in figure 8. The spatial map shows that cereal grain and fruit/vegetables have greater variability in the footprint values. The larger uncertainty associated with the footprint values necessitates improving the estimates for these specific regions and SCTG classes.

We ranked states from highest to lowest based on standard deviation values (figure 9). Sampling uncertainty is comparatively higher for the states Kansas, Nebraska, and Iowa, which also have a larger N footprint. To gain additional insight into the uncertainty
in footprints, we fitted the power-law relationship between standard deviation and footprint values. We found that for cereal grain, sampling error tends to vary linearly with an exponent equal to 0.99 and $R^2 = 0.98$. We found similar linear relationships between sampling error and N footprint values for other two classes (fruit/vegetable and meat/seafood), but did not present those figures.

This approach to calculating uncertainty only represents exploration of one type of uncertainty associated with this study, the sampling variability of the CFS survey data. There are of course numerous other sources of uncertainties associated with the quality of the data, estimation methods, and parameters. Data limitations are a function of modeling approaches such as ours that utilize secondary government
agency databases for analyses. Parameter uncertainties include challenges with utilizing virtual N contents and water footprint intensities that are based on averages derived from previous studies. This can present a challenge, for example, because the virtual N content values represent averages that may not be accurate in every specific case particularly since N fertilizer application by farmers varies from year to year and biological uptake in various crops also varies by soil type, texture, slope, and other influential characteristics. This uncertainty is one that influences all similar studies that seek to estimate embedded resources such as nitrogen. As such, this area is deserving of attention for future research trajectories in the embedded resource accounting and footprint family scholarship. Other areas worthy of consideration for future pursuit include studying temporal dynamics of trade alongside sustainability metrics such as water and N footprints. Despite these numerous sources of uncertainty, our approach to estimating sampling variability within the CFS survey data represents our recognition of the importance of recognizing limitations in data analysis and presenting approaches for understanding these limitations, even if only in part.

4. Conclusions

Food production and consumption can increase the loss of 
$\text{Nr}$ to the environment. Therefore, to fill multiple gaps in the existing literature, this study explored the virtual N networks embedded in three classes of food commodities across the US. We find that most of the US states exhibit a high nitrogen footprint for meat/seafood and a larger water footprint for cereal grain products. Additionally, we found that both the meat/seafood virtual nitrogen and virtual water networks indicates high density and larger connectivity properties. We also examined uncertainty in the footprint values due to the variability in the commodity trade across the US and found that sampling errors tend to vary linearly with the footprint values. The sampling uncertainty in the N footprint values indicate greater variability in the cereal grain and fruit/vegetable products. In addition, Kansas, Nebraska, and Iowa exhibit larger uncertainty associated with the N footprint values.

Network based approaches to studying trade of environmental resources has showcased the usefulness of these techniques for suggesting potential sustainability policy changes (Oita et al 2016, Xu et al 2019). In this case, if states within the US wanted to target reducing their environmental footprint, they ought to consider transfers of material flows from outside their boundaries and similarly, states wishing to reduce localized nitrogen pollution might wish to consider how to share the burden of their production onto states which consume those products. Likewise, lessons may be learned from states who have managed to maintain production of commodities while
minimizing local environmental externalities. Other nitrogen footprint scholars have suggested a variety of mitigation strategies across spatial scales to potentially address N losses to the environment (Oita et al 2016, Shibata et al 2017) that include leveraging trade analyses of nation to nation flows of nitrogen between pollution hotspots and consumption destinations (Oita et al 2016). Likewise, the results of our study could be utilized to aid in management structures that distribute the externalities associated with nitrogen pollution from food production locations to those locations that consume the nitrogen intensive products at a sub-national level.

Future research in this area could improve the estimates for some specific regions (such as California, Kansas, Nebraska, and Iowa) and SCTG classes (cereal grain, fruit/vegetable) to reduce the uncertainty associated with the footprint values. In the future, this study can also be linked to international trade analyses or within-state analyses to further understand local, regional, and global implications of virtual N trade. Combined analyses of multiple footprints have the potential to allow for sustainability decisions to investigate and understand implications across multiple criteria, for example water quantity (water footprint) and water quality (nitrogen or perhaps phosphorus footprints).

**Data availability statement**

The data that support the findings of this study are available upon reasonable request from the authors.

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**References**

Asmala E, Saikku I and Vienonen S 2011 Import-export balance of nitrogen and phosphorus in food, fodder and fertilizers in the Baltic Sea drainage area Sci. Total Environ. 409 4917–22

Bastian M, Heymann S and Jacomy M 2009 Gephi: an open source software for exploring and manipulating networks Int. AAAI Conf. Weblogs and Social Media

Bellmore R A, Compton J E, Brooks J R, Fox E W, Hill R A, Sobota D J, Thornbrugh D J and Weber M H 2018 Nitrogen inputs drive nitrogen concentrations in U.S. streams and rivers during summer low flow conditions Sci. Total Environ. 659 1349–59

Castner E A et al 2017 The nitrogen footprint tool network: a multi-institution program to reduce nitrogen pollution Sustainability 10 79–88

CFS 2015 2012 Economic Census (available at: www.census.gov/data/datasets/time-series/demo/popest/2010s-state-total.html)

Chini C M, Djejdlian L A, Lubega W N and Stillwell A S 2018 Virtual water transfers of the US electric grid Nat. Energy 3 1115

Csardi G and Nepusz T 2006 The igraph software package for complex network research Interf. Complex Syst. 1695 1–9

D’Odorico P et al 2018 The global food-energy-water nexus Rev. Geophys. 56 546–531

Dalin C, Konar M, Hanasaki N, Rinaldo A and Rodriguez-Iturbe I 2012 Evolution of the global virtual water trade network Proc. Natl. Acad. Sci. USA 109 8353

Diaz R J and Rosenberg R 2008 Spreading dead zones and consequences for marine ecosystems Science 321 926–9

EPA 2010 Waters assessed as impaired due to nutrient-related causes (available at: www.epa.gov/nutrient-policy-data/waters-assessed-impaired-due-nutrient-related-causes)

Galloway J N et al 2004 Nitrogen cycles: past, present, and future Biogeochemistry 70 153–226

Galloway J N et al 2007 International trade in meat: the tip of the pork chop Ambio 36 622–9

Galloway J N, Aber J D, Erisman J W, Seitzinger S P, Howarth R W, Cowling E B and Cosby B J 2003 The nitrogen cascade BioScience 53 341–56

Galloway J N, Townsend A R, Erisman J W, Bekunda M, Cai Z, Freney J R, Martinelli L A, Seitzinger S P and Sutton M A 2008 Transformation of the nitrogen cycle: recent trends, questions, and potential solutions Science 320 889–92

Galloway J N, Winówarter W, Leip A, Leach A M, Bleeker A and Erisman J W 2014 Nitrogen footprints: past, present and future Environ. Res. Lett. 9 115003

García S and Mejía A 2019 Characterizing and modeling subnational virtual water networks of US agricultural and industrial commodities Adv. Water Resour. 130 314–24

Gephart J A, Davis K E, Emery K A, Leach A M, Galloway J N and Pace M L 2016 The environmental cost of subsistence: optimizing diets to minimize footprints Sci. Total Environ. 553 120–7

Gu B, Leach A M, Ma L, Galloway J N, Chang S X, Ge Y and Chang J 2013 Nitrogen footprint in China: food, energy, and nonfood goods Environ. Sci. Technol. 47 9217–24

Hwang H L, Hargrove S, Chiu S M, Wilson D, Lim H, Chen J, Taylor R, Peterson B and Davidson D 2016 The Freight Analysis Framework Version 4 (FAF4) building the FAF4 Regional Database: Data Sources and Estimation Methodologies (Oak Ridge, TN: Oak Ridge National Lab. (ORNL))

Karl T R and Koss W J 1984 Regional and National Monthly, Seasonal, and Annual Temperature Weighted by Area, 1895-1983. Historical Climatology Series 4-3 (Asheville, NC: National Climatic Data Center)

Konar M, Dalin C, Suweis S, Hanasaki N, Rinaldo A and Rodriguez-Iturbe I 2011 Water for food: the global virtual water trade network Water Resour. Res. 47 5

Lassaletta L, Billen G, Grizzetti B, Garnier J, Leach A M and Galloway J N 2014 Food and feed trade as a driver in the global nitrogen cycle: 50-year trends Biogeochemistry 118 225–41

Leach A M, Galloway J N, Bleeker A, Erisman J W, Kohn R and Kitzes J 2012 A nitrogen footprint model to help consumers understand their role in nitrogen losses to the environment Environ. Dev. 1 40–66

Lin X, Dang Q and Konar M 2014 A network analysis of food flows within the United States of America Environ. Sci. Technol. 48 5349–47

Liu J et al 2007 Coupled human and natural systems Ambio 36 659–49
MacDonald G K, Brauman K A, Sun S, Carlson K M, Cassidy E S, Gerber J S and West P C 2015 Rethinking agricultural trade relationships in an era of globalization *Bioscience* 65 275–89
Mahjabin T, Garcia S, Grady C and Mejia A 2018 Large cities get more for less: water footprint efficiency across the US *PLoS ONE* 13 8
Mahjabin T, Mejia A, Blumsack S and Grady C 2020 Integrating embedded resources and network analysis to understand food-energy-water nexus in the US *Sci. Total Environ.* 709 136153
Mekonnen M M and Hoekstra A Y 2016 Sustainability: four billion people facing severe water scarcity *Sci. Adv.* 2 2
Natzkaj J L, Castner E A, D’Odorico P and Galloway J N 2017 Virtual water as a metric for institutional sustainability *Sustainability* 10 237–45
Oita A, Malik A, Kanemoto K, Geschke A, Nishijima S and Lenzen M 2016 Substantial nitrogen pollution embedded in international trade *Nat. Geosci.* 9 111–5
Pierer M, Winiwarter W, Leach A M and Galloway J N 2014 The nitrogen footprint of food products and general consumption patterns in Austria *Food Policy* 49 128–36
Rockström J et al 2009 Planetary boundaries: exploring the safe operating space for humanity *Ecol. Soc.* 14 2
Ruddell B L, Adams E A, Rushforth R and Tidewell V C 2014 Embedded resource accounting for coupled natural-human systems: An application to water resource impacts of the western US electrical energy trade *Water Resour. Res.* 50 7957–72
Sartori M and Schiavo S 2015 Connected we stand: a network perspective on trade and global food security *Food Policy* 57 114–27
Shibata H et al 2017 Nitrogen footprints: regional realities and options to reduce nitrogen loss to the environment *AMBIO* 46 129–42
Steﬀen W et al 2015 Planetary boundaries: guiding human development on a changing planet *J. Educ. Sustain. Dev.* 9 235–235
USDA 2012 NASS QuickStats Ad-hoc Query Tool (available at: https://quickstats.nass.usda.gov/)
Van Metre P C, Frey J W, Musgrove M, Nakagaki N, Qi S, Mahler B J, Wieczorek M E and Button D T 2016 High nitrate concentrations in some Midwest United States streams in 2013 after the 2012 drought *J. Environ. Qual.* 45 1696–704
Vanham D et al 2019 Environmental footprint family to address local to planetary sustainability and deliver on the SDGs *Sci. Total Environ.* 693 133642
Vora N, Shah A, Bilec M M and Khanna V 2017 Food-energy-water nexus: quantifying embodied energy and GHG emissions from irrigation through virtual water transfers in food trade *ACS Sustain. Chem. Eng.* 5 2119–28
Wickham H 2016 *Ggplot2: Elegant Graphics for Data Analysis* (Berlin: Springer)
Xu Z, Chau S N, Ruzzenenti F, Connor T, Li Y, Tang Y, Li D, Gong M and Liu J 2019 Evolution of multiple global virtual material flows *Sci. Total Environ.* 658 659–68
Xue X and Landis A E 2010 Eutrophication potential of food consumption patterns *Environ. Sci. Technol.* 44 6450–6
Zhang C, Chen X, Li Y, Ding W and Fu G 2018a Water-energy-food nexus: concepts, questions and methodologies *J. Clean. Prod.* 195 625–39
Zhang J et al 2010 Natural and human-induced hypoxia and consequences for coastal areas: synthesis and future development *Biogeosciences* 7 1443–67
Zhang Y, Liu Y, Shibata H, Gu B and Wang Y 2018b Virtual nitrogen factors and nitrogen footprints associated with nitrogen loss and food wastage of China’s main food crops *Environ. Res. Lett.* 13 014017