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A Systems Approach To Assess Trade Dependencies in U.S. Food−Energy−Water Nexus

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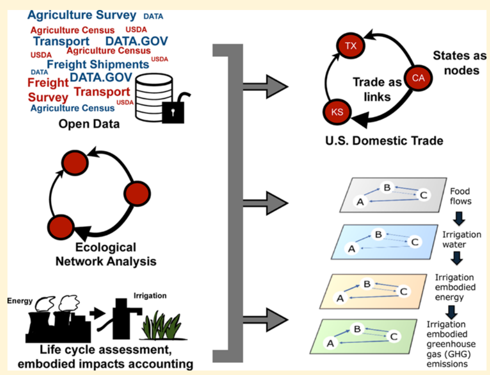
Supporting Information

ABSTRACT: We present a network model of the United States (U.S.) interstate food transfers to analyze the trade dependency with respect to participating regions and embodied irrigation impacts from a food−energy−water (FEW) nexus perspective. To this end, we utilize systems analysis methods including the pointwise mutual information (PMI) measure to provide an indication of interdependencies by estimating probability of trade between states. PMI compares observed trade with a benchmark of what is statistically expected given the structure and flow in the network. This helps assess whether dependencies arising from empirically observed trade occur due to chance or preferential attachment. The implications of PMI values are demonstrated by using Texas as an example, the largest importer in the U.S. grain transfer network. We find that strong dependencies exist not only just with states (Kansas, Oklahoma, Nebraska) providing high volume of transfer to Texas but also with states that have comparatively lower trade (New Mexico). This is due to New Mexico's reliance on Texas as an important revenue source compared to its other connections. For Texas, import interdependencies arise from geographical proximity to trade. As these states primarily rely on the commonly shared High Plains aquifer for irrigation, overreliance poses a risk for water shortage for food supply in Texas. PMI values also indicate the capacity to trade more (the states are less reliant on each other than expected), and therefore provide an indication of where the trade could be shifted to avoid groundwater scarcity. However, some of the identified states rely on GHG emission intensive fossil fuels such as diesel and gasoline for irrigation, highlighting a potential tradeoff between crop water footprint and switching to lower emissions pumping fuels.



■ INTRODUCTION

The United Nations General Assembly adopted the Sustainable Development Goals (SDGs) in 2015 to provide a roadmap for tackling 17 distinct issues with the overarching theme of human health and well-being, economic security, and environment sustainability. While diverse in subjects, these goals are termed as an "indivisible whole" and require managing for overlap in policymaking to avoid suboptimal outcomes.[1] For instance, SDG 2 outlines ending hunger, providing nutrition, achieving food security, and promoting sustainable agriculture. It directly ties in with Goal 12 of sustainable production and consumption of resources, which in turn requires planning for quality and plentiful supply of water (Goal 6) and renewable, affordable energy (Goal 7). As such, a single goal cannot be achieved in isolation while disregarding effects of others as it may result in unintended consequences. Instead, a holistic systems perspective is required that considers the complexity of interconnections. A crucial dilemma in applying a systems perspective is to avoid falling into an abyss of an infinitely connected system. Therefore, an appropriate boundary can help constrain the system and limit relevant interactions within and with the system. The study of interactions within food, energy, and water resources, termed as food−energy−water (FEW) nexus, can be seen as an example of drawing such a system boundary from many other interwoven and equally important SDGs. Albeit, FEW nexus itself represents a complex web of interconnections as energy and water are consumed across the entire food supply chain, energy is needed for abstraction, treatment, and distribution of water, and a large amount of water is consumed for power generation. Therefore, systems analysis needs to be complemented with a context-specific study at specific geographic scales and sectors to understand effects of interconnections. Recently, many such studies have adopted nexus approach to assess a variety of interactions at different spatial scales[2−5]

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including wastewater management to simultaneously reduce water energy demand and boost nutrient cycling for London,[6] developing a scenario analysis for competing water use in transboundary Brahmaputra River Basin,[7] impact of city-level FEW nexus actions in Delhi,[8] and China's increasing environmental impacts due to focus on international exports.[9]

The FEW nexus challenges associated with an agriculture-centric nation such as the United States (U.S.) are different from developed countries that rely on agriculture imports or developing agro-economies. For the U.S., one critical piece in understanding FEW nexus challenges is the energy and greenhouse gas (GHG) emission burden of irrigated food production.[10] Irrigation adds significant value to food and feed production in the U.S.,[11] providing a crucial link to study the domestic FEW systems. Irrigation is the second largest freshwater withdrawal sector in the U.S.,[12] while irrigation pumping accounts for substantial agricultural energy expenses.[13] Additionally, regional variation exists between agricultural resources availability and densely populated food demand centers. For instance, the High Plains in the U.S. is labeled the "breadbasket region" due to significant grain production; California provides a sizable portion of fruits, nuts, and vegetables for domestic and international consumption. On the other hand, Illinois, Louisiana, Texas, and Florida import a large amount of food due to their large population or geographically strategic position as ports.[14] As the imbalance between consumption and production increases, understanding the patterns of trade dependencies becomes an important consideration for regional food security.

Trading partner selections, and the subsequent dependencies, economic pressures, and vulnerabilities of such preferences, have been discussed widely in the trade literature.[15−17] Specific to food trade, dependency is a complex issue as it may strengthen food security (through diversifying trade partners) or harm food supply (reducing self-sufficiency). Prior work has investigated dependencies arising from indirect resource use to produce traded food commodities (referred to as virtual/embodied trade of resources).[18−20] Virtual resource trade (popularized by the virtual water concept[21]) refers to the trade of resource that is not physically embedded but used in producing the traded food commodity. Through virtual resource trade, regions can sustain greater food demand than local production capacity by depending on external virtual water and land imports to meet the demand.[22,23]Dependencies can also arise due to the structure and arrangement of how trade links are formed. Prior work has investigated community patterns,[24] central players,[10,25] robustness and resilience,[26,27] and dynamics of the networks[28,29] by quantifying structural properties of trade networks through graph theory-based approaches. However, the dependencies arising from interlinkages between food, energy, and water resources and trading partners have been understudied due to the complexity of the issue. Additionally, prior work addressing these issues have focused on larger components and backbones,[28,30] and dominant flows in the network.[10,31] However, little emphasis has been placed on examining weaker links and their role in the network structure.

The importance of considering ties with weaker strength was outlined by Granovetter[32] in his essay on social networks. Granovetter noted that weak ties between individuals (i.e., acquaintances) are instrumental in maximum diffusion of information, mobility, and community organization. From a trade perspective, this translates to the fact that dependency exists in both directions and weaker links may be important when all connections are considered. Therefore, we combine the resource and structure dependency narrative and examine the importance of weak ties in the network. Specifically, we analyze the pattern of regional food trade dependencies in the U.S. food trade. Here, a dependency denotes a level of preferential attachment (structural dependency) and reliance on resources (embodied resource dependency). We do this by comparing observed trade to a null model of trade. The null model represents the most probable trade given each state's import needs and export supply with no other specific preference in how links are formed.[33] The emergent patterns in actual trade, not observed in the null model, provide insights into dependence (level of preferential attachment) in the network. Additionally, we extend the analysis to quantify virtual water (accounting for only irrigation), irrigation-related embodied energy (referred to as embodied energy in the manuscript), and irrigation energy-related embodied GHG emissions (referred to as embodied GHG emissions) to assess a state's indirect dependency on resources through trade. While trade typically refers to international exchanges, we limit the analysis and discussion to the U.S. and refer to interstate trade as transfers.[25]

Specifically, we leverage empirical data and compare existing patterns of domestic transfers with calculated probabilities of association between participating states. To this end, we create four distinct networks: (i) interstate physical food flows (U.S. tons), (ii) virtual water (m^3),
(iii) embodied energy (MJ), and (iv) embodied GHG emissions (kg CO_2 equivalent). Building on the framework for the network analysis of physical food trade and embodied impacts first presented in our previous work,[10] we limit the focus of the present study to grain and feed crop transfers with states representing nodes in the network and volume of transfers and embodied environmental impacts represented by links (edges) between nodes. In this study, we assess how much more often than chance do two events occur together.[34] This is valuable information to gain for an extremely well-connected network such as the U.S. domestic trade. Our previous analysis noted that on average, a state is connected to 36 other states out of 51 states.[10] Therefore, if a state produces a specific crop, unlike international trade, it is not restricted to trade with a particular state (no political conflicts, trade agreements, etc.).[14] Therefore, by comparing observed trade connections (empirical network) to those that may occur by chance (null model), we highlight the presence of preferential attachment. Instead of purely empirical analysis, this provides statistical support to understand the significance of what we are observing and provides valuable contribution to the literature. The rest of the article is organized as follows: material and methods section discusses the data behind constructing four networks and introduces the PMI measure. Result and discussion section applies the PMI measure to the system under study and discusses insights with the case of Texas as an example. Details regarding the PMI measure, including relevant derivations, are provided in the Supporting Information.

■ MATERIALS AND METHODS

Domestic Food Transfer Network. We built the domestic food transfer and embodied impact networks using existing empirical datasets. The framework along with data sources are detailed in the Supporting Information, Table S1.

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The bilateral domestic food transfer data were obtained from the Freight Analysis Framework (FAFv4).[35] FAF provides estimates for tonnage and value of freight transported by origin and destination, commodity type, and transportation mode. The latest available data are for 2012 and serve as the base year for this analysis. FAF data are for groups of commodities based on Standard Classification of Transported Goods (SCTG) classification system. The US agriculture is quite oligopolistic in terms of mass-producing selected agricultural crops, with cereal and animal feed alone constituting 53% of the national agricultural production.[36] Additionally, compared to fruits and vegetables, grains are widely produced by many states, providing sufficient data to compare production practices and assess resulting dependencies arising from embodied impacts. Therefore, in this work, we focused on commodities covered by SCTG 02 (cereal grains) and SCTG 04 (animal feed, eggs, honey, and products of other origin). For SCTG 04, we specifically focus on only the animal feed related commodities as they comprise the majority of this group.[25,35] We included wheat, corn, rice, sorghum, rye, barley, and oats for grains and corn silage, sorghum silage, alfalfa hay, and hay for animal feed. Corn diverted to bioethanol production was excluded based on the national corn use statistics for 2012.[37] We note that some of the grains from the cereal grains category may end up as animal feed for nonruminant livestock; however, accounting for all final uses falls outside the scope of this study.

The embodied impacts are estimated for specific commodities, while the trade data exists for aggregated groups of commodities. To disaggregate shipment data, we assumed that composition of grains in a shipment is similar to composition of production at origin. Therefore, if rice production in Arkansas was 80% of total grains production, the grain shipments coming out of Arkansas would consist of 80% rice. While transport-based surveys provide a best available substitute for interregional transfers accounting, they suffer from several limitations such as overassigning inflows to transport hubs and not distinguishing between point of production versus point of last value added.[38] We corrected for this limitation as follows: we limited the analysis to transfer of raw grains, animal feed, and associated impacts and did not track processed products. Therefore, food transfers to a particular location may not represent the final consumption of a food item but the first set of consumers (e.g., processing plants) in the supply chain. As such, the discussion on dependency still remains relevant, but we avoid overestimating environmental impacts of processed goods. Additionally, by disaggregating transfers based on state production data, we overcome the possibility of incorrectly attributing production to nonproducing states. Similar approach for interregional disaggregation has been employed previously.[10,25,39] A brief discussion on regional commodity transfer limitations and reconciliation issues is provided in the Section S2. Next, we constructed weighted and directed matrices of food transfer referred to as flow matrices (T). Each matrix element (T_{ij}) represents flow of mass of grains and animal feed from origin (i) state to destination (j) state. The focus of this work is limited to irrigation impacts of food trade. By irrigation impacts, we specifically mean irrigation water, embodied energy, and embodied GHG emissions related to irrigation. A discussion on GHG impacts of U.S. food transport can be found elsewhere.[40−42]

Embodied Energy and GHG Emission Networks. First, we calculated the fraction of irrigated food transfers by assuming proportional shares to irrigated production. We converted food transfer matrices into distinct matrices of virtual water, embodied energy, and embodied GHG emissions by using data from the Farm and Ranch Irrigation Survey,[43] U.S. agriculture census,[44] Energy Information Administration data[45] combined with life cycle assessment methods. In particular, we use cumulative energy demand[46] and IPCC 100 year global warming potential to calculate our life cycle impacts.[47] The detailed methodology and assumptions were first described by framework provided by Vora et al.[10]

Pointwise Mutual Information (PMI). We analyze state-wise trade dependencies through pointwise mutual information (PMI) measure. The PMI measure is based on concepts from information theory, graph theory, probability, and statistics.[48] Commonly applied in linguistics,[34,49,50] PMI calculates the probability of co-occurrence or colocation of two words (events). A classic example involves comparing two synonym adjectives "strong" and "powerful" from the English language. A set of specific words is used more commonly with one or the other. As an example, "strong tea" and "powerful car" have a higher probability of appearing together than "powerful tea" and "strong car"; although the adjectives convey the same message.[51] In a set containing these four, if the information of the first word being "strong" is known, then "tea" has a higher probability of being the next word, thereby reducing indeterminacy of the system.[52] We extend the same logic to assess trade dependencies by asking, for example, if we know a state is importing food, can we predict any information about its partners given the set of data? We perform this exercise not to predict new links but as a way of assessing statistical significance of empirically observed data. PMI is defined by the following eq 1. The complete derivation of PMI measure is provided in the Supporting Information

$$\mathrm{PMI}_{ij} = k \log_2 \frac{p_{ij}}{p_{i.}p_{.j}} \tag{1}$$

p_{ij} is the probability of i and j co-occurring. k is a scalar constant. If events i and j are independent of each other, then the probability of their co-occurrence is given by their marginal probability of occurrences. Marginal probability of occurrence for event i is $p_{i.}$ (eq 2) and for j is given as $p_{.j}$ (eq 3)

$$p_{i.} = \sum_j p_{ij} \tag{2}$$

$$p_{.j} = \sum_i p_{ij} \tag{3}$$

For flow networks such as the system under consideration, we can replace the probabilities of occurrence with measured frequency of flow in the network. T_{ij} represents flow of trade from origin (i) to destination (j). A "dot" notation is used to represent summation over that index such that $T_{i.}$ gives the total outgoing flows of i, $T_{.j}$ gives the total incoming flows to j, and $T_{..}$ gives the total trade in the network, referred to as total system throughput.

$$p_{ij} = {T_{ij}}/{T_{..}};\ p_{.j} = {T_{.j}}/{T_{..}};\ p_{i.} = {T_{i.}}/{T_{..}} \tag{4}$$

Therefore, PMI can be rewritten as,

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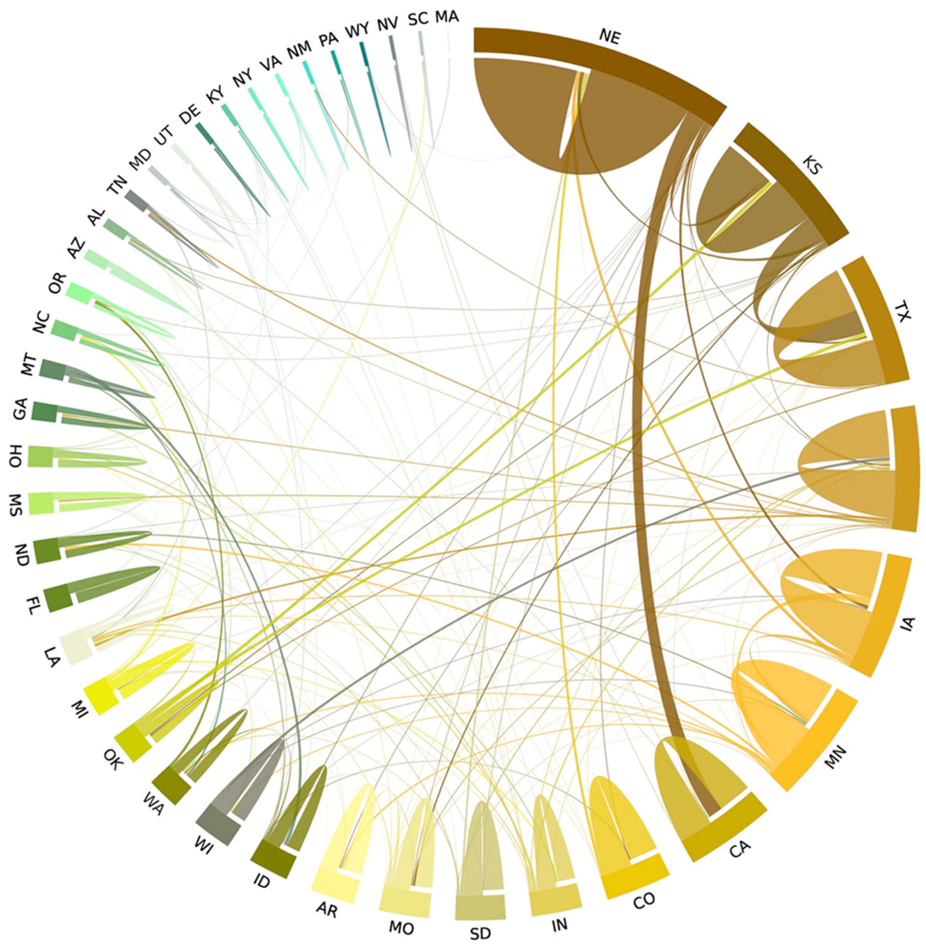

Figure 1. Cereal and feed grains transfer among the U.S. states. For visualization purpose, links with at least 1% of maximum link weight are shown.[19] Each circular segment represents participating states. The white gap indicates incoming transfers, while the same colored links originating from the segment represent outgoing transfers. The segments are arranged in a descending order based on their total outgoing (both within state and out-of-state) transfers. The figure is prepared using the Circos visualization tool.[55]

$$\mathrm{PMII}_{ij} = \log \frac{T_{ij}T_{..}}{T_{i.}T_{.j}} \tag{5}$$

In network trade studies, null modes or random networks have been used as a benchmark to compare significance of structural properties of the observed/actual trade. If a random network can generate higher order properties similar to those in observed trade, then an observed structure of the trade network is a result of random formation and estimating its properties does not give us any useful information.[33] PMI measure essentially compares an observed trade network with a pseudo-random network (which is referred to as a null model). We use the term pseudo-random because trade cannot be random, therefore comparing an observed network to a completely random network would not yield any meaningful insight. To make the null model comparable to the observed network, some of the bare minimum properties of the observed network need to be preserved to an otherwise randomly formed network. Here, the null model used to generate PMI values constrains the network to keep the total inflow (demand) and outflow (supply) from each state constant. This is an important constraint from sustainability perspective as it prevents states from supplying more than their current reported capacity. This constraint results in a singular solution. The flow matrix M, representing the null model of trade, can be given by the following equation

$$M = F_{\mathrm{out}}F_{\mathrm{in}}T_{..} \tag{6}$$

$$F_{\mathrm{out}} = \begin{bmatrix} T_{1.}/T_{..} \\ T_{2.}/T_{..} \\ \vdots \\ T_{n.}/T_{..} \end{bmatrix} F_{\mathrm{in}} = [\, T_{.1}/T_{..} \;\; T_{.2}/T_{..} \; \cdots \; T_{.n}/T_{..} \,] \tag{7}$$

Here, F_{out} (51×1) and F_{in} (1×51) represent vectors of out-flows from and in-flows to each state, respectively, normalized by the total flow in the system. Therefore, M is calculated by rewiring network flows among each trade connection. A unique property of the null model is that it redistributes flow in a way that the trade becomes more equitable (not equal) while considering current sending and receiving capacity of each state. Therefore, PMI values indicate how far each trade interaction is from being more equitable. An example of how the null model divides flow equitably is provided in Section S4.

The PMI measure can potentially take positive, negative, or zero values. If states i and j are completely independent (basis

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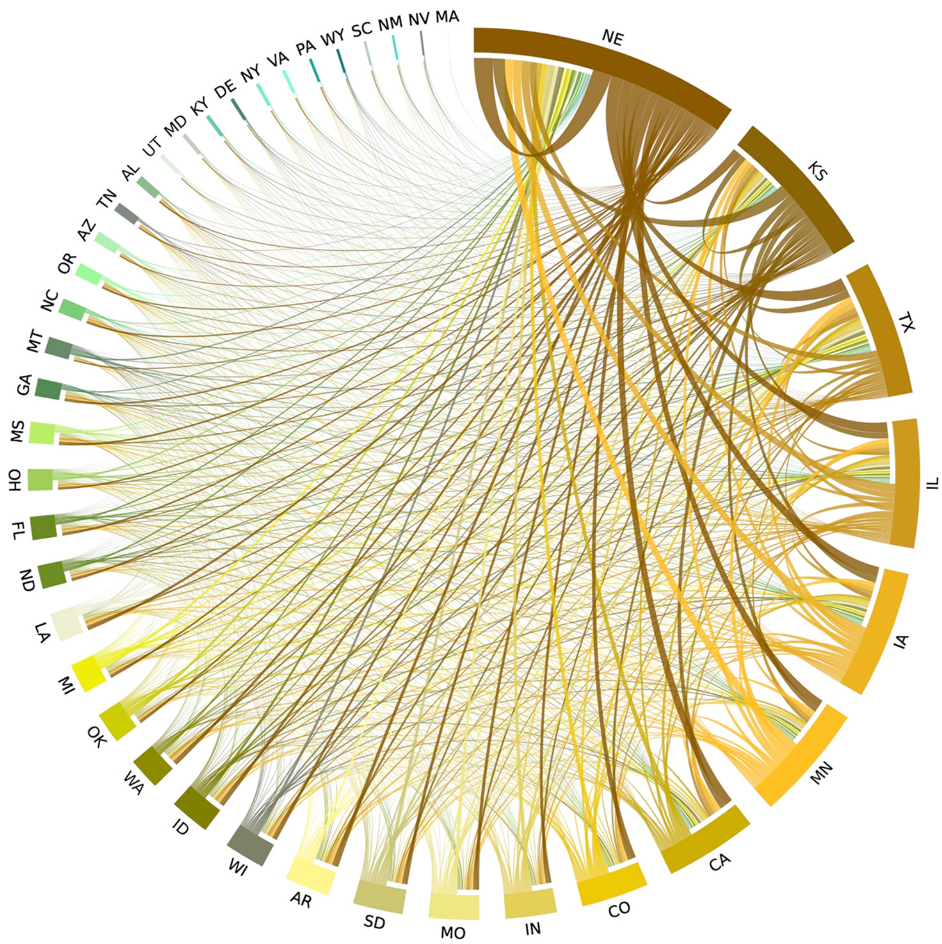

Figure 2. Cereal and feed grains trade between U.S. states for null model (zero dependency). The flow structure is redistributed considering network flow constraints such that total throughput (both incoming and outgoing transfers) in each state remains constant. For consistency, links with at least 1% of maximum link weight are shown. Each circular segment represents participating states. The white gap indicates incoming transfers, while same colored links emanating from the segment represent outgoing transfers.

for null model), the value of PMI becomes 0. When i and j have a high probability of trading but their actual trade is low, PMI values become negative (eq 8). Similarly, a positive PMI indicates that states are more dependent than expected.

$$\log(p_{ij}) < \log(p_{i.}p_{.j}) \quad (8)$$

Previously, Kharrazi and Fath discussed the value of utilizing PMI measures to evaluate preferential trade policies within the context of international oil trade.[53] Based on PMI values, the aforementioned formulae can help evaluate policies for (un)desired trade relationships. It is to be noted that the goal is to not move toward a null model, as trade can never be random, but to understand more deeply the relations between dyads and to reverse the PMI value signs depending on policy objectives, when desired. If a move from positive PMI to a negative PMI value is desired (reduced trade) for a particular trade relationship, then trade volumes can be recalculated to identify partners that can meet the additional demand. However, rearranging even one pair would alter the entire pattern of network flows indicating importance of considering interactions within the entire system.

■ RESULTS

Network Indicators. We consider food transfers between 50 states plus the District of Columbia, creating a 51-node size (n) network. There are 1145 links (L) within these states dedicated to cereal grains and animal feed trade. The density (L/n^2) of the network is 0.44 and reciprocity (proportion of links in both directions to total number of links) of 0.64, indicating a well-connected structure with high level of flow between states. The total flow in the network amounts to 613 million U.S. tons, with 166 billion m^3 of virtual water, 633 billion MJ of embodied energy, and 42 billion kg CO_2 equivalents of GHG emissions embodied within the flows. Cereal grains represent 75% of total food transfers by mass and subsequently represent a larger portion of embodied irrigation impacts (Table S3). Figure 1 provides a visualization of irrigated transfers within the U.S. The segments are arranged in a descending order based on their total out-going activity. For a majority of the states, the highest volume of transfers is their within-state flows. Nebraska's irrigated agriculture primarily includes corn for grain, corn silage, and alfalfa hay. The large self-loop may indicate shipments going toward feeding the large cattle and hog industry.[54] The largest (out-of-state) outgoing transfers are from Kansas, Nebraska, Minnesota, Indiana, and Iowa. The largest inflows are to Texas, California, Nebraska, Illinois, and Iowa. The largest out-of-state transfer is from Kansas to Texas of 18 million U.S. tons and primarily consists of corn, corn silage, alfalfa hay, and wheat in shipments.

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Next, we visualize flow values according to null model in the system (Figure 2). These values are rearranged in a more uniform fashion considering the mass of the product of total flow going and coming out of states. It should be noted that the flows are not redistributed to become equal in volume but based on equity in distribution. The degrees (number of connections) distribution and weighted degree distributions for the observed flow and null model are provided in Section S4 and indicate maximum connectivity of the null model while preserving total throughput from each state. Additionally, the density of the null model network is 0.9 with a reciprocity of 0.79, indicating an overly connected structure with more flows being reciprocated. When we compare the structure of observed flow with the null model, the observed flow presents a preference in their transfers. As there are no political boundaries compared to international trade,[14] the preference represents the presence of "additional information" in how ties are formed.

Dependencies in the Network. Generally, direct dependencies of trade relationships are identified listing top importers/exporters for each trading partners. However, direct relationships do not incorporate the role of considered relationship in the context of other relationships out of the two states. This translates to how overall connections in the network (the system) affect one relationship being studied. Additionally, a large volume of inflows may not translate to a higher dependency for the pair, but low inflows may be more valuable to the network.[32,53] This is explained in more detail next.

PMI values are calculated for each interaction between the dyads and therefore result in a 51 × 51 matrix for each network. As an example, we focus on Texas, the largest importer, and its trading partners to demonstrate the usefulness of considering system dependencies. Texas received incoming transfers amounting to 49 million U.S. tons from 34 states including a large chunk of within-state transfers. Texas's largest inflows (apart from within-state flows) are from Kansas, Oklahoma, Nebraska, Louisiana, and Indiana. Therefore, in a conventional sense, Texas highly depends on these states for food flows. We rank PMI values from Texas's top 10 import partners in a descending order and compare with ranks of direct incoming transfer volume (Table 1). Mismatches between PMI ranks and direct trade volume ranks show that associating dependencies based on direct trade observations may not account for important but less visible states. The PMI value for New Mexico borders is zero, indicating the observed flow's proximity to the null model behavior. Considering all transfers from New Mexico, a substantial portion is already being transferred to Texas, with a little room for increase (negative PMI), indicating a higher dependency of the connection. On the other hand, Nebraska has a lower PMI rank and negative PMI value, denoting that despite substantial volume of flows already going in to Texas, Nebraska has the ability to send more, resulting in a lower bilateral dependence than possible. Kansas and Oklahoma have the largest PMI values as Texas' exporting partners, indicating Texas's over reliance on these two states. As observed from Table 1, majority of connections have negative PMI values compared to positive values. This is consistent across the network in both import and export connections for majority of states (Section S3), indicating that at the network level, a few states control the throughput of flow. This has important implications for local network structural resiliency as reliance on a few states makes a state more prone to effect of shocks. Additionally, some of the PMI rankings are consistent with mass/volume-based rankings, denoting that the high flows empirically observed are not by chance but statistically significant. A visualization of the null model and observed flows along with extended PMI table for Texas is provided in Section S5. We emphasize that by providing comparison of rankings, our motive is not to recommend PMI method over traditional approaches but to provide complementary insights along with other commonly used measures.

Table 1. Texas' Top 10 Importing Partners Ranked by Their PMI Value in a Descending Order Compared with Observed Incoming Transfers and Respective Rank[a]

incoming flow	PMI	PMI rank	flow (U.S. tons)	flow rank
Texas	3.31	1	3.23×10^7	1
Kansas	1.61	2	1.77×10^7	2
Oklahoma	1.10	3	2.76×10^6	3
Louisiana	0.23	4	9.38×10^5	5
New Mexico	−0.05	5	1.19×10^5	11
Indiana	−1.59	6	6.60×10^5	6
Missouri	−2.17	7	4.06×10^5	7
Tennessee	−2.51	8	5.99×10^4	16
Nebraska	−2.76	9	1.37×10^6	4
Arizona	−2.81	10	6.01×10^4	15

[a]Positive PMI indicates higher than expected dependency and negative PMI indicates lower than expected dependency.

Negative PMI values indicate a state's capacity to trade more (as the states are less reliant on each other than expected) and therefore provide a first indication of where the trade could be rewired without extensive economic and physical system modeling (such as used in crop displacement studies).[56,57]

Embodied Impacts and Implications for FEW Nexus. Next, we analyze trade interactions and dependencies within a FEW nexus context focusing on virtual water, embodied energy, and embodied GHG emissions.

A spatial display of the PMI values for virtual water transfers to Texas shows the pattern of near neighbors being ranked higher (Figure 3). The dark gray-shaded states represent high PMI values and therefore represent higher dependence. Previous work has discussed the prevalence of gravity law[62,63] based relationship of distance enabling trade in international virtual water trade.[64] The size of the pie chart represents total virtual water transfers out of each state. The scale of the pie chart accounts for irrigation intensity of crops (m^3/ton) as well as volume of transfers. Statewide irrigation intensities are provided in the Supporting Information. Nebraska, Kansas, Louisiana, and Missouri have lower irrigation water application intensity but overall higher volume of transfers. This may be attributed to metering of groundwater due to regulations[65] along with high crop yields in the area. However, high PMI-ranked states New Mexico, Arizona, Colorado, and Utah have high water application intensities, indicating virtual water hotspots in Texas' imports.

The pie charts show distribution of virtual groundwater and surface water used for production of food transfers. A majority of Texas' exporters and Texas rely on groundwater for food imports. Therefore, groundwater depletion is an important aspect in considering regional virtual water flow dependencies. We overlay the PMI map with a layer of groundwater stress in major groundwater basins, derived from Gleeson et al.[58] and

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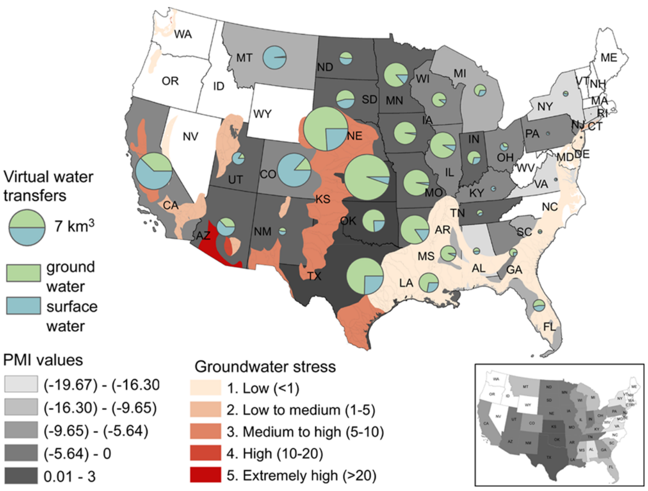

Figure 3. PMI values for virtual water transfers to Texas (also included in inset for clearer visualization). The pie chart indicates portion of virtual surface and groundwater in food trade. The scale of pie chart represents total virtual water transfer out of each state (within-state flows included). The states colored in white represent absence of virtual water transfer to Texas. The primary groundwater aquifers of USA are overlaid in the graph with associated groundwater stress obtained from Gleeson et al. and Aqueduct water risk atlas.[58,59] The underlying basemap is from the US Census Data,[60] and the figure is compiled in the ArcGIS software.[61]

Aqueduct database.[59] Groundwater stress represents groundwater footprint over total aquifer area and is computed by setting up a water balance between groundwater withdrawal, recharge, and environmental flows.[58] From South Dakota to Texas, eight states heavily depend on the Ogallala Aquifer as an important common groundwater source for irrigation. The Ogallala Aquifer's current use exceeds natural recharge with significant decline in Kansas and Texas.[66] Scanlon et al.[67] estimate that if the current depletion rate continues, then 35% of the southern plains would not be able to support irrigation in the next 30 years. Therefore, despite lower water application intensity for some states, virtual water imports to Texas from within-state flows and neighbors Kansas, Oklahoma, and New Mexico may be affected by groundwater depletion in the long run, especially as pressure on the shared Ogallala Aquifer increases from population demand and changing climate.[68]

From a demand side, the possibility of groundwater shortage can be managed by restructuring existing trade to explore alternate states that have a higher potential to trade by looking at negative PMI values. In such cases, states with policies that support sustainable irrigation can be given a preference to build a water scarcity-resilient food supply chain. For example, lighter gray-shaded states such as Alabama, South Carolina, Florida, Kentucky, and Ohio have lower PMI value, low water application intensity, and a balanced use of irrigation water sources, making them potential candidates for increasing trade. However, the marginal environmental impact of increasing trade, specifically on water quality in gulf states, would have to be examined. From a supply side, majority of Ogallala states have implemented state-level groundwater management plans, along with some moving beyond conservation and planning for depletion targets. Jarvis and Wolf[69] note that the next set of Ogallala strategies will require managing adaptation challenges for all the stakeholders involved. In such cases, the mutual dependence due to regional trade can act as an incentive for negotiations toward sustainable management of common source.

Figure 4 indicates PMI values for embodied GHG emission transfers to Texas. Each pie chart represents the distribution of

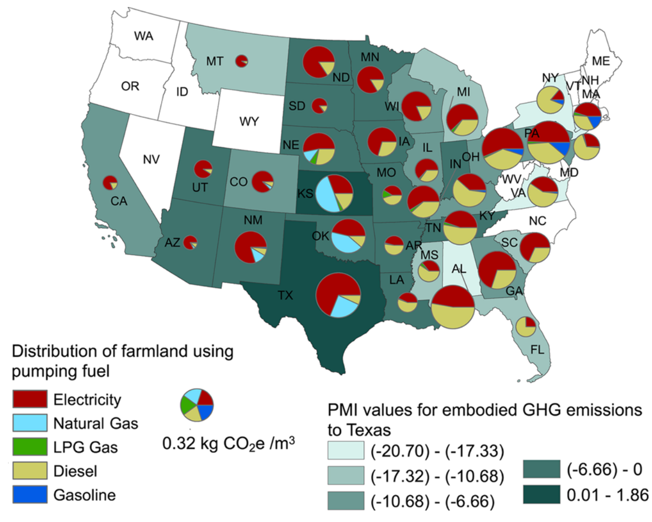

Figure 4. PMI values for embodied GHG emissions in imports to Texas. The pie chart indicates distribution of acreage using specific pumping fuel for on-farm irrigation pumps. The size of the pie chart indicates GHG emission intensity in kg CO_2 equivalent per m^3 of water abstracted. The states colored in white represent absence of GHG transfer to Texas. The underlying basemap is from the US Census Data,[60] and the figure is compiled in the ArcGIS software.[61]

pumping fuels used in every state with all states employing electricity and diesel-based pumps with a handful using natural gas (Texas, Oklahoma, Kansas, Nebraska), gasoline- (Pennsylvania, Ohio, Rhode Island, New York) and LPG (Nebraska, Missouri)-based pumps. The size of the pie chart indicates GHG emission intensity in kg CO_2 equivalent per m^3 of water abstracted. Barring electricity, natural gas-based pumps have the lowest embodied GHG emission intensity among all four fuels considered. Life cycle emissions attributable to electricity-based pumping differ considerably across states due to differences in regional grid mixes. Apart from electricity, all the states use diesel-based pumps in some capacity, with eastern states using diesel pumps on significant acreage. In addition to fuel mix, pumping energy requirements depend on other factors such as type of irrigation system (gravity- vs pressure-based), system pressure, depth to water for lift, velocity, and pipe losses.[70] Contrarily to water intensity for crops, California, Colorado, Arizona, Arkansas, and Utah have lower GHG emission intensity per m^3 of water withdrawn. These states primarily use gravity-based irrigation or rely on lower to medium pressure systems. Many of the Ogallala states, despite using substantial natural gas in their pumping mix, have higher GHG emissions per m^3 of water withdrawn. This could be attributed to the high coal-based electricity mix in their grid (e.g., Kansas, Nebraska, and Oklahoma have more than 60% coal-based generation), water depth for groundwater pumping, and use of water-efficient but energy-intensive pressurized sprinkler systems. High use of diesel- and/or gasoline-based pumps combined with pressurized irrigation systems could be contributing to high GHG emission intensity of states such as Pennsylvania, Ohio, Alabama, and Kentucky.[43] These states represent a clear example of water scarcity versus GHG

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emission tradeoff and denote an area of farm conservation policy focus for improving pumping energy and emission profile of irrigation by upgrading fuel pumps. As part of Ogallala conservation efforts, several programs have been underway since 2008 to reduce irrigation withdrawals and as a result have also reduced energy requirements of farms, suggesting that groundwater conservation and irrigation emission reductions may not be mutually exclusive goals.[71]

■ DISCUSSION

This work provides a system-level perspective in analyzing domestic food−energy−water interactions (within regional transfers and between embodied systems) through interdisciplinary methods spanning information theory, graph theory, water footprint, embodied energy, and emissions quantification. We demonstrate the usefulness of considering interactions at a network level to provide a comprehensive indication of trade dependencies. Using Texas as an example, we show that major importing partners of Texas by volume may not rank high in expected trading as expressed here in the index of PMI values and vice versa. A bilateral trade relationship consists of an interaction between a dyad, with both partners playing an equally important role. Ranking Texas' exporters by volume only showcases Texas' dependency of the transfer but not of its partners. As PMI accounts for the overall transfer activity and the potential to increase (or decrease) activity between a dyad, it provides a thorough accounting of their mutual dependency. This clearly exhibits the importance of Texas-New Mexico trade connection, despite being of a lower volume, and reiterates the importance of also considering weak ties.[32]

When we compare the visual difference between flow in a null model and actual trade, the heterogeneous distribution in trade concertation becomes apparent with a few links/states dominating the network (Section S3). Another visible trend is the importance of geographical distance in forming trade relationships. Our results indicate that distance drives the grain and animal feed trade preference for Texas, specifically as a significant portion may be dedicated to providing cost-effective animal feed for Texas' sizable cattle industry or for food and beverage manufacturing. By combining PMI results and a groundwater stress indicator, we highlight the regional reliance of Texas' and neighboring states on Ogallala Aquifer for irrigation while engaging in substantial transfer among themselves and discuss alternate potential states with less stressed irrigation systems. In fact, dependence through regional trade can serve as a motivation to manage common water resources and help avoid water allocation disputes such as the recent one between New Mexico and Texas[72] and between users of Colorado River basin.[73] Further, a considerable geographic variation exists in recharge rates across the Ogallala Aquifer due to its subsurface hydrology.[67] Therefore, our estimates can be improved in the future by characterizing the portion of domestic food consumption attributed to nonrenewable groundwater withdrawals from U.S. aquifers.[74]

The analysis presented in this work has its limitations. An important limitation of this work is the FAF dataset's inability to trace the final point of consumption (e.g., household consumption). This would require integration and reconciliation of a larger scale of datasets to accurately track the supply chain, such as the recent study of corn supply chain by Smith et al.[75] Additionally, future domestic trade analysis should involve employing origin tracing algorithms[76] used in international trade studies to remove re-exports from the data. From a system-level analysis, we emphasize that no one method is universally superior over other methods including techniques such as life cycle assessment, material flow analysis, network analysis, and so forth. Additionally, we note that while PMI provides information on structural dependency based on trade data, it cannot differentiate between a (un)desirable option based on embodied impacts such as type of water resource, water scarcity, and fossil fuel used as this information is not inherently built into snapshot of trade. Therefore, it needs to be supplemented with footprint approaches and life cycle assessment methods to provide a complete picture.

Furthermore, we do not account for energy and emissions associated with off-farm water supply (prevalent in the western U.S.)[77] due to lack of national data, making our estimates conservative and likely to increase. Therefore, if future policies internalize the cost of GHG emissions in trade, states may look for cost-effective and cleaner energy options with natural gas currently being one of the easily accessible choices. As our results demonstrate, this may be at odds with other equally important goals to achieve a sustainable and resilient food supply. Specific policies have long been in place under the U.S. Farm Bill to subsidize switching to water-efficient irrigation systems, but a rebound effect of over-pumping may lead to water depletion[78] and salinization.[79] At the same time, the discussion on FEW nexus should incorporate electric utilities and authorities that can devise demand-response programs for farmers to offer electricity at lower prices off-peak and potentially manage the emissions profile of generators.[80−82] Finally, PMI values demonstrate the potential to trade less (positive PMI) or more (negative PMI) given the existing network constraints compared to the situation of no preference. Therefore, it may serve as a valuable policy aid in building sustainable and resilient food systems by indicating the overall effect of potential trade (dis)preferences for diversifying trade partners.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge on the ACS Publications website at DOI: 10.1021/acs.est.8b07288.

Additional information regarding data sources, code for PMI, and the modeling approach (PDF)

Additional information regarding cereal grains, feed, and intensity factors (XLSX)

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Notes

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