A Systems-level Framework for Understanding Sustainability and Resilience of the U.S. Food-Energy-Water Nexus

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Global population growth, environmental change, and increasing urbanization are pressurizing already constrained resources such as food, energy, and water. Food, energy, and water systems are interconnected in myriad ways and require an integrated management approach (referred to as the FEW nexus) to avoid unintended consequences. This work focused on irrigation and phosphorus fertilizer as critical avenues to understand interdependencies between FEW systems in the United States (U.S.). Specifically, we focused on modeling and analyzing FEW systems through the lens of domestic food trade. Food trade networks represent pathways for displacing vast quantities of embodied environmental impacts associated with agriculture production. Therefore, quantifying the origin and destination of food flows and associated environmental impacts is central for understanding the sustainability and resiliency of the FEW nexus. Combining food trade data with information on water use, fertilizer application, irrigation energy expenses, and life cycle assessment methods, this work quantified embodied phosphorus fertilizer, irrigation water, energy, and greenhouse gas (GHG) emissions associated with food trade. Through a network theory approach, this work further characterized the network structure and its implications for the sustainability and resilience of the FEW systems. Finally, an optimization model was developed to assess the feasibility of rewiring the food trade network for enhancing the environmental sustainability of FEW systems. Results showed that the GHG emissions associated with irrigation are similar to emissions from the US cement industry. For

food trade networks, proximity to a trading partner is an important factor driving the trade with neighboring states trading more, but it could be a potential risk if these states depend on the same water source for agriculture. The findings of this work also highlight the challenges in restructuring trade to avoid tradeoffs between water and energy use. The results of the interstate phosphorus trade model revealed phosphorus fertilizer use savings with states using phosphorus fertilizer efficiently exporting to less efficient states. Finally, this work discussed challenges and opportunities in improving our current understanding of resource use in the U.S. agriculture.

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Nomenclature

AAPFCO	Association of American Plant Food Control Officials
ARMS	Agriculture Resource Management Survey
CED	Cumulative Energy Demand
CFS	Commodity flow survey
EIA	Energy Information Administration
FAF	Freight Analysis Framework
FEW nexus	Food-Energy-Water nexus
FRIS	Farm and Ranch Irrigation Survey
GHG	Greenhouse gas
IPNI	International Plant Nutrition Institute
IWRM	Integrated Water Resource Management
LCA	Life Cycle Assessment
NASS	National Agricultural Statistics Service
O-D	Origin-Destination
P	Phosphorus
PMI	Pointwise Mutual Information
PNB	Partial Nutrient Balance
RQ	Research Question
SCTG	Standard Classification of Transported Goods
SDG	Sustainable Development Goals

SI	Supporting Information
USDA	United States Department of Agriculture
U.S.	United States
USGS	United States Geological Survey
VWTN	Virtual Water Trade Network

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1.0 Introduction

1.1 Food-Energy-Water nexus

To secure the nation's energy supply from foreign oil, transition to renewable fuels, and boost farmer's incomes, the U.S. Congress has promoted the biofuel industry for over one decade. As part of the Energy Security Act of 2005 and later Energy Independence and Security Act in 2007 the government introduced and expanded the Renewable Fuel Standards (RFS). RFS promoted the biofuel industry by mandating a reservation quota for biofuels in the current transportation fuel mix, provided tax credits, loans, and large research grants. While RFS went under many revisions with increasing focus on cellulosic and advanced biofuels, the initial promotion of corn ethanol and other food-crops based biofuels sparked the debate on diverting valuable agricultural resources from feeding the population to producing biofuels[1-3]. A major related concern was the use of large quantities of water for crop production and subsequent downstream pollution due to excessive agriculture runoff and nutrient overloading in waterbodies.[4] This is one of the classic examples on how an effort to secure one resource (i.e. energy) has caused unintended consequences on other resources (food, land, and water) in the United States.

Food, energy, and water resources are deeply interconnected, and the connections are known as the FEW nexus. The interdependencies between food, energy, and water are very apparent in day-to-day lives and yet historically each resource has been managed separately.[5] For example, water and energy are required for irrigating agriculture to produce food, energy is used across the entire food supply chain[6], water is needed for producing biofuels[7],

hydropower[8], and thermoelectric power plants[9]. Energy is required to treat[10] and desalinate water.[11] Generally, decisions regarding management of each resource are made separately and by assuming abundance of the other is available. As the world population is expected to surpass 9 billion people in 2050, the challenges associated with securing access to food, energy, and water for the entire population will be an uphill battle.[12] Thus "silos" thinking of managing individual resources can result in overlooking important tradeoffs. Therefore, future management and planning will require considering these interactions as we invest in long-term financial and infrastructure decisions.[5]

In 2011, Hoff et al.[13] highlighted the concept of "nexus approach" to simultaneously target food, energy, and water security for the background paper at the Bonn Conference. Numerous studies previously and around the same time discussed similar issues and outlined the significance of these interlinkages through case studies and calls for action.[14-20] The concept of nexus is not new, similar calls for integrated water resource management (IWRM), an approach to promote simultaneous development of water and associated resources for social and economic benefits, date back to 1962.[21] Similarly, the Integrated Natural Resource Management concept was put forward to integrate farm level objectives with ecosystem services.[22] However, each previous concept was defined based on a singular system as opposed to jointly investigating food, energy, and water systems.[23] For instance, following the framework of IWRM, water would be considered a resource while food and energy system the end users.[17] Therefore, FEW nexus was an improvement in the sense that a clearly outlined three-pronged approach was put forth.[13, 24] Recently, international and national funding for research on the topic[25-27] have mobilized the approach with many studies providing and continuing to provide quantitative assessment for these interconnections.[28-35] Many variations of the concept exist with studies coining the terms

Energy-Water-Food (EWF) nexus[17], Water-Energy-Food (WEF) nexus[36], Climate-Land-Energy-Water (CLEW nexus)[37] etc., however, the underlying message of the concept remains the same.

1.1.1 Systems Analysis and The FEW nexus

There is a consensus amongst proponents of FEW nexus to adopt an integrated holistic systems perspective to aide in decisionmaking.[5, 17, 18, 38] Here, systems analysis refers to using a collection of models and assumptions to represent reality of social and environmental interactions for informing policy relevant decisions. Before discussing specific systems methods used in this work for modeling the FEW nexus, this section introduces the concept of systems analysis and distinguishes it from the term “a system”.

A system is a collection of many components working together as a network to provide/support a function. Each component of a system interacts and is interdependent on others. Through these interactions, specific properties, patterns, or structures arise which are not observed by just considering the individual components, therefore a system is said to be greater than the sum of its parts. This property unique to a system is termed as “emergence”.[39] To understand why this phenomenon occurs, a holistic perspective is required which is termed as systems thinking or systems analysis. Systems analysis not only looks at interaction within a system, but also external interactions including feedbacks between a system and its environment. The concept of systems analysis goes beyond a linearized cause-effect way of approaching a problem and

recognizes that real world problems are complex and nonlinear and may arise not from a single cause-effect interaction but due to numerous feedbacks between involved components.

1.1.1.1 Network analysis

Networks are an inherent part of systems analysis as network analysis or graph theory focuses on connectivity between individual systems. A network represents a collection of nodes (vertices) connected with links (edges/arcs). Application of network analysis has been prevalent in analyzing social networks[40], brain networks[41], ecological networks[42], and transportation networks[43]. Recently, it has gained traction to tackle sustainability and industrial ecology related issues[44-46] including work on virtual water[47-50] and food trade networks.[51, 52]. As developed network measures are rooted in disparate disciplines, there are no universal interpretations for environmental sustainability. Thus, an important contribution of this work is contextualizing network analysis for the U.S. FEW nexus challenges.

1.1.1.2 Operations research

Early literature on systems analysis started with the discussion on soft operations research used qualitative case-study approaches[53] to solve problems, but since then, operations research as part of systems analysis has evolved into rigorous quantitative models used for policy decisions[54-56]. This work specifically focuses on optimization as a method to assess whether competing food, energy, and water resource goals can be balanced for simultaneous gains. The aim is to reveal tradeoffs associated with optimizing for a singular objective (i.e. water use) vs. multiple objectives. Additionally, this work develops a robust optimization model that considers uncertainty in datasets to arrive at solutions that are feasible.

1.1.1.3 Life cycle assessment

Life cycle assessment (LCA) provides a systematic tool to evaluate and measure environmental impact associated with the entire life-cycle of a product or a service. Based on the defined system boundary, an LCA study may consider various stages of a supply chain ranging from raw material extraction to end- use and disposal phase. Therefore, LCA provides a comprehensive accounting of direct and indirect environmental impacts of a product or a service's life cycle. It is primarily useful in identifying inefficiencies and hotspots for environmental burdens within the supply chain or in comparing environmental performances of two similar products. From a sustainability perspective, life cycle assessment (LCA) has emerged as the preferential method for evaluating the environmental impacts of the FEW nexus. Previous work has focused on the LCA of food crops with an emphasis on life cycle energy consumption and greenhouse gas (GHG) emissions.[6, 57-63] There have been dedicated studies focusing on energy-water interrelationships[64-67],and food-water relationships with a focus on water footprinting studies.[68-70] Recently, studies have extended the system boundary and begun addressing the entirety of food-energy-water systems with a life cycle perspective.[28, 71-73]

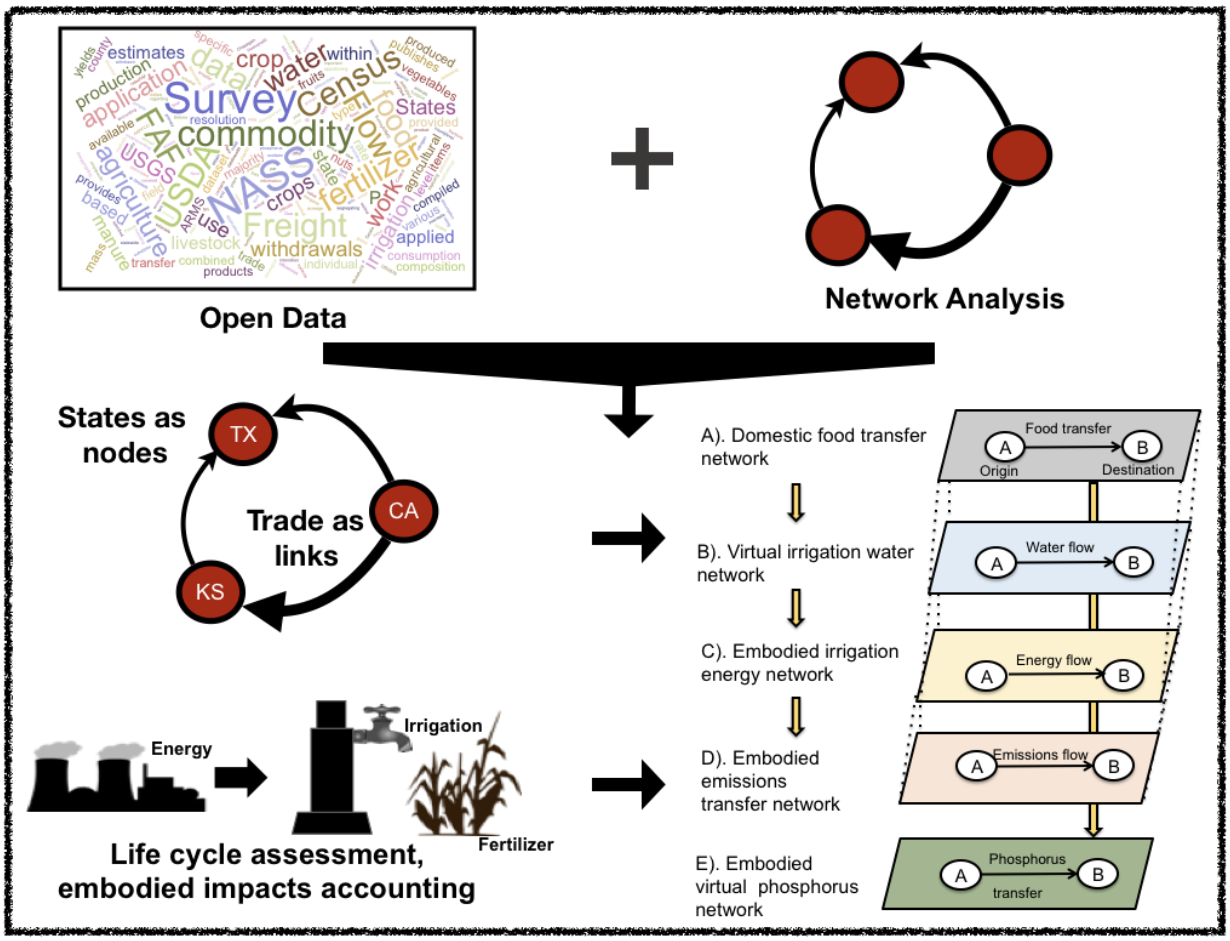

Figure 1. A schematic of FEW nexus framework

1.1.2 Food-Energy-Water nexus for the United States

The FEW nexus challenges associated with an agriculture-centric developed nation such as the U.S. are different from developed countries that rely on external imports or developing agro-economies. This work specifically addresses two issues for the U.S: 1) impact of irrigation in domestic food trade and 2) assessment of phosphorus fertilizer use for food production and trade. While irrigation provides a complementary support to rain-fed agriculture, inappropriate use may impact current groundwater levels and soil salinity as well as contribute to GHG emissions through the use of inefficient and non-renewable irrigation pumps.[28, 32] Additionally, production of

chemical fertilizers is energy intensive[74] and unregulated excessive use may cause nutrient overloading in waterbodies with subsequent eutrophication[75].

1.1.2.1 The role of food trade in US FEW nexus

There is a growing disconnect between place of food production and consumption globally. Even within the U.S., regional variation exists between agricultural resource 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; and California, Florida, and Washington produce majority of fruits, nuts and vegetables. Depending on the agriculture practices in the production region, trade can alleviate or increase environmental impacts associated with food consumption.[76] This work connects the environmental impacts of agriculture with food trade through networks of virtual water, energy, and nutrient flows. Trade of embodied (or virtual) resources refers to resource use and environmental impacts resulting due to food production but are not actually physically embedded in the trade. The concept of embodied resources aids in a) better management of local resources through quantification b) helps drive the dialogue of internalizing the cost of pollution. The idea was popularized through a growing interest in estimating water embodied in the trade of food commodities (identified as water footprint and virtual water literature).[77-83] Virtual water refers to the quantity of water associated with food production and trade.[84] First introduced by Allan,[85] virtual water flow from water rich to water scarce regions through food trade can help alleviate stress from agricultural production in arid regions, thus preventing substantial investment in building water conveyance systems for physical water transfers. Although previous studies have reported the opposite occurring in China[86] and India.[87] The concept of water footprint is similar to virtual water, but clearly distinguishes source through separately accounting for blue water footprints (surface water, or ground water), green

water footprints (rainwater) and grey water footprints (polluted water).[88] Similar concepts have been adopted for virtual nutrients[89-91], embodied carbon[92], land[93], and embodied air pollution.[94]

1.1.3 Criticism of the Food-Energy-Water nexus

A few have criticized the overuse of the word FEW nexus indicating that while it is conceptually sound and unarguable that these resources are interconnected, the term is ambiguous in terms of prescribing a methodology.[95, 96] Here some of the criticism is addressed: the strength of the FEW nexus lies in the ambiguity of not prescribing a comprehensive framework as the successful implementation of national and local policies depend on being adaptable to local requirements.[97] It is also pointed out that by setting such an arbitrary bounds on these resources, FEW nexus misses the opportunity to consider other factors such as human health, livelihood, farm chemicals etc.[96] This is interestingly in direct contradiction to criticism on IWRM, which was considered unsuccessful in translating to policy as it was too broad in scope.[98] Wichelns[96] particularly pointed out that many studies apply similar concepts to study exchanges between food, energy, water systems, without explicitly defining the nexus concept. And therefore, terming a policy or an approach “a nexus approach” does not increase the scientific merit by defining it.[96] While it is true that a study or policy’s effectiveness cannot be judged based on whether it uses a specific term or not, having a general umbrella under which such case studies, policies, and research can be compiled provides a huge opportunity to mobilize large-scale funding, exchange knowledge, and support interdisciplinary and interagency collaboration. While FEW nexus has indeed become a buzzword[95], the interest garnered can be positive for science and policy. An important consideration that FEW nexus proponents should keep in mind is that an integrated

approach may not be the panacea which always provide optimal outcomes.[99] In fact, considering too many factors at once may make a system unsolvable or at best provide a pareto optimal solution which may not be agreeable to all. Additionally, it should be kept in mind that realistically, one interest lobby may be stronger than the others and no consensus may be reached as to the best approach forward.[97].

1.2 Sustainability and Resilience

As the framework discussed in the thesis refers to assessing the sustainability and resilience of the FEW nexus, this section introduces the context for the two terms that are often used interchangeably and have many definitions.[100] The case studies presented in subsequent chapters are not prospective studies but rather evaluations based on recently published government data. Therefore, rather than referring to the traditional definition of "meeting the needs of the future" from the Brundtland report[101], here the sustainability has a narrower definition limited to environmental sustainability and interpreted with a focus on life cycle thinking.

The concept of resilience stems from many disciplines including disaster management, ecology, engineering, and psychology.[102] Resilience can either be interpreted as ability to withstand pressure/shock or adapt to maintain function. Here, resilience of a system is defined from a complex network perspective, and includes examining behavior of a network under shock.[103] The shock is defined either as a random failure, or a targeted removal of nodes.[103] As domestic trade is not hindered by international trade barriers and self-protectionist policies, the response of a region to shocks in food system may not follow a similar pattern as a country's policy in eliminating international exports, at best it may reduce exports to neighboring regions.

Therefore, resilience is also examined from the lens of ecology where it is defined as a balance between efficiency and redundancy.[104] A network with efficient connections may be brittle, while redundant connections would result in waste but be more robust. It is important to note that this definition of balance is often at odds with the view of sustainability where it only refers to resource use efficiency[105] and redundancy may be viewed unfavorably. However, this often is not the case when long-term sustainability goals are considered.[105] Although, it is useful to note that resilience does not always carry positive connotation and may not be desired.[106] Agriculture's resilience to withstand drought by relying on groundwater for irrigation may not be sustainable in the long run. This is a very relevant distinction for food production systems, where often policies are implemented as a protection against a shock, need to be considered in light for long term sustainability.

It is worth mentioning here that there is often a discussion regarding whether resilience is a subset of sustainability or vice versa. As mentioned above, resilience may not always be desirable and work in opposition to long term sustainability goals. Therefore, sustainability can be seen as an umbrella under which resilience is but one component of it.

1.3 Research questions and objectives of the study

The objective of this study was to develop a network theory-based framework to assess food-energy-water nexus impacts in the U.S. with a focus on irrigation and nutrients. This was a data-driven study and employed the use of interdisciplinary methods derived from industrial ecology, life cycle assessment, probability & statistics, operations research, and network theory. The proposed work had three broader objectives:

Objective 1. Develop a systems-level framework for modeling domestic food trade incorporating virtual water, embodied irrigation energy, and greenhouse gas (GHG) emissions.

Objective 2. Apply network theory techniques utilizing metrics from social network analysis and ecological network analysis to identify the overall structure, patterns in node-level interactions, and key players across the food and embodied resource/impact networks.

Objective 3. Develop an optimization- based approach (***collaborative***) to improve trade efficiency through minimizing environmental impacts and resource consumption, and assess trade-offs and synergies across the domestic FEW nexus.

Objective 4. Quantify embodied inorganic phosphorus in U.S. food trade and assess data gaps in the current understanding of phosphorus application in the U.S. agriculture.

With these objectives, we sought to answer the following research questions (RQ):

RQ 1. What is the magnitude of irrigation impacts across US food production system?

RQ 2. How different are the spatial trends in environmental emissions and resource use across states?

RQ 3. What is the network structure of the food trade? And what are the resulting dependencies arising from how states trade with each other?

RQ 4. Is the food trade organized in a way that results in resource use savings or losses?

RQ 5. Can we optimize food trade to achieve simultaneous energy-water savings?

Published and anticipated journal publications resulting from the PhD:

Vora, N., Shah, A., Bilec, M. M., & Khanna, V. (2017). Food–Energy–Water Nexus: Quantifying Embodied Energy and GHG Emissions from Irrigation through Virtual Water Transfers in Food Trade. *ACS Sustainable Chemistry & Engineering*, *5*(3), 2119-2128.

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Organization of the Dissertation

The dissertation is organized as follows:

Chapter 2 presents the framework for assembling disparate data sources to construct domestic food trade networks across the U.S. It also quantifies a) virtual water, b) embodied energy, and c) embodied greenhouse gas emissions in the food trade. Additionally, the framework is presented in a graph theory format with metrics from social network analysis computed.

Chapter 3 further builds on the FEW nexus framework and analyzes the dependencies arising from the a) structure of the network, and b) use of specific energy and water resources in production of food. Additionally, the chapter introduces the concept of null model for food trade (i.e., a random network) and compares it to the observed trade to assess statistical significance of observed interactions.

Chapter 4 develops an optimization routine for rice trade across the U.S. with a view to optimize water and greenhouse gas emissions impact. It further explores various scenarios regarding reducing impacts and assesses synergies and tradeoffs arising in the embodied irrigation network.

Chapter 5 quantifies embodied phosphorus in the domestic food trade network and whether current food trade results in phosphorus use savings or losses. This is done by comparing production and fertilizer use practices for states producing similar crops. Furthermore, the chapter discusses data gaps in the current understanding of inorganic phosphorus application. Chapter 6 discusses conclusions and future work.

1.4 Intellectual merit and broader impacts

The goal of this research is to construct a systems level framework to understand FEW nexus at the national level. To this end, this work quantifies and provides comprehensive estimates of embodied impacts and resource consumption within the domestic food trade. Specifically, this work builds a spatially explicit inventory of irrigation specific virtual water, embodied energy, embodied GHG emissions, and embodied inorganic phosphorus fertilizer estimates within the U.S. food trade. As significant regional variation exists between water quantity, energy supply, and crop-fertilizer management practices across the U.S., quantifying origin and destination of food trade will support in understanding interdependencies of domestic food production and consumption. The network analysis will add novel insights to the food security issue by analyzing vulnerable and critical nodes in food and embodied impact networks. For instance, various network indicators will be used to identify whether a small group of critical states influence the network by

supplying a high throughput, or a few states solely depend on a few connections for trade, making them vulnerable to disruptions. Additionally, this work compares observed trade connections to those that may occur by chance to understand significance of patterns formed in domestic trade. With the network optimization, the previously observed insights will be used to design ways to improve overall system performance by re-wiring the trade links and re-distributing food production and trade. The observed insights will help understand challenges and potential for achieving an optimal outcome that simultaneously considers competing demands for food, energy, water resources in the current domestic trade structure.

2.0 Quantifying embodied energy and GHG emissions from irrigation in U.S. food trade

The following chapter is based on a peer-reviewed article published in *ACS Sustainable Chemistry & Engineering* with the citation:

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2.1 Introduction

The world population is expected to surpass 9 billion people by the year 2050, posing pressing challenges for food, energy, and water systems.[12, 107] Food production and global water withdrawals are expected to increase by 60% and 55% respectively by the year 2050.[108, 109] Concurrently, global energy consumption is expected to increase by 50% in the same time period. A significant portion of the world population lacks secure access to at least food, energy, or water, exacerbating the situation.[17] On a national level, the U.S. food production faces new challenges as the agriculture sector competes with energy, industrial, and residential sectors for water and energy resources.[110] Food, energy, and water (FEW) systems are highly interdependent, interconnected, and interact in myriad ways. Energy and water are required across the food supply chain including irrigation, harvesting, transportation, and food processing. Energy is required to extract, treat, and distribute water for industrial, agricultural, and residential uses.

Additionally, large quantities of water are required for power generation and production of biobased fuels and products. Yet for all the dependencies, decisions regarding management of FEW systems are often made in isolation with minimal attention to their interactions, frequently resulting in suboptimal solutions. To encourage better decisions and avoid unintended consequences, there is an urgent need to examine FEW systems from an integrated holistic systems perspective. The importance of applying a systems thinking approach for the FEW nexus has been advocated and is slowly gaining traction.[5, 17, 18, 38]

Previous research has utilized numerous modeling and analysis techniques to identify interactions between FEW systems, often focusing on either a single or two dimensions of the nexus.[6, 67, 111, 112] Recent work has applied network science for modeling and analysis of international food trade networks.[52, 113] Network science refers to the mathematical study of systems that are essentially a collection of nodes joined by links.[114] Lin et al.[51] studied the structure of the U.S. food trade network and asserted that it has a well-mixed structure resembling a social network. On the food-water front, much attention has been paid to the water use in agriculture and food systems. In his seminal work on virtual water, Allan[84] introduced the concept of water embodied in the production of food commodities. Virtual water refers to the quantity of water associated with food production and trade. Allan[85] asserted that instead of major investments in building water conveyance systems for physical water transfers, virtual water flow from water rich to water scarce regions through food trade can help alleviate stress in water deficit regions. Since then, numerous studies have contributed to the virtual water literature through study of water footprint of food and virtual water trade.[115-117] The concept of water footprint is similar to virtual water, except it distinguishes water use by source (surface water or groundwater, rainwater, polluted water).[88] Hoekstra and Hung[115] quantified volume of virtual

water flows in international crop trade and estimated that 13% of the water used for crop production was embedded in virtual water exports and not domestic consumption. On a regional scale, studies on virtual water flows in China showed that water deficient North China exported more water through food transfers to feed water rich South China.[118, 119] Mubako and Lant[112] quantified water footprints and virtual water flows associated with crops and livestock products for the 48 contiguous U.S. states. They estimated that North-Central and arid Southwest had large virtual water exports. Eastern and Southeastern coastal states were leading net virtual water importers. On the water-energy front, studies have focused on understanding and quantifying interactions at national,[120] regional,[121, 122] and local scales.[67]

Prior research has also applied network theory to understand the structure of the global virtual water trade network (VWTN),[47] predict future network structure,[123] and identify community patterns.[124] Additionally, studies have investigated temporal evolution of the VWTN associated with international trade of select food commodities and highlighted the growing efficiency in global water use.[125, 126] Sartori and Schiavo[49] demonstrated increase in number of countries and volume of virtual water flow in international food trade between 1986-2010. They discussed the increasing homogeneity in the VWTN with a reduction in the role of key central countries over time and its implications for systemic vulnerability. More recently, Dang et al.[48] developed a network model of agricultural virtual water flows for the United States (U.S.). Their findings highlighted that the U.S. VWTN is vulnerable to disruptions on a core group of states that are essential for the network structure and functionality. While these studies represent important systems-level contributions, their focus is exclusively on food alone or food and water instead of examining FEW systems in an integrated manner. Additionally, with the exception of virtual

water, other life cycle impacts such as embodied energy and greenhouse gas (GHG) emissions are not considered.

From an environmental sustainability perspective, life cycle assessment (LCA) has become popular for evaluating the environmental impacts of agriculture and food products and can be applied to FEW nexus. Previous work on LCA has focused on quantifying the environmental impacts of food crops,[57] livestock,[127-129] milk,[58, 130, 131] and meat products[132] with a significant emphasis on life cycle energy consumption and GHG emissions. Several studies have conducted comprehensive assessment of energy use[6] and emissions[133] in all stages of U.S. food supply chain with Cuéllar et al.[60] extending the system boundary to include impacts of food waste. Pelletier et al.[134] provide a comprehensive review of literature and trends in life cycle energy intensity of food systems. A rich body of work also exists on the water footprint of food crops and meat products including important contributions by Hoekstra and co-workers.[80, 115, 135, 136] For the U.S., Kahn estimated uncertainty in freshwater consumption impacts for staple crops including energy required for irrigation.[137] However, the focus in most LCA studies is on food items alone with minimal attention to integrating a network perspective using food trade. Food trade networks represent pathways for vast quantities of embodied resource (energy, water etc.) and emissions flows. Quantifying the origin and destination of food flows in conjunction with associated embodied resource flows is central for understanding the sustainability and resiliency of FEW nexus.

A significant knowledge gap and critical pinch point in our understanding of the FEW nexus is embodied energy and GHG emissions in irrigation water associated with domestic food trade in the U.S. Here, embodied energy and GHG emissions refer to the life cycle energy consumption and life cycle GHG emissions associated with irrigation pumping energy

requirements. A quantifiable understanding of the energy footprint of water embodied in food trade can help in developing policies for promoting simultaneous water and energy savings in the context of the FEW nexus. Significant regional variations exist in the water footprint of food production and available water resources.[69, 138] Furthermore, energy mixes vary considerably across regions in the U.S. The goal of our present work is to provide a quantitative understanding of the embodied energy and GHG emissions associated with irrigation water for interstate food exchanges in the U.S. It has been previously noted that food trade represents exchanges between international borders, while food transfers refer to domestic food exchanges.[48, 139] Therefore, we refer to interstate food exchanges as food transfers throughout the article. Using Commodity Flow Survey (CFS)[140] for food commodities and state-level data on production of individual food items provided by National Agricultural Statistics Service (NASS),[141] we develop a detailed network model of domestic food transfers. The network model is coupled with available water withdrawal data for irrigation and livestock rearing, farm-level irrigation energy consumption data, and life cycle energy and emissions data. We restrict our focus to interstate food transfers and associated irrigation impacts for 29 commodities including 14 grains and livestock products. These commodities account for approximately 70% of per capita national calorie consumption.[142] The resulting model and analysis provides several important insights for the FEW nexus including 1) quantifying spatial trends in food flows and associated water withdrawals transferred across the U.S., 2) the first comprehensive estimates of embodied energy and GHG emissions associated with on-farm irrigation water, and 3) understanding of structure and vulnerabilities in the network. It is important to note that our study does not focus on embodied energy and GHG emissions of food commodities themselves, but is limited to embodied energy and GHG emissions of virtual water associated with food commodities produced in the U.S.

Additionally, we do not account for water embodied in the energy used for irrigation. For the purpose of this article, we define virtual water as the quantity of water withdrawn (not just consumptive use) for crop and livestock production and trade.

2.2 Methods

The methodological framework including data sources used in our study are discussed in detail below. A schematic diagram representing key steps in the model is provided in the appendix A Figure 17. We translated data on food transfers into networks by creating adjacency matrices. An adjacency matrix consists of rows representing origin states and columns representing destination states. Each element (i, j) in an adjacency matrix represents transfer from state i to j. If a transfer exists between states i and j, the corresponding matrix element is set to 1; otherwise, it is set to 0. The resulting network is termed as an unweighted-directed network where states are referred to as nodes and food transfers as links. The directed network differentiates between incoming and outgoing links. We also considered magnitude of food transfers resulting in weighted-directed network. The weighted-directed food transfer network is converted into networks of virtual water withdrawal, embodied energy, and GHG emissions associated with virtual irrigation water. Specifically, we created four networks: 1) food transfer network 2) virtual water withdrawal network 3) embodied irrigation energy network and 4) embodied irrigation GHG emissions network. For the remainder of this article, we refer to virtual water withdrawal, energy and GHG emissions embodied in irrigation water as simply virtual water, embodied energy, and GHG emissions respectively.

2.2.1 Construction of the U.S. food transfer network model

2.2.1.1 Domestic food transfer network

We obtained bilateral food transfer data from CFS, jointly published as part of the economic census by Census Bureau and Bureau of Transportation Statistics every five years. The CFS data are collected through a survey of selected representative establishments and extended to represent interstate and within-state transfers across the U.S. For 2012, a sample of over 10,000 establishments was collected covering commodities from mining, manufacturing, wholesale trade, and retail services. Data include national and state-level statistics on freight shipment, value and weight of commodities, and mode of transportation. The provided data are based on reported values from the survey and consequently, do not consider internal hubs/stop. Additionally, CFS data are limited for transfers within the U.S. and do not include international transfers. We utilized CFS-2012 for creating weighted-directed networks representing domestic food transfers between states. We provide CFS data collection methodology in more depth in the SI section S2. CFS data are classified using the Standard Classification of Transported Goods (SCTG) coding system ranging from codes 01 to 43. We focused on food commodities covered by codes 01 (livestock), 02 (cereal grains), 05 (meat), and 06 (milled products), listed in SI table S2. Consistent with the methodology outlined by Dang et al.[48], we did not consider fish and other aquatic species in livestock and meat categories as they are considered as low or non-water consumptive products.[143] We excluded fish related food transfer data by subtracting fraction of produced fish from total animal items produced in a given state. We estimated fish fraction by using a ratio of fish production to overall animal production for a particular state and multiplying with food transfers. We obtain the requisite production data from NASS dataset.[141]

While CFS data are available for broad food commodity groups, water withdrawal intensities are estimated for individual food items. We bridged this resolution gap by disaggregating the interstate transfer of food commodities into individual food items. We make an important assumption that composition of food transfer between states is similar to composition of food production. We used the latest available state level production data from NASS. [141]

2.2.1.2 Virtual water network

Next, we constructed the virtual water network using the interstate food transfer network and water withdrawals for irrigating individual food items. National and regional water withdrawal data are published by United States Geological Survey (USGS) every five years.[144] The latest available data are for 2010 and cover water withdrawals from thermoelectric power plants, irrigation, livestock, aquaculture, public supply, and mining. The USGS compiles irrigation withdrawal data from state and federal crop reporting programs, irrigation districts, canal reporting companies, and incorporated management areas. We used state-level data on irrigation and livestock withdrawals for this analysis. Irrigation water withdrawals are published by type of irrigation system (sprinkler, micro-irrigation, and surface) and by water source (groundwater and surface water). We used published average water application rates (gallons/acre), weighted by type of irrigation, to account for variations in efficiencies of different irrigation systems. To differentiate between water withdrawals for various crops considered in our analysis, we divide application rate by crop specific yields to arrive at water withdrawal intensity per mass of food item produced. We used the average crop yields reported by Farm and Ranch Irrigation Survey (FRIS)[145] dataset to estimate water withdrawal intensity for individual crops. For missing grains, we used irrigated yield values from NASS. To estimate the water withdrawal intensity for animal based commodities, we followed the methodology detailed in Mubako.[146] In the absence

of data on statewide production and withdrawals of various meat products, we assumed that meat withdrawals are similar to water withdrawals for livestock, thus resulting in conservative estimates.[48] Specific details and equations for estimating water withdrawal intensities for crops, milled grain products, and animal based commodities are provided in Appendix. In addition, calculated water withdrawal intensities for grains, livestock, and animal feed are provided in table 9-12.

2.2.1.3 Embodied irrigation energy and GHG emissions networks

Next, we translated the virtual water network to networks of embodied energy and GHG emissions. We used the FRIS dataset to obtain irrigation energy expenditures. FRIS-2013 is published as a supplement to 2012 agriculture census and provides data regarding on-farm irrigation operations in the U.S. It publishes state level energy expense data including type of water source (surface/groundwater) and type of energy used for pumping. As reported by FRIS, farms in the U.S. employ primarily four types of pumps, i.e. electricity, diesel, gasoline, and LPG/propane/butane pumps. We combined the energy expenditure data with Energy Information Administration (EIA) published state level energy prices to obtain total energy consumption.[147] It is to be noted that FRIS energy expense estimates only account for the cost of moving water during on-farm operations. Expenses incurred in conveying water to the farm by entities such as irrigation districts are not accounted for in such estimates. Finally, we obtained life cycle GHG emissions and embodied energy estimates for each energy type using USLCI[148] and Ecoinvent database.[149] We utilized cumulative energy demand (CED)[150] method to quantify embodied energy and IPCC 100 year global warming potential characterization factors[151] to quantify life cycle GHG emissions associated with each energy type.

2.2.2 Network analysis

We analyzed both unweighted and weighted networks to understand interdependencies and trends in environmental sustainability of the domestic FEW nexus. Unweighted networks only account for food transfer connections whereas weighted networks account for magnitude of food transfers and associated virtual water, embodied energy, and GHG emissions. The network measures discussed below have their origins in social network analysis and may not contain a universal interpretation from a sustainability or resilience perspective. We present multiple network measures while providing context specific interpretation of the various metrics for sustainability and resilience of the FEW nexus.

2.2.2.1 Unweighted network analysis

We calculated standard network analysis measures for the unweighted food transfer network to understand its overall structure. We quantify network size by accounting for number of nodes in the network. Network density quantifies interconnectedness in a network by measuring ratio of actual links to maximum possible links. For a given set of states, a lower density indicates a sparse network with a few transfers between states. A higher density suggests larger number of food transfers and consequently higher interconnectedness. Another useful measure is the extent of bi-directional transfers among states, measured by reciprocity.[152] Reciprocity (r) measures tendency of nodes to form mutual links in a network. It is the ratio of bi-directional links to the total number of links. A value of 1 indicates a purely bidirectional network and 0 indicates a purely unidirectional network.

Next, we calculated node degree, which measures number of food transfers to/from a node. For directed networks, in-degree represents number of incoming links and out-degree measures

number of outgoing links. We also calculated characteristic path length and clustering coefficient. The characteristic path length of a network describes average shortest distance between nodes from all other nodes in the network. A lower characteristic path length is an indicator of network flow efficiency. Local clustering coefficient measures tendency of nodes to cluster together, an indication of network completeness.

2.2.2.2 Weighted network analysis

We conducted weighted network analysis to provide insights into virtual water, energy, and GHG emissions for the U.S. food transfer network. Node strength represents magnitude of flow through a node, calculated by summing individual link weights between nodes. Analogous to in- and out- degrees, strengths can be defined as in- and out-strengths. To understand structure of the weighted networks, we computed strength distributions, discussed in detail in the appendix A.

2.2.2.3 Node Centrality

We calculated centrality measure to capture information on position and importance of individual nodes within various networks considered in our work. Several measures of centrality have been proposed and used in the literature, each measuring a different aspect of the position of individual nodes in a network.[153] Degree centrality measures direct connections of a node, closeness centrality measures how quickly others can reach a node, betweenness centrality ranks nodes based on their influence over the flow of information between other nodes, and eigenvector centrality ranks nodes based on their connection's influence.[154, 155] Previous works on trade and virtual water networks have used betweenness centrality,[47, 51] eigenvector centrality,[49, 156] degree and closeness centrality[157] to understand influence of nodes. The interstate food transfer network in our work captures bilateral food exchanges between states, but does not

distinguish physical paths or identify intermediate hubs in the network. Furthermore, we assumed that food production occurs at origin state and consumption at destination state. Therefore, we did not apply geodesic-based measures of betweenness and closeness centrality. Instead, we identified immediate neighbors using degree centrality. Degree centrality ranks nodes based on their number of connections. We calculated in-, out-, and total degree centralities for both weighted and unweighted networks. Equations for degree centrality measures are given in the appendix A.

2.2.2.4 Mixing patterns

Mixing patterns identify whether there are patterns in connections between two nodes. For instance, a common pattern of like-minded individuals connecting with each other is observed in social networks. Existing studies on trade networks have examined network mixing patterns by analyzing whether highly connected countries form connections with other highly connected countries.[156] This behavior is known as assortative mixing and helps identify network structure and implications for network resilience.[157] Conversely, in disassortative mixing, a node connects to another node with unlike characteristics. This results in a core-periphery structure (hub and spokes structure) with a single strong component with high levels of peripheral nodes engaging in a few transfers. This is a more commonly observed structure for trade networks.[47, 157] Core and periphery exhibit different resilience characteristics where a core is more stable against disruptions. Mixing characteristics can be determined by calculating a node's average nearest neighbor degree (k_{nn}) as a function of its degrees. k_{nn} of a given node is measured by adding all of its neighboring nodes' average connectivity.[158]. A network can be assortative or disassortative depending on magnitude and sign of assortativity coefficient. Assortativity coefficient is the Pearson correlation coefficient (τ_i) between k_{nn} *and* degrees. If k_{nn} increases with degrees, the network is assortative. Conversely, if k_{nn} decreases with degrees, network is disassortative. We

calculate four different measures of assortativity coefficient based on direction of flow ($k_{nn}^{in,in}$, $k_{nn}^{out,out}$, $k_{nn}^{in,out}$, $k_{nn}^{out,in}$).[159] For example, $k_{nn}^{out,in}$ identifies all nodes that node *i* exports to, and calculates their importing behavior.[47] Correspondingly, $\tau_i^{out,in}$ determines correlation between $k_{nn}^{out,in}$ and out-degrees.

2.3 Results

2.3.1 Virtual water, embodied energy and GHG emissions in food transfers.

Analysis of the domestic food transfer network reveals that 643 million tons of staple food commodities were transferred across the U.S. in 2012. A majority of these transfers (88%) belonged to cereal grains and milled products, while animal-based commodities constituted a smaller share (12%) (Figure 2). Figure 2 contains both interstate and within state transfers. The imbalance can be attributed to the higher cost of transferring meat and livestock as meat requires refrigerated transport and livestock is difficult to handle for long distance shipments.[48, 160] The total virtual water transfers amounted to 322 billion m^3, with cereal and animal based products contributing 67% and 33%, respectively. The higher percentage share of animal based products in virtual water transfers compared to food transfers is attributable to the high water intensity of animal and meat products.[138] The energy and GHG emissions embodied in virtual water transfers are observed to be significantly high at 584 billion MJ and 42 billion kg CO_2 equivalents, respectively. 38% of the energy and GHG emissions embodied in virtual water transfers result from the livestock and meat transfers across the states.

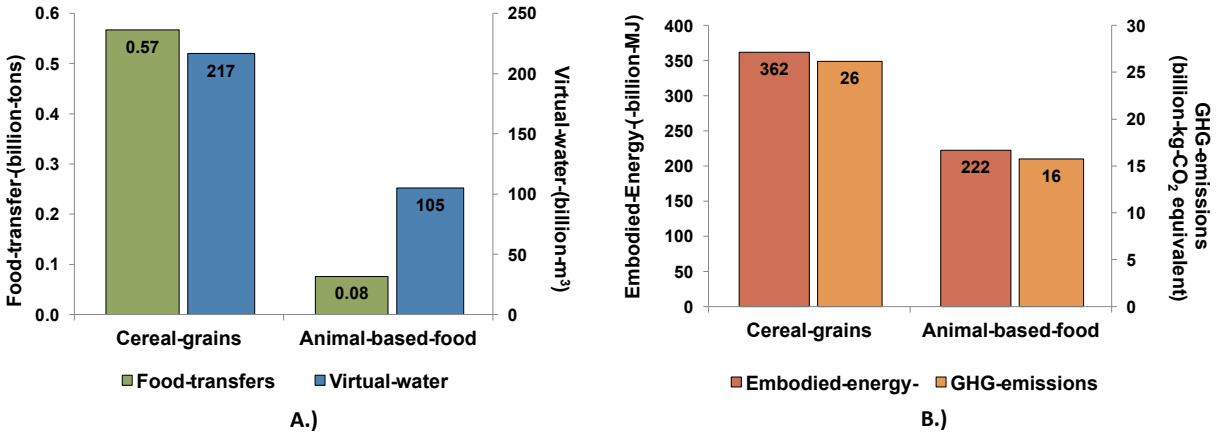


Figure 2. A.) Food and virtual water transfers in the U.S. B.) Life cycle embodied energy and greenhouse gas (GHG) emissions in irrigation virtual water withdrawals in the U.S.

2.3.2 Food vs. virtual water transfers

The top five exporting states in the food transfer network are KS, MN, NE, IL, and IA. In comparison, the top five exporting states in the virtual water network are KS, MT, ID, SD, and OK. The appearance of MT and ID in the top 5 virtual water exporting states is particularly interesting and is explained as follows. MT and ID have the second and third largest water withdrawal rates (m^3/acre).[144] This translates into high water withdrawal intensity (m^3/ton) for both cereal and animal-based products exported by these states. While AZ has the highest water withdrawal rate, it has much lower food exports and hence virtual water exports. The top five importing states in the food transfer network are TX, IL, CA, LA, and IA. TX, WA, IL, OR, and CA are the top five virtual water importing states. The high rankings for WA and OR for virtual water imports is explained by the high water withdrawal intensity of food products from their importing partners. The largest imports to WA are from MT whereas the largest imports to OR are from WA (cereals and grains) and ID (meat and livestock).

2.3.3 Embodied Energy and GHG Emissions in food transfers

Figure 3. presents a visualization of embodied energy in the U.S. domestic food transfers using Circos visualization tool.[161] The network represents 1719 food transfers amounting to 274 billion MJ of embodied energy transfers (within-state flows are excluded) between 51 states. Each segment represents states participating in food transfers across the U.S. Outgoing links from a state are shown with the same color as the origin state; incoming links to a state are of different color and separated from the destination state by white space. The states are ranked by combined incoming and outgoing transfers of embodied energy. States with the highest incoming transfers are TX, IL, WA, CA, and LA. MT, ND, NC, CO, and SD have the highest outgoing transfers of embodied energy. The largest embodied energy transfer is from MT to WA with a magnitude of 13 billion MJ. It is important to keep in mind that Figure 3 does not show within state embodied energy transfers. Over 300 billion MJ of embodied energy flow was attributable to within-state flows in 2012, which is not surprising as geographic distance plays a major role in food trade.[162] Additionally, a food supply study[163] on NY city based on CFS data asserted that in some regions food may not be transported to the direct point of consumption, but to a distribution center in that region. The flows from distribution center to the final destination may be counted as within-state flow.[163]

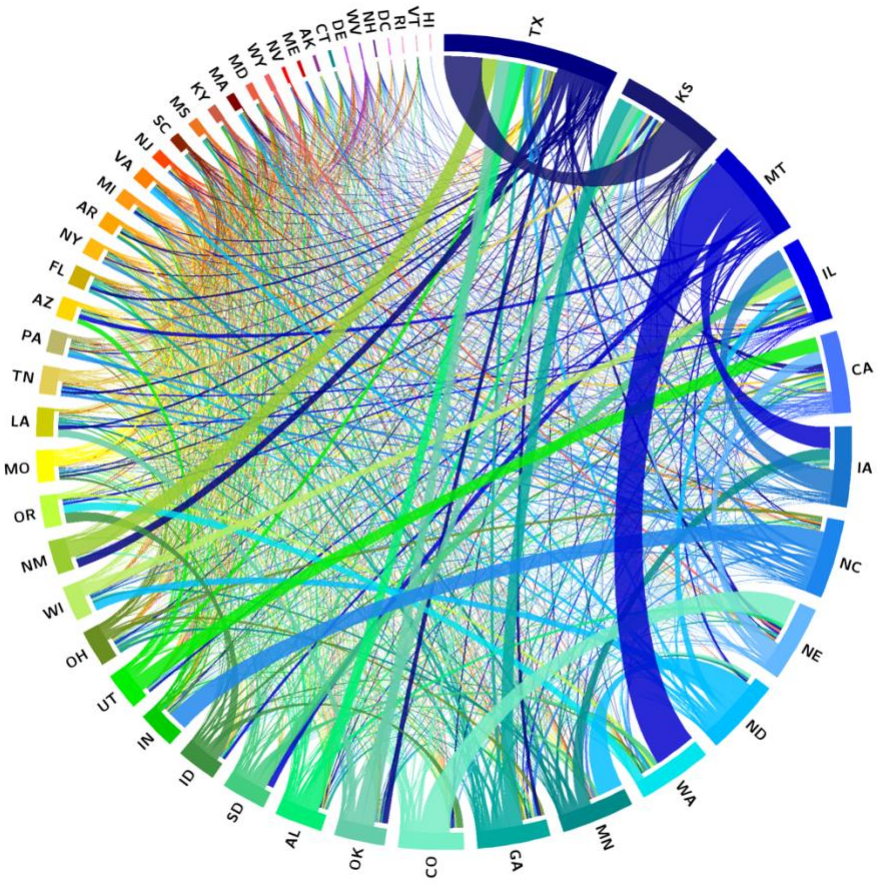


Figure 3. Embodied energy from irrigation water in U.S domestic food transfers

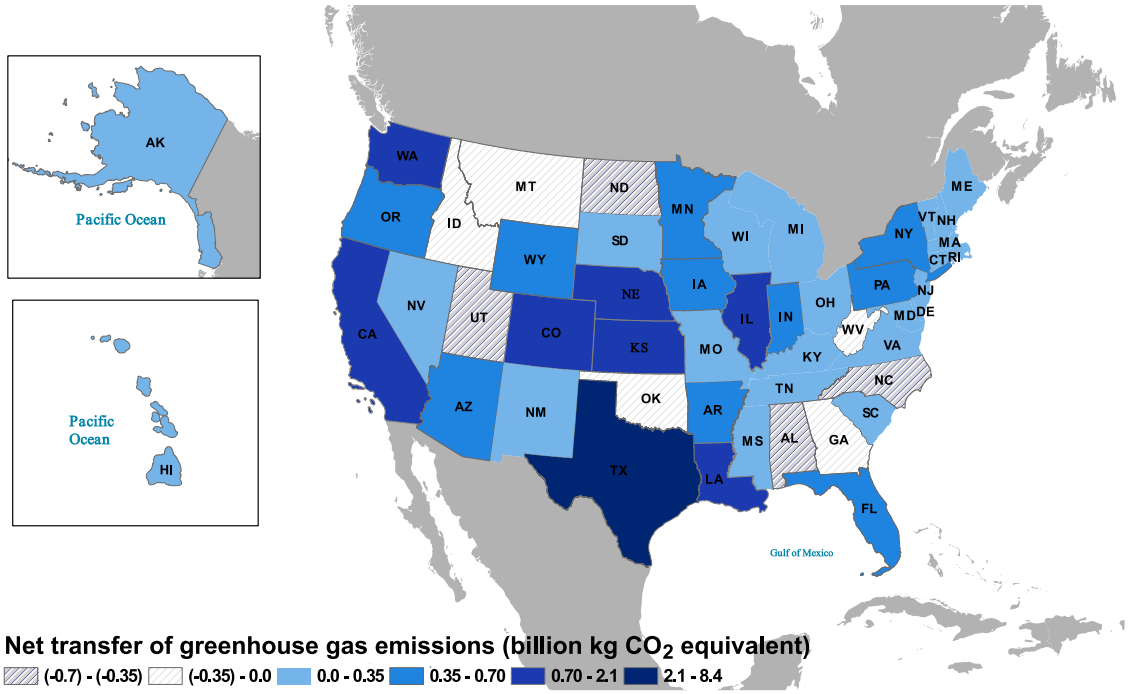


Figure 4. Net greenhouse gas (GHG) emissions embedded in virtual water associated with domestic food transfers (in billion kg CO_2 equivalent).

Figure 4. presents a spatial distribution of net embodied GHG emissions. Net embodied GHG emissions are calculated by subtracting total outgoing flows from the sum of incoming flows and within-state flows for each state. Negative values indicate net exporters, whereas positive values indicate net importers. A state can be a net GHG emissions importer due to high emissions in-flows from its trading partners including within-state transfers. Similarly, a state can be a net GHG exporter due to high embodied emissions outflows. TX is the largest net GHG importer followed by IL, CA, CO, and WA. The states with gray and white hatched lines in Figure 4 represent net exporters of GHG emissions. ND, NC, AL, UT, and ID are top net exporting states. Absolute values for net transfer of food, virtual water, embodied energy and GHG emissions for all states are provided in the appendix A table 15. We also estimated the GHG emissions intensity of irrigation for each state and found that 40% of the states are above average (0.15 kg CO_2 equivalents/m^3 irrigation water). High GHG emissions intensity for states is a result of the pump

fuel type used and the energy mix for each state. For example, WV has the highest GHG emissions intensity due to heavy reliance on gasoline and electricity-based pumps with a significant share of coal-powered electricity. Additionally, with the exception of ID the top five net exporting states have higher than average GHG emissions intensity. Approximately 50% of irrigation pumps are diesel based in net exporting states of AL and NC, while 70% are coal electricity based in ND and UT, thus increasing their GHG emissions intensity. Conversely, ID farms depend on electricity-based irrigation with a significant share of hydroelectric power (71%).

2.3.4 Network analysis of embodied energy and GHG emission

Table 1. Network analysis measures for embodied energy and GHG emissions networks

Degrees	Average degree		In-degrees range		Out-degrees range	
	36		6-48		0-50	
Strength	Embodied energy (billion MJ)		Embodied GHG emissions (billion kg CO_2 equivalent)			
Average strength	5.4		0.4			
In-strength range	0.02-36		0.001-2.6			
Out-strength range	0-30		0-2.3			
Total Degree centrality	Unweighted Network		Embodied Energy Network		Embodied GHG Emissions Network	
1	IL	0.95	TX	0.04	TX	0.036
2	CA	0.93	KS	0.024	MT	0.023
3	TX	0.92	MT	0.023	KS	0.022
4	OH	0.91	IL	0.019	IA	0.018
5	PA	0.91	CA	0.018	IL	0.018
Assortativity Coefficient	$\tau_i^{in\text{-}out}$		$\tau_i^{in\text{-}in}$	$\tau_i^{out\text{-}out}$	$\tau_i^{out\text{-}in}$	
Unweighted	-0.89		-0.84	-0.73	-0.83	
Embodied Energy	-0.06		-0.29	0.03	0.03	
GHG Emissions	-0.06		-0.30	0.03	-0.22	

Table 1 summarizes network level metrics for the unweighted and weighted embodied energy and GHG emissions networks. Network statistics do not include within-state flows. Summary statistics for food and virtual water network are provided in the appendix A. The in-degree ranges from 6 (HI) to 48 (IL), and out-degree from 0 (DC) to 50 (MA). The U.S. domestic food transfer network has a density of 0.7 indicating a high degree of interconnectedness. The average degree of 36 indicates that on average a state in the food network is connected to 36 other states. In addition, high reciprocity value of 0.7 indicates presence of many mutual ties between states. The unweighted network has a low characteristic path length (~1.3) and high clustering coefficient (0.77). These statistics signify a fully connected topology of the network. These findings are in agreement with previous work on U.S. food transfers and can be attributed to the absence of trade barriers for domestic food transfers between states.[48, 160] From a network robustness perspective, a highly connected structure signifies high redundancy and therefore resilience against random or targeted disruptions in the network.

For weighted networks, in-strengths for embodied energy range from 0.02 billion (HI) to 36 billion MJ (TX). Out-strengths for embodied energy range from 0 (HI, DC, AK, VT) to 30 billion MJ (MT). Similarly, in-strengths for embodied GHG emissions range from 1 million to 2.6 billion kg CO_2 equivalents and out-strengths range from 0 to 2.3 billion kg CO_2 equivalents with identical state rankings. Compared to degrees, strength distributions have a larger skew where a handful of states with very high throughputs forming tail of the distribution (Appendix A, figure 20).

We present both weighted and unweighted degree centrality measures to identify key states and their importance in the domestic FEW nexus. TX, KS, MT, IL, and CA emerge as the top five states with highest total degree centrality for embodied energy. Similar results are observed for the

GHG emissions network with the exception of IA as the state with the fourth-highest total degree centrality. IA's high total degree centrality is a result of large imports and exports of irrigation intensive animal based products. The results for degree centrality for the unweighted networks provide interesting insights. Highly connected nodes such as IL, CA, and TX rank in the top five with the highest unweighted total degree centrality. In addition, PA and OH are amongst the top five states. The higher ranks for the unweighted total degree centrality is attributed to large number of food transfers going in and out of these states. However, the low magnitude of these food transfers results in PA and OH not ranking amongst the top 5 states for net embodied energy and GHG emissions. Degree centrality ranks states according to their direct connections such that highly central nodes indicate states involved in high trade activity. While weighted total degree centrality is useful for identifying critical states for the food transfer network from a total throughput perspective, unweighted total degree centrality is equally critical for identifying states that contribute the most to the food transfer network from a connectivity perspective.

Table 1 also presents results for assortativity, characterized by assortativity coefficient τ_i. Negative values for unweighted τ_i indicate a disassortative behavior, implying that states with large number of connections are connected to states with fewer connections. This pattern of a core-periphery like structure (also known as hub and spokes structure) resulting from disassortative behavior is consistently recognized in trade networks.[161] Disassortative behavior in the U.S. food transfer network is primarily a result of extremely low degrees of states such as HI, DC, AK, WY, VT, and RI (figure 19). The peripheral positions of these states could be attributed to factors such as long geographical distances from major exporting hubs (AK and HI) and smaller residential populations (WY, DC, RI).[160] The results of weighted τ_i indicate that all three irrigation impact weighted networks exhibit a mixture of assortative and disassortative structure.

For embodied energy, $\tau_i^{out,out}$ and $\tau_i^{out,in}$ values are positive and indicate that major exporting states are connected to both major importing and exporting states. KS, WI, NE, IA, and MI have the high average nearest neighbor degrees and high out-degrees, indicating their preferential attachment to other highly connected nodes. On the other hand, major importing states connect to other importing states that have fewer in-coming connections. For example, states with high in-degrees- IL, CA, CO, TX, and AZ also have the low average nearest neighbor degree. The mixture of assortative behavior (a characteristic of social networks), and disassortative behavior (technology and biological networks) indicates a hybrid network structure previously observed in trade networks. This resemblance is attributed to the complex interplay between biophysical, geographical and social factors.[51, 113]

2.4 Discussion

This work is an attempt to fill a significant knowledge gap in our understanding of the FEW nexus, focusing on the energy footprint and GHG emissions of irrigation water embodied in interstate food transfers. We analyzed interstate food transfers and associated irrigation impacts for 29 commodities accounting for approximately 70% of per capita national calorie consumption. The results highlight the energy and GHG intensiveness of irrigated food production. As a comparison, the embodied GHG emissions in irrigation considered in our work (42 billion kg CO_2-equivalent) are comparable to the total GHG emissions from the U.S. cement industry (35.1 million metric tons CO_2-equivalent), one of the most GHG intensive industry in the U.S.[164] From an

environmental sustainability perspective, the results highlight the large irrigation water and hence associated energy and GHG emissions intensity of animal-based food compared to cereal-based products. These results reinforce the importance of changing diet patterns such as curtailing consumption of water intensive red meat, dairy, and highly processed foods.[133, 165]

A related pressing issue is the reduction in food waste and its impact on environmental sustainability of the FEW nexus. The USDA estimates for 2010 indicate that cereals and meat products constituted one-third of total food waste in the U.S.[142] Food waste represents a major efficiency loss and environmental hotspot in the U.S. food system. The results from our work highlight the large embodied energy and GHG emissions of virtual water in interstate food transfers. As such, identifying and implementing strategies for reduction in food losses and waste could represent a significant leap towards reducing the resource use and emissions intensity of food production. Our results also show that major net virtual water exporting states such as North Carolina, North Dakota, and Utah also employ high energy and emissions intensive irrigation practices, thus increasing the overall energy and GHG footprint of irrigation. These results highlight the need for evaluating and implementing farm level strategies such as switching to energy and water efficient low-pressure irrigation systems, reducing water losses in irrigation, improving pump motor/engine efficiency, and switching away from fossil fuel to renewable fuel sources for irrigation pumping.[166] Visualizing food transfer and embodied resources as networks also provides an elegant framework to identify and evaluate possible interventions and their subsequent effect on food transfer networks and associated environmental impacts. Additionally, multiple Pacific, Mountain, and Plains states supplying large food transfers depend on Ogallala aquifer and Colorado River basin for irrigation. These water bodies are already facing water-level declines and over allocation issues.[167, 168] Future work should focus on modeling

irrigation specific changes in food transfers due to water scarcity, climate change, and agricultural policies similar to virtual water specific models developed by Konar and colleagues for virtual water trade.[82, 169, 170] As such, systems analysis should become an integral part of proposing and evaluating the efficacy of strategies for improving the sustainability of the FEW nexus. This is critical to identify interventions that result in net positive system-level benefits for the FEW nexus versus those that result in isolated benefits and unintended consequences.

As with any large-scale systems analysis, the framework and results presented in this work are subject to several sources of uncertainty and have their own limitations. While CFS database provides estimates of interstate food transfers, it does not differentiate between intermediate food transfers. Additionally, we do not explicitly account for energy required for large-scale conveyance for irrigation water supply for all states. The reason for this is discussed as follows. Tidwell et al.[111] conducted a comprehensive analysis of energy used by large scale water conveyance systems across 17 western states. Their analysis included estimation of energy expended for lifting and conveying water for large scale water supply projects. The energy used for water conveyance was highly variable across 17 states with AZ, WA, and CA having the largest energy expenses.[111] The authors attributed high values in these states to a few projects including Gila and Central Arizona Projects in AZ, Columbia Basin Project in WA, and State Water and Central Valley Projects in CA. Due to the lack of available data for Eastern states and non-federally operated pumps and conveyance projects in Western states, we do not include energy used for conveyance in our analysis. However, it highlights the importance and need for comprehensive data to understand and quantify the contribution of energy requirements associated with water conveyance to the irrigation energy requirements of agriculture. Third, water withdrawals for states spanning larger landmass, multiple watersheds, and different geographies such as Texas,

Washington, and California may vary considerably. Incorporating spatial variations within states will require additional fine scale data. Further, competition for freshwater use by the energy, agriculture, and other industrial sectors will strain the already limited freshwater sources. As a result, interest in irrigation with brackish and reclaimed water is gaining traction.[171, 172] While the use of wastewater for irrigation purposes is attractive, it is likely to increase the energy intensity of irrigation due to additional pretreatment. Its economic and environmental implications are not understood and should be quantified in the future. Although tracking and quantifying uncertainty across datasets and models in a statistically rigorous manner is critical, it is beyond the scope of our present work and merits investigation. Finally, we interpret our estimates as not deterministic values of embodied transfer flows, but as indicators of the complex interdependencies between FEW systems and a guide for integrated management of these highly connected systems.

3.0 An information theory approach to measure trade dependencies

The following chapter is based on an article submitted in *ACS Environmental Science & Technology and is currently under second round of peer review.*

3.1 Introduction

The United Nations General Assembly adopted the Sustainable Development Goals (SDGs) in 2015 to provide a roadmap for tackling seventeen 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.[173] 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, the systems analysis needs to be complemented with a context-specific study at specific geographic scales and sectors to understand effects of interconnections.

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.[28] Irrigation adds significant value to food and feed production in the U.S.[110], providing a crucial link to study the domestic FEW systems. Irrigation is the second largest freshwater withdrawal sector in the U.S.,[144] while irrigation pumping accounts for substantial agricultural energy expenses.[174] 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; and 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.[51] As the imbalance between consumption and production increases, understanding the patterns of trade dependencies becomes an important consideration for regional food security.

Depending on the origin of production, trade can alleviate or aggravate environmental impacts associated with food consumption.[76] Virtual water trade refers to the trade of water that is not physically embedded but used in producing the traded commodity.[84] Similarly, food trade can be represented as networks of embodied resources and environmental impact flows. 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.[175, 176] Recently, studies have examined the risks and dependencies transported through international[177, 178] and regional[179] virtual water trade. Dependency in food trade is a complex issue for food security as it may strengthen (through diversifying trade partners) or harm food supply (reducing self-sufficiency). In this article, we analyze the pattern of regional food trade dependencies by comparing it to a null model of U.S. food trade. Here, the null model represents the most probable trade given each state's import needs and export supply.[180] Therefore, trade links are randomly assigned given they satisfy the constraint of consistent demand and supply out of each state. The emergent patterns in actual trade, not observed in the null model, provides insights on dependence (level of preferential attachment) in the network. Additionally, we extend the analysis to quantify and assess the risk associated with irrigation, irrigation-related embodied energy, and irrigation energy-related embodied GHG emissions. While trade typically refers to international exchanges, we limit the analysis and discussion to the U.S. and refer to interstate trade as transfers.[48, 139]

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: 1) interstate physical food flows (US tons), 2) virtual irrigation water (m^3), 3) embodied irrigation energy (MJ), and 4) embodied irrigation GHG emissions (kg CO_2

equivalent). Building on the framework for the multi-layer network analysis first presented in our previous work[28], 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 seek to understand the emergent patterns of trade dependencies in the US domestic food transfers when compared to a null model; and, how dependencies are affected by FEW interactions in an irrigation context. Finally, we discuss the usefulness of a systems perspective in gaining food trade and agriculture policy insights to build resilient and sustainable food supply systems in a FEW nexus context. 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 Appendix B.

3.2 Materials and Methods

3.2.1 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 (SI) table S1. The bi-lateral domestic food transfer data were obtained from the Freight Analysis Framework (FAFv4).[181] 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 select agriculture crops, with cereal and animal feed alone constituting 53% of national agricultural production.[182] 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.[48, 181] 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 national corn use statistics for 2012.[183] We note that some of the grains from the cereal grains category may end up as animal feed for non-ruminant 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 disaggregated shipments 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 consists of 80% rice. While transport based surveys provide a best available substitute for interregional transfers accounting, they suffer from several limitations such as over-assigning inflows to transport hubs, and not distinguishing between point of production vs. point of last value added.[184] 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 end consumption, but the first-set of consumers 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 non-producing states. Similar approach for interregional disaggregation has been employed previously.[28, 48, 185] A brief discussion on regional commodity transfer limitations and reconciliation issues is provided in the Appendix B. 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 virtual irrigation water, embodied irrigation energy, and embodied irrigation GHG emissions. A discussion on GHG impacts of U.S. food transport can be found elsewhere.[133, 186, 187] For the remainder of the article, "*embodied energy*" refers to "*embodied irrigation energy*" and "*embodied GHG emissions*" refer to "*embodied irrigation GHG emissions*".

3.2.2 Embodied irrigation energy and GHG emissions 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 irrigation water withdrawal, embodied irrigation energy, and embodied irrigation GHG emissions by using data from the Farm and Ranch Irrigation Survey[145], U.S. agriculture census[188], Energy Information Administration data[189] combined with life cycle assessment methods. In

particular, we use cumulative energy demand[150] and IPCC 100 year global warming potential to calculate our life cycle impacts.[151] The detailed methodology and assumptions were first described by framework provided by Vora et al.[28]

3.2.3 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.[104] Commonly applied in linguistics[190-192], PMI calculates the probability of co-occurrence or co-location of two words (events). A classic example involves comparing two synonym adjectives “strong” and “powerful” from English language. A set of specific words are 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.[193] 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.[194] 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? This is also 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 Appendix B,

$$PMI_{ij} = klog_2 \frac{p_{ij}}{p_{i.}p_{.j}} \quad \textbf{(1)}$$

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, $T_{..}$ 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 re-written as,

$$PMI_{ij} = \log \frac{T_{ij} T_{..}}{T_{i.} T_{.j}} \tag{5}$$

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 observed structure of the trade network is a result of random formation and estimating its properties does not give us any useful information.[180] PMI measure essentially compares observed trade network with a pseudo-random network (which is referred to as a situation of maximal indeterminacy). We use the term pseudo-random because trade cannot be random, therefore comparing 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

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

$$F_{out} = \begin{bmatrix} T_{1\cdot}/T_{..} \\ T_{2\cdot}/T_{..} \\ \vdots \\ T_{n\cdot}/T_{..} \end{bmatrix} \quad F_{in} = \begin{bmatrix} T_{\cdot 1}/T_{..} & T_{\cdot 2}/T_{..} & \cdots & T_{\cdot n}/T_{..} \end{bmatrix} \tag{7}$$

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 re-wiring network flows amongst each trade connection. A unique property of the null model is that it re-distributes 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 indicates how far each trade interaction is from being more equitable. An example of how the null model divides flow equitably is provided in the appendix B.

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

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

Previously, Kharrazi and Fath discussed the value of utilizing PMI measures to evaluate preferential trade policies within the context of international oil trade.[195] 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 towards a situation of maximal indeterminacy, 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, re-arranging even one pair would alter the entire pattern of network flows indicating importance of considering interactions within the entire system.

3.3 Results

3.3.1 Network indicators

We consider food transfers between 50 states plus 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 bi-directional connections: links in both directions/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 US tons, with 166 billion m^3 of virtual irrigation 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 26). Figure 5 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 visualization purpose, links with at least 1% of maximum link weight are shown.[178]

For a majority of the states, the highest volume of transfers are 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 towards feeding the large cattle and hog industry.[196] 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 US tons and primarily consists of corn, corn silage, alfalfa hay, and wheat in shipments.

Next, we visualize flow values according to maximal indeterminacy (null model) in the system (Figure 6). These values are re-arranged in a more uniform fashion considering mass of the product of total flow going and coming out of states. It should be noted that the flows are not re-distributed 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 Figure 22 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 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, [51] the preference represents presence of "additional information" in how ties are formed.

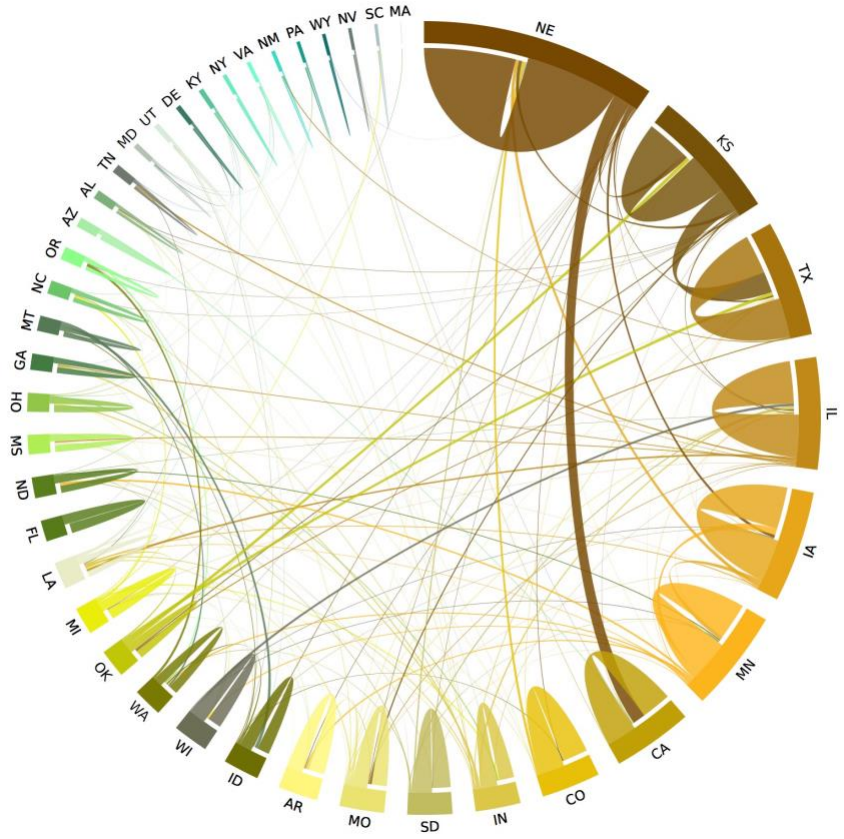


Figure 5. Cereal and feed grains transfer amongst the U.S. states.

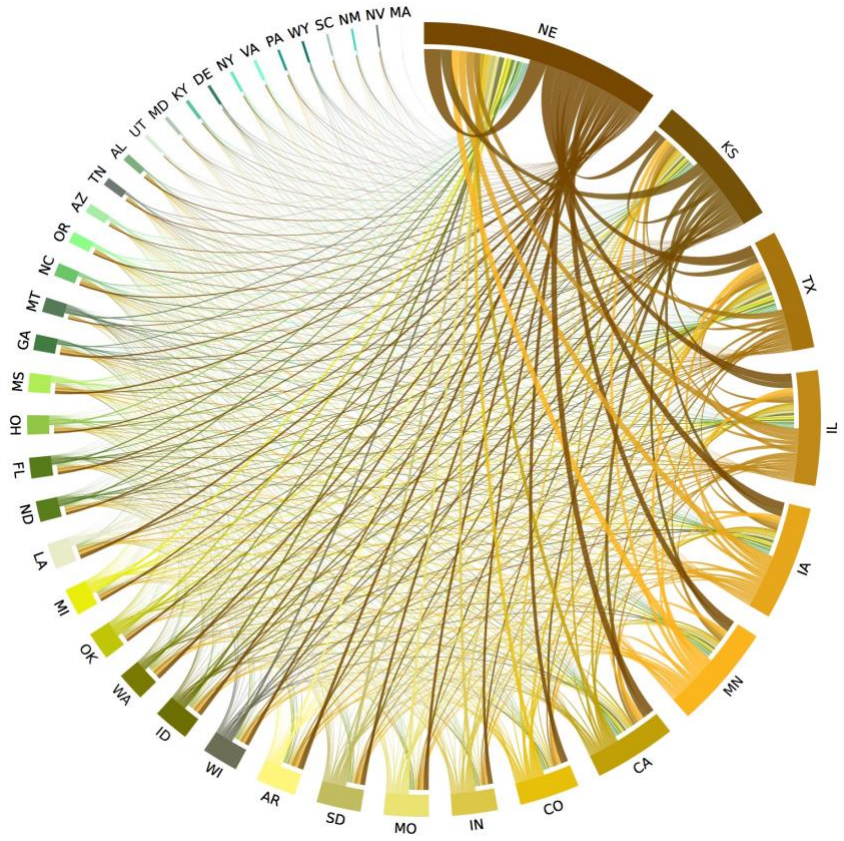


Figure 6. Cereal and feed grains trade between U.S. states for a situation of maximal indeterminacy (zero dependency).

3.3.2 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 trading relationship being considered compared to other relationships out of the two states. This translates to how overall connections in the network (the system) affects 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.[195, 197] 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 US 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 ten import partners in a descending order and compare with ranks of direct incoming transfer volume (Table 2). Positive PMI indicates higher than expected dependency and negative PMI indicates lower than expected dependency. 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 on zero, indicating the observed flow's proximity to 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 bi-lateral 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 2, 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 (Figure 22) 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 the Table 27. We emphasize that by providing comparison of rankings, our motive if not to recommend PMI method over traditional approaches, but to provide complementary insights along with other commonly used measures.

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 [54, 198]

Table 2. Texas' top 10 importing partners ranked by their PMI and incoming transfers.

Incoming flow	PMI	PMI Rank	Flow (US tons)	Flow Rank
Texas	3.31	1	3.23E+07	1
Kansas	1.61	2	1.77E+07	2
Oklahoma	1.10	3	2.76E+06	3
Louisiana	0.23	4	9.38E+05	5
New Mexico	-0.05	5	1.19E+05	11
Indiana	-1.59	6	6.60E+05	6
Missouri	-2.17	7	4.06E+05	7
Tennessee	-2.51	8	5.99E+04	16
Nebraska	-2.76	9	1.37E+06	4
Arizona	-2.81	10	6.01E+04	15

3.3.3 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 higher ranked (figure 7). The PMI values are also included in inset for clearer visualization. The states colored in white represent absence of virtual water transfer to Texas. The dark grey shaded states represent high PMI values, and therefore higher dependence. Previous work has discussed the prevalence of gravity law[199, 200] based relationship of distance enabling trade in international virtual water trade.[160] 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 appendix B. 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[145, 201] 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.[202] and Aqueduct database.[203] 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.[202] 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.[167] Scanlon et al.[204] 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, combined with geographic nearness, virtual water imports to Texas from within-state flows, Kansas, Oklahoma, and New Mexico carries risk associated with groundwater depletion in the long run, especially as pressure on Ogallala increases from population demand and changing climate.[205]

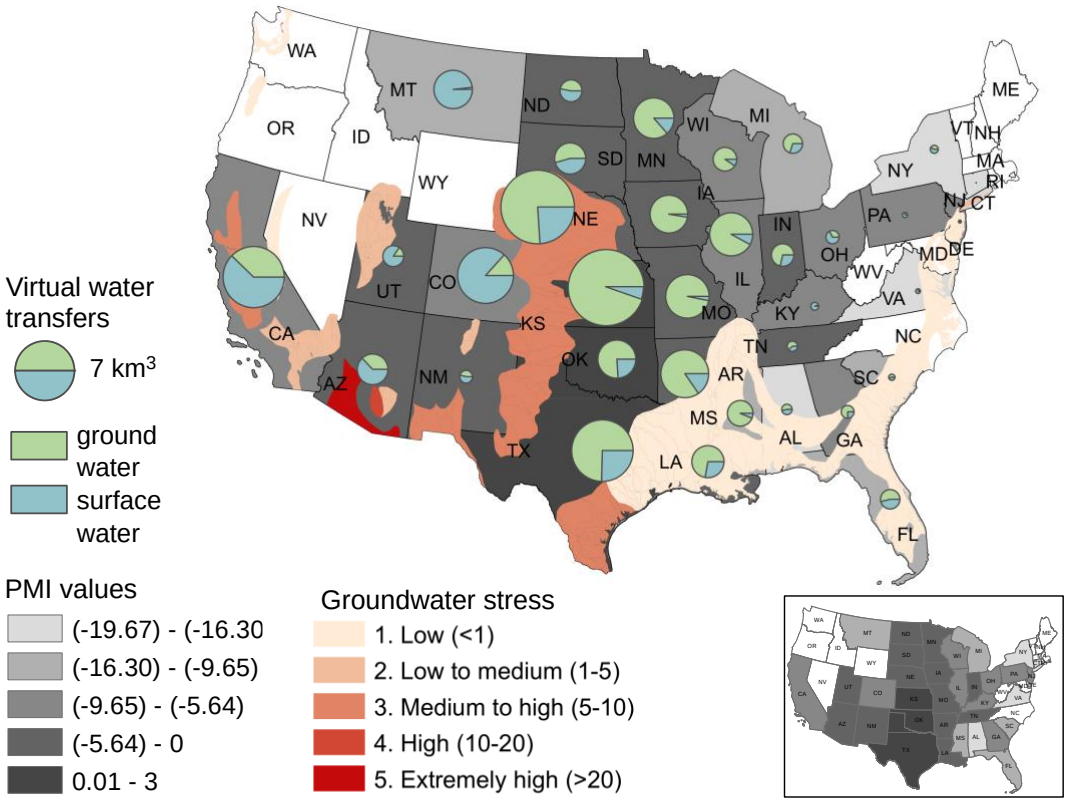


Figure 7. PMI values for virtual water transfers to Texas.

From the demand side, the potential risk of groundwater depletion can be managed by re-structuring existing trade to explore alternate states that have a higher potential to trade and support sustainable irrigation to build a water-scarcity resilient food supply chain. For example, lighter grey 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.[206] Schipanski et al.[207] 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 towards sustainable management of common source.

Figure 8 indicates PMI values for irrigation embodied GHG emissions transfers to Texas. Each pie chart represents the distribution of 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 emissions intensity in kg CO_2 equivalent per m^3 of water abstracted. Barring electricity, natural gas-based pumps have the lowest embodied GHG emissions intensity amongst all four fuels considered.

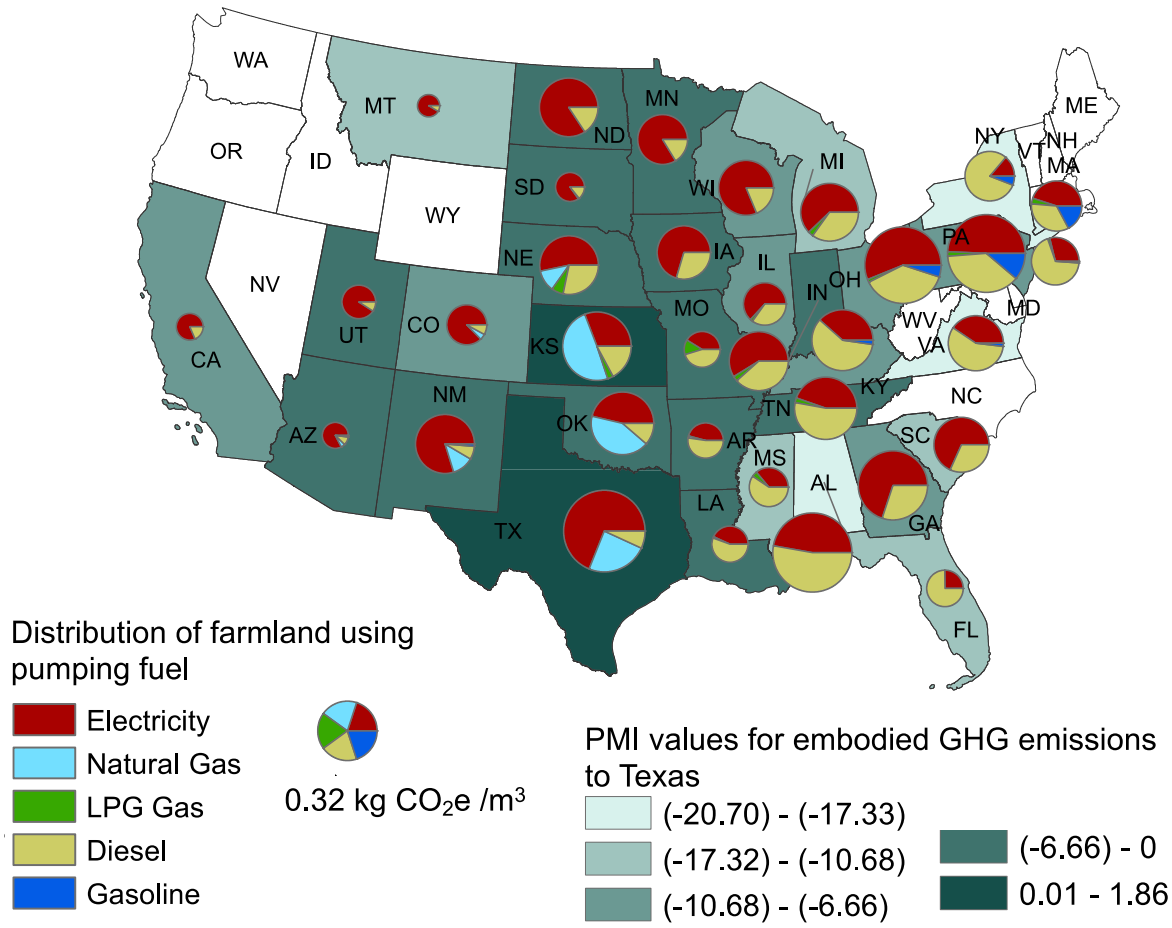


Figure 8. PMI values for embodied irrigation GHG emissions in imports to Texas.

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.[137] Contrarily to water intensity for crops, California, Colorado, Arizona, Arkansas, and Utah have lower GHG emissions 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 high coal-based electricity mix in their grid (e.g. Kansas, Nebraska, 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 emissions intensity of states such as Pennsylvania, Ohio, Alabama, and Kentucky.[145] These states represent a clear example of water scarcity vs. GHG emissions tradeoff and denote an area of farm conservation policy focus for improving pumping energy and emissions 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 emissions reductions may not be mutually exclusive goals.[208]

3.4 Discussion

This work provides a systems-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 bi-lateral 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 overall transfer activity and the potential to increase (or decrease) activity between a dyad, it provides a thorough accounting of their mutual dependency. This is clearly exhibited in importance of Texas-New Mexico trade connection despite being of a lower volume, and reiterates the importance of also considering weak ties.[197]

When we compare the visual difference between flow in a maximal indeterminacy situation and actual trade, the unequal distribution in trade concertation becomes apparent with a few links/states dominating the network. 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. The analysis presented in this work has its own limitations. An important limitation of this work is the FAF dataset's inability to trace the final point of 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.[209] Additionally, future domestic trade analysis should involve employing origin tracing algorithms[210] used in international trade studies to remove re-exports from the data.

While PMI provides information on regional dependency based on trade data, it does not explicitly consider type of water resource and resulting vulnerability. Therefore, accounting for the source of water abstraction is important when considering the impact of agriculture on water resources. Previous work[178, 179] has demonstrated the U.S. domestic food production and consumption reliance on groundwater extraction with Dalin et al.[178] distinguishing impact attributable to unsustainable groundwater extraction. By combining PMI results and ground water

stress indicator, we highlight the regional reliance of Texas' and neighboring states on Ogallala aquifer for irrigation while engaging in substantial transfer amongst 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[211] and between users of Colorado River basin.[212] Further, considerable geographic variation exists in recharge rates across the Ogallala aquifer due to its sub-surface hydrology.[204] 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.[213]

Additionally, we do not account for energy and emissions associated with off-farm water supply (prevalent in the western U.S.)[111] 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 choice. As our results demonstrate, this may be at odds with other equally important goals to achieve a sustainable and resilient food supply. Going forward, one crucial research area will be understanding ways to re-wire the domestic trade network to serve multiple objectives for more sustainable and resilient national trade.

Spatially disparate water, energy, and GHG emissions intensities highlight the scope of improving farm-level irrigation efficiencies. 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[214] and salinization.[215] 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.[216-218] 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 overall effect of potential trade (dis)preferences for diversifying trade partners.

4.0 Re-wiring the U.S. rice trade for reducing irrigation impacts

4.1 Introduction

The Malthusian theory of insufficient food to meet the growing population demand[219] has not yet materialized due to a number of factors including trade liberalization.[220, 221] Food availability does not solely depend on a region's capacity for agriculture production, but access to food. A nation's inability to reach food self-sufficiency either due to local crop failure, rising population, or limited agriculture potential can be met with exchange of food either through trade or assistance. At present, 66 countries rely on imports as they do not have access to sufficient land and water resources to produce adequate food.[175] Additionally, a substantial population depends on trade for diverse and out of season food items available at competitive market prices. Proponents of trade for food security argue that trade provides an opportunity for nations to improve agriculture efficiencies by focusing on suitable crops while importing other crops.[222]

There exists a singularity even between similar crop producing systems due to the difference in agricultural practices, resource use efficiencies, and policies. Therefore, depending on the origin of production, food trade can reduce or increase environmental impacts and risks associated with it.[76] A growing body of literature has discussed indirect trade of resources and environmental consequences of physical food trade within the context of the U.S.[28, 48, 223, 224] The concept of impacts being traded indirectly with food trade was popularized by Allan by coining the term "virtual water trade".[85] Virtual water refers to water required to produce a commodity, and the trade refers to displacement of this valuable source in producing food for exports. Studies have shown that global food trade has resulted in overall water savings[125, 225]

with exporting countries being water-efficient in agriculture, particularly with large quantity exports of soybeans driving the savings.[125] Similarly, studies have assessed embodied impacts in trade to assess land[226, 227], biodiversity[228], and nutrients displaced through trade[91, 223, 229] with the goal of promoting discourse on internalizing the trade externalities. Such comparison of relative impacts of agriculture through traded food can help drive the discussion regarding food trade's role in alleviating resource depletion.

However, trade is not designed to be environmentally sustainable.[76] Global demand of commodities such as palm oil[230], soy[231], coffee[232], shrimps[233] and their rising agriculture expansion in specific regions have resulted in the loss of biodiversity. Similarly, reliance on unsustainable groundwater aquifers in the U.S. domestic and export food supply chains have been reported in Marston et al.[179] In India, water intensive paddy rice is supported through a series of agricultural subsidies causing salinization and depletion of groundwater sources.[234] Therefore, one of the next steps in embodied trade literature is answering whether trade can be re-structured to meet environmental sustainability and resilience goals. Studies have already begun addressing the possibility of redistributing crops to maximize nutritional gains while reducing water use at regional[198] and global level.[54] Such measures require focusing on growing nutrient and calorie rich crops and moving away from crops such as rice, wheat, and sugar.[54] Previous work has argued for similar measures to tackle climate change and provide healthy affordable diets.[235] However, cultural acceptance of changing diets, economic implications of crop distribution, and feasibility are complex issues to tackle and will require a large scale multi-sector and multilevel action.[236] The role of trade will be an important driver for realizing crop re-distributions through shifting market demands. Therefore, we combine these two narratives of

embodied impacts of trade and potential for crop re-distribution to assess whether trade can be a valuable tool in realistically shifting specific crops to places with conducive natural endowments.

To manage overlap in sustainable development goals, policies have begun to piece together distinct impacts into a more holistic framework.[173, 237] This work focuses on one such an interaction between food-energy-water systems, termed as the FEW nexus[13] by assessing the embodied irrigation impacts of trade, specifically embodied greenhouse gases in irrigation and irrigation water required. Crop redistribution may occur for varying reasons: market demand and price hike, policy changes, scarcity of water may drive farmers to switch to dryland farming. Here, by re-distributing crops with FEW nexus objectives, we do not prescribe policy strategies to follow based on results, but rather explore how the crop patterns would change if a singular goal or multiple goals are kept in mind. For example, optimizing for virtual water may result in some states reducing their production, and in such instances our strategy is to not prescribe this reduction but to assess feasibility of such change to achieve a particular goal. Through this study, we focus on current agricultural practices and resource use that reward or penalize a state by increasing or reducing crop production respectively.

Rice has been a crop of choice to eliminate/reduce in a path to more environment friendly and nutritious diets,[235] nonetheless, it is a staple food to more than half of the global population with significant cultural and economic importance.[238] Therefore, this research focuses on domestic trade and international exports of rice in the United States. The U.S. exports 45% of its total rice production and ranks in the top five largest exporters.[239] Additionally, US rice is completely irrigated, making an excellent case study to assess a) current tradeoffs and synergies existing between rice irrigation system, b) whether re-wiring trade alleviates or exacerbates energy-water tradeoffs in the U.S. irrigation system. We use publicly available data from the

Bureau of Transportation and create domestic rice trade network consisting of 6 major rice producing states and 51 receiving states. Combining open data on irrigation water applied on farm, U.S. energy prices, mode of transportation, and pumping fuel types with life cycle assessment methods, we create four distinct layered networks of rice trade, virtual irrigation water (blue water), transportation emissions, and irrigation embodied greenhouse gas emissions. We rewire the rice trade network by keeping the food demand constant and evaluating a series of constraints pertaining to energy-water usage. We add additional constraints regarding type of rice produced and place of production to allow for climate, soil, and plant physiological constraints.

4.2 Data and Methods

4.2.1 Data

Trade and Production data: The U.S. food trade network model will be built leveraging existing freight shipment data from the Freight Analysis Framework (FAF).[181] FAF is jointly published by Bureau of Transportation Statistics and U.S. Federal Highway Administration and provides estimates for tonnage, value, mode of transport, and distance of freight transported across the U.S. The latest available year data are for 2012 and will be the year for this analysis. For international shipments, the database details the domestic origin-destination pair as well as their international counterpart (e.g. for exports, the data includes origin of the shipment and the port of exit). The FAF shipment data are provided for aggregated commodity groups. This study uses commodity group of cereal grains and applies production data from United States Department of Agriculture (USDA) to disaggregate into raw grain rice shipments. For example, if rice accounts

for 97% of total grain production in Arkansas, then 97% of grain shipped from Arkansas are assumed to be rice transfers. As approximately 30-40% of rice exports contain rough grain rice, the analysis includes domestic shipments as well as shipments intended for exports.**[239]** However, since the analysis is limited to the U.S., only the domestic leg of the exports is analyzed.

In this work, our model differentiates between distinct classes of rice grown across the U.S. namely, long grain, medium grain, and short grain. Due to favorable soil and climate conditions, 91% of medium grain rice is produced in California, while southern states mostly produce long-grain rice. Short grain rice production is limited to California (8%) and to a smaller extent Arkansas (0.1%). Therefore, the trade wiring occurs keeping in mind the feasibility of each class in a specific state. Due to lack of class specific demand data, the demand composition is kept consistent with production composition of rice. All production related data are obtained from USDA's agriculture survey. In order to model the FEW nexus as an applied network optimization problem, we define the set N as the nodes of the network, where each node $i \in N$ represents a state. Let $N_P \in N$ be the set of rice-producing states. Then the set A of directed links (i, j) between node pairs i and j represents trade of rice between rice-producing states $i \in N_P$ and the other states, including self-loops for a state's production sent to itself. Each rice-producing state N_P produces one or several types of rice, designated $k \in K$, where K is long, medium, and short-grain rice

Virtual water transfers: Virtual water transfers are obtained by combing physical trade data (i.e. tons of rice traded) with water application intensities (m^3/ton) for type of rice in a specific region. State and crop specific water applied per acre (m^3/acre) are obtained from the Farm and Ranch Irrigation survey 2013.[240] The yields for specific rice type (i.e. long, medium, and short grains) are obtained from the USDA. To account for yield anomalies (i.e. 2012 drought in Texas) for specific years, we select five year timeframe (2010-2014) to minimize yield trend effects (i.e.

increase in yields due to technology) over time.[241] The yield values are assumed to be of uniform distribution, and based on minimum and maximum values 10,000 samples are simulated. The average of the simulated rice yields are combined with water applied per acre to estimate water application intensities.

$$w_i = \sum_{k \in K} c_{ik}^{w} \sum_{j \in N} t_{ijk} \quad \textbf{(9)}$$

$$i \in N_p, j \in N, k \in K$$

N_p= rice producing states (6), N = Exporting states (51), K= set of rice types

w_i = virtual water used in producing commodity at i in (m^3)

t_{ijk}= trade of commodity k from i to j (US ton)

c_{ik}^{w}= water applied per unit cro produced (m^3/ton)

Transportation emissions: The FAF data labels transportation modes in six categories: truck, rail, water, air, multiple modes and mail, and other or unknown. The other and unknown category are treated following specified FAF mode reassignment method where if a shipment is greater than 80,000 pounds (0.04 tons), then it is assumed to be transported through rail, or else truck. Multiple modes and mail category may include travel by a combination of truck-rail, truck-water, and rail-water or though parcel delivery services, for any of which specific data are not available.[140] Additionally, depending on the type of mode, vehicle freight capacity, and combination of distance travelled by specific mode, the associated GHG emissions may vary significantly.[186, 242] Considering that multiple modes shipment routes carry less than 5% of

tonnage for the six rice producing states (appendix C Figure 24), we replaced it with the dominant shipment mode (e.g. truck) for that route. The life cycle GHG emissions associated with each four type of modes considered are obtained from Ecoinvent[149] database and listed in the appendix C

$$g_{ij} = m_{ij} c_{ij}^{gt} \sum_{k \in K} t_{ij,k} \quad \textbf{(10)}$$

g_{ij}= life cycle transportation emissions in kg CO_2 equivalent

m_{ij}= mean distance from *i* to *j a*s total ton miles per ton to get a weighted average distance by tonnage

c_{ij}^{gt}= GHG emissions associated with shipping from *i* to *j* weighted based on transportation mode (kg CO_2 equivalent/ ton-mile)

Irrigation emissions: The irrigation emissions are derived from Vora et al.[28] and include greenhouse gas emissions associated with on-farm irrigation pumping. The primary data source for pumping energy expenses are Farm and Ranch Irrigation Survey.[240] These reported expenses are converted into energy quantities by obtaining energy prices from US Energy Information Administration.[189] The pumping energy expenses account for varying pumping requirements from both groundwater and surface water sources and type of irrigation system employed. Life cycle GHG emissions are calculated based on IPCC 100 year global warming potential[151] using Ecoinvent[149] and US Life cycle inventory databases.[148] The irrigation emissions are combined with estimates of virtual water to arrive at embodied GHG emissions.

$$g_i = c_i^{gw}\, w_i \tag{11}$$

g_i= embodied irrigation greenhouse gas emissions trade in kg CO_2 equivalent

c_i^{gw}= embodied greenhouse gas emissions per unit water applied (kg CO_2 equivalent/m^3)

4.2.2 Optimization model

The optimization model is formulated with linear programming techniques, and it is implemented in C++ using the IBM CPLEX concert technology solver.[243] The decision variables for the model encompass both production and transportation decisions. Thus, we require the amount of each type of rice produced, as well as the amount shipped to/from each state along the link (i, j). We explore four scenarios 1) Minimize overall virtual water usage, 2) minimize irrigation GHG emissions 3) minimize transport emissions 4) reducing all three impacts. The objective of the model 1 is to minimize overall virtual water usage (Scenario 1); however, we also define input parameters α and β, which represent the factor by which irrigation and transportation GHGs, respectively are allowed to increase over their present values or forced to decrease. That is, let $\bar{g}_o^{gt}$ be the initial amount of total transportation GHGs produced by the system, then we constrain $\sum_{(i,j)\epsilon A} g_{ij} \leq \alpha \bar{g}_o^{gt}$ for some factor $\alpha > 0$. Similarly, let $\bar{g}_o^{gw}$ be the initial amount of total irrigation GHG, and then we constrain $\sum_{i\epsilon N_p} g_i \leq \beta \bar{g}_o^{gw}$ for some factor $\beta > 0$. Through tuning of values of α and β, we explore the case of minimizing virtual water as well as a case where we simultaneously reduce all impacts. Model 2 describes scenario 2 of minimizing irrigation GHG emissions. The constraint 12 and 13 remain consistent for all the models. Constraint 12 enforces

that each state should continue to receive the same amount of each type of rice it receives. Constraint 13 ensures that yields do not exceed the defined upper bound yields (described in detail in the next section)

$$min \sum_{i \epsilon N_p} w_i \qquad \text{(model 1)}$$

$$min \sum_{i \epsilon N_p} g_i \qquad \text{(model 2)}$$

Subject to:

$$\sum_{i \epsilon N_p} t_{ijk} \geq d_{jk} \qquad (12)$$

$$y_{ik} \leq y_{ik}^{UB} \qquad (13)$$

Land constraints and potential yields: There has been a decrease in land allocated for rice production in recent years with national rice acreage declining by 20% in 2018 compared to

2010.[188] Therefore, the model is constricted to only consider the current acreage when re-distributing trade. Instead, we allow the yield values to increase up to its yield potential. The potential yields, also known as yield ceilings represent maximum achievable yields for the given crop in a given location without constraints from water, nutrients, pests, and diseases.[244] The data for potential yields for rice are obtained from the global yield gap atlas.[245] The potential yields are calculated for 14 weather stations spanning six major rice producing states. Based on the modeled acreage, we scale-up the data at the state level. Due to diminishing economic returns on investment for yields, farmers may not target to achieve 100% of the yield potential. Therefore, based on literature, we assume 85% of the reported yield potential can be exploited by the farmers and use it as our yield ceiling.[241] The exploitable yields are provided as the upper bound in constraint 5. The potential yields are estimated without differentiating between rice classes and represent values for the dominant rice systems in a given region. A dominant system for a given state is determined based on maximum acreage dedicated to a particular rice class (e.g. California's dominant system is medium grain rice). To estimate yield potentials for secondary systems (i.e. long grain rice production in CA), we assume the same percentage increase in yield can be achieved as the dominant system. For example, if current yields have reached 70% of their yield potential for the dominant system, a similar efficiency is assumed to be possible to achieve for the secondary system. Therefore, in case of secondary rice systems, our assumptions make the yield values conservative. Table 28 contains exploitable yields for all states and rice types. The yield values reported by the model indicate the minimum yield that would be required (on the existing land) to support the desired level of production. The minimum yields are based on the current yield data. Hence, it is possible that lower yields could be reported by the model, but the interpretation

is that, since production would have decreased, a smaller yield would be required. This is interpreted as decrease in the land usage.

4.2.3 Sensitivity analysis

We combined disparate data sources and models together to arrive at rice trade and embodied FEW nexus impacts. Therefore, the data used are subject to uncertainties. We accounted for it by using methods of robust optimization in order to maintain computational tractability of optimization.[246] We assumed that c_{ik}^{w}, c_{i}^{gw}, c_{i}^{gt} are unknown quantities, but the bounds on their ranges can be established. We used Monte Carlo simulation to account for uncertainty and propagation of uncertainty in the model. For c_{ik}^{w}, we combine uncertainty in yields with water applied per unit land. We simulated 10,000 samples for yields (long, medium, and short) assuming a uniform distribution to arrive at 10,000 values of c_{ik}^{w} for each state. Here, we assumed water applied per unit land to be constant. The uncertainty values for life cycle GHG emissions of transport are obtained from life cycle assessment software SimaPro.[247] We use the simulated 10,000 values for each mode and combine it with m_{ij} to estimate bounds for transportation emissions associated with a specific route. For irrigation emissions, we again utilized SimaPro[247] to estimate uncertainty in emissions associated with each pumping fuel type. These values were propagated with energy pricing data and virtual water estimates to arrive at 10,000 simulated values for embodied irrigation emissions from *i* to *j*. The average and 95% confidence bounds were estimated for each simulation. The supporting information contains detailed equations and derivations for the deterministic and robust models.

4.3 Results and Discussion

4.3.1 Network-level savings

We explore three scenarios to compare against the baseline case. The baseline represents current rice trade and associated embodied impacts. We compare it with rewiring 1) to optimize water, 2) optimize GHG emissions, and 3) to achieve simultaneous reductions for water and emissions impact.

Figure 9 represents network wide optimization results compared with baseline scenario for virtual water and embodied emissions including irrigation and transport. The solid bars in GHG emissions represent contribution of transport emissions and the hatched bar represents irrigation emissions. For the baseline case, embodied irrigation GHG emissions amount to 5.8 billion kg CO_2 equivalent and transport 0.7 billion kg CO_2 equivalent. This can be primarily attributed to the large quantity of water used in rice production and relatively few states producing and exporting rice. As seen from the case of optimizing for water, there is a tradeoff between reducing water and emissions. Therefore, the last scenario explores maximum amount of water that could be saved while also simultaneously reducing emissions.

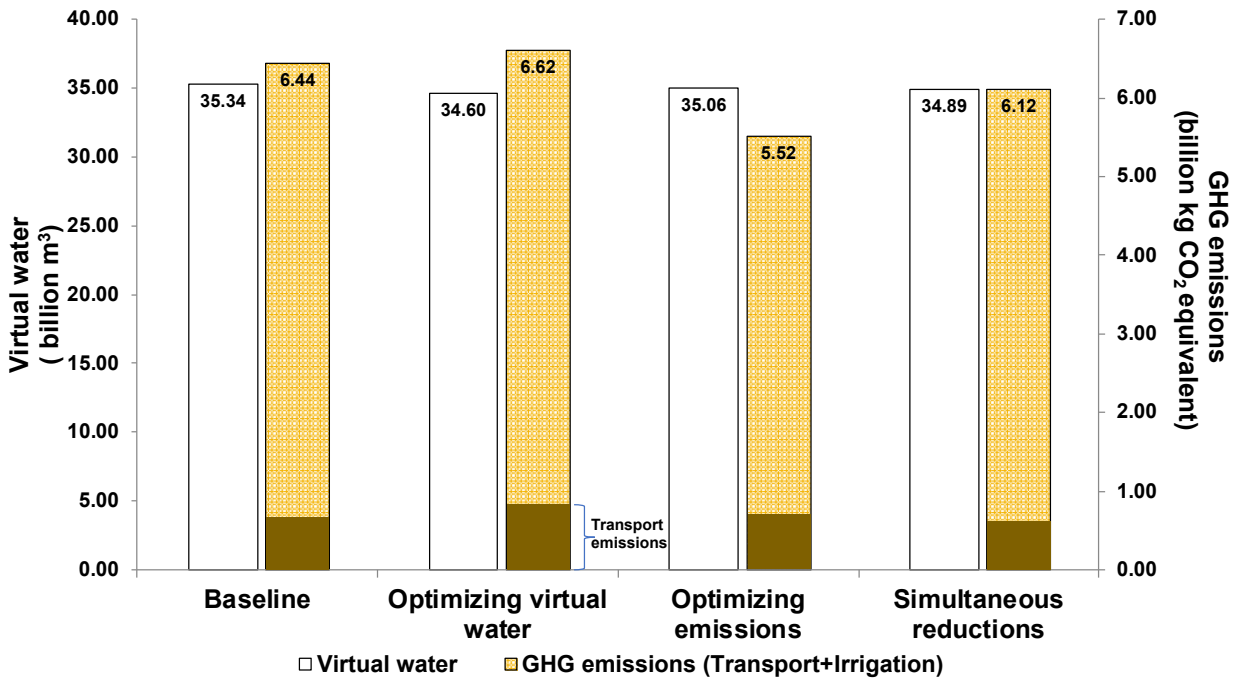


Figure 9. Network wide rewiring results for virtual water and embodied GHG emissions

In optimizing virtual water, we reduce network wide virtual water by 2% and increase transport emissions by 26%. Irrigation related emissions remain unchanged, and are an order of magnitude higher than transport resulting in the net emissions increase by 3%. In optimizing irrigation GHG emissions, the model manages to reduce irrigation emissions by 17% with 1% reductions in virtual water and 7% increase in transport. In scenario where we attempt to reduce all three, the model manages to reduce irrigation and transport emissions by 5% each and virtual water by 1%.

4.3.2 Redistribution at state-level

Next, we assess the state-wide changes in environmental impacts due to rewiring. Figure 10 represents state level changes in virtual water and total GHG emissions under various cases. For embodied GHG emissions, the solid bars represent transportation emissions which vary

between 4%-24% of total emissions. In all scenarios, the total number of trade links are reduced with the model increasing number of shipments carrying a large throughput. All of the states that increase their production do so by increasing the yield up to the maximum exploitable yield. This strategy of both intensifying some systems while reducing production in other states, results in 12% reduction in total land use. In the other two cases, we reduce land use by 11% (optimizing irrigation emissions) and 8% (reducing all three).

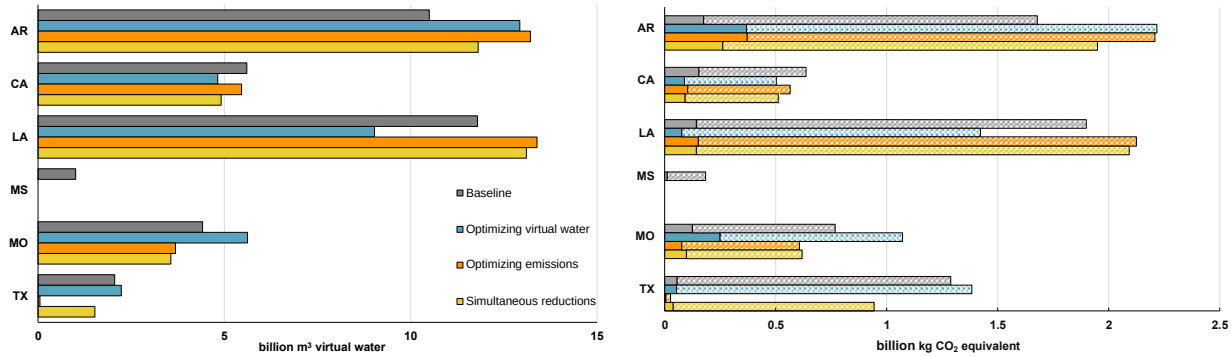


Figure 10. State-level changes in virtual water and embodied emissions

In each of the cases, California reduces its production of rice by 5-14% with corresponding reductions in virtual water and total emissions. The model reduces the maximum amount of production in the case of optimizing for water (14% reductions) and simultaneous reductions (12%). California has the largest water footprints (m^3/ton) across all three rice types prompting the model to slash more production. However, apart from the footprints, the rewiring occurs with consideration to types of rice produced in each state. For example, the majority of medium and short grain rice is produced in California. Therefore, despite high water application rates in California for growing rice, the model cannot shift a large production from California due to other state's inability to mass produce medium/short grain rice. Figure 25 visualizes state level changes in rice-type exports for all scenarios. On the other hand, California has the lowest irrigation

emissions intensity (kg CO_2 equivalent/m^3 water applied) resulting in only 5% reduction in total rice production for optimizing irrigation emissions scenario. The embodied irrigation GHG emissions are a function of total energy used in pumping and type of pumping fuels employed. California's extensive use of grid-based electricity for pumps and dependence on gravity systems for irrigation results in lower GHG emissions per cubic meter of water withdrawn**.**

When rewiring for minimizing virtual water, Texas increases its production and corresponding impacts by 8%, but reduces by 26% and 98% in the other two scenarios. Additionally, as seen from Figure 10, Texas has relatively large overall emissions compared to other states (specifically comparing relative state contributions in GHG emissions). This is primarily due to Texas's large irrigation emissions intensity per m^3 of water applied (Table 30). However, more than half of Texas's pumping fuel mix is powered by natural gas including pumps dependent on grid electricity. Natural gas has one of the lowest life cycle GHG emissions compared to other fuels used in for irrigation pumps. Therefore, the large intensity is actually a result of low groundwater levels requiring greater depths for lifting water and unrestrained pumping rights. Texas is one of the interesting cases where food- energy- water goals are in synergy, albeit both pointing to declining groundwater levels and excessive emissions. Therefore, strategies need to be implemented not only for improving irrigation efficiency but reducing overall use of water, including perhaps reduction of rice production.

Similar to Texas, Missouri increases production by 28% in optimizing for water scenario and reduces production by 18-19% in the other two cases. After Arkansas, Missouri has the lowest water application rate, therefore the model increases production to reduce overall water use. However, unlike Texas, it does not have a high irrigation based GHG emissions intensity. Therefore, the net reduction comes from shifting long grain rice production to medium grain up to

its maximum exploitable yield and within transportation constraint. Louisiana on the other hand has the opposite pattern where it reduces production by 23% for optimizing water scenario but increases production by 11-12% in the other two cases. The reductions in Louisiana can be attributed to the model's inability to reduce much of the California production and therefore targeting the next highest water users. Additionally, Louisiana reduces its long grain rice production to partially offset increase in medium grain production.

As Mississippi has the second largest water footprint after California, the model manages to eliminate the production completely to gain modest water savings. In fact, in all of the cases, Mississippi stops producing rice entirely, as it also has the second largest irrigation intensity after Texas. This is one of the most drastic results where the model recommends completely stopping production in all cases considered. One of the disadvantages of shifting rice production is that soil's inability to produce other crops/ rotations in place of rice. Rice can only be grown in soil with ability to retain water, which makes it unsuitable for a growing majority of other crops. Mississippi is one of the few states that grows other crops for rotation along with rice, and therefore demonstrates land suitability for alternative cropping.[239] Currently, Mississippi farmers do not purchase irrigation water and rely on groundwater from underlying aquifer system.[239] Therefore, unlike other states, irrigation costs are not prohibitive to continued production. Although declining groundwater levels have prompted the state government to stipulate farm level water conservation efforts and install meters for the continued access to groundwater for irrigation. However, current farming practices or policies do not indicate that Mississippi will need to completely cut back on production.

We observe Arkansas increasing production by 12-23% in all the scenarios considered. Arkansas has the lowest water footprint amongst all states and second lowest irrigation emissions

intensities. Additionally, it has the ability to produce all three types of rice, although not at the scale of California. Therefore, the model maximizes on benefits by increasing production in all cases. Arkansas farmers do not purchase water and primarily rely on groundwater for irrigation.[239] However, declining groundwater levels could make future expansion expensive. From an irrigation emissions perspective, Arkansas primarily relies on electricity and diesel-based pumps, with grid electricity primarily consisting of coal, natural gas, and nuclear. Thus, there is room for improvement in switching away from diesel-based pumps.

While the GHG emissions through transportation are an order of magnitude less than irrigation GHG emissions, they are considered as direct emissions compared to the latter being a second order impact in the food supply chain.[72] As such, they can be used as a separate lever in managing FEW nexus tradeoffs. For instance, minimizing virtual water and irrigation GHG emissions result in increase in transport emissions by 26% and 7% respectively. The significant emissions increase in virtual water scenario is due to transport emissions from Arkansas and Missouri (corresponding to their production increase) with reduction in many exporting state's within-state flows. In Figure 11, we compare transportation emissions from the baseline scenario with emissions from optimizing water (largest transportation emissions amongst all cases considered) and optimizing transportation emissions. The size of each segment representing a state inside the diagram is based on relative contribution to embodied GHG emissions for that network. The similar colored segments and links represent export links and different colored links represent imports. The size of the segment represents total incoming and outgoing links. The size of each circular diagram is not scaled to represent total network level transport emissions.

In rewiring the trade to optimize transport, we save 25% network level GHG emissions from transport. The size of each circular diagram is not scaled to represent total network level

transport emissions. However, the size of each segment representing a state inside the diagram is based on relative contribution to transport emissions. Compared to baseline, both cases have fewer but larger links. For example, Texas' demand was satisfied through number of partners in the baseline scenario. Now, the demand is satisfied through within-state flow from Texas and a large flow from Arkansas in the two comparative cases. In fact, for optimizing transport emissions, the model manages to satisfy a majority of the demand though directing within-state flows as seen from larger self-loops for Louisiana, California, and Arkansas. Optimizing transport is the only case where production from Mississippi isn't completely stopped. However, the rewiring routes all the flows from Mississippi to within-itself to partially satisfy demand with the rest sourced from Louisiana. For the optimizing water case, the model chooses to eliminate completely production from Mississippi and the demand is satisfied through a large flow from Arkansas.

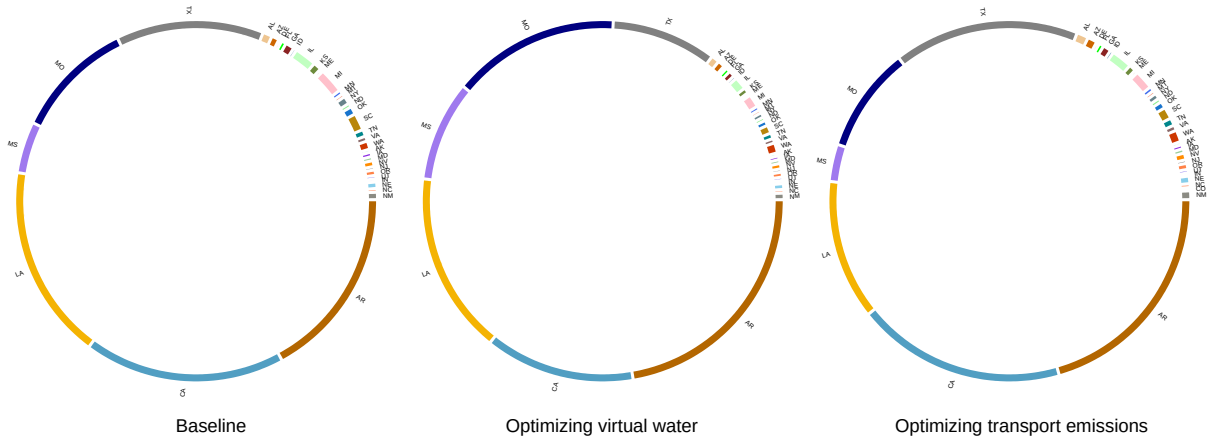


Figure 11. Rewiring resulting from GHG emissions from transport for baseline, optimizing virtual water, and optimizing transport emissions scenarios.

Generally, rice mills are located in or nearby states with rice production[248] making within-state demands larger. Since U.S. also exports raw grain rice directly,[239]some of the flow goes to international shipping hubs. For the rice trade, the largest mode of shipment carrying

significant tonnage is trucks, followed by rail and water- based shipments. Water based shipping has the lowest life cycle GHG emissions followed by rail, and truck. Specifically, Louisiana, and Mississippi have on average higher water-based shipments, reducing their transportation emissions intensity while California, Texas, and Arkansas ship significantly through trucks. A clear alternative is to move away from truck-based shipments, specifically for longer distances travel where rail or multiple-mode transport might be more suitable and infrastructure available. However, previous studies have discussed the limited opportunities for shifting modes to reduce emissions and have called for the more aggressive penetration of zero emissions vehicles.[249] While rewiring for each scenario results in large fluctuations in transport emissions, virtual water undergoes modest reduction of 0.5%.

Overall, we do not obtain significant reduction for virtual water in the network through optimization. The constraint of rice type imposes very stringent requirements on the rewiring scheme. As a theoretical exercise, we remove constraint for type of rice and assume all types can be grown in production states. We find that we can reduce virtual water up to 5% from baseline scenario. The modest results despite relaxing the binding constraint are not surprising as Davis et al. reported similar low savings for water when redistributing cropping patterns in the U.S.[198] However, since the reductions achieved are relatively small, we also examine the robustness of results under uncertainty. For robust optimization, we introduce the parameter Γ that controls the level of uncertainty a decision-maker is willing to tolerate - higher values ensure that the optimal solution to the robust model will remain feasible given increasingly worse-case realizations of the data. Conversely, values of $\Gamma=0$ would imply that the decision-maker is absolutely certain of the data, and the problem reduces to the deterministic optimization discussed here. We use $\Gamma= (1,10,1)$ as being reasonably confident in data and $\Gamma= (4,40,4)$ as less confident and therefore more

uncertain. There are 14 state-rice type combinations and approximately 10 times as many links between them for trade. Therefore, $\Gamma = (1,10,1)$ refers to changing one state-rice type combination for virtual water, 10 links for associated transportation uncertainty, and one state-rice type for irrigation. These number of parameters are changed to the top of their allowed ranges (upper bound on the confidence interval). Depending on the objective (i.e. minimizing virtual water), the robust optimization selects the solution in a way that considers all possible worst-case scenarios by changing Γ number of parameters and still obtain feasible solution. Appendix C represent robust solutions for both case of uncertainty. In examining both deterministic and robust results, we note that it is much easier to achieve large reductions in greenhouse gas emissions and multiple rewiring combinations as opposed to reducing water. While we consider water applied on farms and not consumptive requirements, the values still represent an indication of theoretical requirements. Rice fields need to be flooded up to a certain level which drives up water use as well as energy requirements.[239] Although there is a limit to implementing on farm water conservation strategies based on crop water requirements, large scale energy decisions are easier to implement including investing in renewable fuel pumps.

As majority of rice is irrigated through gravity systems, we also look at the states employing water management and conservation practices such as using tail water pipes, dikes, precision-leveling, alternative row irrigation along with gravity irrigation. California followed by Texas, and Missouri have the most acreage under some kind of water management system.[145] Mississippi, Louisiana, and Arkansas have less acreage, indicating scope of improvement. Given that the optimization model attempts to reduce production in California and Texas signals that these conventional practices may not be sufficient. At the same time, improving water efficiency of rice irrigation in Arkansas and Louisiana indicates more water savings can be obtained while

intensifying production in these areas. Another area of promise in rice irrigation research is exploring the potential of alternative wet and dry technique for rice irrigation where the fields are only periodically flooded and then flushed out to dry out in-between. Apart from saving water, the technique has the added benefit of also reducing atmospheric methane emissions associated with methanogenesis in rice fields. The disadvantage with the method is reported loss of yields in rice due to low water stress tolerance[250], and therefore such methods require more analysis and field trials before widespread adaptation.

Studies have shown that improving efficiencies alone may not be able to meet the growing food demand, with calls for more emphasis on demand side behavioral changes[251] and focusing on improving yields[250]. In this case, we explore another alternative for reducing water and energy impacts: namely targeting maximum exploitable yields to achieve resource savings. Here, we make an important assumption that exploitable yield are not water limited and therefore no additional water is applied to increase the yield. We justify this assumption as for all states and rice types, at least 70-75% of exploitable yields are already achieved. We assume the small yield gap can be closed with the help of proper nutrient and agriculture management practices.[252] Figure 12 compares baseline virtual water use for exports with yield intensification values. Our estimates suggests that by reaching the maximum exploitable yields, production and trade increase by 7%. Resulting network-level water savings are 15% with corresponding similar percentage reductions in irrigation GHG emissions. The reduction for virtual water are significantly larger than all the optimization scenarios considered here. Although, through rewiring we can achieve a larger reduction in embodied irrigation emissions, we also increase transport emissions. Since there is no rewiring for yield intensification, transport emissions remain the same.

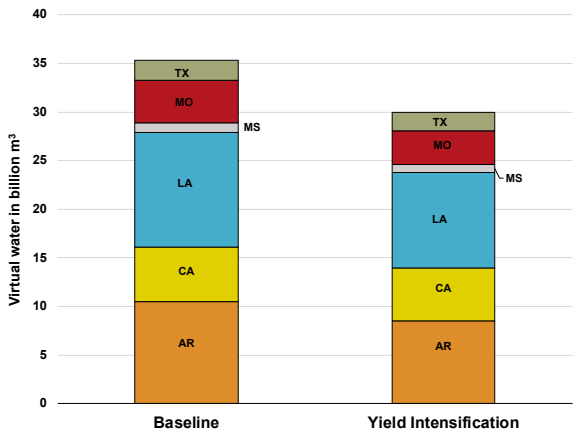


Figure 12. Comparison of virtual water savings from achieving maximum exploitable yields for all rice types.

Sustainable intensification recommends increasing yields while minimizing environmental impacts. In this study, we explore the potential of selective sustainable intensification where we recommend intensifying systems that are efficient at producing a crop with respect to water and energy and shifting away production from places using more resources. This strategy recommends growing more with current resources by penalizing those states that are using excessive resources. We compare our results to a yield intensification strategy where we intensify all systems, ceteris paribus. For producing rice in the United States, this seems to be a better strategy as we gain large network level savings for virtual water and irrigation emissions and without requiring re-wiring. However, the utility of wide-spread intensification is case specific as other studies have reported large increase in water and fertilizer use.[253] The optimization scenarios we explore for singular objectives (i.e. optimizing for virtual water, irrigation, and transport emissions) represent extreme cases. While network level savings are modest in most cases, the rewiring results in drastic changes at state level. This also poses a question on the usefulness of assessing national savings for virtual resource studies as water use and emissions resulting from inefficient diesel gasoline pumps have larger impact on the local environment.

While there are no national estimates published on the proportion of rice irrigated through surface water or ground water, based on total acreage under each source, we can estimate that majority of rice in Arkansas, Mississippi, Texas, Louisiana, Missouri is irrigated through ground water and California's from surface water, although there may be exceptions at county or farm level. If irrigation costs are considered, states such as Missouri that use groundwater with lower water tables, would benefit over states such as California that purchase irrigation water at a significant price.[239] Although there is an increased attention to issues associated with overdrawing ground water, penalizing a state for using more groundwater may not work as the hydrology between surface and groundwater is complex and connected, and overuse of one may pose deleterious effect on another. A significant improvement going forward would be to integrate basin level water scarcity risks to contextualize water savings, keeping in mind data assimilation issues for different spatial scales. It is important to note that the values reported here are for water applied for irrigation, and not consumptive water use, as such, a portion of the water applied could be collected back. In such cases, resulting water savings would be more.

Our study focuses on GHG emissions from transport and on-farm irrigation of rice. Other major sources of emissions include GHG emissions from submerged rice fields due to methanogenesis[164] and post-harvest crop burning to clear rice stubble.[254] Specifically, GHG emissions from methanogenesis are an order of magnitude greater than irrigation associated emissions. However, they depend on many factors including soil characteristics, climate, on-farm water management such as aeration, continuous flooding practices.[164] These emissions can be managed with better on-farm practices despite crop redistribution and therefore not considered in the study. Our strategies presented here results in net land savings, but production reductions also mean loss of livelihood. A complementary strategy would be to encourage farmers to plant

alternative suitable crops, which may result in less savings. Another drawback to reduction would be loss of biodiversity as submerged rice fields provide a habitat for diverse living organisms. Finally, we recognize that national trade cannot be realistically optimized to save embodied resources, however, many farmers make production decisions keeping water supply in mind, specifically in times of drought or in water scarce areas.[255] Our results indicate that for water intensive crops such as rice that are produced in very limited areas, regional crop replacement shifting may reduce overall production as the limited areas may not have capacity to grow sufficient quantity. This would affect the entire downstream supply chain including loss in national revenue. Therefore, there is an urgent need to start thinking about sustainable policies to protect the U.S. agriculture and reduce associated environmental impacts.

5.0 Quantifying virtual phosphorus flows in interstate food trade

5.1 Introduction

Modern agriculture relies heavily on nitrogen, phosphorus, and potassium-based fertilizers for enhancing agricultural yields to feed the growing population. Management of inorganic phosphorus fertilizer presents a complex issue as it is a non-renewable, geographically constrained and yet overused resource.[256] Phosphorus fertilizers are mined from rock phosphate sources concentrated in a handful of countries such as Morocco, the United States (U.S.), China, Jordan, Russia, and Australia.[257] While the time scale of phosphate reserve depletion is debatable[258], a lack of viable competitive substitutes in the near-term and importance of phosphorus (P) fertilizer for food production requires that we manage phosphate resources judiciously. U.S. is the largest manufacturer and exporter of inorganic P fertilizers, but consumes a significant amount for supporting food production and exports. Therefore, it may risk a supply- demand imbalance in the near future with continuation of current use patterns.[223] Additionally, flow of phosphorus in food systems is highly inefficient as a significant fraction of applied P is lost through soil erosion, agricultural runoff, and retained in the soil due to limited mobility, resulting in only ~8% of the applied P ending up in food in the U.S.[223] Excess P entering the water systems through agricultural runoff results in nutrient overload and eutrophication and exacerbates the situation further by reacting with nitrogen and fixing it in surface water[259], subsequently causing detrimental impacts on aquatic life and water quality[260-263].

Eutrophication of waterbodies is not a new issues for the US and there have been formal mechanisms in place (e.g., The Clean Water Act, The Great Lakes Water quality agreement) since the 1970s with dedicated strategies for Phosphorus reduction.[264] More recently, the focus has been on reducing non-point source pollution occurring through agriculture runoff [265]with an ongoing effort across the nation to help farmers reduce their impact on water bodies through best management practices and providing technical solutions.[266, 267] For instance, the Florida Everglades restoration efforts have managed to reduce significant amount of phosphorus loading than the mandated amount through best management practices implemented by the agriculture community.[268, 269] Currently, 47% of U.S. coastal water systems have hypoxia (low levels of dissolved oxygen), with eutrophication from nutrient overload being one of the casues.[270] The solutions to combat eutrophication at the farm level require implementing comprehensive nutrient management plans and appropriate best management practices.

In the nutrient management discourse, food consumers are often left out of the consideration as the cost associated with on-farm nutrient management strategies are supported through policies and not directly reflected in the price of food. There is a disconnect between places of food production and consumption resulting in distancing the consumer from environmental impacts of agriculture. For instance, nutrients from animal waste are not recycled back to the farm because of increasing decoupling of feedlots and feed producion.[229] A study by Metson et al.[271] assessed that 37% of P obtained through recycling manure, human, and food waste was sufficient to meet the entire U.S. corn fertilizer demand. The study did recommend accounting for issues on human[272] and environment health[273] before implementing such solutions.[271] Theoretically, the comparative advantage of endowments (natural resources, technology, labor, etc.) form the basis of trade between nations with a country better at producing

certain goods will export it and import the rest.[274] This theory has been suggested to consider the sustainability and efficiency of resource use in agriculture trade through concept of "virtual" or "embodied" trade.[275] Virtual/Embodied trade of resources (land, water, nutrients) and impacts (GHG emissions, water pollution) refers to not physical trade, but impacts/and resources used to produce the food/agriculture items. For example, Allan first proposed the concept of "virtual water" where water poor countries can save water by importing water intensive products.[85] The role of nutrients, particularly phosphorus and nitrogen in food trade has been analyzed by numerous studies, [89, 224, 276-278] with each defining the system boundary and nutrient use terms differently. Most commonly studies use the terminology "virtual" or "embodied" resources to indicate resources that are involved in production but not physically contained in the final traded product while "embedded" resources are resources contained in the shipped product.[229] The studies associated with embodied trade focus on the supply side resource use efficiencies[277, 279] and eutrophication issues while embedded resource studies focus on end of life recycling and waste management issues.[229, 280] Schipanski and Bennett assessed embodied P in global food and feed trade and noted trade to be efficient in terms of phosphorous use. However, the study found that high efficiencies result from soil P mining and not due to effective fertilizer use.[279] As such, a comprehensive systems approach for understanding P use associated with food production and trade can aid in identifying and managing inefficiencies and losses.

From a U.S. perspective, Suh and Yee[224] calculated national life cycle P use efficiency of the food system and emphasized improving crop and livestock production for effective P management. MacDonald et al.[223] further improved on the assessment by including international trade and estimated that despite substantial food exports out of the U.S., 70% of

national P use was attributed to domestic consumption. We expand on previous analysis by focusing on domestic trade across the U.S. and evaluate spatial patterns associated with virtual P trade across the U.S. To the best of our knowledge, this is the first study to quantify state level virtual phosphorus flows. The environmental impacts of resource use can be highly variable and, depending on the agriculture production practices of trading partners can result in net resource savings or losses.[175],[86] However, little attention has been paid to assess whether embodied trade results in net P savings, particularly at the US level. Therefore, we compare phosphorus use for specific crops across the domestic trading partners and quantify resulting savings or losses through P trade. We also discuss the implication of our findings in terms of phosphorus management practices and identify current gaps in our understanding of phosphorus management and fertilizer use across the US.

5.2 Methods

We create a network of physical food trade across the U.S. and quantify flow of virtual phosphorus embodied within the trade. The data and methods are explained in the following section with schematic of methodology provided in figure 13.

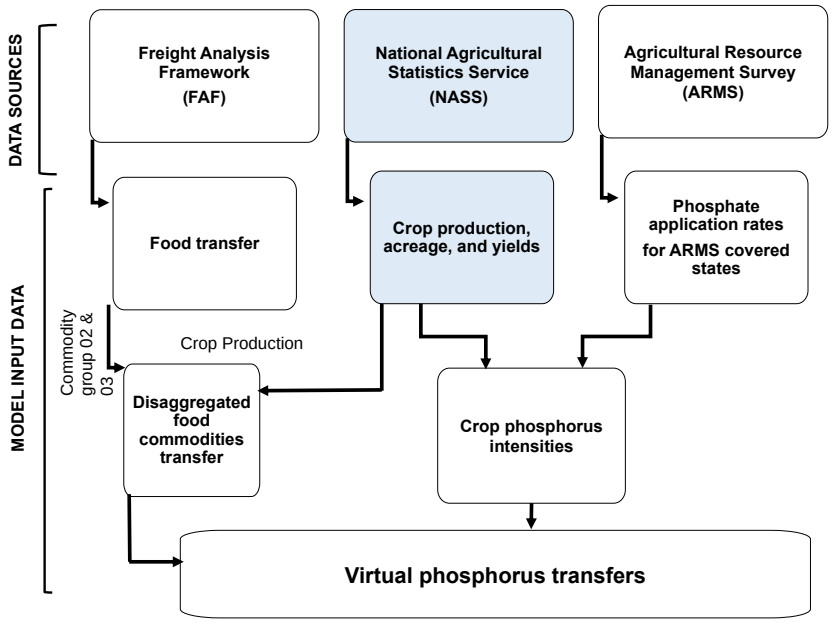


Figure 13. A schematic of data sources used for quantifying embodied phosphorus transfers

Domestic food trade. Unlike international trade statistics provided by the COMTRADE database[281], no such record for U.S. domestic trade exists. Therefore, we use freight shipment data hosted by the freight analysis framework (FAF)[181] as a substitute for domestic trade. FAF is a shipment survey published by Bureau of Transportation every five years and reports data on Origin (O), Destination (D) of the shipments, type of commodity, monetary value, weight of commodity, and modes of transport. We use the O-D shipment metrics provided at the states (51×51) level. The latest dataset is published for 2012 and will be used as base year for this study. The FAF datasets are constructed for broad commodity groups, aggregated based on Standard Transportation Goods and Practices (SCTG) codes. The food trade data include SCTGS code 01 (Animal and fish, live), SCTG02 (Cereal grains and seed), SCTG 03 (Agricultural products), SCTG 04 (Animal feed, eggs, honey and products of other origin), SCTG 05 (Meat, poultry, fish,

Seafood and their preparations), SCTG 06 (milled grains, products, preparations, and bakery products), SCTG 07 (other prepared food stuff, fats, and oils). We perform the analysis for 47 crops in total within the two trade commodity groups (SCTG 02 & 03). The groups, referred to as cereal grains, and fruits, legumes, nuts, and vegetables together account for approximately 47% of mass loss through food waste[142], providing a motivation to examine P food system application and potential efficiency losses. A complete list of commodities considered is provided in the Appendix D Table 31.

We apply a production based [28, 48] disaggregation method to link crop level phosphorus application data to commodity group-level trade data. For this, we make an important assumption that composition of food transfer is similar to composition of agriculture production in a given state.[48] For example, if one fourth of grain production in Alabama consists of wheat, than 25% of grain shipped out of Alabama is wheat. The production data used for disaggregation are obtained from National Agriculture Statistics Services (NASS).[141] This study uses state level production data for 2012 or closest year available from the agriculture census database. Crop yields are also obtained from the NASS database.

Phosphorus fertilizer requirements for interstate U.S. trade. Next, we estimate the P fertilizer intensity (amount of P applied per ton of crop) for each crop and each state considered in the study. There are two primary datasets detailing fertilizer requirements for the U.S. As part of Agricultural Resource Management Survey (ARMS) and agricultural chemical usage database, US Department of Agriculture (USDA) publishes data on fertilizer use for select crops including fruits, vegetables, and nuts for major production states (states covering at least 80% of commodity acreage are included in the survey).[282] We limit our fertilizer intensity calculations to these crops and states. Another dataset, that we do not consider, is derived by combining fertilizer sales

data from AAPFCO (Association of American Plant Food Control Officials, 2010). United States Geological Survey (USGS) publishes county level estimates for nitrogen and phosphorus fertilizer applications for years 1986 though year 2006 derived from AAPFCO.[283] We refrain from using this source as fertilizer sales may differ from actual fertilizer application, specifically within the same county or counties bordering between states. Additionally, fertilizers may have been purchased in bulk and not all of it applied within the same year, skewing application rates. Additionally, the USGS does not differentiate between various crops. An ongoing work by International Plant Nutrition Institute (IPNI) in developing a spatially explicit nutrient tool employs USGS data for estimating trends over the years.[284] As we limit the analysis to 2012 with respect to the latest available trade data, with an emphasis on states as well as crops, we use the ARMS dataset.[285]

Virtual Phosphorus Transfers. We combine trade data with P intensity (lb of P applied/ ton of crop produced) to quantify interstate food transfers and associated virtual phosphorus flows. Flow of virtual phosphorus ($P_{virtual}$) refers to the quantity of phosphorus-based fertilizer applied (in tons of elemental P) in exporting states for producing food products for trade.

$$P_{virtual,i\rightarrow j,k} = T_{i\rightarrow j,k} \times {}^{1}/_{y_{i,k}} \times P_{applied,i,k} \qquad \textbf{(14)}$$

$P_{virtual,i\rightarrow j,k}$ represents virtual phosphorus for crop k embodied in shipments from state *i* to *j*.

$T_{i\rightarrow j,k}$ represents food trade of *k* from state *i* to *j* (tons)

$y_{i,k}$ is yield of crop *k* in state *i* (ton/acre)

$P_{applied,i,k}$ represents phosphorus fertilizer applied to *k* in origin state *i* (lb P/acre)

Virtual P savings through trade. To estimate virtual P savings, we compare virtual phosphorus values between two trading states *i* and *j*. $P_{j,k}$ represent phosphorus applied for crop *k* in producing state *j*. The equation for virtual P savings is modeled based on Dalin et al.'s calculations on virtual water savings.[125] Here, we only consider trading partners that are both producing the crop to assess the comparative advantage, and therefore we only look at 31 commodities in our assessment.

$$S_{P,i\rightarrow j,k} = T_{i\rightarrow j,k} \times (P_{j,k} - P_{i,k}) \quad \textbf{(15)}$$

$$P_{j,k} > 0,\ P_{i,k} > 0$$

To understand if savings and losses from fertilizer use are actually excessive and wasteful or required due to soil and crop demand, we compare P application rate (lb P applied/ acre land) with agronomic P demand. Agronomic P demand is a complex issue governed by many factors such as soil characteristics, plant physiology, legacy phosphorus, and application of P fertilizers. Due to lack of comprehensive nationwide data, we estimate agronomic P demand with crop nutrient removal from USDA's crop nutrient database.[286] The repository is kept as a reference for calculating the nutrient balance sheets for animal waste management programs. The crop nutrient database estimates the nitrogen, phosphorus, potassium removed by crops during harvest based on user provided crop yields and published national crop nutrient percentages. Based on crop yields from NASS, we estimate P removed in crops for specific states and define a partial nutrient balance (PNB) as a ratio between P in harvested crop to inorganic P fertilizer applied to a crop.

5.3 Results and Discussion

Figure 14 presents network wide food flows and virtual P flows across the U.S. There were 553 cereal grains transfers (SCTG 02) and 1304 transfers of fruits, legumes, and vegetables combined (SCTG 03) between 51 states. In total, 1310 million US tons of food was transferred in 2012 and associated embodied P amounted to 5.18 million US tons. Food and Agriculture Organization estimates that 2 million US tons P was used for agriculture in 2012.[287] The difference in estimates may arise from FAO using national food-balance sheets, while domestic trade being a disaggregated dataset. The domestic trade may include trade of stocks from previous years and re-exports which may drive up the P use estimate for a specific year. Despite the lower number of links, 66% of food transfers were cereal grains transfers (Figure 14). From a virtual P perspective, legumes had higher on average P intensity (amount of P per ton of crop) followed by cereals, vegetables, and fruits. Figure 28 in the appendix provides the distribution of P intensities (lb P/ ton crop) across specific crop items. The range for grains varies between ~3 - 18 lb P/ ton of crop, vegetables ~0.80 - 18 lb P/ton crop, fruits between ~0.75 - 23 lb P/ton crop, and legumes between 9 - 21 lb P/ton of crop. However, care should be taken in comparing phosphorus intensities across crops as P application and intake may vary between perennial crops vs. annual crops.

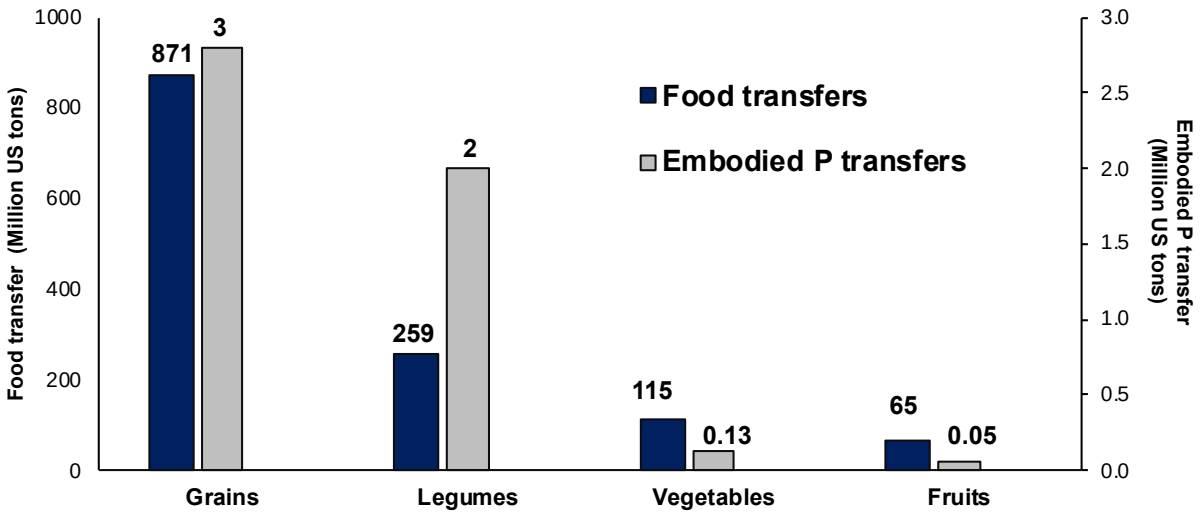


Figure 14. Food and embodied phosphorus flows in US food trade.

Apart from P application intensities, the scale of production is an important factor when considering potential implications for downstream pollution. Figure 15 examines the distribution of virtual P embodied by state. Embodied P is obtained by combining production with crop P application intensities (lb P/ ton crop). Dark shaded states represent states with significant P application and include North Dakota, Minnesota, Iowa, Illinois, and Kansas. The lighter states represent states with low P application for all the crops considered. The size of the pie chart indicates total production in 2012 of fruits, vegetables, grains, and legumes. The fractions of the pie chart represent individual commodities or groups. The legumes category contains soybeans and peanuts, which dominate the production in midwestern and southeastern states. Despite having some of the highest P applications per ton of crop, their scale of production is small compared to fruits and vegetables produced in CA. In fact, the darker colored states coincide with cereals and soybeans and peanut crops that have the lowest fertilizer application across commodities, denoting the importance of considering the scale of production in phosphorus management. Apart from California, significant fruit and vegetable production occurs in handful of states including Florida, Washington, Idaho, Arizona, New Mexico, and Oregon. Some of the larger fruit and vegetable

producing states such as Oregon, Washington, Arizona, Florida have comparatively lower P application for total crop production. This could be attributed to comparatively lower P intensities of crops produced.

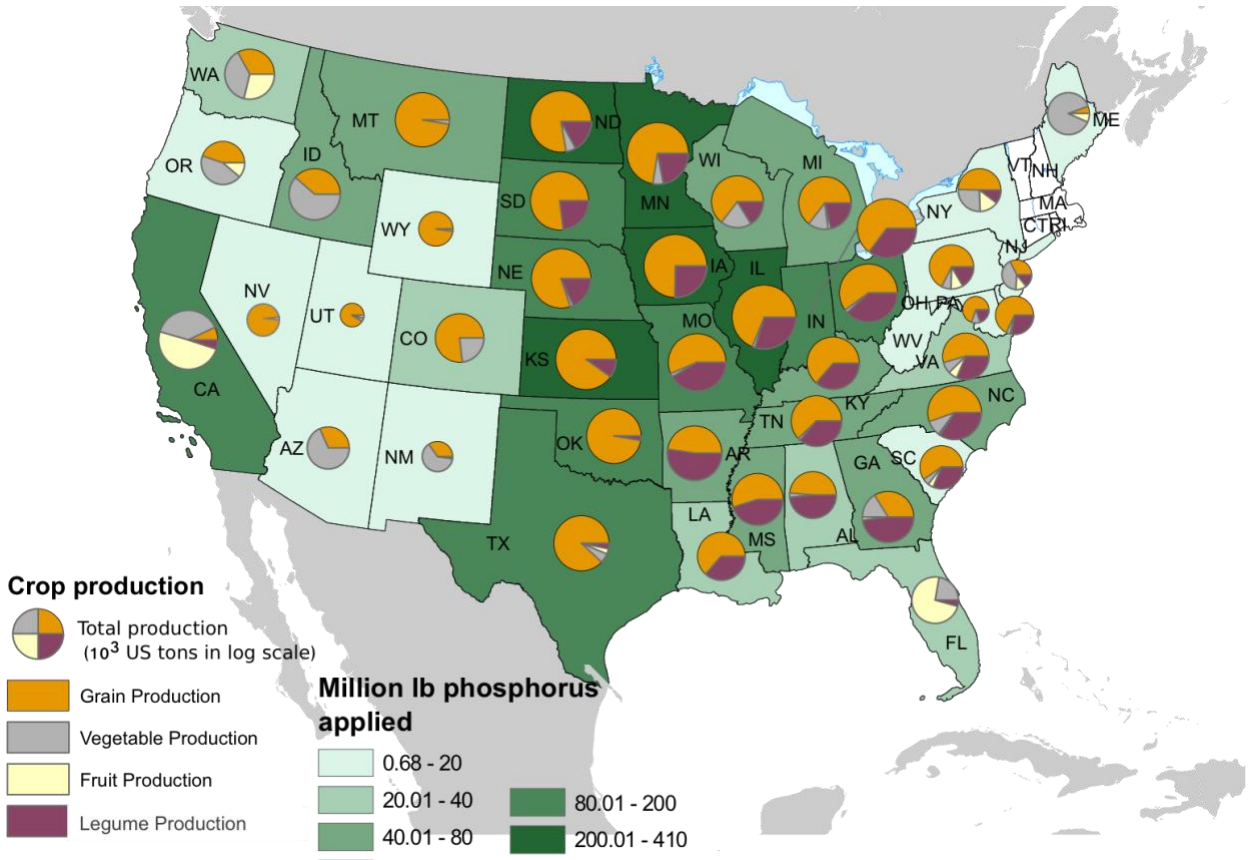


Figure 15. Embodied P (in lb) applied for crop production across the contiguous U.S.

P intensities are a factor of agriculture yields as well as the amount of P applied per unit land. Therefore, variation in agriculture yields and phosphorus application would result in varying levels of total P applied across commodities and states. **Figure** 16 shows whether the current trade patterns benefit from these variations by P- efficient states exporting to states with high P intensities. The positive values indicate savings resulting from trade where states with lower P intensity (P applied/ ton of crop produced) export to states with high P intensity. Here, only states

that produce and trade the crop are considered. Therefore, specialty commodities produced in specific states such as dates predominantly grown in California are not considered. The commodities considered under grains are colored orange and fruits, legumes, and vegetables colored light blue. Here only top 15 commodities with maximum savings/losses are shown. Figure 32 contains rest of the commodities and their calculated savings.

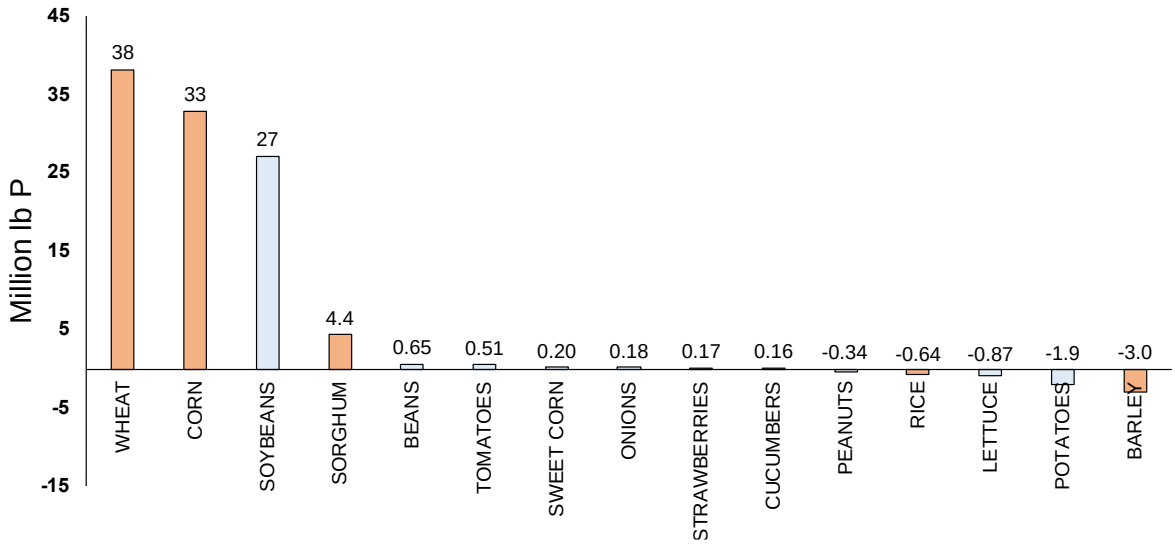


Figure 16. Embodied P Savings through domestic trade of grains, fruits, legumes, and vegetables.

For cereal grains commodity group, except for rice and barley, grains trade result in substantial P savings with net savings of 72 million lb. The negative values (losses) result from states with high P intensity (lb P/ lb crop) exporting to states with comparatively lower values. For rice, the largest losses come from Arkansas's trade to Louisiana, Mississippi, and California. Arkansas is a major rice producing states and has the highest P intensity compared to other producing regions. In case of barley, two significantly large losses arise from Montana and Idaho exporting to Washington. Washington has one of the lowest P intensities, and imports a significant amount from these states. Additionally, Montana has one of the higher intensities and as a major

barley producer, has multiple trading connections, with some resulting in significant losses. Despite overall positive savings for corn and wheat, comparative high P intensities in states such as Iowa, Illinois, Indiana, and Oklahoma result in total P losses through exports. Overall exports from Montana, Oklahoma, Illinois, Iowa, and Indiana result in large losses while Kansas, Wisconsin, Minnesota, South Dakota, and Michigan result in savings through exports.

For the fruits, legumes, and vegetables category, net savings are 26 million lb P. The trade of soybeans result in significant savings while potatoes, lettuce, and peanuts result in large losses. Despite net positive savings, the largest trade losses are also through trade of soybeans. Soybean's sizeable production across many states coupled with higher P application intensities result in large savings and losses. Particularly, exports from Illinois, Tennessee, Missouri, Kentucky result in largest losses. For potatoes, Idaho and North Dakota's P intensities are some of the highest across states, resulting in large losses for some of the trade shipments. Large peanut shipments from Georgia, Alabama, and Texas result in significant losses due to higher than average P application intensities. Only Arizona and California produce and export lettuce with Arizona's P intensity being more than double of California's. Therefore, shipments from Arizona to California result in loss. On the savings front, apart from soybeans, trade of fruits and vegetables such as beans, tomatoes, sweet corn, and strawberries result in P- efficient trade. The savings are the result of states with low P intensities such as California, Florida, Oregon, Wisconsin trading with high P intensity states. Total largest savings for the commodity group are through exports from Louisiana, Michigan, Indiana, Wisconsin, and Ohio. Total largest negative losses are through exports from Illinois, Tennessee, Missouri, Kentucky, North Dakota. A list of all net exports and imports out of each state for each commodity group is given in Table 32.

From the aforementioned discussion, Illinois, Missouri, Kentucky, Arkansas appear consistently high in the list of net loss through exports rankings. While exports from Kansas, Louisiana, Wisconsin, Michigan, Minnesota appear to result in maximum embodied P savings. However, it is difficult to assess whether the phosphorus intensities for a given crop in a given state are high/low due to inefficient on-farm management practices or required due to the soil/crop type. Therefore, we compare crop P demand based on P removed in harvested crops with P applied. We find that for grains, average PNB across states ranges from 0.5 (Illinois) to 1.57 (Wisconsin). For fruits, nuts, and vegetables, the values range from 0.14 (Arizona) to 0.88 (Nebraska). States with negative savings have average PNBs ranging from 0.5 to 0.8 (for grains) and 0.3 to 0.6 for fruits, nuts and vegetables (Table 3). From commodity perspective, we find that for grains, the average PNB across commodities ranges from 0.7 (wheat) to 1.08 (rice), with greater than 1 efficiency for corn and rice. For fruits, vegetables, and nuts, the range is from 0.02 (plums) to1.08 (garlic). Figure 32-34 include PNBs for all the commodities considered. Due to the immobile nature of P in the soil, P uptake values are generally reported in the range of 10 - 15%. However, literature using the PNB method have observed high levels of P removal (>50%) compared to application, primarily due to varying levels of P bio-availability and reaction chemistry in soil.[288] In this mass-balance, we do not consider several other inputs including manure application, bio-solids application, and legacy (accumulated) phosphorus already in the soil. Consideration of the additional P sources may increase amount of P input in several places compared to uptake and therefore decrease the PNB values, specifically for field crops such as corn, soybeans, wheat, barley, sorghum, and peanuts that may use manure.[289] Previous work has reported correlation between global fertilizer application rates and market value of crops, identifying “austere” vs. “affluent” crops.[290] The high fertilization rates across high valued

crops such as fruits and vegetables may indicate that in some cases market value rather than actual P need may drive fertilizer application rates.

However, nutrient balance alone is not a sufficient to assess soil P management practices. Not all applied phosphorus is readily available for plant uptake as applied P may react with acidic soils or minerals such as iron, aluminum, or calcium. There is a critical level of readily available P beyond which additional fertilizer is not required to maintain/increase the crop yield. This is measured by analytical soil tests in the lab and supplemental P application rates are recommended based on the results. Based on the soil and crop type, 1) the application rates can be recommended to build up more phosphorus in the soil and apply higher P than removed by crop (PNB<1), 2) maintain current level by only applying to replace fraction removed by crop (PNB≈1), or 3) apply less P fertilizer than removed by crop to use up the already available P (PNB>1).[288] The International Plant Nutrition Institute (IPNI) compiles and publishes national critical levels for states based on collected soil tests samples from private and public labs across the U.S.[291] The samples that tested below critical levels for major crops for each state are presented in Table 3. The comparison of PNB values with percentage samples below critical levels provides an indication of whether fertilizer applied is used for building up soil levels or for maintenance to supplement crop removal. For instance, states with PNBs less than one and majority of soil test levels significantly below critical level indicates that excess fertilizer applied is necessary. Similarly, states with PNB≥ 1 and low percentage of samples below critical indicate that soil P drawdown is recommended and followed. This is the case for Tennessee, North Dakota, Iowa, Michigan, Wisconsin. On the other hand, Illinois's PNB indicates that more P is applied compared to removed in the harvest, but soil tests indicate that majority of samples meet the critical level. Therefore, Illinois farms may be applying more fertilizer than required. However, these are state

level data and cannot be compared for specific crops (as seen by differing values for Michigan for grains and fruits, legumes, and vegetables). Additionally, low sample size received from some states, representativeness of soil management practices, more responses from livestock operations may inflate soil P level and cannot be used to gauge soil fertility and P management practices at farm or crop level. Therefore, more comprehensive data are needed on soil sample tests before any conclusions can be derived on farm P management.

Table 3. Comparison of top 10 net savings and losses resulting from exports, partial nutrient balance, and percentage soil tests below critical levels.

Grains					**Fruits, legumes, and vegetables**				
No	Origin State	Embodied P savings (1000 lbs)	PNB	% below critical level	No	Origin State	Embodied P Savings (1000 lbs)	PNB	% below critical level
1	MT	-16	0.65	65	1	IL	-11	0.33	39
2	OK	-9	0.60	74	2	TN	-8	0.26	65
3	IL	-8	0.51	39	3	MO	-3	0.59	54
4	IA	-3	1.05	40	4	KY	-2	0.64	54
5	IN	-2	0.74	31	5	ND	-2	0.54	83
6	MI	5	1.42	36	6	OH	3	0.38	48
7	SD	6	0.84	65	7	WI	3	0.45	48
8	MN	7	0.80	47	8	IN	4	0.76	31
9	WI	11	1.58	48	9	MI	5	0.32	36
10	KS	37	0.91	47	10	LA	15	0.79	84

5.4 Conclusion

With our study, we analyzed trade of approximately 50 commodities across the U.S. and quantify that overall trade results in phosphorus savings with states using less phosphorus fertilizer for agriculture exporting to states applying more fertilizer to produce the same crop. We also assess whether these savings result from efficient P use or due to soil mining. We find that this is a challenging question to answer with currently available data. Through a partial nutrient balance method and soil test samples summary data, we find that some states such as Michigan and Wisconsin indeed seem to be efficient in using phosphorus fertilizer for agriculture. While Illinois seems to be applying more fertilizer than necessary. However, comprehensive data collection efforts are needed to understand how farm level practices truly affect embodied P trade patterns. IPNI recommends using 4Rs of nutrient for best management practices: right nutrient, at the right time and right rate and at the right place. This requires periodic sampling of soil to make accurate assessment. Additionally, the majority of eutrophication plans put in place require farmers to employ some kind of conservation and nutrient management practices to reduce nutrient loading through runoff. Therefore, it is critical to understand how fertilizer is applied and managed at the farm scale and its implication at the state and watershed level. With the adaption of precision agriculture, more soil sampling is taking place to help make accurate fertilizer decisions. However, no comprehensive database exists except by efforts from IPNI to collect soil sample data for state level decisions. This will not only help manage for water quality issues but also help implement sustainable management practices for phosphorus fertilizer use.

6.0 Conclusions and Future Work

The idea of using an integrated framework for effective policy decisions is not new.[97] However, the recent awareness and promotion of the food-energy-water nexus has reignited the interest of academia, industry, and governments across the world to focus on "nexus issues". The majority of this research centers on irrigation impacts of food production and trade with one case study assessing inorganic phosphorus fertilizer use for food trade.

In chapter 2, we present a network model of interstate food trade and report comprehensive estimates of embodied irrigation energy and greenhouse gas (GHG) emissions in virtual water trade for the United States (U.S.). We consider trade of 29 food commodities including 14 grains and livestock products between 51 states. A total of 643 million tons of food with a corresponding 322 billion m^3 of virtual water, 584 billion MJ of embodied irrigation energy, and 42 billion kg CO_2-equivalent GHG emissions were traded across the U.S. in 2012. We show that the estimated embodied GHG emissions in irrigation water are similar to CO_2 emissions from the U.S. cement industry, highlighting the importance of reducing environmental impacts of irrigation (RQ 1.) We also differentiate between the trade of animal-based commodities vs. grains and show that while animal-based commodities represented 12% of food trade, they accounted for 38% of the energy and GHG emissions irrigation. From a network perspective, we showed that the food trade network is a robust, well-connected network with the majority of states participating in food trade (RQ 2).

In chapter 3, we further explore the network structure of food trade by applying concepts from ecological network analysis. To this end, we utilize the pointwise mutual information (PMI) measure to provide an indication of interdependencies by estimating the 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. We further explore how these dependencies arise due to given trade structure and through embodied impacts. We demonstrate this by using Texas as an example, the largest importer in the US grain transfer network. We find that strong dependencies exist not 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, over-reliance poses a water risk 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 water scarcity. However, some of the identified states as alternatives to High Plains states rely on GHG emissions intensive fossil fuels for irrigation, highlighting a potential tradeoff between water risk and GHG emissions (RQ 3).

In Chapter 4, we explore whether these tradeoffs can be avoided by re-structuring the food trade with a case study of rice (RQ 5). Specifically, we optimize the domestic trade of rice with respect to its irrigation and transportation emissions impact. Our study finds that rewiring for virtual water results in modest savings of 2%. On the other hand, optimizing for GHG emissions in irrigation results in 17% savings and optimizing to reduce transport emissions result in 25% network level reduction. Transport emissions are one order of magnitude less than irrigation emissions. Additionally, these savings come at the price of complete local reduction in states such as Mississippi. Other rice producing states undergo a varying degree of changes in production,

partly to offset rice production from California. California's rice production is highly water intensive in the US, but its unique ability to produce specific types of rice at a large scale makes it invaluable for current rice trade (RQ 2).

In chapter 5, we look at another important food-nutrient nexus issue of inorganic phosphorus use across the US food trade. Our results indicate that phosphorus trade results in net 98 million lb savings in terms of states efficient in P use exporting to states requiring more fertilizer to produce the same crop (RQ 4). Particularly, wheat, corn, soybeans account for 94% of P savings. From state exports, we find that exports from Kansas Wisconsin, Michigan, Louisiana result in large net savings while exports from Illinois, Missouri, Montana, Oklahoma result in large net P losses. To estimate whether calculated P application rates are excessive or necessary for specific soil type, we compare the fraction of P removed in harvest to the fraction of P fertilizer applied. We find the metric to be insufficient without the knowledge of P levels in the soil. Therefore, we discuss the need of national repository of soil test levels to enhance our current understanding of on-farm phosphorus use.

Finally, there have been some discussion and contention against whether analyzing one chain of interaction (i.e. food←water←energy) or (food←nutrients) can be considered a FEW nexus study. Specifically, this work looks at the food sector and not across multiple sectors as is usually adopted by top-down input-output approaches. The introductory text demonstrates that the benefit of FEW nexus concept lies in its lack of a set framework and therefore more freedom to interpret local issues. Although growing competition for resources such as water and land between agriculture, municipal use, energy sector, and industry are critical issues where FEW nexus concepts should be applied to, we demonstrate that by addressing a single sector also reveals much complexity between FEW nexus connections.

This dissertation has shown that second order impacts in food supply chain such as embodied energy and emissions of irrigation can play a crucial role in environmental impacts of food production. Additionally, we discuss the growing distance between production and consumption and its effect on nutrient cycling. As such, this work focuses on supply-side measures and analysis. It is estimated that 31% of U.S. food is wasted post-harvest with approximately 10% waste from retail side and 21% from consumer.[292] Therefore, management of food waste provides an excellent opportunity to tackle FEW nexus challenges from a consumer perspective. This will require changing consumer perception towards the need for food aesthetics and "sell-by dates".[293] Another important consumer side intervention will be shifting to more environmentally sustainable and nutritious diets that include more vegetables, fruits, legumes, and whole grains as opposed to red meat, starchy vegetables, refined sugars, and processed grains.[294] A recent report by World Resource Institute summarizes sustainable pathways to produce food for 10 billion people without increasing the environmental footprint of our measures.[295]

This work is based on merging open data from government surveys that are often collected with specific goals unrelated to the study. For instance, through our framework we demonstrate the use for freight shipment surveys (produced for help in transportation planning) for substituting data on domestic food trade. However, we also discuss shortcomings of relying on such government datasets alone, specifically when disjointed datasets prepared by two separate agencies do not match and violate the first principles of mass-balance. Future work should focus on methodically constructing and treating state level commodity shipment data and follow similar procedures recommended for constructing country input-output tables.[296] Additionally, the farm-based surveys provide an incomplete picture of the food production system as not all counties

and farms are surveyed for every year. Therefore, future integration of remote sensing algorithms with satellite datasets as a supplement to government surveys are imperative to form informative analysis.[297] This work has been limited in its temporal scope as the trade data available is for a singular year (2012) and cannot be compared across previous rounds of surveys. However, FAF datasets provide projections of trade up until 2045 which can be used for dynamic system assessment. For such prospective analyses, use of integrated assessment models on agriculture such as GAEZ[298] and GLOBIOM[299] can be combined with narratives provided by the shared socio-economic pathway projections.[300] Finally, we lack an understanding of energy expenditures related to off-farm irrigation. The majority of western states use more surface water over ground water for irrigation purposes. These waters are provided by off-farm water suppliers through long- distance canals and conveyance systems which may drive up the energy expenses.[144] Several organizations including Bureau of Reclamation and the Army Corps of Engineers serve as off-farm irrigation water suppliers. Another potential research direction could be developing a national repository of off-farm energy expenses by individually contacting each irrigation districts and obtaining costs of pumping and delivery.[111] Finally, any sustainability work using government data should seek out active engagement and potential collaboration with respective data collection agencies to communicate drawbacks of current usage and help make future estimates useful for environmental policy analysis.

It is important to note that despite enthusiasm for the integrated management of resources, there is always going to be a tradeoff when limiting the analysis to just three resources. In chapter 4, we show that through optimizing trade, we save water, reduce GHG emissions, and gain land-use savings, but we also eliminate the livelihood of many farmers by slashing production in some states and eliminate habitat for biodiversity that rely on submerged rice fields. Therefore, we note

that FEW nexus approach may not always provide optimal outcomes, and a context specific analysis that prioritizes local stakeholders benefits should be adopted in policymaking with an overarching goal of achieving the sustainable development agenda.

Appendix A Supplementary Information for Chapter 2

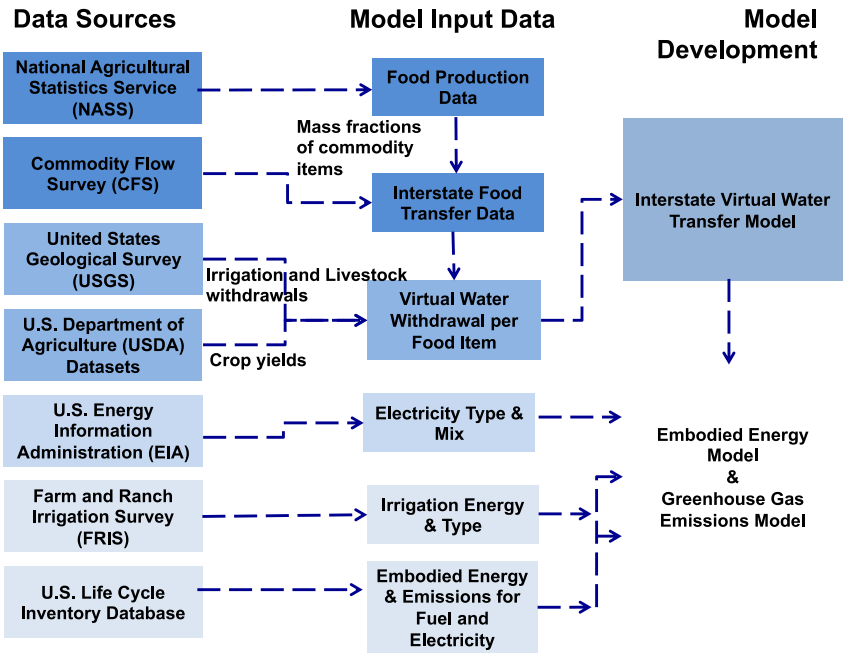


Figure 17. Methodological framework for food-energy-water (FEW).

Table 4. List of U.S. state abbreviations

State	Code	State	Code
Alabama	AL	Montana	MT
Alaska	AK	Nebraska	NE
Arizona	AZ	Nevada	NV
Arkansas	AR	New Hampshire	NH
California	CA	New Jersey	NJ

Table 4 continued

Colorado	CO	New Mexico	NM
Connecticut	CT	New York	NY
Delaware	DE	North Carolina	NC
Florida	FL	North Dakota	ND
Georgia	GA	Ohio	OH
Hawaii	HI	Oklahoma	OK
Idaho	ID	Oregon	OR
Illinois	IL	Pennsylvania	PA
Indiana	IN	Rhode Island	RI
Iowa	IA	South Carolina	SC
Kansas	KS	South Dakota	SD
Kentucky	KY	Tennessee	TN
Louisiana	LA	Texas	TX
Maine	ME	Utah	UT
Maryland	MD	Vermont	VT
Massachusetts	MA	Virginia	VA
Michigan	MI	Washington	WA
Minnesota	MN	West Virginia	WV
Mississippi	MS	Wisconsin	WI
Missouri	MO	Wyoming	WY

Table 5. Food items included in Commodity Flow Survey (CFS-2012)[140] **and considered in the study.**

Code	Commodity name	Considered
01	Live animals and fish	Cattles, hogs, goats, chickens, turkeys, sheep, horses
02	Cereal Grains and seeds	Wheat, rice paddy, barley, maize, rye, oats, sorghum
05	Meat poultry, fish, seafood and their preparations	Cattle, hogs, chickens, turkeys, sheep, goats
06	Milled grain products and preparations and bakery products	Wheat products: wheat or meslin flour, dry pasta, wheat groats and meal, wheat pellets, Rice products: rice husked (brown), Rice semi-milled or whole, Rice flour, Rice groats and meal Barley products: Barley rolled, Barley hulled Maize products: Maize flour, Maize (corn) hulled pearled sliced or kibbled, Maize (corn) groats and meal Rye: Rye flour, Oats: Oats groats and milled, oats rolled or flaked; oats hulled pearled sliced or kibbled.

A.1 Food transfer data

The Commodity Flow Survey (CFS)[140] data are collected through surveys of selected representative establishments and extended to represent interstate and within-state transfers across the United States (U.S.). CFS respondents provided data for a sample of shipments made in a survey quarter. For each establishment, census produces an estimate of that establishment's total value of shipments for the entire survey year. This estimate is adjusted through application of seven types of weight factors to obtain a final shipment value for the entire region and for a specific commodity group. These weight factors account for several effects such as error in respondent's data, lack of information regarding shipment weight, interpolation of sample of quarterly data to represent entire year, interpolation of an establishment's data to represent all such establishments

etc.[140] The data provided are based on reported values from the survey and consequently do not consider internal hubs and stops.

$$T_t = \sum_{i=1}^{n} T_{if} * T_{is} \tag{16}$$

Where T_t represents total tonnage for a given transaction. i indexes shipment in a given domain and n represents total shipment in a given domain. Domain represents shipment of a commodity from one state to another or to a same state. T_{if} represents weight factor and T_{is} shipment weight in given domain i.

We estimate water withdrawal intensities by combining United States Geological Survey(USGS)[144] water withdrawal estimates with published yield data (Eq. 2). USGS provides average application rate, weighted by type of irrigation system for each state in acre-ft per acre. 1 acre-ft/acre equals to 1233 m^3 of water applied per acre. We require yield for cereal grains and animal feed considered in the study to obtain withdrawals per mass of food item. We obtained majority of yield data from Farm and Ranch Irrigation Survey (FRIS).[145] FRIS provides yields for wheat, grain corn, corn silage, sorghum, soybeans, rice, and dry hay/alfalfa. Yields for barley, rye, oats, and canola were obtained from National Agricultural Statics Service.[141] We used yields published for irrigated crops for this analysis.

$$Water\ withdrawal\ intensity\left({m^3}/{ton}\right) = \frac{Average\ application\ rate\ (m^3/acre)}{crop\ yield\ \ (ton/acre)} \quad (17)$$

Product and value fractions for milled grains:

For milled grain products, we allocated water withdrawals for primary crops through product and value fractions listed in Chapagain and Hoekstra.[116] Product fraction *(pf)* represents weight of primary product (W*p*) obtained per ton of primary crop *(Wc)*(Eq.3). Subscript *p* represents primary product and *c* primary crop.

$$pf_p = \frac{W_p}{W_c} \quad \textbf{(18)}$$

When more than two products were obtained per primary crop, water withdrawals were allocated based on value fraction *(vf)* and *(pf)*. Value fraction represents the ratio of market value(v_p) of the product to the market value of all products from the given crop. (Eq.4)

$$vf = \frac{v_p \times pf_p}{\sum v_p \times pf_p} \quad \textbf{(19)}$$

$$Water\ withdrawal\ intensity_p = \frac{Water\ withdrawal_c \times vf_p}{pf_p} \quad \textbf{(20)}$$

Table 6. Product and value fractions for milled grains.[69]

Product	Product fraction (pf)	Value fraction (vf)
Wheat flour	0.79	0.8
Dry Pasta	1	1
Wheat groats and meal	1	1
Wheat pellets	0.18	0.2
Rice husked (brown)	0.77	1
Rice semi-milled or wholly milled whether or not polished	0.9	1
Rice flour	0.95	1
Rice groats and meal	0.75	1
Barley rolled or flaked grains	0.72	1
Barley hulled, pearled, sliced or kibbled	0.72	1
Corn flour	0.82	0.84
Maize groats and meal	0.11	0.1
Maize hulled, pearled, sliced or kibbled	0.93	1
Rye flour	0.8	1
Oat groats and meal	0.2	0.28
Oats rolled or flaked grains	0.53	0.72
Oats hulled pearled sliced or kibbled.	0.73	1
Soybean flour and meals	0.85	1

In order to estimate the water withdrawal intensity for animal based commodities, we followed the methodology detailed in Mubako[146] explained as follows. Water withdrawals for animals consist of two main contributions-water withdrawals for irrigating animal feed and water withdrawals for raising the animal during their lifetime.

Animal feed requirements:

Water withdrawals for feed were obtained by following work of Mubako[146] for estimating virtual water content of animal feed in the U.S. We assume that water and animal feed

required for a given animal is produced within the origin state. Animal feed requirements are dependent on livestock production system (grazing, industrial, and mixed) and type of animal. Feed withdrawals are normalized by weight of animal *(W_a)* at a time of slaughter and estimated for an animal's entire lifetime (Eq. 6).[146] Here, *a* represents animal type, *c* represents feed crop type and $feed_c^a$ represents quantity of feed crop *c* consumed by animal *a*.

$$Withdrawal_{feed(a)} = \frac{\int_{birth}^{slaughter} (\sum_{c=1}^{n_c} withdrawal_c \times feed_c^a) dt}{W_a} \tag{21}$$

Mubako compiled feed quantity data for industrial system from Statistics Canada and for grazing from Chapagain and Hoekstra.[81] Values for mixed system are assumed to be average of grazing and industrial system. Table S4 and S5 list livestock production systems and feed requirements for each animal obtained from Mubako's study. Animal feed mixture consists of grains such as wheat, oats, barley, corn grain and the non-grain portion consists of hay, pasture, and other roughages. Water withdrawals for feed were estimated in a similar manner as described for cereal grains. For pasture and dried peas, we used global blue water footprint estimates.[69] Blue water footprint refers to the quantity of surface and ground water used for supplementing crop water requirements.[88] Here, blue water footprints represent theoretical irrigation water requirements. As actual water withdrawn includes conveyance losses; we applied national water withdrawal efficiency ratio (61%) from AQUASTAT database[301] to better represent water withdrawal. Water withdrawal efficiency is a ratio of theoretical irrigation water requirement and the actual amount of water withdrawn. We do not include roughages category given in the original data, as no associated water withdrawal data were available. However, roughages are mainly rain-

fed crops, making their irrigation withdrawal estimates low.[135] Table S7-8 provides details on water withdrawal intensities for cereal grains and non-grain feedstocks considered for animal feed.

Table 7. Livestock production system.

Animals	Grazing	Mixed	Industrial
Beef Cattle		X	
Swine			X
Broilers			X
Turkey			X
Sheep	X		
Goat	X	X	
Horses		X	
Adopted from Mubako.**[146]**			

Table 8. Feed quantity (tons/year).

Animal	Beef Cattle		Swine	Broiler Chicken	Turkey	Sheep	Goats	Horses	
	GRA	IND	IND	IND	IND	GRA	GRA	GRA	IND
Wheat	3.8E-03	9.5E-03	3.5E-02	5.5E-03	1.6E-02	2.5E-04	1.0E-03	2.0E-04	5.0E-04
Oats	5.1E-02	1.3E-01	1.9E-02	0	0	1.3E-03	3.3E-03	3.9E-02	1.0E-01
Barley	7.9E-02	2.0E-01	2.0E-01	0	0	6.5E-03	3.0E-04	1.6E-02	3.9E-02
Other small grains	2.4E-03	6.0E-03	2.0E-03	0	0	2.5E-04	1.5E-03	2.4E-03	6.0E-03
Grain corn	2.1E-02	5.0E-02	1.2E-01	5.0E-03	1.4E-02	1.3E-03	5.0E-04	5.0E-03	1.3E-02
Dry peas	2.6E-03	6.5E-03	9.0E-03	0	0.0E+00	2.5E-04	3.0E-04	4.0E-04	1.0E-03
Soybean meal	5.0E-03	1.3E-02	2.9E-02	1.7E-03	4.7E-03	5.0E-04	6.8E-03	5.0E-03	1.3E-02
Canola	4.4E-03	1.1E-02	2.5E-02	1.0E-03	2.8E-03	2.5E-04	3.0E-04	6.0E-04	1.5E-03
Pasture	1.1E+00	1.0E+00	0	0	0	9.0E-02	0	9.1E-01	7.6E-01

Livestock withdrawals represent water required for upkeep of animals and other livestock related farm activities. USGS publishes state level estimates of water withdrawals. We used apportioning fractions provided by Mubako[146] to allocate water withdrawals to different livestock categories. The apportioning factors were calculated by using statewide animal production data from U.S. Department of Agriculture(USDA) and water footprints from literature.[146] In the absence of data on statewide production and withdrawals of various meat products, we assumed that meat withdrawals are similar to water withdrawals for livestock, thus resulting in conservative estimates.[48] This study does not consider laying hens and milk cows but data is included for summation purposes.

Table 9. Livestock water withdrawals for 2010 in million m^3/animal/year.

State	Total	Milk cows	Beef cattle	Swine	Broilers	Laying hens	Turkey	Sheep	Goats	Horses
AL	36.61	23.97	2.29	1.14	5.98	1.56	0.00	0.05	0.23	1.40
AZ	37.31	11.97	23.09	0.50	0.00	0.49	0.00	0.36	0.09	0.82
AR	53.89	37.14	3.00	1.88	6.98	2.32	1.08	0.05	0.15	1.29
CA	259.76	47.49	204.50	0.62	1.02	2.25	0.49	1.22	0.25	1.91
CO	50.98	31.87	13.26	3.34	0.00	0.39	0.08	0.79	0.09	1.17
CT	1.40	0.17	1.04	0.01	0.00	0.11	0.00	0.01	0.00	0.05
DE	1.81	0.16	0.64	0.03	0.88	0.05	0.00	0.00	0.01	0.03
FL	29.43	16.41	10.61	0.06	0.25	0.99	0.00	0.02	0.09	1.00
GA	40.48	17.49	11.22	1.38	6.56	2.59	0.00	0.03	0.20	1.02
ID	65.63	17.41	47.02	0.10	0.00	0.08	0.00	0.37	0.03	0.62
IL	49.88	16.37	12.37	19.33	0.00	0.62	0.07	0.12	0.07	0.93
IN	54.16	10.68	21.46	17.18	0.15	2.98	0.51	0.12	0.10	0.99
IA	187.91	58.13	28.52	92.57	0.05	6.77	0.35	0.51	0.12	0.90

Table 9 continued

KS	157.51	125.22	18.97	11.20	0.00	0.29	0.06	0.25	0.13	1.38
KY	60.52	40.15	13.54	1.89	1.49	0.65	0.00	0.10	0.24	2.45
LA	11.09	7.68	2.20	0.03	0.56	0.15	0.00	0.01	0.03	0.44
ME	3.16	0.50	2.48	0.01	0.00	0.06	0.00	0.02	0.01	0.09
MD	11.40	1.85	6.83	0.43	1.54	0.30	0.02	0.05	0.03	0.34
MA	1.93	0.33	1.35	0.04	0.00	0.01	0.00	0.02	0.01	0.17
MI	27.08	4.59	19.20	2.09	0.01	0.48	0.07	0.08	0.03	0.53
MN	81.93	18.53	37.71	22.76	0.15	0.83	0.99	0.22	0.05	0.70
MS	25.42	15.13	3.06	1.65	3.91	0.78	0.00	0.02	0.07	0.81
MO	100.72	65.53	14.85	15.12	1.26	0.92	0.75	0.19	0.22	1.88
MT	57.75	51.04	2.98	1.12	0.00	0.06	0.00	0.84	0.03	1.68
NE	157.51	125.80	9.01	19.61	0.03	1.65	0.08	0.23	0.09	1.02
NV	6.99	4.26	2.44	0.01	0.00	0.00	0.00	0.11	0.02	0.15
NH	1.23	0.17	0.96	0.01	0.00	0.01	0.00	0.01	0.00	0.06
NJ	1.35	0.25	0.73	0.02	0.00	0.11	0.00	0.02	0.01	0.21
NM	49.46	14.57	33.93	0.01	0.00	0.13	0.00	0.24	0.06	0.53
NY	31.23	4.04	26.47	0.13	0.00	0.16	0.00	0.05	0.03	0.34
NC	99.48	15.76	8.35	64.34	5.24	2.11	2.03	0.09	0.29	1.28
ND	29.84	25.10	3.20	0.79	0.00	0.01	0.04	0.20	0.01	0.51
OH	33.16	7.76	18.08	4.41	0.14	1.72	0.09	0.15	0.08	0.75
OK	122.69	94.56	10.07	13.25	1.35	0.48	0.09	0.21	0.32	2.36
OR	23.49	12.34	9.72	0.06	0.07	0.22	0.00	0.33	0.05	0.70
PA	72.26	11.70	52.49	4.02	0.54	2.00	0.22	0.17	0.09	1.05
RI	0.25	0.05	0.15	0.01	0.00	0.00	0.00	0.00	0.00	0.04
SC	16.58	7.79	3.13	1.86	1.56	0.77	0.62	0.02	0.12	0.70
SD	65.49	47.63	9.79	6.13	0.00	0.31	0.17	0.69	0.02	0.75
TN	38.00	27.47	7.00	0.57	0.94	0.19	0.00	0.06	0.25	1.52
TX	357.86	262.01	68.41	7.08	4.02	3.06	0.22	2.90	3.20	6.94
UT	22.80	9.28	8.96	2.89	0.00	0.36	0.15	0.53	0.03	0.59
VT	7.78	0.73	6.95	0.01	0.00	0.01	0.00	0.01	0.01	0.06

Table 9 continued

VA	37.86	20.86	12.08	1.64	1.07	0.37	0.50	0.17	0.13	1.03
WA	38.41	10.55	25.98	0.11	0.10	0.59	0.00	0.10	0.06	0.91
WV	7.02	4.80	1.21	0.03	0.26	0.12	0.11	0.07	0.05	0.36
WI	101.00	16.33	82.14	1.04	0.10	0.31	0.16	0.11	0.06	0.75
WY	22.80	19.50	0.85	0.50	0.00	0.00	0.00	0.96	0.02	0.96

A.2 Water withdrawal intensities

Table 10. Cereal grain water withdrawal intensities in m^3/ton.

State	Wheat	Rice	Barley	Maize	Rye	Oats	Sorghum
AL	614	0	0	261	0	0	0
AK	0	0	0	0	0	0	0
AZ	2040	0	2210	1072	0	0	1910
AR	1283	590	0	487	0	0	822
CA	961	626	1367	553	0	0	1327
CO	2128	0	1346	764	0	2792	1561
CT	0	0	0	0	0	0	0
DE	514	0	0	189	0	0	0
DC	0	0	0	0	0	0	0
FL	0	0	0	404	0	0	1062
GA	405	0	0	149	1211	0	646
HI	0	0	0	1746	0	0	0
ID	1728	0	2107	1024	0	0	1234
IN	182	0	0	87	0	0	185
IA	0	0	0	56	0	0	0

Table 10 continued

KS	1014	0	0	252	0	0	425
KY	255	0	0	117	0	0	0
LA	606	338	0	256	0	0	519
ME	0	0	0	0	0	0	0
MD	440	0	0	173	0	0	419
MA	0	0	0	1332	0	0	0
MI	256	0	0	104	0	0	0
MN	241	0	0	100	0	0	0
MS	855	380	0	301	0	0	477
MO	705	357	0	281	0	0	476
MT	2920	0	2963	1384	0	4607	2249
NE	406	0	0	159	0	0	315
NV	1133	0	0	0	0	0	0
NH	0	0	0	0	0	0	0
NJ	1226	0	0	357	0	0	0
NM	2319	0	0	781	0	0	1546
NY	357	0	0	178	0	0	0
NC	850	0	0	390	0	0	977
ND	492	0	0	207	0	0	0
OH	0	0	0	201	0	0	0
OK	1183	0	0	249	1999	0	642
OR	1262	0	1831	653	0	2343	0
PA	0	0	0	102	0	0	0
RI	0	0	0	0	0	0	0
SC	594	0	0	211	0	0	413
SD	1053	0	0	487	0	0	964
TN	431	0	0	196	0	0	400

Table 10 continued

TX	1263	437	0	288	0	0	631
UT	1088	0	1492	668	0	0	0
VT	0	0	0	0	0	0	0
VA	292	0	0	127	0	0	0
WA	830	0	1279	470	0	0	2530
WV	0	0	0	0	0	0	0
WI	638	0	0	248	0	0	0
WY	2328	0	2425	1313	0	4157	0

Table 11. Animal feed water withdrawal intensities in m^3/ton.

State	Other small grains	Dry peas	Soybean meal	Canola	Pasture	Dry hay/ Alfalfa	Corn silage
AL	0	0	967	0	523	355	0
AZ	0	0		0	523	767	227
AR	590	1186	2106	0	523	0	103
CA	626	0	0	0	523	460	110
CO	0	0	3285	0	523	1087	168
CT	0	0	1480	0	523	0	0
DE	0	0	806	0	523	0	48
FL	0	0	2144	0	523	506	112
GA	0	170	679	0	523	102	34
IN	0	0	320	0	523	87	19
IA	0	0	225	0	523	65	15
KS	0	0	976	0	523	236	68
KY	0	0	475	0	523	119	0
LA	338	0	918	0	523	0	77

Table 11 continued

ME	0	0	273	0	523	0	0
MD	0	0	745	0	523	176	38
MA	0	6	0	0	523	0	0
MI	0	0	405	0	523	92	23
MN	0	0	405	519	523	97	24
MS	380	14	1112	0	523	0	77
MO	357	3	1209	0	523	247	74
MT	0	0	5387	7849	523	1634	263
NE	0	0	570	0	523	170	38
NV	0	0	0	0	523	770	157
NH	0	1143	0	0	523	0	0
NJ	0	0	1500	0	523	1195	0
NM	0	0	0	0	523	832	193
NY	0	6	0	0	523	0	0
NC	0	0	1575	0	523	337	0
ND	0	0	813	1071	523	207	44
OH	0	265	730	0	523	215	44
OK	0	0	1142	2079	523	280	77
OR	0	0	0	4780	523	814	147
PA	0	0	403	0	523	101	20
RI	0	104	0	0	523	0	0
SC	0	0	957	0	523	0	51
SD	0	934	1814	0	523	617	144
TN	0	0	774	0	523	362	60
TX	437	0	1248	0	523	249	64
UT	0	0	0	0	523	709	139
VT	0	31	0	0	523	0	0

Table 11 continued

VA	0	0	501	0	523	0	27
WA	0	0	2007	3251	523	439	99
WV	0	24	0	0	523	7	1
WI	0	0	967	0	523	229	56
WY	0	0	3320	0	523	1510	243
Other grain represents mixture of barley, oats, and rye.							

Table 12. Total livestock withdrawal (feed + rearing) intensities in m^3/animal.

State	Beef cattle	Swine	Broiler chickens	Turkey	Sheep	Goats	Horses
AL	1037	71	7	0	2	13	764
AZ	3155	619	4	9	36	44	1743
AR	240	153	9	2	5	30	31
CA	2046	352	3	6	23	24	1046
CO	4167	500	4	7	31	68	2607
CT	1	0	0	0	0	0	0
DE	99	56	2	0	2	11	11
FL	1608	39	1	0	1	1	1084
GA	370	47	7	0	1	9	225
ID	3802	574	4	8	34	38	2264
IL	366	53	1	0	1	6	227
IN	306	39	1	1	1	4	191
IA	236	98	0	0	1	0	141
KS	831	110	2	1	3	21	520
KY	364	32	2	0	1	6	259
LA	151	70	2	0	2	14	16
ME	2	0	0	0	0	0	0

Table 12 continued

MD	580	49	2	0	1	9	382
MA	84	128	1	1	3	2	13
MI	324	31	1	0	1	5	200
MN	359	50	1	1	1	5	212
MS	165	94	6	1	3	19	20
MO	856	94	3	1	2	16	542
MT	6549	912	6	14	60	101	3979
NE	563	65	1	0	1	8	370
NV	2423	83	2	1	2	23	1656
NH	10	9	0	0	1	1	1
NJ	3419	124	2	1	3	25	2551
NM	2772	245	4	2	7	48	1811
NY	52	43	1	0	1	7	6
NC	1010	164	7	3	3	18	729
ND	678	57	1	0	2	10	450
OH	696	26	0	0	1	1	462
OK	963	124	3	1	3	24	617
OR	3374	496	3	8	34	47	1995
PA	369	15	1	0	0	0	217
RI	1	1	0	0	0	0	0
SC	110	66	3	1	2	12	13
SD	2016	137	2	1	4	23	1335
TN	1133	51	2	0	1	9	779
TX	924	128	6	1	6	31	557
UT	2623	394	2	6	24	24	1577
VT	7	0	0	0	0	0	0
VA	69	35	2	1	1	6	7

Table 12 continued

WA	1755	318	2	5	20	18	991
WV	22	0	0	0	0	0	14
WI	842	72	1	1	2	13	500
WY	5950	765	5	12	51	85	3657

A.3 Estimation of irrigation embodied energy

We obtain energy expense of irrigating land ($/acre) and acres of area farmed through Farm and Ranch Irrigation Survey (FRIS) to estimate total energy expenditure. We estimate total quantity of energy (in MJ) by using EIA published prices[147] ($/MJ) for each energy source and multiply it with total energy expenditure for each state.

$$E_i^S = p_i^s \times A^s \times e_i \tag{22}$$

Here E_i^S is total quantity of energy of type *i* used for irrigation in state s.

p_i^s is energy expense of irrigating land for state *s* and type *i*. A^s is total acres farmed and e_i is energy expense for agriculture in $/MJ obtained from EIA. Water withdrawn for each state is estimated by multiplying total acres farmed with published values of acre-ft/acre ratio.

$$q = \frac{E_i^s}{A^s \times r^s} \tag{23}$$

Table 13. Total irrigation energy consumption per state by source of energy in 2012.

States	Electricity (MJ)	Natural Gas (m^3)	LP gas, propane, and butane (gallon)	Diesel (gallon)	Gasoline, ethanol, and blends (gallon)
AL	5.67E+07	1.80E+01	0	4.04E+05	2.30E+01
AK	0	0	0	0	3.40E+01
AZ	1.80E+09	6.82E+05	0	7.30E+04	3.25E+02
AR	2.07E+09	1.96E+05	6.60E+03	1.23E+07	3.85E+03
CA	1.49E+10	1.83E+05	1.10E+04	4.23E+06	0
CO	3.14E+09	1.15E+06	2.10E+01	7.20E+04	1.60E+02
CT	1.69E+06	0	1.03E+02	2.16E+03	9.95E+02
DE	2.32E+07	0	1.00E+01	3.16E+05	5.80E+01
FL	1.56E+08	1.57E+03	1.90E+01	8.55E+06	6.50E+01
GA	1.21E+09	0	2.08E+02	9.63E+05	1.00E+00
HI	3.47E+07	0	0	1.76E+02	0
ID	9.79E+09	2.58E+02	0	2.45E+04	4.00E+00
IL	3.16E+08	7.40E+02	3.01E+03	4.90E+05	7.00E+01
IN	1.72E+08	5.82E+03	8.00E+03	4.56E+05	2.00E+00
IA	9.45E+07	5.30E+01	1.08E+02	1.19E+05	2.90E+01
KS	9.28E+08	2.45E+08	4.08E+04	9.45E+05	0

Table 13 continued

KY	3.13E+06	2.40E+01	0	2.97E+04	2.81E+02
LA	4.06E+08	6.29E+04	9.90E+01	2.87E+06	1.30E+01
ME	7.82E+04	0	0	5.30E+04	3.80E+01
MD	1.23E+07	0	0	3.18E+05	1.00E+00
MA	5.45E+06	0	6.63E+04	1.52E+05	3.48E+02
MI	2.93E+08	0	9.95E+03	7.30E+05	0
MN	4.53E+08	0	0	1.30E+05	0
MS	4.30E+08	3.39E+02	4.93E+04	5.87E+06	0
MO	2.51E+08	9.80E+01	2.33E+05	1.49E+06	2.99E+02
MT	1.02E+09	2.87E+03	4.60E+01	3.74E+04	7.80E+01
NE	5.41E+09	2.38E+07	8.70E+05	1.00E+07	3.51E+02
NV	1.43E+09	0	0	9.49E+04	0.00E+00
NH	1.47E+05	0	0	5.35E+02	7.19E+02
NJ	1.41E+07	0	1.02E+02	5.09E+05	2.52E+02
NM	1.53E+09	1.85E+06	2.07E+03	9.65E+04	7.38E+02
NY	1.72E+06	0	0	2.74E+05	2.45E+03
NC	6.98E+07	0	1.17E+02	1.58E+05	2.50E+01
ND	2.20E+08	0	8.00E+00	6.87E+03	0
OH	2.70E+07	0	1.31E+02	6.64E+04	6.37E+02
OK	2.82E+08	1.73E+07	1.03E+03	4.83E+04	3.40E+01
OR	3.35E+09	1.30E+01	1.30E+01	1.33E+04	0.00E+00
PA	1.10E+07	1.60E+01	9.40E+01	2.99E+04	5.94E+03
RI	1.38E+05	0	5.74E+03	6.99E+03	5.00E+00

Table 13 continued

SC	1.29E+08	0	0	7.99E+04	0
SD	3.24E+08	0	0	5.64E+04	0
TN	3.15E+07	1.00E+03	9.17E+02	2.74E+05	7.70E+01
TX	9.71E+09	1.25E+08	2.55E+02	3.47E+05	2.30E+01
UT	1.22E+09	0	0	2.59E+04	2.20E+01
VT	1.77E+06	0	0	5.20E+02	2.94E+03
VA	5.93E+06	0	0	2.06E+05	0
WA	6.89E+09	0	7.13E+02	2.50E+04	2.40E+01
WV	1.41E+06	0	0	0	8.55E+02
WI	4.97E+08	0	2.24E+02	3.06E+05	1.20E+01
WY	8.E+08	4.11E+03	7.61E+03	1.02E+04	5.20E+01

A.4 Life Cycle Data Acquisition

We use cumulative energy demand method[150] for calculating embodied energy and IPCC 2013 method (100 year time horizon)[151] for calculating embodied GHG emissions.

Table 14. Life cycle data sources.

Material/Process Description	Unit	Database	Cumulative Energy Demand (MJ/Unit)	GWP (kg CO_2 equivalent/ unit)
Electricity, bituminous coal, at power plant/US	MJ	USLCI	3.9	0.30
Electricity, high voltage (US avg)| electricity production, hydro, reservoir, alpine region | Alloc Def, U	MJ	Ecoinvent3	0.02	0.23
Electricity, natural gas, at power plant/US	MJ	USLCI	3.51	0.20
Electricity, nuclear, at power plant/US	MJ	USLCI	0.05	0.00
Wood, particleboard, generated onsite, combusted in industrial boiler/kg/RNA	MJ	USLCI	0.03	0.52
Electricity, biomass, at power plant/US	MJ	USLCI	0.01	0.01
Electricity, high voltage (RoW)| treatment of blast furnace gas, in power plant | Alloc Rec, U	MJ	Ecoinvent3	0.01	0.52
Electricity, diesel, at power plant/US U	MJ	USLCI	4.3	0.32
Electricity, production mix photovoltaic, at plant/US U	MJ	Ecoinvent3	1.31	0.01
Electricity, high voltage (US avg)| electricity production, wind, >3MW turbine, onshore | Alloc Def, U	MJ	Ecoinvent3	0.02	0.00
Electricity, onsite boiler, softwood mill average, NE-NC/kWh/RNA	MJ	USLCI	0.21	0.01
Diesel, combusted in industrial boiler/US	m^3	USLCI	46,500	3,190

Table 14 continued

Natural gas, combusted in industrial boiler/US	m^3	USLCI	42	2.4
Liquefied petroleum gas, combusted in industrial boiler/US	m^3	USLCI	29,000	2,050
Gasoline, combusted in equipment/US	m^3	USLCI	41,500	2,540
GWP indicates global warming potential				

A.5 Net transfer results

Table 15. Net imports (Incoming + Within-state - Outgoing) for food transfer and environmental impacts

State	Food million tons	State	Water billion m^3	State	Embodied Energy billion MJ	State	GHG emissions billion kg CO_2 equivalent
TX	66.03	TX	46.12	TX	105.81	TX	7.29
IL	42.26	CA	15.06	CA	25.94	IL	1.86
LA	42.02	WA	13.94	IL	25.00	CA	1.78
IA	36.01	LA	13.32	CO	23.12	CO	1.67
CA	29.12	IL	13.14	WA	18.88	WA	1.42
NY	15.61	OR	9.80	NE	17.11	NE	1.25
NE	14.49	CO	8.95	LA	15.66	LA	1.07
FL	12.86	NE	7.11	KS	12.02	KS	0.82
AR	11.68	IA	6.87	WY	8.54	WY	0.66
GA	11.42	FL	4.65	IA	8.46	IA	0.63
WA	9.97	AR	4.45	OR	8.05	OR	0.59

Table 15 continued

PA	8.92	NY	3.82	FL	8.03	IN	0.57
CO	7.47	WY	3.71	IN	8.01	FL	0.55
SD	7.35	AZ	3.33	NY	7.85	NY	0.54
NV	0.29	DC	0.04	NH	0.22	NH	0.02
ID	0.22	VT	0.03	DC	0.08	DC	0.01
VT	0.20	WV	0.03	RI	0.06	RI	0.00
DC	0.18	RI	0.03	VT	0.04	VT	0.00
MI	0.12	HI	0.02	HI	0.02	HI	0.00
KY	0.09	**KY**	**-0.27**	**WV**	**-0.04**	WV	0.00
RI	0.04	**AL**	**-0.87**	**OK**	**-1.76**	**GA**	**-0.10**
WV	0.01	**MO**	**-1.24**	**GA**	**-1.85**	**OK**	**-0.11**
WY	**-0.22**	**UT**	**-1.30**	**MT**	**-2.62**	**MT**	**-0.21**
OK	**-0.48**	**ND**	**-1.52**	**ID**	**-4.26**	**ID**	**-0.28**
MT	**-0.92**	**NC**	**-1.79**	**UT**	**-5.77**	**UT**	**-0.43**
MN	**-3.83**	**OK**	**-2.36**	**AL**	**-6.49**	**AL**	**-0.43**
KS	**-3.83**	**MT**	**-2.40**	**NC**	**-8.32**	**NC**	**-0.60**
ND	**-4.31**	**ID**	**-6.13**	**ND**	**-10.20**	**ND**	**-0.80**

Negative values highlighted in bold represent net outgoing flows and positive values indicate net incoming flows. The states are ranked in descending order of net imports

A.6 Network Statistics

Characteristic path length: The characteristic path length of a network describes the average shortest distance between nodes from all other nodes in the network. The shortest path in a network would be the path of the least resistance, often interpreted as the path with the least link weight. In trade networks, it makes sense to give importance to paths with maximum link weight (i.e. states engaging in large physical transfers). As such, we use an inverse definition where a path with least resistance (or a shortest path) would be the path with maximum link weight. We estimate that the food transfer network has a characteristic path length of 1.3.

A.7 Degree and strength distributions

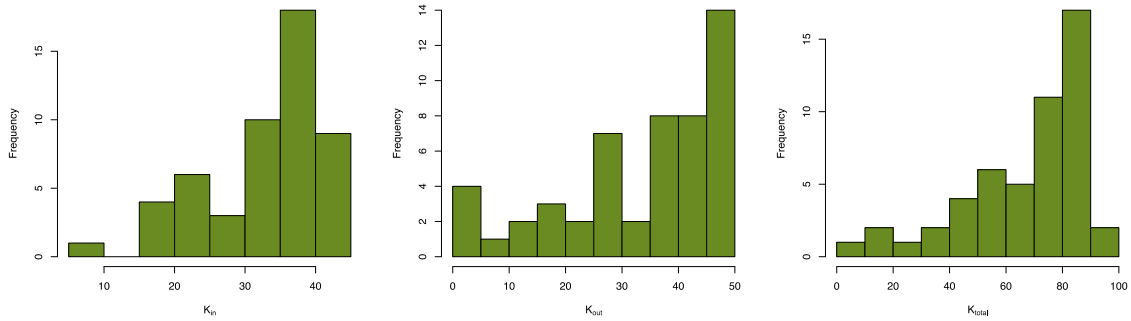


Figure 18. Distribution of in-degrees (k_{in}), out-degrees (k_{out}) and total degrees (k_{tot})..

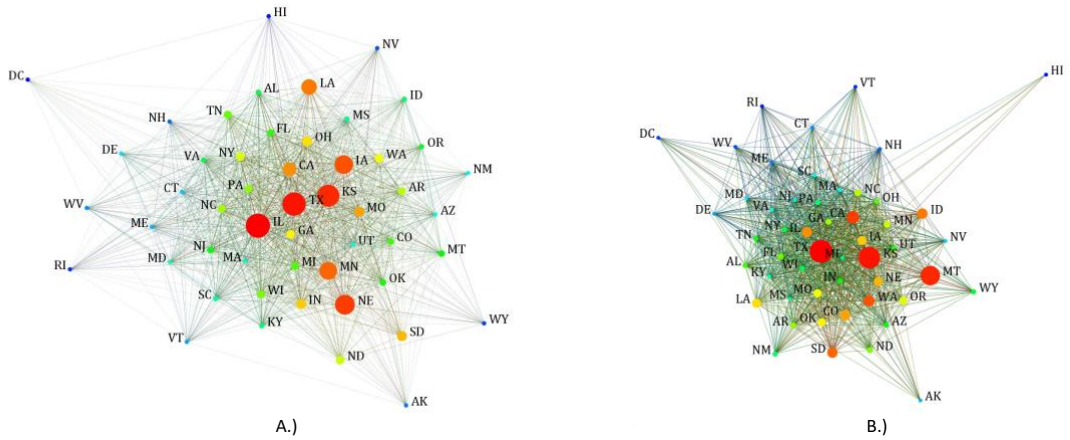


Figure 19. A.) Food transfer network and B.) Virtual water network.

Network topology: Network topology is the structural organization of nodes and links in a network. Along with standard network measures such as density, characteristic path length, and clustering coefficient, degree distribution is widely used for understanding a network's topological features. It is characterized by probability distribution $p(k)$, where $p(k)$ is the probability that a randomly chosen node will have k degrees. In figure 18, in- and out- degrees have a peak at 36, suggesting that on average each state is connected to 36 other states. This highly connected topology can also be visualized from figure 19 for virtual water network. The nodes are sized and colored according to their total degree centrality. The red nodes in the network have higher weight and therefore higher degree centrality. Blue nodes indicate nodes with lowest magnitude of flow in the network. The visualization is created using network analysis software ORA.**[302]** The food transfer network closely resembles a core-periphery structure with a well-connected core in the middle with Hawaii, DC, Rhode Island, Nevada, Vermont, Wyoming, and Alaska forming the periphery. While some of the peripheral node such as Hawaii and Alaska are positioned further outside in virtual water network, the core becomes more connected and shrinks in size.

Another way to represent weighted networks is through characterizing strength distribution. Strength distribution *p(s)* is a weighted extension of degree distribution and characterizes range of throughput in the network. The strength distributions in figure 20 exhibit fat tails, suggesting possibility of a scale free topology.[303] A scale free network's degree distribution follows power law $p(k) \propto k^{-\varepsilon}$, where ε is constant and exhibits a fat-tail.[303] A good power-law fit would suggest that there are a handful of states involved in large volume of transfers, while majority of states transfer small volume making the entire network vulnerable to targeted disruptions. For all three weighted networks, we test for power law and other fat-tailed distributions by following statistical framework provided by Clauset et al.[304] First, we examine presence of right tailed distributions (exponential, lognormal and power law) through Kolmogorov Smirnov test. *p* value greater than 0.10 indicates a good fit. To further differentiate between each distribution, we use composite hypothesis of log likelihood ratio (LLR) and Vuong's statistics.[304] Contrarily to previous test, a high p-value here indicates that we are unable to differentiate between two hypothesized distributions. Power law is generally defined for some values greater than a minimum value x_{min} rather than over an entire distribution. Due to already small sample size (51 states), this routine does not provide us with sufficient evidence regarding power law behavior. However, we cannot disregard presence of a few key states with significantly high throughput. We use complementary cumulative distribution functions to show power law behavior in the networks. The blue curve represents actual data point, and the dashed black line presents a power law fit, calculated according to the method outlined in Clauset et al.**[304]** The highlighted nodes represent key states in the distribution tail. The plots were created using poweRlaw package provided by Gillespie.**[305]** Figures A and E indicate in-strengths (S_{in}) and out-strength (S_{out}) distributions for food. Figures B and F indicate in- and out-strength distributions

for virtual water withdrawals. Figures C and G indicate in- and out-strength distribution for irrigation embodied energy. Figures D and H indicate in- and out-strength distribution for irrigation embodied GHG emissions.

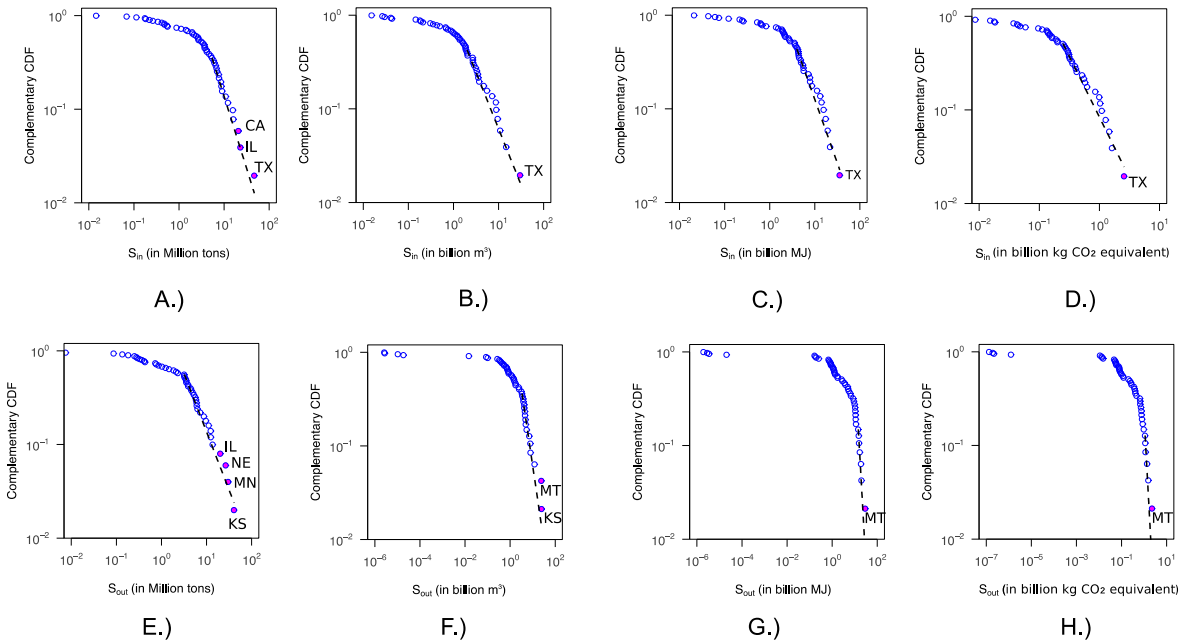


Figure 20. Complementary cumulative distribution functions (CDFs) of food, virtual water, embodied energy, and GHG emissions network.

Table 16. *p*-values for Kolmogorov–Smirnov test.

Strength (Network)	Power law	Exponential	Lognormal
S_{in} (Food)	0.99	0.97	0.91
S_{in} (Virtual water)	0.99	0.84	0.91

Table 16 (continued)

S_{in} (Embodied energy)	0.99	0.95	0.83
S_{in} (GHG emissions)	0.99	0.95	0.84
S_{out} (Food)	0.99	0.85	0.81
Sout (Virtual water)	0.99	0.69	0.18
Sout (Embodied energy)	0.99	0.46	0.09
Sout (Embodied GHG emissions)	1	0.45	0.10

Table 17. Log likelihood ratio test (LLR) and Vuong's test (p-value) for food and environmental impact networks.

Network	Power Law vs. lognormal		Power Law vs. exponential		Power Law vs. Weibull		Observations ($X>X_{min}$)
	LLR	p-value	LLR	p-value	LLR	p-value	N
S_{in}(food)	-0.14	0.44	3.00	1.00	3.92	0.88	26
S_{in} (Virtual water)	-0.14	0.44	0.96	0.83	5.42	0.90	24
S_{in} (Embodied energy)	-0.23	0.41	0.60	0.73	0.30	0.56	26
S_{in} (GHG emissions)	5.64	1.00	0.47	0.68	4.36	0.84	24
S_{out}(food)	-0.21	0.42	1.04	0.85	6.00	0.91	28
Sout (Virtual water)	0.17	0.57	1.44	0.92	5.51	0.94	17
Sout (Embodied energy)	0.28	0.61	0.23	0.59	2.15	0.80	7
Sout (GHG emissions)	0.28	0.61	0.23	0.59	2.37	0.81	7

A positive LLR suggests that the first distribution tested is a better fit. *p* value greater than 0.10 suggests that sample size is not statistically sufficient to differentiate between the two distributions. S_{in} indicates in-strength and S_{out} indicates out-strength for respective networks.

A.8 Centrality

We identify key states by calculating node level degree centrality for all four networks. To consider directions, we calculate set of in-degree, out-degree and total degree centralities. We normalize the results by dividing with a scaling factor.[306] The scaling factor depends on network symmetry and presence of self-loops. Since we do not consider self-loops for our asymmetric (directed) networks, the scaling factor is given by (Eq.9-14).

$$C_{D_{total}}(i) = \sum_{j=1, i \neq j}^{N} W_{i,j} + \sum_{j=1, j \neq i}^{N} W_{i,j} \tag{24}$$

$$C_{D-in}(i) = \sum_{j=1, j \neq i}^{N} W_{j,i} \tag{25}$$

$$C_{D-out}(i) = \sum_{j=1, j \neq i}^{N} W_{i,j} \tag{26}$$

$$C'_D(i) = \frac{C_D(i)}{C_D^{max}} \quad \textbf{(27)}$$

$$C_{D-in/out}^{max} = (N-1) \times W^* \quad \textbf{(28)}$$

$$C_{D-total}^{max} = (2N-2) \times W^* \quad \textbf{(29)}$$

Here $C_D(i)$ represents degree centrality for node *i*. The subscript *in, out, and total* represent type of centrality calculated. $W_{i,j}$ represents weighted adjacency matrix. $W_{j,i}$ represents transpose of the matrix. C_D^{max} represents the scaling factor. W^* represents link with the maximum value in the network. *N* represents number of nodes in the network. The subsequent results are calculated by not considering self-loops.

Table 18. Top 10 states with highest scaled values of weighted total degree centrality.

Rank	State	Un weighted	State	Food	States	Virtual water	State	Embodied energy	State	GHG emissions
1	IL	0.95	TX	0.017	TX	0.018	TX	0.04	TX	0.036
2	CA	0.93	KS	0.016	KS	0.017	KS	0.024	MT	0.023
3	TX	0.92	IL	0.014	MT	0.013	MT	0.023	KS	0.022
4	OH	0.91	MN	0.013	WA	0.01	IL	0.019	IA	0.018
5	PA	0.91	IA	0.01	CA	0.007	CA	0.018	IL	0.018
6	MA	0.90	NE	0.01	IA	0.007	IA	0.018	ND	0.017
7	NY	0.89	CA	0.008	ID	0.007	NC	0.018	WA	0.017
8	MI	0.88	LA	0.007	IL	0.007	ND	0.017	CA	0.016
9	MN	0.88	GA	0.006	MO	0.006	NE	0.017	MN	0.016
10	NC	0.88	MO	0.006	OR	0.006	WA	0.017	NC	0.016

Table 19. Top 10 states with highest scaled values of out-degree centrality.

Ranks	State	Un Weighted	State	Food	States	Virtual water	State	Embodied energy	State	GHG emissions
1	MA	0.98	KS	0.027	KS	0.026	MT	0.044	MT	0.044
2	CA	0.94	MN	0.02	MT	0.025	ND	0.03	ND	0.03
3	IL	0.94	NE	0.017	ID	0.013	NC	0.028	NC	0.026
4	KS	0.94	IL	0.013	OK	0.008	TX	0.025	KS	0.023
5	IN	0.92	IA	0.009	SD	0.008	CO	0.023	TX	0.022
6	MI	0.92	MO	0.008	MO	0.007	KS	0.023	CO	0.021
7	MN	0.92	ND	0.008	NC	0.006	GA	0.021	GA	0.019
8	NC	0.92	IN	0.007	CA	0.005	AL	0.017	SD	0.017
9	PA	0.92	OH	0.006	CO	0.005	SD	0.017	IA	0.016
10	TX	0.92	SD	0.006	NE	0.005	IA	0.016	AL	0.015

Table 20. Top 10 states with highest scaled values of in-degree centrality.

Ranks	State	Un-weighted	States	Food	States	Virtual water	States	Embodied energy	State	GHG emissions
1	IL	0.94	TX	0.03	TX	0.031	TX	0.053	TX	0.05
2	CA	0.90	IL	0.015	WA	0.015	IL	0.032	IL	0.031
3	OH	0.90	CA	0.014	IL	0.011	WA	0.029	WA	0.028
4	TX	0.90	IA	0.01	OR	0.01	CA	0.026	CA	0.025
5	CO	0.88	LA	0.01	CA	0.009	KS	0.023	KS	0.021
6	GA	0.88	GA	0.008	IA	0.009	NE	0.021	NE	0.02
7	PA	0.88	WA	0.007	KS	0.008	IA	0.02	IA	0.019
8	FL	0.86	AR	0.006	NE	0.006	MN	0.017	MN	0.016
9	MO	0.86	KS	0.006	LA	0.005	IN	0.013	IN	0.012
10	IL	0.94	MN	0.006	GA	0.004	LA	0.012	LA	0.011

A.9 Assortativity

Here, we have used four types of assortativity considering directions of transfer (in-in, out-out, in-out, and out-in). An in-out connection can be interpreted as tendency of nodes with high/low in-degrees to be connected with nodes with high/low out-degrees. For example, $Knn_i^{(out,in)}$ indicates j exporting neighbors of node i and their importing characteristics.[159] Weighted measures can be calculated by simply replacing corresponding degrees with strengths.

$$Knn_i^{(in,in)} = \frac{1}{k_{in}} \sum_j A_{ji} * k_{inj} \quad \textbf{(30)}$$

$$Knn_i^{(in,out)} = \frac{1}{k_{in}} \sum_j A_{ji} * k_{inj} \quad \textbf{(31)}$$

$$Knn_i^{(out,out)} = \frac{1}{k_{out}} \sum_j A_{ji} * k_{inj} \quad \textbf{(32)}$$

$$Knn_i^{(out,in)} = \frac{1}{k_{out}} \sum_j A_{ji} * k_{inj} \quad \textbf{(33)}$$

$$Knn_i^{W(in,in)} = \frac{1}{s_{in}} \sum_j W_{ji} * k_{inj} \quad \textbf{(34)}$$

$$Knn_i^{W(in,out)} = \frac{1}{s_{in}} \sum_j W_{ji} * k_{outj} \quad \textbf{(35)}$$

$$Knn_i^{W(out,out)} = \frac{1}{s_{out}} \sum_j W_{ji} * k_{outj} \quad \textbf{(36)}$$

$$Knn_i^{W(out,in)} = \frac{1}{s_{out}} \sum_j W_{ji} * k_{inj} \quad \textbf{(37)}$$

Here, *k* represents degrees with subscripts representing in- or out- degrees. Similarly, *s* represents strength with subscript indicating the direction. A_{ij} is adjacency matrix with binarized links and W_{ij} is the weighted adjacency matrix. $Knn_i^{(ii)}$ represents assortativity value for node *i* for a specific direction. $Knn_i^{W(ii)}$ represents its weighted counterpart.

Table 21. Values for degree correlation coefficients (τ) for measuring assortativity.

Network	$\tau_i^{(io)}$	$\tau_i^{(ii)}$	$\tau_i^{(oo)}$	$\tau_i^{(oi)}$
Unweighted	-0.89	-0.84	-0.73	-0.83
Food	-0.12	-0.37	-0.09	-0.09
VirtualWater	-0.03	-0.29	0.03	-0.04
EmbodiedEnergy	-0.06	-0.29	0.03	0.03
GHG emissions	-0.06	-0.30	0.03	-0.22

Appendix B Supplementary Information for Chapter 3

B.1 Tracing origin of production in trade datasets.

The Freight Analysis Framework (FAF) data are derived from a shipper-based commodity flow survey (CFS).[140] CFS surveys selected shipper establishments in a given quarter and extrapolates to represent interstate and within-state shipments across the U.S. for the entire year. Ideally, the respondent would provide information related to the entire trip of a shipment, but a few may not explicitly specify internal hubs and stops for the shipment or the respondent would only be responsible for part of the route. Therefore, the trade data may not be able to distinguish hubs/ warehouses from intermediate states vs. actual origin and destinations of shipment. This may lead to double counting in trade statistics and potentially inaccurate estimates of location-based consumption impacts. For instance, rice produced in Arkansas may travel to New York through Ohio, where only the shipment from Ohio to New York is recorded, thereby inaccurately attributing environmental impacts of rice consumed in New York to Ohio's production. In actual case, Ohio may have only served as a shipment hub and no rice was produced in Ohio. This is a common issue in consumption-based accounting through food trade and usually solved through use of some form of origin tracing algorithms.[210, 307, 308]

FAF data provide trade for specific aggregated commodity groups based on Standard Classification of Transported Goods (SCTG) classification system (e.g. shipment of cereal grains). To reconcile trade with item-based impacts, we disaggregate commodity groups based on grains production (e.g. production of rice in Arkansas). Therefore, if a state does not produce a given crop (e.g. Ohio), it will not be sending out that commodity in the resulting trade matrix.

Similar production-based origin tracing method have been used in USDA estimates[309] of origin of agriculture exports as well as other trade studies.[185] Therefore, our method ensures that we do not incorrectly allocate production to non-producing states. However, in some cases, re-exports may come from production states as well. For example, Tennessee produces rice but imports some fraction from Arkansas and ships certain amount to New York. Therefore, the New York shipment from Tennessee may contain some of the re-exports from Arkansas along with local production from Tennessee. Additionally, in inter-regional trade, a state may be shipping some of the grains from previous year's stock, which is not usually considered in the mass-balance equations used in the origin tracing algorithms. To our knowledge, state level data on supply and demand is not available for all food commodities and requires building a comprehensive supply chains from bottom up such as demonstrated by Smith et al. for corn in the U.S.[209] This is an area of future work for reconciling subnational trade datasets.

B.2 Tracing supply chain of raw grains.

In this work, we assume the origin and destination to be production and consumption states respectively. With origin-tracing methods specified above, one can trace place of actual production. However, due to unavailability of complete supply chain data (raw grains transferred to milled products, and ultimately consumed), it is a common practice to assume processed products have locally sourced raw ingredients to avoid double counting.[28, 48, 115, 179] This poses a risk of underestimating consumption flows in specific states. For example, if New York mills rice sourced from Arkansas, and does not produce the rice itself, that flow will not be accounted for in production-oriented approach discussed in S2.1. Therefore, if the milled rice

was subsequently sent to Pennsylvania from New York, the consumption of rice in Pennsylvania through trade would be underestimated. By only focusing on raw grains and feed in the study, we account for the first step of supply chain. Therefore, we do not distinguish the place of destination as place of final consumption. However, our results of dependence still hold true as a disruption in production state will cause impacts to both place of final consumption and industries and services reliant on middle-hubs in the chain.

B.3 Ground water withdrawal intensities for irrigation.

We estimate water withdrawal intensities (WWI) by combining Farm and Ranch Irrigation Survey (FRIS)[145] applied water estimates with irrigated yield data. FRIS provides average application rate specific to crops, weighted by type of irrigation system for each state in acre-ft per acre. Our primary data source for irrigated yields is also from FRIS[145] with missing information supplemented from agriculture census database.[141] To estimate groundwater specific WWI depicted in figure 7, we multiply the WWI with state-specific fraction of groundwater withdrawals. The state specific fraction of withdrawals attributed to groundwater is calculated from USGS irrigation withdrawals data for 2010.

B.4 Derivation of PMI measure

We analyze state-wise trade dependencies through pointwise mutual information (PMI) measure. Originally from information theory, the PMI concept is adopted from ecological network

analysis.[104] Information-based ecological network analysis is based on concepts from information theory, graph theory, probability, and statistics. It is rooted in understanding what is missing[104] and embodies the principle that reduced indeterminacy of the system is a measure of the information gain. Mathematically, it is represented using Shannon's entropy for a system's macro-state (H) and its relation to the probability distribution of possible microstates (p)[310] (also similar to Boltzmann's equation of entropy). The equation can be seen as quantifying the non-occurrence (indicated by the –ve sign) of an event (with probability p of occurring).[104]

$$H = -klog(p) \tag{38}$$

Here, k is a scalar constant. PMI measures probability of two events occurring together. To understand the relationship between dyads i and j, eq. 1 can be re-written as,

$$H_{ij} = -klog\left(p_{ij}\right) \tag{39}$$

Here, H_{ij} represents indeterminacy of a random event i and j occurring together. p_{ij} is the probability of i and j co-occurring. The log base for the analysis is 2, giving the information unit "Shannon".

Conversely, if events i and j are completely independent of each other, knowing one would not reduce indeterminacy of other's occurrence. Therefore, it is assumed that a situation where

both events are independent of each other represents a state of maximal indeterminacy (eq.5).[104] 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. 3) and for j is given as $p_{.j}$ (eq. 4)

$$p_{i.} = \sum_{j} p_{ij} \tag{40}$$

$$p_{.j} = \sum_{i} p_{ij} \tag{41}$$

We re-write eq. 2 for maximal indeterminacy H_{ij}^{*} as,

$$H_{ij}^{*} = -klog(p_{i.}p_{.j}) \tag{42}$$

The maximal indeterminacy is also referred to as the null model in the main manuscript. Comparing a state of maximal indeterminacy with observed flow would yield additional information that is present in the system. The difference between maximal indeterminacy and

actual indeterminacy can be described as the measure of mutual information between i and j[195], termed as pointwise mutual (PMI) information

$$PMI_{ij} = H_{ij}^{*} - H_{ij} = -klog\left(p_{i.}p_{.j}\right) - \left(-klog\left(p_{ij}\right)\right) = klog\frac{p_{ij}}{p_{i.}p_{.j}} \tag{43}$$

B.5 An example of flow distribution in null model

To further explain what we mean by trade equitability, we present a toy model of trade (T) in Table 1 and associated null model (M) in table 2 in the SI. The $M_{i.}$ and $M_{.j}$ represent sum of columns and rows of M respectively which correspond to the Ti. and T.j for matrix T. From Table 3, it can be seen that the proportion of outgoing mass from a state to other states is the same across all states. In table 4, the proportion of incoming mass to a given state from other states is the same across the board. The trade direction is from i (row) to j (column). In this case, B consumes the most (22), and therefore receives highest portion (47% of their outgoing flow) from each state. C exports the most (36), and therefore each state receives highest portion (77% of all incoming flow) from C.

Table 22. Example of a hypothetical trade matrix (T)

T	A	B	C	Ti.
A	0	6	1	7
B	0	4	0	4
C	12	12	12	36
T.j	12	22	13	47

Table 23. Calculated null model matrix (M) for given trade

M	A	B	C	Mi.
A	1.79	3.28	1.94	7
B	1.02	1.87	1.11	4
C	9.19	16.85	9.96	36
M.j	12	22	13	47

Table 24. Outgoing flow distribution in null model (Tij/Ti.)

Fraction outgoing contribution	A	B	C
A	1.79/7=0.26	3.28/7=0.47	1.94/7=0.28
B	1.02/4=0.26	1.87/4=0.47	1.11/4=0.28
C	9.19/36=0.26	16.85/36=0.47	9.96/36=0.28

Table 25. Incoming flow distribution in null model (Tij/T.j)

Fraction incoming contribution	A	B	C
A	1.79/12=0.15	3.28/22=0.15	1.94/13=0.15
B	1.02/12=0.09	1.87/22=0.09	1.11/13=0.09
C	9.19/12=0.77	16.85/22=0.77	9.96/13=0.77

B.6 Results

Table 26. Total flows in the network

Networks	Cereal grains	Animal feed
Irrigated food transfers (US tons)	4.60E+08	1.53E+08
Virtual water transfers (m^3)	1.35E+11	3.09E+10
Irrigation embodied energy transfers (MJ)	5.46E+11	8.69E+10
Irrigation embodied GHG emissions transfers (kg CO_2 equivalent)	3.66E+10	5.78E+09

Table 27. Texas's importing partners and actual food imports

Incoming flow	PMI	PMI Rank	Volume (US tons)	Volume Rank
Texas	3.31	1	3.23E+07	1
Kansas	1.61	2	1.77E+07	2
Oklahoma	1.10	3	2.76E+06	3
Louisiana	0.23	4	9.38E+05	5
New Mexico	-0.05	5	1.19E+05	11
Indiana	-1.59	6	6.60E+05	6
Missouri	-2.17	7	4.06E+05	7
Tennessee	-2.51	8	5.99E+04	16
Nebraska	-2.76	9	1.37E+06	4
Arizona	-2.81	10	6.01E+04	15
Iowa	-3.48	11	3.66E+05	8
North Dakota	-3.56	12	6.99E+04	14
Arkansas	-3.62	13	1.07E+05	12
Utah	-3.99	14	1.87E+04	20
Minnesota	-4.20	15	2.24E+05	9
South Dakota	-4.25	16	9.94E+04	13
Pennsylvania	-4.29	17	5.86E+03	23
Illinois	-4.44	18	1.88E+05	10
Georgia	-4.63	19	2.07E+04	19
Colorado	-5.49	20	5.17E+04	17
Ohio	-5.57	21	1.72E+04	22
Wisconsin	-5.91	22	2.42E+04	18

Table 27 (continued)

New Jersey	-6.22	23	3.60E+02	28
California	-7.04	24	1.86E+04	21
Michigan	-7.91	25	4.91E+03	24
Kentucky	-8.30	26	5.86E+02	27
Mississippi	-8.45	27	1.76E+03	25
Florida	-9.65	28	9.67E+02	26
South Carolina	-11.46	29	4.86E+01	30
Montana	-12.64	30	1.18E+02	29
Virginia	-15.70	31	2.61E+00	32
Alabama	-15.99	32	4.08E+00	31
New York	-18.04	33	5.90E-01	33

Figure 21 compares expected food incoming transfers (shaded grey area) and observed transfers for top ten partners for Texas. The values are represented on a log scale and units are in US tons. The visualization is useful in comparing which states are exporting close to their null model (Louisiana, New Mexico) and which are over/under transferring.

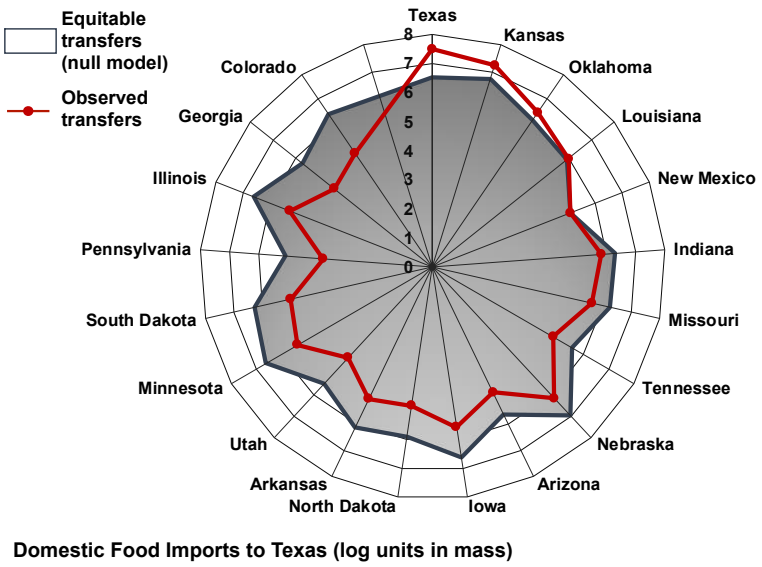
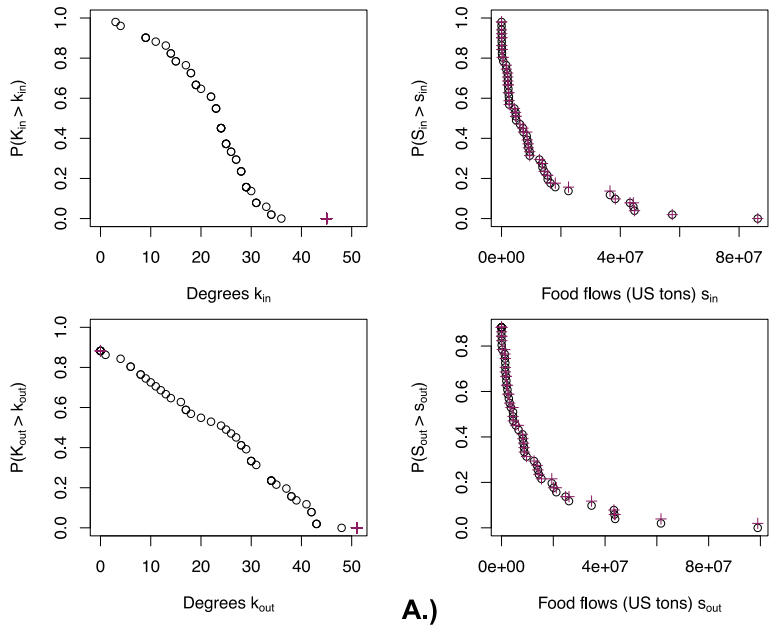


Figure 21. Comparison of expected imports (shaded grey area) and observed transfers

B.7 Degree and Strength Distribution Comparison

Degree and strength are primary descriptive network statistics. Degree calculates number of connections and depending on the direction of the connection, it can be separated into in-degree (incoming connections) or out-degree (out-going connection) of a network. Strength of a network represents weights in the network, and similar to degrees are subdivided into in-coming strength and out-going strengths. Figure 22 compares degree and strength distribution for observed and expected network flows and connections. The black circles represent observed transfers and connections, the red cross represents the expected flow. As seen from the strength distributions of each network (s_{in}/s_{out}), the total flow remains the same in the null model and observed flow. However, individual links are re-wired to create an equitable structure, which can be shown

through degree connections. The null model's degree distribution (k_{in}/k_{out}) exhibits a fully connected topology denoted by all states having the same indegrees: 45 and out-degrees 51 or 0. The 0 out-going degrees are for states with no outgoing flow of grains or feed crops and consists of Alaska, Maine, New Hampshire, Rhode Island, Vermont, Washington DC. As the difference in each network is due to change in weights, the degree distribution remains same for each layer.



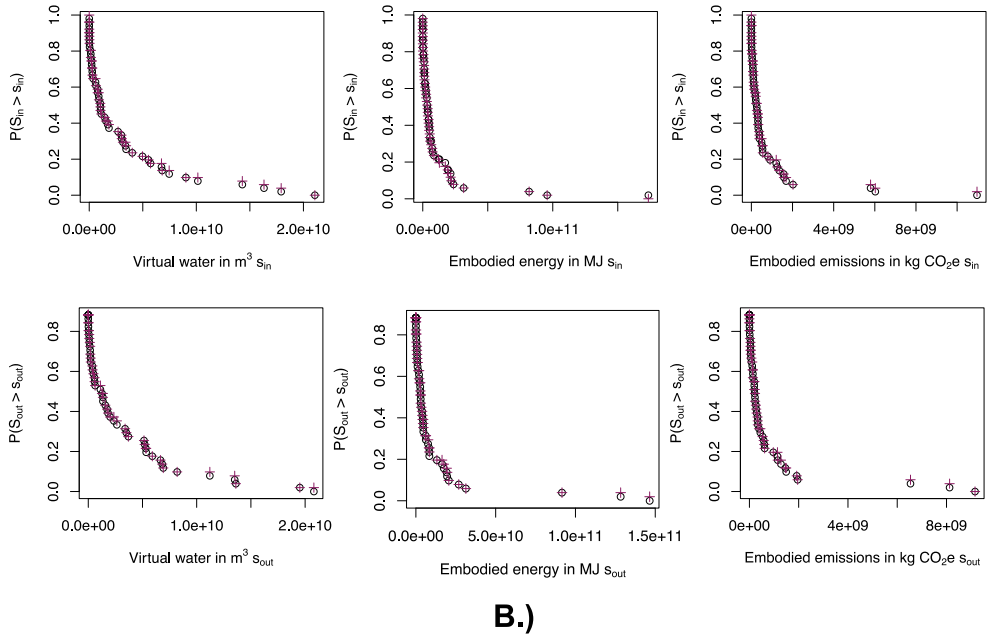


Figure 22. Cumulative distributions of in(/out) degree (k_{in}/k_{out}) and strength distribution (s_{in}/s_{out}) of food flows (A) and strength distributions (s_{in}/s_{out}) of irrigation impact flows (B).

Figure 23 shows that majority of states have lower percentage of positive PMI values in their import and export connections. This indicates that states are highly reliant (based on mass flux) on a few states in their export and import connections, and therefore prone to vulnerability in those connections.

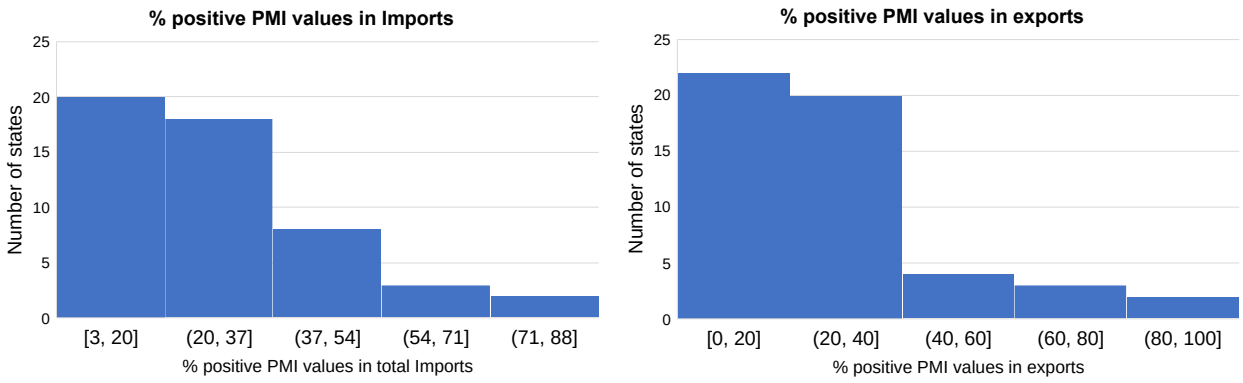


Figure 23. Presence of positive PMI values in import and export relations

Appendix C Supplementary Information for Chapter 4

C.1 Transportation mode emissions

Multiple modes and mail category may include travel by a combination of truck-rail, truck-water, and rail-water or though parcel delivery services, for any of which specific data are not available.[140] Therefore, we replaced the intermodal route with the dominant shipment mode for that route. We justify this step as multiple modes carry 1% to 3% of the total tonnage. (Figure 24) For example, if maximum tonnage is transferred by rail between California and New York, then the intermodal route is replaced with rail. If there are no other routes specified, we replace the intermodal shipments with truck, as trucks represent the preferred mode of shipment for the US.

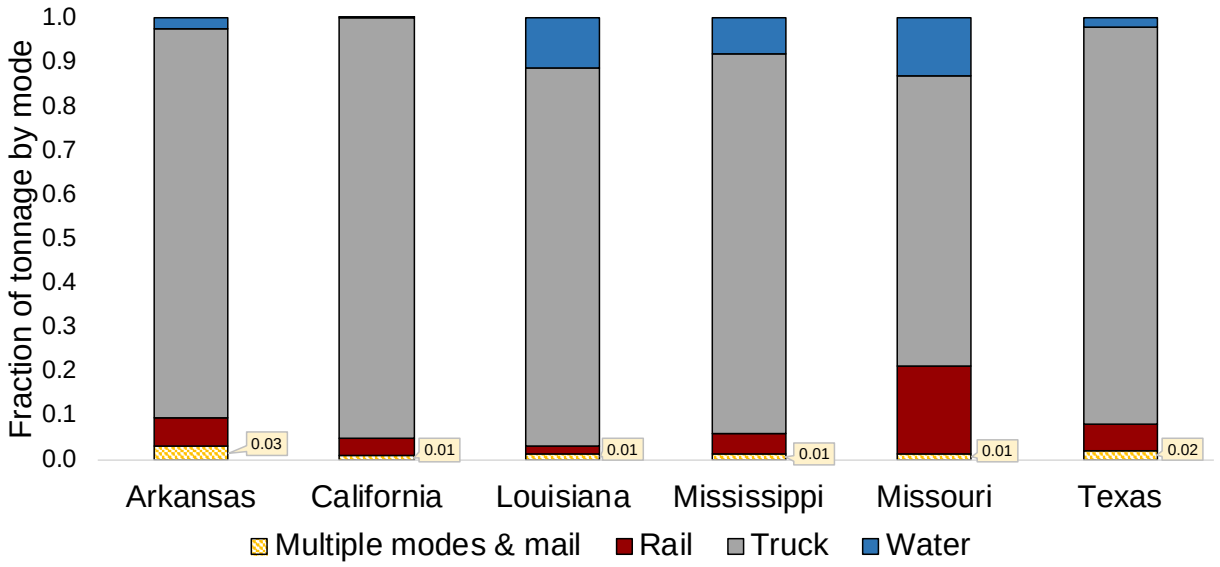


Figure 24. Fraction of tonnage shipped through various modes of transportation

Table 28 contains exploitable yields, which are assumed to be 85% of potential yields. Exploitable yields for the dominant system of rice type produced in a state are extracted from Espe et al.[241]

Table 28. Exploitable yields

Attainable Yield	Long grain	Medium grain	Short grain
Arkansas	4.32	4.38	3.70
California	3.15	4.36	3.36
Louisiana	4.03	3.89	
Mississippi	4.24	4.28	
Missouri	4.30	4.49	
Texas	4.18	4.18	

Table 29. Virtual water intensity (m3/ton rice) for each rice type

Values in m^3/ton		Mean	Lower Confidence bound 2.5%	Upper Confidence bound 97.5%
	Arkansas	705	654	760
	California	1828	1533	2194
	Louisiana	773	709	843
	Mississippi	865	833	899
	Missouri	732	703	762
	Texas	729	678	785
	Arkansas	695	654	739
	California	1307	1264	1351
	Louisiana	801	741	867
	Mississippi	857	857	857
	Missouri	704	639	779
	Texas	957	805	1146
	Arkansas	822	822	822
Long grain	California	1697	1613	1785

Table 30. Embodied Irrigation emissions intensity (g CO2 equivalent/ m^3 water applied) for rice producing states.

	Mean	Lower Confidence bound 2.5%	Upper Confidence bound 97.5%
Arkansas	143	142	144
California	85.88	85.65	86.20
Louisiana	149	147	151
Mississippi	171	170	172
Missouri	146	145	147
Texas	599	547	671

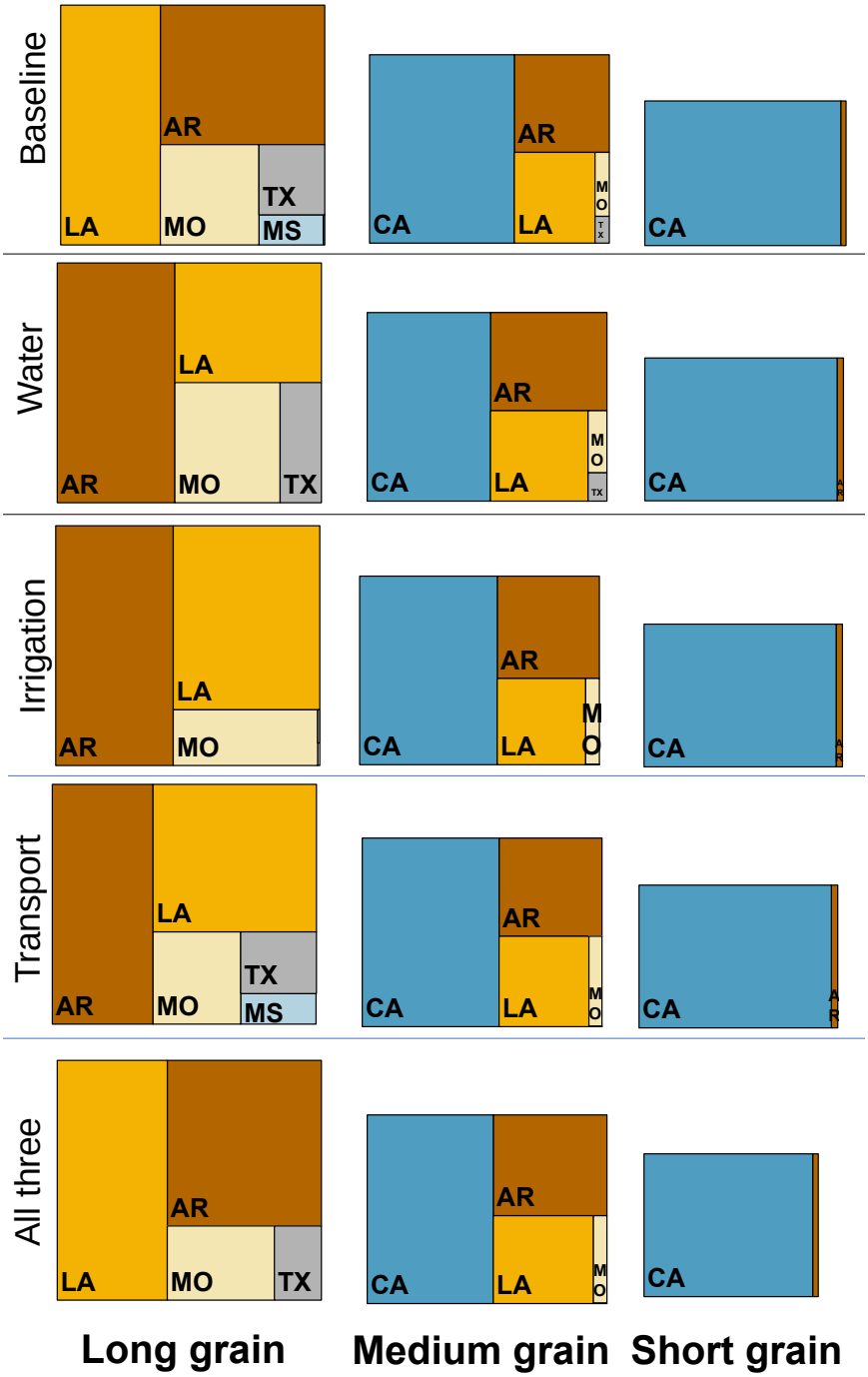


Figure 25. State-level export changes in rice types for optimizing virtual water

Figure 25 contains state-level export changes in rice types for optimizing virtual water (virtual water), optimizing irrigation emissions(irrigation), transport emissions (transport), and simultaneous reductions (all three) compared to baseline state-level exports. The size of each block of tree map represents comparative total production of each type of grain of rice in the U.S with long grain rice dominating total US rice production followed by medium grain and short grain.

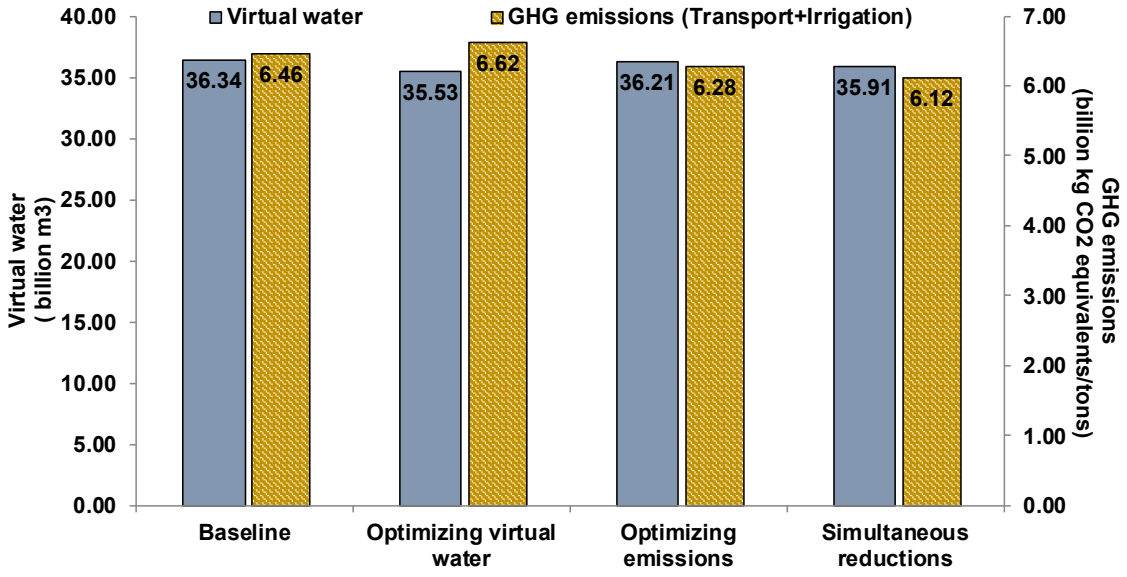


Figure 26. Robust optimization results for Γw=(1,10,1)

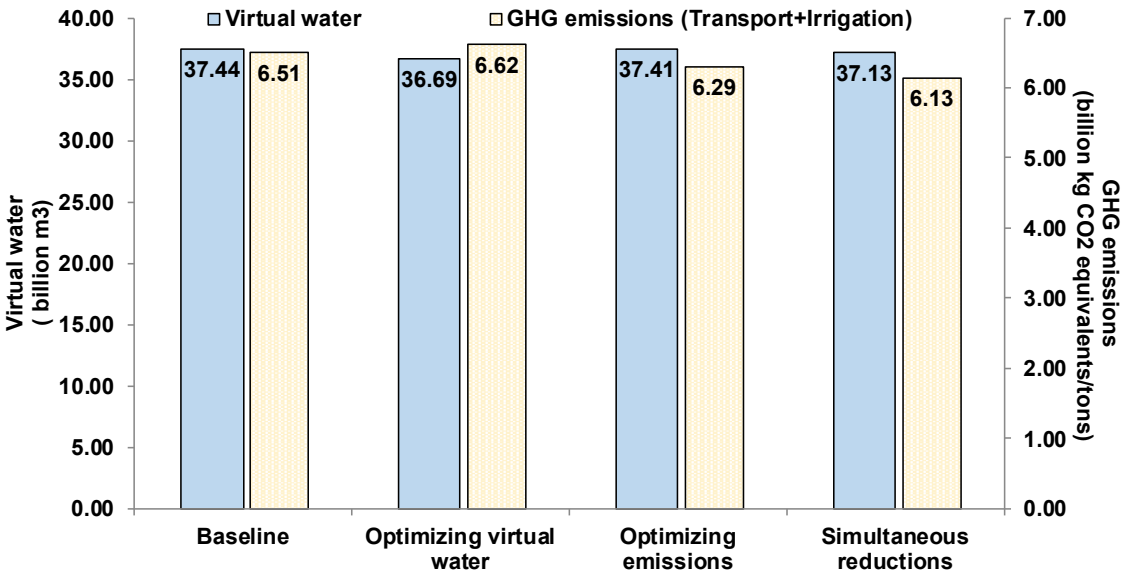


Figure 27. Robust optimization results Γw=(4,40,4)

Appendix D Supplementary Information for Chapter 5

Table 31. Food items included in Freight Analysis Framework

commodity group	Food groups	Items
03	Fruits	apples, apricots, avocados, blackberries, blueberries, cherries, dates, grapefruit, grapes, kiwifruit, oranges, olives, peaches, pears, plums, prunes, raspberries, strawberries, tangelos, tangerines
03	Legumes and nuts (referred to as legumes)	peanuts, pistachios, soybeans
03	Vegetables	asparagus, beans, broccoli, cabbage, carrots, cauliflower, celery, cucumbers, garlic, lettuce, melons, onions, peas, peppers, potatoes, pumpkins, spinach, squash, sweet corn, tomatoes
02	Grains	barley, corn*, rice, sorghum, wheat

* In 2012, 42% of corn was diverted to ethanol and not considered here.

We estimate the P fertilizer intensity (amount of P applied per ton of crop) for each crop and each state considered in the study. Figure 28-31 provides the distribution of P intensities across crop items. The boxplots represent 25th, 50th, and 75th percentile of the distribution. The range for

grains varies between ~3-18 lb P/ ton of crop, vegetables ~0.80-18 lb P/ton crop, fruits between ~0.75-23 lb P/ton crop, and nuts between 9-21 lb P/ton of crop.

Figure 28 shows distribution of Phosphorus application intensities for grains with values in pounds of phosphorus applied per ton of crop produced. The lines in the boxplots represent 25th, 50th and 75th percentiles. The end of the whiskers represent minimum and maximum values. The dots represent all the states that are producing these crops.

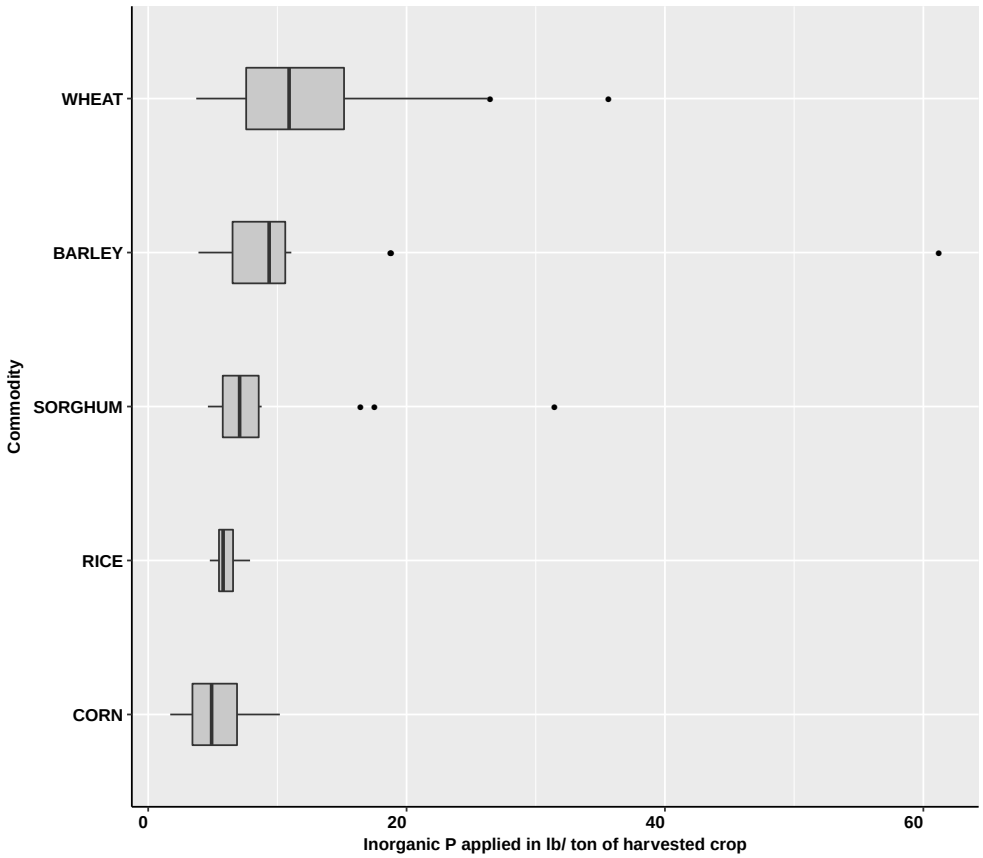


Figure 28. Distribution of Phosphorus application intensities for grains

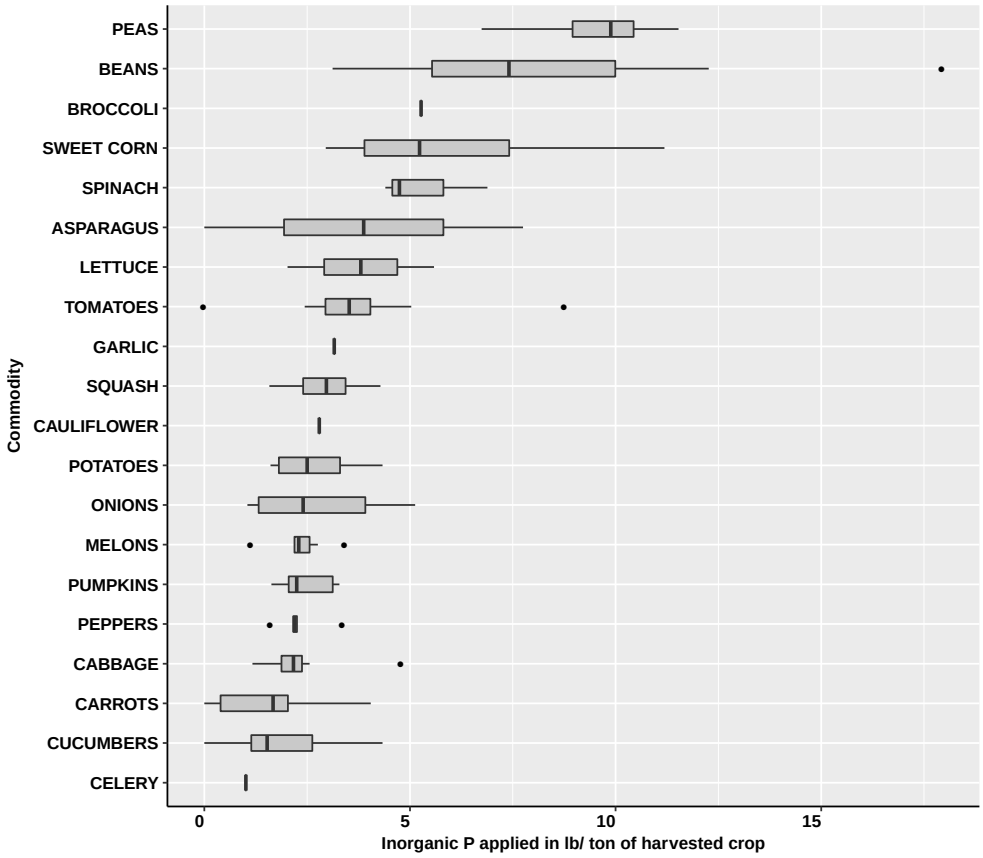


Figure 29. Distribution of Phosphorus application intensities for vegetables.

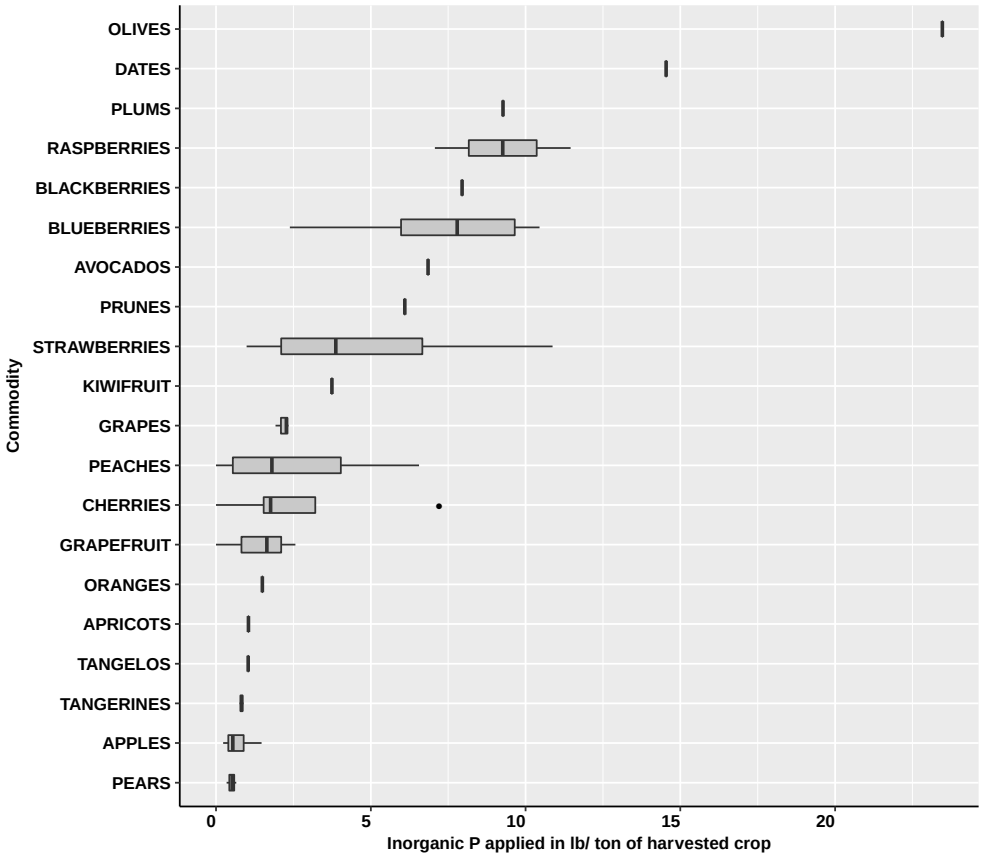


Figure 30. Distribution of Phosphorus application intensities for fruits

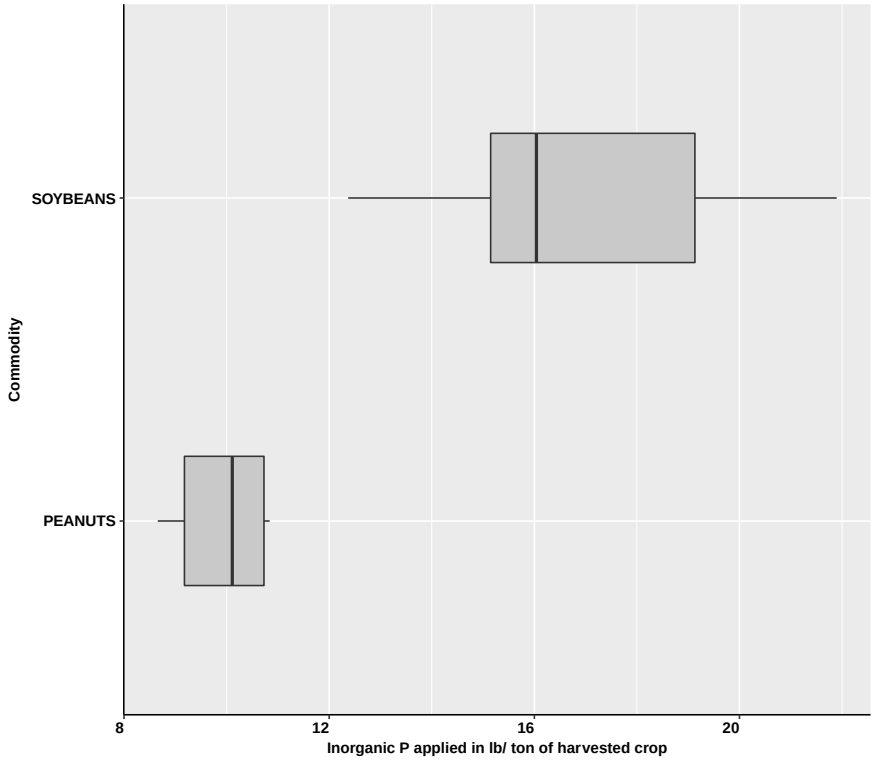


Figure 31. Distribution of Phosphorus application intensities for legumes

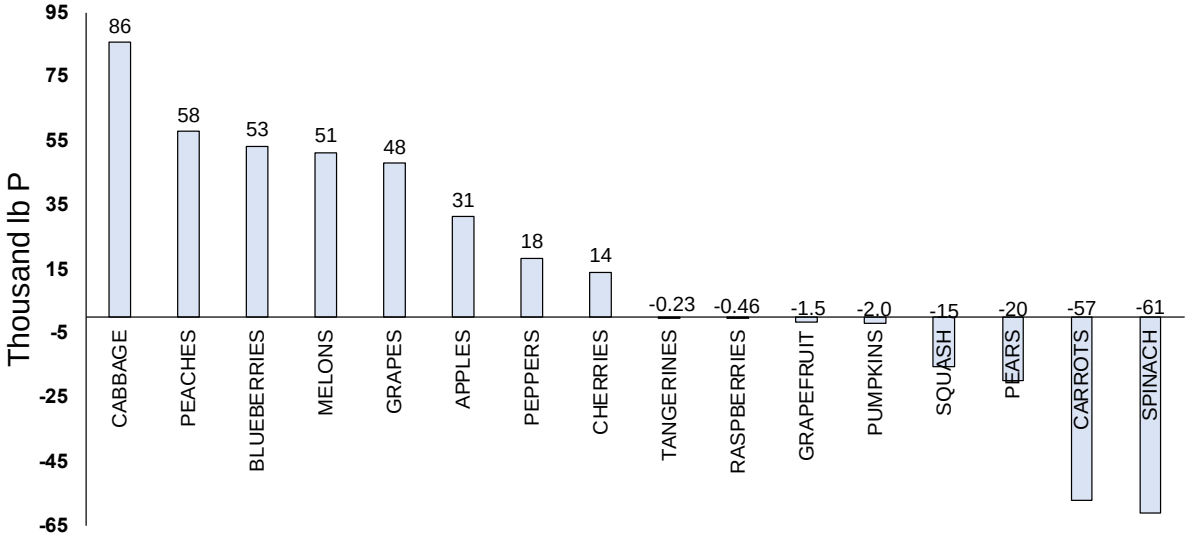


Figure 32. Embodied P Savings through domestic trade of fruits, legumes, and vegetables.

Table 32. Net savings and losses from total exports and imports out of each states through trade of cereal grains and fruits, legumes, and vegetables.

Grains				Fruits, legumes, and vegetables			
Origin State	Savings from exports (US tons)	Destination State	Savings from imports (US tons)	Origin State	Savings from exports (US tons)	Destination State	Savings from imports (US tons)
MT	-1.62E+04	WA	-1.40E+04	IL	-1.14E+04	LA	-2.19E+04
OK	-9.08E+03	KS	-7.13E+03	TN	-7.92E+03	WI	-3.96E+03
IL	-7.84E+03	ID	-5.94E+03	MO	-3.19E+03	MN	-3.76E+03
IA	-2.81E+03	NE	-4.13E+03	KY	-2.29E+03	NE	-2.01E+03
IN	-1.76E+03	MN	-3.59E+03	ND	-2.02E+03	MI	-7.52E+02
MO	-1.12E+03	GA	-3.12E+03	AZ	-4.86E+02	WA	-6.26E+02
KY	-9.27E+02	WI	-2.19E+03	ID	-3.92E+02	KS	-5.82E+02
AR	-5.34E+02	MI	-1.84E+03	GA	-2.51E+02	CA	-4.91E+02
NY	-1.17E+02	PA	-1.24E+03	AR	-1.54E+02	FL	-1.25E+02
OR	-4.64E+01	OR	-6.69E+02	TX	-4.60E+01	SC	-5.89E+01
GA	-4.43E+00	LA	-2.86E+02	NC	-2.76E+01	ME	3.73E+00
VA	-4.15E+00	CA	-1.02E+02	AL	-2.63E+01	CO	9.30E+00
AZ	0.00E+00	MS	-4.76E+01	PA	-7.29E+00	OH	1.04E+01
OH	2.10E+01	AZ	-1.75E+01	CO	-6.82E+00	ID	1.16E+01
NC	3.33E+01	WY	-1.23E+01	ME	-8.29E-01	NJ	1.87E+01

Table 32 continued

WY	4.58E+01	NY	-1.17E+01	OR	4.31E+01	AZ	2.77E+01
CA	4.60E+01	VA	7.26E+01	SC	4.88E+01	AL	2.91E+01
MS	5.64E+01	AR	2.93E+02	NJ	6.61E+01	SD	3.55E+01
LA	7.91E+01	SD	3.60E+02	WA	6.97E+01	NY	3.84E+01
TX	1.76E+02	NC	3.83E+02	NY	1.02E+02	OR	4.53E+01
WA	2.03E+02	CO	8.57E+02	CA	1.86E+02	PA	6.26E+01
PA	7.08E+02	OH	9.03E+02	VA	2.24E+02	TX	1.02E+02
ND	7.87E+02	OK	1.35E+03	FL	2.85E+02	AR	3.32E+02
CO	2.47E+03	MT	1.39E+03	MS	3.77E+02	VA	3.66E+02
NE	3.61E+03	IA	1.50E+03	SD	1.21E+03	GA	4.12E+02
ID	3.71E+03	KY	1.89E+03	MN	1.43E+03	ND	5.47E+02
MI	5.09E+03	IN	2.16E+03	IA	2.13E+03	KY	1.41E+03
SD	5.57E+03	ND	3.18E+03	NE	2.41E+03	TN	1.46E+03
MN	6.62E+03	MO	4.73E+03	KS	2.82E+03	IN	2.01E+03
WI	1.05E+04	TX	2.77E+04	OH	3.20E+03	IA	2.18E+03
KS	3.66E+04	IL	3.35E+04	WI	3.31E+03	NC	3.46E+03
				IN	3.51E+03	IL	1.01E+04
				MI	4.78E+03	MS	1.09E+04
				LA	1.50E+04	MO	1.37E+04

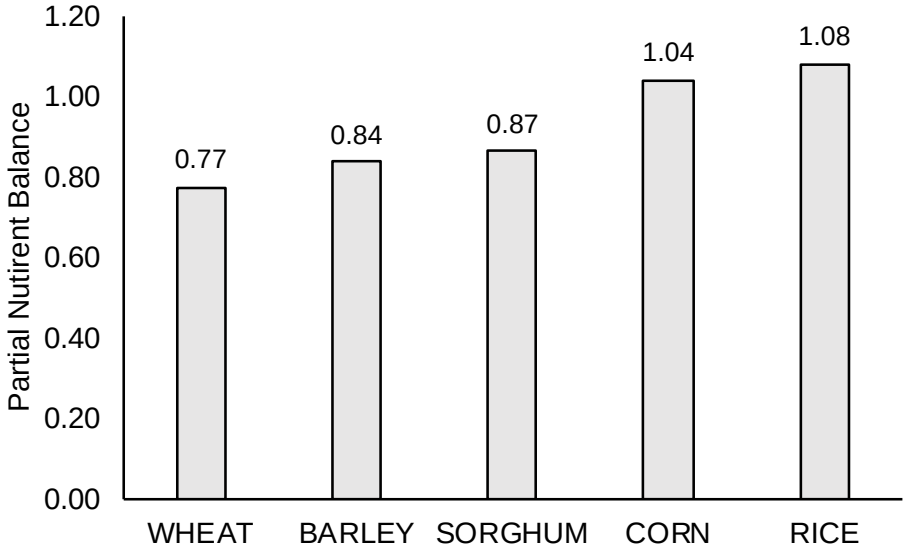


Figure 33. Average Partial Nutrient Balance (P removed in crop/ P applied) across grains.

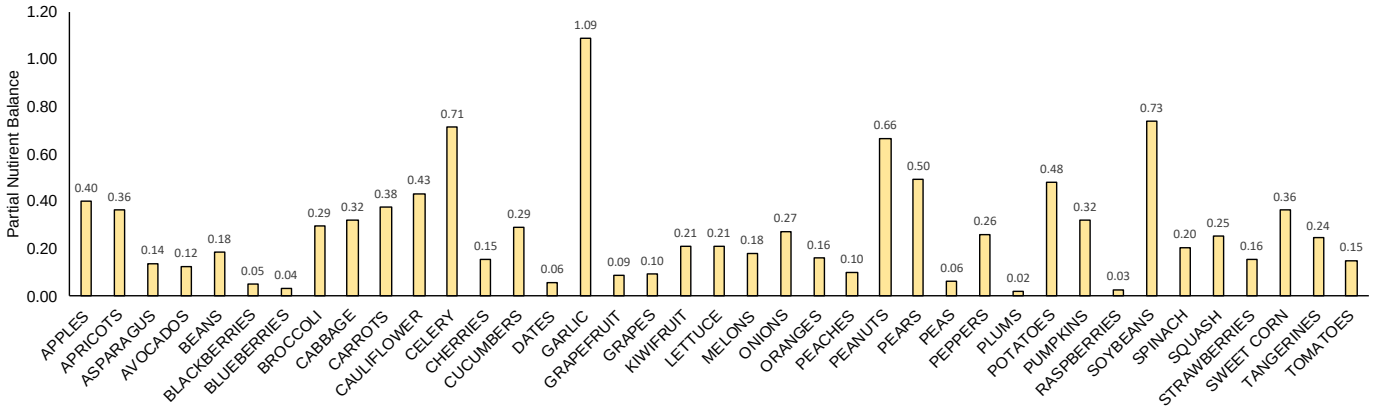


Figure 34. Average partial nutrient balance (P removed in crop/ P applied) across fruits, legumes, and vegetables.

Table 33. Average PNB for grains, fruits, legumes, and vegetables across states

Grains		Fruits, legumes, and vegetable	
State	Average PNB	State	Average PNB
AR	0.79	AL	0.61
AZ	0.66	AR	0.63
CA	1.31	AZ	0.15
CO	1.01	CA	0.32
GA	0.85	CO	0.29
IA	1.05	FL	0.27
ID	1.16	GA	0.21
IL	0.51	IA	0.76
IN	0.74	ID	0.34
KS	0.91	IL	0.33
KY	0.53	IN	0.76
LA	1.09	KS	0.80
MI	1.42	KY	0.64
MN	0.80	LA	0.79
MO	0.59	ME	0.26
MS	1.06	MI	0.32
MT	0.65	MN	0.50
NC	0.98	MO	0.59
ND	0.74	MS	0.68

Table 33 continued

NE	0.98	NC	0.29
NY	1.03	ND	0.54
OH	0.73	NE	0.89
OK	0.60	NJ	0.23
OR	1.49	NY	0.24
PA	0.97	OH	0.38
SD	0.84	OR	0.19
TX	0.89	PA	0.28
VA	0.55	SC	0.34
WA	1.52	SD	0.75
WI	1.58	TN	0.26
WY	0.74	TX	0.22
		VA	0.65
		WA	0.31
		WI	0.45

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