Final report

# U.S. Food Flows: A Coldchain Network Analysis of Freight Movements to Inform Local and Regional Food Issues

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*Disclaimer: The opinions and conclusions expressed do not necessarily represent the views of the U.S. Department of Agriculture or the Agricultural Marketing Service.*


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## Executive summary

This report documents network dynamics, geographic concentration and disparities in cold chain food supply networks for temperature-controlled food distribution. Perishable food supply networks are energy-intensive, provide nutritious foods, and have high economic value in U.S. food systems. As disruptions - both natural and human - change food systems, network analysis can provide useful insight on cold chain transportation infrastructure created by truck routes and refrigerated trucks, processing facilities, warehouses, electric charging stations, etc.. Understanding how the network structure shapes specific food movements can highlight unique transportation challenges and infrastructure needs for perishable foods, as well as reveal opportunities for regional market development. In this report we identify specific counties and regions that form the core of our food supply networks, and upon which we are highly dependent. We also identify counties and regions that are peripheral to national supply networks, where wholesale food distribution is not reaching rural underserved communities. These insights can help us to identify infrastructure necessary to improve food access.

The objective of this research was to better understand national food supply networks providing high value, cold chain dependent foods for US consumers. Both public and private sectors can use this research to understand supply chain risk, vulnerability to disruption, and regional adaptive capacity. This research is unique in three ways. First, this study analyzes how national food systems and supply chains operate at a local and regional scale, the scale where most food for US consumption is produced, and where system dynamics are first encountered. This is unlike prior studies which are conducted at a global scale and do not capture these dynamics. Second, it provides more granular information on food movements by using county level publicly available data. Third, it improves upon earlier work by separating the refrigerated portion of the primary total data on food, to better approximate refrigerated truck movements within the continental US, since most perishable food travels by truck.

We measured food movement from the point of processing (predominantly in rural areas) to the point of consumption (primarily in urban regions) and used food movements to reveal network infrastructure. We found that meats were the most important perishable products distributed by refrigerated trucks from point of processing to retail markets, given their very high monetary value and high weight. Perishable prepared foods (including dairy, juices, and frozen produce) ranked second (less value but slightly more mass than meat). Bakery items ranked third in cold chain importance in both value and mass. Fresh produce was fourth in value, although nearly comparable in mass to bakery movements. Some of the findings from our network analysis are:

(1) Meat supply networks, more so than but as well as perishable prepared foods networks, show geographic concentration. To lessen geographic concentration and its unintended consequences, targeted investments in transportation and logistics infrastructure are necessary to improve the structure of perishable supply networks.

(2) Counties surrounding Los Angeles form a super node, that is groups of counties that are close to each other in the network and are core to the network by moving high volumes of food. Counties around Chicago form a secondary super node in perishable food supply networks. Disruptions at these chokepoints, natural or human-induced, may profoundly impact downstream and upstream supply chain partners given their current importance in supply networks. Network improvements to food flow in these regions could be accomplished through

infrastructure development in nearby regions to lessen the pressure on networks in the super node counties, market policy to incentivize structural change, and tools to improve information and capital flow.

(3) There are counties and regions that are peripheral to national supply networks and could be more active in food networks but are not. Some of these counties are close to core counties in the network, indicating that targeted investments in cold chain infrastructure and small changes to business rules and relationships may improve the supply network structure so that these counties may readily access nearby wholesale assets. In low participation multi-county regions in the network, especially in areas where food is produced, modest investments in rural cold chain infrastructure could quickly address disparities in food access. For example, there is historical awareness that the Appalachian region requires special attention to address food and market access. This region showed us that interstate route development may be necessary but insufficient to improve supply networks in rural regions. Investment in logistics infrastructure in rural areas is another way to improve flow. In addition to Appalachia, our network analysis indicates two other regions are peripheral to national perishable food networks, that of Montana, North and South Dakota, and counties in Arizona, Texas, New Mexico, and other parts of the Southwest, despite those regions' agricultural contributions to food production.

## Introduction

Perishable food supply chains are energy-intensive, nutritious, and high-value parts of US food systems, making them particularly important to monitor if we are to meet public goals of food access, economic development and reduced GHG emissions. Improved food transport and distribution are critical for both mitigation and adaptation during disruptive events, such as climate change.[1] The goal of our research was to better understand national food supply networks for U.S. residents for high value, cold chain dependent foods. Understanding the network structures for these specific food movements highlights unique transportation challenges for perishable products. This study is an effort to advance our thinking on food systems resilience using data and methodology used to assess supply networks that may be applied in future studies.

Our methodology builds on earlier work to model food flows. Prior studies in this field are conducted at the global scale. However, viewing food systems and supply chains from a global scale will not capture system dynamics at other scales, especially the local and bioregional scales where most food is produced, and where system dynamics are first encountered.[2] Global scale analysis is also problematic because it obscures the tradeoffs that may be made at the local and bioregional levels.[3] Our research is unique in that it provides more detailed information on food movements by downscaling publicly available Commodity Flow Survey data to the county level and examining network characteristics that may help us determine food systems resilience. We graphed food network relationships between US counties to identify those that were critical to cold chain food movements and to explore the structure of the national cold chain food supply network. There are several network measures that characterize its health. For insight into network structure, we look at two centrality measures in this study. Centrality analysis measures how important or "central" a node is in a network.

Determining centrality is a standard network planning task for large vertically integrated supply chains. Degree of Connectivity indicates the number of connections a node – in our study, a county – has in a food supply chain network. Betweenness indicates how well counties are connected into the network through linear connections – such as interstate highways. Counties with high centrality have more network control. Centrality analysis allows supply chain managers and policy makers to monitor and take proactive steps to reduce bottlenecks in counties with high centrality and improve flow to regions with low centrality. As natural and human-induced disruptions alter food systems, this study may assist supply chain managers and transportation professionals to identify existing chokepoints in the critical cold chain transportation infrastructure and support targeted decision-making. The results provide a better idea of the network structure of food and where the network weak spots are limiting the flow of food, especially to low income, rural parts of the US.

We suggest that centrality may be used as a proxy for network resilience. Counties identified as core to the network are high efficiency. Counties that are peripheral to the network exhibit low efficiency. Those that lie somewhere in the middle are likely to contribute resilience to the system.

[1] C. Rosenzweig et al., 2020.
[2] Haila, Y., 2002.
[3] González-Esquivel, C.E., et al., 2015.

## Literature review

We reviewed over thirty journal articles and reports on food flow, cold chain, supply networks and supply chain resilience to provide context for the final report. This emerging field of study, accelerated by supply chain disruptions resulting from COVID-19 Pandemic, is rapidly progressing and may inform how the market is structured to ensure equitable food and market access. The literature review forms the basis for understanding the models and analysis used to characterize national food flow and its network structure, for developing the methodology for the current study, shaping data curation, and ways to interpret the findings.

Our food systems are complex sets of interactions between numerous entities - food production, wholesaling, processing, transportation, warehousing, and retailing. Over the last seventy years, studies show changes in food transportation concurrent with urbanization. At the city level, where once we moved food to people through a network of small independent grocery stores, we now move people to food using personal vehicles (and sometimes public transportation) to big box stores run by concentrated and vertically integrated companies.[4,5]

Understanding food supply "chains" as food "webs" brings environmental economics, agroecology and food sovereignty to the fore.[6] In his 2023 book The Nature of Supply Networks, Thomas Choi investigates this conceptual switch from chains to networks.[7] He explores the power dynamics between businesses in a supply network, noting that innovation and systems transformation rely on trust and cooperation between partners. Choi contends that supply network mapping is critical in this age of "regression to the tail", where extreme events are becoming more common and human global systems are increasingly connected, all the while natural systems are more profoundly impacted by human systems. He notes that during the COVID-19 Pandemic, companies operating with a supply network map were months ahead of their unprepared counterparts and moved quickly to mitigate supply chain disruptions. Significant regional differences in food network disruptions were observed during the Pandemic, reflecting differences in network structures.[8]

Lin, Dang, and Konar (2014) provided the first network analysis of US food systems. They used US Department of Commerce 2012 Commodity Flow Survey (CFS) data to describe how agricultural products in aggregate move through the US in the context of global food movements. CFS reports aggregated data at the state level, obscuring finer detail in movements, especially in rural areas. The 2014 study aggregates data for seven agricultural products categories, including large-scale grain movements. Empirical findings indicated that there are nine core nodes within a network of 123 nodes, with 4,198 links between nodes. The core nodes play a central role in network architecture for agricultural products, so disruption at these points may lead to cascading disruptions in food movements throughout the US and with our trading partners.

To better capture food movements, Lin, Ruess, Marsten, and Konar (2019) developed a novel model of food flows at the county scale, called the Food Flow Model.[9] The Food Flow Model integrates machine learning, network properties, production and consumption statistics,

[4] Tangires, H., 1997.

[5] *As we heard from several speakers at the 2020 Transportation Research Board conference in Washington, D.C., eCommerce is disrupting this pattern and COVID19 accelerated eCommerce, as companies with deep capital assets like Amazon increasingly distribute food through fulfillment centers, termed "dark stores", located near metro-regions to reduce the cost of last-mile delivery.*

[6] Francis, C., et al., 2013.

[7] Choi, T., 2023.

[8] Peterson, H.H., et al., 2023.

[9] Lin, X., et al., 2019.

mass balance constraints, and linear programming. They downscaled empirical information on food flows using the Freight Analysis Framework 4 (FAF4) 132 metro regions, derived from CFS. The Food Flow Model provides data on 3,142 counties and county-equivalents of the United States. In addition to CFS and FAF4 data, data from six additional sources was used to capture food production and processing, transportation assumptions, consumer demand, and port activity. This analysis of subnational food flow estimates may then be used to determine the food supply network's critical infrastructures, enable spatially detailed footprint assessments, and identify vulnerable points in the system.

Recent research built on the Food Flow Model to estimate food flows between counties over time. Karakoc, Wang, and Konar (2022), developed an improved version of the Food Flow Model to estimate food flows (kg) between all county pairs across all food commodity groups for the years 2007, 2012, and 2017 (which required estimating 206.3 million links).[10] They determined the core counties to the US food flow networks through time with a multi-criteria decision analysis technique. The Food Flow Model used data to capture the flow of all agricultural products but does not specifically focus on cold chain food flows or break down specific commodity supply chains.

Karakoc and Konar (2021) also considered the relationship between network efficiency and network resilience at the global food trade level.[11] They found that when looking solely at the geographic and physical network structure, the two appear to be in competition. Networks that contain core nodes are more efficient but also more vulnerable. Networks with a lattice structure are less efficient but more resilient to disruption. As the food network becomes denser, and the quantity of goods traded increases, the differences between efficient and resilient network structures fade and a cooperative relationship may emerge. Trade intensity and network structure together can achieve higher efficiency and resilience simultaneously. This requires that more nations (the nodes in this particular study) participate in trade rather than depend on a few nations to supply the bulk of food products, as is the case with the grain trade. They point out that the global grain trade network is the least well-designed network, comparatively.

Earlier studies on the relationship between efficiency, diversity, and resilience in food systems explored carbon transfer between predators and prey in the Everglades, concluding that systems must be sufficiently organized to allow for flexibility (resilient), a characteristic of the system structure.[12,13] There is a sweet spot, a "window of vitality", between efficiency and diversity that allows the system to self-organize and evolve during disruption and change. From the engineering perspective, Woods (2018) captures this idea of flexibility and unused capacity in the term "adaptive capacity" or "graceful extensibility", that is, the ability of a system to extend its capacity and to adapt to surprising and changing circumstances.[14] Further, resilience can be considered in terms of brittleness, tradeoffs, human initiative, and reciprocity (cooperation).[15]

Others describe social resilience where conventional resilience (recovery after disruption) and transformational resilience (systemic adaptation and renewal) are considered along with equitable resilience (access to power and resources).[16] Shifting conceptually from supply chains to supply networks or "food webs" provides an opportunity to address issues of power

[10] Karakoc, D., et al., 2022.
[11] Karakoc, D, & Konar, M., 2021.
[12] Ulanowicz, R.E., et al., 1996.
[13] Ulanowicz, RE., et al., 2008.
[14] Woods, D.D., 2018.
[15] Woods, D.D., 2019.
[16] Matin, N., et al., 2018.

dynamics, trust and cooperation between network participants and governance.[17,18,19] Another recent study found that vertical diversification reduces an individual firms' resilience, whereas horizontal diversification increases firms' resilience, suggesting that supply chain governance (and information access) is an important component of resilience.[20]

Networks, whether they be transportation networks, food networks or social networks, can be characterized by measures other than resilience, such as system asymmetry, interconnectedness, nonlinearity, and tipping points.[21] Future studies on food networks are needed to explore these dimensions, as well.

## Methodology

This study focused on cold chain food flows and the networks they create, considering movements of refrigerated trucks between counties, the nodes in this study, in the continental US. We measured food movement from the point of production, where possible (predominantly in rural areas) to the point of consumption (primarily in urban regions). This involved several steps. First, we created a Community of Practice (CoP) to learn about the food flow model, guide data choices and model development. Linking modelers with domain experts is a transformative approach to engineering design. The CoP brought deep domain expertise from applied economists, planners, social scientists, and supply chain practitioners from across the US. This team met almost monthly throughout the project and evaluated the project from its inception.[22]

Second, we collaborated with the University of Illinois, Urbana Champaign's Konar Lab to understand and refine the Food Flow model, originally developed in 2019, refine existing and identify additional data sources, run the model and review findings with the CoP. The refined modeling offers several advantages. (1) It provides more granular information on food movements by downscaling publicly available 2017 CFS and FAF data to the county level. (2) It employs machine learning strategies to navigate large databases and capture the relationships that exist in the data, and (3) it refines the transportation analysis from straight-line distance to routing on actual roadways.[23]

Third, using the 2017 network statistics provided by Konar Lab we conducted further analysis on food networks using centrality measures at the county, state, regional, and multistate scales. These statistics allow us to understand the network structure of perishable foods. We considered two ways to measure centrality: 1) degree of connectivity measuring the relationship between node (county) connectivity to the network and 2) betweenness which measures a node's importance in the overall network.[24] These measures are more precisely defined below.

Fourth, we identified ares where the supply networks resulted in high- and low-flow conditions in order to highlight weakness and adaptive capacity in these supply chains. Finally, we estimated CO2 emissions from cold chain food transport. The next section discusses the model and the centrality analysis in detail.

[17] Francis, C., et al., 2013.
[18] Busch, L., 2018.
[19] Choi, T., 2023.
[20] Stevens, A.W., & Teal, J., 2024.
[21] Hynes, W., et al., 2020.
[22] The CoP is now taking these data and information derived from modeling for further analysis. See appendix one for participants and their affiliation in the CoP.
[23] Prior studies use the Haversine distance, meaning "as the crow flies" or the shortest distance between two points on a sphere.
[24] Assessing centrality has been used for decades in the private sector to optimize proprietary global supply chain networks. Quetica, 2016. Also Choi, T., 2023.

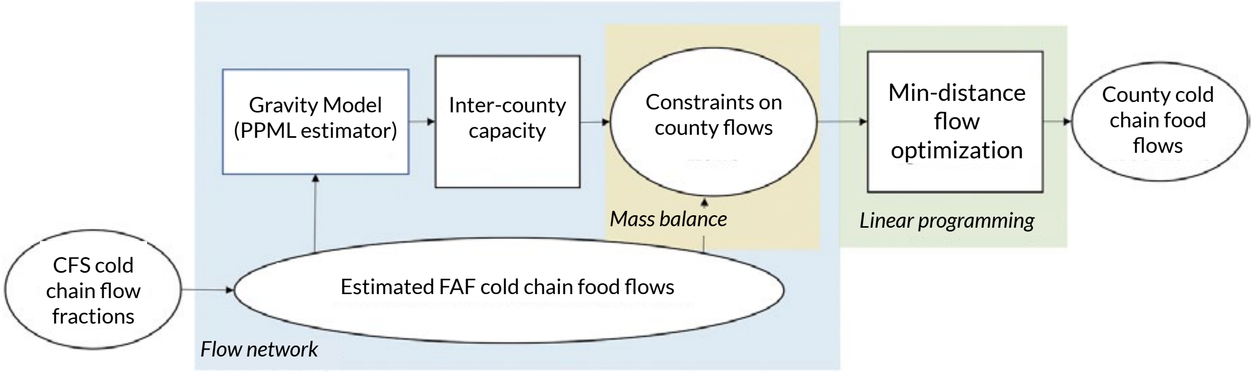
## Modeling

Though several proprietary models exist that use public and private data for supply chain management, these models lack transparency and are costly to access. The Food Flow model developed and used by the Konar Lab is open source, fully transparent, and easily adapted to address specific issues, such as cold chain flows in the food supply network (Figure 1).

The CFS and FAF data provide information on food flows at a relatively aggregated geospatial level. Using the CFS and FAF data, the Konar Food Flow Model uses a process called downcasting to estimate flows at a more granular, county level. The process involves estimating using a statistical model that relates food flows between FAF zones to variables describing those zones, including data on population, employment, income, production, and storage (Table 1). The estimated model is then applied using similar county-level variables—along with additional constraints that ensure estimated county flows sum to FAF totals—to estimate county-level flows. The model used in this process draws from eleven data sources and has been peer reviewed.

Using the estimated county-to-county flows, we then assigned the origin-destination flow to the shortest-distance route on the national highway network. Prior studies used haversine distance, but the use of roadway travel distance provides a more precise estimate of miles traveled. This improved accuracy, although the approach is limited by its inability to differentiate between roads designated for freight travel or capture delivery logistics chosen based on congestion issues or client locations.

***Figure 1.*** *Schematic of the model components to estimate cold chain food flows*




## Data

There are multiple, distinct supply chains that make up supply networks. This study improves upon earlier work by refining and curating data used in modeling to better approximate food movements. We used the refrigerated portion of the primary data only, and focused on truck movements, since most perishable food travels by truck.

As with prior studies using the Food Flow Model, we used data from CFS, and its refinement known as the Freight Analysis Framework (FAF).[25] The Commodity Flow Survey for 2017 broke down food movements based on temperature control for each of the four freight modes: air, rail, truck and multimodal. It then broke down movements by broad categories termed Standard Classification of Transported Goods (SCTG).[26] This study modeled food

[25] The FAF refines CFS data for the last five CFS five-year cycles. FAF5 and the 2017 CFS were released in Spring 2021.
[26] There are 42 two-digit SCTG categories, and the first seven related to food. Each category contains five-digit categories of items.

movements by weight and the value of food distributed but movements by value were not modeled in this study.

There are distortions inherent in CFS survey data, as discussed at the Commodity Flow Survey workshop held virtually September 24, 2020, organized by the Transportation Research Board's Standing Committee on Freight Transportation Data.[27] First, CFS over-emphasizes large movements and may not capture smaller movements adequately. Second it is uncertain whether CFS data captures large grower shipments (as opposed to shipments from another entity, such as a wholesale company) which are increasingly common for west-to-east movements. Third, ports which may not be the true shipping or receiving points, are overemphasized in CFS, while much of the food distribution data is privatized and so may be unavailable. CFS fails to accurately capture seasonal movements which are critical to understanding the movement of perishable food and the non-linear nature of food systems. Despite its limitations, CFS is the best available public data source on food movements.[28]

***Table 1.*** *The cross-sectional dataset and references used in the cold chain Food Flow gravity model*

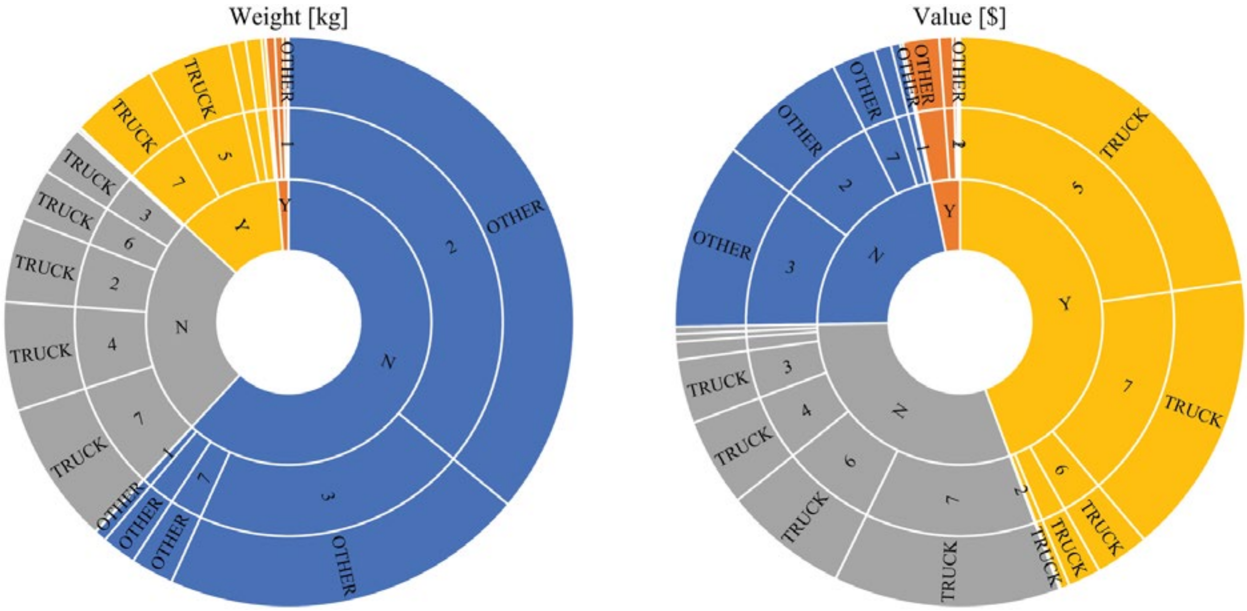
| Data | References | Description | Purpose |
|---|---|---|---|
| CFS | Commodity Flow Survey (2017) | The CFS provides an in-depth multimodal view of national freight flows. Data for over 100,000 shippers include the origin, destination, type of commodities, value and weight of the freight and mode of transit | CFS data guided us in determining the focus of the study. We used CFS data to calculate the refrigeration coefficients for each FAF region pair |
| FAF v5 | Oakridge National Laboratory (2020) | The FAF incorporates supplementary data to estimate freight quantities from establishments that are not covered by the CFS, which serves as the framework's foundation. FAF data use the same divisions of regional areas, commodity categories, and modes of transportation as CFS statistics | FAF data are used to train the FAF region-level regression model as well as to provide mass balance for county food flows simulation |
| Distance | OSRM (Luxen and Vetter 2011), United States Census Bureau (2020) | Travel distance via roadway between all OD pairs | Travel distance is used in the regression model and to assign food flows to shortest paths in the linear programming algorithm. Travel distance is also used to calculate the carbon emissions in cold chain food flows |
| Employment | United States Census Bureau (2019) | Employment number by NAICS by county | As we assume the same production efficiency across the CONUS, employment is treated as production equivalents. We extracted the employment data of industries related to "meat" and "prepared foodstuffs" by matching the NAICS code to the SCTG code. Employments are variables in the regression model |

[27] Report authors Konar and Miller attended the workshop in person and discussed our interactions with the full research team. An official account of the meeting was prepared by Hernandez, S., January 2021.
[28] See Table 1 for more information on CFS and FAF.

| Data | References | Description | Purpose |
|---|---|---|---|
| IO table | US Bureau of Economic Analysis (2019) | Latest domestic commodity by commodity IO table in 2012 describes the demand and consumption relationships between 405 industries | The sum of the multiplication of production equivalents (employment) of all industries and input requirements of "meat" and "prepared foodstuffs" commodity for unit production in each industry represents consumption equivalents of "meat' and 'prepared foodstuffs' are variables in the regression model |
| Population | United States Census Bureau (2019) | Population data per county | Population is a variable in the regression model |
| Personal income | United States Census Bureau (2019) | Personal income per county | Income is a variable in the regression model |
| Unprocessed food and livestock production | Unprocessed food and livestock production | Agricultural production and livestock inventory data by county on goods that are important raw materials for 'meat' and 'prepared foodstuffs' | Production of unprocessed fresh produce and livestock are variables in the regression model |
| Meat processing industry data | US Department of Agriculture (2021) | The number of large and medium meat processing plants by county | Meat packing capacity by county is a variable in the regression model |
| Refrigerated storage data | Infrastructure Foundation-Level Data (2019) | Refrigerated storage by county | Total refrigerated storage capacity by county is a variable in the regression model |
| Port trade data | US Bureau of Transportation Statistics (2020) | Data on the value and weight of shipments made by the United States to Canada and Mexico, broken down by commodity and US port of entry or exit | Port-level trade data are collected and assigned to the counties in which they are located. We consolidated the industries corresponding to the 'meat' and 'prepared foodstuffs' and keep only those freight flows that utilized the trucking mode. The amounts of import and export from/ to port counties are variables in our regression model |

We found that cold chain movements are low weight and have high economic value relative to shelf stable commodities. This is illustrated below. The focus of the study is on perishable food moved by truck, the gold segments. Other perishable products moved by other transportation modes are in the orange segments. Shelf stable items moved by truck are depicted in gray, while similar items moved by other modes such as rail, barge and air are dark blue. This study modeled food movements by weight, the first "iris" in this figure. The second "iris" illustrates the value of food distributed and was not modeled in this study.

***Figure 2.*** *Food flows in the United States by weight and value*




***Source:*** *US Census Bureau, Commodity Flow Survey 2017. Graphic – Junren Wang.*[29]
***Notes:*** *1.'Y' represents cold chain food flows; 'N' represents the non-refrigerated supply chain. 2. The numbers represent food commodity groups as given by the SCTGs in Table 2. 3. Food SCTGs are further broken down by transportation mode: "truck" and "other". "Other refers to the sum of rail waterway, air, and multimodal freight transport. 4. The colors divide the modal and perishable categories. The gold slices represent the focus of the study: perishable food moved by truck.*

The CFS organizes food movements in seven two-digit SCTG categories (Table 2). The categories represent a mix of products at the five-digit level, some similar and some dissimilar (for example, Table 3). For example, SCTG 03 includes 'Agricultural Products Except for Animal Feed, Cereal Grains, and Forage Products' and includes fresh produce and large-scale soybean movements. Produce was originally included in the project scope, but Figure 2 shows that SCTG 03 does not have much refrigerated transport, either in terms of mass or value (note that in the 'Y' arc the SCTG 03 variable does not show up). This means that SCTG 03 data related to cold chain food flows was minimal and insufficient to model. Instead, we focused on the bulk of cold chain food flows, which are SCTG 05 and 07, and then limited the study to refrigerated portions. SCTG 05 'Meat, Poultry, Fish, Seafood, and Their Preparations' (Table 3) is the movement of meat from the point of slaughter to sale.[30]

[29] Wang, J., et al., 2022.

[30] Our findings do not include the movement of live animals, SCTG 01 "Live Animals and Fish", to the point of harvest (SCTG 05), since live animal movement is not part of the cold chain. Future modeling of SCTG 01 will be necessary to understand the full meat supply network.

**Table 2.** *List of SCTG food commodity groups*

| SCTG code | Food Commodity |
|---|---|
| 01 | Live animals and fish |
| 02 | Cereal grains |
| 03 | Agricultural products (except for animal feed, cereal grains, forage products) |
| 04 | Animal feed, eggs, honey, other products of animal origin |
| 05 | Meat, poultry, fish, seafood and preparations |
| 06 | Milled grain products and preparations, and bakery products |
| 07 | Other prepared foodstuffs, fats and oils |

***Table 3.*** *Detailed list of SCTG 05*

| SCTG 05 | Meat, poultry, fish, seafood, and preparations |
|---|---|
| 05111 | Meat, except poultry, fresh or chilled |
| 05112 | Meat, except poultry, frozen |
| 05121 | Poultry, fresh or chilled |
| 05122 | Poultry, frozen |
| 05130 | Meat, salted, in brine, dried, or smoked, including smoked hams, pork bellies, back bacon, cottage rolls, pickled beef, edible flours and meals, and pig or poultry fat, not rendered |
| 05201 | Fresh or chilled fish including fillets |
| 05203 | Fish, salted, in brine, dried, or smoked, and edible fish meal |
| 05204 | Aquatic invertebrates, live, fresh, shilled, frozen, salted, in brine, or dried, and crustaceans in shell (such as lobsters, shrimps, crabs) cooked by steaming or by boiling in water |
| 05310 | Preparations, extracts, and juices of meat including poultry (except soups and broths, see 07720) |
| 05320 | Preparations, extracts, and juices of fish or seafood (aquatic invertebrates) (except soups and broths, see 07720) |

***Source: US Census Bureau, https://bhs.econ.census.gov/bhsphpext/brdsearch/scs_code.html Notes: 1. This project modeled only the refrigerated portion of this category. 2. Data was available at the two-digit level. 3. Data at the three- or five-digit level may be available with special permission.***

SCTG 07 'Other Prepared Foodstuffs, Fats and Oils', referred to as 'prepared foods' in this study, includes carbonated drinks, oils, potato chips, and sugars (Table 4)**.** Since dairy is the food item within SCTG 07 most likely to be refrigerated, we assume that dairy comprises much of the weight in this category. However, the category also includes frozen and otherwise prepared perishable fruits and vegetables. 'Fresh cut' and other minimally prepared fruits and vegetables would be included in this category. These are: frozen vegetables (SCTG 07210); other processed or prepared (SCTG 07229) vegetables; other processed or prepared fruit (SCTG 07239); frozen fruit and vegetable juices (SCTG 07241) and processed eggs (SCTG 07791). The nine states in the USDA's Economic Research Service's "Fruitful Rim" region[31] likely reflect cold chain streams for fruits and vegetables, as may other states.[32]

[31] The Fruitful Rim is comprised of parts of nine states along the west and southern coasts – Washington, Oregon, Idaho, California, Arizona, Texas, Florida, Georgia, and South Carolina. These regions produce and process large amounts of fruits and vegetables for shipment to other states and internationally.

[32] USDA Economic Research Service Farm Resource Regions, accessed 5/1/2024. https://www.ers.usda.gov/webdocs/publications/42298/32489_aib-760_002.pdf

***Table 4.*** *Detailed list of SCTG 07*

| SCTG 07 | Other prepared foodstuffs, fats and oils |
|---|---|
| 07111 | Milk and cream, unconcentrated and unsweetened |
| 07112 | Milk and cream, in powder, granules, or other solid form |
| 07119 | Other prepared foodstuffs, fats, and oils, not elsewhere classified, including evaporated or condensed whole milk |
| 07120 | Cheese and curds |
| 07130 | Ice cream, ice milk, sherbets, and ices (excludes frozen yogurt, see 07199, and ice cream and ice milk mixes, see 06399) |
| 07191 | Butter and other fats and oils derived from milk |
| 07199 | Other dairy products, including yogurt, buttermilk, sour cream, whey, and casein (Excludes mixtures of butter and vegetable oil, see 0743x, preparations based on milk see 06399, eggnog and flavored milk drinks, see 07899 |
| 07210 | Frozen vegetables and vegetable preparations (including french fries and vegetable mixtures) |
| 07221 | Potato chips, including from potato flour preparations |
| 07229 | Other processed or prepared vegetables (including canned and pickled vegetables, relishes, and olives, but excluding: frozen or dried vegetables, see 03221, 03229, or milled vegetables, see 06299; soup mixes, see 07720; tomato sauces, see 07711; or other sauces, see 07719 |
| 07231 | Jams, jellies, marmalades, fruit or nut purees, and fruit or nut pastes |
| 07232 | Processed or prepared nuts, peanuts, or seeds (except shelled, see 03342, purees and pastes, see 07231, but including roasted nuts and peanut butter |
| 07239 | Other processed or prepared fruit, including frozen or canned fruit (except dried, see 0333x) |
| 07241 | Frozen fruit and vegetable juices (does not include beverages based on juices, such as ades or nectars, see 078xx) |
| 07301 | Processed coffee, including roasted beans, decaffeinated or instant coffee, and coffee substitutes such as roasted chicory |
| 07302 | Fermented (processed) tea, including tea bags and decaffeinated tea |
| 07303 | Spices, including unprocessed spices |
| 07410 | Animal fats and oils and their fractions, not chemically modified, includes fats and oils of fish or marine mammals (does not include inedible flours, meals, and pellets, see 04120) |
| 07421 | Soybean oil |
| 07422 | Colza (canola) oil |
| 07423 | Corn oil |
| 07429 | Other fixed vegetable fats and oils and their fractions, including peanut, olive, palm, sunflower, safflower, cottonseed, coconut (copra), palm kernel, mustard, linseed, castor, tung, sesame, jojoba, or wheat germ oil, not chemically modified (except byproducts of wet corn milling, see 04199, and oil seed waste and residues, see 04140) |
| 07431 | Non-liquid margarine (for liquid margarine, see 07439) |
| 07432 | Shortening |
| 07439 | Chemically modified fats and oils, animal or vegetable waxes, and prepared edible fats, not elsewhere classified. Including margarine, vegetable shortening, blended salad oils, crude glycerol, glycerol waters and lye. (Excludes oils and fats treated for use as biodiesel, see 18210.) |
| 07440 | Flours and meals of oil seeds (except flours and meals of mustard, see 07719, and oil seed waste and residues, see 04104) |
| 07501 | Raw cane or beet sugar, in solid form |
| 07502 | Refined cane or beet sugar and chemically pure sucrose, in solid form, including icing or cubed sugar |
| 07503 | Glucose (corn sugar) and glucose syrup (corn syrup) |

| SCTG 07 | Other prepared foodstuffs, fats and oils |
|---|---|
| 07509 | Other sugars in solid form, molasses, and sugar syrups with no added flavoring or colorings, not elsewhere classified, including maple sugar and syrup, chemically pure fructose and maltose, and invert sugars (excludes byproducts of sugar extraction, see 04199. Syrups with added flavor / color see 07793) |
| 07611 | Sugar confectionery not containing cocoa, including sugar candy, and nuts, nut pastes, and fruit, fruit peel, and vegetables preserved by sugar glace products (except sugarless gum see 07799) |
| 07612 | Chocolate confectionery including chocolate-coated nuts |
| 07620 | Cocoa beans, paste, butter, and power, and cocoa preparations including instant chocolate |
| 07711 | Tomato sauces (including ketchup and chili sauces) |
| 07719 | Other sauces and sauce mixes, including prepared mustard, mustard flours and meals, soya sauce, mayonnaise, salad dressings including dried, ad mixed condiments and seasonings, not elsewhere defined |
| 07720 | Soups and broths (including mixes) and baby or dietetic foods |
| 07731 | Syrups and concentrates used in food preparations or beverages |
| 07732 | Flavoring powders, extracts, or essences including cocktail mixes |
| 07791 | Processed eggs including egg albumin |
| 07792 | Yeasts and baking powder |
| 07793 | Sugar syrups with added flavors and / or colors, including table syrups |
| 07799 | Edible preparations, not elsewhere classified, including protein concentrates, tofu, vegetable preparations for flavoring, jelly powders, concentrated fruit juice fortified with vitamins or minerals, and vinegar |
| 07811 | Carbonated soft drinks |
| 07819 | Other sweetened or flavored water |
| 07891 | Water, unsweetened and unflavored, including potable, spring, carbonated or mineral |
| 07899 | Ice and other non-alcoholic beverages, including soya, almond, coconut, chocolate, and other milk drinks, and juices fortified with vitamins and minerals, not concentrated, and not elsewhere classified (excludes dry ice / carbon dioxide see 20241) |

***Source:*** *US Census Bureau, https://bhs.econ.census.gov/bhsphpext/brdsearch/scs_code.html Notes: 1. This project modeled only the temperature-controlled portion of this category. 2. Data was available at the two-digit level. Data at the three- or five-digit level may be available with special permission. 3. Most of these product categories are shelf stable. 4. Dairy (071xx) and perishable processed foods (072xx, 077xx) are categories within "other prepared foodstuffs, fats and oils" that are most likely to be perishable, although we don't have information by sub-category. Highlighted codes are most likely to be refrigerated.*

## Network Centrality Analysis

We used the county scale network statistics provided by Konar Lab to analyze network structures for perishable foods. There are several ways to use these statistics to understand how the network is structured so we concentrated on two centrality measures in this report: degree of connectivity and betweenness. First, we use degree of connectivity (including degree in and degree out) to measure how many connections any single county has to other counties in the food flow. The more connections a county has, the higher the county's degree of connectivity. Degree-in refers to product moving in, and degree-out refers to product moving out. Karakoc and Konar (2021) found that flow direction (in or out) is less important to node centrality at the village scale than it is at the national and global scales.[33] Since a county is closer in scale to a village than a nation, we used the degree measure, rather than parsing degree in and out.

The second centrality measure we used was betweenness. Betweenness indicates the pathways between counties. Those counties that are enroute to other counties have more control

[33] Karakoc, D., & Konar, M., 2021.

over the network and the flow of food. Betweenness indicates how frequently a county connects with other counties in a network, and therefore reflects access to transportation infrastructure. Together, these measures indicate where food supply chains are geographically concentrated and food is plentiful, as well as where farmers may have difficulty entering the wholesale market and consumers may have difficulty accessing food due to missing connections.

The relationship of connectivity and betweenness is similar across spatial scales.[34] We used the relationship between degree of connectivity and betweenness, referred to in this report as centrality, to analyze and graph national supply chain network relationships for meat and perishable prepared foods. We offer centrality as a proxy for system resilience, where high betweenness connectivity may indicate relative brittleness in the network and low values indicate insufficient network infrastructure to support flow, relative to other counties.

Social resilience (the combination of conventional, transformational, and equitable resilience) may be roughly identified through this approach. Our analysis highlights counties that are extremely important in food supply networks, as well as under-utilized and underserved counties peripheral to the network. As illustrated in the study of the global grain network, as more nodes participate in food flow, systems resilience and efficiencies complement each other.[35] Balancing trade intensity across the network structure can achieve higher efficiency and resilience simultaneously, and improves social resilience. Centrality analysis points to strengths and weaknesses both upstream and downstream in the supply chain, to address conventional resilience. For instance, if we know that there is a severe weather event in a county that is extremely important to the supply chain, downstream partners that rely on food shipments from those counties will know that they are also vulnerable to disruption.

We compared regional perishable meat and prepared foods supply chain networks across multicounty regions to investigate differences and similarities in network structures organized around the Los Angeles metro region, the Twin Cities metro region and the Miami metro region. (Detailed regional attributes and counties are listed in Appendix Two.) Geographic concentration of meat and perishable prepared food networks is strongly evident. From these results, our team discussed the need to find ways to quantify geographic network resilience at both the national and regional levels. To further illustrate scale differences, we added Michigan's rural Upper Peninsula to the analysis, where we found that this region is peripheral to national distribution network, more so than the urban regions included in the study.

Using our centrality measure, we identified core and peripheral counties in the network using hotspot analysis and state by state comparisons. This was based on the logic that those counties in the top tier of core network counties had less adaptive capacity, equating core counties with highly efficient networks. We also identified counties on the periphery of national distribution networks since these counties may not have sufficient wholesale infrastructure to participate in national cold chain networks. Infrastructure could include Primary and Secondary Freight Routes as defined by the US Department of Transportation, roads and bridges capable of supporting 53' refrigerated trucks twelve months of the year, cold storage warehousing, and processing facilities. California State University mapped centrality values to identify spatial clusters using cluster and outlier analysis. To qualify as a statistically significant hot spot indicating high network centrality (pink) or cold spot indicating low centrality (light blue) on the map, a county was surrounded by other counties with statistically significant high or low

[34] Lin,X., et al., 2019.
[35] Karakoc, D., & Konar, M., 2021.

network values, thus forming clusters. The tool then created output raster data sets of statistically significant spatial clusters for network centrality.[36]

To capture the relative importance of national supply networks to each state, the number of core and peripheral counties were divided by the number of counties in each state, resulting in a percent of the state's counties as core or peripheral. This demonstrates an analysis option for state planners and policy makers with limited access to mapping tools, We identified states with more than 20 percent of their counties core to national networks or limited access due to their peripheral network connections. Additional parameters such as access to capital, extreme weather and climate risk, ruralness, and percent of Indigenous population were also included in the analysis.

We calculated the refrigerated truck fuel consumption and CO2 emissions from cold chain food transport more accurately. This was done using two components: the fuel to move the trucks, and fuel used for refrigeration, including leaking refrigerants. Delivery time was estimated, and warehouse refrigeration was not incorporated in calculations. To project future carbon emissions, we made two assumptions. First, climate-related parameters, such as wind velocity and temperature, are fixed to current climate values. Second, we assumed that the structure of the network stays the same as it is currently organized. The model used a future scenario where CO2 concentrations peak in about 2040, with an atmospheric concentration of about 650 ppm.[37]

The results are similar to earlier estimates, but available at a finer spatial resolution and only for CO2 emissions. Computing travel distance between counties rather than using the haversine distance added significantly more mileage to the modeled distribution system.

## Mapping Methodology

To develop refined maps that illustrate the network structures, we used a three-step process to identify county clusters and county outliers to visualize core counties with high centrality and peripheral counties with low centrality, and then optimize those findings. The variable mapped is the relationship between two centrality measures, degree of connectivity and betweenness. These data are then further refined by aggregating data and applying algorithms to identify the appropriate scale in which to analyze the data while adjusting for multiple testing and spatial dependence.

In step one, we used Anselin Local Moran's I, also known as Cluster and Outlier Analysis. Developed in 1995, this mapping tool identifies hot spots and cold spots that are statistically significant. It allows us to see geographic patterns in data and is part of the Environmental Systems Research Institute (ESRI) mapping toolset for geographic information systems. Researchers in industry, government and academia use these tools to understand the geographic patterns that underlie human and natural systems.

In step two, Getis-Ord Gi was used to identify high and low centrality, and in step three we further refined the information based on optimal settings for analysis. This process sorts out high value clusters from low value clusters and determines if they are statistically significant based on neighboring values. It is commonly applied to traffic and other transportation analysis, demographics, and epidemiology. In this study, the betweenness connectivity value of a county

[36] See Appendix 3 for additional detail on mapping methodology.
[37] For more detailed information on model development, see Wang, J., et al., 2022.

and its eight neighboring counties is compared proportionately to the sum values of all the counties. When the sum of a county's betweenness connectivity is different than expected, and when that difference is too large to be a result of random chance, it is significantly significant.

## Findings and discussion

Empirical findings from gravity modeling for 2017 SCTG 05 and 07 temperature-controlled movements may be accessed from the University of Illinois data repository at https://databank.illinois.edu/datasets/IDB-8455093. Network statistical data is available through the University of Wisconsin data repository at http://digital.library.wisc.edu/1793/84167. Simple statistical analyses of these data may be useful to public planners to assess freight movements and food systems. Government program leaders and other planners in transportation and food systems may use the information to distribute resources and evaluate program effectiveness. Small businesses and non-profit organizations may also find the network statistics analysis useful in planning enterprises and addressing community food security. Readers are encouraged to access these data for their own targeted analyses. The Smart Foodsheds team at the National Science Foundation Artificial Intelligence Institute Intelligent Cyberinfrastructure with Computational Learning in the Environment (ICICLE) intends to make models and data such as these more readily available, and provide visualizations for planners and businesses to use in the future.

There are several key findings from this analysis that we discuss below.

### Summary Statistics

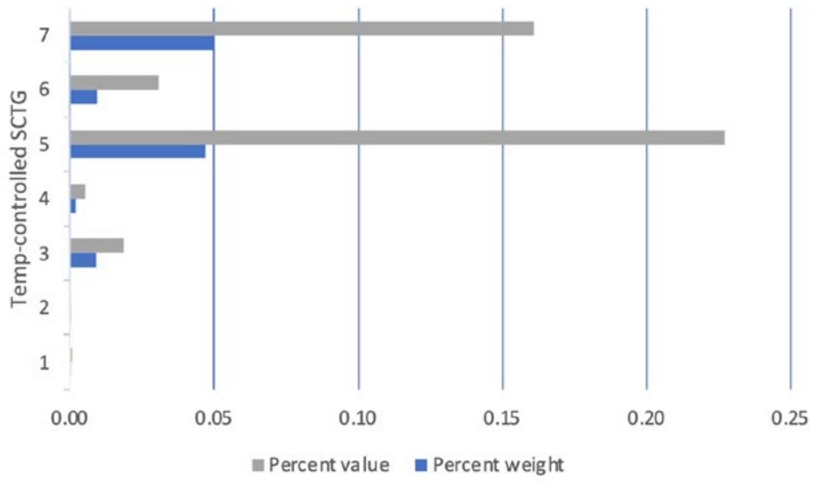
In 2017, temperature-controlled food shipments constituted over 36 percent of the mass and almost 48 percent of agricultural product value moved nationally via all transportation modes (rail, barge, air, and truck). Truck movements of perishable products constitute over 93 percent of the value and over 57 percent of the mass. By far the highest value items moving by temperature-controlled truck were meats (22.72% value, 4.71% mass). Perishable prepared foods ranked second in value (16.09%), with slightly more mass (4.98%) than meat. SCTG 06 'bakery' ranked third in cold chain importance in both value (3.05%) and mass (0.95%). Fresh produce was fourth in value (1.86%), although nearly comparable in mass (0.89%) to bakery movements. A portion of fresh produce movements are to processing facilities, then captured in SCTG 07. SCTG 07 also captures movements from dairy farms to processing facilities, since milk is refrigerated at the farm.

Our analysis covers truck movements for perishable SCTG 05 'meat' and perishable SCTG 07 'prepared foods'. This represents 74% of total refrigerated food movements for all transportation modes for commodity and prepared foods (SCTG 01-07) for the continental US.[38]

SCTG 02 'Cereal Grains (including seed)' and SCTG 04 'Animal Feed, Eggs, Honey, and Other Products of Animal Origin' constitute a small portion of perishable food movements (0.3% mass, 0.7% value), with SCTG 04 relying most heavily on temperature control. We did not anticipate that bakery - SCTG 06 - would rank third in importance for temperature-controlled movements and did not include it in the original project scope. See Figure 3.

[38] Wang, J., et al., 2022.

*Figure 3.* *US food cold chain movements by truck*



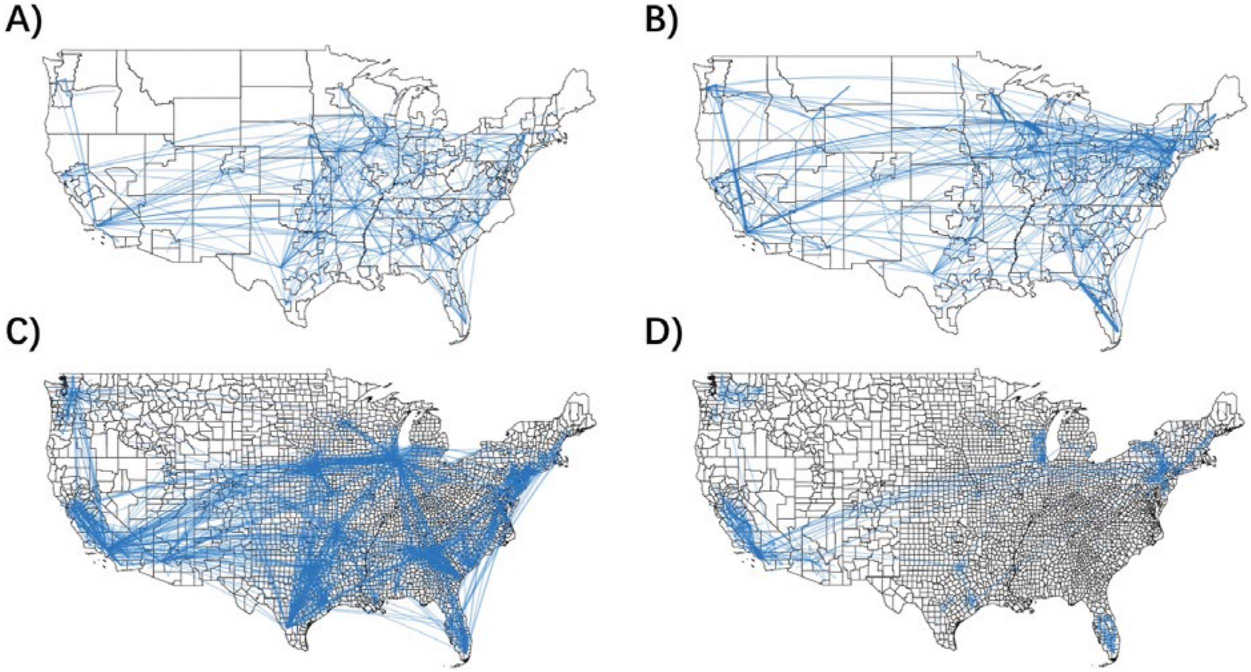

***Source:*** *2017 Commodity Flow Survey. Note: SCTG categories are provided in Table 2.*

Other freight modes are used to move food, albeit only a small fraction. In addition to truck freight, bakery moves by air; fresh produce and perishable prepared foods move by air and rail; and meat moves by air, rail, and water. Altogether, less than 1% of perishable foods by weight move via air, rail and water. In some cases, two or more modes were used on a single food movement, though still under 1%. Considering how these other modes were employed in 2017 may indicate opportunities to move temperature-controlled food freight in ways that reduce carbon emissions.

## Comparison of The Food Flow Model to the FAF

County scale matters. We found that the Food Flow Model provides a clearer picture of food movements compared to FAF and may be particularly useful to food system planners seeking to remedy low food access. Because the FAF aggregates counties into metropolitan regions and the 'remainder of' regions by state, it fails to capture the extent of geographic concentration in our food systems. Figure 5 provides visual comparisons of the two models for meat and perishable prepared foods. Urban concentration in the meat sector is evident (C) when downscaling to the county level, and obscured by the FAF (A), while geographic concentration in perishable prepared foods/dairy is considerably less so in both models (B and D). Urban concentration of prepared foods is still evident, with Seattle, LA, Chicago, Florida, and the New York region showing high flow in the food flow model.

*Figure 4.* *cold chain food flows (weight) comparing FAF- and county-level networks*




***Note:*** *We plot the top 1000 FAF-level flows and the top 0.1% of the county-level flows to illustrate the spatial patterns most clearly. Several flows evident in FAF maps, for instance from the Pacific Northwest to California, don't make the top 0.1% of flows in the Konar model since the counties are disaggregated.*

## Finding #1: Product supply chains have unique network characteristics.

Networks for perishable meat and prepared foods show similar patterns of geographic concentration, as well as some significant differences (Figure 5). Perishable meat and prepared foods networks are structurally similar. The primary difference between these two cold chains are the number of core and peripheral counties. Meat networks have many more core counties than do perishable prepared foods networks. This indicates that meat supply networks from processing to retail sales are more geographically concentrated than are perishable prepared foods from farm to retail. Unlike meat supply chains, produce and dairy cold chains begin at the farm. Dairy farms are licensed and required to keep fluid milk refrigerated. Produce is less regulated at the point of production, although wholesale buyers (packing houses and processors) often set on-farm refrigeration requirements to ensure product quality.

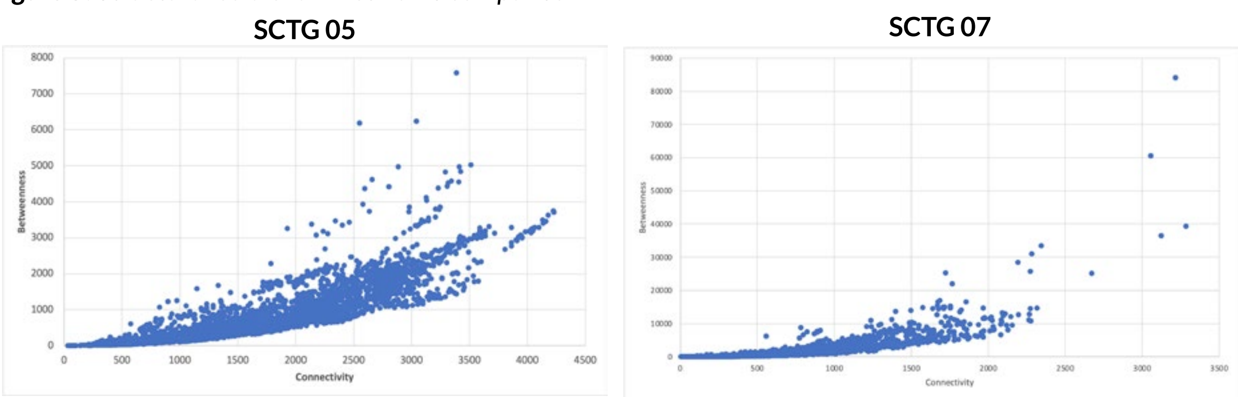
It is important to note that policies to encourage regional dairy production have been in place since the 1930s due to historical limitations on product shelf life and have helped slow geographic concentration in the dairy sector. The cost to move fluid milk and live animals to the processor (first mile) is paid by the farm but cannot be passed along to the processor because of the biological nature of food production - milk and animals for meat are produced regardless of what price they may receive on the wholesale market. Dairy farmers are resistant to adapt production based on profitability in the short and medium term, as they wait for inevitable market corrections in volatile times.[39] Meat transportation is paid by the processor, and the cost passed along to the buyer, since processors can freeze product to extend shelf life. According to

[39] In a webinar on April 15, 2020, economist Torsten Hemme, lead of IFCN Dairy Research Network, characterized this as "unfair organization of the supply chain…there is almost no supply response to the price…The family farm creates the stability but it is also the Achilles Tendon because the milk is always there. With family labor and stable equity, they withstand the low prices and the fact that they are not always getting their "fair share."

the Government Accountability Office, in 2017 dairy cooperatives handled nearly 85 percent of the milk marketed by U.S. producers. There are no large meat processing cooperatives, although there is recent interest in developing small cooperatives for meat processing, especially in farming communities far from processing facilities.

In Figure 5 below, each dot represents a county, or a node in the supply network. The dots scattered in the top right corner on each graph are the counties core to the network, those that most often serve as bridges between counties in the meat supply chain (SCTG 05) and the prepared foods/dairy supply chain (SCTG 07) combined with any connections each of those counties have to the system overall. The more product volume that is moved through a county, the more connections it is likely to have, thus counties in the upper right of the graphs are likely tied to large processing plants, warehouses, wholesale, and retail markets linked by the interstate transportation system and point to potential systems bottlenecks. Large volume movements are more likely to have experienced supply chain disruptions during the Pandemic simply because of their scale and because the system was operating at or near capacity so that these nodes were as efficient as possible and lacked resilience. When facilities are functioning well, the bottlenecks become evident in transportation systems, resulting in heavy and slowed traffic, traffic jams, excessive road damage, traffic fatalities, and air pollution. From a network perspective, facilities serve as nodes and roads are edges that connect the nodes.

***Figure 5.*** *Structural cold chain networks comparison*




***Note:*** *Overall, the national network structure (shape) is similar for meat (SCTG 05) and perishable prepared foods/dairy (SCTG 07). The meat supply chain is more geographically concentrated as illustrated by the greater number of outlier counties in the network.*

**Transportation Implications:** Geographic concentration occurs where roadways and warehousing are placed. To lessen geographic concentration and its unintended consequences, targeted investments in transportation and logistics infrastructure are necessary.

## Finding #2: Geographic concentration in perishable meat and prepared foods supply chains follows transportation infrastructure.

Betweenness centrality measures indicate routes between counties. Logistics is more than a routing challenge. As product flows through the system, up to eighty percent of supply chain costs are attributable to facility location and access to transportation networks that determine routing.[40,41] In a Mid-America Freight Coalition study, they found that fifty percent of businesses

[40] Quetica, 2016.
[41] Distribution companies define their service area and client selection based on several factors in addition to facility location and

and 60 percent of their employees are located along the Primary Highway Freight System or Critical Urban and Rural Freight Corridors.[42] In response, businesses concentrate facilities in areas where transportation routes are cost effective, not necessarily to meet the local demand for food. From food supply network data, we identify a range of counties that host supply chains that are “too small to thrive” to “too big to fail”. This may assist policy makers to target resources to underserved areas or establish market rules to limit geographic dominance.

There are outlier counties that act as transit super nodes and disproportionately bear the weight of food flow in both these categories. Identifying the top ten counties out of more than 3,000 counties is somewhat arbitrary yet may illustrate geographic concentration (Table 5). These counties are not necessarily those one would expect when thinking about commodity production. Instead, they are counties with high infrastructure investments. Disruption in these counties would quickly disrupt national food supply networks up- and downstream. Of most concern are the five Southern California counties that dominate in both meat and perishable prepared foods categories.

For meat network strength, five southern California counties rank in the top seven. Chautauqua County, NY ranks 4th and is located along Lake Erie between Erie and Buffalo, New York. Three Tennessee counties near Memphis make the cut, and Webb County, Texas places tenth. Webb County is along the Mexican border, between Monterrey, Nuevo Leon (Mexico) and San Antonio, Texas. Five Chicago area counties dominate the perishable prepared foods/dairy category, and two California counties rank one and two. Graham County, North Carolina ranks seventh, and adjacent Cherokee County, North Carolina ranks ninth. They are near both Chattanooga and Knoxville, TN. Webb County, Texas rounds out the list with a rank of eight.

**Table 5.** *Counties with high network centrality for meat and prepared foods*

| Rank | SCTG 05 ‘meat’ | SCTG 07 ‘prepared foods’ |
|---|---|---|
| 1. | Imperial County, CA | San Bernardino County, CA |
| 2. | Inyo County, CA | Riverside County, CA |
| 3. | San Bernardino County, CA | Kankakee County, IL |
| 4. | Chautauqua County, NY | Lake County, IL |
| 5. | Kern County, CA | Grundy County, IL |
| 6. | Shelby County, TN | Cook County, IL |
| 7. | Riverside County, CA | Graham County, NC |
| 8. | Fayette County, TN | Webb County, TX |
| 9. | Tipton County, TN | Cherokee County, NC |
| 10. | Webb County, TX | Putnam County, IL |

These seventeen counties are where concentration is greatest, and the network is most vulnerable as food is moved through large private supply chains and their distribution centers. Additional infrastructure is necessary outside these counties to reduce geographic concentration thereby improving the resilience of our food systems to withstand disruption. Aggregation facilities in other regions are needed to accommodate multiple commodity types (produce, meat, dairy) for small and medium food businesses to reduce the reliance on LTL food movements.

access to highways. These include fleet capacity, truck capacity, order size, distance, and time to load and unload.

[42] Han, Y., et al., 2018.

Disaggregation facilities are needed in major metropolitan areas and rural areas alike to facilitate last mile distribution. There may be a need to build out more transportation routes for large trucks to traverse rural regions, but these need to be carefully considered in the context of other network infrastructures.

As discussed by practitioners in our CoP, the decline of multi-tenant cross docking[43] in favor of private distribution centers is at the heart of supply chain concentration and has given rise to inefficient Less than Truck Load (LTL) food distribution, especially for independent businesses. As noted earlier, about 80% of transportation costs are attributable to facility location and access to transportation networks. Facility and transportation infrastructure determine routing decisions for products flowing through the systems.[44] Because there are insufficient aggregation and distribution points or 'termini', small and midsize trucking firms are at a disadvantage and trucks from large firms are running with less-than-optimal loads as they make a series of short hauls instead of one long haul. These movements are more expensive and increase the cost of products in rural areas where poverty and food insecurity may be high.

**Transportation Implications:** The freight burden from perishable food supply networks is particularly high in seventeen counties, especially for constellations of counties in Southern California and the Chicago metropolitan region. Distributing this burden will add resilience to both freight transportation and perishable food supply networks.

### Finding #3: There are regional differences between supply chain structure.

Using the network statistics generated by this analysis, it is also possible to compare regional differences in supply networks. To understand network support for flow, we calculated centrality for SCTG 05 and 07. Counties with higher centrality have more control over the supply chain networks examined (Figures 6 and 7). We compared the centrality for meat and perishable processed foods supply networks for ten counties in the Los Angeles region, thirty-two counties in the Minneapolis/St. Paul (Twin Cities) region, and 41 counties in Florida / Georgia (Miami region), again controlling for acreage and population density. We also assessed a remote rural region to consider peripheral network engagement and chose fifteen counties in Michigan's Upper Peninsula (UP). These counties are sandwiched between Lake Superior and Lake Michigan. Food freight must travel from Chicago along the west coast of Lake Michigan or from Detroit over the Mackinac bridge. Some freight also moves from Canada. The northern freight route runs along State Highway 28 and US Highway 2 is the southern freight route serving the UP.

Looking at SCTG 05 'meat', five Los Angeles area counties fall into the same approximate scale for centrality as the other metro regions, but the other five Los Angeles counties have extremely high centrality scores. The entire Los Angeles metro region is an outlier for perishable foods centrality. Four Southern California counties overshadow all the other counties: Imperial, San Bernardino, Kern and Riverside, especially in SCTG 07 (Figure 7, highlighted portion). In comparison, rural Michigan's centrality is at the opposite end of the spectrum: five counties - Chippewa, Mackinac, Luce, Schoolcraft, and Alger - fall into the bottom 10% nationally.

[43] Multi-tenant cross docking occurs at a centralized location where fresh food arrives in bulk quantities, is broken down into smaller lot sizes, and then is distributed to retail operations like stores and restaurants. Unlike distribution centers used by large businesses with private supply chains and proprietary infrastructure, multi-tenant cross docking warehouses serve many wholesalers and buyers. Small businesses can readily access the market, where they can view the products, negotiate price among the competitive wholesalers, and purchase products from both the commodity and specialty sectors.

[44] Quetica, 2016.

***Figure 6.*** *Regional network comparisons 'meat'*

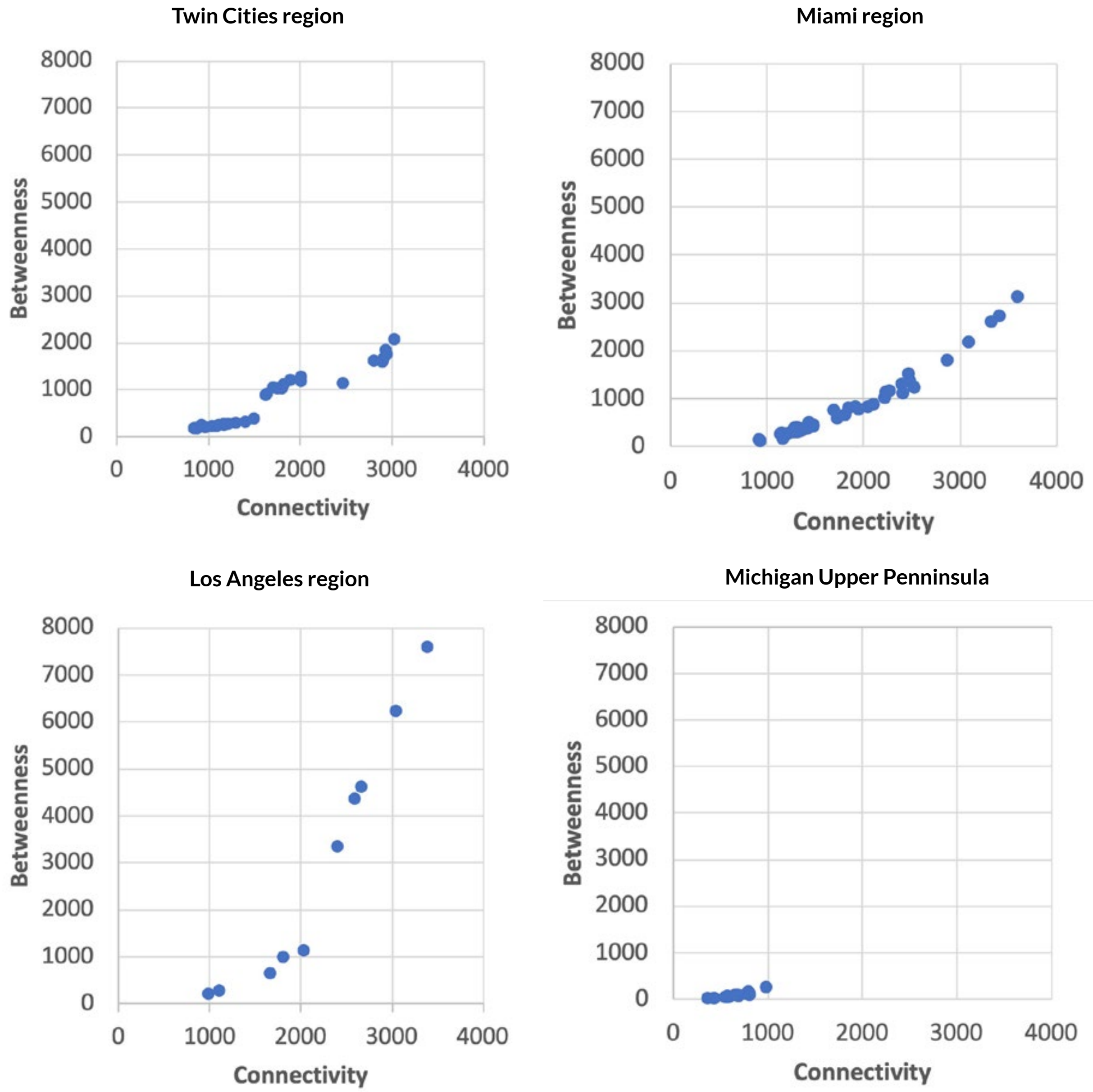
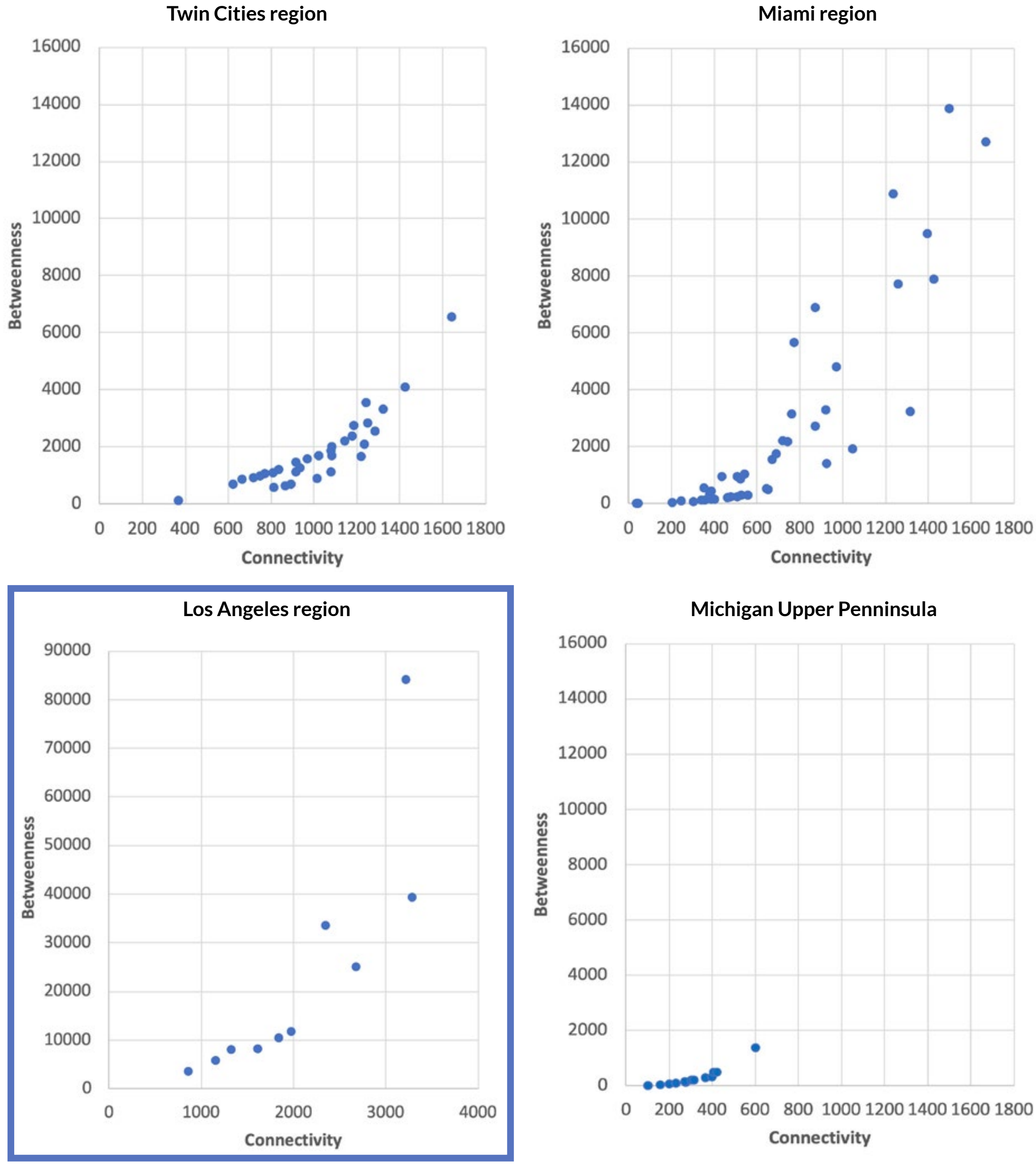


***Figure 7.*** *Regional network comparisons 'prepared foods'*




Network centrality measures for perishable prepared foods show the highest regional variation (Figure 7). The Los Angeles metro region chart is highlighted to emphasize the difference in axis values, essentially "off the charts". The Los Angeles region's perishable prepared foods supply network is operating at the highest flow nationally. This region has a greater impact on the national flow than does any other region. The Miami region chart also includes several county outliers, likely due to production and processing of fruits and vegetables. Rural Michigan counties Chippewa, Luce and Mackinac fall into the bottom 10% nationally again. Even though

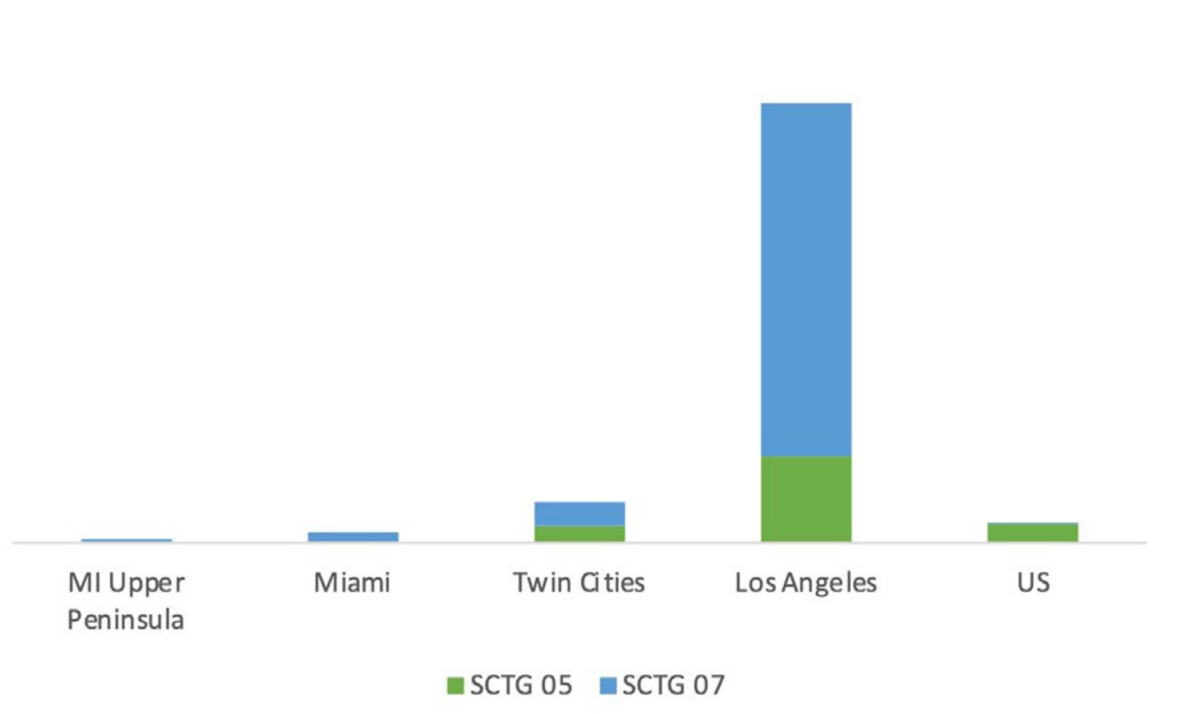
Gogebic County is at the high end of flow for the Upper Peninsula region, it is comparable to the low end of the flow moving through the Twin Cities and Miami regions.

**Transportation Implications:** Transportation and food planners at the national level may want to consider supporting infrastructure outside of the Los Angeles region so that the food network is less concentrated, especially for perishable prepared foods. Depending on further study as to the complex factors that drive geographic concentration, this may involve improving port conditions in other regions (for instance, along the Gulf coast), strategically locating new interstate routes, food aggregation and processing to encourage network development in peripheral regions, or instituting market policies that signal the true public costs of overbuilt centralized supply networks.

### Finding #4: Comparing regional median flow is another way to highlight regional differences.

Comparing median centrality to indicate network flow ('median flow') may be another way to illustrate these data. A snapshot of median centrality compares regions to the US median network centrality (Figures 8 and 9). It indicates that the counties in the Los Angeles study region in Southern California form a super node in the network. Metro Miami counties and counties in the Twin Cities region are both metropolitan regions, yet they serve the network differently. The Twin Cities region produces food and serves as a route for food moving from more distant rural areas into the greater Chicago region. The Miami region produces food and is at the "headwaters" of a network that moves food along the Eastern Seaboard, building in volume as it moves north toward markets in urban megaregions. The Upper Peninsula median network centrality is considerably lower than the national median.

***Figure 8.*** *Median network centrality for counties in five distinct regions compared to the overall US median*




***Note:*** *Centrality values represent betweenness connectivity.*

**Figure 9.** *Median network centrality for counties in four similar regions (minus outlier super node Southern California)*

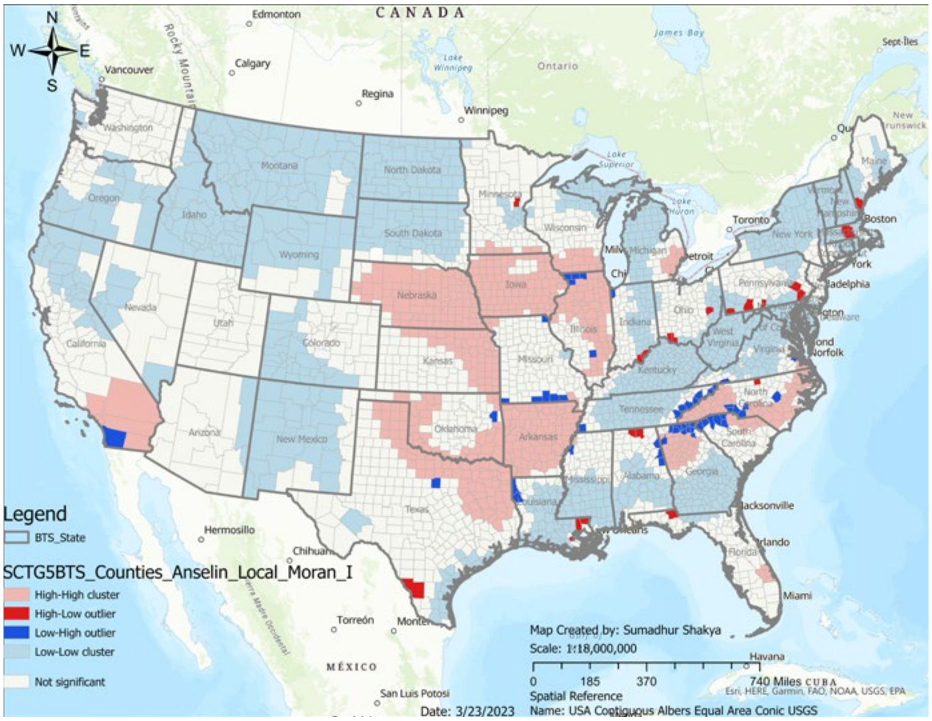

***Note:*** *Centrality values represent betweenness connectivity.*

**Transportation Implications**: No two regions are alike. Regional supply network analysis may inform business owners, government agency program leaders and transportation and food planners on current conditions and opportunities to increase or decrease access to national supply networks or create stronger regional networks through infrastructure investments.

## Finding #5: There are patterns for high and low cold chain flow.

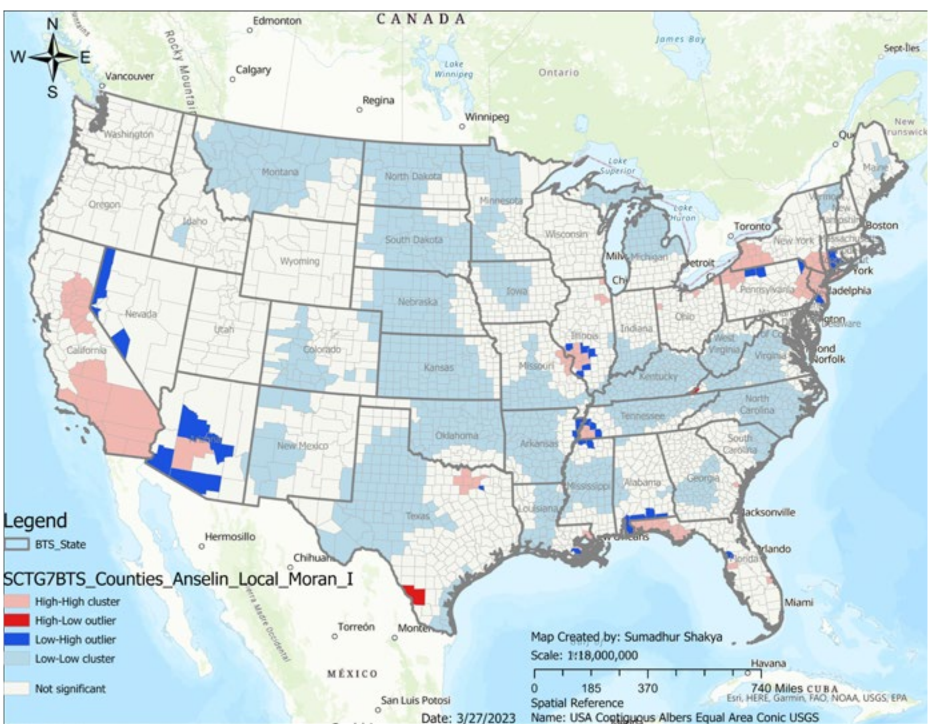
We mapped hot and cold spots to see larger variations. Figures 10 and 11 show network centrality for perishable meat and perishable prepared foods respectively. Pink counties are core to the network and light blue counties are peripheral. The blue indicates insufficient infrastructure to support flow and the red counties are where infrastructure may be overbuilt from a resilience perspective. White counties fall in the midrange, indicating relative adaptive capacity. The regions of high-low centrality (dark red adjacent to light blue) and low-high centrality (dark blue adjacent to pink) indicate counties that are not well-linked to their surrounding counties, creating localized disparity in network access. Large swaths of low flow in rural regions are also of concern and may be more difficult to remedy.

*Figure 10.* *High and low network centrality for perishable 'meat' SCTG 05*




***Note:*** *This map was made using a complex cluster and outlier analysis (Anselin Local Moran's I) for betweenness connectivity in perishable SCTG 05. See appendices 3 and 4 for methodological detail.*

*Figure 11.* *High and low network centrality for perishable 'prepared foods' SCTG 07*




***Note:*** *This map was made using a complex cluster and outlier analysis (Anselin Local Moran's I) for betweenness connectivity in perishable SCTG 07. See appendices 3 and 4 for methodological detail.*

**Transportation Implications:** Transdisciplinary studies for high-low and low-high county outliers are needed to understand the extent to which these areas are disconnected and why. A transportation component is critical to this analysis. Similar studies for high and low clusters could point to ways that these regions could best increase or decrease flow through crop and livestock production diversification, processing facilities, highway access, information and risk sharing along the supply chain, financial supports, and policy supports. A closer look at counties that mapped white could yield clues about the conditions necessary for a more resilient food system.

### Finding #6: Several states are heavily invested in cold chain food movements and support networks for high flow, while other states are functioning outside supply networks.

Because many planners and government agency program leaders think in terms of state boundaries, we identified the top 10 percent of counties (n=314) with the highest network centrality and the bottom 10 percent of counties (n=314) with lowest centrality and mapped them (Figures 12 and 13). Although 10 percent is an arbitrary cut off point, it suggests that some counties and their states may have greater adaptive capacity than others. This analysis is less informative than the hot-cold spot maps above. The advantage of this approach is that it provides a plainer way to organize and interpret the data.

***Figure 12.*** *Counties in top and bottom 10 percent of network centrality for SCTG 05 'meat'*

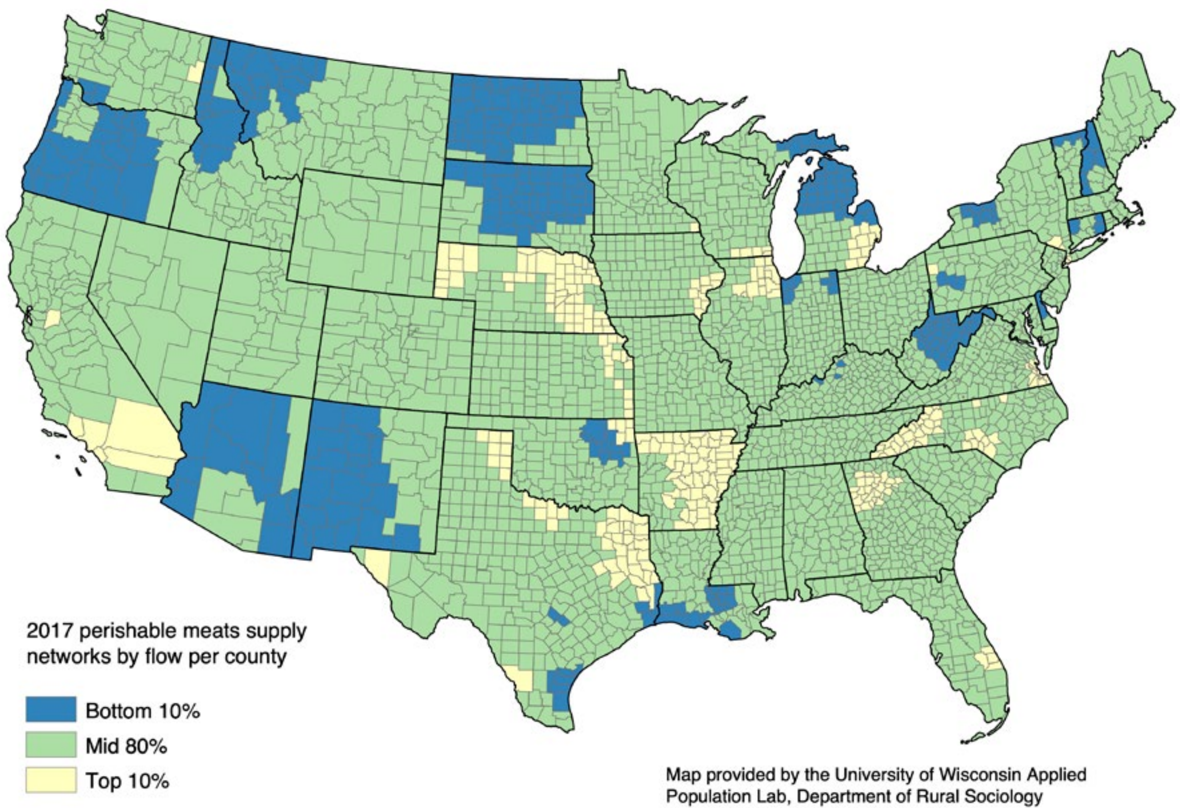
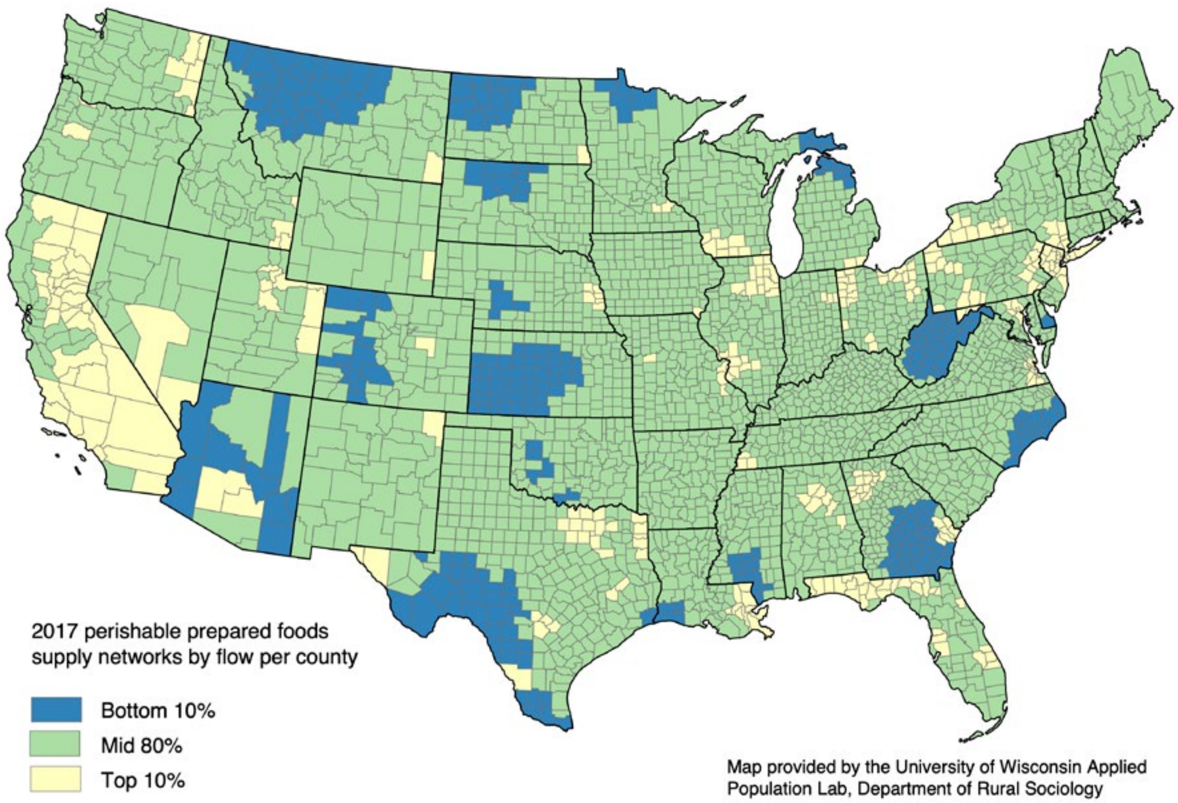


*Figure 13.* *Counties in top and bottom 10 percent of network centrality for SCTG 07 'prepared foods'*




We then organized county centrality values by state, since governmental programs to alleviate imbalances in systems are likely to be offered at the state level. The findings are similar to figures 10 and 11, that is, most states have counties at the core, periphery and somewhere in between. To capture their relative importance to the state, the number of counties in these categories were divided by the total number of counties in each state, resulting in a percent of the state's counties with high or low participation in supply networks. This analysis also helps us to see large regional variations.

Some states have counties with uneven connections to the supply network, with counties at both the core and periphery of supply networks (Tables 6 and 7 – blue highlighted states). This indicates that while there may be foods moving through some parts of the state, other parts are not well-linked to national supply networks and may indicate areas where state departments of agriculture could improve rural network efficiency by adding regional infrastructure and by diversifying meat, dairy and produce production and processing.

The states highlighted in Table 6 'meat' include Michigan, Oklahoma, Pennsylvania, Texas, and Washington. Michigan has many more counties at the low end of the 'meat' spectrum (43% low, 12% high), while Texas has more at the high end (19% high, 5% low). While 'prepared food' supply networks are less concentrated, there are more states that have both core and peripheral counties, highlighted in Table 7. Arizona is a Fruitful Rim state with 13% of their counties in high centrality, yet 60% of Arizona counties experience low connection to networks for perishable prepared foods. Texas is another Fruitful Rim state, with 11% of its counties with high network centrality and 15% of its counties exhibiting low centrality. Other states with large disparities in the 'prepared foods' supply network are Montana (high 2%, low 39%); Georgia (high 13%, low 35%), North Dakota (high 2%, low 25%); Colorado (high 2%, low 20%); Mississippi (high 17%, low 2%); Louisiana (high 16%, low 5%). Other states are Nebraska (high 6%, low 4%) and Minnesota (high 2%, low 5%).

State-level concentration in the meat sector was evident. Eighteen states rank in the top 10 percent of network flow, while three states show high dependence on and service to meat supply chains (Table 6). Arkansas with 73 percent of its counties functioning as core to the network, is known for chicken processing, Nebraska with 60 percent core counties is known for beef processing, and North Carolina with 35 percent core counties, is known for pork processing. Four states have 5% or fewer of their counties in the top 10% of the network core.[45] Blue highlighting indicates states with counties both core and peripheral to national supply networks, and where states may be able to assist in spreading network assets.

***Table 6.*** *High and low network centrality for perishable SCTG 05 at the state level, % counties*

| *High 'meat'* | *% counties* | *Low 'meat'* | *% counties* |
|---|---|---|---|
| Arkansas | 73% | North Dakota | 76% |
| Nebraska | 60% | Arizona | 67% |
| North Carolina | 35% | West Virginia | 67% |
| Texas | 19% | Delaware | 66% |
| Georgia | 17% | New Mexico | 64% |
| Virginia | 15% | Oregon | 64% |
| Illinois | 13% | South Dakota | 62% |
| Kansas | 13% | Michigan | 43% |
| Michigan | 12% | New Hampshire | 40% |
| New York | 11% | Connecticut | 38% |
| California | 10% | Montana | 29% |
| Oklahoma | 7% | Vermont | 29% |
| Wisconsin | 7% | Idaho | 25% |
| Florida | 6% | Louisiana | 23% |
| **+4 states less than or equal to 5%** | | **+7 states under 20%** | |

***Note:*** *Highlighted states exhibit both high and low network centrality.*

As of 2017, twenty-one states have peripheral counties in the bottom 10% of the meat supply network. Of those, fourteen states exhibit very low participation in the supply network, with more than 20% of their counties in low centrality (Table 6).[46] While some of the states with low centrality have significant metro regions, several of them are predominantly rural and with significant agricultural receipts from animal production. For instance, the National Agricultural Statistics Survey (NASS) compiles state overviews on agriculture.[47] NASS indicates that in 2023 Arizona produced 390,000 beef cattle, sheep and hogs; New Mexico 601,700; Oregon 656,000;

[45] These states are Minnesota (1%); Pennsylvania (2%); Washington (3%), and Iowa (5%).

[46] States not listed in the table with counties in the top 10% of low flow for meat are Kentucky and Pennsylvania (3%); Texas (5%); Washington (8%); Indiana (10%); and Oklahoma (13%).

[47] USDA National Agricultural Statistics Survey, State Overviews 2023. Accessed May 1, 2024 https://www.nass.usda.gov/Statistics_by_State/Ag_Overview/

and North Dakota 1,073,000. South Dakota produced 4,022,000 beef cattle, sheep and hogs, as well as 3,300,000 turkeys. Although they produced only 228,000 beef cattle, sheep and hogs, West Virginia produced more than 87 million turkeys and chickens in 2023. Both South Dakota and West Virginia statistics suggest concentrated 'meat' production. Checking Figure 10 map of the 'meat' network, in West Virginia it appears that this production may be mostly limited to one county, while the rest of the state is peripheral to networks. For South Dakota, it appears that much of the production may occur on the fringe (white counties) bordering Nebraska, where the big processing plants are located and where the shipping distance is short. Midsize and small farmers in these states may rely on other states for processing their animals and pay to ship livestock to processing facilities far from their farms. Many of these states are building capacity for meat processing in response to the Biden-Harris Administration's efforts to support supply chain resilience.

SCTG 07 is considerably less geographically concentrated. Thirty-two states have counties strongly connected to supply networks, with nine states supporting >20% of their counties in high centrality (Table 7).[48] There may be several reasons for this finding. Network statistics for perishable SCTG 07 may start at the farm rather than a separate processing facility. For perishable prepared foods including dairy, there is a refrigeration requirement to cool field heat from fruits, vegetables, and fluid milk. Long-standing policy to support market regionalization for dairy products also shapes the market and has slowed concentration relative to other food markets. Teasing apart supply chains for produce, perishable prepared produce (such as "fresh cut" fruits and vegetables), and dairy would help clarify supply network concentration.

There are several states where seasonal produce production is low and dairy is likely the primary portion of SCTG 07. Some states in this analysis have both a strong dairy sector and grow and process large amounts of fruits and vegetables that may significantly alter analysis. States in the USDA Economic Research Service's 'Fruitful Rim' region likely include perishable prepared food flows, as may other states. Fruitful Rim states are noted in the tables with an asterix.[49] Several states border Mexico and Canada or serve as international ports. Their network statistics may be influenced by an influx of perishable products produced internationally.

[48] States not listed in the table with counties in the top 10% of high centrality for perishable prepared foods are Georgia, Nevada, and Wisconsin (each at 13%); Texas* (11%); Alabama (10%); Idaho* (9%); Nebraska and Oregon (6%); Mississippi and Wyoming (4%); Indiana, Tennessee, and New Mexico (3%); Michigan, Minnesota, North Dakota, Montana, and Colorado (2%); Iowa (1%).
[49] USDA Farm Resource Regions, accessed May 1, 2024. https://www.ers.usda.gov/webdocs/publications/42298/32489_aib-760_002.pdf

***Table 7.*** *High and low network centrality for perishable SCTG 07 at state level, % counties*

| High centrality 'prepared foods' | % counties | Low centrality 'prepared foods' | % counties |
|---|---|---|---|
| New Jersey | 67% | West Virginia | 89% |
| California* | 60% | Arizona* | 60% |
| Florida* | 45% | Kansas | 45% |
| New York | 37% | Montana | 39% |
| Maryland | 30% | Georgia* | 35% |
| Pennsylvania | 28% | North Dakota | 25% |
| Utah | 28% | Colorado | 20% |
| Ohio | 27% | Mississippi | 17% |
| Illinois | 22% | Texas* | 15% |
| Louisiana | 16% | North Carolina | 15% |
| Washington* | 15% | South Dakota | 14% |
| Virginia | 14% | Michigan | 12% |
| Arizona* | 13% | Oklahoma | 8% |
| | | Louisiana | 5% |
| **+19 states less than or equal to 13%** | | **+2 states 5% and under** | |

***Notes:*** *1. *Fruitful Rim state. USDA designates nine agricultural resource regions, depicting geographic specialization in production of U.S. farm commodities. The Fruitful Rim produces fruit, vegetable, nursery and cotton, and has the largest share of large and very large family farms and nonfamily farms. https://www.ers.usda.gov/webdocs/publications/42298/32489_aib-760_002.pdf 2. Highlighted states exhibit both high and low network centrality.*

There are fewer states with low connection to national supply networks for SCTG 07 perishable prepared foods. Overall, 16 states have counties that fall into this category, with seven states experiencing 20% or more of their counties on the network periphery (Table 7).[50]

**Transportation Implications:** Prioritizing public infrastructure development in peripheral regions where national supply networks fail to serve may improve access to larger supply chains, especially in those states where supply networks are uneven and there are adjacent core and peripheral counties.

## Finding #7: When comparing cold chain centrality between categories, seven states are left behind.

Considering cold chain centrality for both meat and perishable prepared foods, seven states appear on both 'low centrality' lists (Table 8). They are Arizona, Michigan, Montana, North Dakota, Texas, and West Virginia. These states contain Frontier and Remote (FAR) areas as designated by USDA Economic Research Service.[51] Apart from West Virginia, all these states are more than 20% rural (FAR acres total) and at least 10% remote (FAR designation 4), with Montana, South Dakota, and North Dakota as the most rural and remote.[52] Of the seven states on

[50] States not listed in the table with counties in the top 10% of low centrality for perishable prepared foods are Minnesota (5%) and Nebraska (4%).

[51] USDA Economic Research Service Frontier and Remote (FAR) Zip Code Areas, Accessed May 1, 2024. https://www.ers.usda.gov/webdocs/DataFiles/51020/52626_farcodesmaps.pdf?v=5365.2

[52] Deeper geographic analysis may show relationships between low centrality, FAR designation, or other geographic features such as national forests, mountains, or waterways that inhibit transportation. In the last two centuries, Indigenous peoples were forcibly

both ‘low’ lists, the Indigenous population is higher in four states than the national average: South Dakota indigenous 10%; Montana 8%; North Dakota 6%, and Arizona 5%.[53] Texas has the highest African American population in the US, at 12.38% of their total population. Michigan’s African American population is also higher than the nation at 15.18%.[54]

***Table 8.** Characteristics of states with low network centrality for perishable ‘meat’ and perishable ‘prepared foods’*

| Low centrality state | SCTG 05 ‘meat’ | SCTG 07 ‘prepared foods’ | Average % SCTG 05 + 07 | State Indigenous / Black population % (2024) | % State FAR acres (2010) | % State FAR4 (remote acres 2010) |
|---|---|---|---|---|---|---|
| W Virginia | 67% | 89% | 78% | 0.76% / 4.8% | 15% | 8.5% |
| Arizona | 67% | 60% | 63.5% | 5.41% / 5.67% | 43.9% | 21.4% |
| N Dakota | 76% | 60% | 50.5% | 6.46% / 3.63% | 72.3% | 53.2% |
| S Dakota | 62% | 14% | 38% | 9.82% / 2.8% | 78.4% | 54% |
| Michigan | 43% | 12% | 27.5% | 1.47% / 15.18% | 48.9% | 15.4% |
| Montana | 29% | 39% | 19.7% | 7.66% / 1.05% | 78.9% | 57.8% |
| Texas | 5% | 15% | 10% | 1.2% / 12.38% | 26.5% | 10.4% |

**Transportation Implications**: As we learned in the 1980s in West Virginia,[55] interstate development alone may not improve national supply network connections and improve wholesale food access. Logistics infrastructure, especially cold chain warehousing at a scale appropriate for low population regions, may be a better investment to improve wholesale food access in underserved areas. Another improvement could be an information platform to assist small businesses in their efforts to collaborate on logistics for efficiencies and build regional markets to undergird national supply networks.

## Finding #8: Fourteen states are strongly connected to perishable food supply networks and are moving large amounts of both SCTG 05 and SCTG 07.

Large scale perishable food networks for meat, dairy and frozen or perishable prepared fruits and vegetables are concentrated in 14 states (Table 9). None of these states are strongly committed to SCTG 05 movements (all are under 20%). Five states are heavily invested in SCTG 07: California, Florida, Illinois, New York, and Pennsylvania. Averaging the two SCTG categories together, the three states most heavily invested in perishable food networks (>20%) are California, Florida, and New York. Access to capital is critical for private sector cold chain development, and the top eight states also ranked very high for access to capital in 2021.[56] This may indicate that businesses in these states may find raising private investment easier for emerging food infrastructure and wholesale readiness than businesses in other states. Financial

relocated by the United States Government to remote regions and so are disproportionately harmed by geographic concentration of food supply networks.

[53] The national average Indigenous population was 2.09% as of 2024. World Population Review. Accessed May 1, 2024. https://worldpopulationreview.com/state-rankings/native-american-population

[54] The national average Black population was 13.75% as of 2024. World Population Review. Accessed May 1, 2024. https://worldpopulationreview.com/state-rankings/black-population-by-state

[55] Raitz, K.B., Ulock,R., 1984.

[56] CNBC, America’s Top States for Business, 2021. Accessed May 1, 2024. https://www.cnbc.com/2021/07/13/americas-top-states-for-business.html

investments in perishable supply networks may be concentrated, in addition to concentrated infrastructure and food supplies.

The Department of Homeland Security (DHS) provides a rating of expected annual economic loss (EAL) due to risk from eighteen natural hazards, including extreme weather, wildfires, and drought.[57] The rating considers the average economic loss in dollars resulting from natural hazards each year. It is calculated for each hazard type and quantifies loss for relevant consequence types: buildings, people, and agriculture. Of the states that are central to cold chain food movements, California and Texas rank very high for hazards, both states in the Fruitful Rim production region. Further, Washington, Florida and Illinois rate relatively high. Wisconsin has a relatively low rate and the remaining nine states rate relatively moderate.

The National Oceanic and Atmospheric Administration (NOAA) offers a 2022 weather and climate risk measure[58] on a state by state basis.[59] The state risk scores are based on county level data. Based on the data, the overall US risk score is 13.3 while California and Florida have very high-risk scores at 26.21 and 24.39, respectively. Comparing these risk scores from DHS and NOAA to Figures 10 and 11, we can match core counties to state risks where localized disruptions may endanger supply networks.

***Table 9.*** *Characteristics of states with strong network centrality for perishable products*

| High centrality state | SCTG 05 % | SCTG 07 % | Average | Capital access rank (2021) | DHS EAL rating (2021) | NOAA hazard risk (2022) |
|---|---|---|---|---|---|---|
| California* | 10% | 60% | 35% | 1 | Very high | 26.21 |
| Florida* | 6% | 45% | 25.5% | 5 | Relatively high | 24.39 |
| New York | 11% | 37% | 24% | 2 | Relatively moderate | 14.20 |
| Illinois | 13% | 22% | 17.5% | 4 | Relatively high | 12.56 |
| Georgia | 17% | 13% | 15% | 10 | Relatively moderate | 11.21 |
| Pennsylvania | 2% | 28% | 15% | 12 | Relatively moderate | 11.36 |
| Texas* | 19% | 11% | 15% | 3 | Very high | 17.29 |
| Virginia | 15% | 14% | 14.5% | 9 | Relatively moderate | 8.46 |
| Wisconsin | 7% | 13% | 10% | 21 | Relatively low | 9.95 |
| Washington* | 3% | 15% | 9% | 11 | Relatively high | 8.39 |
| Michigan | 12% | 2% | 7% | 20 | Relatively moderate | 10.44 |
| Oregon* | 3% | 6% | 4.5% | 28 | Relatively moderate | 11.49 |
| Iowa | 5% | 1% | 3% | 36 | Relatively moderate | 14.58 |
| Minnesota | 1% | 2% | 1.5% | 14 | Relatively moderate | 11.61 |

***Note:*** **Fruitful Rim state. 2.The overall NOAA risk score for the United States is 13.3.*

[57] US Department of Homeland Security, Federal Emergency Management Agency, National Risk Index. Accessed May 1, 2024. https://hazards.fema.gov/nri/data-resources#csvDownload

[58] The hazard risk score combines a state's risk to natural hazards representing several factors: the annualized hazard frequency; the potential hazard cost related to building value, crop value and population exposure; and social vulnerability and resilience to recover from hazard impacts based on dozens of socioeconomic variables. The hazard risk scores should be considered a guideline for determining hazard risk but should not be used as an absolute measurement of risk. All scores are relative, as each county's score is evaluated in comparison with all other counties.

[59] NOAA National Centers for Environmental Information (NCEI) U.S. Billion-Dollar Weather and Climate Disasters 2022. Accessed May 1, 2024. https://www.ncei.noaa.gov/access/billions/, DOI: 10.25921/stkw-7w73

**Transportation Implications**: Anticipating transportation disruptions in these fourteen states due to natural hazards is a food systems priority given their current importance in supply networks. Access to capital may affect private investment in logistics infrastructure and indicate where public investment could ease food freight challenges, especially in the mid- to long-term. Public response is a given in the short term should disruptions occur in these areas with high network centrality.

### Finding #9: Multi-state regional differences provide a glimpse into food movements between as well as within regions.

To understand how multi-state regions fared in the food supply network, we took composite averages of states with a high percentage of core counties and grouped them. We see high centrality for four distinct regions: the West Coast, Upper Midwest, the Eastern Coast, and the South (Table 10). Georgia and Florida serve Southern and Eastern Seaboard markets. States along the West Coast and Eastern Seaboard are heavily invested in the network for SCTG 07 products, while the other two regions are more balanced in their investments in both categories.

***Table 10.*** *Multi-state regions and their dominance in cold chains*

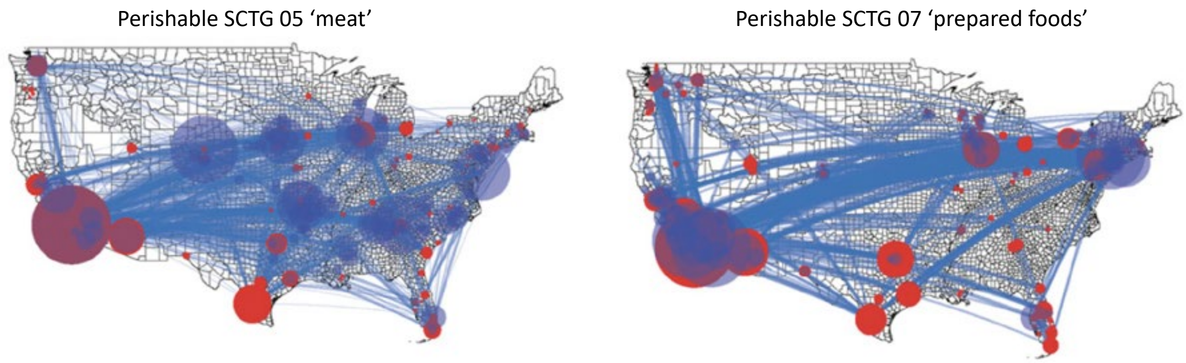
| Region | SCTG 05 | SCTG 07 |
|---|---|---|
| Upper Midwest average | 8% | 8% |
| Illinois | 13 | 22 |
| Wisconsin | 7 | 13 |
| Michigan | 12 | 2 |
| Minnesota | 1 | 2 |
| Iowa | 5 | 1 |
| South average | 14% | 23% |
| Florida | 6 | 45 |
| Georgia | 17 | 13 |
| Texas | 19 | 11 |
| East average | 10% | 27% |
| Florida | 6 | 45 |
| New York | 11 | 37 |
| Georgia | 17 | 13 |
| Pennsylvania | 2 | 28 |
| Virginia | 15 | 14 |
| West average | 5% | 27% |
| California | 10 | 60 |
| Washington | 3 | 15 |
| Oregon | 3 | 6 |

**Transportation Implications:** This analysis suggests that supply networks could be improved between and within regions to optimize several public goals (ie: improved wholesale food access, risk reduction to national food networks from extreme weather disruptions, greenhouse gas emissions reduction, etc.) with efficiencies (energy economy across a diversified supply network, ease of food production, high asset utilization, etc.). For example, discussions about electrifying freight fleet routes will use information on current movements to place charging units. However, as companies seek to optimize their routes by reorganizing to regional hub and spoke logistics, placing chargers based on historic route information may not result in the best investment of resources.

## Finding #10: cold chain transport contributes significantly to greenhouse gas emissions.

Meat distribution emitted $8.4 \times 10^6$ t $CO_2$ $yr^{-1}$ and dairy/prepared foodstuffs emitted $14.5 \times 10^6$ t $CO_2$ $yr^{-1}$, with a spatial distribution of CO2 consistent with some earlier studies (Liu et al. 2015 a & b). When using highway distance between counties, meat traveling from processor to market has a longer average temperature-controlled transport distance, averaging 78.71 more miles. This results in higher transport $CO_2$ emissions per kg. For cold chain SCTG 07 the increase is 58.98 more miles on average.

***Figure 14.*** *Carbon emissions from cold chain food trucking for 'meat' and 'prepared foods'*




***Note: Counties with the highest carbon footprint inflow (red) and outflow (blue) are represented with bubbles, where the sizes of the bubbles are proportional to the carbon footprint.***

Figure 14 shows the carbon footprint of county-level cold chain food flows for 'meat' and 'perishable prepared foods /dairy'. Emissions mirror regional importance in supply networks (Figure 14 compared to Tables 5 and 11). Emissions associated with outflow (blue circles) indicate areas carrying air pollution loads to support national food supply. Outflow locations and intensity differs depending on the supply chain in question. Southern California carries a heavy load of air pollution from perishable food movements for North America.[60] Tradeoffs between large efficient food movements and associated pollution may be renegotiated considering such information.

Our study estimated refrigeration as a percentage of fuel required to move the refrigerated truck. This does not necessarily consider the amount of cooling time required. In 2017, trucking companies did not operate under the current Hours of Service (HOS) regulations.[61] Time on the road and the energy necessary for cooling trailers may now be higher due to HOS. Also, this analysis did not include emissions from moving live animals or produce to point of processing, although it captures the movement of fluid milk from the farm to processor.[62]

[60] Food freight is not the only freight moving through Southern California, but as we reported earlier, temperature-controlled food shipments constituted over 36 percent of the mass and almost 48 percent of perishable product value moved nationally. Truck movements of perishable products constitute over 57 percent of the mass and over 93 percent of the value. .

[61] Hours of Service is a Federal Motor Carrier Safety Administration rule that sets the maximum amount of time commercial drivers are permitted to be on duty, including driving time. It sets the number and length of rest periods for drivers to ensure they are alert.

[62] A 2022 study by Li and colleagues, 2022, suggests that it is important to tie supply chain emissions to the full supply chain, which

**Table 11.** *Counties with the highest carbon emissions attributable to cold chain movements*

| Perishable SCTG 05 'meat' | | | Perishable SCTG 07 'prepared foods' | | |
|---|---|---|---|---|---|
| Rank | County | $CO_2$e (t) | Rank | Carbon footprint | $CO_2$e (t) |
| 1 | Los Angeles Co., CA | 5.95 x 105 | 1 | Los Angeles Co., CA | 6.31 x 105 |
| 2 | Maricopa Co., AZ | 2.66 x 105 | 2 | Orange Co., CA | 6.28 x 105 |
| 3 | Webb Co., TX | 2.40 x 105 | 3 | Maricopa Co., AZ | 4.28 x 105 |
| 4 | Cook Co., IL | 2.22 x 105 | 4 | San Bernardino Co., CA | 3.84 x 105 |
| 5 | King Co., WA | 1.55 x 105 | 5 | Cook Co., IL | 3.59 x 105 |
| 6 | Hall Co., GA | 1.47 x 105 | 6 | Riverside Co., CA | 3.13 x 105 |
| 7 | Dallas Co., TX | 1.44 x 105 | 7 | Tulare Co., CA | 3.12 x 105 |
| 8 | Alameda Co., CA | 1.40 x 105 | 8 | Dallas Co., TX | 2.80 x 105 |
| 9 | Riverside Co., CA | 1.39 x 105 | 9 | Orange Co., CA | 2.47 x 105 |
| 10 | San Bernardino Co., CA | 1.34 x 105 | 10 | Lehigh Co., PA | 2.15 x 105 |

**Transportation implications:** Optimizing entire food supply networks is necessary to reduce GHG emissions from our food supply, as well as meet other public goals. Research on optimizing wholesale food freight with consumer transit for food provisioning is needed. Regional optimization of processing and warehousing for the system as a whole could also improve air quality in low income urban neighborhoods and food access in low income rural communities. Lessening geographic concentration in food production, processing, wholesaling and retailing will likely require that food transportation and logistics infrastructure placements are reorganized to reshape the network.

## Conclusions

Data curation and network modeling on perishable food movements give us a glimpse into the geographic structure of specific food flows across the continental United States. This can be used by both the public and private sectors to understand supply chain risk, vulnerability to disruption, and regional adaptive capacity. Food movements could be improved between regions as well as within regions by reshaping the structure of supply networks. To optimize transportation and food systems, reorganization at a national systems level is needed to attain public resilience goals such as improved food access and air quality, risk reduction from extreme weather disruptions, and other social resilience goals. Reorganization may also improve food supply chain efficiencies such as energy economy across the full supply chain, ease of food production, high asset utilization, etc.. We've identified counties and regions that may exhibit greater food systems resilience. Exploring how these areas attain resilient systems may reveal opportunities and challenges ahead.

We can see how specific counties and regions form the core of our food systems, upon which we are highly dependent. In 2017, meat supply chains are more concentrated than perishable prepared foods and dairy supply chains, but geographic concentration is evident for all these products. Geographic concentration occurs where transportation and logistics

would also include the manufacture and transportation of production inputs, such as animal feed and fertilizers used to grow feed, which is then fed to livestock for food production. This would significantly increase the contribution of food production to greenhouse gas emissions unless efforts are made to integrate agricultural systems at the farm or ecoregion level.

infrastructure are placed. To lessen geographic concentration and its unintended consequences, targeted public and private investments in transportation and logistics infrastructure are necessary.

Counties surrounding Los Angeles form a super node in perishable food supply networks. Counties around Chicago form a secondary super node. Disruptions in these regions, natural or human-induced, may profoundly impact downstream and upstream supply chain partners. Anticipating transportation disruptions in these states due to natural hazards is a food systems priority given their current importance in food supply networks. A closer look at these regions to better understand their role in food supply networks is necessary, and efforts to lessen the burdens these super node regions incur will improve overall transportation and food systems functioning. Supply network improvements could be accomplished through infrastructure development, market policy and other improvements in information flow.

Rural regions may also benefit from deeper analysis to inform and systemically address low wholesale market access. Consumer food access is dependent on many factors, including access to wholesale supply chains. Findings from this study highlight regional differences in food distribution due to the structure of our supply networks. There are peripheral counties and regions that could be more active in food supply networks but are not. Some of these peripheral counties are close to core counties in the network, indicating that targeted investments in cold chain infrastructure and small changes to business rules may accelerate improvements so that these counties may access nearby wholesale food networks.

In multi-county regions on the periphery of national networks, especially in areas where food is produced, modest investments in rural cold chain infrastructure could quickly address disparities in food access. For example, there is historical awareness that Appalachia requires special attention to address food and market access. This research indicates that Montana, North Dakota and South Dakota create another large region on the periphery of perishable food supply networks, despite the region's agricultural contributions. Another multistate region that deserves special attention to address these disparities are counties in Arizona, Texas, New Mexico, and other parts of the Southwest.

Interstate development alone may not improve food network access. Logistics infrastructure in rural areas is a necessary investment to improve supply network functioning. Supply network concentration is in part the result of geographic concentration in processing and declining multi-tenant cross dock warehousing for smaller wholesalers in favor of private distribution centers that serve an increasingly urban population. Appropriately scaled and located processing and aggregation facilities are needed to accommodate multiple commodity types (produce, meat, dairy) to reduce the reliance on LTL food movements. The current Administration's USDA Resilient Food Systems Infrastructure Program has the potential to address the need for logistics infrastructure investment in underserved areas.

## Next Steps

Data and network statistics from this project are open access and we encourage others to explore them. The website www.foodflows.org provides available data from 2009, 2012 and 2017. The University of Wisconsin and University of Illinois data repositories[63] hold raw data on perishable food movements in this study so that users can build spreadsheets with flow and network data for the analysis on multiple counties of their choice. For instance, this analysis looks generally at food network centrality measures for the degree of connectivity and betweenness. We did not separately consider centrality measures for products moving in and out of counties. We did not consider network strength statistics, a useful measure to examine power law relationships within the network.

Two other projects are using these data to understand food movements and provide useful public analysis. The USDA-AFRI project 'Lessons from COVID-19: Positioning Regional Food Supply Chains for Future Pandemics, Natural Disasters and Human-made Crises' brought together a team of researchers from across the United States to explore regional supply chain resilience in three metro regions detailed in Appendix Two. Another project led by Ohio State University, ICICLE, aims to democratize artificial intelligence and cyberinfrastructure, targeting 'Smart Foodsheds' as a use case. The modeling and data analysis required to use the Food Flow Model may become available through a model and data commons, thus empirical findings could become more easily and regularly accessed.

This study had insufficient data to run fresh fruit and vegetable flow through the model in order to provide county scale network statistics. Refrigerated products (not frozen) are the least stable products throughout supply chains. Retailers in low-density markets may be operating in an anti-competitive wholesale market environment as low flow inhibits their efforts to maintain their produce sections, further eroding food access and concentrating the market. Future research to explore fresh produce movements will require one or more alternative ways to access data, such as special sworn status to access US Census data at a finer resolution, or access to proprietary data from data services such as TransSearch or IMPLAN.[64,65] There may be alternative modeling methods to approximate fresh produce movements. Further, a comparison of the Food Flow Model with proprietary models may help to assess model accuracy and usefulness.

In this analysis, we used additional characteristics at the state level, such as access to capital, weather risks, remoteness, and Indigenous and Black population concentration. It may be possible to look at these and other characteristics at various scales (national, regional, county), as policy makers find useful. The Smart Foodsheds team is committed to developing a standardized vocabulary, an ontology, so that several databases could be strung together enabling machine learning to analyze and provide expanded network statistics.

Case-based qualitative synthesis could add depth to this analysis. For instance, working with companies to consider their up- and downstream strategic partners and their geographic strengths and weaknesses could assist companies in assessing their supply chain risk. Other lines of inquiry could include correlation analysis that would indicate networks [and subnetworks] flexibility. It is unclear the extent to which existing food systems networks rely on built, fixed

[63] University of Illinois data repository provides county downscaled data at https://databank.illinois.edu/datasets/IDB-8455093. Network statistical data is available through the University of Wisconsin data repository at http://digital.library.wisc.edu/1793/84167
[64] SP Global, Transearch. Accessed May 1, 2024. https://www.spglobal.com/marketintelligence/en/mi/products/transearch-freight-transportation-research.html
[65] IMPLAN, Accessed May 1, 2024. https://implan.com/

infrastructure and how that may affect how quickly the cold chain can respond to disruptions. This quantitative approach provides users with a glimpse into the geographic structures of our food supply networks and suggests ways to support reciprocity and collaboration so that we may optimize both efficiency and diversity to create more resilient food systems. Transdisciplinary studies, such as this one, are needed to understand the organization of our food supply networks to ensure that rural counties are connected to, and urban counties are not burdened with food systems functions. Analyses of global food trade and other systems indicates that cooperation and reciprocity are important qualities of systems with high adaptive capacity that is necessary for resilience. Developing quantitative measures of reciprocity and resilience at the regional level will assist both public and private sectors in realizing that goal. Additionally, there are other network qualities that deserve exploration in food systems work, such as system asymmetry, interconnectedness, nonlinearity, and tipping points. A transportation component is critical to on-going convergent work to improve food supply networks.

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## Appendix One - Community of Practice participants

Practitioners
- Phil Gottwals, Agriculture and Community Development Services
- Laura Lengnick, Cultivating Resilience
- Cullen Naumoff, Food Fare
- Lindsey Smith, Metropolitan Washington Council Of Governments

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- Steve Deller, applied economics
- Lindsey Day Farnsworth, planning and community food systems
- Michelle Miller, economic anthropology
- Ernest Perry, civil engineering, Mid-America Freight Coalition
- Andrew Stevens, applied economics
- David Long, Applied Population Lab

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- Megan Konar, civil engineering
- Junren Wang, graduate student

University of Minnesota
- Hikaru Peterson, applied economics

University of Florida
- Christa Court, applied economics

Oregon State University
- Zhaohui Wu, supply chain logistics management

New York University
- Quanyan Zhu, systems engineering

California State University – Monterrey Bay
- Sumadhur Shakya, operations management

USDA-Agricultural Marketing Service – Transportation Services Division
- Matt Chang, economist
- Kranti Mulik, economist

## Appendix Two - Regional analyses

Three regions are compared for the USDA-AFRI project "Lessons from COVID-19: Positioning Regional Food Supply Chains for Future Pandemics, Natural Disasters and Human-made Crises". Megaregions, as defined by the Regional Plan Association, represent a cluster of cities that: include a Core Based Statistical Area as defined by the Office of Budget and Management; are expected to experience population and employment growth over 25 years; and share similar environmental systems and topography, infrastructure systems, economic linkages, settlement and land use patterns, and culture and history.

This project considered geographic representations of three megaregions in the US: Great Lakes, Southern Florida, and Southern California (Fig 1). Given the physical expansiveness of the Great Lakes mega-region, we focused on the Minneapolis-St. Paul MSA and their surrounding outstate areas consisting of 32 counties in Minnesota and Wisconsin that form a congruent but distinct cluster. The megaregions, Southern California and Southern Florida, coalesce around the urban cores of Los Angeles (LA) and Miami, respectively. The three study regions highlight regional differences in sociodemographic and COVID-19 prevalence (Table 1), as well as agri-food systems.

***Figure 1.*** *Study regions*


*Source: Hagler (2009)*

***Table 1.*** *Characteristics of study regions*

| Characteristics | Midwest MN-WI | Southern CA | Southern FL |
|---|---|---|---|
| Counties (#)[a] | 32 | 10 | 42 |
| Area (sq mi) | 19,164 | 61,081 | 36,406 |
| Population 2010 (millions)[b] | 4/4 | 24.4 | 17.3 |
| Percentage Non-White[c,d] | 9.0 | 21.4 | 17.9 |
| Percentage Hispanic or Latino[c] | 4.4 | 47.9 | 19.6 |
| Per Capita Income[c] | $38,435 | $29,983 | $29,248 |
| Confirmed cases of COVID-19, Total[e] | 20,708 | 94,738 | 52,591 |
| Confirmed cases of COVID-19, per 100K[e] | 442 | 367 | 262 |

*[a]Hagler (2009), [b]2010 U.S. Census, [c]U.S. Census Bureau QuickFacts, accessed June1, 2020, [d]Computed as 100 - "white alone percent," [e]Center for Disease Cotnrol, as of 6/1/2020.*

Food and agriculture are important to all three study regions. In their surrounding states, food system sectors, including input supply, farming, processing, distribution/wholesaling, retailing, and waste/recovery, account for 17-24 percent of state-wide employment.

Farming in the three regions is distinct since climate and growing conditions vary dramatically. Top grossing crops in California and Florida are fruits, vegetables, and tree nuts. The primary crops for Minnesota and Wisconsin are grains and oilseeds, and their livestock sectors are relatively large, particularly for Wisconsin due to its dairy sector. Farm size reflect these primary crops; median farm size in Minnesota (140 acres) and Wisconsin (221 acres) are considerably larger than the median farm size in California and Florida (20 acres). California has nationally prominent processing and distribution sectors, owned by companies like Del Monte, Pacific Coast Producers and Del Mar Food Products. Minnesota is home to three of the country's 20 largest food processing companies (Cargill, General Mills, and Hormel Foods) as well as many smaller meat, poultry, ethanol, and oil processors. Food processing activity in Wisconsin contributes $82.7 billion to industrial sales.

Counties in the Minneapolis-St. Paul study region

- Anoka, MN
- Benton, MN
- Carver, MN
- Chisago, MN
- Dakota, MN
- Dodge, MN
- Goodhue, MN
- Hennepin, MN
- Houston, MN
- Isanti, MN
- Kandiyohi, MN
- McLeod, MN
- Olmsted, MN
- Ramsey, MN
- Rice, MN
- Scott, MN
- Sherburne, MN
- Stearns, MN
- Steele, MN
- Wabasha, MN
- Washington, MN
- Winona, MN
- Wright, MN
- Barron, WI
- Chippewa, WI
- Dunn, WI
- Eau Claire, WI
- La Crosse, WI
- Monroe, WI
- Pierce, WI
- Polk, WI
- St. Croix, WI

Counties in the Los Angeles study region

- Imperial, CA
- Kern, CA
- Los Angeles, CA
- Orange, CA
- Riverside, CA
- San Bernadino, CA
- San Diego, CA
- Santa Barbara, CA
- San Luis Obispo, CA
- Ventura, CA

Counties in the Miami study region

- Alachua, FL
- Baker, FL
- Brevard, FL
- Broward, FL
- Charlotte, FL
- Citrus, FL
- Clay, FL
- Collier, FL
- Desoto, FL
- Duval, FL
- Flagler, FL
- Glades, FL
- Hardee, FL
- Hendry, FL
- Hernando, FL
- Highlands, FL
- Hillsborough, FL
- Indian River, FL
- Lake, FL
- Lee, FL
- Manatee, FL
- Marion, FL
- Martin, FL
- Miami-Dade, FL
- Monroe, FL
- Nassau, FL
- Okeechobee, FL
- Orange, FL
- Osceola, FL
- Palm Beach, FL
- Pasco, FL
- Pinellas, FL
- Polk, FL
- Putnam, FL
- St Johns, FL
- St Lucie, FL
- Sarasota, FL
- Seminole, FL
- Sumter, FL
- Volusia, FL
- Camden, GA
- Glynn, GA

In response to a request from Andrea Carbine with New Venture Advisors who is working on food access in Michigan's Upper Peninsula, network data for these 15 counties was included in the regional analysis.

- Alger, MI
- Baraga, MI
- Chippewa, MI
- Delta, MI
- Dickenson, MI
- Gogebic, MI
- Houghton, MI
- Iron, MI
- Keweenaw, MI
- Luce, MI
- Mackinac, MI
- Marquette, MI
- Menominee, MI
- Ontanagon, MI
- Schoolcraft, MI

## Appendix 3 - Anselin Local Moran's 1 mapping methodology

To develop refined maps that illustrated network structure, Sumadhur Shakya at California State University – Monterrey Bay volunteered to work with us. Appendix 3 and 4 document his methodology to map network structure.

Anselin Local Moran's I is also known as Cluster and Outlier Analysis. Developed in 1995, this mapping tool identifies hot spots and cold spots that are statistically significant. It allows us to see geographic patterns in data and is part of the Environmental Systems Research Institute (Esri) mapping toolset for geographic information systems. Business, government and researchers use these tools to understand the geographic patterns that underlie human and natural systems.

The null hypothesis for the mapping toolset is Complete Spatial Randomness (CSR), either of the features themselves or of the values associated with those features. In a two-tailed test, tail values of Z score with low p-values indicate either a statistically significant hot spot or a statistically significant cold spot (a rejecting null hypothesis is when the observed spatial pattern reflects the theoretical random pattern). The centrality variable mapped is "betweenness connectivity", the relationship between how connected the county is with other counties and its importance to the network in total, or the relationship between degree of connectivity and betweenness.

A more complex analysis aggregates data and applies algorithms to identify the appropriate scale in which to analyze the data and adjusts for multiple testing and spatial dependence. In this study, the threshold distance was found to be 147000 meters, given the scale of spatial extent. The spatial relationship for centrality (betweenness connectivity) was set to inverse distance squared, with the type of distance set to Euclidean (a straight-line distance between two points (as the crow flies)). Spatial weights are standardized; each county's betweenness connectivity is divided by the sum of the betweenness connectivity of the neighboring counties. The False Discovery Rate (FDR) was applied to account for multiple testing and spatial dependency . FDR correction estimates the number of false positives for a given confidence level and adjusts the critical p-value accordingly. For this method statistically significant p-values are ranked from smallest (strongest) to largest (weakest), and based on the false positive estimate, the weakest are removed from this list. Statistical significance is based on a corrected 95 percent confidence level. The number of permutations was set to 999 to improve the random sample distribution, which improves the precision of the pseudo-p-value. Analyzing betweenness connectivity provided Local Moran's I index, z-score, pseudo-p-value, and cluster/outlier type, results of which are presented below. The smallest possible pseudo p-value is 0.001 and all other pseudo p-values are multiples of this value. We set the minimum number of neighboring counties to be considered to eight.

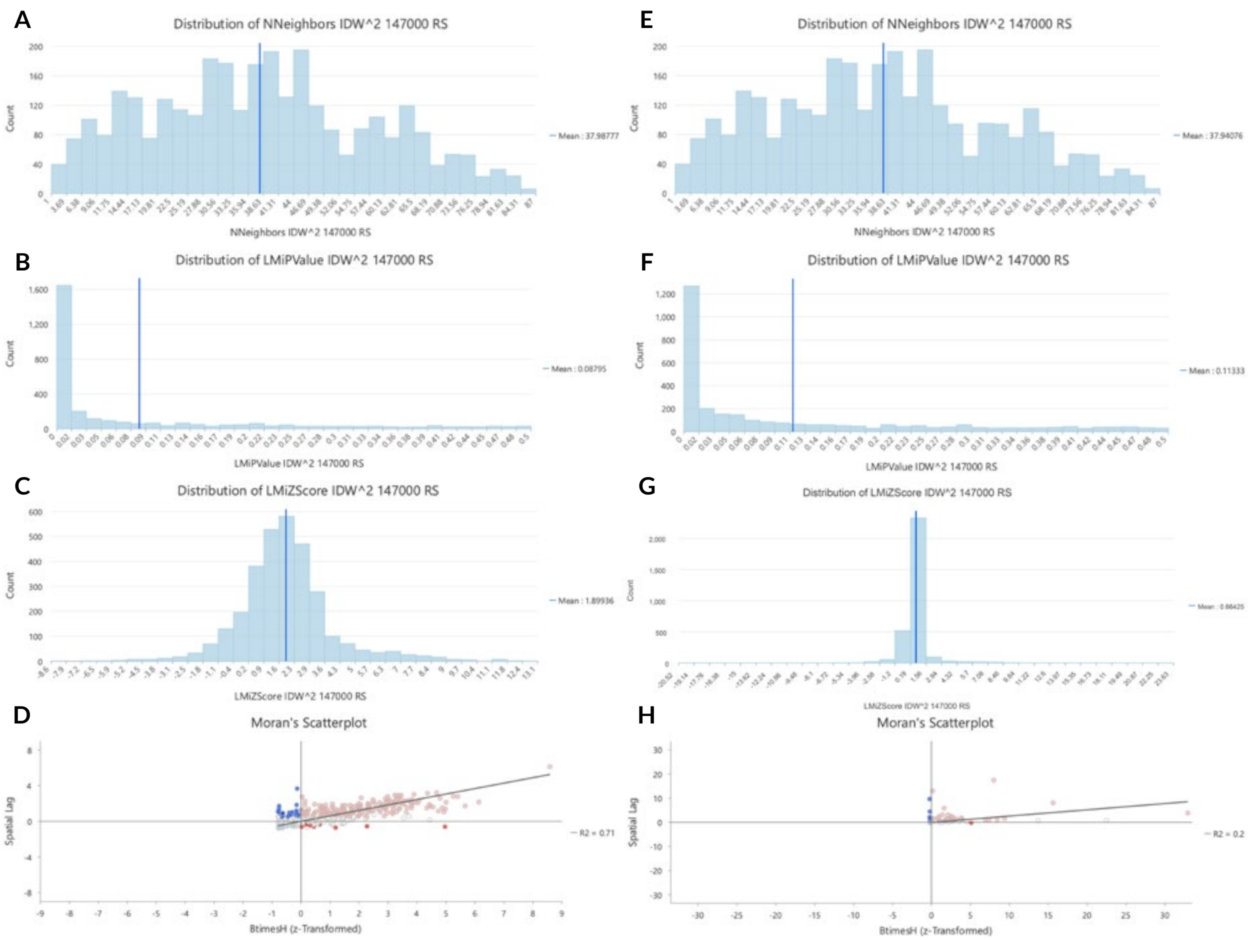
A high positive z-score for a feature indicates that the surrounding features have similar values (either high values or low values). The cluster type field in the figure is presented as High-High (HH) for a statistically significant cluster of high values and Low-Low (LL) for a statistically significant cluster of low values. A low negative z-score for centrality measure betweenness connectivity indicates a statistically significant spatial data outlier represented as having a high value and is surrounded by features with low values (HL) or if the feature has a low value and is surrounded by features with high values (LH). The process of analysis was done for SCTG 05 ( Figure 1) and SCTG 07 (Figure 2).

*Table 1. Results from Anselin Local Moran's 1 analysis*

| SCTG 0 5 Cluster Type | Max of LMiZScore | Min of LMiZScore2 | Max of LMiPValue | Min of LMiPValue2 | Max of NNeighbors | Min of NNeighbors2 |
|---|---|---|---|---|---|---|
| HH | 13.10656015 | 2.139746183 | 0.029 | 0.001 | 80 | 1 |
| HL | -1.526918185 | -3.40568128 | 0.028 | 0.001 | 80 | 13 |
| LH | -2.077048624 | -8.563679583 | 0.028 | 0.001 | 73 | 3 |
| LL | 4.137093948 | 0.772764432 | 0.029 | 0.001 | 87 | 1 |

| SCTG 07 Cluster Type | Max of LMiZScore | Min of LMiZScore2 | Max of LMiPValue | Min of LMiPValue2 | Max of NNeighbors | Min of NNeighbors2 |
|---|---|---|---|---|---|---|
| HH | 23.63242223 | 1.573873276 | 0.021 | 0.001 | 69 | 1 |
| HL | -0.71571763 | -0.756793133 | 0.001 | 0.001 | 66 | 13 |
| LH | -2.559476537 | -20.51599139 | 0.021 | 0.001 | 53 | 1 |
| LL | 1.443101969 | 0.173154077 | 0.021 | 0.001 | 87 | 2 |

***Figure 1.** Results from Cluster and Outlier Analysis (Anselin Local Moran's I). for centrality measure betweenness connectivity in temperature controlled SCTG 05(a-d) and SCTG 07(e-h)*



## Appendix 4 - Getis-Ord Gi and Optimized Hot Spot Analysis

To develop refined maps that illustrated network structure, Sumadhur Shakya at California State University – Monterrey Bay volunteered to work with us. Appendix 3 and 4 document his methodology to map network structure.

Getis-Ord Gi is a statistic that describes each data point. It sorts out high value clusters from low value clusters and determines if they are statistically significant based on neighboring values. It is commonly applied to traffic and other transportation analysis, demographics, and epidemiology. In this study, the betweenness connectivity value of a county and its eight neighboring counties is compared proportionately to the sum values of all the counties. When the sum of a county's centrality (betweenness connectivity) is different from expected, and when that difference is too large to be a result of random chance, it is significantly significant.

For all analyses, the tool identified 3109 valid features (counties in the contiguous United States) using a distance band determined by the optimized hot spot analysis tool. The optimized hot spot analysis tool performed a two-tailed test and reported the values (network centrality measure betweenness connectivity) associated with counties as significant, with confidence levels of 90%. These are visually depicted as ranging in intensity where hot spots are depicted in bright red and cold spots in deep blue.

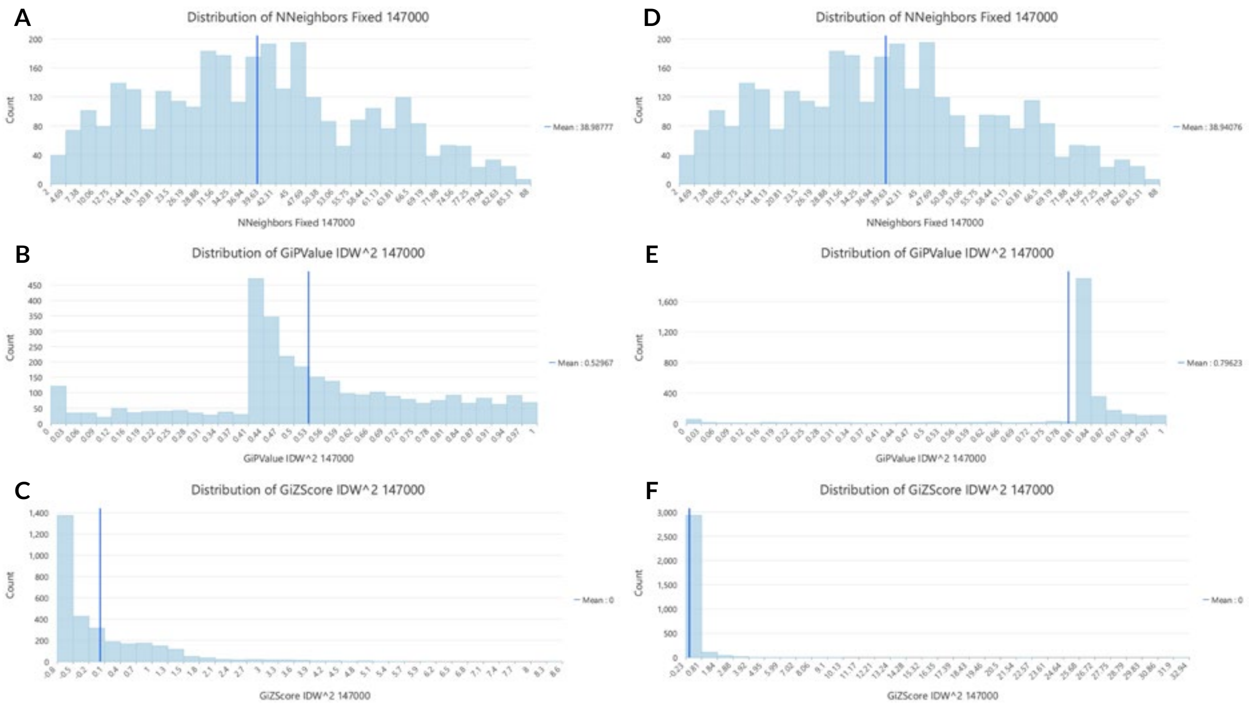
### Hot Spot Analysis (Getis-Ord Gi)

***Table 1.*** *Getis-Ord Gi (Gi_Bin IDW^2 at 147000 FDR) results*

| SCTG5 Gi Bin | Max of GiZScore | Min of GiZScore2 | Max of GiPValue | Min of GiPValue2 | Max of NNeighbors | Min of NNeighbors2 |
|---|---|---|---|---|---|---|
| 0 | 3.049746864 | -0.797442423 | 0.999561187 | 0.002290343 | 88 | 2 |
| 1 | 3.32537452 | 3.0915046 | 0.001991449 | 0.000882998 | 68 | 15 |
| 2 | 3.95068131 | 3.343828962 | 0.000826307 | 7.7929E-05 | 71 | 4 |
| 3 | 8.586906101 | 4.01877519 | 5.85015E-05 | 0 | 70 | 2 |

| SCTG7 Gi Bin | Max of GiZScore | Min of GiZScore2 | Max of GiPValue | Min of GiPValue2 | Max of NNeighbors | Min of NNeighbors2 |
|---|---|---|---|---|---|---|
| 0 | 3.33565394 | -0.230311659 | 0.999728423 | 0.00085099 | 88 | 2 |
| 1 | 3.53323238 | 3.53323238 | 0.000410511 | 0.000410511 | 54 | 54 |
| 2 | 3.945396993 | 3.819005988 | 0.000133991 | 7.96679E-05 | 42 | 14 |
| 3 | 32.93590515 | 4.512907285 | 6.3945E-06 | 0 | 48 | 2 |

*__Figure 1.__ Results from Hot Spot Analysis (Getis-Ord Gi*). for centrality measured as betweenness connectivity in temperature controlled SCTG 05 (a, b, c), and SCTG 07 (d, e, f)*




## Optimized Hot Spot Analysis

This further refines the information provided in the first two steps. It interrogates the database to determine optimal settings for analysis. Maps provided in the report on page 30 (Fig.10, SCTG 05 'meat', Fig.11, SCTG 07 'prepared foods') are the result of optimized hotspot analysis, visually depicted as ranging in intensity where hot spots are depicted in bright red and cold spots in deep blue.

*__Table 2.__ Optimized Hot Spot Analysis (Gi_Bin) results*

| SCTG 05 Gi Bin | Max of GiZScore | Min of GiZScore2 | Max of GiPValue | Min of GiPValue2 | Max of NNeighbors | Min of NNeighbors2 |
|---|---|---|---|---|---|---|
| -3 | -2.84147165 | -6.035362663 | 0.004490584 | 1.58606E-09 | 87 | 13 |
| -2 | -2.183835171 | -2.838353323 | 0.028974362 | 0.004534696 | 76 | 8 |
| -1 | -1.842069578 | -2.181216659 | 0.065464973 | 0.029167395 | 83 | 6 |
| 0 | 1.839244533 | -1.83955623 | 0.999816868 | 0.065833415 | 88 | 2 |
| 1 | 2.179664148 | 1.847243684 | 0.064711831 | 0.029282366 | 75 | 9 |
| 2 | 2.838328549 | 2.188747899 | 0.028615168 | 0.004535048 | 79 | 4 |
| 3 | 13.23452352 | 2.841020843 | 0.004496937 | 0 | 81 | 2 |

| SCTG 07 Gi Bin | Max of GiZScore | Min of GiZScore2 | Max of GiPValue | Min of GiPValue2 | Max of NNeighbors | Min of NNeighbors2 |
|---|---|---|---|---|---|---|
| 0 | 2.852572164 | -1.99531244 | 0.999749236 | 0.004336696 | 88 | 2 |
| 1 | 3.054526347 | 2.872586545 | 0.004071265 | 0.002254162 | 54 | 15 |
| 2 | 3.543530547 | 3.127047628 | 0.001765713 | 0.000394808 | 52 | 4 |
| 3 | 28.36513995 | 3.640426049 | 0.000272187 | 0 | 56 | 2 |

***Figure 2.*** *Results from Optimized Hot Spot Analysis for centrality measured as betweenness connectivity in temperature controlled SCTG 05(a, b, c), and SCTG 07 (d, e, f)*