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PAPER

# Network centrality in perishable food distribution networks in the United States

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## Abstract

This analysis quantifies the network dynamics, geographic concentration, and disparities in perishable food supply networks for temperature-controlled food shipments in the United States. The United States forms the core of global food systems and produces more high-quality data for network analysis than most other countries. We use the 2017 US Census Commodity Flow Survey and other publicly available data to derive empirical results from the Food Flow Model for perishable meats and perishable prepared foods. We identify the top ten counties for perishable food distribution and find that the Los Angeles and Chicago regions support the greatest volumes of perishable food movements. States that largely exist outside national perishable food networks are Arizona, Michigan, Montana, North Dakota, Texas, and West Virginia. Our analysis of US data highlights the importance of certain counties, states, and regions in perishable food networks and illustrates how data and logistics optimization models shape the geography of food. Findings suggest areas where interventions could improve systems' functions by reducing reliance on core areas, increasing access to markets for farmers, and improving access to food for under-served communities, especially those in rural regions.

## 1. Introduction

Food distribution is an integral food systems function, left largely to the private sector. Using network centrality analysis to uncover patterns in perishable food distribution, we explore how improvements to distribution may improve food security and meet other social goals [1]. Recent policy focus on supply chain improvements (for instance the 2022 Bi-partisan Infrastructure Act to improve broadband access, freight routes, and accelerated reporting on state freight plans) [2], and the White House Council on Supply Chain Resilience [3]) indicate public interest in food movements using network analyses.

Perishable foods are valued for their high nutritional content. They have high commercial value and are costly to distribute. Compared to other food supply networks, cold chain carbon emissions are high, due in part to refrigeration necessary for food safety. As we transform food systems to support health, equity, resilience, and sustainability rather than to simply provide calories [4], understanding costs and benefits of perishable food networks may be useful in negotiating systems trade-offs.

Perishable foods move through supply chains distinct from shelf stable products, largely via temperature-controlled trucks, from one cold storage location to another. Several recent studies use materials flow data and modeling to ascertain network structures that contribute to resilience, including food systems resilience [5–9]. This study contributes to this growing body of knowledge by considering perishable food movements specifically and identifying core and peripheral geographic regions in these networks using transportation flow data. The United States is the central country in global food trade networks and can affect global food systems' stability [6, 10]. Unlike most of the rest of the world, researchers in the US have access to large amounts of public data that we can use to understand systemic patterns that commonly develop in food distribution, and thus make a unique contribution to countries without these public resources. At global, national and bioregional scales there is increasing agreement that transforming agri-food systems is needed to meet high level goals, including the seventeen United Nations Sustainable Development Goals [11]. Participants at United Nations summits are calling to renegotiate food systems [12–14]. However, the policy pathways for achieving such a vision are inevitably contested, and the enabling conditions are insufficient. Currently, we lack quantitative data to support negotiations for systems transformation [15]. The US government and private firms collect some of the data necessary to assess food networks thereby providing a data-rich environment in which to analyze US network structures that affect regional, national and global food supply networks. We intend for this analysis to contribute factual knowledge that describes current national food networks and to inform discussions around values, interests, and trade-offs in policy negotiations.

Our study is unique in that we modeled two *perishable* food flows for the United States (US), estimating county-level flows based upon data from the 2017 US Census Commodity Flow Survey. The model incorporated additional variables to create a supervised learning model of food flows [16]. The Census collects data on agricultural product distribution and organizes them into Standard Classification of Transported Goods (SCTG) categories 01–07 (supplementary table 1). Using these transportation data, we estimated network centrality measures for two perishable food supply networks (the temperature-controlled portions of SCTG 05 'meat' and SCTG 07 'prepared foods', supplementary tables 2 and 3). We limited our analysis to products moving via truck, thereby capturing 74% of all perishable food movements by truck using weight as our measure.

Centrality metrics are the structural indicies that supply chain managers use to optimize supply networks [7]. Taken together, these optimized supply chains create a digitized geography based on data and modeling to meet private enterprise goals [17]. Vertically integrated firms determine centrality at nodes (i.e.: warehouse, processing plant) and system (supply chain) levels as a routine management task. Centrality informs managerial decisions on the strategic use of materials, infrastructure, capital, and information given the firm's goals. We applied this method to the nation's food supply networks, identifying centrality values for counties as network nodes. We then looked for geographic patterns at state and regional levels. This study provides valuable insights into perishable food networks, such as geographic concentration and dispersion. We highlight the network importance of certain counties, states, and regions and suggest areas where interventions may improve food distribution, given the importance of fresh food to health and economic well-being, as well as costs incurred to distribute perishable foods.

We mapped the relationship between two centrality measures, degree of connectivity and betweenness. Connectivity indicates first order relationships, while betweenness is a global network measure, thus providing complimentary insights. Three other centrality measures were available to us: stress, closeness and eigenvector. Since earlier research indicates they would be redundant to measure, we focused on connectivity and betweenness [6, 18].

Degree of connectivity indicates the number of connections a network node—in our study, a county—has in a food supply chain network. Betweenness indicates how well counties connect into the supply network through linear connections. These two centrality measures allow us to delineate between core and peripheral counties [19]. Core counties have high centrality, and geographically concentrated food distribution resources necessary for efficiency. Peripheral counties have low centrality, indicating that national food distribution resources are scarce, and dispersed. Counties that are neither core nor peripheral may exhibit resilience, the sweet spot between efficiency and diversity [20]. We uncover system dynamics at the regional scale to highlight the trade-offs at local and bioregional scales to support national networks [21].

## 2. Methods

### 2.1. Modeling

Although 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 perishable food flows in food supply networks.

Public data provide information on food flows at a relatively coarse geospatial level. The Konar Food Flow Model estimates food commodity flows at a more granular, county level. The process uses a statistical model that relates food flows between domestic regions to variables describing those domestic regions, including data on population, employment, income, production, and storage. The estimated model is then applied using similar county-level variables—along with additional constraints that ensure estimated county flows sum to totals at the domestic region level. The model's accuracy in estimating county-level flows was assessed for the coarse spatial resolution and then applied to the fine spatial resolution, assuming the regression equations hold across spatial scales. It draws from eleven public data sources (supplementary table 4) and has been peer reviewed [22]. For more detailed information on model development, see Wang *et al* [16]. Empirical findings from gravity modeling for 2017 SCTG 05 and 07 temperature-controlled movements can be accessed from the University of Illinois data repository at https://databank.illinois.edu/datasets/IDB-8455093.

### 2.2. Data

There are multiple, distinct supply chains that make up supply networks that move food from farm to fork. This study improves upon earlier work by refining and curating data used in the modeling process to better approximate movements of perishable food by refrigerated truck between counties within the Continental US. This was accomplished by using the refrigerated portion of the primary data only, and focusing on truck movements, since we know that most perishable food travels by truck.

As with prior studies using the Food Flow Model, we used data from the CFS, and its refinement known as the Freight Analysis Framework. There are distortions inherent in CFS survey data, as discussed at a workshop held virtually 24 September 2020, organized by the Transportation Research Board's Standing Committee on Freight Transportation Data [23]. First, CFS over-emphasizes large movements and may not capture smaller movements adequately. Second it is uncertain whether CFS data sufficiently captures large grower shipments, which are increasingly common for west-to-east movements. Third, ports that might not be the true shipping or receiving points, are overemphasized in CFS, while much of the food distribution data are privatized and so may be unavailable. CFS data is collected every five years and then provides freight movement data for the collection year. It cannot accurately capture seasonal movements that are critical to understanding the movement of perishable food given the nonlinear nature of food systems. Despite its limitations, CFS is the best available public data source on food movements.

The 2017 CFS separated food movements based on temperature control for each of the four freight modes: air, rail, truck, and multimodal, and disaggregated movements by SCTG categories. It was then possible to sort, model, and analyze perishable food movements across the US. Perishable movements are low weight and have high economic value relative to shelf stable commodities. This study modeled perishable foods movements by weight only and did not model movements by value.

The CFS organizes food movements by SCTG category (supplementary table 2). Each category represents a mix of products, some similar and some dissimilar. For example, SCTG 03 includes 'Agricultural Products Except for Animal Feed, Cereal Grains, and Forage Products' and includes both fresh produce and large-scale soybean movements. We focused on the bulk of perishable foods flows, which are SCTG 05 'meat' and SCTG 07 'prepared foods', and then limited the study to refrigerated portions of these two categories. Since dairy—including fluid milk—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 refrigerated fruits and vegetables, and juices. The nine states in the USDA's Economic Research Service's 'Fruitful Rim' region likely represent perishable streams for 'fresh cut', juiced, and frozen fruits and vegetables. Fruitful Rim states are Washington, Oregon, Idaho, California, Arizona, Texas, Florida, Georgia, and South Carolina [24].

### 2.3. Mapping methodology

To develop refined maps that illustrate the network structures, we used a three-step process to identify clusters and outliers, determine counties with high and low centrality, and then optimize those findings. The variable mapped is 'betweenness connectivity', the relationship between how connected the county is with other counties and its importance to the network in total, in other words the relationship between degree of connectivity and betweenness centrality, or betweenness connectivity. 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 [25–27].

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 tool set for geographic information systems. Researchers in industry, government, and academia use these tools to understand the geographic patterns that underlie human and natural systems.

Spatial relationships are not always uniform across space, and this can impact the validity of spatial autocorrelation measures. To account for this, we conducted additional tests to account for spatial non-stationarity, including an optimized hotspot analysis that adjusts for spatial dependence using a False Discovery Rate (FDR) correction. We also examined different spatial weighting schemes, including K-nearest neighbors and inverse distance weighting, to assess whether the results were sensitive to the choice of spatial structure. The Moran's I results were interpreted in conjunction with Getis-Ord Gi* and other clustering techniques, such as Anselin Local Moran's I, to ensure robustness across different methodological approaches. Given the inverse relationship to distance, we also incorporated spatial influence beyond immediate neighbors by evaluating varying neighborhood structures. While we acknowledge that non-stationarity is an inherent challenge in spatial analysis, our multi-method approach allowed us to validate key patterns and avoid undue reliance on a single spatial structure.

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 analyses, and within 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 betweenness connectivity is different than expected, and when that difference is too large to be a result of random chance, it is statistically significant.

To mitigate potential distortions arising from scale mismatches, we implemented several sensitivity analyses. We performed optimized hotspot analysis using multiple configurations, such as K-nearest neighbor distances, Inverse distance weighting, Anselin Local Moran's I, and optimized hotspot analysis using FDR correction. We cross-validated with subject matter experts in supply chain logistics and regional food systems to ensure consistency with empirical knowledge of perishable food distribution. We compared results across different spatial weight matrices and clustering techniques to ensure that the observed patterns in food network centrality were not artifacts of a particular analytical choice.

Additional information and results are available for each of the three steps in supplementary information.

### 2.4. Analysis

We used the network statistics by county provided by the Konar Lab to conduct further analysis of the network structure of perishable foods. Network statistical data are available through the University of Wisconsin data repository [28]. There are several ways to use these statistics to improve understanding of how networks are structured to allow food flows between counties. We apply two centrality measures in this analysis:

$$\text{degree of connectivity } \mathrm{D_o} \sum_{d}^{N} lod$$

$$\text{betweenness } \mathrm{B_o} \sum s \neq o \neq t \frac{\sigma_{st}^{0}}{\sigma_{st}}.$$

First, we use degree of connectivity (a combined metric for degree in and degree out) to measure the number of 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 into a county, and degree-out refers to product moving out. Karakoc and Konar 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, based on data from three Alaskan villages [29]. Since a county is closer in scale to a village than a nation, we used the overall degree measure, rather than parsing the degree of connectivity by degree-in and degree-out. The second centrality measure we used was betweenness. Betweenness indicates the pathways between counties. Those counties that are en route to other counties have more control 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. The relationship between degree of connectivity and betweenness is similar across spatial scales.

We used the relationship between degree of connectivity and betweenness to represent overall network centrality for perishable meat and perishable prepared foods. High centrality indicates where food supply chains are geographically concentrated and food is plentiful, while low centrality indicates where farmers may have difficulty entering the wholesale market or consumers may have difficulty accessing food due to missing connections. Centrality analysis allows supply chain managers, planners, and policy makers to monitor, identify, and take proactive steps to reduce bottlenecks, enhance flow, and improve the management of material assets such as transportation infrastructure, warehousing, and processing facilities. Our approach captures the upper and lower centrality measures of perishable supply networks, providing a boundary analysis of food supply networks. High centrality values may indicate a county's function as part of the network core, although relatively brittle in the network. Low centrality values indicate peripheral connection and insufficient network infrastructure to support flow, relative to other nodes.

To visualize perishable food networks across the nation, we mapped centrality using hotspot analysis at the county scale and completed state-scale comparisons. This assumed that those counties in the top tier of centrality—core counties—contributed to highly efficient movements. We also studied peripheral counties in the bottom tier of centrality since these counties may not have sufficient wholesale infrastructure to participate in national perishable supply networks for temperature-controlled food shipments in the US. To capture the relative importance of these supply networks to each state, the number of counties with high and low network centrality were divided by the number of counties in each state, resulting in a per cent of the state's counties with high or low participation in supply networks. Additional parameters such as access to capital, extreme weather, and climate risk, ruralness, and per cent of Indigenous population were also included in the analysis.

## 3. Results

### 3.1. Summary statistics

In 2017, temperature-controlled food shipments constituted over 36% of the mass and almost 48% of agricultural product value moved nationally via all transportation modes (rail, barge, air, and truck). Truck movements of perishable products constitute over 93% of the value and over 57% 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.

Our analysis covers truck movements for perishable SCTG 05 'meat' and perishable SCTG 07 'prepared foods' (supplementary figures 2 and 3). This represents 74% of total refrigerated food movements for all transportation modes for commodity and prepared foods (SCTG 01-07, supplementary figure 1) for the continental US [16].

### 3.2. Network analysis

We mapped county-level network centrality to uncover geographic variations and identify core and peripheral counties (figures 1 and 2). The more product volume that moves through a county, the more connections that county is likely to have with networks serving that flow, a pattern also found in international trade [29, 30]. Perishable food distribution infrastructure could include Primary and Secondary Freight Routes as defined by the US Department of Transportation, cold storage warehousing, and processing facilities. Core counties suggest large processing plants, private distribution warehouse centres, and vertically integrated wholesale and retail markets, all linked by and dependent upon the interstate transportation system. Peripheral counties have insufficient connections to the national distribution networks.

Pink (light red) indicates core counties, while light blue counties are peripheral. Large swaths of low network centrality in rural regions, such as the Great Plains and the Southwest, may be more difficult to connect to existing networks. White counties fall in the midrange and suggest areas requiring further research to determine the nature of food movements. 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 disparities in network access. Note the differences between networks for 'meat' and 'prepared foods'. This more granular modeling of perishable movements for products that move independently, as meat and prepared foods usually do, uncovers different patterns in these networks.

### 3.3. Geographic concentration at the county level

Perishable meat and prepared foods networks show similar patterns of geographic concentration, as well as some significant differences at the county scale. The primary difference between these two types of perishable networks is the extent of geographic concentration. Perishable meat networks have more core counties (pink and red) and are therefore more geographically concentrated than perishable prepared foods networks.

There are core counties that disproportionately bear the weight of perishable food distribution and are freight transit choke points. Identifying the top ten core counties out of 3108 counties illustrates the extent of regional geographic concentration (table 1). Most notably, two Southern California counties are choke points in both perishable foods categories.

For perishable meat networks, five southern California counties rank in the top seven, along with three Tennessee counties near Memphis. Chautauqua County, NY, located between Erie, Pennsylvania and Buffalo, New York, ranks fourth. Webb County, a border crossing, between Monterrey, Nuevo Leon (Mexico) and San Antonio, Texas, places tenth.

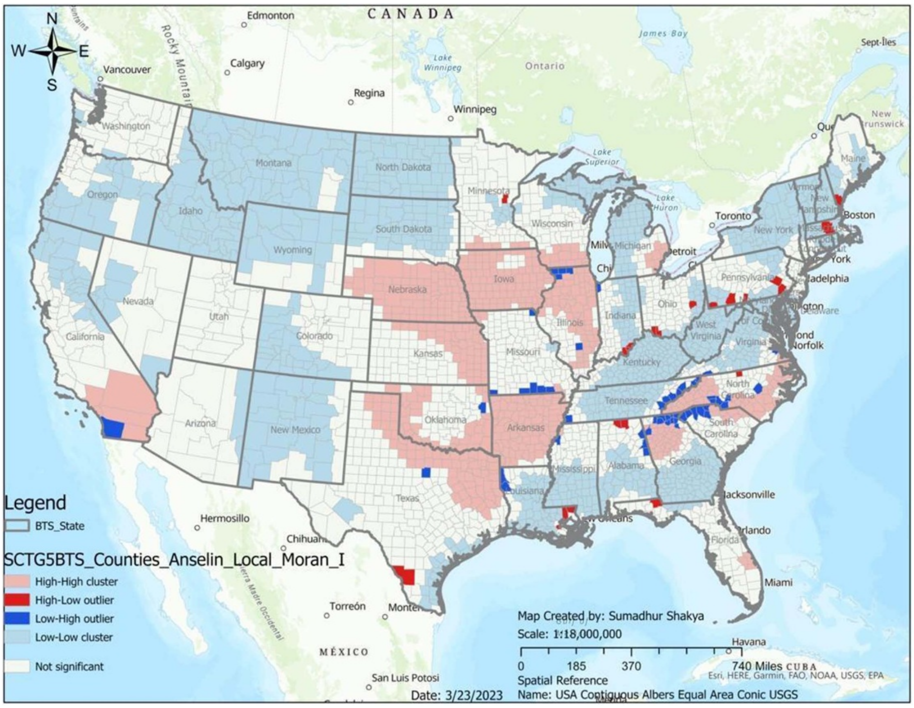


**Figure 1.** Network centrality for perishable 'meat' SCTG05.
*Note*: See supplementary information for methodological detail.

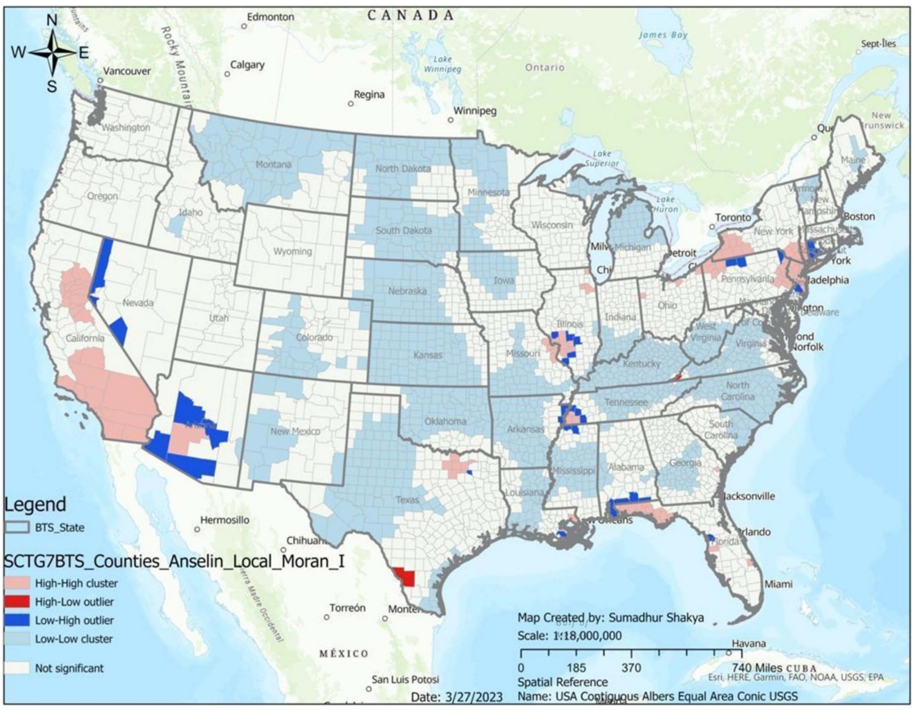


**Figure 2.** Network centrality for perishable 'prepared foods' SCTG 07.
*Note*: See Supplementary Information for methodological detail.

For perishable prepared foods networks, San Bernardino County, CA ranks first, Riverside County, CA ranks second, followed by five Chicago area counties. Graham and adjacent Cherokee Counties in North Carolina rank seventh and ninth, respectively. These counties are near urban Chattanooga and Knoxville, Tennessee. Webb County, Texas rounds out the list with a rank of eight.

**Table 1.** Choke point counties 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 |

**Table 2.** 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%*** | |

*Notes:* 1) Bolded and italicised states exhibit both high and low network centrality.
2) States not listed are included in supplementary information.

### 3.4. State concentration of perishable meat networks

We then aggregated county-level centrality values by state, since federal programs to alleviate systems imbalances are typically administered by states. States exhibit high or low network centrality, and some have both concurrently. To capture the relative importance of these perishable networks to each state, the number of counties in the top and bottom 10% centrality were divided by the total number of counties, resulting in a per cent of the state's counties with high or low centrality for each supply network (table 2 and supplementary information).

Eighteen states had counties in the top 10% of the perishable meat network. State-level geographic concentration in this sector was evident in three states: Arkansas 73% (chicken processing), Nebraska 60% (beef processing), and North Carolina 35% (pork processing). Four states have less than 5% of their counties strongly connected to national meat networks—Minnesota (1%); Pennsylvania (2%); Washington (3%), and Iowa (5%).

Comparing these values with figure 2, we can see each state has a different relationship with meat supply networks, giving us more insight into how these networks function. For instance, even though few Iowa counties fall into the top 10%, the state lies between Nebraska and Illinois, resulting in a high centrality score in meat networks (mapping pink). Minnesota and Pennsylvania have a few core counties, and these counties are not well connected to surrounding counties (red counties proximate to light blue). Washington has a few core counties, and it is likely that they are not well connected to the national network, but instead the core may be connected to local or regional networks (mapping as white) and require further exploration.

Twenty-one states have counties in the bottom 10% of perishable meat networks. Of those, fourteen states have more than 20% peripheral counties. While some of the states with low network centrality have significant metropolitan regions, several of them are predominantly rural and have significant agricultural receipts from animal production, such as North Dakota, Arizona, New Mexico, Oregon, and South Dakota. Many of these states are building capacity for meat processing in response to the Biden Administration's

**Table 3.** 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) '*' indicates 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 non family farms [24].
2) Bolded and italicized states exhibit both high and low network centrality.
3) See supplemental information for the full list of states.

efforts to support supply chain resilience, such as the US Department of Agriculture's Meat and Poultry Processing Expansion Program [31].

Some states have uneven connections to meat supply networks, with some counties operating at the core and others on the periphery. This indicates that meat moves through some counties, but other counties are not well-linked to supply networks. State governments could efficiently add regional infrastructure to rectify these disparities. These states are Michigan, Oklahoma, Pennsylvania, Texas, and Washington. Michigan has many more peripheral counties (43% low, 12% high), while Texas has more core counties (19% high, 5% low).

### 3.5. State concentration of perishable prepared food supply networks

Perishable 'prepared foods' networks are less geographically concentrated than perishable 'meat'(compare tables 2 and 3, supplementary information). Thirty-two states have core counties in the top 10%, with nine states supporting >20% of their counties in high centrality. Further, there are fewer peripheral counties for SCTG 07 perishable prepared foods compared to meat. Overall, 16 states have counties in the bottom 10%, with seven states experiencing 20% or more of their counties in the bottom 10%.

There are several states with core and peripheral counties, bolded and italicized above. Arizona is a Fruitful Rim state with 13% of its counties in the core, yet 60% of Arizona counties are peripheral for perishable prepared foods. Texas is another Fruitful Rim state, with 11% of its counties in the core and 15% of its counties at the periphery. Other states with large disparities 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%); Nebraska (high 6%, low 4%); and Minnesota (high 2%, low 5%).

### 3.6. Under-served states with overall low network centrality

Perishable supply networks under-serve seven states, suggesting insufficient cold chain infrastructure for national distribution (table 4). They are West Virginia, Arizona, North Dakota, South Dakota, Michigan, Montana, and Texas. These states contain Frontier and Remote (FAR) areas as designated by the USDA Economic Research Service [32]. 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. Low centrality in rural regions may disproportionately affect ethnically and racially distinct communities.

**Table 4.** 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 population % (2024) | % State FAR acres (2010) | % State FAR4 (remote) acres (2010) |
|---|---|---|---|---|---|---|
| W Virginia | 67% | 89% | 78% | 0.76% | 15% | 8.5% |
| Arizona | 67% | 60% | 63.5% | 5.41% | 43.9% | 21.4% |
| N Dakota | 76% | 60% | 50.5% | 6.46% | 72.3% | 53.2% |
| S Dakota | 62% | 14% | 38% | 9.82% | 78.4% | 54% |
| Michigan | 43% | 12% | 27.5% | 1.47% | 48.9% | 15.4% |
| Montana | 29% | 39% | 19.7% | 7.66% | 78.9% | 57.8% |
| Texas | 5% | 15% | 10% | 1.20% | 26.5% | 10.4% |

## 4. Discussion

These results advance our ability to monitor and manage network infrastructure for perishable foods distribution as a public good. We highlight geographic concentration and disparities in perishable supply networks to target actions that may improve food supply networks. Perishable foods are nutritious, high value, and cost more to distribute. Federal support for irrigation and other infrastructure supports perishable foods production, influencing where crops are grown and animals raised, which then may affect costs to distribute. Compared to shelf stable food supply networks, cold chain carbon emissions are high for perishables, in part because of the refrigeration required to ensure food safety and value, the distance between production regions and markets, and because refrigerated trucks are the primary transportation mode. As we transform food systems to support health, equity, resilience, and sustainability rather than to simply provide calories [4], a better understanding of perishable networks may inform regional, national and international negotiations around trade-offs such as food insecurity, food loss, water use and air pollution.

We found that Los Angeles and Chicago metro regions are dominant in national perishable food distribution. Comparing choke point counties from our findings for perishable networks to an earlier study examining the broader agri-food network using similar methods [6], there are four county choke points in common (San Bernardino CA, Riverside CA, Shelby TN, and Cook IL) and sixteen choke points that are unique to the two analyses (supplementary table S7). Findings also differ on areas of regional importance in North Carolina, Arizona, New York, Tennessee and San Francisco metro counties (supplementary table S8). These differences illustrate the value of data curation.

Perishable supply networks vary regionally due to differences such as agriculturally-related seasonality, water availability, proximity to markets, and international trade routes at border crossings and ports [6]. Significant regional differences in food network disruptions were observed during the COVID-19 Pandemic, reflecting differences in network structures [33]. Businesses invest in network management to efficiently direct resources and navigate disruptions, such as COVID-19. Choi advises that supply network mapping, such as the mapping in this research, is critical in this age of 'regression to the tail', where extreme events are increasingly common, and natural systems are profoundly impacted by human systems. Networks tend to centralize and form core nodes where goods for final sale are produced (i.e. packing houses and processing facilities), concurrently increasing system efficiencies and vulnerabilities [7].

In a review of supply chain resilience literature early during the Pandemic (2020), the authors noted a move from looking at supply chains to supply networks was possible as more research utilized network science and AI tools such as machine learning, as we did in this study. Of the 94 articles published from 2017–2019, none of the ten US studies covered food and agriculture supply chains, while several European studies did. They also noted that only 48% of the papers used quantitative methods and 26% used characteristics of resilience as proxies rather than directly quantify resilience. A key recommendation was to address transportation networks when assessing resilience [34]. Others during this period reminded us that while network resilience is important, there are other systems properties to keep in mind, such as tipping points, non-linearity, asymmetry, and interconnectedness. The systems approach can promote cross-sectoral collaboration in policy formulation by accounting for linkages between and within different specializations and institutional 'silos' [35].

Further work to understand how supply network structures contribute to food systems resilience is needed. Measuring resilience is much discussed in food systems circles drawing on several disciplines. Differences between assessing system operations or outcomes, or by type of resilience such as robustness, recovery and reorientation [36], aligns somewhat with logistics literature that calls for a 'plan-absorb-recover-adapt' approach [34]. A 2023 review of agrifood supply chain resilience discusses two types of interrelated and complementary resilience: inherent resilience and adaptive resilience [37]. Inherent resilience is derived from network structure, buffer capacity and high social connection, while adaptive resilience is a result of transportation flows, storage, information flows and demand management. Interestingly, this study finds that adaptive resilience was not the result of planning and preparation but arose from the components of inherent resilience. In our research, we use transportation flows to uncover the system structure, thereby incorporating freight transportation into the analysis.

The Volpe National Transportation Assistance Center analyzed seventeen high-volume highway corridors to understand their role in moving agricultural freight. Comparing their findings with ours, we can see how corridors align with network structure. For instance, the rural network concentration for perishable meat in Nebraska, Iowa and Illinois can be linked to two highway corridors in the Volpe analysis. The corridors connecting Omaha, NE westbound to Salt Lake City and eastbound to Chicago, IL are moving high volumes of meat east and west. They estimate about 659 million ton-miles of meat are moving east and 1.37 billion ton-miles are moving west [38].

Research suggests that identifying core nodes in food logistics networks is critical to improving food systems resilience and recommends that geographic risk assessment profiles be developed for each node in the network, similar to Choi's recommendations and the Volpe Center's work on highway corridors [7, 37, 38]. However, focus on network concentration is insufficient. We also need to understand challenges encountered where networks are weak: the peripheral nodes where food supply is relatively scarce. Networks could be transformed by developing lattice structures, thereby lessening the importance of core nodes, and trading some efficiency for more network resilience [39].

In our study, we identified structural boundaries to perishable food systems by modeling core and peripheral geographic nodes, and do not investigate those nodes that fall in between. Our approach captures the upper limits (core nodes) and lower limits (peripheral nodes) of perishable supply networks, providing a boundary analysis of relative network geographic centrality, while other works of note measured food systems resilience with a proxy resilience measure. The three quantitative studies below have further explored resilience based on earlier research on the global grain network, that indicated network resilience and efficiencies complement each other as more nodes participate in trade[39]. Trade intensity together with network structure can achieve higher efficiency and resilience simultaneously.

Gomez *et al* explored urban food supply resilience based on the finding that increasing trade diversity increases system resilience [40]. They found that food shock risk decreases with supply chain diversity (a diversity of sources and trading partners) using an intensity—duration—frequency model. Subsequent work (2023) using supply chain diversity as a proxy for food supply resilience concluded that increasing the number of trading partners a city utilizes may concurrently reduce the environmental impacts of food systems and improve supply resilience between cities. Importantly, this study linked urban resilience to nitrogen, carbon and water environmental impacts from different agricultural production systems and found that the meat production sector has the highest footprint [41]. Omaha scores relatively high on urban food supply resilience and has a high environmental footprint, while our analysis indicates Omaha is core to the meat network as is much of Nebraska and Iowa.

Bingham *et al* employed a novel food flow model with 2012 data and found commensurate results to ours [9]. They curated food flow data similar to our approach and modeled differently, in that they measured resilience by quantifying the diversity of food supply chain sources rather than the connections to food supply networks. The Bingham study found that low population regions exhibit low food supply resilience, and urban and suburban counties have high overall resilience, where low food access is masked at the neighborhood scale [42]. Unlike our approach which considers supply chains from the moment the food is refrigerated to when it is consumed, these approaches consider the production and consumer ends of supply chains, and do not provide insight into the processing and transportation network connections.

There are clearly economic benefits to core counties and their food businesses, as well as costs and challenges from geographic concentration. Core counties are critical to the food supply while their residents, especially the working poor and other marginalized populations, might disproportionately bear the costs from network concentration, including air pollution, traffic congestion, draw on the energy grid, high levels of food loss, poor working conditions, and a greater need for enforcement of labor and other regulations. For example, warehouse concentration in poorer parts of Southern California (Los Angeles, Riverside, San Bernardino and Orange counties) is associated with air pollution from diesel combustion [43]. Twelve Illinois counties rank in the top 9% of US counties at risk of health, societal and economic impacts from diesel fine particle air pollution, including prepared food choke point counties Cook, Lake, Grundy and Kankakee [44]. The growth in freight is a major contributor to traffic congestion on urban and intercity routes [45]. In 2021, the most congested metro regions measured by minutes of delay include Los Angeles and Chicago [46]. Low income regions are challenged to meet the energy, capital and cooling requirements for perishable foods, leading to food loss post-harvest [47]. The risk for forced labor in the US food industry, based on known occurrences, is particularly high for meat and processed produce [48].

We identified areas insufficiently connected to national food distribution networks. Arizona, Michigan, Montana, North Dakota, Texas, and West Virginia are positioned on the periphery of these networks. Appalachia, the High Plains and Southwest contain FAR areas, with higher-than-average Indigenous populations and rural poverty. Some states exhibit uneven connections to supply networks, where core counties are adjacent to peripheral counties, and vice versa. Research documents how low access to capital, energy and cold chain infrastructure inhibits perishable food supply chain development in low-income contexts [47]. Opportunities to alleviate these disparities are likely to be locally specific and require assistance to access the necessary capital. State programs to support infrastructure development could integrate peripheral counties into vigorous adjacent networks to improve economic conditions and reduce the pressure on core counties.

Research indicates that geographic concentration in food supply networks shapes and is shaped by transportation infrastructure and those data businesses used to optimize infrastructure location. Facility and transportation infrastructure determine routing decisions for products flowing through the networks. About 80% of transportation costs are attributable to facility location and access to transportation networks [49]. The Mid-America Freight Coalition working across ten states found 50% of businesses and 60% of their employees are located along designated freight corridors [50]. Firms concentrate facilities where transportation routes are cost effective to their firm, not necessarily to meet food needs, improve regional market access, or to optimize food freight and transit across networks as a whole. The geography of food and market access is produced by digitalization [51].

Concentration in food distribution inhibits rural entrepreneurship as reported by the USDA Economic Research Service in a 2021 study [52]. They indicate that independent grocers in rural and remote regions are disadvantaged in a concentrating wholesale environment dominated by proprietary infrastructure. Rural groceries are the most important rural retailer type and are likely to be independently owned. Independents rely on wholesale distributors that may also serve chain store competitors that have resources to benefit from wholesale volume discounts. Structural changes such as increasing supply network concentration have widespread implications for rural quality of life beyond simple access to food, such as employment opportunities and other community services [52].

## 5. Conclusion

Although these findings on core and periphery geography are specific to food supply networks in the US, they may point to similar network disparities and challenges in other regions and countries. Much attention is paid to food production and its connection to food access, even though food distribution also affects market access for farmers, food access for low-income and low-density regions, and food loss throughout perishable supply networks. Globally, remote rural regions may face similar challenges to perishable food access as may other countries that rely on vertically integrated food firms and are concentrated in highly populated regions. Since the US is core to global food supply networks, changes in US network structure may lead to disruptions in supply networks worldwide.

Policymakers can use network analysis combined with geographic modeling to identify, monitor and alleviate choke points, target resources to under-served areas, or establish rules to curtail geographic dominance. For instance, US policies enacted in the 1930s supported regional dairy production and could be updated and applied to other foods. These policies influence regional market dynamics and may have slowed geographic concentration in the dairy sector. In-depth and qualitative studies could provide greater insight on counties, regions and countries that fall in between the core and peripheral extremes, as well identify specific interventions to better balance supply networks geographically.

Several efforts are underway to democratize food systems data, information, and knowledge that can further analysis of this type. The National Science Foundation Artificial Intelligence Institutes are creating data pipelines between public data and public and private models to improve information access. Ontologies to facilitate data interoperability and model development to optimize rural food logistics through collaboration are under development. These steps are necessary so that small and medium-sized businesses and public interest researchers can easily visualize and monitor essential supply networks, including food [53, 54].

## Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: http://digital.library.wisc.edu/1793/84167.

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## Author contributions

M M and M K conceptualized the project. M M, M K, H P, C C, and A S developed the methodology. M K curated the data and provided network statistics. M M conducted the formal analysis and investigation. S S performed analysis for Anselin Local Moran's I, Getis-Ord GI* and generated the data visualizations. M M wrote the original draft of the paper. M K, H P, C C, A S, and S S reviewed and edited the paper. M M and M K supervised the project.

## Conflict of interest

There are none.

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