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Structural chokepoints determine the resilience of agri-food supply chains in the United States

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The agricultural and food systems of the United States are critical for ensuring the stability of both domestic and global food systems. Thus, it is essential to understand the structural resilience of the country's agri-food supply chains to a suite of threats. Here we employ complex network statistics to identify the spatially resolved structural chokepoints in the agri-food supply chains of the United States. We identify seven chokepoints at county scale: Riverside CA, San Bernardino CA, Los Angeles CA, Shelby TN, Maricopa AZ, San Diego CA and Cook IL; as well as seven chokepoints at freight analysis framework scale: Los Angeles–Long Beach CA, Chicago–Naperville IL, New York–New Jersey NJ, New York–New Jersey NY, Remainder of Texas, Remainder of Pennsylvania, and San Jose–San Francisco–Oakland CA. These structural chokepoints are generally consistent through time (2007, 2012, 2017), particularly for processed food commodities. This study improves our understanding of agri-food supply-chain security and may aid policies aimed at enhancing its resilience.

The United States plays a key role in a highly integrated global food system[1,2]. The United States is a major producer and consumer of agri-food commodities[3,4], and is connected to countries around the world through trade[5,6]. Shocks to the US food supply chain may limit its ability to export to the rest of the world, which would restrict global supplies and raise prices, with ripple effects for the availability and affordability of staple foodstuffs[7,8]. The ability of the United States to reliably move food from producers to consumers contributes to a stable, affordable and accessible global food supply[9]. Hence, resilient and secure US agri-food supply chains are important for global food security[2,10].

Agricultural and food supply chains within the United States are complex, critical infrastructures that provide society with food every day[11]. The food services and drinking places industry underpins the US economy, according to domestic input–output tables[12]. Importantly, disruptions to the agri-food system would probably have the largest cascading effect in the US economy, of all critical infrastructure[13]. For this reason, agricultural and food systems underpin political and economic stability, which is a key part of national security. Food system security and resilience is thus increasingly recognized as a non-traditional defence objective in the national security community, and is critical to the mission of US national defence agencies[14].

The Executive Order on America's Supply Chains (#14017) calls for researchers and policy-makers to propose more resilient, diverse and secure supply chains[15]. Other federal programmes, such as the Global Food Security Strategy[10] and the Infrastructure Investments and Jobs Act, also aim to increase resilience in agri-food supply chains, due to their importance for both national and global security[16]. Yet, most research on agri-food supply chains has been from the perspective of industrial firms[17,18], with a focus on firm-level logistics[19,20], cost savings[21,22] and resilience[23]. In this Article, however, we take a national and global security perspective on agri-food supply chains due to growing

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Table 1 | List of food commodity groups included in this study

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

Both FAF and county-scale data categorize food commodities by SCTG.

threats, such as pandemics[23,24], extreme weather events and climate shocks[25–27], and cyber and terrorist attacks[28,29].

In this Article we aim to provide insight into the structural chokepoints of US agri-food supply chains. Specifically, we conduct a component-importance study on US food-flow networks to identify the critical locations for the delivery of agri-food commodities. We adopt the term 'structural chokepoints' of agri-food supply chains to indicate the locations that are logistics hubs in supply-chain networks[30]. Structural chokepoints are the critical distribution hubs within the United States that hold the physical network structure together and contribute to the efficient movement of goods[31]. Thus, identifying these structural chokepoints is important for future preparedness planning and investment to enhance resilience to threats[32].

This study determines the logistically critical chokepoints of US agri-food supply chains at a fine spatial scale. We study both freight analysis framework (FAF) zones and county-level spatial resolutions, for Standard Classification of Transported Goods (SCTG) agri-food commodities as listed in Table 1 in 2007, 2012 and 2017. The research questions that guide our study are as follows. (1) What are the structural chokepoints of US agri-food supply chains? (2) How do the structural chokepoints change by commodity? (3) How stable are the structural chokepoints through time?

Results and discussion

Structural chokepoints of US agri-food supply chains

We identify the structural chokepoints of the 'aggregated agri-food network' within the United States. In 2017, the chokepoints are Riverside CA, San Bernardino CA, Los Angeles CA, Shelby TN, Maricopa AZ, San Diego CA and Cook IL (counties) and Los Angeles–Long Beach CA, Chicago–Naperville IL, New York–New Jersey NJ, New York–New Jersey NY, Remainder of Texas, Remainder of Pennsylvania and San Jose–San Francisco–Oakland CA (FAF zones), as shown in Supplementary Fig. 1 (for chokepoints in 2007 and 2012, see Supplementary Table 1).

Several of the identified chokepoints show a spatial correspondence between FAF and county scales (for example, Cook County IL and Chicago–Naperville IL CFS Area; Los Angeles County CA and Los Angeles–Long Beach CA CFS Area). At the FAF scale, the structural chokepoints are more homogeneously distributed across the continental United States, with the inclusion of Remainder of Texas and Remainder of Pennsylvania. The other chokepoints at the FAF scale contain some of the busiest freight transportation hubs—cities such as Los Angeles CA, Chicago IL and New York NY[33], as illustrated in Fig. 1. At the county scale, we observe that chokepoints still correspond to the transit hubs, but they are more concentrated in California. This is mainly due to the importance of the Los Angeles–Long Beach CA CFS Area to the county-scale network, which is not apparent at the more coarse FAF scale.

Chokepoints represent the locations that are critical for distributing agri-food commodities throughout the country, as shown in Fig. 2. In this study, chokepoints represent transportation and processing hubs, rather than mass supply points. A disruption to these locations (for any reason, such as a targeted cyber attack or extreme weather event) would require rerouting, which may or may not be feasible, depending on the transport mode and other logistical constraints. For example, roadway disruptions may be able to reroute through the dense highway networks within the United States, but rail and waterway transport disruptions are less adaptable and may lead to more food loss and waste if transportation by mode is considered. Thus, shocks to chokepoints would probably require more intermediate steps, reducing logistical efficiency and potentially increasing food loss. As such, these locations may be important to prioritize for infrastructure preparedness and recovery investments against disruptions, to enhance their resilience.

Commodity-specific structural chokepoints

The structural chokepoints differ by commodity, as shown in Fig. 3. Each agri-food commodity group has unique production, processing and distribution requirements, leading to differences in chokepoint locations (Supplementary Figs. 2–8 provide a list of chokepoints broken down by commodity, both at FAF and county spatial scales). For example, for SCTG 01 (live animals), Atlanta–Athens–Clarke County–Sandy Springs GA CFS Area and Remainder of Ohio are the chokepoints. In SCTG 02 (cereal grains), the chokepoints are Remainder of Iowa, Remainder of Indiana, Remainder of Illinois and Remainder of Idaho. For SCTG 05 (meat and their preparations), chokepoints are replaced by Dallas–Fort Worth TX CFS Area, Remainder of Georgia and Atlanta–Athens–Clarke County–Sandy Springs GA CFS Area.

At the county scale, we also observe differences among chokepoints per commodity. However, these differences are not as pronounced as at the FAF scale. Some of the different chokepoints per commodity are listed as follows: in SCTG 02 (cereal grains) Sarpy County NE is identified as a chokepoint, whereas in SCTG 03 (agricultural products), Indian River County FL and Fresno County CA are identified as chokepoints. Also, Linn County IA becomes a

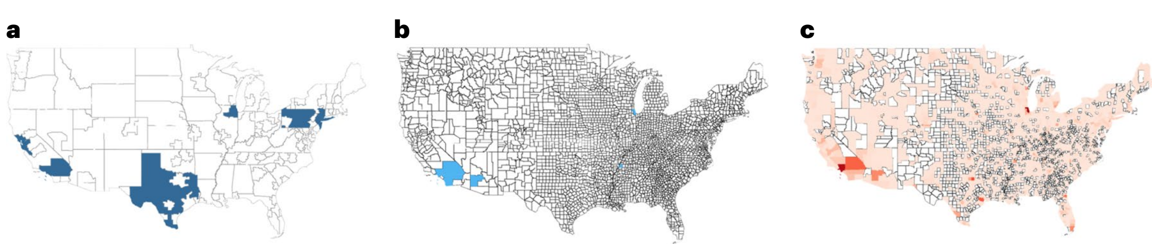

Fig. 1 | Structural chokepoints correspond to the freight transit hubs within the United States in 2017. a, Structural chokepoints for the FAF-scale aggregated agri-food network. **b**, Structural chokepoints for the county-scale aggregated agri-food network. **c**, Logistics sector revenue (in US$) computed with the data in Supplementary Table 2 at the county scale. Darker red indicates higher logistics sector revenue—the freight transit hubs within the United States. The logistics sector data to identify transit hubs are directly adopted from the literature[33].

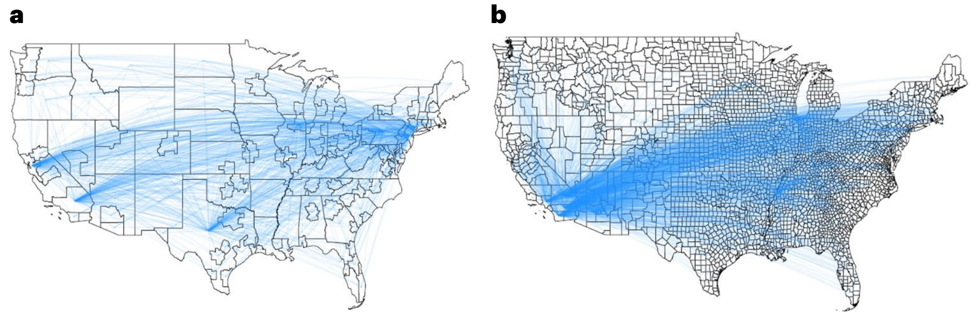

Fig. 2 | Plots of the links originating from the structural chokepoints. a,**b**, Links plotted for the aggregated agri-food network at FAF (**a**) and county (**b**) scales for 2017. The US basemap with geographic region boundaries is obtained from the US Census Bureau[54]. Note that flow mass carried along the links is not included.

unique chokepoint in SCTG 04 (animal feed), but in SCTG 05 (meat and their preparations), Sussex County DE, Berks County PA and Denver County CO are the chokepoints.

Chokepoints vary across commodities due to regional specialization in the production of different food commodities. Generally, the chokepoints for each SCTG commodity network are located within the main production region for that commodity. However, chokepoints are not the same as the mass production points, but rather typically capture nearby transportation hubs that maintain the delivery of goods (see Supplementary Fig. 9 for the map of all transit hubs across the United States[33]). For example, for SCTG 01 (live animals), one of the chokepoints is the metropolitan area of Georgia FAF zone, which contains the transit hub of Atlanta, whereas Georgia is the top poultry producing state within the nation[34]. Similarly, for SCTG 05 (meat and their preparations), the chokepoints are again some of the transit hubs located in Texas and Georgia. Texas is the top state in the United States in terms of the market value of meat products sold[35], and Atlanta–Athens–Clarke County–Sandy Springs GA CFS Area contains Hall County GA, which is the self-proclaimed poultry capital of the world[34]. Furthermore, for SCTG 02 (cereal grains), all of the chokepoints are located in the Corn Belt[36]. Even though cereal grains are produced throughout the United States, production is concentrated in the Corn Belt, where Iowa and Illinois are the top corn-producing states and typically account for about one-third of the total domestic crop[37].

Regional production patterns also lead to chokepoint differences across commodities at the county scale. For example, Sarpy County NE is located in the Corn Belt and it is identified as a chokepoint for SCTG 02 (cereal grains), as shown in Fig. 4. For SCTG 03 (agricultural products), Fresno County CA is a chokepoint that is in the top three counties for agricultural product market value[38]. Similarly, for SCTG 04 (animal feed), Linn County IA is identified as a chokepoint, as 30% of the corn produced in Iowa is used for animal feed[39]. For SCTG 05 (meat and their preparations), Sussex County DE is identified as a chokepoint—this is the largest broiler-producing county in the United States for 2017[40].

Chokepoints for the aggregated agri-food network correlate most with the chokepoints in SCTG 06 (milled grain products) and SCTG 07 (other prepared foodstuff) (Supplementary Figs. 7 and 8), because the processed food industry is more homogeneously distributed throughout the nation than the regional specialization in agricultural production[41], as shown in Fig. 5. Similar to the chokepoints for the aggregated agri-food network (section Structural chokepoints of US agri-food supply chains), the major hubs/ports of the continental United States are the chokepoints for these processed food commodities. Thus, these national transit hubs, such as Chicago, Los Angeles and New York, enable the distribution of processed commodities throughout the country, and also connect domestic and global supply chains. These findings align with the previous literature, which concludes that urban locales provide manufactured food[42].

Stability of structural chokepoints through time

The results in the previous two sections are for 2017 (the most recent study year). In this section, we determine the structural chokepoints for 2007 and 2012, the other years with available data, and assess the stability of chokepoints over time. Generally, structural chokepoints are more stable through time at the FAF scale. Additionally, the chokepoints of more processed food commodities (for example, SCTG 06, SCTG 07 and 'aggregated agri-food network') are more stable through time. Overall, there is a high degree of similarity in the chokepoints through time, across spatial scales, and by commodity (Supplementary Tables 3–9 present chokepoints broken down by SCTG group in 2007 and 2012). In Fig. 6, we plot the heatmap of aggregated agri-food network structural chokepoints based on how frequently FAF zones and counties are located within the top ten through time (Supplementary Figs. 10–16 present stability heatmap of chokepoints broken down by SCTG group).

At the FAF scale, Chicago–Naperville IL CFS Area, Los Angeles–Long Beach CA CFS Area and Remainder of Pennsylvania are identified as aggregated agri-food network chokepoints consistently through time. They are followed by New York–New Jersey NY CFS Area and Remainder of Texas. The same stability applies to the SCTG 07 (other prepared foodstuff) chokepoints, with the exception that Remainder of Texas is replaced with Remainder of Iowa. For SCTG 06 (milled grain products), Remainder of Pennsylvania and Chicago–Naperville IL CFS Area are consistent chokepoints through time, and these locations are followed by Atlanta–Athens–Clarke County–Sandy Springs GA CFS Area. As we move to more specialized agricultural commodities, the stability of chokepoints through time decreases. Yet, we do not completely lose commonality.

At the county scale, Cook County IL, Shelby County TN, Los Angeles County CA and Maricopa County AZ are identified as aggregated agri-food network chokepoints constantly through time. Similarly, for the SCTG 07 (other prepared foodstuff) network, the constant chokepoints through time are Cook County IL, Shelby County TN and Los Angeles County CA. Chokepoint stability decreases for the rest of the commodities more drastically at the county scale. For example, in SCTG 05 (meat and their preparations), Maricopa County AZ is a constant chokepoint, and for SCTG 03 (agricultural products), San Diego County CA is a constant chokepoint through 2007, 2012 and 2017. However, for SCTG 01 (live animals), SCTG 02 (cereal grains) and SCTG 04 (animal feed), there is substantial variation in the chokepoints through time.

Our results highlight that the distribution network of processed food commodities is fairly stable, as similar FAF zones and counties are identified as the structural chokepoints in 2007, 2012 and 2017. Thus, prioritizing these critical locations for national security investments may be possible for the entire agri-food supply. However, for more specific and raw food commodities, pinpointing FAF zones and counties for future disruption preparedness and restoration investments may be more challenging, as the chokepoints vary through time.

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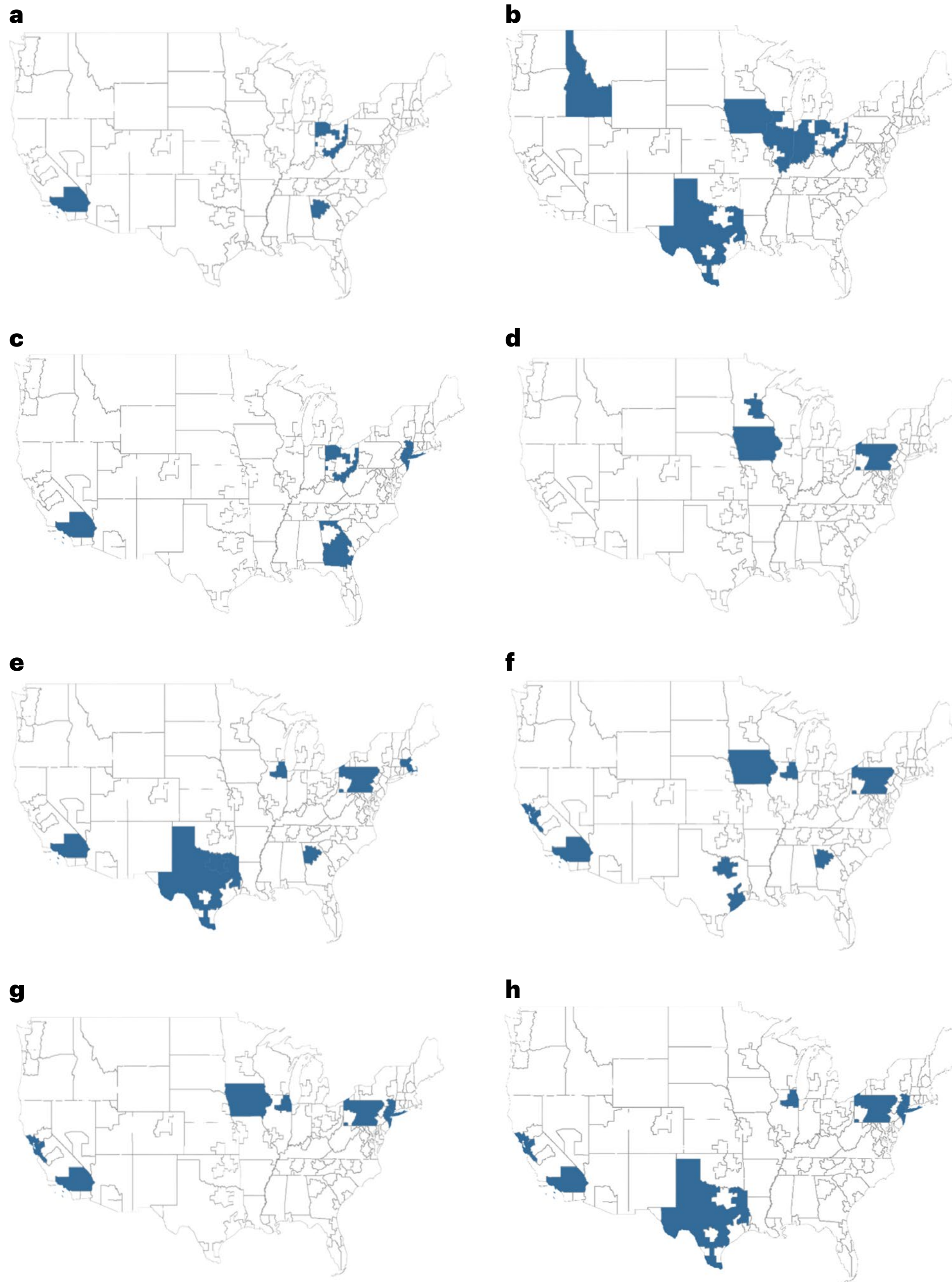

Fig. 3 | Structural chokepoints of FAF-scale food-flow networks by commodity in 2017. a–**h**, SCTG 01 (live animals, **a**), SCTG 02 (cereal grains, **b**), SCTG 03 (agricultural products, **c**), SCTG 04 (animal feed, **d**), SCTG 05 (meat and their preparations, **e**), SCTG 06 (milled grain products, **f**), SCTG 07 (other prepared foodstuff, **g**) and aggregated agri-food network (**h**).

Policy implications

We develop a complex network framework to identify structural chokepoints in agri-food supply chains of the United States, which are important for both domestic and international food security. We observe a strong correlation across and within the structural chokepoint criteria that we adopt (Supplementary Fig. 17). This means that our proposed framework is comprehensive and consistent. The chokepoints represent the hubs that connect production, processing and consumption locations, and whose disruption would most impact agri-food supply-chain networks. These chokepoints accumulate agri-food commodities from their production regions, to be further processed and redistributed to final consumption points across the United States.

To mitigate any threats posed to these chokepoints, government agencies and industry stakeholders should establish policies, strategies and regulations that would ensure prioritized infrastructure investments, such as repair and expansion, continuous manpower and labour, safe handling precautions, and health and quality control of food commodities along the food systems and related transit facilities within these locations. For example, supply-chain managers could institute temperature-controlled storage, production and distribution infrastructure that is resilient against power outages, railroad delays and differing temperature standards. Engineers could put smart sensors into freight bridges so they have better predictive maintenance and are less likely to fail in hurricanes. Producers, distributors and processors may want to invest in cybersecurity infrastructure, particularly within

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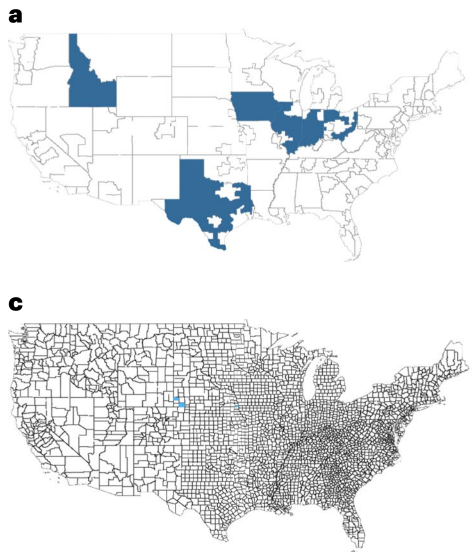

Fig. 4 | A sample of how structural chokepoints are concentrated around supply regions for raw food commodities in 2017. a–**d**, For SCTG 02 (cereal grains), structural chokepoints at the FAF scale (**a**), the total production of cereal grains (tons) at the FAF scale (**b**), structural chokepoints at the county scale (**c**) and total production of cereal grains (tons) at the county scale (**d**). Blue highlighted regions in **a** and **c** are the chokepoints. Darker red highlighted regions in **b** and **d** have higher production mass.

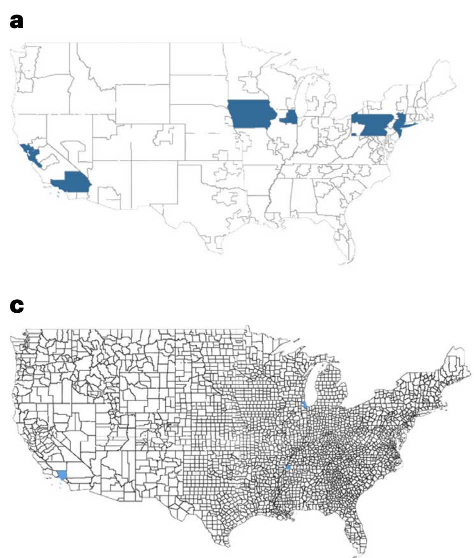

Fig. 5 | A sample of how structural chokepoints are concentrated around supply regions for processed food commodities in 2017. a–**d**, For SCTG 07 (other prepared foodstuff), structural chokepoints at the FAF scale (**a**), processing industry revenue (US$) that uses SCTG 07 as input at the FAF scale (**b**), structural chokepoints at the county scale (**c**) and processing industry revenue (US$) that uses SCTG 07 as input at the county scale (**d**). Blue highlighted regions in **a** and **c** are the chokepoints. Darker red highlighted regions in **b** and **d** have higher processing industry revenue.

these identified chokepoints. As with any intervention or investment, analysis is needed to ensure that the benefits outweigh the costs, as well as to determine the likelihood of unintended consequences.

More specifically, this study could be used to address the call for more resilient, diverse and secure supply chains through the Executive Order on America's Supply Chains (#14017). Furthermore, our work could be useful for informing other national programmes, such as the Infrastructure Investments and Jobs Act, Inflation Reduction Act[43], and related regular appropriations, which aim to enhance the resilience and security of agricultural and food supply chains[44]. Ongoing efforts to address sustainability and food emissions[45,46] should ensure that the resilience and security of the US food system is not undermined[47].

Limitations and future work

The definition of structural chokepoints we adopt is focused on the logistical distribution hubs that connect production and consumption to each other. Thus, our scope is limited to the frequency of connections in each FAF zone and county, not the mass carried through these locations in the food flows network.

The heterogeneous distribution of flow intensities may lead to the identification of distinct chokepoints if explicitly considered. Some weighting schemes may show more overlap than others with the topological chokepoints that we have identified in this study. For example, we hypothesize that food flows weighted in value (US$) would be likely to capture similar transit hubs to the ones we have identified

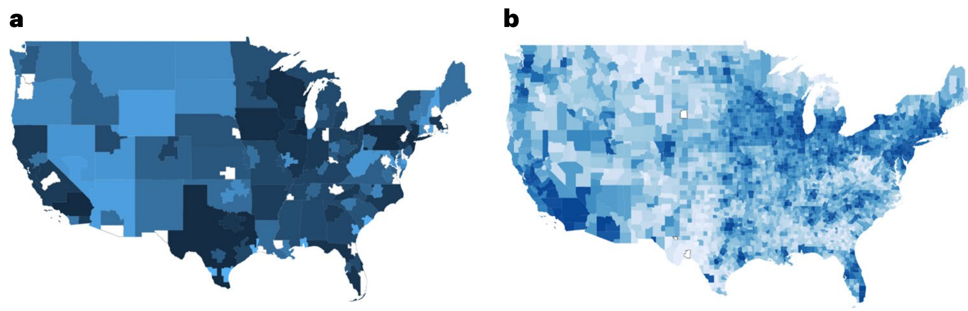

Fig. 6 | Stability of structural chokepoints through time for the aggregated agri-food network. a,**b**, Stability through time for the aggregated agri-food network at the FAF (**a**) and county (**b**) spatial scales. FAF zones and counties that are shaded the darkest are always ranked within the top ten of the component-importance analysis through time (2007, 2012 and 2017). Thus, dark-shaded locations are the most stable chokepoints for the physical network structure.

here, as the value associated with processed food commodities would be more emphasized. On the other hand, food flows weighted in mass (kg) would probably highlight production locations, as the mass associated with the raw commodities (especially grain) would drive the final list of chokepoints. There are a variety of potential weighting schemes that are important to food supply chains—such as mass (kg), value (US$), calories and nutrients—so a weighted analysis warrants a separate approach rather than the simple inclusion of link weights into our topological framework.

Future research could improve on our approach by determining the combination of locations that would most disrupt the network when they are removed together. Such a study could examine whether damage to US food-flow networks by an attack would also depend on the set of locations removed, which is not given (or predictable) by the simple sum of the effect due to the removal of any single location[48].

Also, additional sensitivity and uncertainty analyses could be performed. Since food flows are most sensitive to distance between nodes[49], which is fixed over time, our chokepoint detection carries low uncertainty. Yet, the sensitivity of the final list of chokepoints to each network metric could be examined in future work, as more granular food flow data becomes available.

Our chokepoint identification is mainly a static analysis, even though eigen-decomposition-based centrality and resilience metrics take the dynamic nature of flow propagation along the network into account. Future research could propose a more comprehensive dynamic model with consideration of shock propagation and redistribution of load across the network once a component is removed. Such a model may be able to better capture how the food-flow networks would react in the event of a disruption.

Finally, future research could address the dependencies of chokepoints on the modes of transport. In the case where a roadway blockage occurs, it would be relatively easy for trucks to reroute, compared with a blockage along railways or waterways. Such future research could provide a more realistic and practical guide for transportation infrastructure investments. A better understanding of adaptability to supply chain shocks could also be highlighted.

Conclusion

In this Article we have identified the structural chokepoints of agri-food supply chains within the United States. The chokepoints are generally the same geographical areas at FAF and county spatial scales. The chokepoints at the county scale are Riverside CA, San Bernardino CA, Los Angeles CA, Shelby TN, Maricopa AZ, San Diego CA and Cook IL. At the FAF scale, the chokepoints are Los Angeles–Long Beach CA, Chicago–Naperville IL, New York–New Jersey NJ, New York–New Jersey NY, Remainder of Texas, Remainder of Pennsylvania and San Jose–San Franscisco–Oakland CA. The chokepoints are fairly consistent across study years, especially Chicago–Naperville IL CFS Area, Los Angeles–Long Beach CA CFS Area, Remainder of Pennsylvania and New York–New Jersey NY CFS Area at the FAF scale and Cook IL, Shelby TN, Los Angeles CA and Maricopa AZ at county scale for processed food commodities. These chokepoints are predominantly transit hubs, but each commodity group has its own unique structural chokepoints corresponding to its distinct geographical signature of production.

Methods

We adopt a complex network approach to determine the chokepoints within US agri-food supply chains for the years 2007, 2012 and 2017. Below, we detail the data requirements (Input data), network construction (Food flow networks) and chokepoint identification (Identifying structural chokepoints). Please note that our study was restricted to the continental United States (that is, Alaska and Hawaii are excluded).

Input data

We have two sets of input data, one for each spatial scale of food flow in the United States. The FAF data for 2007, 2012 and 2017 are created through a partnership between the US Bureau of Transportation Statistics and the Federal Highway Administration[50]. FAF-scale data provide information on the domestic and international transfer of commodities by the SCTG within the FAF zones of the United States. These FAF zones generally represent states and their metropolitan areas (Supplementary Table 10 presents a list of 132 FAF zones). Here we limit our FAF-scale data only with a redistribution of the domestically produced and consumed commodities to capture the importance of locations as domestic distribution hubs rather than as international trade ports.

For the second set of data, we use the county-scale domestic food flows within the United States for 2007, 2012 and 2017, which are estimated with an improved version of the Food Flow Model[51]. The Food Flow Model accounts for the geography of production, transportation, input–output requirements, intermediate processing and final consumption stages in the supply chain to estimate county-scale food flows. Hence, the processing of commodities from raw to more refined items is also considered within our study. Note that county-scale food-flow data exist only for 2007, 2012 and 2017.

Food flow networks

We construct directed networks from the food-flow data without consideration of flow amounts, as our focus is pinpointing logistics hubs rather than mass suppliers. Nodes (N) are the spatial locations (that is, FAF zones and counties) that serve as the origin and destination of food flows. Links (L) indicate binary connections (that is, whether a food flow exists or not) between origin (o) and destination (d) nodes, and the direction of the food flow travels from origin to destination. Thus, all metrics are calculated from the origin node point of view.

For each commodity, we create a separate binary, directed network per spatial scale and year. We also create one additional

Table 2 | Statistical network metrics used to determine the structural chokepoints of agri-food flow networks within the United States

Centrality metrics			
Symbol	**Metric**	**Equation**	**Definition**
D_o	Degree centrality	$D_o = \sum_d^N l_{od}$	The total out degree per node. Nodes with higher out degree are more connected with the rest of the network.
E_o	Eigenvector centrality	$E_o = \frac{1}{\lambda_1}\sum_d a_{d,o} E_d$	The influence of a node. Nodes that have a lot of neighbours where those neighbours also have a lot of neighbours are more influential.
C_o	Closeness centrality	$C_o = \frac{1}{\sum_d^N d_{od}}$	The shortest path length from each node to every other node. Nodes with lower shortest path lengths to every other node are more central.
S_o	Stress centrality	$S_o = \sum_{s\neq o\neq t}\sigma_{st}^o$	The number of shortest paths passing through each node. Nodes with higher number of shortest paths passing through them are more central.
B_o	Betweenness centrality	$B_o = \sum_{s\neq o\neq t}\frac{\sigma_{st}^o}{\sigma_{st}}$	The portion of shortest paths passing through each node over the total number of shortest paths. Nodes with higher portion are more central.
Efficiency and resilience metrics			
Symbol	**Metric**	**Equation**	**Definition**
$\bar{\lambda}$	Change in dominant eigenvalue	$\bar{\lambda} = \frac{(\lambda_1-\lambda_1')}{\lambda_1}\times 100$	The change in a network's ability to propagate flow by node removal. Networks with lower change in the dominant eigenvalue are more resilient.
τ	Epidemic threshold	$\tau = \frac{1}{\lambda_1}$	The epidemic threshold of the network. Networks with higher epidemic threshold are more resilient against the contamination spread risk.
$\hat{d}$	Average shortest path length	$\hat{d} = \frac{1}{N(N-1)}\sum_{(o,d):o\neq d} d_{od}$	The average number of stops between any two nodes. Networks with lower average path lengths are more efficient in flow propagation.

Statistical network metric formulations are in italic. For the first category, we compute per node *o* centrality metric values. For the second category, we compute the change in average network centrality following the one-at-a-time node *o* removal. For the third category, we compute the change in network efficiency and resilience after the one-at-a-time node *o* removal. *N*, number of nodes in the food-flow networks; l_{od}, number of links starting from origin node *o* and ending at destination node *d*; *a*, adjacency matrix of unweighted food-flow network; d_{od}, minimum number of hops (that is, shortest path length) between node *o* and *d* in the unweighted food-flow network; *s*, *t*, any two nodes in the unweighted food-flow network; σ_{st}^o, number of shortest paths between any two nodes *s* and *t* in the network that are passing through node *o*; λ_1, dominant eigenvalue of the original unweighted food-flow network adjacency matrix; λ_1', dominant eigenvalue of the unweighted food-flow network adjacency matrix after the removal of a node.

network to represent agri-food flows aggregated across SCTG commodities: 'aggregated agri-food network'. Hence, in total we create 48 unweighted, directed networks, that is, eight in FAF scale and eight in county scale, separately for each study year (2007, 2012 and 2017).

Identifying structural chokepoints

For each food-flow network, we conduct a component-importance study to identify the chokepoints according to their importance for the physical network structure. We first determine a ranked list of nodes for each one of the three statistical network categories: node centrality, impact of node removal on average network centrality and impact of node removal on network efficiency and resilience.

- *Node centrality*. We identify the nodes with the highest centrality metrics. Specifically, we calculate the following: degree centrality, or the number of connections each node has; eigenvector centrality, the influence of each node in the network; closeness centrality, the farness of each node to every other node in the network; and stress and betweenness centrality, which identify the bridging attribute of nodes.
- *Impact of node removal on average network centrality*. We identify the nodes that drive the greatest change in the average network centrality. To do this, the nodes are removed one at a time, and the change in mean centrality for the remainder of the network is observed as each node removed, using the same centrality metrics in the 'node centrality' category.
- *Impact of node removal on network efficiency and resilience*. We again remove nodes one at a time, and identify the nodes whose removal is most impactful to the efficiency and resilience of the entire network. Here, we calculate the change in the dominant eigenvalue, which accounts for the change in the flow propagation attribute; the change in the epidemic threshold, which identifies the tendency of a contagion to spread throughout the network; and the change in the average shortest path length, which represents the average number of traverses along the network.

The complete list of statistical network metrics used to identify each ranked list of nodes is provided in Table 2. We use the centrality metrics in Table 2 to identify the first and second ranked list of nodes, and we use the efficiency and resilience metrics to determine the third ranked list of nodes (additional details for the methods are provided in Supplementary Information). We use a multi-criteria decision-analysis technique, 'technique for order preference by similarity to ideal solution' (TOPSIS)[52,53], to obtain the ranked list of nodes within each category, because there are multiple metrics available (the Supplementary Information provides a more detailed explanation of TOPSIS). The final set of structural chokepoints represents the common nodes that are ranked within the top ten across these three categories (Supplementary Fig. 18).

Here, we study food-flow networks—with a focus on transit of perishable goods. FAF zones and counties that are identified as structural chokepoints based on the adopted metrics in Table 2 indicate the most central and connected locations that bridge the production, processing and consumption points to each other. They are also the core locations for maintaining the efficient movement of goods within the United States. If these chokepoints are disrupted, connectivity along the physical network would be the most undermined.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this Article.

Data availability

All data sources are listed in Methods and are freely available online. Freight analysis framework (FAF)-scale food-flow data are collected from https://faf.ornl.gov/faf5/Default.aspx. The county-scale food flows data are collected from https://doi.org/10.13012/B2IDB-9585947_V1.

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Code availability

Code for identifying the structural chokepoints of US food-flow networks in this study was developed in RStudio version 4.0.2. All code will be made available upon reasonable request from the corresponding author.

References

1. Ercsey-Ravasz, M., Toroczkai, Z., Lakner, Z. & Baranyi, J. Complexity of the international agro-food trade network and its impact on food safety. *PLoS ONE* **7**, e37810 (2012).
2. Brown, M. et al. *Climate Change, Global Food Security and the US Food System* (USDA, 2015).
3. Gbegbelegbe, S., Chung, U., Shiferaw, B., Msangi, S. & Tesfaye, K. Quantifying the impact of weather extremes on global food security: a spatial bio-economic approach. *Weather Clim. Extremes* **4**, 96–108 (2014).
4. Durand-Morat, A., Nalley, L. L. & Thoma, G. The implications of red rice on food security. *Glob. Food Secur.* **18**, 62–75 (2018).
5. Walton, R., Miller, J. O. & Champagne, L. Simulating maritime chokepoint disruption in the global food supply. In *Proc. 2019 Winter Simulation Conference* (*WSC*) 1708–1718 (IEEE, 2019).
6. Bailey, R. & Wellesley, L. *Chokepoints and Vulnerabilities in Global Food Trade* (Chatham House, 2017).
7. Laborde, D., Martin, W., Swinnen, J. & Vos, R. COVID-19 risks to global food security. *Science* **369**, 500–502 (2020).
8. Manikas, I., Sundarakani, B., Anastasiadis, F. & Ali, B. A framework for food security via resilient agri-food supply chains: the case of UAE. *Sustainability* **14**, 6375 (2022).
9. Falkendal, T. et al. Grain export restrictions during COVID-19 risk food insecurity in many low-and middle-income countries. *Nat. Food* **2**, 11–14 (2021).
10. Biden, J. R. *National Security Strategy* (The White House, 2022); https://www.whitehouse.gov/wp-content/uploads/2022/10/Biden-Harris-Administrations-National-Security-Strategy-10.2022.pdf
11. Ericksen, P. J. Conceptualizing food systems for global environmental change research. *Glob. Environ. Chang.* **18**, 234–245 (2008).
12. Xu, M., Allenby, B. R. & Crittenden, J. C. Interconnectedness and resilience of the US economy. *Adv. Complex Syst.* **14**, 649–672 (2011).
13. Chopra, S. S. & Khanna, V. Interconnectedness and interdependencies of critical infrastructures in the US economy: implications for resilience. *Phys. A Stat. Mech. Appl.* **436**, 865–877 (2015).
14. Jahn, M. M. et al. in *Strategic Latency Unleashed*: *The Role of Technology in a Revisionist Global Order and The Implications for Special Operations Forces* (eds Davis, Z. S. et al.) 148–158 (Lawrence Livermore National Laboratory, 2021).
15. Biden, J. R. *Executive Order on America's Supply Chains* (The White House, 2021); https://www.whitehouse.gov/briefing-room/presidential-actions/2021/02/24/executive-order-on-americas-supply-chains
16. Food and agriculture sector-specific plan 2015. *CISA* https://www.cisa.gov/sites/default/files/publications/nipp-ssp-food-ag-2015-508.pdf (2020).
17. Margolis, J. T., Sullivan, K. M., Mason, S. J. & Magagnotti, M. A multi-objective optimization model for designing resilient supply chain networks. *Int. J. Prod. Econ.* **204**, 174–185 (2018).
18. de Sá, M. M., de Souza, M. P. L., de Brito, R. P. & Pereira, S. C. F. Supply chain resilience: the whole is not the sum of the parts. *Int. J. Oper. Prod. Manag.* **40**, 92–115 (2019).
19. Wahdat, A. Z. & Lusk, J. The achilles heel of the US food industries: exposure to labor and upstream industries in the supply chain. Am. *J. Agr. Econ.* **105**, 624–643 (2023).
20. Li, Z., Zhao, P. & Han, X. Agri-food supply chain network disruption propagation and recovery based on cascading failure. *Phys. A Stat. Mech. Appl.* **589**, 126611 (2022).
21. Aramyan, L. H., Oude Lansink, A. G. J. M., van der Vorst, J. G. A. J. & van Kooten, O. Performance measurement in agri-food supply chains: a case study. *Supply Chain Manag.* **12**, 304–315 (2007).
22. Manzini, R. & Accorsi, R. The new conceptual framework for food supply chain assessment. *J. Food Eng.* **115**, 251–263 (2013).
23. Chenarides, L., Manfredo, M. & Richards, T. J. COVID-19 and food supply chains. *Appl. Econ. Perspect. Policy* **43**, 270–279 (2021).
24. Mussell, A., Bilyea, T. & Hedley, D. *Agri-food Supply Chains and COVID-19: Balancing Resilience and Vulnerability* (Agri-Food Economic Systems, 2020).
25. Thorpe, J. & Fennelly, S. *Climate Change Risks and Supply Chain Responsibility*: *How Should Companies Respond when Extreme Weather Affects Small-Scale Producers in their Supply Chain?* (Oxfam, 2012).
26. Levermann, A. Climate economics: Make supply chains climate-smart. *Nat. News* **506**, 27–29 (2014).
27. Godde, C. M., Mason-D'Croz, D., Mayberry, D. E., Thornton, P. K. & Herrero, M. Impacts of climate change on the livestock food supply chain; a review of the evidence. *Glob. Food Secur.* **28**, 100488 (2021).
28. Davis, Z. S., Rager, C. B., Gac, F., Snow, J. & Reiner, P. *Strategic Latency Unleashed: The Role of Technology in a Revisionist Global Order and the Implications for Special Operations Forces* (Lawrence Livermore National Laboratory, 2021).
29. Schneider, C. M., Moreira, A. A., Andrade, J. S., Havlin, S. & Herrmann, H. J. Mitigation of malicious attacks on networks. *Proc. Natl Acad. Sci. USA* **108**, 3838–3841 (2011).
30. Sheffi, Y. *The Resilient Enterprise*: *Overcoming Vulnerability for Competitive Advantage* (Zone Books, 2007).
31. Karakoc, Deniz Berfin & Konar, M. A complex network framework for the efficiency and resilience trade-off in global food trade. *Environ. Res. Lett.* **16**, 105003 (2021).
32. Wellesley, L., Preston, F., Lehne, J. & Bailey, R. Chokepoints in global food trade: assessing the risk. *Res. Transp. Bus. Manag.* **25**, 15–28 (2017).
33. Rivera, L., Sheffi, Y. & Welsch, R. Logistics agglomeration in the US. *Transp. Res. A Policy Pract.* **59**, 222–238 (2014).
34. *As COVID-19 Hit Georgia Meatpacking Counties*, *Officials and Industry Shifted Blame* (Facing South, 2020); https://www.facingsouth.org
35. *NASS Census of Agriculture*, *State Profile*: *Texas* (USDA, 2017); https://www.nass.usda.gov/Publications/AgCensus/2017/Online_Resources/County_Profiles/Texas/cp99048.pdf
36. Prokopy, L. S. et al. Useful to usable: developing usable climate science for agriculture. *Clim. Risk Manag.* **15**, 1–7 (2017).
37. *Economic Research Service*: *Feedgrains Sector at a Glance* (USDA, 2022); https://www.ers.usda.gov/
38. *NASS Census of Agriculture State Profile*: *California* (USDA, 2017); https://www.nass.usda.gov/Publications/AgCensus/2017/Online_Resources/County_Profiles/California/cp06019.pdf
39. *Iowa Corn. Food Facts* (Iowa Corn Growers Association, 2022); https://www.iowacorn.org/education/food-facts
40. *Blog Archives*: *Broiler Industry Stretches Its Economic Wings in Delaware* (USDA, 2017); https://www.usda.gov/media/blog/2015/01/08/broiler-industry-stretches-its-economic-wings-delaware
41. Wang, J., Karakoc, D. B. & Konar, M. The carbon footprint of cold chain food flows in the United States. *Environ. Res. Infrastruct. Sustain* **2**, 021002 (2022).
42. Bingham, D. R., Rushforth, R. R., Stevens, B. & Ruddell, B. L. Mapping local food self-sufficiency in the US and the tradeoffs for food system diversity. *Appl. Geogr.* **143**, 102687 (2022).
43. *Inflation Reduction Act of 2022* (Library of Congress, 2022); https://www.congress.gov/bill/117th-congress/house-bill/5376/text

44. *H.R.4346–117th Congress (2021–2022): Chips and Science Act* (Library of Congress, 2022); https://www.congress.gov/bill/117th-congress/house-bill/4346
45. Weber, C. L. & Scott Matthews, H. Food-miles and the relative climate impacts of food choices in the United States. *Environ. Sci. Technol.* **42**, 3508–3513 (2008).
46. Foong, A., Pradhan, P., Frör, O. & Kropp, J. P. Adjusting agricultural emissions for trade matters for climate change mitigation. *Nat. Commun.* **13**, 3024 (2022).
47. Robinson, C., Shirazi, A., Liu, M. & Dilkina, B. Network optimization of food flows in the US. In *Proc. 2016 IEEE International Conference on Big Data* (*Big Data*) 2190–2198 (IEEE, 2016).
48. Osat, S., Faqeeh, A. & Radicchi, F. Optimal percolation on multiplex networks. *Nat. Commun.* **8**, 1540 (2017).
49. Lin, X., Ruess, P. J., Marston, L. & Konar, M. Food flows between counties in the United States. *Environ. Res. Lett.* **14**, 084011 (2019).
50. *Freight Analysis Framework Version 5* (Oak Ridge National Laboratory, 2020); https://faf.ornl.gov/faf5/
51. Karakoc, D. B., Wang, J. & Konar, M. Food flows between counties in the United States from 2007 to 2017. *Environ. Res. Lett.* **17**, 034035 (2022).
52. Karakoc, D. B., Barker, K., Zobel, C. W. & Almoghathawi, Y. Social vulnerability and equity perspectives on interdependent infrastructure network component importance. *Sustain. Cities Soc.* **57**, 102072 (2020).
53. Hu, J., Du, Y., Mo, H., Wei, D. & Deng, Y. A modified weighted TOPSIS to identify influential nodes in complex networks. *Phys. A Stat. Mech. Appl.* **444**, 73–85 (2016).
54. *Cartographic Boundary Shapefiles* (United States Census Bureau, 2021); https://www.census.gov/geographies/mapping-files/2016/geo/carto-boundary-file.html

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Author contributions

D.B.K., M.K., M.J.P. and L.R.V. conceptualized the project. D.B.K. and M.K. developed the methodology. D.B.K. curated the data, conducted the formal analysis and investigation, and generated the data visualizations. D.B.K. and M.K. wrote the original draft of the paper. M.J.P. and L.R.V. reviewed and edited the paper. M.K. supervised the project.

Competing interests

The authors declare no competing interests.

Additional information

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Data collection	The custom code is developed for the reading and analyzing the publicly available Freight Analysis Framework (FAF) and county-scale food flows datasets. The custom code is developed in RStudio version 4.0.2, and it is available upon request.
Data analysis	The custom code is developed for identification of structural chokepoints of the existing FAF-scale and county-scale food flow networks datasets. The custom code is developed in RStudio version 4.0.2, and it is available upon request.

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The Freight Analysis Framework (FAF) data for the years 2007, 2012, and 2017 that supports the findings of this study are available in Oak Ridge National

Laboratory, https://faf.ornl.gov/faf5/. The county-scale food flow networks within the United States data for the years 2007, 2012, and 2017 that supports the findings of this study are available in University of Illinois Library Data Bank, https://doi.org/10.13012/B2IDB-9585947_V1.

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Study description	Structural chokepoints of food flow networks across spatial scales are identified by calculating some of the most common statistical network connectivity and centrality metrics, such degree betweenness, eigenvector, closeness, and stress centrality. Also, through time stability and by commodity changes along the structural chokepoints of food flow networks are analyzed.
Research sample	Empirical data consists of the bilateral (i.e., in and out) food flow information between Freight Analysis Framework (FAF) and counties within the United States for both single commodities individually and aggregated commodities together. The data is collected for the years 2007, 2012, and 2017 separately. The food flow information is available in net amount (weight), and they are separated by 7 SCTG (Standard Classification of Transported Goods) codes.
Sampling strategy	From the existing datasets, food flows between Freight Analysis Framework (FAF) zones and counties are analyzed for higher granularity. The study years are chosen as 2007, 2012, and 2017 since county-level food flow networks data is available only for these years in the literature. From aggregated commodity groups, all agri-food commodity flows is analyzed. For separate food commodity networks, 7 separate SCTG (Standard Classification of Transported Goods) codes are analyzed. These are SCTG 01: live animals and fish, SCTG 02: cereal grains, SCTG 03: agricultural products, SCTG 04: animal feed, SCTG 05: meat and their preparations, SCTG 06: milled grains, and lastly SCTG 07: other prepared foodstuff. The commodity groups also shaped the data availability.
Data collection	The empirical data for Freight Analysis Framework (FAF) scale food flows is obtained from Oak Ridge Laboratory. Oak Ridge Laboratory integrates data from various sources to create a comprehensive picture of freight movement among states and major metropolitan areas by all modes of transportation and Commodity Flow Survey data serves as the backbone. The food flows between counties in the United States are adopted from "Karakoc, D. B., Wang, J., & Konar, M. (2022). Food flows between counties in the United States from 2007 to 2017. Environmental Research Letters, 17(3), 034035". This empirical data for county-scale food flows is obtained from University of Illinois Library Data Bank as it is publicly available.
Timing and spatial scale	The food flow networks in the years 2007, 2012, and 2017 across spatial scales within the United States is analyzed in this study, as it is the only available data at the county-scale. The analyzed food flow networks are in Freight Analysis Framework (FAF) and county scale within the United States. Freight Analysis Framework (FAF) zones divide states within the United States generally into two separate areas, more rural vs urban/metropolitan areas. Therefore, FAF data provides more detail and higher granularity than food flows between states within the United States. The backbone of Freight Analysis Framework (FAF) data is the Commodity Flow Survey (CFS) data which is collected and published once every 5 years (years ending with '2' and '7'). The backbone of the county-scale food flows data is the Freight Analysis Framework (FAF) data.
Data exclusions	The study is restricted to continental United States (i.e., CONUS), so data regarding the food flows within the Freight Analysis Framework (FAF) zones and counties in Alaska and Hawaii are excluded from this study. These locations are excluded as they have different connectivity and centrality properties than the rest of the study area, hence they are treated as outliers.
Reproducibility	The custom code based study is reproducible as it can be implemented on different datasets.
Randomization	Randomization is not relevant to the study as statistical tests are not implemented on the existing datasets. The complex network framework to assess the common node centrality metrics are implemented on the existing food flow networks data.

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