

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

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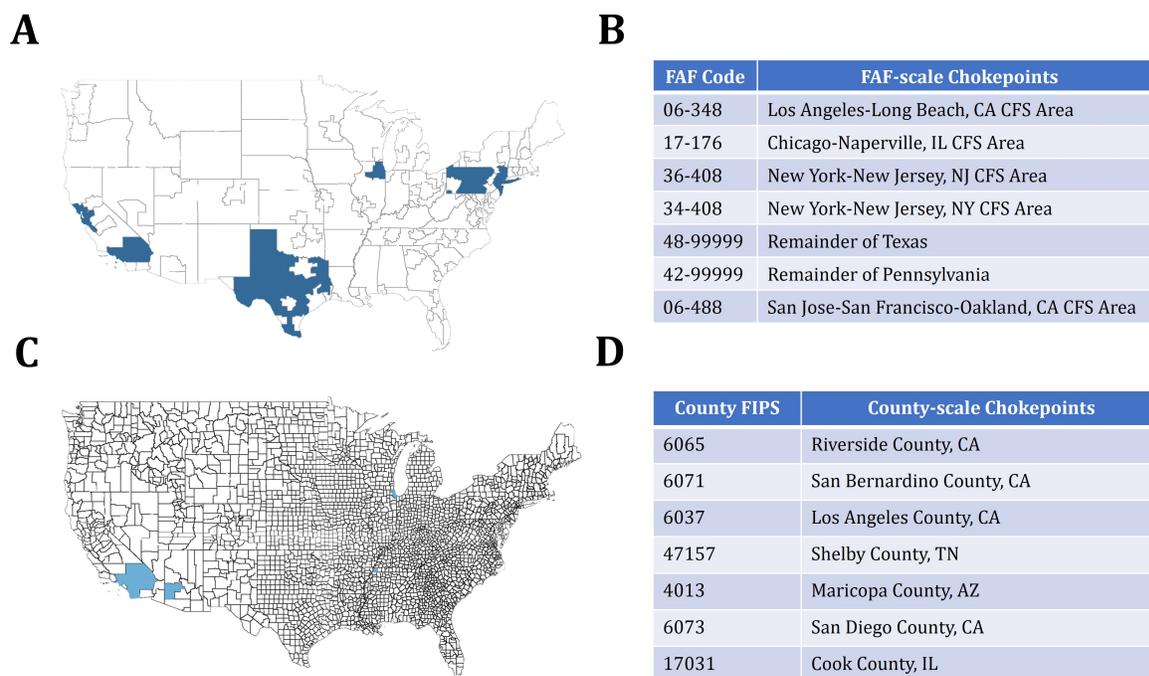
## **Supplementary Information**

Supplementary Methods

Supplementary Figure 1-20

Supplementary Table 1-19

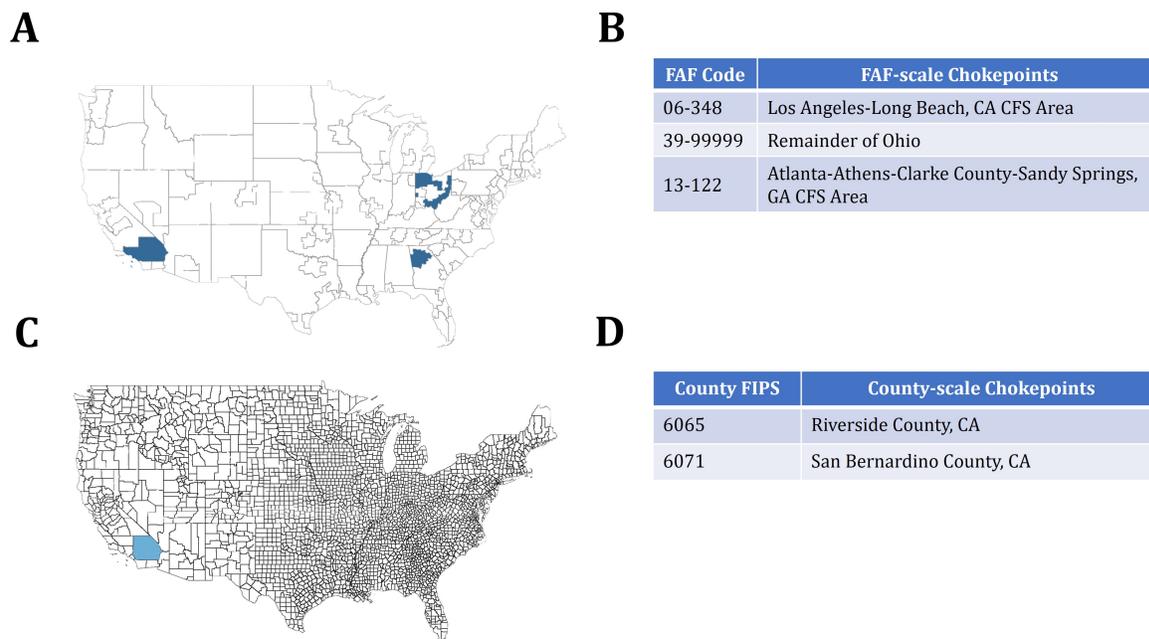
SI References 1-12



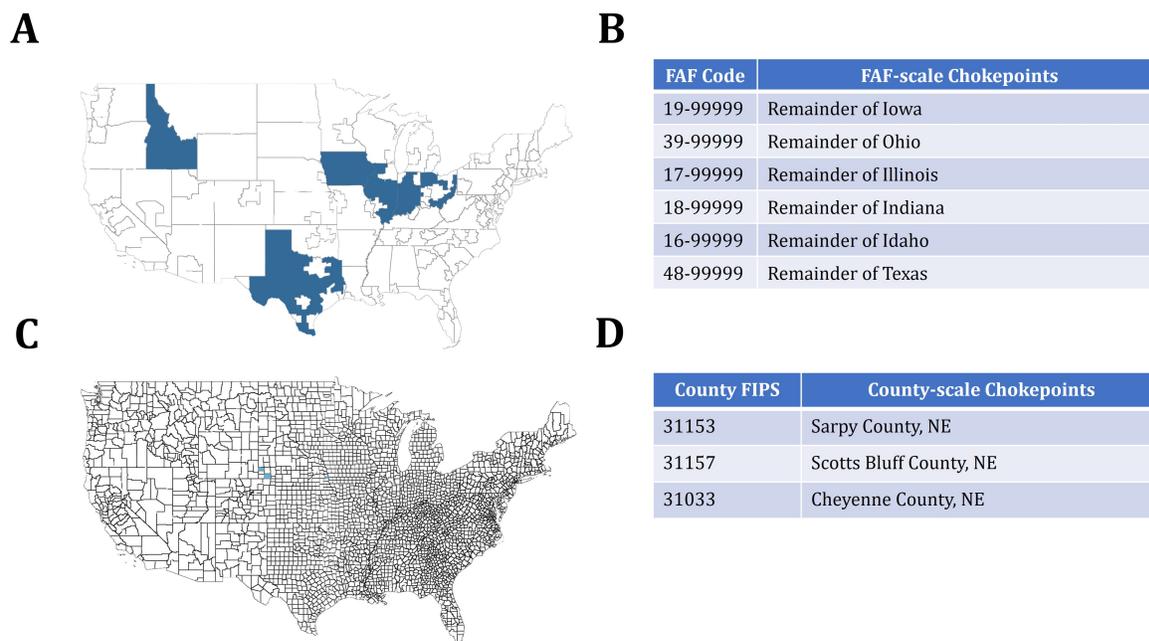
**Suppl. Fig. 1: Locations and list for structural chokepoints of 2017 ‘Agregated agri-food network’ food flow networks. (A) FAF-scale map, (B) FAF-scale list, (C) County-scale map, and (D) County-scale list for the structural chokepoints.**

**Suppl. Table 1: Structural chokepoints of ‘agregated agri-food network’ network through time at FAF and county-scale.**

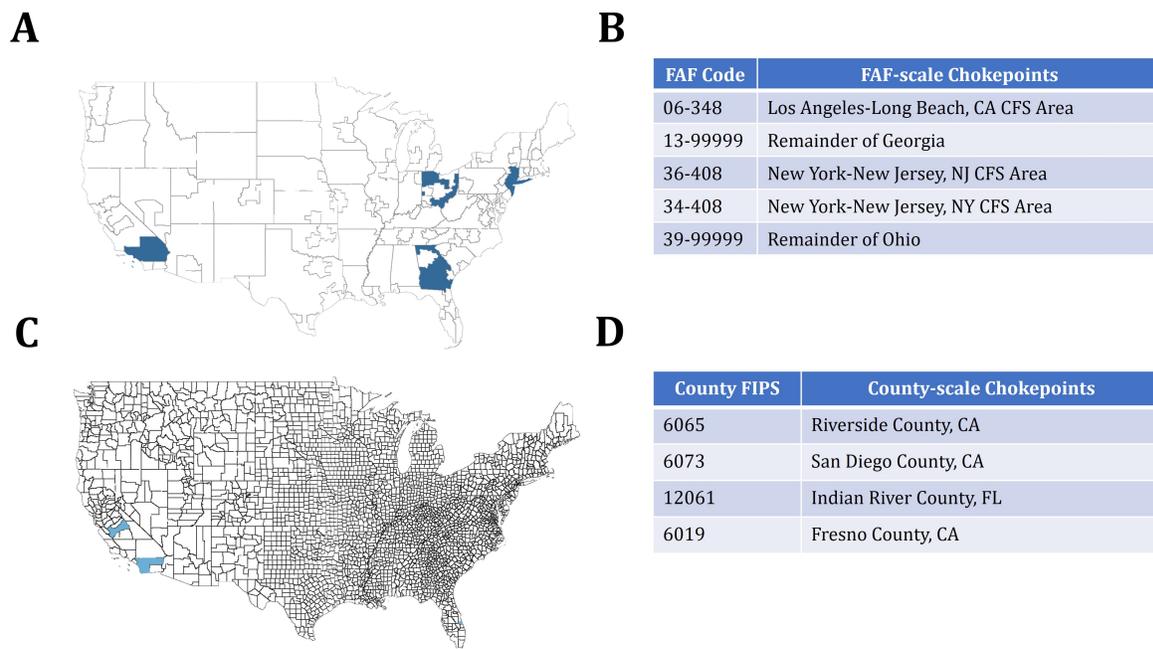
‘Agregated agri-food network’ chokepoints at FAF-scale			
2007		2012	
17-176	Chicago-Naperville, IL CFS Area	17-176	Chicago-Naperville, IL CFS Area
55-99999	Remainder of Wisconsin	06-348	Los Angeles-Long Beach, CA CFS Area
17-99999	Remainder of Illinois	36-408	New York-New Jersey, NJ CFS Area
19-99999	Remainder of Iowa	34-408	New York-New Jersey, NY CFS Area
18-99999	Remainder of Indiana	42-99999	Remainder of Pennsylvania
42-99999	Remainder of Pennsylvania	12-370	Miami-Fort Lauderdale-Port St. Lucie, FL CFS Area
48-99999	Remainder of Texas		
06-348	Los Angeles-Long Beach, CA CFS Area		
‘Agregated agri-food network’ chokepoints at county-scale			
2007		2012	
17031	Cook County, IL	17031	Cook County, IL
47157	Shelby County, TN	6071	San Bernardino County, CA
20091	Johnson County, KS	48113	Dallas County, TX
48201	Harris County, TX	6037	Los Angeles County, CA
6037	Los Angeles County, CA	4013	Maricopa County, AZ
4013	Maricopa County, AZ	6065	Riverside County, CA
		47157	Shelby County, TN



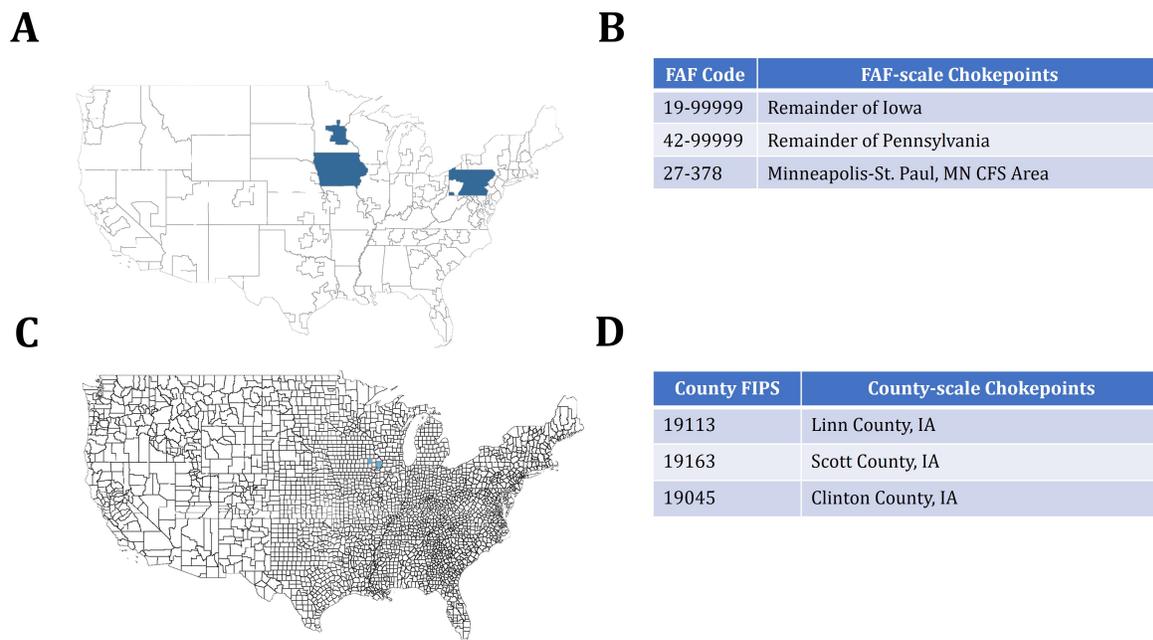
**Suppl. Fig. 2: Locations and list for structural chokepoints of 2017 ‘SCTG 01’ (live animals) food flow networks.** (A) FAF-scale map, (B) FAF-scale list, (C) County-scale map, and (D) County-scale list for the structural chokepoints.



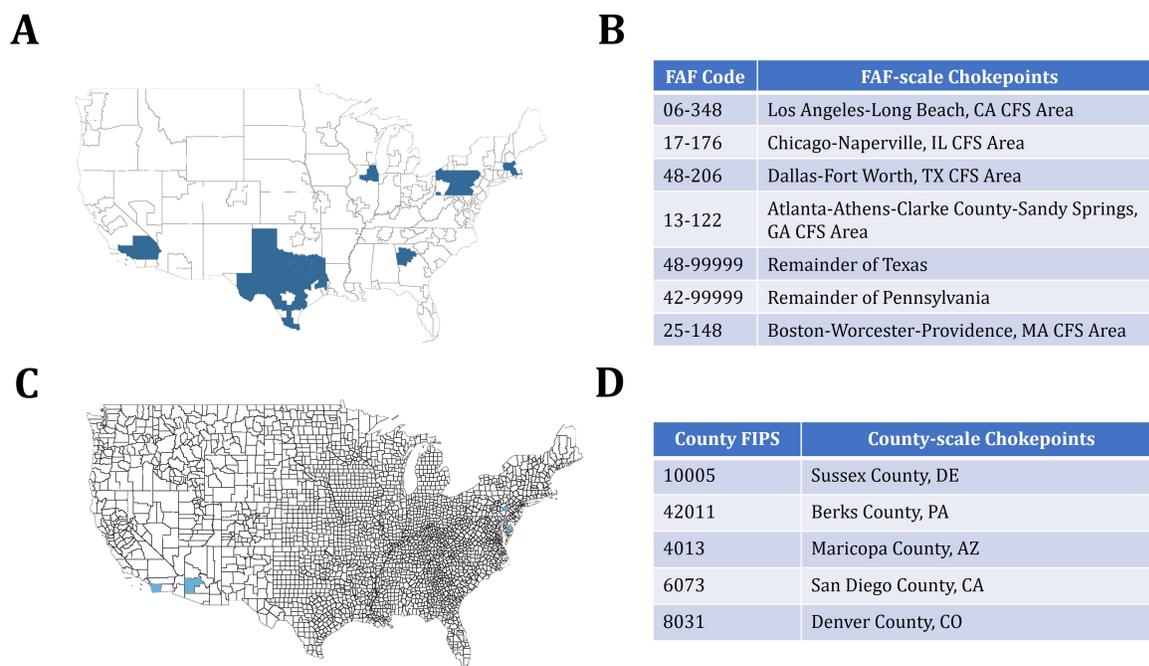
**Suppl. Fig. 3: Locations and list for structural chokepoints of 2017 ‘SCTG 02’ (cereal grains) food flow networks.** (A) FAF-scale map, (B) FAF-scale list, (C) County-scale map, and (D) County-scale list for the structural chokepoints. For county-scale SCTG 02 final chokepoints, we checked the commonality in top 20 locations of each TOPSIS.



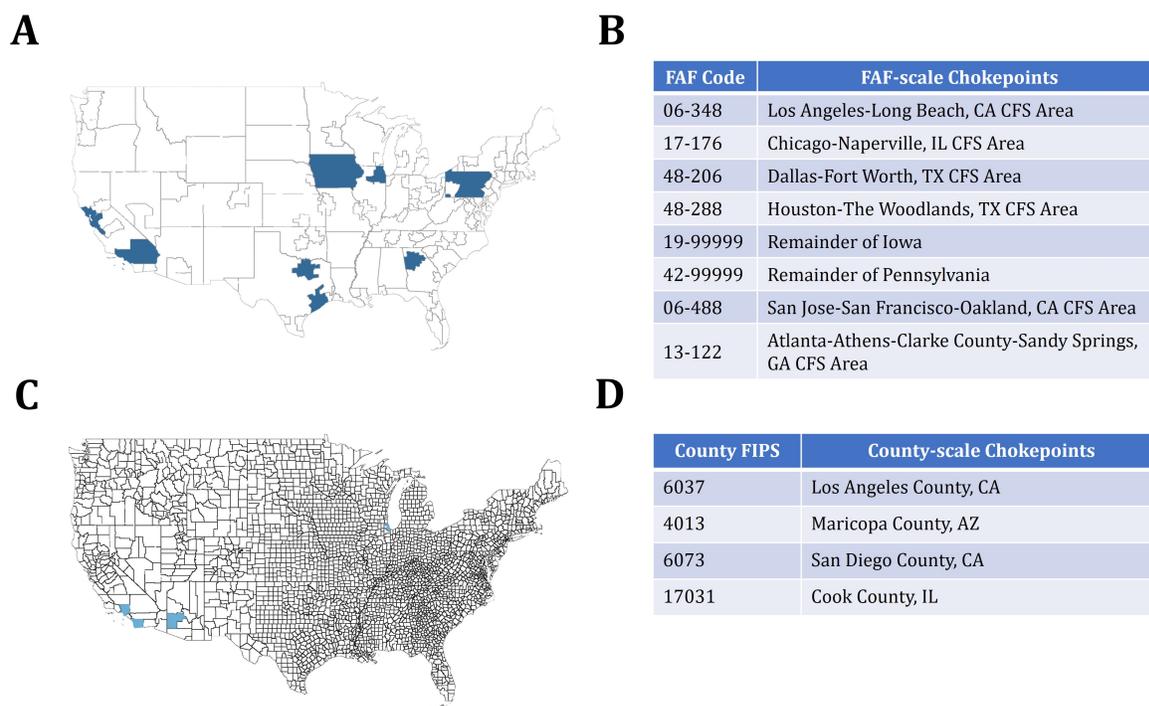
**Suppl. Fig. 4: Locations and list for structural chokepoints of 2017 ‘SCTG 03’ (agricultural products) food flow networks.** (A) FAF-scale map, (B) FAF-scale list, (C) County-scale map, and (D) County-scale list for the structural chokepoints.



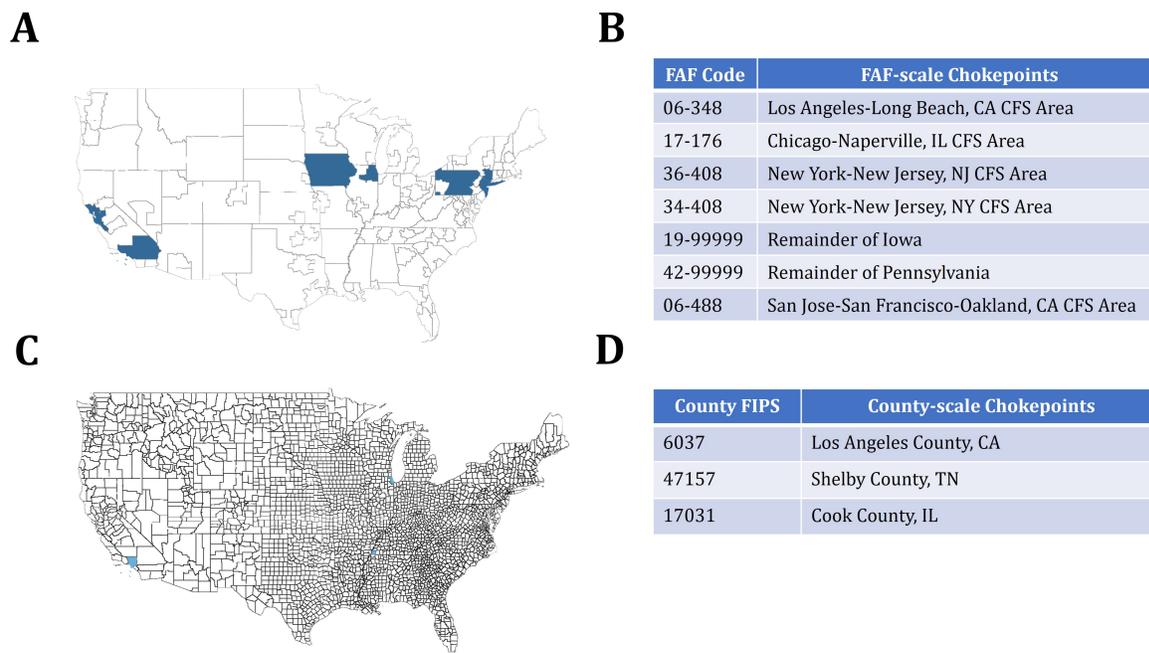
**Suppl. Fig. 5: Locations and list for structural chokepoints of 2017 ‘SCTG 04’ (animal feed) food flow networks.** (A) FAF-scale map, (B) FAF-scale list, (C) County-scale map, and (D) County-scale list for the structural chokepoints. For county-scale SCTG 04 final chokepoints, we checked the commonality in top 20 locations of each TOPSIS.



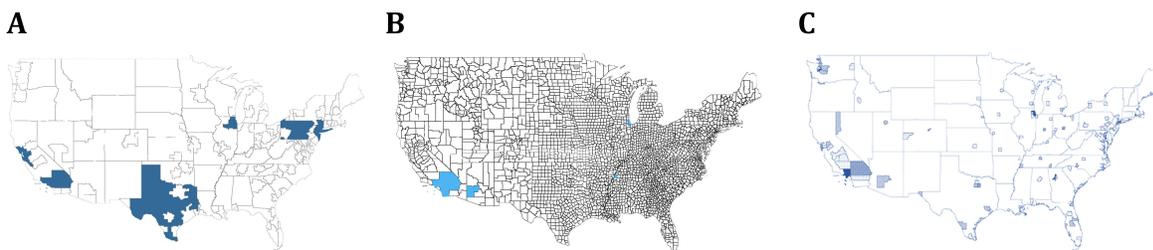
**Suppl. Fig. 6: Locations and list for structural chokepoints of 2017 ‘SCTG 05’ (meat and their preparations) food flow networks. (A) FAF-scale map, (B) FAF-scale list, (C) County-scale map, and (D) County-scale list for the structural chokepoints.**



**Suppl. Fig. 7: Locations and list for structural chokepoints of 2017 ‘SCTG 06’ (milled grain products) food flow networks. (A) FAF-scale map, (B) FAF-scale list, (C) County-scale map, and (D) County-scale list for the structural chokepoints.**



**Suppl. Fig. 8: Locations and list for structural chokepoints of 2017 ‘SCTG 07’ (other prepared foodstuff) food flow networks.** (A) FAF-scale map, (B) FAF-scale list, (C) County-scale map, and (D) County-scale list for the structural chokepoints.



**Suppl. Fig. 9: The spatial correspondence between structural chokepoints of 2017 ‘aggregated agri-food network’ and transit hubs within the United States.** (A) FAF-scale map of ‘aggregated agri-food network’ structural chokepoints, (B) County-scale map of ‘aggregated agri-food network’ structural chokepoints, and (C) Original county-scale map of transit hubs as identified in the literature<sup>33</sup> by the logistics sector data listed in Suppl. Table 2.

**Suppl. Table 2: The list of logistics sector data that is directly adopted from the literature.**<sup>33</sup> In Figure 1C, we simply compute the total revenue (\$) related to the listed logistics industry per county to identify transit hubs within the USA. This data is used in a different methodology to plot Figure 9C.<sup>33</sup> This data is also taken into account while estimating county-scale food flows through time in the United States.<sup>51</sup>

NAICS	Description
481112	Scheduled freight air transportation
481212	Nonscheduled chartered freight air transportation
481219	Other nonscheduled air transportation
483111	Deep sea freight transportation
483113	Coastal and great lakes freight transportation
483211	Inland water freight transportation
484110	General freight trucking, local
484121	General freight trucking, long-distance, truckload
484122	General freight trucking, long-distance, less than truckload
484220	Specialized freight (except used goods) trucking, local
484230	Specialized freight (except used goods) trucking, long-distance
488119	Other airport operations
488190	Other support activities for air transportation
488210	Support activities for rail transportation
488310	Port and harbor operations
488320	Marine cargo handling
488330	Navigational services to shipping
488390	Other support activities for water transportation
488410	Motor vehicle towing
488490	Other support activities for road transportation
488510	Freight transportation arrangement
488991	Packing and crating
488999	All other support activities for transportation
492110	Couriers and express delivery services
492210	Local messengers and local delivery
493110	General warehousing and storage
493190	Other warehousing and storage

**Suppl. Table 3: Structural chokepoints of ‘SCTG 07’ (other prepared foodstuff) network through time at FAF and county-scale.**

‘SCTG 07’ chokepoints at FAF-scale			
2007		2012	
17-176	Chicago-Naperville, IL CFS Area	17-176	Chicago-Naperville, IL CFS Area
55-99999	Remainder of Wisconsin	06-348	Los Angeles-Long Beach, CA CFS Area
17-99999	Remainder of Illinois	36-408	New York-New Jersey, NJ CFS Area
19-99999	Remainder of Iowa	06-488	San Jose-San Francisco-Oakland, CA CFS Area
21-99999	Remainder of Kentucky	42-99999	Remainder of Pennsylvania
42-99999	Remainder of Pennsylvania		
48-99999	Remainder of Texas		
06-348	Los Angeles-Long Beach, CA CFS Area		
34-408	New York-New Jersey, NY CFS Area		
‘SCTG 07’ chokepoints at county-scale			
2007		2012	
17031	Cook County, IL	17031	Cook County, IL
47157	Shelby County, TN	6071	San Bernardino County, CA
55079	Milwaukee County, WI	48113	Dallas County, TX
48201	Harris County, TX	6037	Los Angeles County, CA
6037	Los Angeles County, CA	4013	Maricopa County, AZ
4013	Maricopa County, AZ	42077	Lehigh County, PA
		47157	Shelby County, TN

**Suppl. Table 4: Structural chokepoints of ‘SCTG 06’ (milled grain products) network through time at FAF and county-scale.**

‘SCTG 06’ chokepoints at FAF-scale			
2007		2012	
17-176	Chicago-Naperville, IL CFS Area	17-176	Chicago-Naperville, IL CFS Area
55-99999	Remainder of Wisconsin	06-488	San Jose-San Francisco-Oakland, CA CFS Area
42-99999	Remainder of Pennsylvania	42-99999	Remainder of Pennsylvania
47-99999	Remainder of Tennessee	13-122	Atlanta-Athens-Clarke County-Sandy Springs, GA CFS Area
42-428	Philadelphia-Reading-Camden, PA CFS Area	48-206	Dallas-Fort Worth, TX CFS Area
39-99999	Remainder of Ohio	39-198	Columbus-Marion-Zanesville, OH CFS Area
‘SCTG 06’ chokepoints at county-scale			
2007		2012	
17031	Cook County, IL	6037	Los Angeles County, CA
		48201	Harris County, TX

**Suppl. Table 5: Structural chokepoints of ‘SCTG 05’ (meat and their preparations) network through time at FAF and county-scale.**

‘SCTG 05’ chokepoints at FAF-scale			
2007		2012	
17-176	Chicago-Naperville, IL CFS Area	17-176	Chicago-Naperville, IL CFS Area
37-99999	Remainder of North Carolina	06-348	Los Angeles-Long Beach, CA CFS Area
42-99999	Remainder of Pennsylvania	42-428	Philadelphia-Reading-Camden, PA CFS Area
29-99999	Remainder of Missouri	13-122	Atlanta-Athens-Clarke County-Sandy Springs, GA CFS Area
13-122	Atlanta-Athens-Clarke County-Sandy Springs, GA CFS Area	48-99999	Remainder of Texas
19-99999	Remainder of Iowa	25-148	CBoston-Worcester-Providence, MA CFS Area
‘SCTG 05’ chokepoints at county-scale			
2007		2012	
17031	Cook County, IL	6037	Los Angeles County, CA
6037	Los Angeles County, CA	17031	Cook County, IL
4013	Maricopa County, AZ	6071	San Bernardino County, CA
42101	Philadelphia County, PA	6065	Riverside County, CA
36029	Erie County, NY	4013	Maricopa County, AZ
27123	Ramsey County, MN		

**Suppl. Table 6: Structural chokepoints of ‘SCTG 04’ (animal feed) network through time at FAF and county-scale.**

‘SCTG 04’ chokepoints at FAF-scale			
2007		2012	
18-99999	Remainder of Indiana	42-99999	Remainder of Pennsylvania
21-99999	Remainder of Kentucky		
17-99999	Remainder of Illinois		
29-99999	Remainder of Missouri		
42-99999	Remainder of Pennsylvania		
‘SCTG 04’ chokepoints at county-scale			
2007		2012	
6073	San Diego County, CA	19061	Dubuque County, IA
4013	Maricopa County, AZ		

**Suppl. Table 7: Structural chokepoints of ‘SCTG 03’ (agricultural products) network through time at FAF and county-scale.**

‘SCTG 03’ chokepoints at FAF-scale			
2007		2012	
01-99999	Remainder of Alabama	48-99999	Remainder of Texas
26-99999	Remainder of Michigan	06-348	Los Angeles-Long Beach, CA CFS Area
17-99999	Remainder of Illinois	17-176	Chicago-Naperville, IL CFS Area
55-99999	Remainder of Wisconsin	13-99999	Remainder of Georgia
42-99999	Remainder of Pennsylvania	17-99999	Remainder of Illinois
17-176	Chicago-Naperville, IL CFS Area	36-408	New York-New Jersey, NJ CFS Area
19-99999	Remainder of Iowa		

‘SCTG 03’ chokepoints at county-scale			
2007		2012	
6073	San Diego County, CA	6073	San Diego County, CA
4013	Maricopa County, AZ	6107	Tulare County, CA
36061	New York County, NY		
32003	Clark County, NV		
48113	Dallas County, TX		
48029	Bexar County, TX		

**Suppl. Table 8: Structural chokepoints of ‘SCTG 02’ (cereal grains) network through time at FAF and county-scale.**

‘SCTG 02’ chokepoints at FAF-scale			
2007		2012	
39-99999	Remainder of Ohio	39-99999	Remainder of Ohio
21-99999	Remainder of Kentucky	31-420	Omaha-Council Bluffs-Fremont, NE CFS Area

‘SCTG 02’ chokepoints at county-scale			
2007		2012	
19167	Sioux County, IA	10005	Sussex County, DE

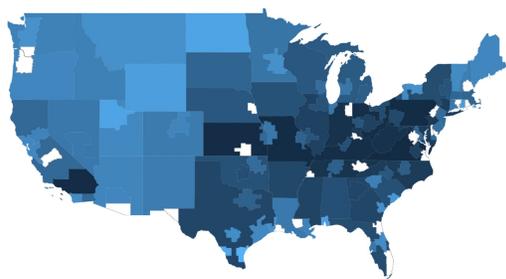
**Suppl. Table 9: Structural chokepoints of ‘SCTG 01’ (live animals) network through time at FAF and county-scale.**

‘SCTG 01’ chokepoints at FAF-scale			
2007		2012	
29-99999	Remainder of Missouri	51-99999	Remainder of Virginia
18-99999	Remainder of Indiana		

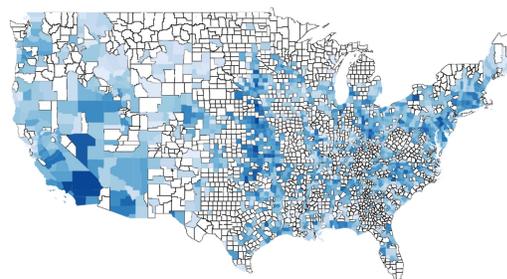
  

‘SCTG 01’ chokepoints at county-scale			
2007		2012	
31043	Dakota County, NE	31053	Dodge County, NE

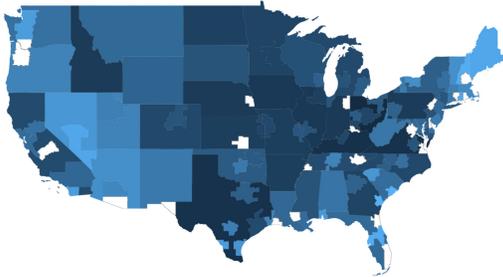
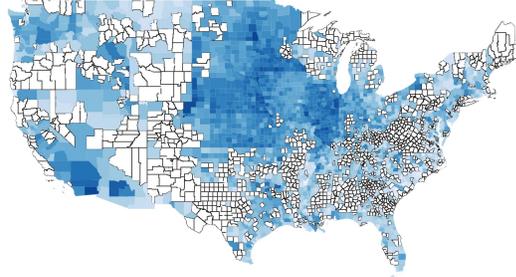
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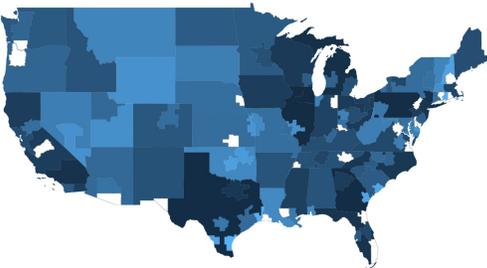
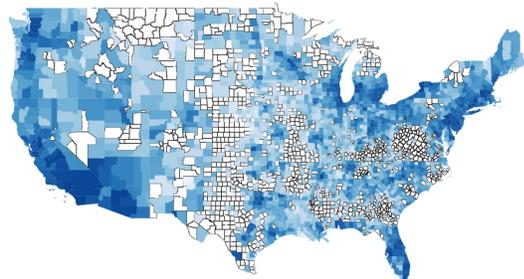
**B**



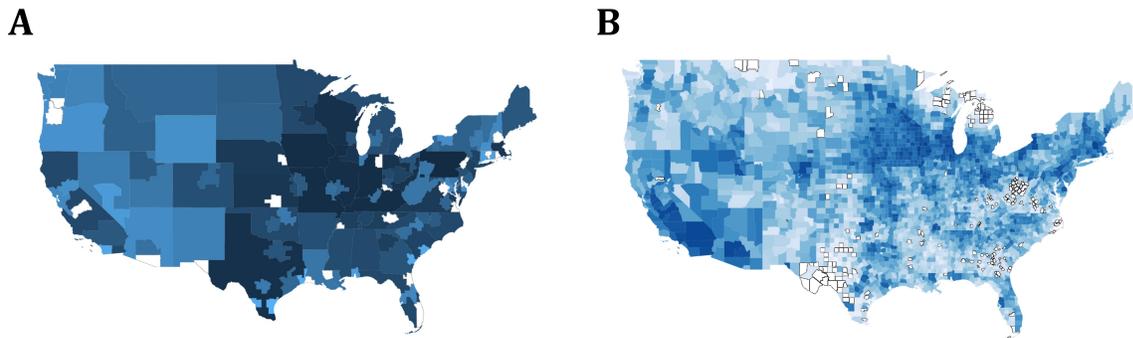
**Suppl. Fig. 10: Stability of structural chokepoints of ‘SCTG 01’ (live animals) network at (A) FAF and (B) County spatial scale.** FAF zones and counties that are shaded the darkest are ranked at the top more frequently for component importance through time. Thus, they are the most critical locations for the physical network structure in 2007, 2012, and 2017.

**A****B**

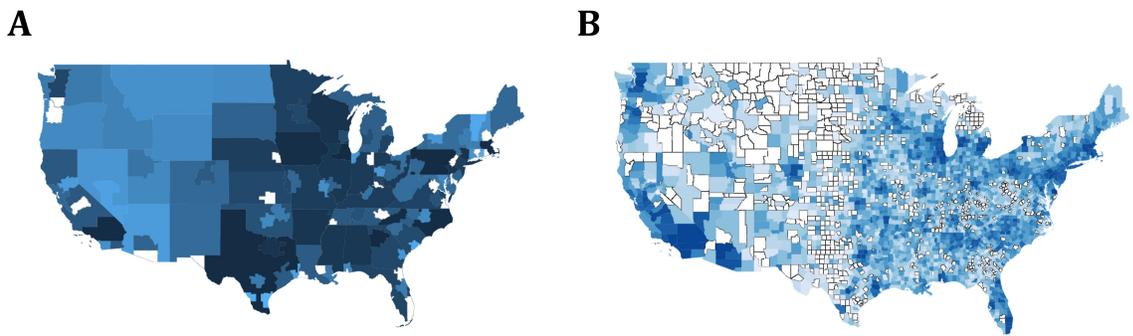
**Suppl. Fig. 11: Stability of structural chokepoints of ‘SCTG 02’ (cereal grains) network at (A) FAF and (B) County spatial scale.** FAF zones and counties that are shaded the darkest are ranked at the top more frequently for component importance through time. Thus, they are the most critical locations for the physical network structure in 2007, 2012, and 2017.

**A****B**

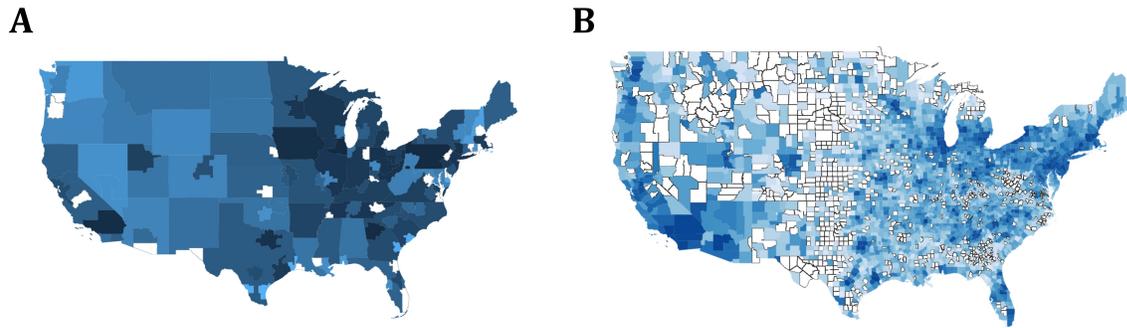
**Suppl. Fig. 12: Stability of structural chokepoints of ‘SCTG 03’ (agricultural products) network at (A) FAF and (B) County spatial scale.** FAF zones and counties that are shaded the darkest are ranked at the top more frequently for component importance through time. Thus, they are the most critical locations for the physical network structure in 2007, 2012, and 2017.



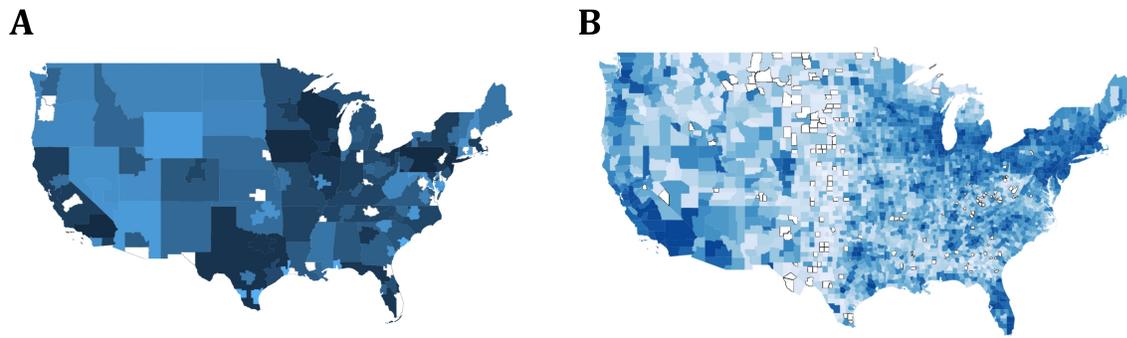
**Suppl. Fig. 13: Stability of structural chokepoints of ‘SCTG 04’ (animal feed) network at (A) FAF and (B) County spatial scale.** FAF zones and counties that are shaded the darkest are ranked at the top more frequently for component importance through time. Thus, they are the most critical locations for the physical network structure in 2007, 2012, and 2017.



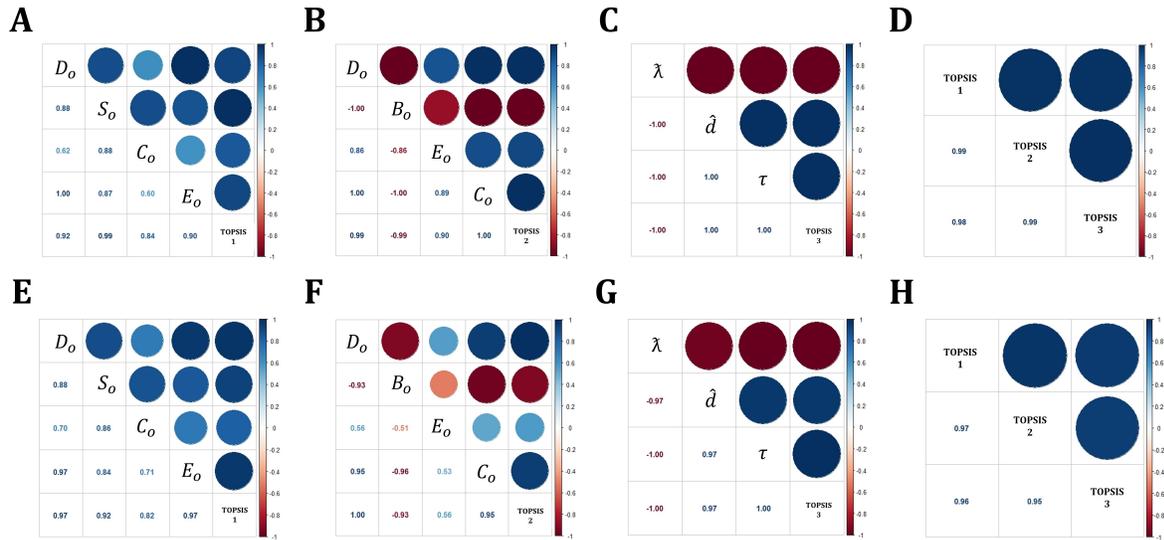
**Suppl. Fig. 14: Stability of structural chokepoints of ‘SCTG 05’ (meat and preparations) network at (A) FAF and (B) County spatial scale.** FAF zones and counties that are shaded the darkest are ranked at the top more frequently for component importance through time. Thus, they are the most critical locations for the physical network structure in 2007, 2012, and 2017.



**Suppl. Fig. 15: Stability of structural chokepoints of ‘SCTG 06’ (milled grain products) network at (A) FAF and (B) County spatial scale.** FAF zones and counties that are shaded the darkest are ranked at the top more frequently for component importance through time. Thus, they are the most critical locations for the physical network structure in 2007, 2012, and 2017.



**Suppl. Fig. 16: Stability of structural chokepoints of ‘SCTG 07’ (other prepared foodstuff) network at (A) FAF and (B) County spatial scale.** FAF zones and counties that are shaded the darkest are ranked at the top more frequently for component importance through time. Thus, they are the most critical locations for the physical network structure in 2007, 2012, and 2017.



**Suppl. Fig. 17: Consistency of our proposed framework illustrated through the correlation across three chokepoint categories and within their criteria (i.e., network metrics) as listed in Table 2.** As per the legend on the right side of figure, dark red represents strong negative correlation between two criteria, whereas dark blue represents strong positive correlation between two criteria. Results are for the ‘aggregated agri-food network’ in 2017 at (A)-(D) FAF-scale and (E)-(H) county-scale. In correlation analysis, darker blue circles indicate the two metrics are strongly positively correlated with each other (i.e., Spearman correlation coefficient is close to 1). This means that for a node, if one of its metric values increases, its other metric values increases as well. For example, if a node has higher degree (more links connected to it), its closeness to every other node in the network would increase as well. On the contrary, darker red circles indicate the two metrics are strongly negatively correlated with each other (i.e., Spearman correlation coefficient is close to -1). The correlation plots do not give information regarding the number of nodes identified as chokepoints. They only indicate that each network metric we computed per node moves in the same direction as each other. If one of the metric values is high for a node, it would also have high values for other metrics. Thus, every metric in our approach identifies the same nodes as (i) the most central, (ii) the most important for average network centrality, and (iii) the most important for network efficiency and resilience. This represents that each criterion and category pinpoints the same location as the structural chokepoint.

**Suppl. Table 10: List of 132 FAF zones with their codes in 2017 FAF5 data.** In this study, we use only 129 of them excluding Alaska and Hawaii FAF-zones.

FAF Code	Name	FAF Code	Name	FAF Code	Name
01-142	Birmingham-Hoover-Talladega, AL	21-178	Cincinnati-Wilmington-Maysville, KY Part	39-198	Columbus-Marion-Zanesville, OH
01-380	Mobile-Daphne-Fairhope, AL	21-350	Louisville/Jefferson County-Elizabethtown-Madison, KY Part	39-212	Dayton-Springfield-Sidney, OH
01-99999	Remainder of Alabama	21-99999	Remainder of Kentucky	39-99999	Remainder of Ohio
02-99999	Remainder of Alaska	22-12940	Baton Rouge, LA	40-416	Oklahoma City-Shawnee, OK
04-38060	Phoenix-Mesa-Glendale, AZ	22-29340	Lake Charles, LA	40-538	Tulsa-Muskogee-Bartlesville, OK
04-536	Tucson-Nogales, AZ	22-406	New Orleans-Metairie-Hammond, LA Part	40-99999	Remainder of Oklahoma
04-99999	Remainder of Arizona	22-99999	Remainder of Louisiana	41-440	Portland-Vancouver-Salem, OR Part
05-99999	Remainder of Arkansas	23-99999	Remainder of Maine	41-99999	Remainder of Oregon
06-260	Fresno-Madera, CA	24-12580	Baltimore-Columbia-Towson, MD	42-408	New York-Newark, PA Part
06-348	Los Angeles-Long Beach, CA	24-47900	Washington-Arlington-Alexandria, MD Part	42-428	Philadelphia-Reading-Camden, PA Part
06-41740	San Diego-Carlsbad-San Marcos, CA	24-99999	Remainder of Maryland	42-430	Pittsburgh-New Castle-Weirton, PA Part
06-472	Sacramento-Roseville, CA	25-148	Boston-Worcester-Providence, MA Part	42-99999	Remainder of Pennsylvania
06-488	San Jose-San Francisco-Oakland, CA	25-99999	Remainder of Massachusetts	44-148	Boston-Worcester-Providence, RI Part
06-99999	Remainder of California	26-220	Detroit-Warren-Ann Arbor, MI	45-16700	Charleston-North Charleston-Summerville, SC
08-216	Denver-Aurora, CO	26-266	Grand Rapids-Wyoming-Muskegon, MI	45-273	Greenville-Spartanburg-Anderson, SC
08-99999	Remainder of Colorado	26-99999	Remainder of Michigan	45-99999	Remainder of South Carolina
09-25540	Hartford-West Hartford-East Hartford, CT	27-378	Minneapolis-St. Paul, MN Part	46-99999	Remainder of South Dakota
09-408	New York-Newark, CT Part	27-99999	Remainder of Minnesota	47-314	Knoxville-Morrisville-Sevierville, TN
09-99999	Remainder of Connecticut	28-99999	Remainder of Mississippi	47-368	Memphis, TN Part
10-428	Philadelphia-Reading-Camden, DE Part	29-312	Kansas City-Overland Park-Kansas City, MO Part	47-400	Nashville-Davidson-Murfreesboro, TN
10-99999	Remainder of Delaware	29-476	St. Louis-St. Charles-Farmington, MO Part	47-99999	Remainder of Tennessee
11-47900	Washington-Arlington-Alexandria, DC Part	29-99999	Remainder of Missouri	48-12420	Austin-Round Rock, TX
12-300	Jacksonville-St. Mary's-Palatka, FL Part	30-99999	Remainder of Montana	48-13140	Beaumont-Port Arthur, TX
12-370	Miami-Fort Lauderdale-Port St. Lucie, FL	31-420	Omaha-Council Bluffs-Fremont, NE Part	48-204	Corpus Christi-Kingsville-Alice, TX
12-422	Orlando-Deltona-Daytona Beach, FL	31-99999	Remainder of Nebraska	48-206	Dallas-Fort Worth, TX Part
12-45300	Tampa-St. Petersburg-Clearwater, FL	32-332	Las Vegas-Henderson, NV Part	48-238	El Paso-Las Cruces, TX Part
12-99999	Remainder of Florida	32-99999	Remainder of Nevada	48-288	Houston-The Woodlands, TX
13-122	Atlanta-Athens-Clarke County-Sandy Springs, GA	33-148	Boston-Worcester-Providence, NH Part	48-29700	Laredo, TX
13-496	Savannah-Hinesville-Statesboro, GA	33-99999	Remainder of New Hampshire	48-41700	San Antonio-New Braunfels, TX
13-99999	Remainder of Georgia	34-408	New York-Newark, NJ Part	48-99999	Remainder of Texas
15-46520	Urban Honolulu, HI	34-428	Philadelphia-Reading-Camden, NJ Part	49-482	Salt Lake City-Provo-Orem, UT
15-99999	Remainder of Hawaii	35-99999	Remainder of New Mexico	49-99999	Remainder of Utah
16-99999	Remainder of Idaho	36-104	Albany-Schenectady, NY	50-99999	Remainder of Vermont
17-176	Chicago-Naperville, IL Part	36-160	Buffalo-Cheektowaga, NY	51-40060	Richmond, VA
17-476	St. Louis-St. Charles-Farmington, IL Part	36-408	New York-Newark, NY Part	51-47900	Washington-Arlington-Alexandria, VA Part
17-99999	Remainder of Illinois	36-464	Rochester-Batavia-Seneca Falls, NY	51-545	Virginia Beach-Norfolk, VA Part
18-176	Chicago-Naperville, IN Part	36-99999	Remainder of New York	51-99999	Remainder of Virginia
18-258	Fort Wayne-Huntington-Auburn, IN	37-172	Charlotte-Concord, NC Part	53-440	Portland-Vancouver-Salem, WA Part
18-294	Indianapolis-Carmel-Muncie, IN	37-268	Greensboro-Winston-Salem-High Point, NC	53-500	Seattle-Tacoma, WA
18-99999	Remainder of Indiana	37-450	Raleigh-Durham-Chapel Hill, NC	53-99999	Remainder of Washington
19-99999	Remainder of Iowa	37-99999	Remainder of North Carolina	54-99999	Remainder of West Virginia
20-312	Kansas City-Overland Park-Kansas City, KS Part	38-99999	Remainder of North Dakota	55-376	Milwaukee-Racine-Waukesha, WI
20-556	Wichita-Arkansas City-Winfield, KS	39-178	Cincinnati-Wilmington-Maysville, OH Part	55-99999	Remainder of Wisconsin
20-99999	Remainder of Kansas	39-184	Cleveland-Akron-Canton, OH	56-99999	Remainder of Wyoming

## 1. Methods

### 1.1. Identifying Structural Chokepoints

For this study, we examine a suite of network statistics-based metrics from the literature before employing some of the most common centrality metrics. We particularly choose metrics that are applicable to directed and asymmetric networks, have a generic formula which do not require a user-defined parameter, highlight the connection structure, and capture the repeat movement of goods along the network. Since we study food flow networks (i.e., transit of perishable goods), any component that would be identified as critical based on the adopted metrics would indicate the main contributor to the flow propagation through the most efficient way (i.e., minimum number of stops between any origin and destination pair). Below is the more detailed explanation of each chokepoints category:

- (i) **Most connected and central nodes:** To find the most connected and central nodes, we initially consider the three most common network statistics-based metrics:<sup>1,2</sup> degree centrality,<sup>3</sup> eigenvalue centrality,<sup>4</sup> and closeness centrality.<sup>5</sup> Additionally, we use stress centrality, a shortest-path based metric, that is suitable for assessing the importance of a node in terms of work done by it in the network.<sup>6</sup> Hence, we include stress centrality to determine the most connected and central nodes. In our case, nodes with the highest stress centrality are the ones that are most critical for the movement of goods (see next subsection for a more detailed explanation of stress centrality and an illustration in Suppl. Fig. 19). In the simplest terms, degree centrality accounts for the number of connections each node has and eigenvector centrality measures their influence. Closeness centrality computes the farness of each node to every other node in the network. Lastly, stress and betweenness centrality identify the bridging attribute of nodes.
- (ii) **Most impactful node removals for network structure:** To determine the nodes that impact the network topology once they are disturbed the most, we first compute the original network average for each network statistics-based metric as seen in Table 11. These network statistics-based metrics are: degree centrality, eigenvalue centrality, and closeness centrality. Additional to these three metrics, we use betweenness centrality. Betweenness centrality is a shortest-path based metric that is suitable for assessing disturbance on a node and the effect of its removal on the network.<sup>7,8</sup> Then, we re-compute network average for each metric by removing nodes one-at-a-time.<sup>9</sup> Thus, we quantify the removal effect of each node in the network topology.<sup>10</sup>
- (iii) **Most impactful node removals for topological efficiency and resilience:** To assess the removal effect of each node on the topological resilience and efficiency of the original network, we use the metrics that are introduced in.<sup>31</sup> Similar to criteria (ii), these metrics are computed for the whole network instead of per node. By the removal of each node, change in these metric values are recorded to account for the impact of each node on the efficiency and resilience. Thus, we first compute the original network  $\lambda$ ,  $\tau$ , and  $\hat{d}$  values as seen in Suppl. Table 11. Then, we measure how the original network  $\lambda$ ,  $\tau$ , and  $\hat{d}$  values change by the removal of each node one-by-one. Average shortest

**Suppl. Table 11: Average of connectivity and centrality metric values of the 2017 empirical FAF and county food flow networks per SCTG.** Also, their summary statistics as well as topological efficiency and resilience metrics are listed.

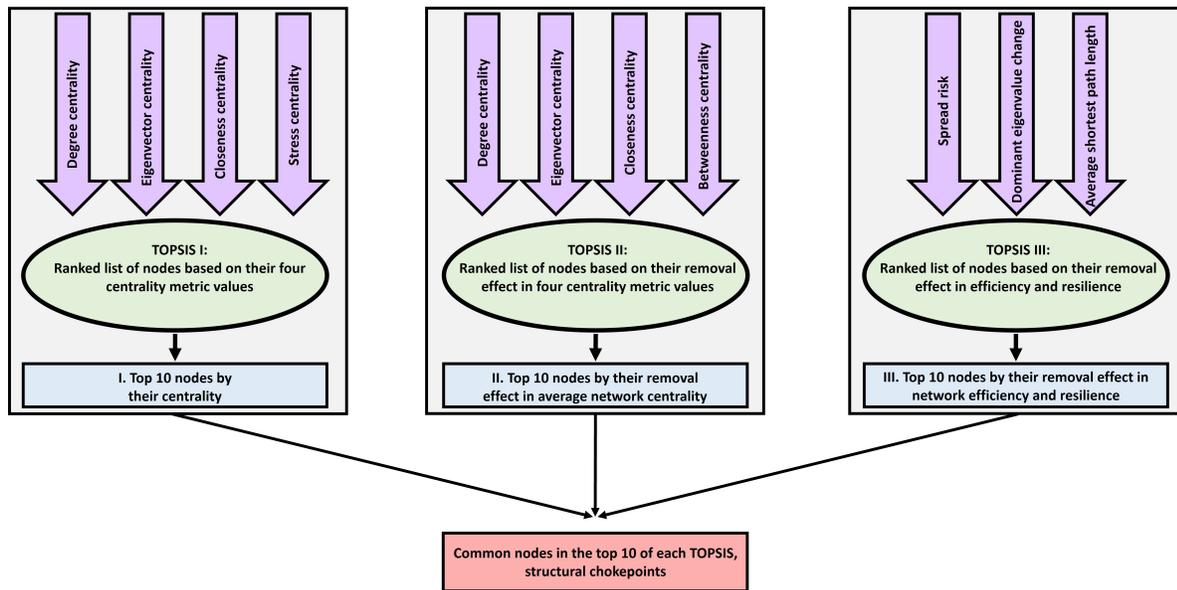
FAF Network												
SCTG	#Nodes	#Links	Density	Mass [kg]	Degree centrality	Eigenvector centrality	Closeness centrality	Stress centrality	Betweenness centrality	$\lambda$	$\tau$	$\hat{d}$
1	129	1444	0.087	8.53E+10	11.19	0.0549	0.00099	1106.53	692.82	9.11	0.074	2.76
2	129	1723	0.104	1.21E+12	13.36	0.0606	0.00172	1209.56	862.60	5.87	0.063	2.58
3	129	5835	0.351	6.47E+11	45.23	0.0704	0.00465	1323.99	452.35	2.67	0.019	1.69
4	129	4952	0.298	4.02E+11	38.39	0.0706	0.00445	1322.30	628.84	3.13	0.022	1.77
5	129	6727	0.404	8.97E+10	52.15	0.0737	0.00481	1472.83	714.09	2.34	0.017	1.64
6	129	7142	0.429	1.32E+11	55.36	0.0775	0.00496	1431.16	324.04	2.16	0.016	1.59
7	129	11219	0.674	6.27E+11	86.97	0.0835	0.00594	1638.30	313.99	1.37	0.011	1.33
Total	129	13283	0.798	3.19E+12	102.97	0.0856	0.00655	1355.24	358.47	1.09	0.009	1.20
County Network												
SCTG	#Nodes	#Links	Density	Mass [kg]	Degree centrality	Eigenvector centrality	Closeness centrality	Stress centrality	Betweenness centrality	$\lambda$	$\tau$	$\hat{d}$
1	1607	3619	0.0014	8.53E+10	2.23	7.25E-19	5.02E-7	4473.74	3713.14	10.30	0.279	10.11
2	2863	30814	0.0038	1.21E+11	10.76	5.66E-21	5.05E-7	123359.04	37486.38	4.68	0.036	5.72
3	2488	17286	0.0028	6.47E+11	6.87	9.91E-3	9.84E-7	26111.17	15482.95	5.79	0.065	3.91
4	3008	38475	0.0043	4.02E+11	12.77	5.49E-3	9.11E-7	62663.76	25862.79	2.88	0.033	3.77
5	2990	21428	0.0024	8.97E+10	7.09	11.25E-3	1.10E-6	40513.56	28322.95	1.83	0.070	4.20
6	2930	29984	0.0035	1.32E+11	10.21	11.07E-3	1.96E-6	51870.16	24117.81	2.80	0.041	3.58
7	3079	74385	0.0079	6.27E+11	24.10	11.18E-3	1.04E-5	87510.28	19715.27	1.44	0.018	2.95
Total	3106	187687	0.0195	3.19E+12	60.21	13.32E-3	1.31E-4	155794.91	16842.42	1.17	0.010	2.49

path length represents the average number of traverses along the network. Change in dominant eigenvalue accounts for the change in the flow propagation attribute, and epidemic threshold identifies the tendency of risk spread within the network due to its connection structure.

Thus, centrality metrics we adopt in this study pinpoint components that have the highest number of connections, highest frequency of shortest paths passing through them, and highest number of heavily connected neighbors as seen in Suppl. Fig. 18. FAF zones and counties identified by these centrality metrics are the most central locations that connect the U.S. and maintain the transit of agri-food commodities between production and consumption. In case any of these chokepoints are disrupted, connectivity along the network would be undermined the most. Thus, transit of perishable goods would require more time and money as higher number of intermediate stops would be taken. This would also lead to higher food waste (see Suppl. Table 12-19 for the top 10 FAF zones and counties per chokepoint category broken down by SCTG in 2017).

### 1.2. Stress Centrality vs Betweenness Centrality

Stress centrality,  $S_o$  is the absolute number of shortest paths passes through each node  $o$ . As one more shortest path passes through node  $o$ , its stress centrality would increase by 1. Hence, it quantifies the stress on each node which is the work done by it in the network. Thus, stress centrality  $S_o$  is preferred in identifying the importance of each node in the network. Then, nodes with highest stress centrality values would represent the nodes that have the highest



**Suppl. Fig. 18: Schematic of the complex network methodology used in this study.** The three categories and their corresponding criteria to identify the structural chokepoints of agri-food flow networks in the United States are listed.

**Suppl. Table 12: Top 10 FAF zones and counties of 2017 ‘aggregated agri-food network’ according to 3 separate TOPSIS analysis.** TOPSIS 1 is for the node centrality and connectivity metric values, TOPSIS 2 is for removal effect of nodes over average network connectivity, and TOPSIS 3 is for the removal effect of nodes over network topological efficiency and resilience.

'Aggregated agri-food network' Top 10 FAF-zones					
Rank	TOPSIS 1	Rank	TOPSIS 2	Rank	TOPSIS 3
1	Los Angeles-Long Beach, CA CFS Area	1	Los Angeles-Long Beach, CA CFS Area	1	Los Angeles-Long Beach, CA CFS Area
2	Chicago-Naperville, IL CFS Area	2	Chicago-Naperville, IL CFS Area	2	Chicago-Naperville, IL CFS Area
3	New York-New Jersey, NJ CFS Area	3	New York-New Jersey, NJ CFS Area	3	New York-New Jersey, NJ CFS Area
4	Remainder of Texas	4	Remainder of Texas	4	Remainder of Wisconsin
5	New York-New Jersey, NY CFS Area	5	Remainder of Pennsylvania	5	San Jose-San Francisco-Oakland, CA CFS Area
6	San Jose-San Francisco-Oakland, CA CFS Area	6	New York-New Jersey, NY CFS Area	6	Remainder of Iowa
7	Remainder of Wisconsin	7	Miami-Fort Lauderdale-Port St. Lucie, FL CFS Area	7	New York-New Jersey, NY CFS Area
8	Boston-Worcester-Providence, MA CFS Area	8	Denver-Aurora, CO CFS Area	8	Denver-Aurora, CO CFS Area
9	Remainder of Pennsylvania	9	San Jose-San Francisco-Oakland, CA CFS Area	9	Remainder of Pennsylvania
10	Miami-Fort Lauderdale-Port St. Lucie, FL CFS Area	10	Dallas-Fort Worth, TX CFS Area	10	Remainder of Texas

'Aggregated agri-food network' Top 10 Counties					
Rank	TOPSIS 1	Rank	TOPSIS 2	Rank	TOPSIS 3
1	Riverside County, CA	1	Harrison County, WV	1	Cook County, IL
2	San Bernardino County, CA	2	Northampton County, PA	2	Los Angeles County, CA
3	San Diego County, CA	3	Alachua County, FL	3	Riverside County, CA
4	Los Angeles County, CA	4	Cook County, IL	4	San Diego County, CA
5	Maricopa County, AZ	5	Maricopa County, AZ	5	San Bernardino County, CA
6	Shelby County, TN	6	Los Angeles County, CA	6	Maricopa County, AZ
7	Cook County, IL	7	Riverside County, CA	7	Shelby County, TN
8	Hillsborough County, FL	8	San Bernardino County, CA	8	Erie County, NY
9	Dallas County, TX	9	Shelby County, TN	9	Worcester County, MA
10	Harris County, TX	10	San Diego County, CA	10	Milwaukee County, WI

number of shortest paths passing through them. Hence, they would correspond to the most central and connect nodes (see Suppl. Fig. 19).

On the contrary, betweenness centrality  $B_o$  is the portion of shortest paths passes through

**Suppl. Table 13: Top 10 FAF zones and counties of 2017 ‘SCTG 01’ (live animals) food flow networks according to 3 separate TOPSIS analysis.** TOPSIS 1 is for the node centrality and connectivity metric values, TOPSIS 2 is for removal effect of nodes over average network connectivity, and TOPSIS 3 is for the removal effect of nodes over network topological efficiency and resilience.

‘SCTG 01’ Top 10 FAF-zones					
Rank	TOPSIS 1	Rank	TOPSIS 2	Rank	TOPSIS 3
1	Los Angeles-Long Beach, CA CFS Area	1	Atlanta-Athens-Clarke County-Sandy Springs, GA CFS Area	1	Remainder of Ohio
2	Remainder of Ohio	2	Los Angeles-Long Beach, CA CFS Area	2	Remainder of Virginia
3	Atlanta-Athens-Clarke County-Sandy Springs, GA CFS Area	3	Remainder of Ohio	3	Remainder of Kentucky
4	Greensboro-Winston-Salem-High Point, NC CFS Area	4	Remainder of Oregon	4	Los Angeles-Long Beach, CA CFS Area
5	Remainder of South Dakota	5	Remainder of Washington	5	Atlanta-Athens-Clarke County-Sandy Springs, GA CFS Area
6	Remainder of Kansas	6	Greensboro-Winston-Salem-High Point, NC CFS Area	6	Remainder of Pennsylvania
7	Remainder of Kentucky	7	Remainder of South Dakota	7	Cincinnati-Wilmington-Maysville, OH CFS Area
8	Remainder of South Carolina	8	Remainder of Maryland	8	Cincinnati-Wilmington-Maysville, KY CFS Area
9	Remainder of Pennsylvania	9	New York-Newark, PA CFS Area	9	Fort Wayne-Huntington-Auburn, IN CFS Area
10	Remainder of Virginia	10	Remainder of Florida	10	Remainder of West Virginia

‘SCTG 01’ Top 10 Counties					
Rank	TOPSIS 1	Rank	TOPSIS 2	Rank	TOPSIS 3
1	San Bernardino County, CA	1	Obion County, TN	1	Riverside County, CA
2	Clark County, WA	2	Bronx County, NY	2	San Bernardino County, CA
3	Lewis County, WA	3	Fayette County, TN	3	San Diego County, CA
4	Riverside County, CA	4	Tipton County, TN	4	Santa Cruz County, AZ
5	Yamhill County, OR	5	Orange County, CA	5	Los Angeles County, CA
6	Obion County, TN	6	Carroll County, GA	6	Imperial County, CA
7	Tillamook County, OR	7	San Bernardino County, CA	7	Kern County, CA
8	Tipton County, TN	8	Fulton County, KY	8	Maricopa County, AZ
9	Pacific County, WA	9	Riverside County, CA	9	Santa Clara County, CA
10	Fayette County, TN	10	Sussex County, DE	10	Fresno County, CA

each node over the total number of shortest paths in the network. In dense networks, there exists multiple alternative shortest paths among any two nodes in the network. Hence, the portion of shortest paths becomes 1 over the number of alternatives. If a node is disturbed and removed from the network, then the number of alternative shortest paths would decrease. Therefore, the portion of shortest paths increases. The change in portion of shortest paths passes through each node would be higher if a more important node is removed from the network. Hence, betweenness centrality quantifies the effect of a disturbance in each node over the network (see Suppl. Fig. 19). Thus, it is preferred in determining the most impactful node removals. This difference between stress and betweenness centrality becomes more vital especially in the dense networks.

### 1.3. TOPSIS: Multi-criteria Decision Analysis Technique

The TOPSIS analysis first computes the performance of each alternative per criteria. Then, alternatives are ranked from best outcome to worst outcome based on their closeness to the positive ideal solution (PIS) and distance to the negative ideal solution (NIS) per criteria. Lastly, weighted sum of per criteria performances of alternatives are computed for the final ranking.<sup>11</sup> In the FAF and county-scale food flows network, the alternatives are the 129 FAF zones and 3134 counties, respectively. For the first category of chokepoints, the criteria are (i) degree, (ii) eigenvector, (iii) closeness, and (iv) stress centrality. For the second category of chokepoints, the criteria are the change in average network centrality metrics per node removal, individually. Lastly, the criteria for the third category of chokepoints are the change in network efficiency and resilience metrics per node removal. By computing the distance of each FAF zone and county from PIS and NIS, we rank all 129 FAF zones and 3134 counties

**Suppl. Table 14: Top 10 FAF zones and counties of 2017 ‘SCTG 02’ (cereal grains) food flow networks according to 3 separate TOPSIS analysis.** TOPSIS 1 is for the node centrality and connectivity metric values, TOPSIS 2 is for removal effect of nodes over average network connectivity, and TOPSIS 3 is for the removal effect of nodes over network topological efficiency and resilience.

‘SCTG 02’ Top 10 FAF-zones					
Rank	TOPSIS 1	Rank	TOPSIS 2	Rank	TOPSIS 3
1	Remainder of Idaho	1	Remainder of Ohio	1	Remainder of Iowa
2	Remainder of Indiana	2	Remainder of Iowa	2	Remainder of Indiana
3	Remainder of Minnesota	3	Remainder of Georgia	3	Remainder of Illinois
4	Remainder of Iowa	4	Remainder of Indiana	4	Remainder of Ohio
5	Remainder of Texas	5	Remainder of Minnesota	5	Remainder of Idaho
6	Remainder of Ohio	6	Remainder of Idaho	6	Remainder of Nebraska
7	Remainder of North Dakota	7	Remainder of Florida	7	Chicago-Naperville, IL CFS Area
8	Remainder of Illinois	8	Remainder of Illinois	8	Minneapolis-St. Paul, MN CFS Area
9	Remainder of Virginia	9	Remainder of Texas	9	Remainder of Texas
10	Remainder of Nebraska	10	Chicago-Naperville, IL CFS Area	10	Remainder of Wisconsin

‘SCTG 02’ Top 10 Counties					
Rank	TOPSIS 1	Rank	TOPSIS 2	Rank	TOPSIS 3
1	Madison County, FL	1	Sullivan County, TN	1	Butler County, NE
2	Franklin County, FL	2	Surry County, NC	2	Dawson County, NE
3	Nye County, NV	3	Orange County, NC	3	Platte County, NE
4	Jackson County, FL	4	Buncombe County, NC	4	Merrick County, NE
5	Darlington County, SC	5	Richmond County, GA	5	Adams County, NE
6	Sarpy County, NE	6	Charlottesville City, VA	6	Knox County, NE
7	Jackson County, MN	7	Sarpy County, NE	7	Buffalo County, NE
8	Gloucester County, NJ	8	Wayne County, OH	8	Hall County, NE
9	Denver County, CO	9	Latah County, ID	9	Wayne County, NE
10	Camden County, GA	10	Douglas County, NE	10	Madison County, NE

in descending order of being a potential chokepoint. For a FAF zone and county to be a chokepoint, it should have relatively high values per criteria. Thus, we identify the top 10 FAF zones and counties as chokepoints per category based on their TOPSIS scores.

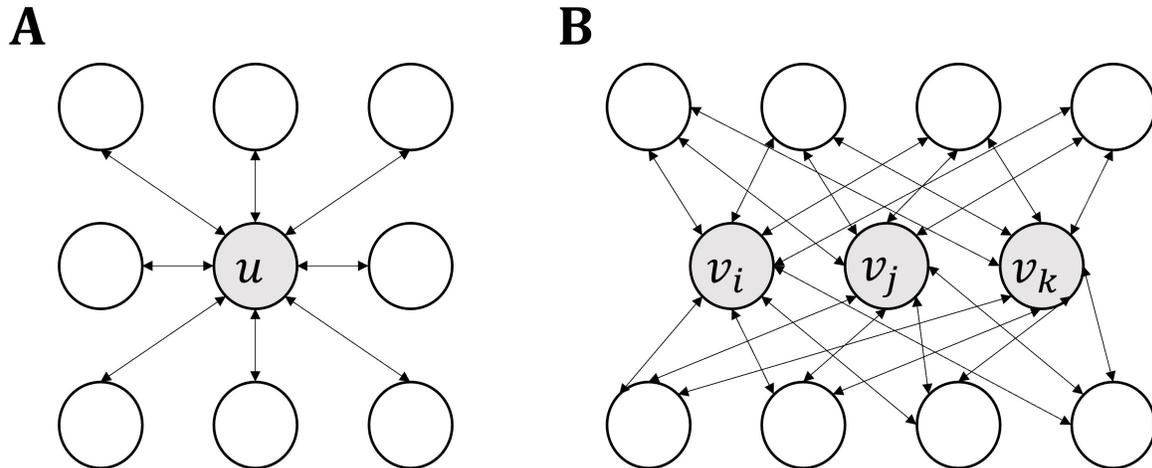
In this study, we choose the number 10 as in ‘top 10 locations per TOPSIS’, based on the rich club analysis.<sup>12</sup> We identify all potential rich clubs and plotted the connections vs number of rich club members in SCTG All network at FAF spatial-scale. We observe that there exists a clear cut-off at 10 nodes. These are the 10 FAF-zones with the highest total number connections as seen in Suppl. Fig. 20. Thus, we set the number 10 as the cut-off for the number of structural chokepoints.

**Suppl. Table 15: Top 10 FAF zones and counties of 2017 ‘SCTG 03’ (agricultural products) food flow networks according to 3 separate TOPSIS analysis.** TOPSIS 1 is for the node centrality and connectivity metric values, TOPSIS 2 is for removal effect of nodes over average network connectivity, and TOPSIS 3 is for the removal effect of nodes over network topological efficiency and resilience.

‘SCTG 03’ Top 10 FAF-zones					
Rank	TOPSIS 1	Rank	TOPSIS 2	Rank	TOPSIS 3
1	Remainder of Texas	1	Remainder of Texas	1	Los Angeles-Long Beach, CA CFS Area
2	Remainder of Georgia	2	Remainder of Georgia	2	New York-New Jersey, NJ CFS Area
3	San Jose-San Francisco-Oakland, CA CFS Area	3	Dallas-Fort Worth, TX CFS Area	3	Chicago-Naperville, IL CFS Area
4	Los Angeles-Long Beach, CA CFS Area	4	New York-New Jersey, NY CFS Area	4	San Jose-San Francisco-Oakland, CA CFS Area
5	New York-New Jersey, NJ CFS Area	5	New York-New Jersey, NJ CFS Area	5	Miami-Fort Lauderdale-Port St. Lucie, FL CFS Area
6	Miami-Fort Lauderdale-Port St. Lucie, FL CFS Area	6	Remainder of Ohio	6	Remainder of Georgia
7	Remainder of California	7	Remainder of Pennsylvania	7	Remainder of Wisconsin
8	Remainder of Ohio	8	Los Angeles-Long Beach, CA CFS Area	8	Remainder of Pennsylvania
9	Dallas-Fort Worth, TX CFS Area	9	Remainder of Illinois	9	Remainder of Ohio
10	New York-New Jersey, NY CFS Area	10	Chicago-Naperville, IL CFS Area	10	New York-New Jersey, NY CFS Area

‘SCTG 03’ Top 10 Counties					
Rank	TOPSIS 1	Rank	TOPSIS 2	Rank	TOPSIS 3
1	San Diego County, CA	1	Orleans County, LA	1	San Diego County, CA
2	Fresno County, CA	2	St. Bernard County, LA	2	Fresno County, CA
3	Indian River County, FL	3	San Diego County, CA	3	Maricopa County, AZ
4	Pima County, AZ	4	Riverside County, CA	4	Indian River County, FL
5	Riverside County, CA	5	St. Louis City, MO	5	Orange County, CA
6	San Joaquin County, CA	6	Orange County, CA	6	Riverside County, CA
7	San Bernardino County, CA	7	Clackamas County, OR	7	Pima County, AZ
8	Fayette County, TN	8	Indian River County, FL	8	San Bernardino County, CA
9	Imperial County, CA	9	Fresno County, CA	9	San Joaquin County, CA
10	Madera County, CA	10	Pendleton County, KY	10	Imperial County, CA



**Suppl. Fig. 19: The difference between stress centrality  $S_o$  and betweenness centrality  $B_o$  per node.<sup>6</sup> Stress centrality of nodes  $u$ ,  $v_i$ ,  $v_j$ , and  $v_k$  are all equal to 16. However, betweenness centrality of node  $u$  is 1 whereas it is  $1/3$  for the nodes  $v_i$ ,  $v_j$ , and  $v_k$ .**

**Suppl. Table 16: Top 10 FAF zones and counties of 2017 ‘SCTG 04’ (animal feed) food flow networks according to 3 separate TOPSIS analysis.** TOPSIS 1 is for the node centrality and connectivity metric values, TOPSIS 2 is for removal effect of nodes over average network connectivity, and TOPSIS 3 is for the removal effect of nodes over network topological efficiency and resilience.

‘SCTG 04’ Top 10 FAF-zones					
Rank	TOPSIS 1	Rank	TOPSIS 2	Rank	TOPSIS 3
1	Remainder of Pennsylvania	1	Washington-Arlington-Alexandria, VA CFS Area	1	Remainder of Pennsylvania
2	Remainder of Iowa	2	Remainder of Pennsylvania	2	Remainder of Iowa
3	Remainder of Texas	3	New York-New Jersey, NY CFS Area	3	Remainder of Wisconsin
4	Remainder of California	4	Remainder of Texas	4	Minneapolis-St. Paul, MN CFS Area
5	Boston-Worcester-Providence, MA CFS Area	5	Remainder of California	5	Remainder of Missouri
6	New York-New Jersey, NY CFS Area	6	Remainder of Iowa	6	Remainder of Illinois
7	Minneapolis-St. Paul, MN CFS Area	7	Minneapolis-St. Paul, MN CFS Area	7	Remainder of Indiana
8	Remainder of Wisconsin	8	Remainder of Tennessee	8	Remainder of Kentucky
9	Remainder of Missouri	9	Remainder of Kentucky	9	Remainder of Kansas
10	Remainder of Kansas	10	Remainder of Maryland	10	Indianapolis-Carmel-Muncie, IN CFS Area

‘SCTG 04’ Top 10 Counties					
Rank	TOPSIS 1	Rank	TOPSIS 2	Rank	TOPSIS 3
1	Scott County, IA	1	Linn County, IA	1	Polk County, IA
2	Douglas County, NE	2	Erath County, TX	2	Linn County, IA
3	Sarpy County, NE	3	Wichita County, TX	3	Dallas County, IA
4	Dallas County, IA	4	Webb County, TX	4	Scott County, IA
5	Muscatine County, IA	5	Riverside County, CA	5	Dubuque County, IA
6	Clinton County, IA	6	Bowie County, TX	6	Story County, IA
7	Dubuque County, IA	7	Taylor County, TX	7	Clinton County, IA
8	Taylor County, IA	8	Sarpy County, NE	8	Black Hawk County, IA
9	Linn County, IA	9	Douglas County, NE	9	Benton County, IA
10	Louisa County, IA	10	San Bernardino County, CA	10	Marshall County, IA

**Suppl. Table 17: Top 10 FAF zones and counties of 2017 ‘SCTG 05’ (meat and their preparations) food flow networks according to 3 separate TOPSIS analysis.** TOPSIS 1 is for the node centrality and connectivity metric values, TOPSIS 2 is for removal effect of nodes over average network connectivity, and TOPSIS 3 is for the removal effect of nodes over network topological efficiency and resilience.

‘SCTG 05’ Top 10 FAF-zones					
Rank	TOPSIS 1	Rank	TOPSIS 2	Rank	TOPSIS 3
1	Chicago-Naperville, IL CFS Area	1	Remainder of New Mexico	1	Chicago-Naperville, IL CFS Area
2	Los Angeles-Long Beach, CA CFS Area	2	Dallas-Fort Worth, TX CFS Area	2	Atlanta-Athens-Clarke County-Sandy Springs, GA CFS Area
3	Remainder of Texas	3	Chicago-Naperville, IL CFS Area	3	Los Angeles-Long Beach, CA CFS Area
4	Boston-Worcester-Providence, MA CFS Area	4	Los Angeles-Long Beach, CA CFS Area	4	Remainder of Texas
5	Atlanta-Athens-Clarke County-Sandy Springs, GA CFS Area	5	Atlanta-Athens-Clarke County-Sandy Springs, GA CFS Area	5	Remainder of Iowa
6	New York-New Jersey, NY CFS Area	6	New York-New Jersey, NY CFS Area	6	Dallas-Fort Worth, TX CFS Area
7	Remainder of Iowa	7	Remainder of Pennsylvania	7	Boston-Worcester-Providence, MA CFS Area
8	Dallas-Fort Worth, TX CFS Area	8	New York-New Jersey, NJ CFS Area	8	Miami-Fort Lauderdale-Port St. Lucie, FL CFS Area
9	Remainder of North Carolina	9	Remainder of Texas	9	Remainder of Pennsylvania
10	Remainder of Pennsylvania	10	Boston-Worcester-Providence, MA CFS Area	10	Remainder of North Carolina

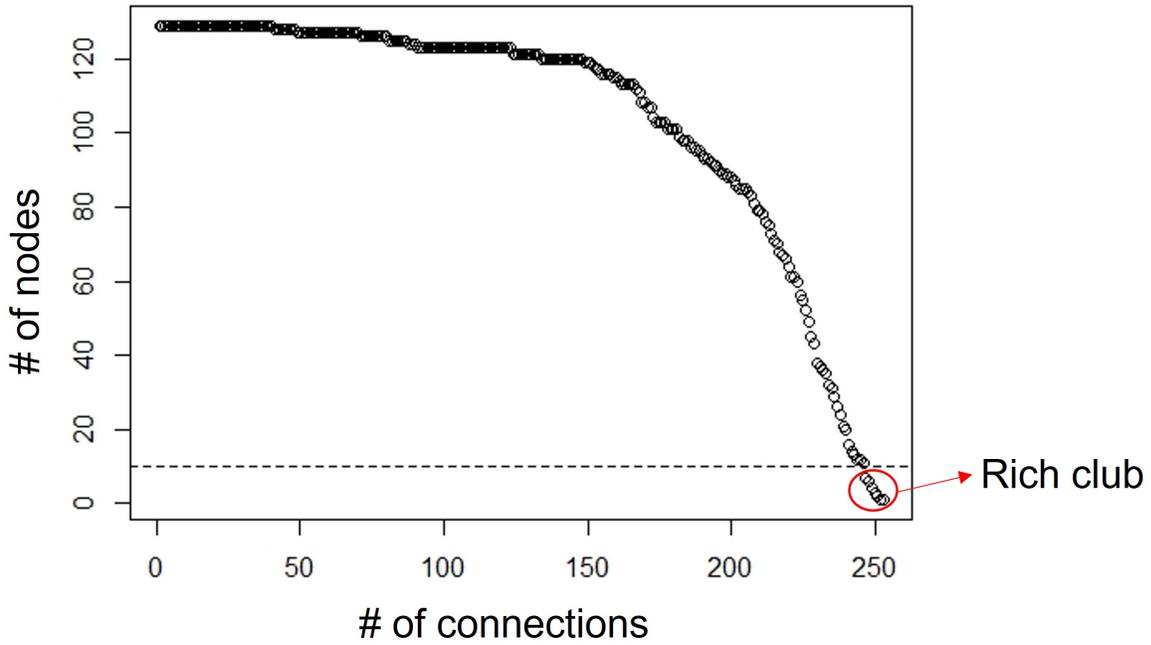
‘SCTG 05’ Top 10 Counties					
Rank	TOPSIS 1	Rank	TOPSIS 2	Rank	TOPSIS 3
1	Sussex County, DE	1	Maricopa County, AZ	1	Sussex County, DE
2	Denver County, CO	2	De Kalb County, GA	2	Maricopa County, AZ
3	Berks County, PA	3	Los Angeles County, CA	3	San Bernardino County, CA
4	San Bernardino County, CA	4	Denver County, CO	4	Los Angeles County, CA
5	Nassau County, NY	5	San Diego County, CA	5	Berks County, PA
6	Maricopa County, AZ	6	Orange County, CA	6	San Diego County, CA
7	Fresno County, CA	7	Berks County, PA	7	Denver County, CO
8	Allegan County, MI	8	Eric County, NY	8	Nassau County, NY
9	San Diego County, CA	9	Sussex County, DE	9	Fresno County, CA
10	Riverside County, CA	10	Multnomah County, OR	10	Prince Georges County, MD

**Suppl. Table 18: Top 10 FAF zones and counties of 2017 ‘SCTG 06’ (milled grain products) food flow networks according to 3 separate TOPSIS analysis.** TOPSIS 1 is for the node centrality and connectivity metric values, TOPSIS 2 is for removal effect of nodes over average network connectivity, and TOPSIS 3 is for the removal effect of nodes over network topological efficiency and resilience.

‘SCTG 06’ Top 10 FAF-zones					
Rank	TOPSIS 1	Rank	TOPSIS 2	Rank	TOPSIS 3
1	Los Angeles-Long Beach, CA CFS Area	1	Los Angeles-Long Beach, CA CFS Area	1	Los Angeles-Long Beach, CA CFS Area
2	Remainder of Pennsylvania	2	Atlanta-Athens-Clarke County-Sandy Springs, GA CFS Area	2	Atlanta-Athens-Clarke County-Sandy Springs, GA CFS Area
3	Atlanta-Athens-Clarke County-Sandy Springs, GA CFS Area	3	Dallas-Fort Worth, TX CFS Area	3	Remainder of Pennsylvania
4	Houston-The Woodlands, TX CFS Area	4	Remainder of Pennsylvania	4	Chicago-Naperville, IL CFS Area
5	Chicago-Naperville, IL CFS Area	5	Chicago-Naperville, IL CFS Area	5	Dallas-Fort Worth, TX CFS Area
6	San Jose-San Francisco-Oakland, CA CFS Area	6	Houston-The Woodlands, TX CFS Area	6	San Jose-San Francisco-Oakland, CA CFS Area
7	Dallas-Fort Worth, TX CFS Area	7	San Jose-San Francisco-Oakland, CA CFS Area	7	Columbus-Marion-Zanesville, OH CFS Area
8	Remainder of Iowa	8	New York-New Jersey, NJ CFS Area	8	Remainder of Iowa
9	Boston-Worcester-Providence, MA CFS Area	9	Remainder of Iowa	9	Houston-The Woodlands, TX CFS Area
10	Columbus-Marion-Zanesville, OH CFS Area	10	Boston-Worcester-Providence, MA CFS Area	10	Minneapolis-St. Paul, MN CFS Area
‘SCTG 06’ Top 10 Counties					
Rank	TOPSIS 1	Rank	TOPSIS 2	Rank	TOPSIS 3
1	Cook County, IL	1	Hartford County, CT	1	Cook County, IL
2	Harris County, TX	2	Cook County, IL	2	San Diego County, CA
3	Los Angeles County, CA	3	Maricopa County, AZ	3	Fairfield County, CT
4	Maricopa County, AZ	4	Harris County, TX	4	Northampton County, PA
5	San Diego County, CA	5	Webb County, TX	5	Los Angeles County, CA
6	Hartford County, CT	6	Los Angeles County, CA	6	Hartford County, CT
7	Orange County, CA	7	Bexar County, TX	7	Maricopa County, AZ
8	Allen County, IN	8	San Diego County, CA	8	Bergen County, NJ
9	Bexar County, TX	9	Riverside County, CA	9	Allen County, IN
10	Riverside County, CA	10	Orange County, CA	10	Lancaster County, PA

**Suppl. Table 19: Top 10 FAF zones and counties of 2017 ‘SCTG 07’ (other prepared foodstuff) food flow networks according to 3 separate TOPSIS analysis.** TOPSIS 1 is for the node centrality and connectivity metric values, TOPSIS 2 is for removal effect of nodes over average network connectivity, and TOPSIS 3 is for the removal effect of nodes over network topological efficiency and resilience.

‘SCTG 07’ Top 10 FAF-zones					
Rank	TOPSIS 1	Rank	TOPSIS 2	Rank	TOPSIS 3
1	Los Angeles-Long Beach, CA CFS Area	1	Los Angeles-Long Beach, CA CFS Area	1	Los Angeles-Long Beach, CA CFS Area
2	Chicago-Naperville, IL CFS Area	2	Chicago-Naperville, IL CFS Area	2	Chicago-Naperville, IL CFS Area
3	New York-New Jersey, NJ CFS Area	3	Dallas-Fort Worth, TX CFS Area	3	Remainder of Iowa
4	San Jose-San Francisco-Oakland, CA CFS Area	4	Remainder of Pennsylvania	4	New York-New Jersey, NJ CFS Area
5	Remainder of Iowa	5	New York-New Jersey, NJ CFS Area	5	Remainder of Pennsylvania
6	Remainder of Pennsylvania	6	Atlanta-Athens-Clarke County-Sandy Springs, GA CFS Area	6	Remainder of Wisconsin
7	Dallas-Fort Worth, TX CFS Area	7	San Jose-San Francisco-Oakland, CA CFS Area	7	San Jose-San Francisco-Oakland, CA CFS Area
8	New York-New Jersey, NY CFS Area	8	Remainder of Iowa	8	New York-New Jersey, NY CFS Area
9	Remainder of Wisconsin	9	New York-New Jersey, NY CFS Area	9	Cleveland-Akron-Canton, OH CFS Area
10	Denver-Aurora, CO CFS Area	10	Remainder of Texas	10	Minneapolis-St. Paul, MN CFS Area
‘SCTG 07’ Top 10 Counties					
Rank	TOPSIS 1	Rank	TOPSIS 2	Rank	TOPSIS 3
1	Cook County, IL	1	Lehigh County, PA	1	Cook County, IL
2	Shelby County, TN	2	Los Angeles County, CA	2	Lehigh County, PA
3	Hillsborough County, FL	3	Maricopa County, AZ	3	Los Angeles County, CA
4	Dallas County, TX	4	Shelby County, TN	4	Milwaukee County, WI
5	Los Angeles County, CA	5	Harris County, TX	5	Northampton County, PA
6	Maricopa County, AZ	6	Dallas County, TX	6	Philadelphia County, PA
7	Riverside County, CA	7	Cook County, IL	7	Dane County, WA
8	Dane County, WI	8	Riverside County, CA	8	Hartford County, CT
9	Milwaukee County, WI	9	Hillsborough County, FL	9	Shelby County, TN
10	Harris County, TX	10	Duval County, FL	10	Erie County, NY



**Suppl. Fig. 20: Number of rich club members vs number of connections for FAF-scale SCTG All network.** There exists a clear cut-off at number of rich club members equal to 10. This group of nodes have the highest number of connections. Thus, we choose '10' as the cut-off for number of top structural chokepoints.

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