Methods and Metrics for Spatial Social Network Analysis

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https://sites.gatech.edu/snoman

Resources: ““‘Snowman Georgia Tech”

OUTLINE

Why SSNs

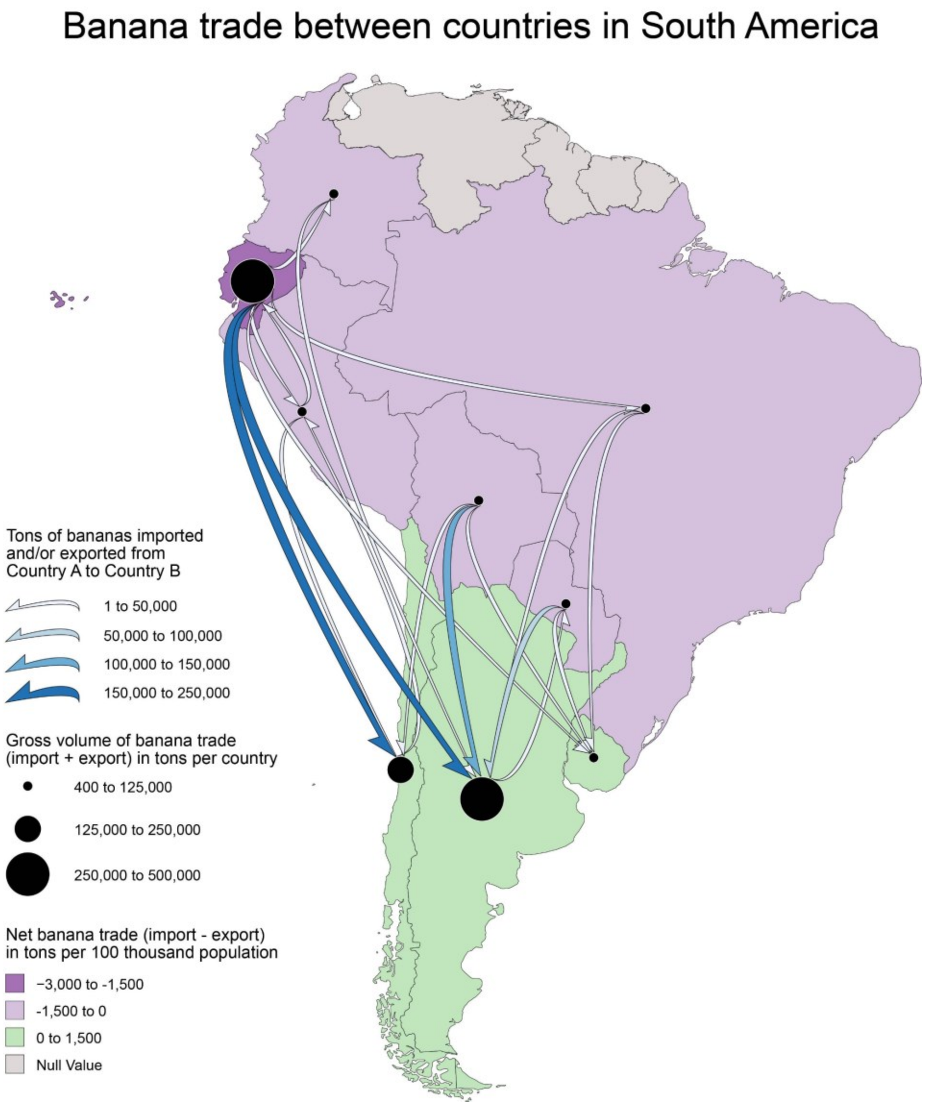
SSN Examples

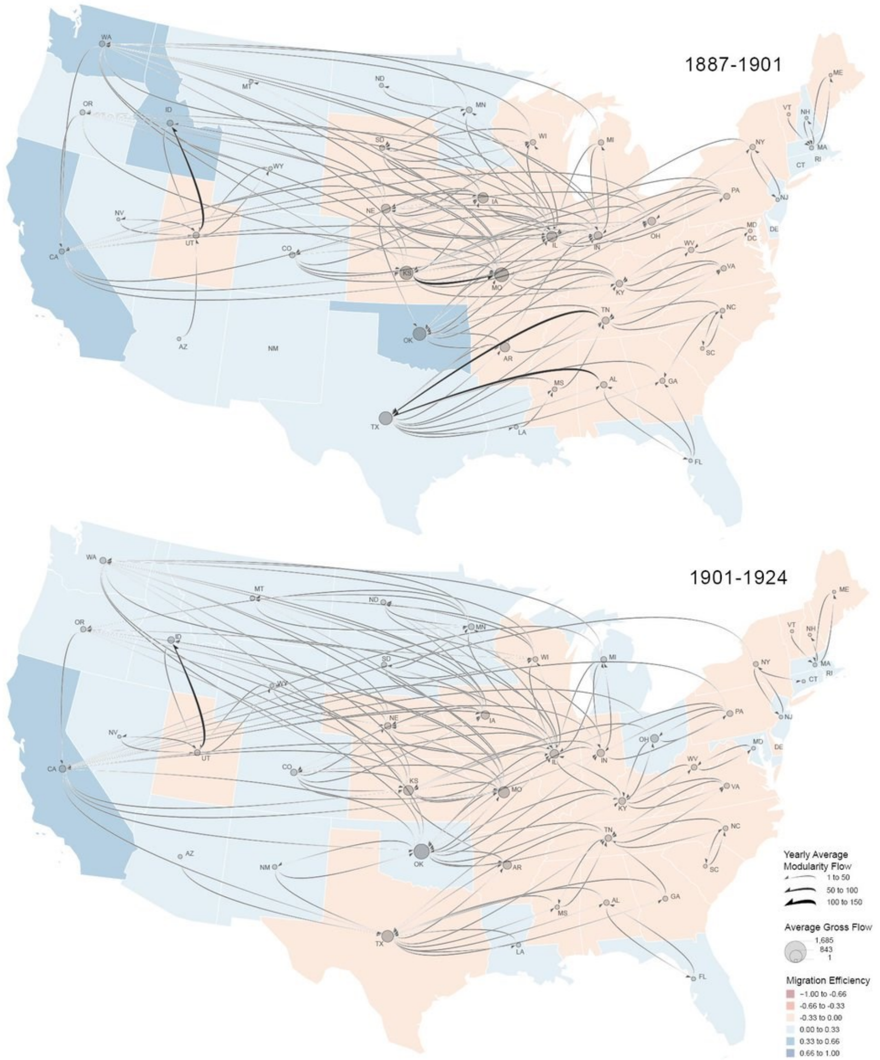
New Research Examples

Software

Conclusion

GEOSPATIAL ANALYSIS OF NETWORKS

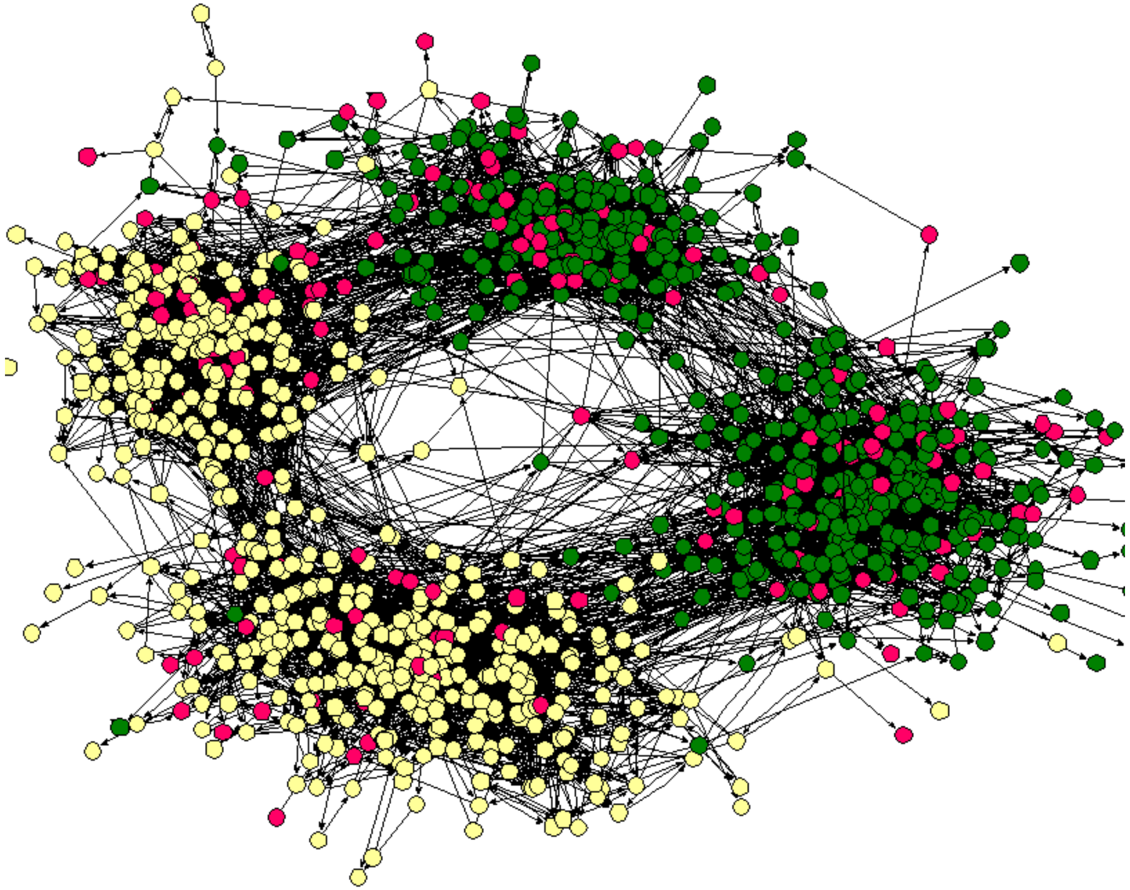




Koylu, C., Tian, G., & Windsor, M. (2022). Flowmapper.org: a web-based framework for designing origin–destination flow maps. *Journal of Maps*, 1-9.

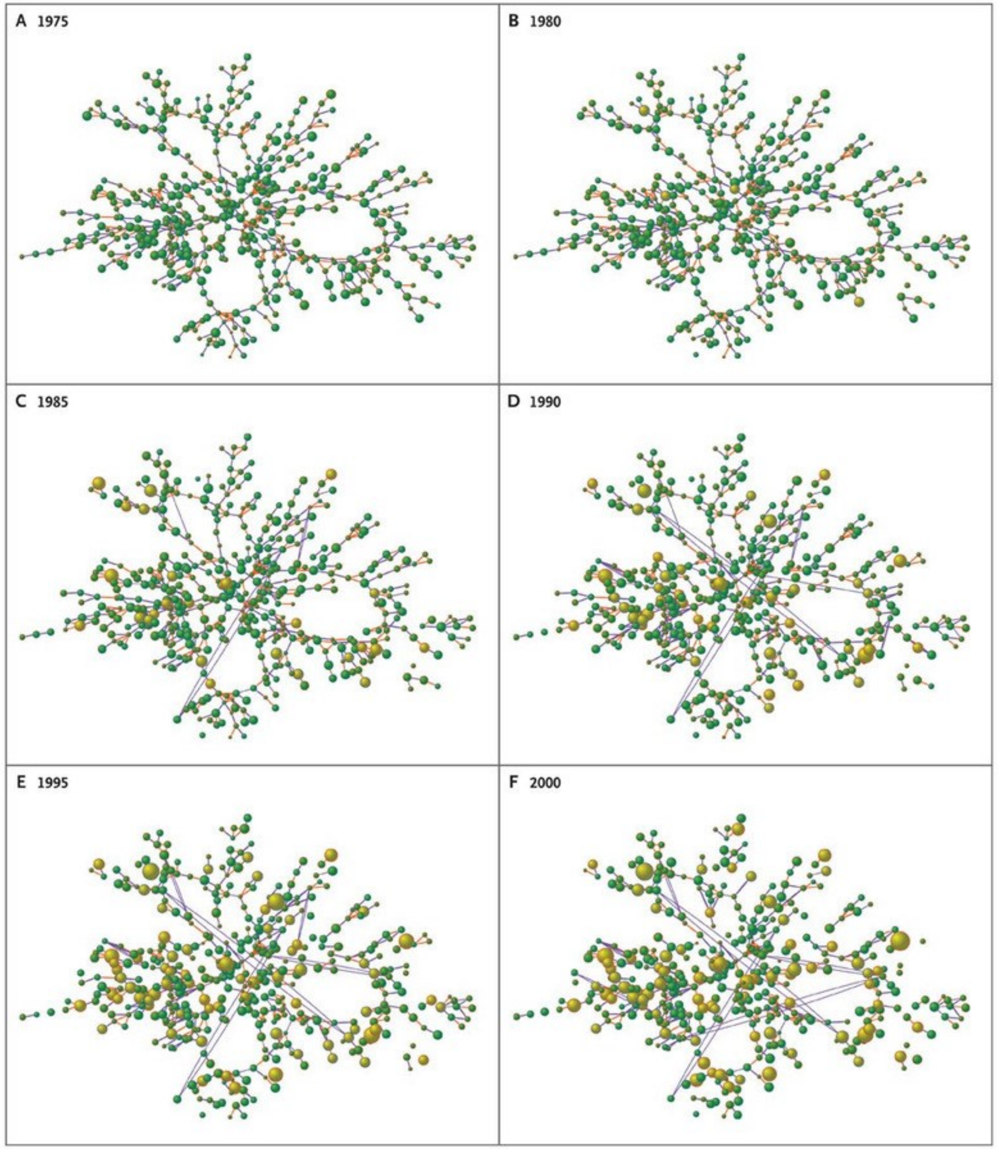
WHAT ABOUT **SOCIAL NETWORKS?**

Middle + High School Friendships | Color represents race (AD health-North Carolina).



Moody, J. (2001). Race, school integration, and friendship segregation in America. *American Journal of Sociology, 107*(3), 679-716.

Patients | Larger dots represent obesity (Framingham Heart Study).



Christakis, N. A., & Fowler, J. H. (2007). The spread of obesity in a large social network over 32 years. *New England Journal of Medicine*, *357*(4), 370-379.

Why SSNs

SSN Examples

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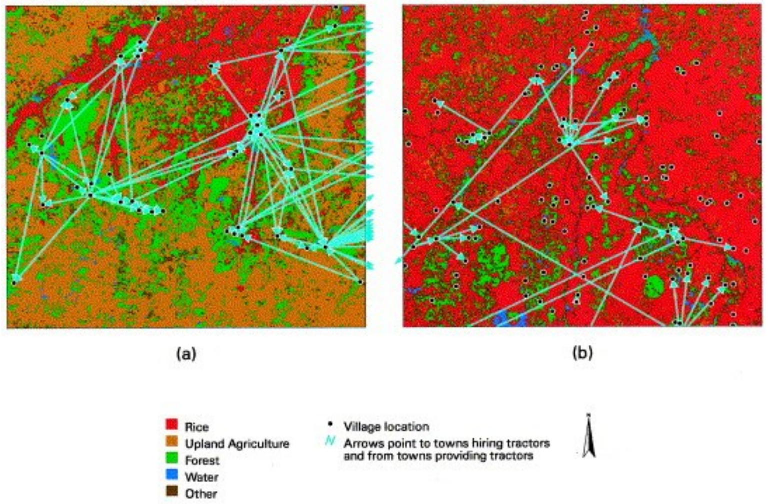
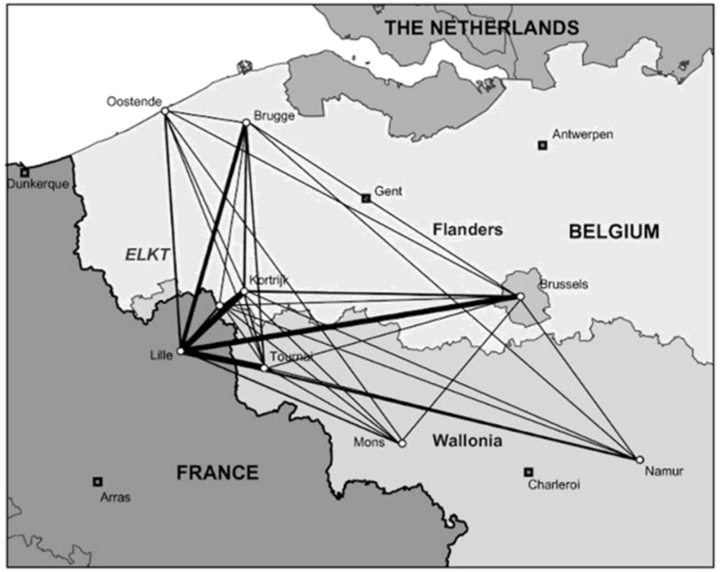
Software

Conclusion

Spatial arrangement of social and economic networks among villages in Nang Rong District, Thailand

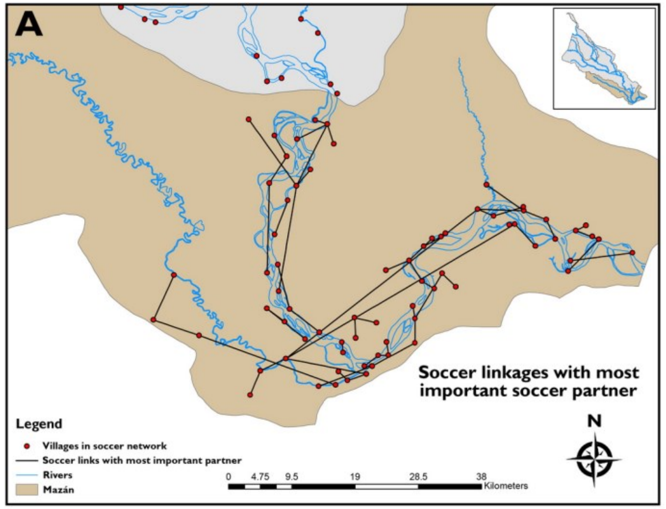


Borders moderating distance: a social network analysis of spatial effects on policy interaction.

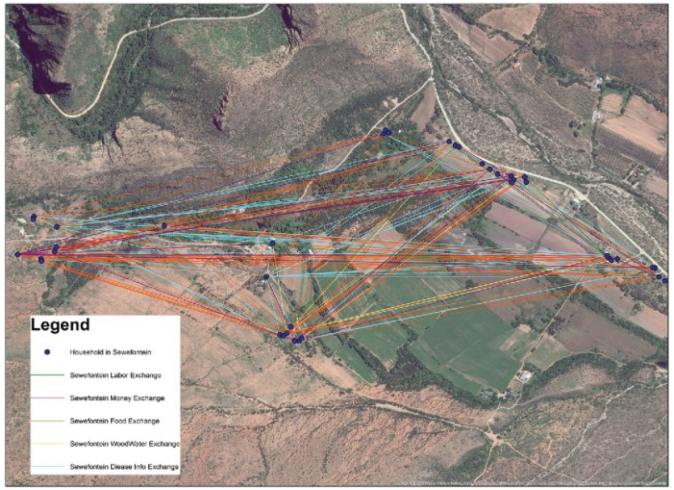


Information exchange

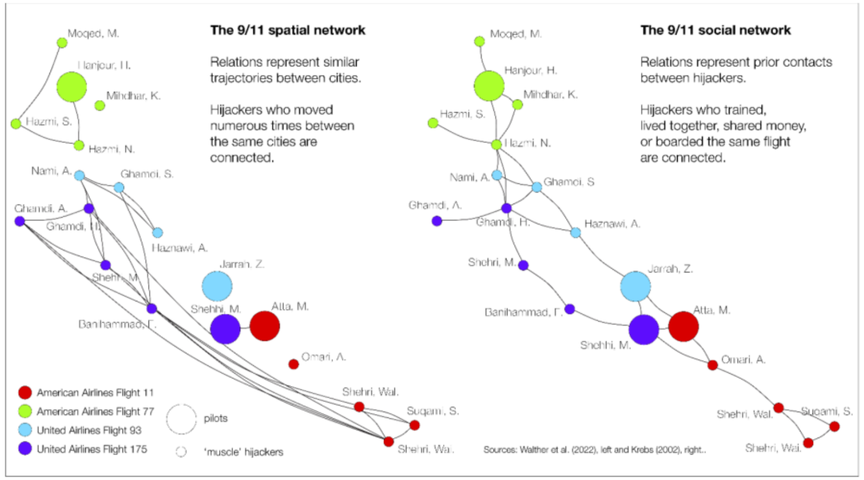
Rural social networks along Amazonian Rivers: Seeds, labor and soccer among communities on the Napo River, Peru



Spatial social network analysis of resource access in rural South Africa



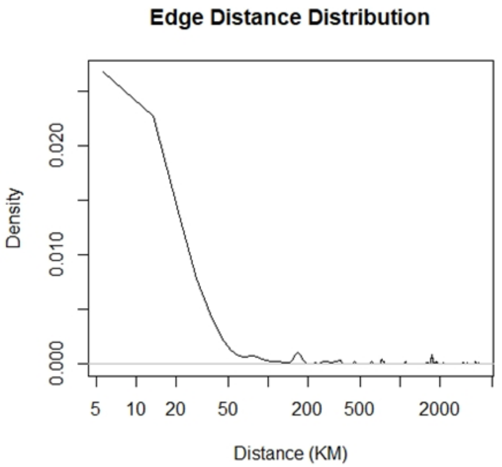
Mapping the travel geography of the 9/11 terrorist network

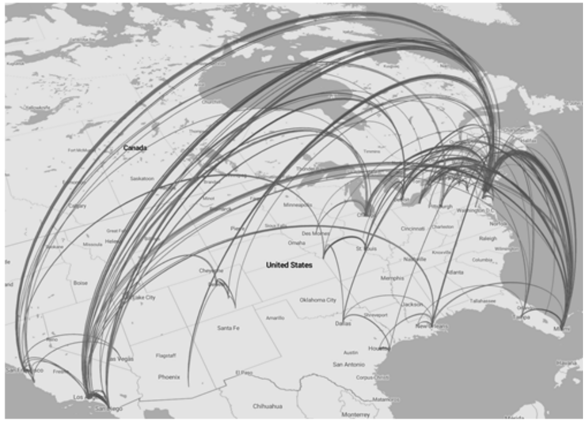


Abizaid, C., Coomes, O.T., Takasaki, Y. and Arroyo-Mora, J.P. (2018). Rural social networks along Amazonian Rivers: Seeds, labor and soccer among communities on the Napo River, Peru. *Geographical Review*, 92-119.
Faust, K., Entwisle, B., Rindfuss, R.R., Walsh, S.J. and Sawangdee, Y., 2000. Spatial arrangement of social and economic networks among villages in Nang Rong District, Thailand. *Social Networks*, 21(4), pp.311-337.
Schramski, S., & Huang, Z. (2016). Spatial social network analysis of resource access in rural South Africa. *The Professional Geographer*, *68*(2), 281-298.
Sohn, C., Christopoulos, D. and Koskinen, J. (2020). Borders moderating distance: a social network analysis of spatial effects on policy interaction. *Geographical Analysis*, 52(3), 428-451.
Walther, O., Prieto-Curiel, R., Padron, J., & Scheuer, J. (2022). Mapping the Travel Geography of the 9/11 Terrorist Network. Available at SSRN.

CHALLENGES

1) Spatial social network analysis produces very different types of output.





	Blocks		Block groups	
	Violent crime	Property crime	Violent crime	Property crime
Diffusion potential	−0.011***	−0.012***	−0.004	−0.009***
	−(6.40)	−(10.30)	−(1.42)	−(3.42)
Mean degree	−0.102***	−0 117***	−0.002	−0.003
	−(21.75)	−(36.56)	−(0.11)	−(0.26)
Proportion ties within block	−1.857***	−1 371***	−1.423***	−0.521**
	−(19.52)	−(20.93)	−(6.90)	−(2.99)
Proportion ties within block group	−0.884***	−0 977***	−1.046***	−1.483***
	−(7.53)	−(12.20)	−(3.70)	−(6.19)
Proportion ties within tract	−1.144***	−0.942***	−0.005	0.283
	−(9.14)	−(10.66)	−(0.02)	(1.10)

2) We can’t (yet) answer very basic questions about a spatial social network.

3) We lack null hypotheses about SSN topology.

We don’t have an expectation, so we can’t compare to actual.

KEY BASIC QUESTIONS

Are "powerful" nodes near advantageous geographic features? (Rivers, grocery store)

Do "powerful" nodes cluster?

What geographic features appear to hinder or enable connections?

What types of social networks exhibit local ties and where are the ties?

What types of social networks are more "efficient" than others?

Do subgroups in social networks also cluster in geographic space?

RESEARCH CONTRIBUTIONS

- Theoretical Advances in Relational Space
- New Statistical Approaches
- Increase the use of GIS in Interdisciplinary Research

Why SSNs

SSN Examples

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GUIDING EXAMPLES

HISTORIC NETWORK

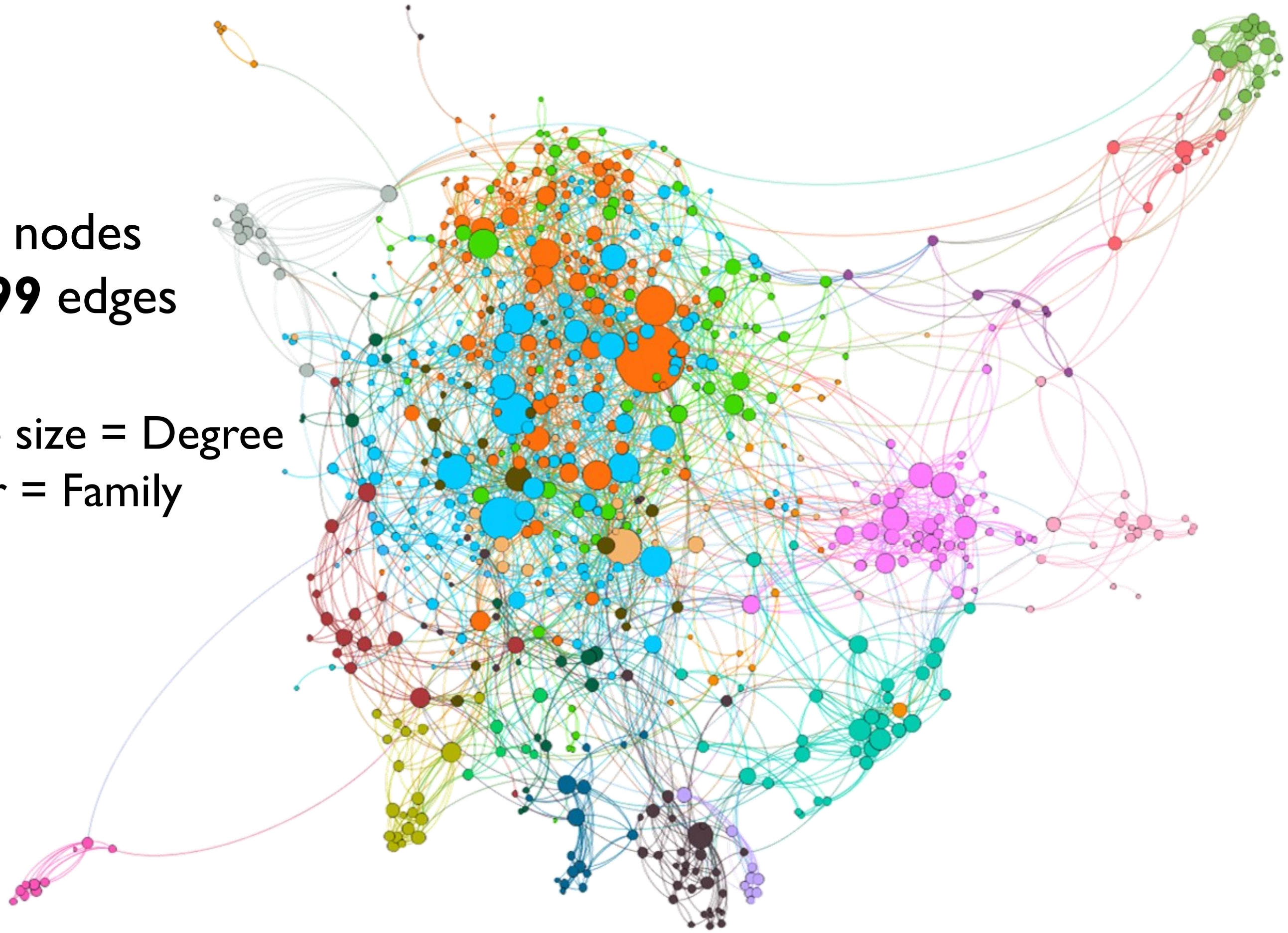
CURRENT NETWORK

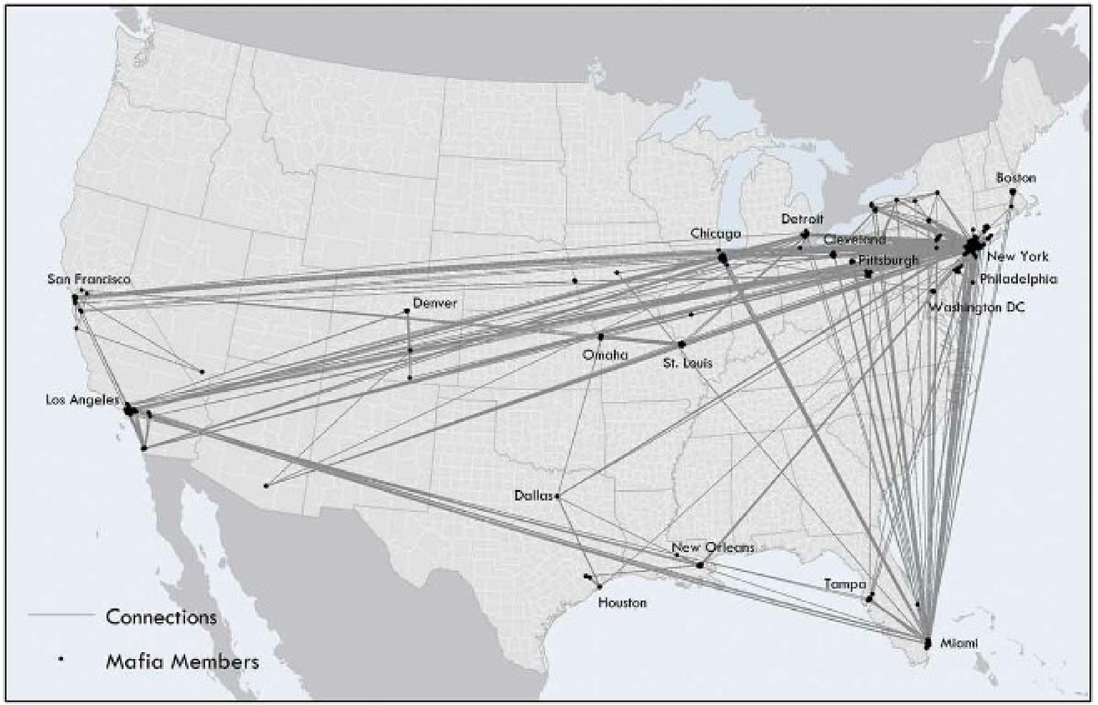
ONGOING WORK

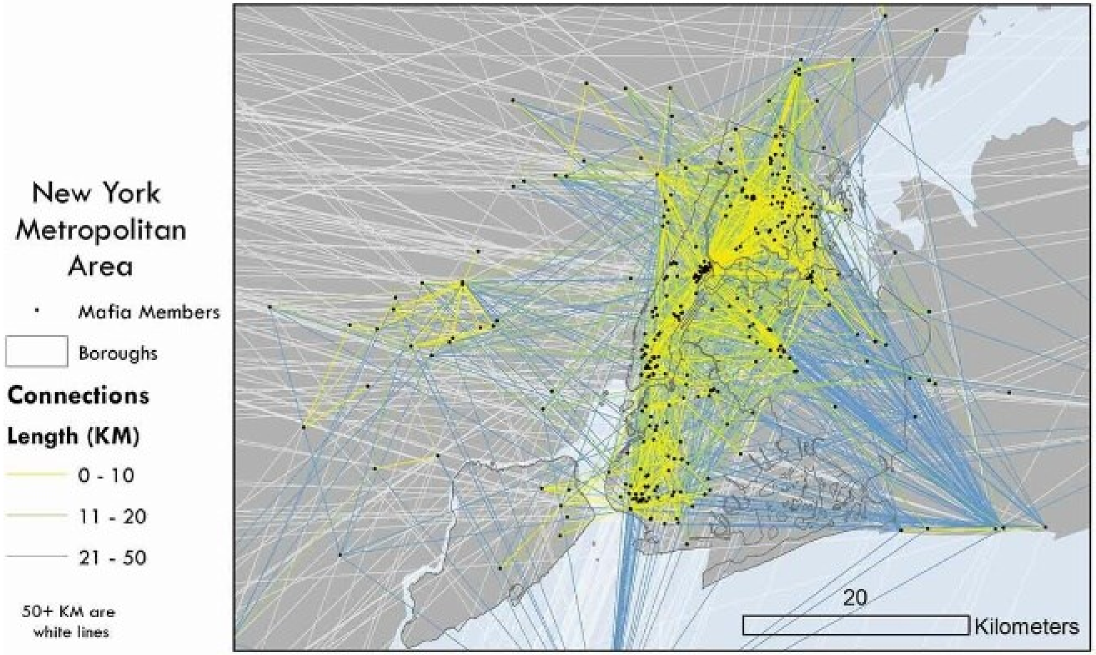
U.S. MAFIA NETWORK

680 nodes
2,699 edges

Node size = Degree
Color = Family





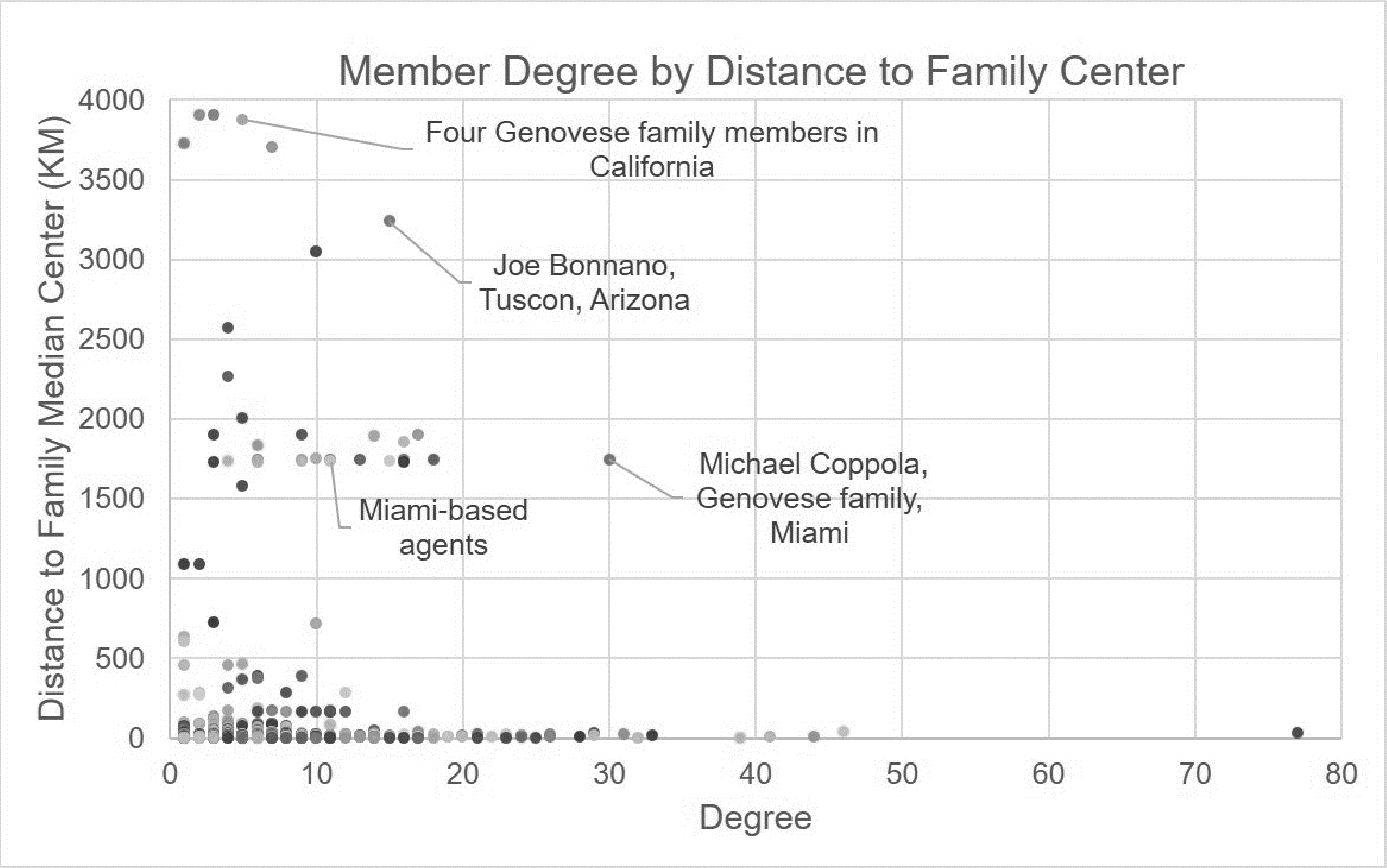


Andris C and DellaPosta D, Freelin B N, Zhu X, Hinger B and Chen H (2021) [To Racketeer Among Neighbors: Spatial Features of Criminal Collaboration in the American Mafia.] *International Journal of Geographical Information Science*, DOI: 10.1080/13658816.2021.1884869. (Sociogram from DellaPosta, D. (2017).)

New Visual Approach: Centrality/Centrality Plot

Research Question:

Do 'powerful' members live near the geographic 'center' of their families?



Research Question: Are high-degree members in central geographic locations?

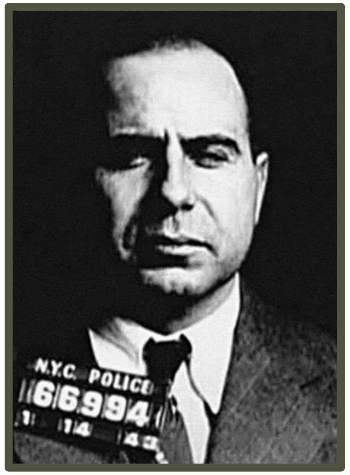
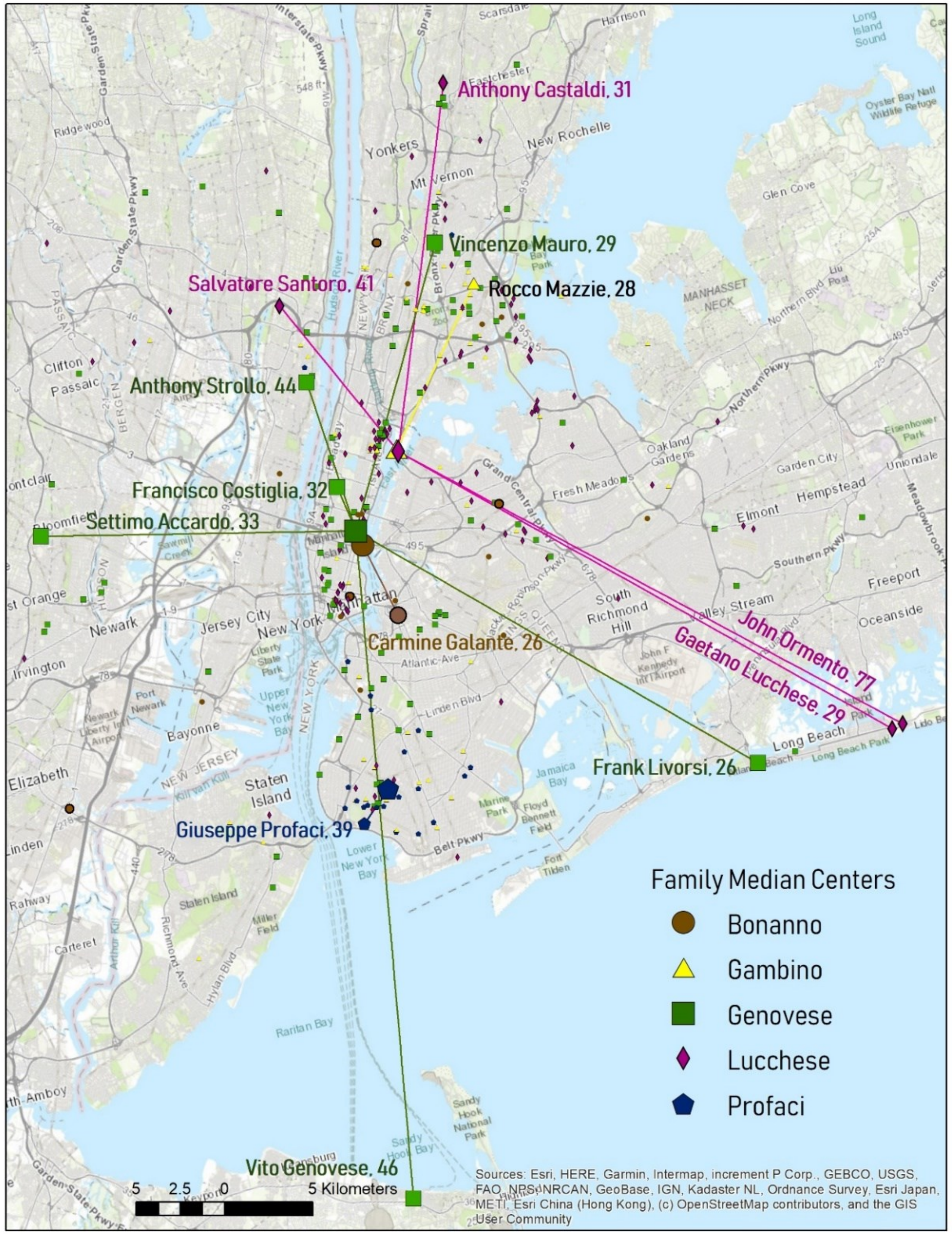
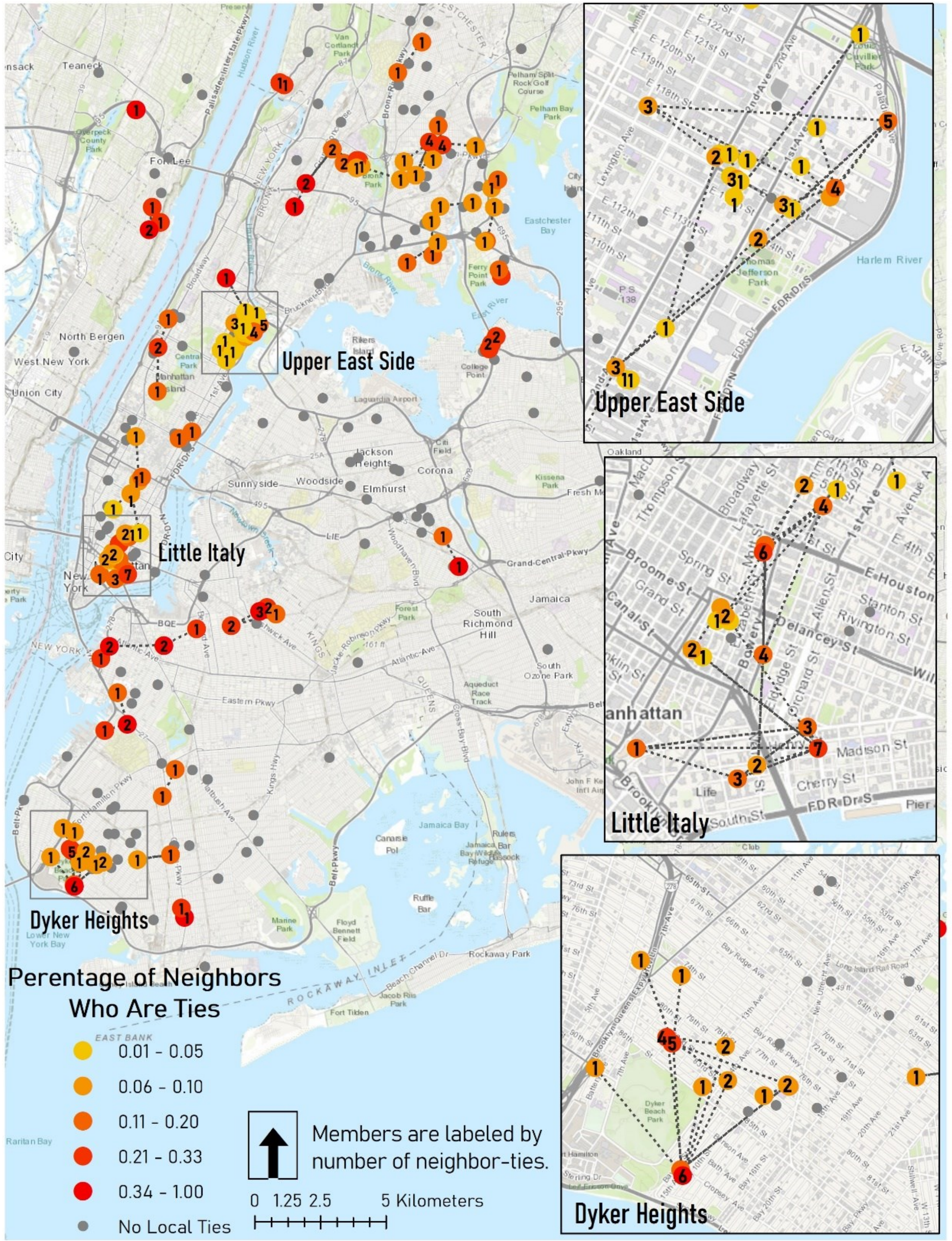


Photo credit: various.



Research Question:
Where are *connected* clusters located?

NEW APPROACH: "SCAN METHODS FOR SPATIAL SOCIAL NETWORK HOTSPOT DETECTION"



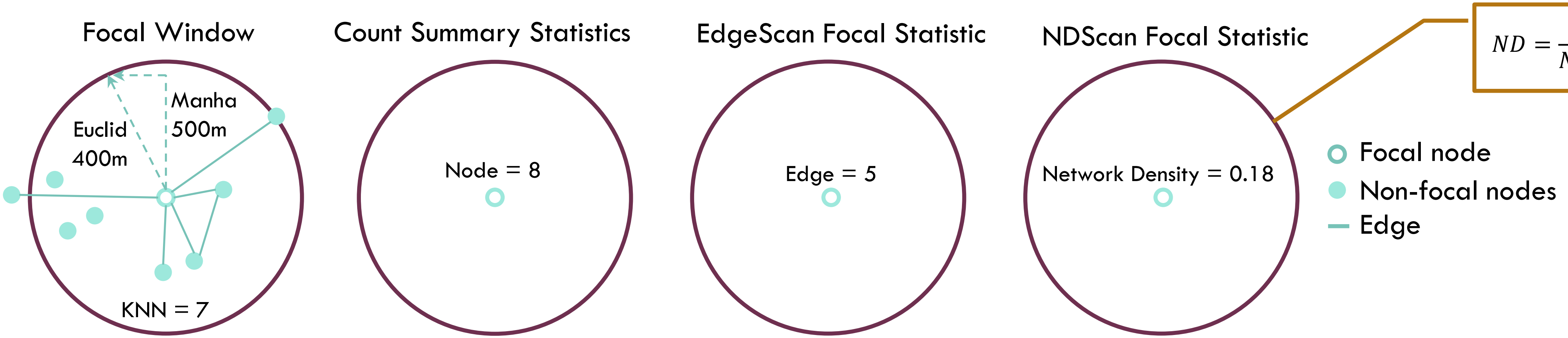
Liang, X., Baker, J., DellaPosta, D., & Andris, C. (2023) Is your neighbor your friend? Scan methods for spatial social network hotspot detection. *Transactions in GIS*. DOI: 10.1111/tgis.13050.

EDGESCAN AND NDSCAN SCAN STATISTICS

Inputs to the EdgeScan and NDScan Algorithms

- Requirement: Nodes and edge list (.txt, .csv, .xls)

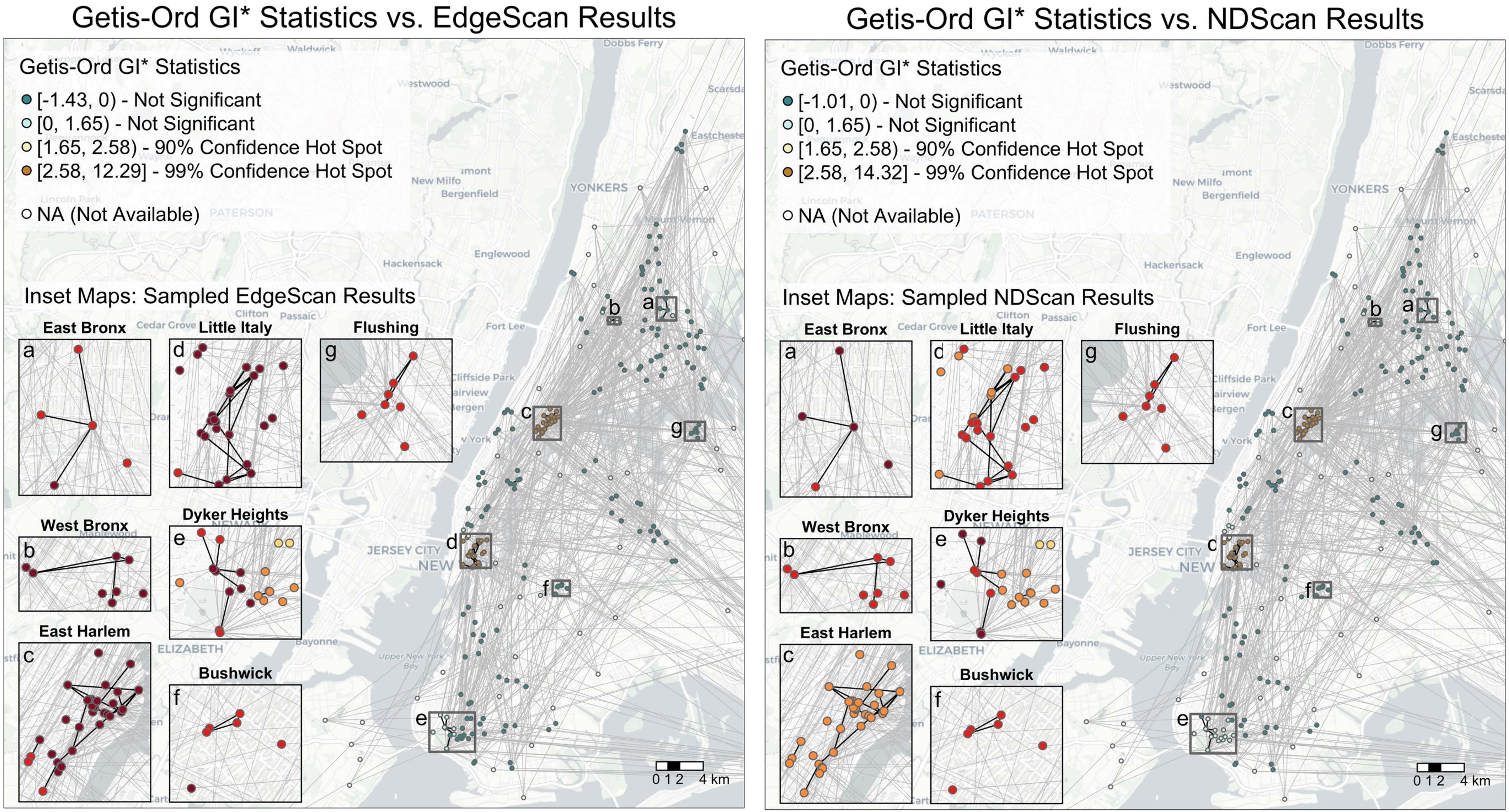
For each node in the spatial social network, calculates the focal statistics:



$$ND = \frac{2 * Edge}{Node * (Node - 1)}$$

-**Comparison** to Getis-Ord GI*

-**Sensitivity test** with three window definitions (Euclidean Distance, Manhattan Distance, K Nearest Neighbors) and sizes (distance or k neighbors)



LocalGi algorithm with 1km distance band and z scores from the number of nodes in the distance band. The inset maps show the sampled NDScan and EdgeScan results of the highlighted areas in Getis-Ord GI* base map.

SENSITIVITY TESTS FOR EDGESCAN AND NDSCAN

By Window Size

- Mean EdgeScan value (and Std) increases with window size, while NDScan value and (Std) may decrease.
- For distance-based methods, the percentage of nodes passes the minimum point threshold increases with window size.

By Neighborhood Definition

- The observations of window size are consistent across neighborhood definitions.
- KNN tends to overestimate EdgeScan values and have more dispersed outcomes.

How should users select neighborhood definition and window size?

New York City

Neighborhood	Mean (St. Dev.) NYC EdgeScan	Mean (St. Dev.) NYC NDScan	N(Node≥ 0) NYC Nodes
Euclid 0.5km	2.99 (3.62)	0.12 (0.16)	118 (40%)
Euclid 1km	5.16 (6.88)	0.1 (0.12)	204 (68%)
Euclid 2km	8.7 (9.23)	0.08 (0.09)	263 (88%)
Manhattan 0.5km	2.49 (2.59)	0.12 (0.15)	83 (28%)
Manhattan 1km	3.94 (5.05)	0.11 (0.13)	172 (58%)
Manhattan 2km	6.96 (8.25)	0.09 (0.11)	246 (83%)
KNN (K = 5)	1.99 (1.85)	0.13 (0.12)	298 (100%)
KNN (K = 10)	8.68 (4.95)	0.16 (0.09)	298 (100%)
KNN (K = 20)	33.14 (13.32)	0.16 (0.06)	298 (100%)

Table: Mean EdgeScan and NDScan values and number of nodes with at least two neighbors (MinPts = 3) at varying neighborhood definitions

City of Detroit

Neighborhood	Mean (St. Dev.) DT EdgeScan	Mean (St. Dev.) DT NDScan	N(Node≥ 0) DT Nodes
Euclid 0.5km	3 (0)	0.3 (0)	5 (12%)
Euclid 1km	3.24 (2.63)	0.3 (0.19)	17 (42%)
Euclid 2km	10.59 (11.45)	0.24 (0.15)	32 (80%)
Manhattan 0.5km	2.2 (1.1)	0.25 (0.07)	5 (12%)
Manhattan 1km	2.38 (1.39)	0.32 (0.18)	13 (32%)
Manhattan 2km	6.81 (7.23)	0.3 (0.16)	27 (68%)
KNN (K = 5)	5.08 (4.08)	0.34 (0.27)	40 (100%)
KNN (K = 10)	28.15 (16.11)	0.51 (0.29)	40 (100%)
KNN (K = 20)	74.6 (12.06)	0.36 (0.06)	40 (100%)

Table: Mean EdgeScan and NDScan values and number of nodes with at least two neighbors (MinPts = 3) at varying neighborhood definitions

GUIDING EXAMPLES

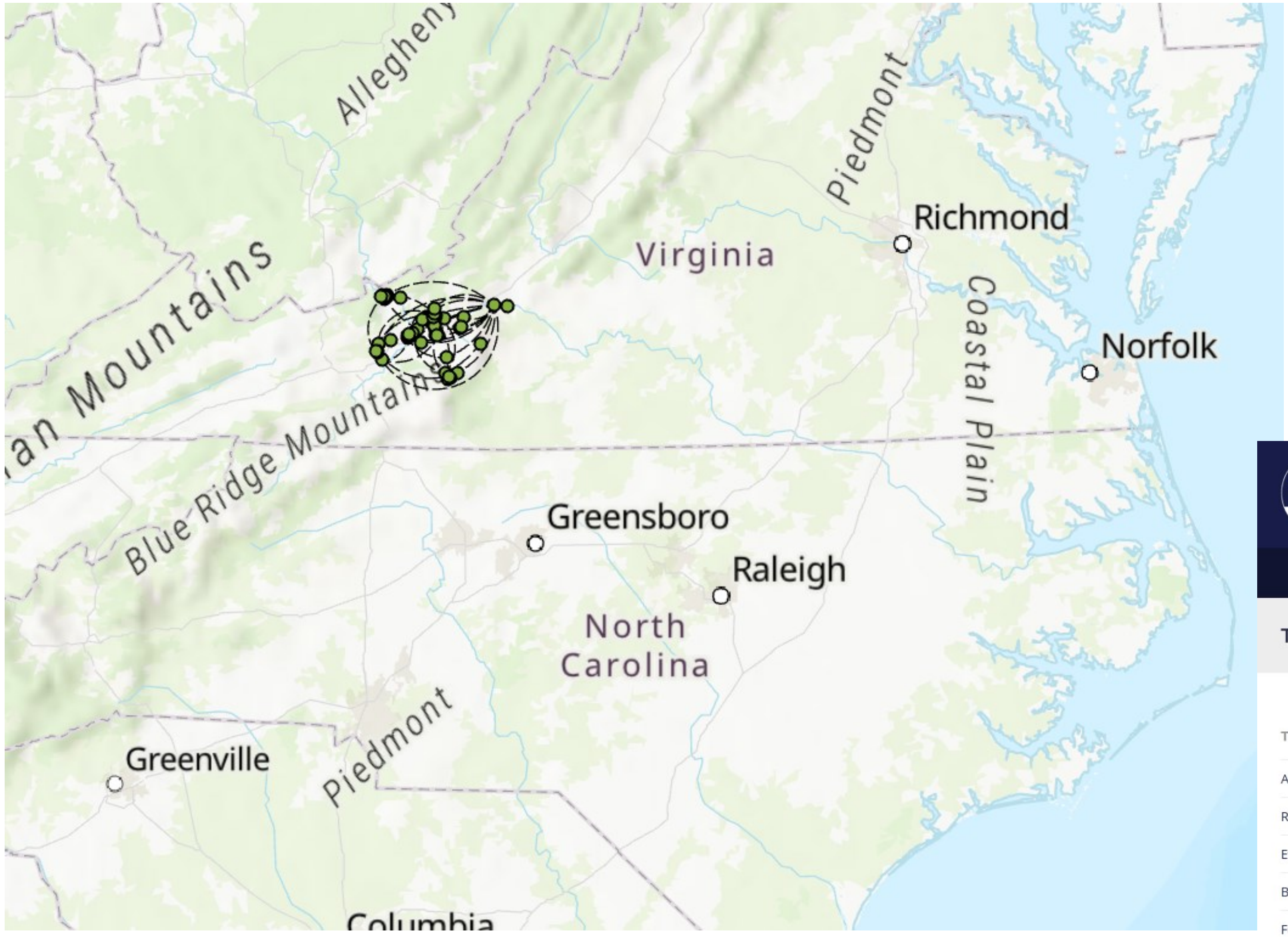
HISTORIC NETWORK

CURRENT NETWORK

ONGOING WORK

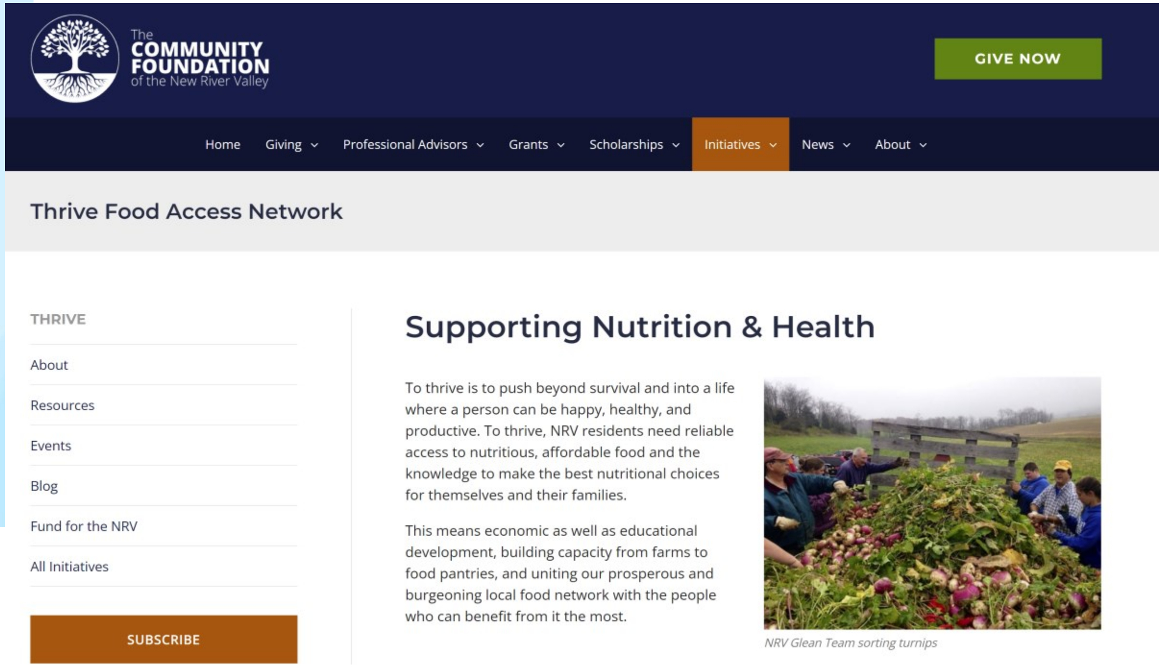
THRIVE Network

THRIVE: *NRV Food Access Network*



Food sharing ties via a survey: 40 nodes and 51 edges.

Kelly J, Sarkar D, and Andris C (2024) [Locality, Personal Ties, and Efficiency in a Food Security Network](). *Annals of the American Association of Geographers*, 1-12.



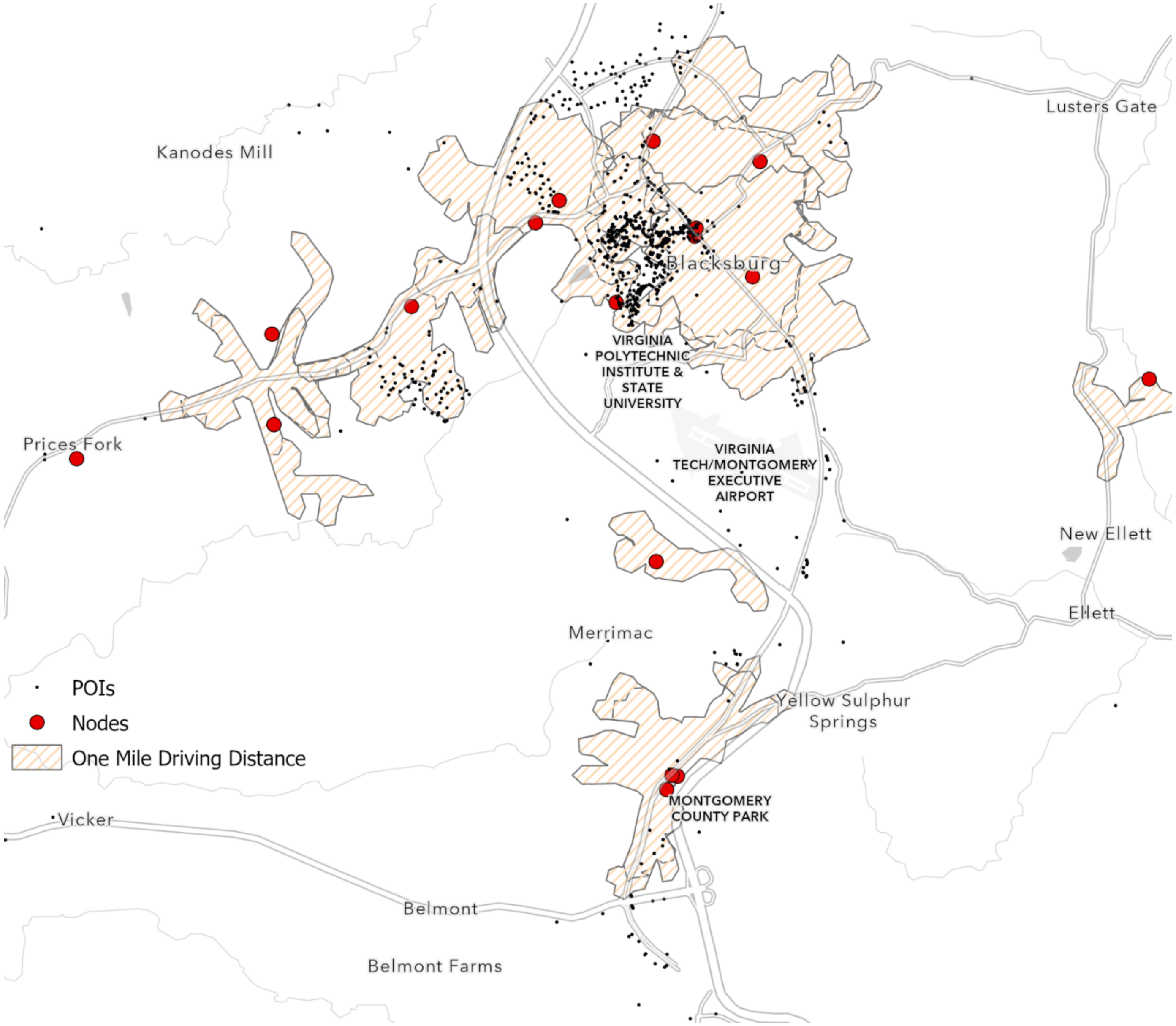
RESEARCH QUESTIONS

1) Power, situation and accessibility:
Are better-connected organizations near *points of interest (POIs)*?

Are they near the *geographic center* of the network?

2) Physical distance:
Which nodes tend to connect to their nearest alters?

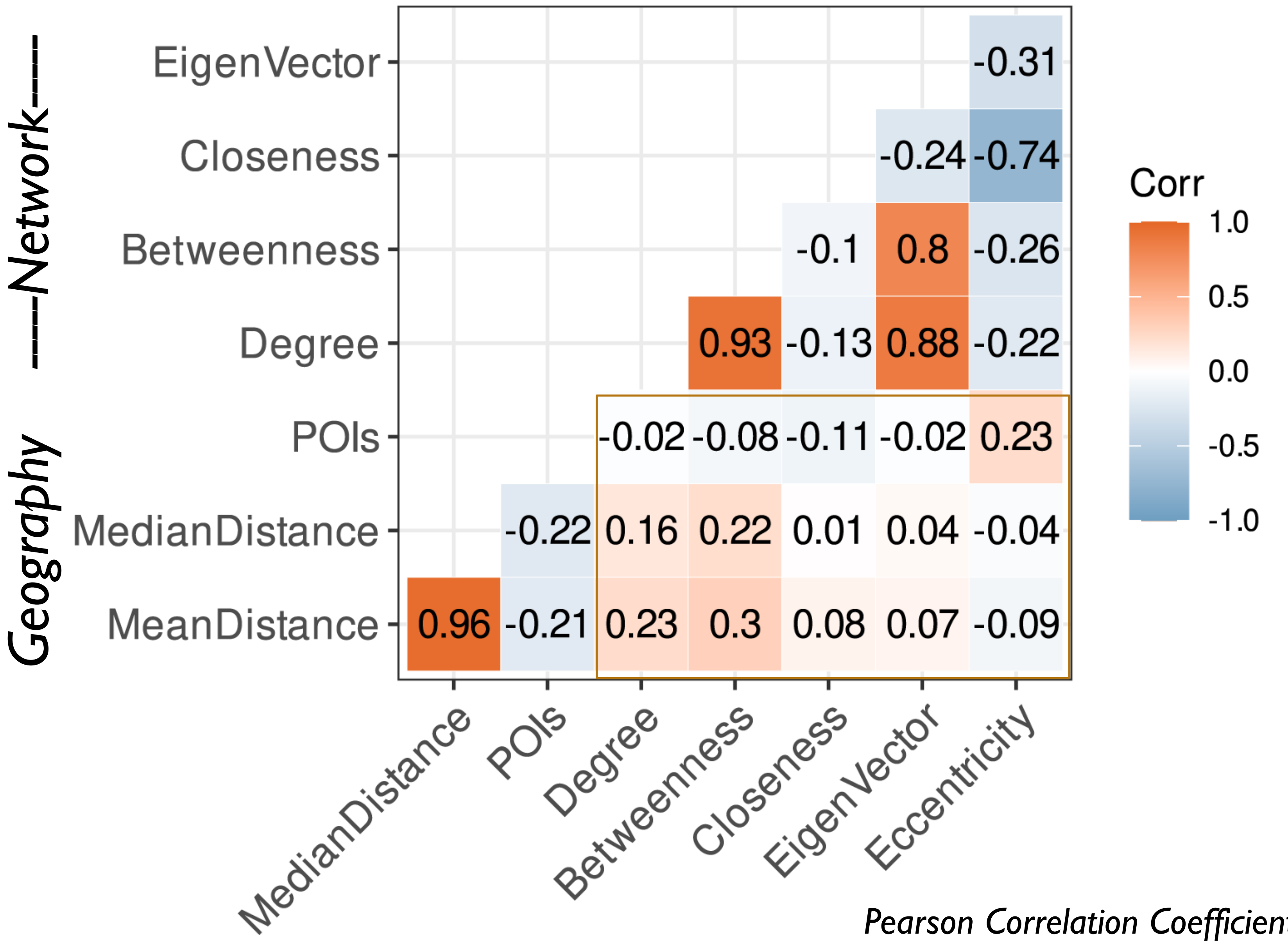
3) Local disconnection:
Which pairs of nodes are nearby but disconnected? We will suggest new ties between these nodes.



POWER, SITUATION AND ACCESSIBILITY

RESEARCH QUESTION:

ARE MORE 'CENTRAL' NODES MORE 'CENTRAL' IN GEOGRAPHIC SPACE?

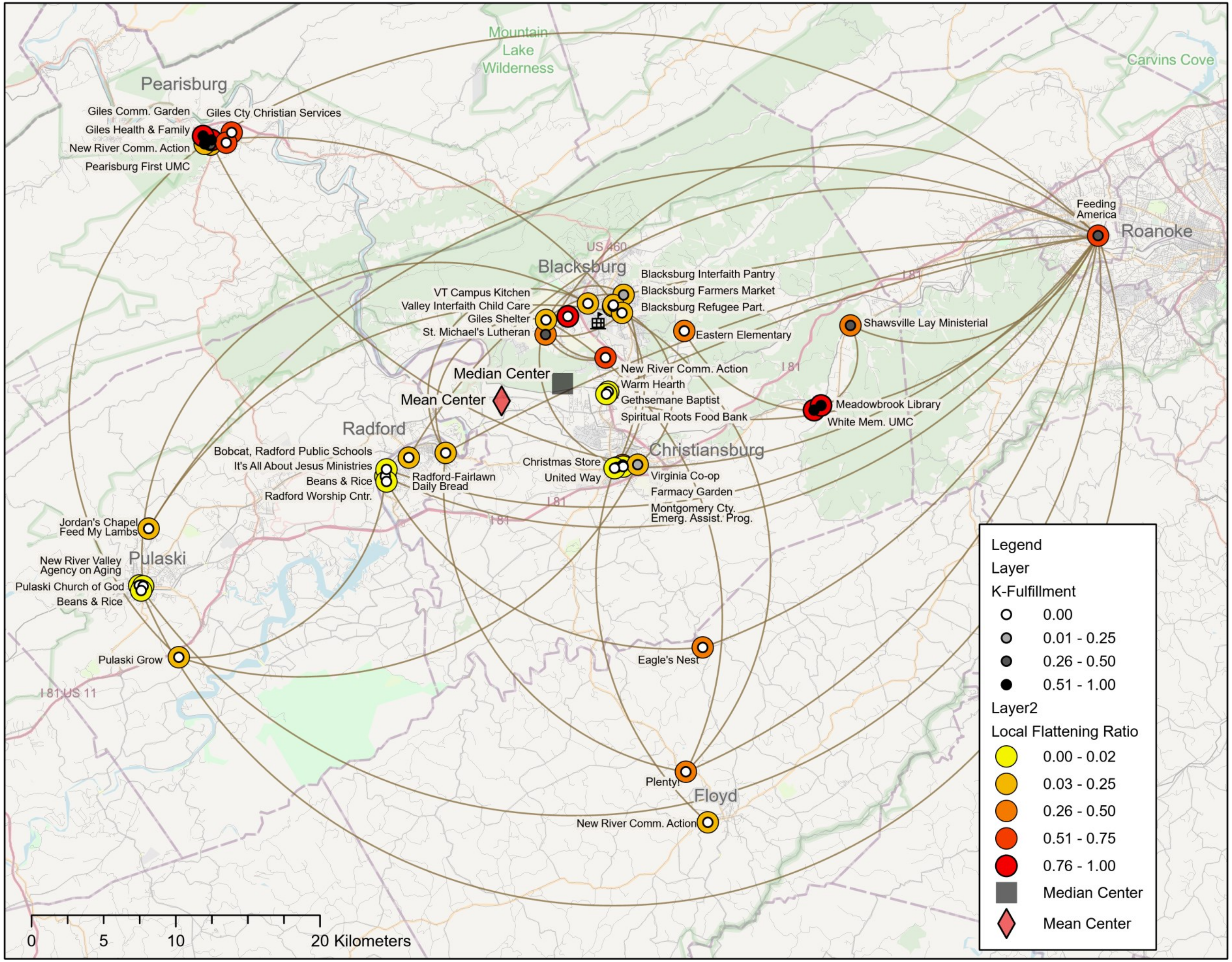


Pearson Correlation Coefficient

RESEARCH QUESTION: WHOSE CONNECTIONS ARE VERY CLOSE / EFFICIENT?

Metric:
"k-fulfillment"
How many of your k nearest neighbors are you connected to?

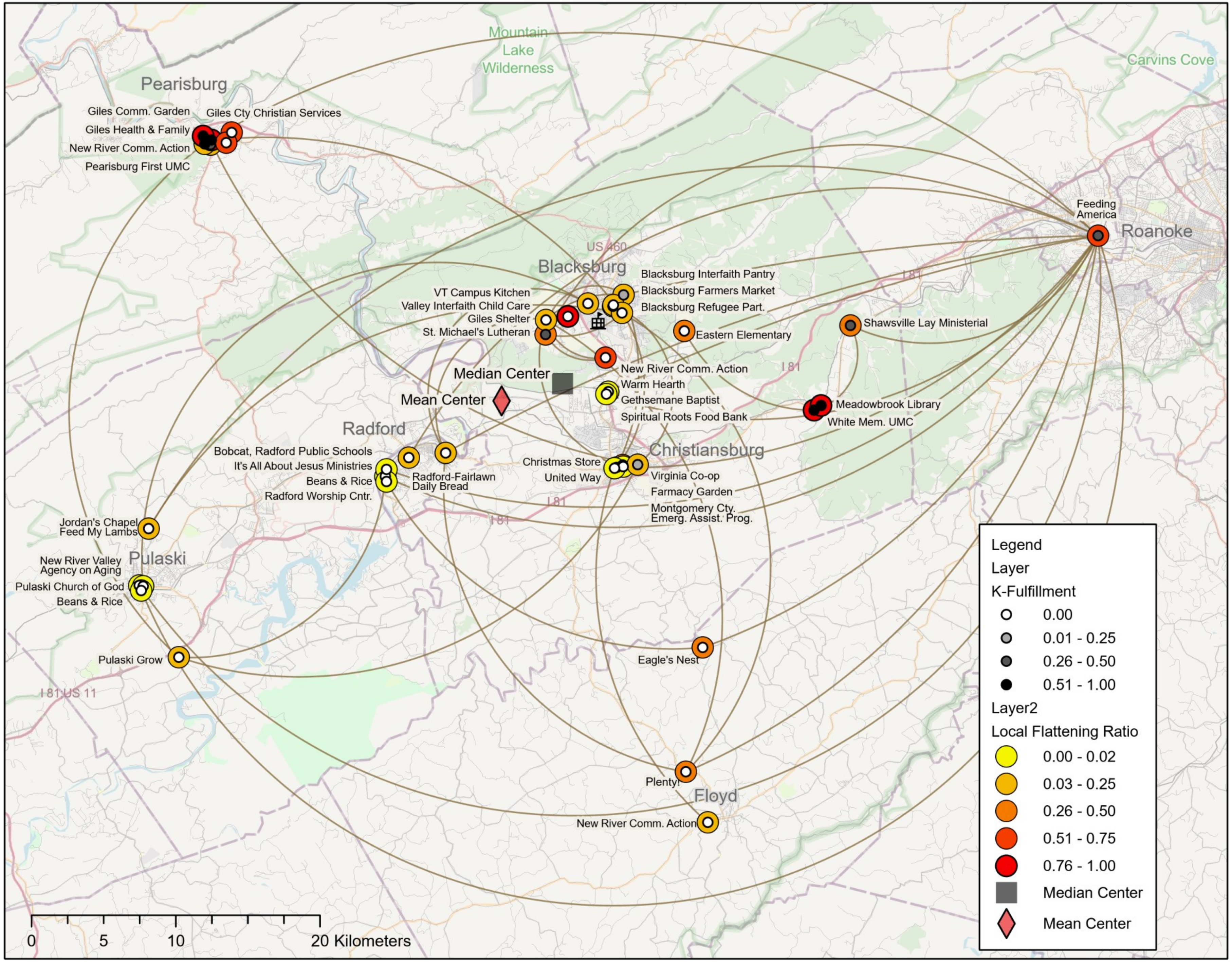
k = degree



Local connections between entities are uncommon.

Only **six** nodes **(12%)** are connected to their nearest neighbor, and **12 (30.0%)** are connected to either their first or second closest neighbor.

Twenty-eight organizations have a k-fulfillment value of 0.



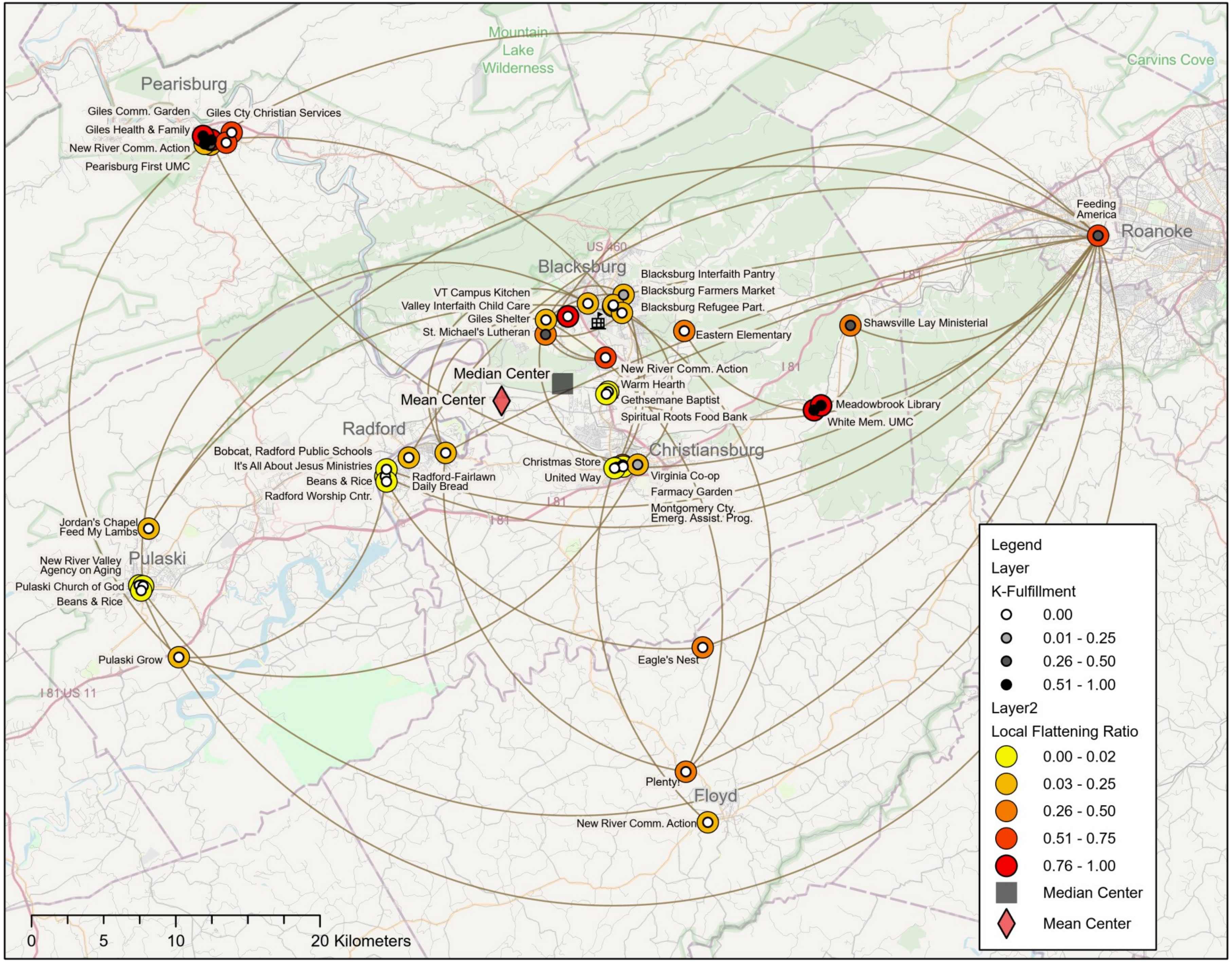
Whose connections are very close / efficient?

Metric: **"Local network flattening ratio"**

Total distance to reach k <u>nearest</u> edges / total distance to reach a node's <u>actual</u> k edges.

k = degree

Nodes range from 0.0039 (Beans and Rice of Pulaski) to 1 (4 organizations) (mean = 0.276).

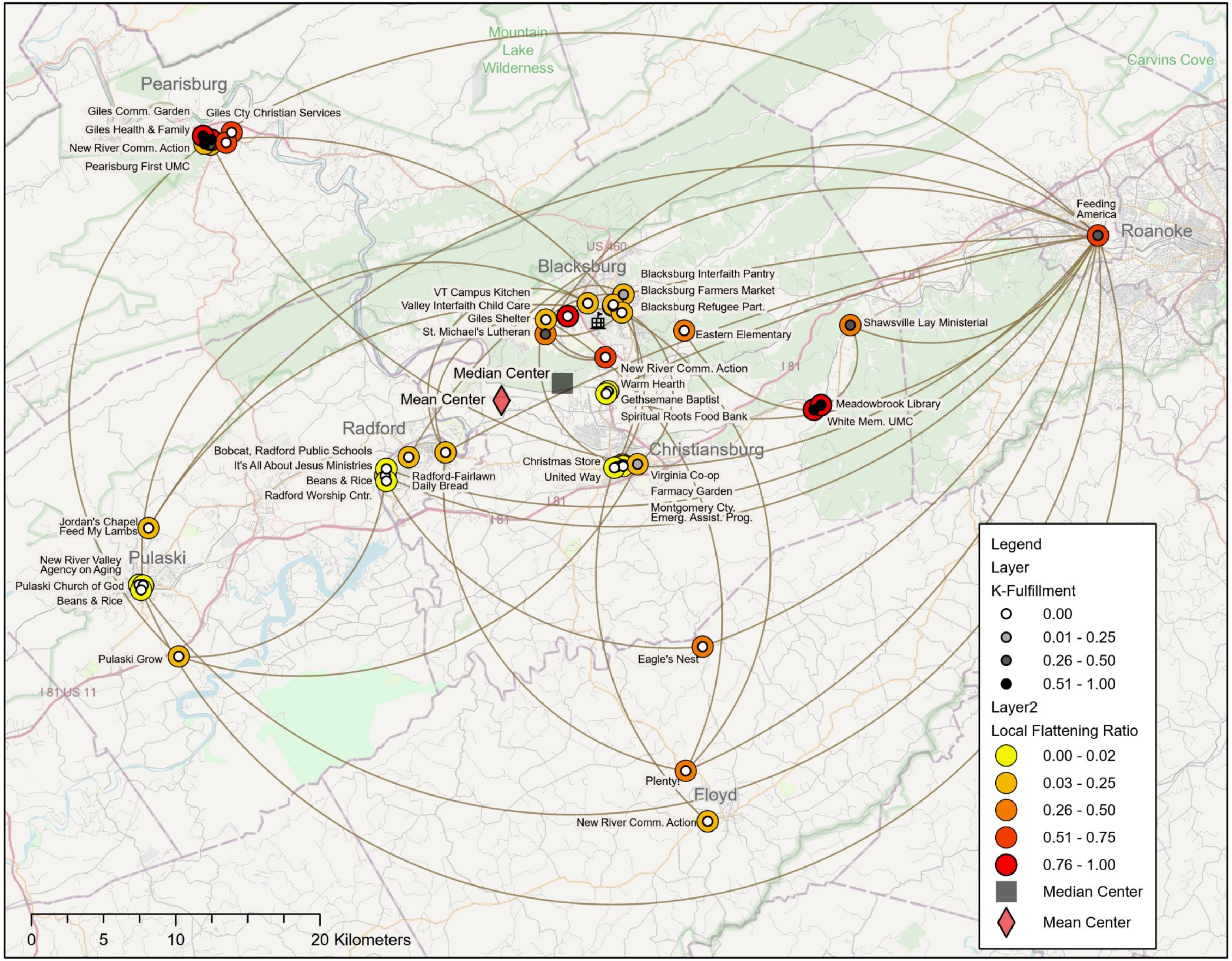


Whose connections are very close / efficient?

Global flattening ratio is ~0.301.**

The Giles Mission has a low local flattening ratio (0.045), implying it forgoes nearby nodes for distant nodes; it connects to nearby nodes, but its flattening ratio is low because it connects with Feeding America.

Feeding America has a low k-fulfillment (0.3) but a high flattening ratio (0.679).



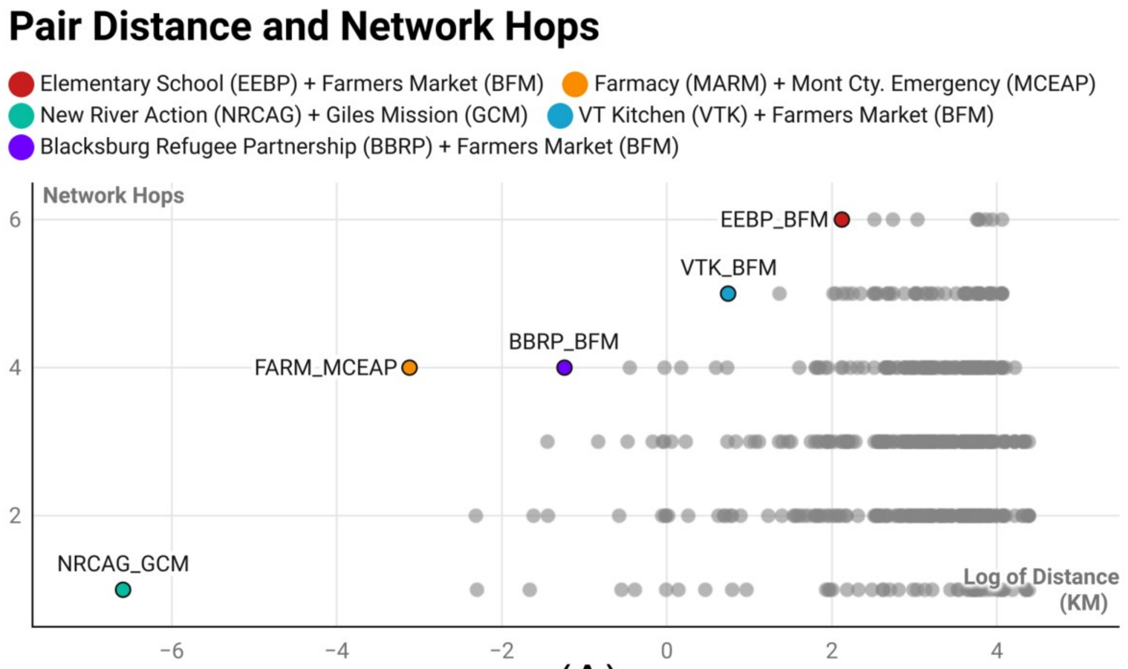
**Sarkar, D., Andris, C., Chapman, C. A., & Sengupta, R. (2019). Metrics for characterizing network structure and node importance in Spatial Social Networks. *International Journal of Geographical Information Science*, 33(5), 1017-1039.

RESEARCH QUESTION:
WHERE SHOULD NEW CONNECTIONS BE MADE?

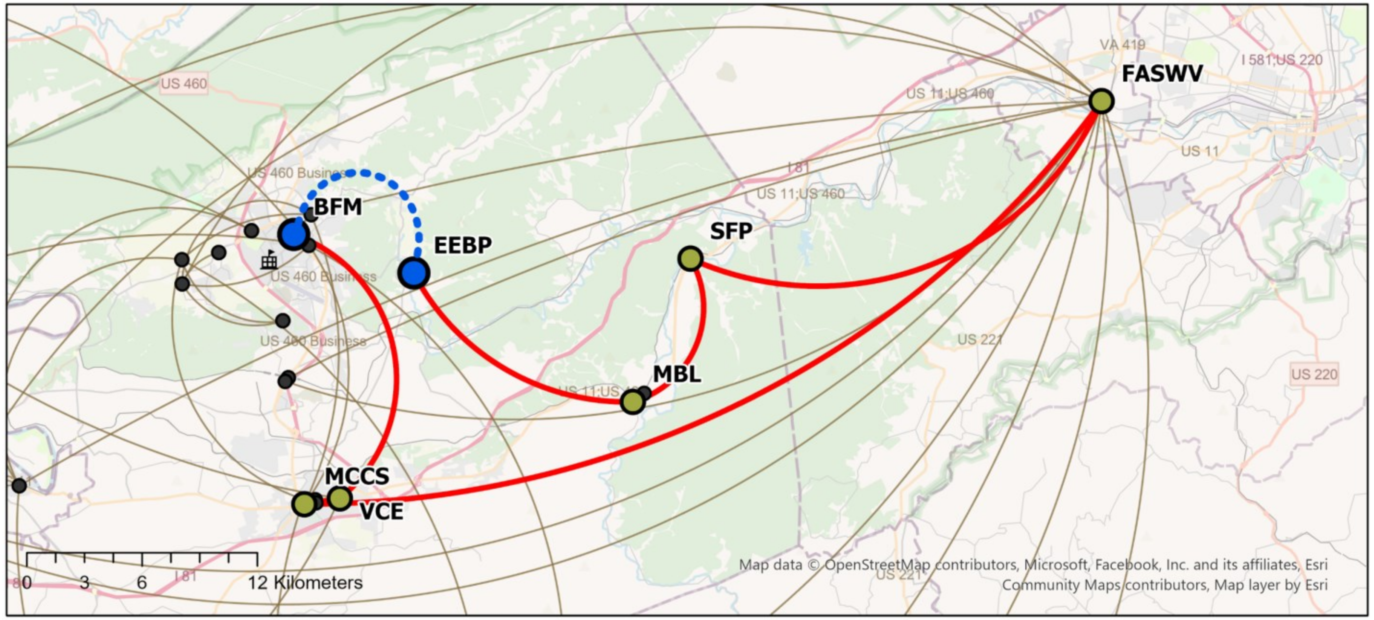
Metric: "**Missed Connections**" based on the 'route factor'

$$Q_{ij} = \frac{d_G(v_i, v_j)}{d_E(v_i, v_j)}$$

Route Factor: See: Black, W. (2003). Transportation: A Geographical Analysis. New York: Guilford Press.



(A)



(B)

GUIDING EXAMPLES

HISTORIC NETWORK

CURRENT NETWORK

ONGOING WORK

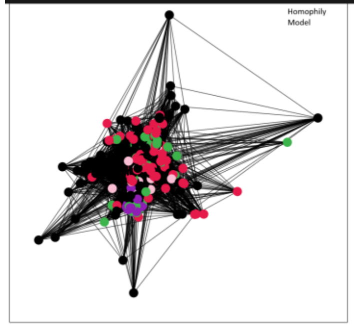
Simulation

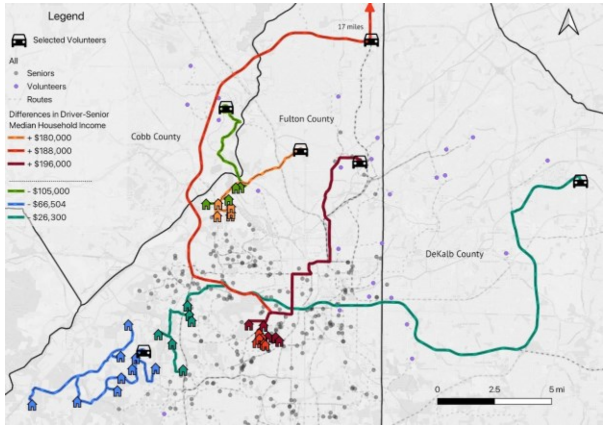
NEEDS

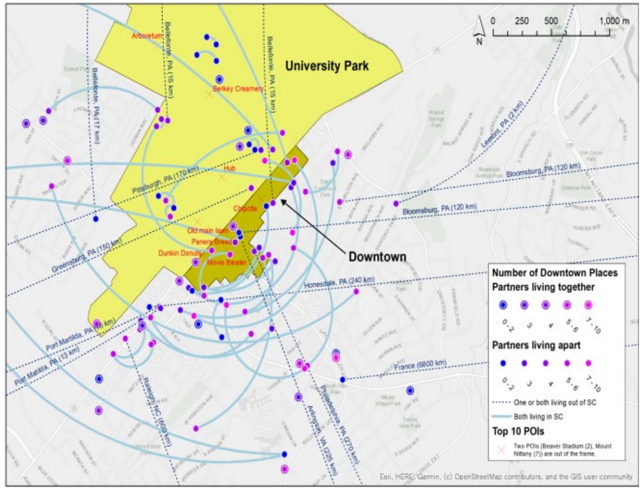
Storytelling

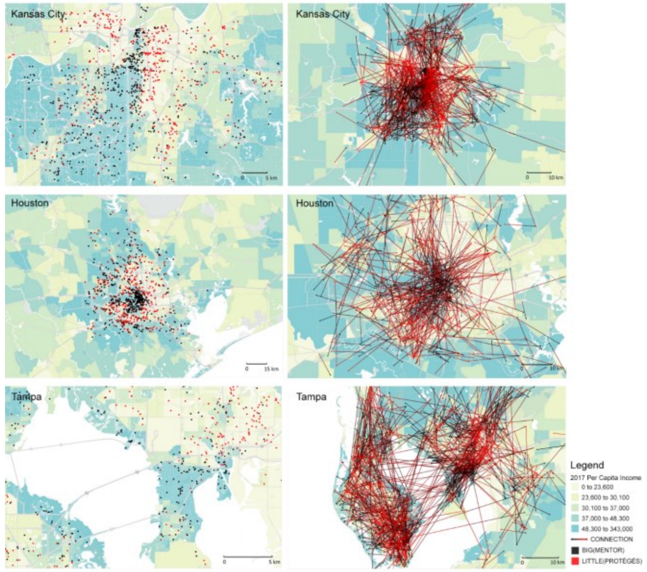
```python
def simple_gravity_model(network, gangsters, average_edge_weight, inc_weight:bool, seed=None):
    # Generate Random Seed
    np.random.seed(seed)
    # Gravity Constant
    g = 2/average_edge_weight
    # Multiplied Weights of Both Nodes
    w = 1
    i = 0
    num_gangsters = len(gangsters.keys())
    while i < num_gangsters:
        g_i = gangsters[i]
        if inc_weight:
            g_i_weight = g_i["Weight"]
        g_i_LonX = g_i["LonX"]
        g_i_LatY = g_i["LatY"]
        j = i + 1
        while j < num_gangsters:
            g_j = gangsters[j]
            if inc_weight:
                w = g_i_weight*g_j["Weight"]
            dist = calc_dist(g_i_LonX, g_i_LatY, g_j["LonX"], g_j["LatY"])
            prob_ij = g*w/max(dist, MIN_DIST)
            if np.random.random() < prob_ij:
                add_gangster_edge(network, gangsters, i, j)
            j += 1
        i += 1
```

```python
def homophily_model(network, gangsters, affinity_val:float, neutral_val:float, seed=None):
    # Generate Random Seed
    np.random.seed(seed)
    i = 0
    num_gangsters = len(gangsters.keys())
    while i < num_gangsters:
        g_i = gangsters[i]
        j = i + 1
        g_i_LonX = g_i["LonX"]
        g_i_LatY = g_i["LatY"]
        while j < num_gangsters:
            g_j = gangsters[j]
            prob_ij = neutral_val
            if g_i["Family"] == g_j["Family"]:
                prob_ij = affinity_val
            # Incorporate Distance into model
            dist = calc_dist(g_i_LonX, g_i_LatY, g_j["LonX"], g_j["LatY"])
            prob_ij /= max(dist, MIN_DIST)
            if np.random.random() < prob_ij:
                add_gangster_edge(network, gangsters, i, j)
            j += 1
        i += 1
    return
```

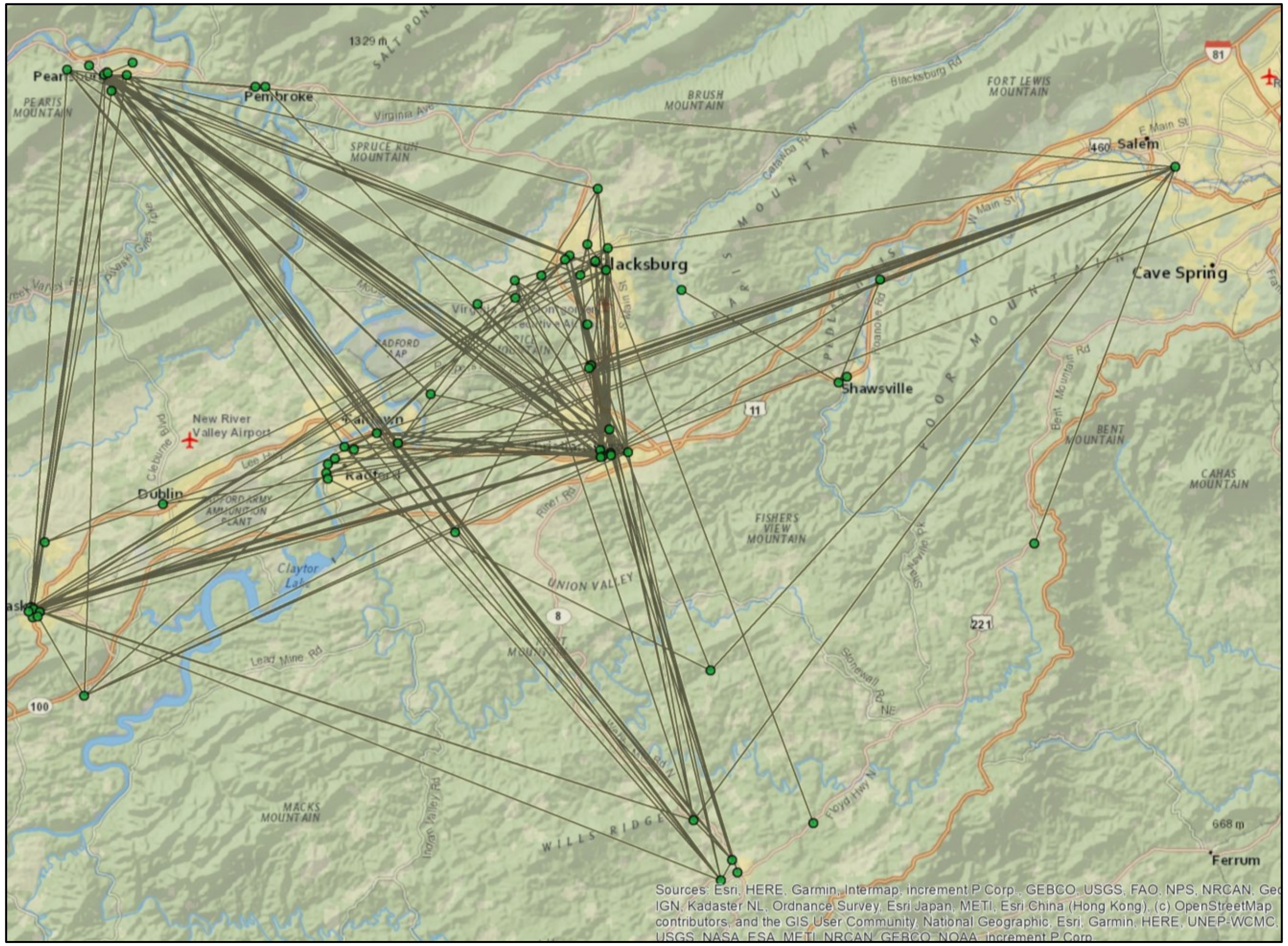


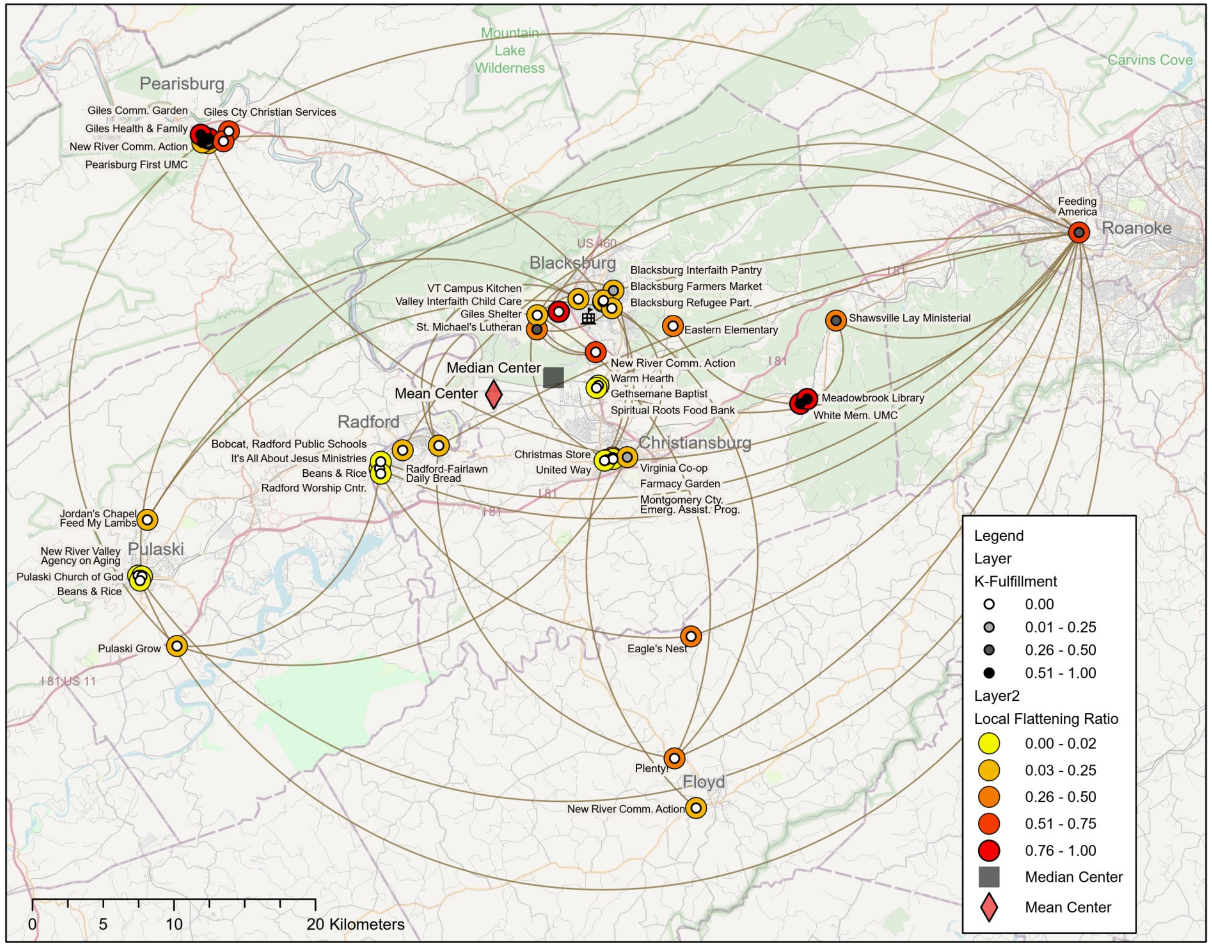


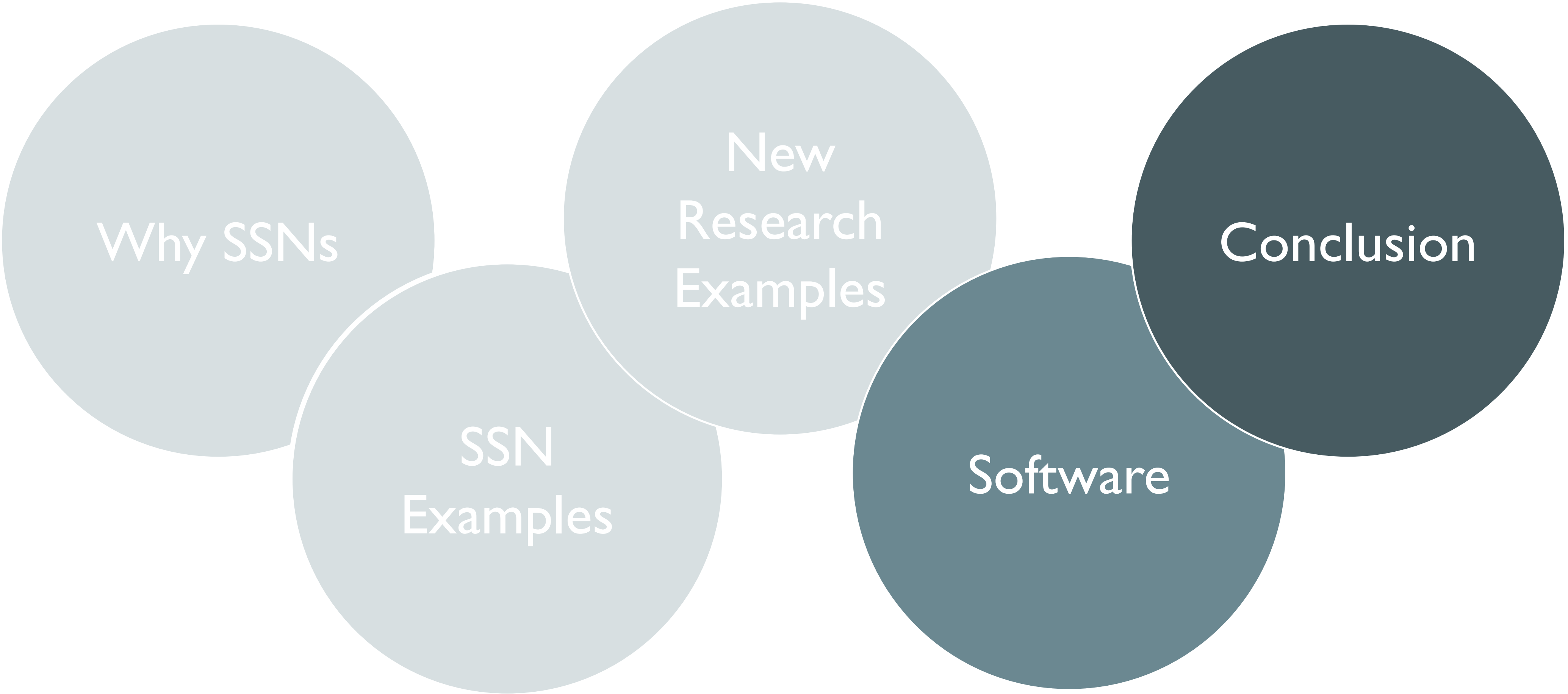




NEEDS: EDUCATION & TRAINING FOR SOCIAL NETWORK RESEARCHERS






Why SSNs
SSN Examples
New Research Examples
Software
Conclusion

What is a SSN?

2023 SSN Workshop
- Agenda
- Fellowship Application
- Registration
- Travel & Lodging
- Fun in Atlanta

Collection of SSN Papers

R Tutorial

SSN Software

SSN Community
- What's New?

About SNoMaN
- Our Team
- Advisory Committee
- Contact

What is a SSN?

A **Spatial Social Network (SSN)** is a set of **nodes** and **edges** where nodes are geolocated to a meaningful location, that is, an anthrospace, and geographic edges connect the nodes. Edge locations specify the conceptual geographic path of information transfer, and difficulty of face-to-face meeting. In a SSN, distance between nodes can be measured as network distance or geographic distance.

This **entry from the *Geographic Information Science & Technology Body of Knowledge*** introduces the concept of a social network (SN), describes their spatial properties, and explains how to embed them into GIS.

This **chapter from the *Handbook of Spatial Analysis in the Social Sciences*** provides further explanation of SSNs and their applications in research.

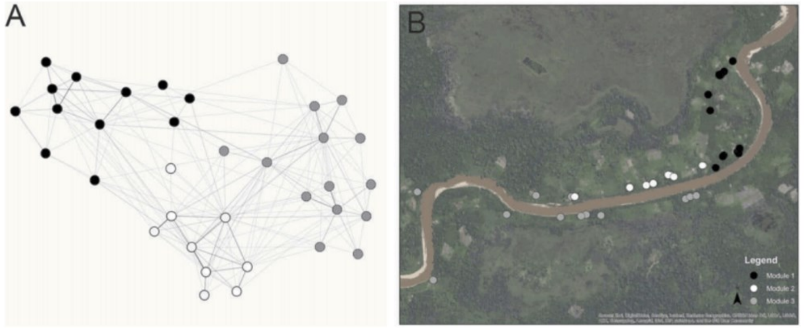
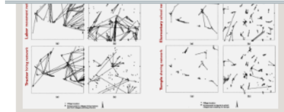


Figure) *A geolocated social network of households in the Amazon where edges represent hosting one another at the home (courtesy of Paul Hooper) is divided into three modules. The households are then mapped atop a spatial image of the study area to show that nearer households tend to be in the same modules (from Andris, 2016).*

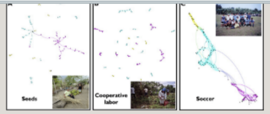
SSN Visualizations

Take a look at these visualizations of Spatial Social Networks! Click on the images below to learn more.



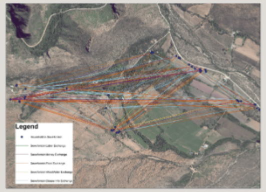
Spatial arrangement of social and economic networks among villages in Nang Rong District, Thailand

Faust, K., Entwisle, B., Rindfuss, R.R., Walsh, S.J. and Sawangdee, Y. 2000. *Social Networks*, 21(4), pp.311-337.



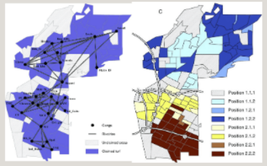
Rural social networks along Amazonian Rivers: Seeds, labor and soccer among communities on the Napo River, Peru

Abizaid, C., Coomes, O.T., Takasaki, Y. and Arroyo-Mora, J.P. 2018. *Geographical Review*, 108(1), pp.92-119.



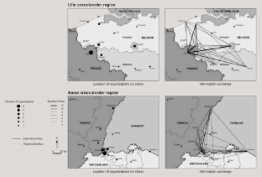
Spatial social network analysis of resource access in rural South Africa

Schramski, S. and Huang, Z. 2016. *The Professional Geographer*, *68*(2), pp. 281-298.



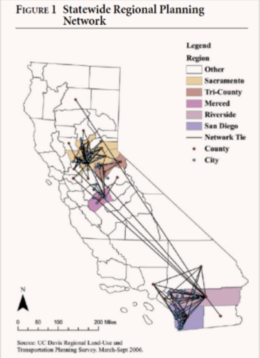
Spatializing social networks: Using social network analysis to investigate geographies of gang rivalry, territoriality, and violence in Los Angeles

Radil, S.M., Flint, C. and Tita, G.E., 2010. *Annals of the Association of American Geographers*, 100(2), pp.307-326.



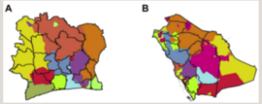
Borders moderating distance: a social network analysis of spatial effects on policy interaction

Sohn, C., Christopoulos, D. and Koskinen, J. 2020. *Geographical Analysis*, 52(3), pp.428-451.



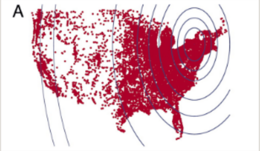
Political homophily and collaboration in regional planning networks

Gerber, Elisabeth R., Douglas Henry, Adam, and Lubell, Mark. 2013. *American Journal of Political Science*, 57(3) pp.598-610.



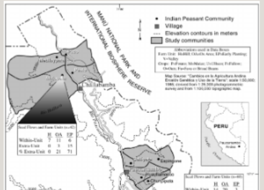
Delineating geographical regions with networks of human interactions in an extensive set of countries

Sobolevsky S, Szell M, Campari R, Couronné T, Smoreda Z and Ratti C. 2013. *PLoS ONE*, 8(12), e81707.



Geographic routing in social networks

Liben-Nowell, David, Novak, Jasmine, Kumar, Ravi, Raghavan, Prabhakar and Tomkins, Andrew. 2005. *Proceedings of the National Academy of Sciences.* 2005. 102, pp.11623-11628.



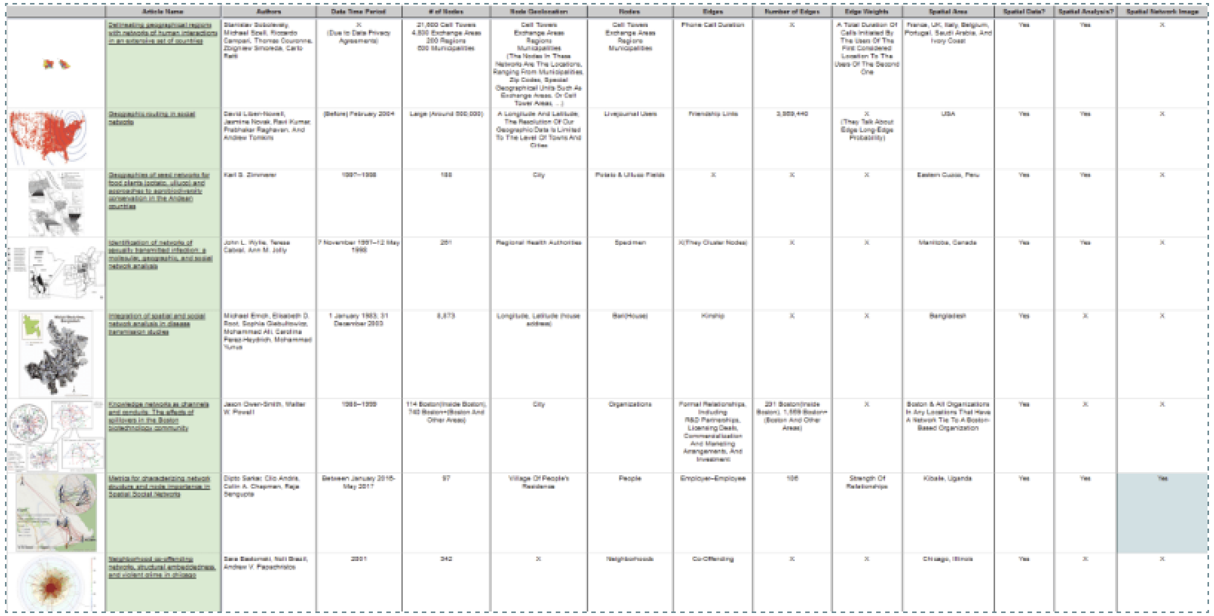
SNoMaN

Social Network Mapping Nexus

Data Repository

Although there are other exciting network repositories (e.g., SNAP and the Network Data Repository), this field lacks a comprehensive repository that is specifically dedicated to Spatial Social Networks. The goal of the SNoMaN data repository is to facilitate data sharing and collaboration. Our team is grateful to have your participation in this free, public repository. If you have any questions, please contact us.

Click on the image below to visit the SNoMaN Community Literature: Preliminary Data Repository.



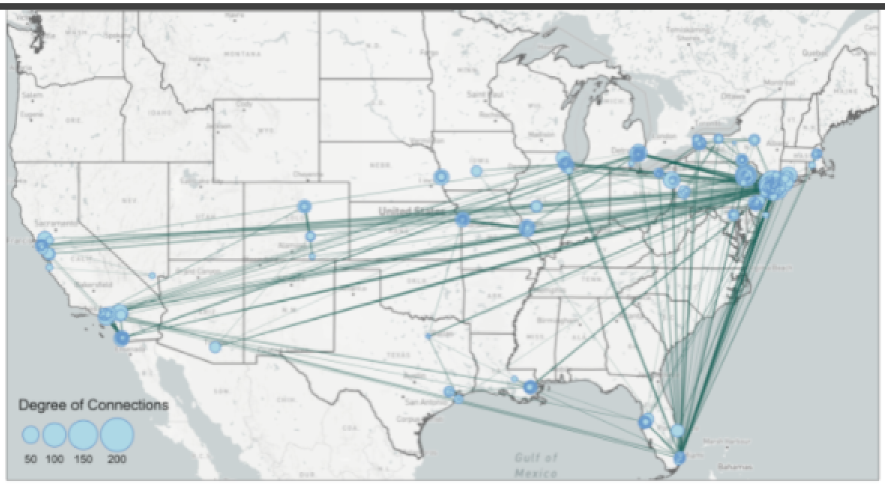
Please send SSNs our way!

clio@gatech.edu

R TUTORIAL AND PACKAGE: SSNTOOLS

map

Published with bookdown



The map shows clearly that many of the connections are going to New York City. There are also a lot of connections that go stragith from west coast to east coast. Let's try edge bundling and see if it makes the map better.

The `edge_bundle_force` function from the `edgebundle` pacakage takes into three arguments: 1) `g` which is the network constructed through `igraph`, 2) `xy` which is the longitude and latitude of all the nodes in the network, and 3) `compatibility_threshold` which indicates the strength of the bundling. A higher value means that the bending and the bundling will be less intense. This package **can only bend the edges into bundles** but not beyond that.

The result of the `edge_bundle_force` returns four columns. `x` and `y` are the coordinates of the points that consist of a bundled edge. `group` indicates that coordinates in the same group are for one bundled edge and `index` indicates the order of points for that particular bundled edge. We can see that for group 1, the fbundle result starts with the first name in the `source` of `FilteredEdges`, BLANDA-CHARLES (-104.6270, 38.2476), and after 34 points, it will end with the `Target`, SMALDONE-EUGENE (-104.9479, 39.7681).

```
library(edgebundle)
#FilteredEdges %>% slice(1:3)
#               Source              Target   distance
# 1     BLANDA-CHARLES    SMALDONE-EUGENE    97252.56
# 2     DIVARCO-JOSEPH        SICA-JOSEPH 6054967.18
# 3 DEMARTINO-BENJAMIN DEMARTINO-THEODORE   182989.39

#The current EdgeSpatial is line geometry
bundle_g = graph_from_data_frame(FilteredEdges, directed=FALSE)
node = data.frame(id = V(bundle_g)$name) %>% mutate(id = as.character(id))
```

[Spatial Social Networks (SSN) Visualization and Metrics with R (friendlycities-gatech.github.io)]


Degree Centrality
Eigenvector Centrality
Betweenness Centrality
Clustering Coefficient
Measure of Power
0.2 0.4 0.6 0.8 1.0

Chapter 6 Advanced SSN Metrics

The following subchapters will introduce advanced SSN metrics. **Spatial Social Network (SSN)** refers to social networks where the nodes are also geolocated. They can be collaborations between organizations, economic hiring between individuals, trades between companies, and friendships. Different from social network metrics or spatial methods, these metrics tend to focus on the interaction between the networks and geographic space. While the metrics are designed for small-scale SSNs, some can also be applied to analyze origin-destination flows, POI visits, and mobility data.

You can download the R codes for the following chapters from GitHub here.

Here is an overview of the metrics:

Metrics	Level	Research Question	Data
SSN Hotspots	Area	Where are areas where nodes cluster in spatial proximity and connected in network space	NYCMafiaNodes NYCMafiaEdges
K-fullfillment	Node	Which nodes tend to connect nearest neighbors than far friends (i.e., ratio of neighbors)	NYCMafiaNodes NYCMafiaEdges
Local Flattening Ratio	Node	Which nodes tend to connect nearest neighbors than far friends (i.e., ratio of distances)	NYCMafiaNodes NYCMafiaEdges
Global Flattening Ratio	Network	Is a SSN spatially tight?	NYCMafiaNodes NYCMafiaEdges
Linked Activity Spaces	Area	Does a node (ego) visit the same set of places as its friends (alters)	EmergencyNodes EmergencyEdges

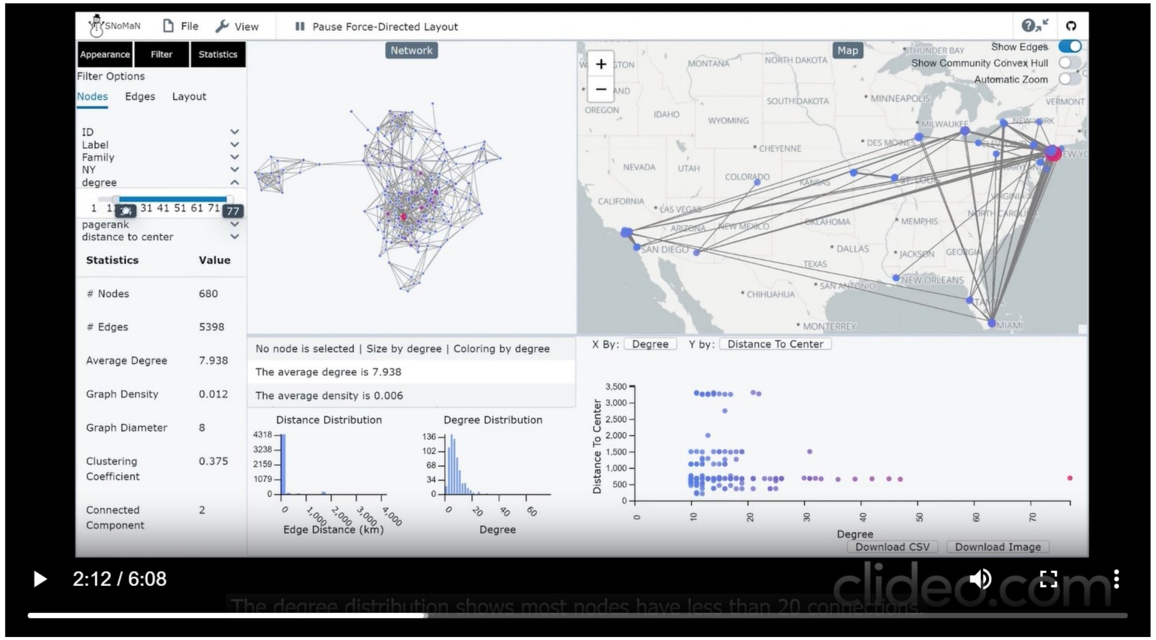
SSN Software

SNoMaN takes in your data and allows you to browse a sociogram and linked map. It also 1) computes traditional network metrics, 2) provides histograms of edge distances and node degrees, and 3) provides an interoperable scatterplot.

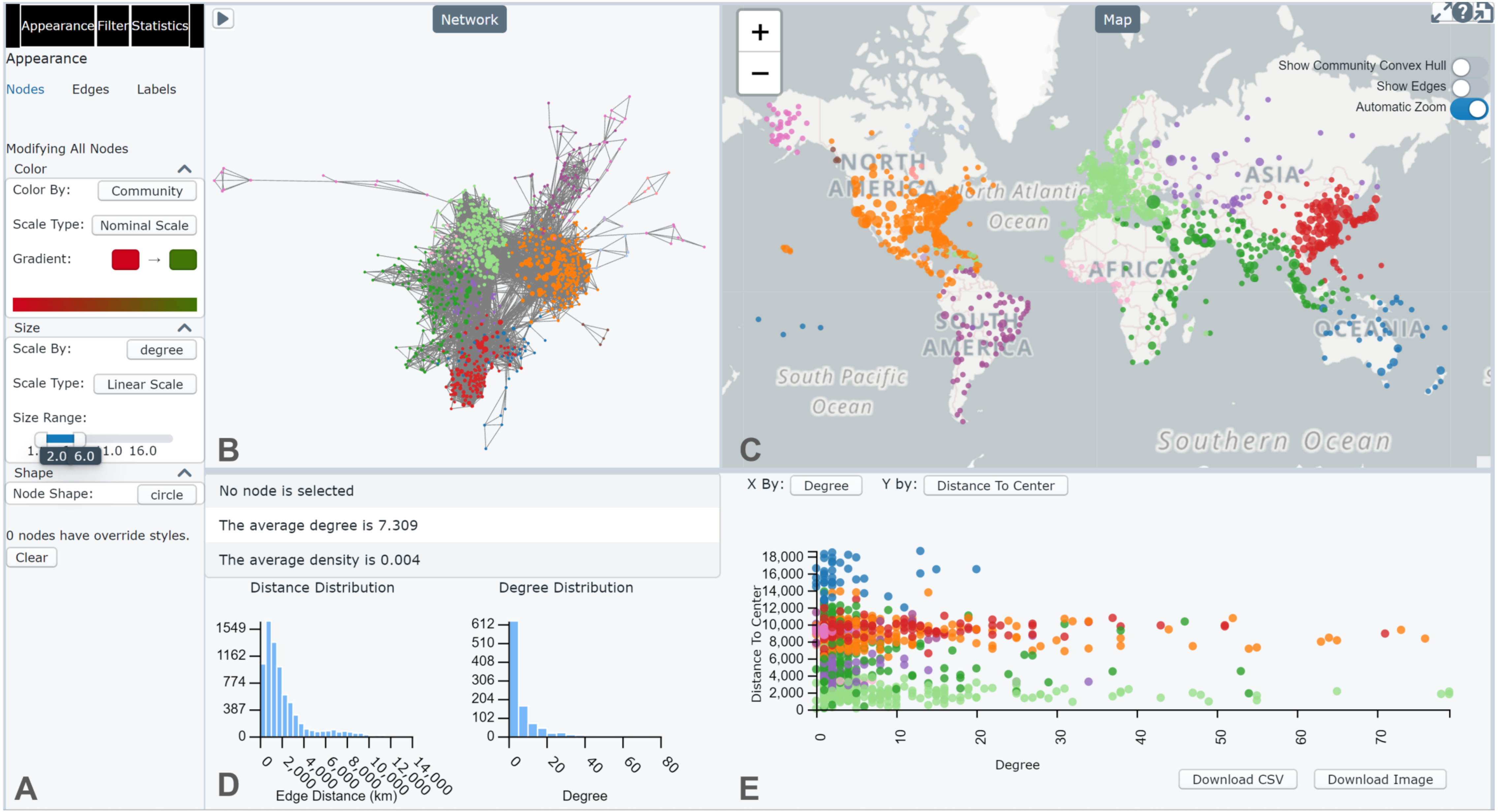
SNoMaN Software

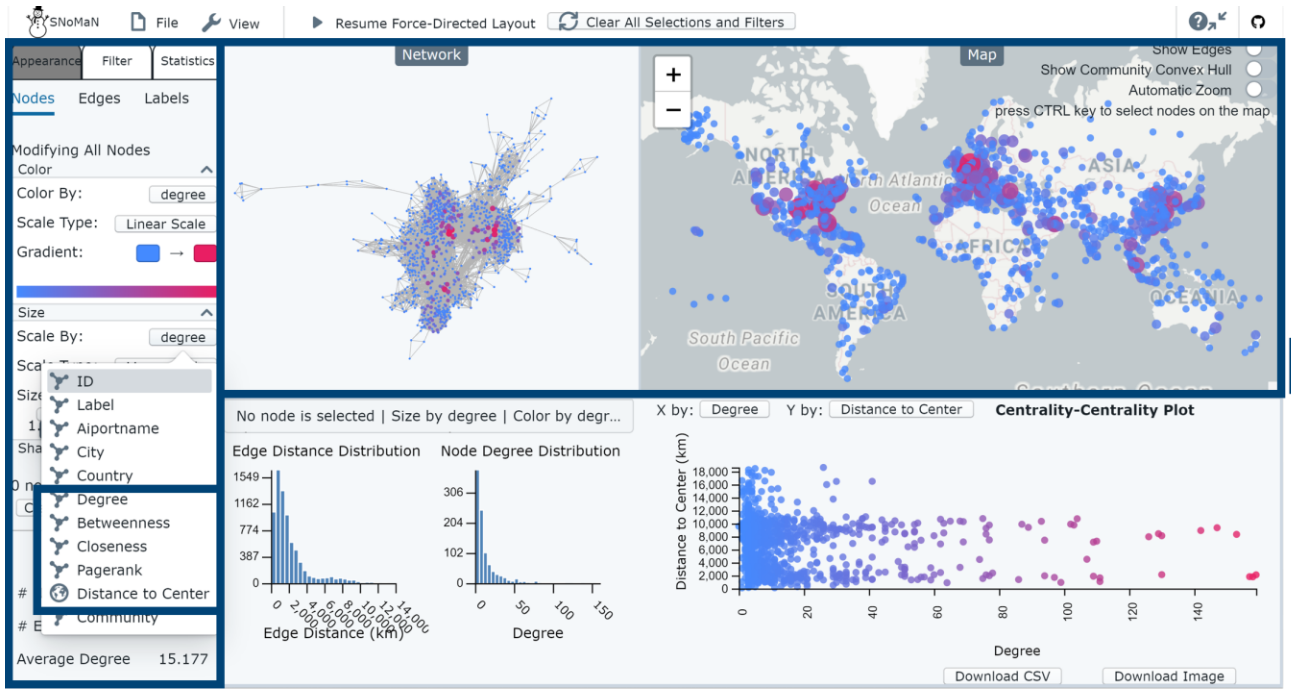
There are some new metrics like **K-fullfillment**[1] (measuring local connection/disconnection), **Local Flattening Ratio**[2] (measuring local connection/disconnection), **Global Flattening Ratio**[3] (measuring the spatial tightness), and mapping **modules via modularity detection**.

For a detailed tutorial of how to use this tool, we encourage you to view the following **demo video**:



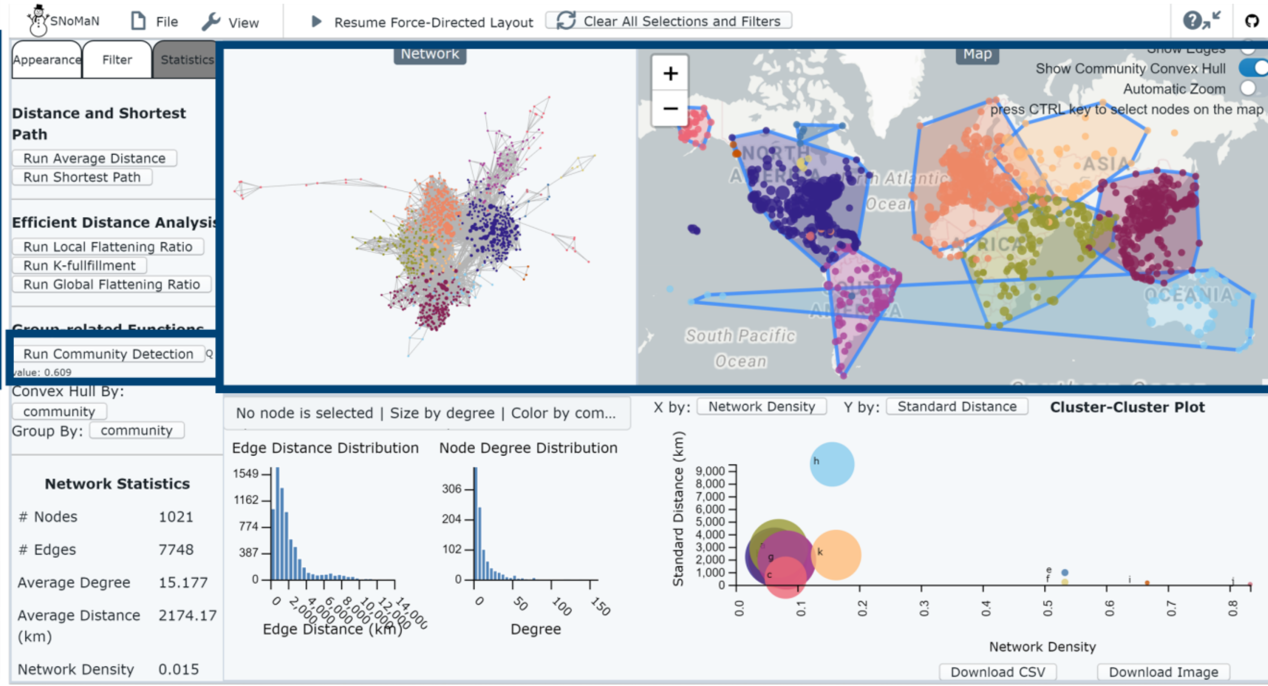
SNOMAN: AN ONLINE OPEN SOURCE TOOL FOR SOCIAL NETWORK MAPPING ANALYSIS





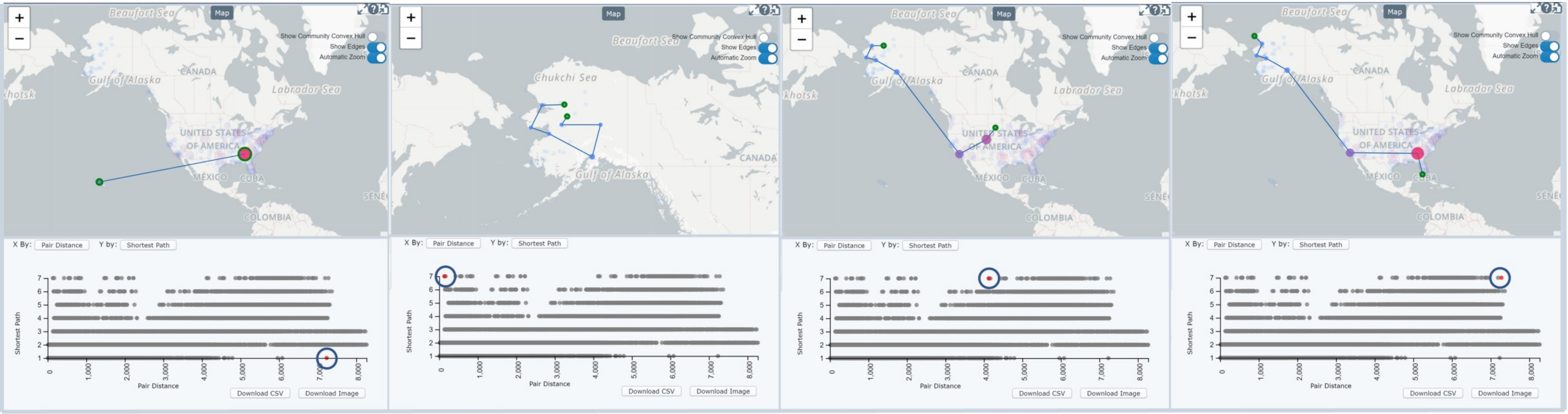
SNoMaN
File
View
Resume Force-Directed Layout
Clear All Selections and Filters
Appearance
Filter
Statistics
Nodes
Edges
Labels
Modifying All Nodes
Color
Color By:
degree
Scale Type:
Linear Scale
Gradient:
Size
Scale By:
degree
ID
Label
Aiportname
City
Country
Degree
Betweenness
Closeness
Pagerank
Distance to Center
Community
Average Degree
15.177
Network
Map
Show Edges
Show Community Convex Hull
Automatic Zoom
press CTRL key to select nodes on the map
No node is selected | Size by degree | Color by degr...
X by:
Degree
Y by:
Distance to Center
Centrality-Centrality Plot
Edge Distance Distribution
Node Degree Distribution
Edge Distance (km)
Degree
Distance to Center (km)
Download CSV
Download Image

(a)



SNoMaN
File
View
Resume Force-Directed Layout
Clear All Selections and Filters
Appearance
Filter
Statistics
Distance and Shortest Path
Run Average Distance
Run Shortest Path
Efficient Distance Analysis
Run Local Flattening Ratio
Run K-fullfillment
Run Global Flattening Ratio
Run Community Detection
Convex Hull By:
community
Group By:
community
Network Statistics
Nodes
1021
Edges
7748
Average Degree
15.177
Average Distance (km)
2174.17
Network Density
0.015
Network
Map
Show Community Convex Hull
Automatic Zoom
press CTRL key to select nodes on the map
No node is selected | Size by degree | Color by com...
X by:
Network Density
Y by:
Standard Distance
Cluster-Cluster Plot
Edge Distance Distribution
Node Degree Distribution
Edge Distance (km)
Degree
Standard Distance (km)
Network Density
Download CSV
Download Image

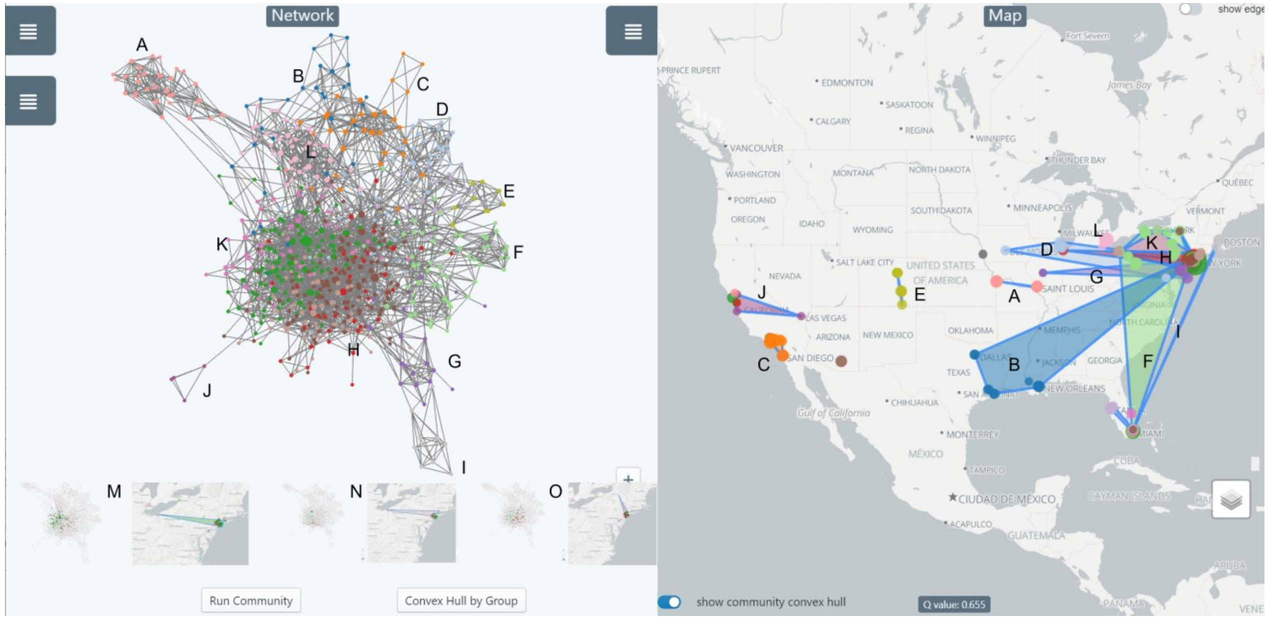
(b)



Map
Show Community Convex Hull
Show Edges
Automatic Zoom
Beaufort Sea
Chukchi Sea
CANADA
Gulf of Alaska
Labrador Sea
UNITED STATES OF AMERICA
MEXICO
CUBA
COLOMBIA
X By: Pair Distance
Y by: Shortest Path
Shortest Path
Pair Distance
Download CSV
Download Image

(a) (b) (c) (d)

SNoMAN
Graph
Tools
Resume Layout
Untitled Graph
Network
Map
X By: shortest path
Y by: pair distance
pair distance
shortest path
Download Image
Download CSV
Run Community
Convex Hull by Group
show community convex hull
Total Nodes: 105, Total Edges: 153, Hidden Nodes: 0



Network
Map
show edge
A
B
C
D
E
F
G
H
I
J
K
L
M
N
O
Run Community
Convex Hull by Group
show community convex hull
Q value: 0.655

TAKE AWAYS

Social networks are understudied in spatial analysis (and vice versa).

To learn about spatial social networks, we require mapping tools and techniques.

Future work includes simulation, storytelling, and education.

Thanks to collaborators: Max Hill, Sichen Jin, Xiaofan Liang, Dipto Sarkar, Jaimie Kelly, and Daniel DellaPosta.