# Integrating Social Network Data into GISystems


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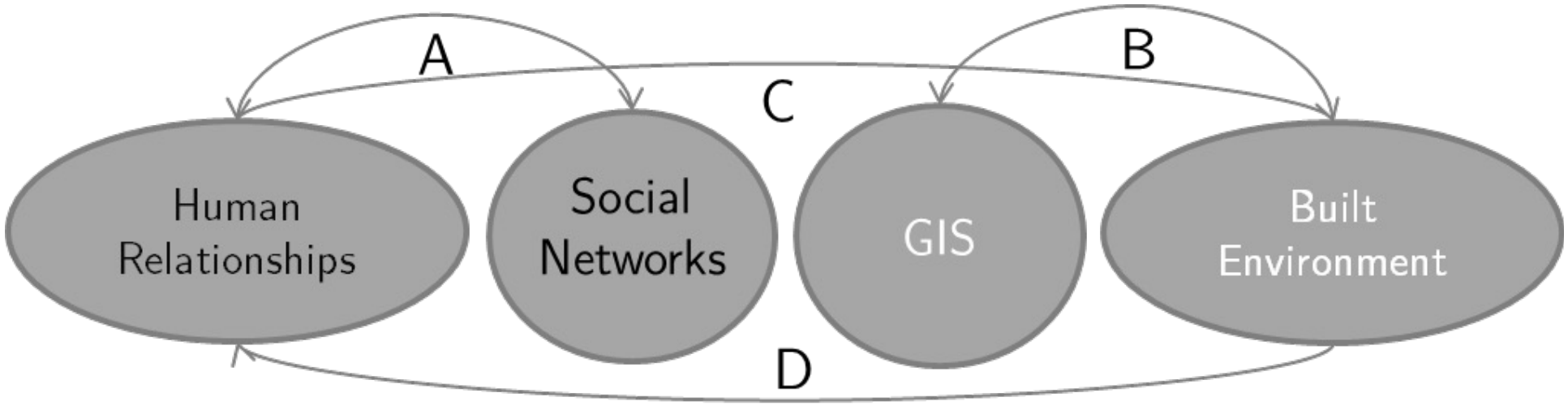

Articles

# Integrating social network data into GISystems

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## ABSTRACT

Today, online social media outlets provide new and plentiful sources of data on social networks (SNs) and location-based social networks (LBSNs), i.e., geolocated evidence of connections between individuals. While SNs have been used to show how the magnitude of social connectivity decreases with distance, there are few examples of how to include SNs as layers in a GISystem. If SNs, and thus, interpersonal relationships, could be analyzed in a geographic information system (GIS) setting, we could better model how humans socialize, share information, and form social groups within the complex geographic landscape.

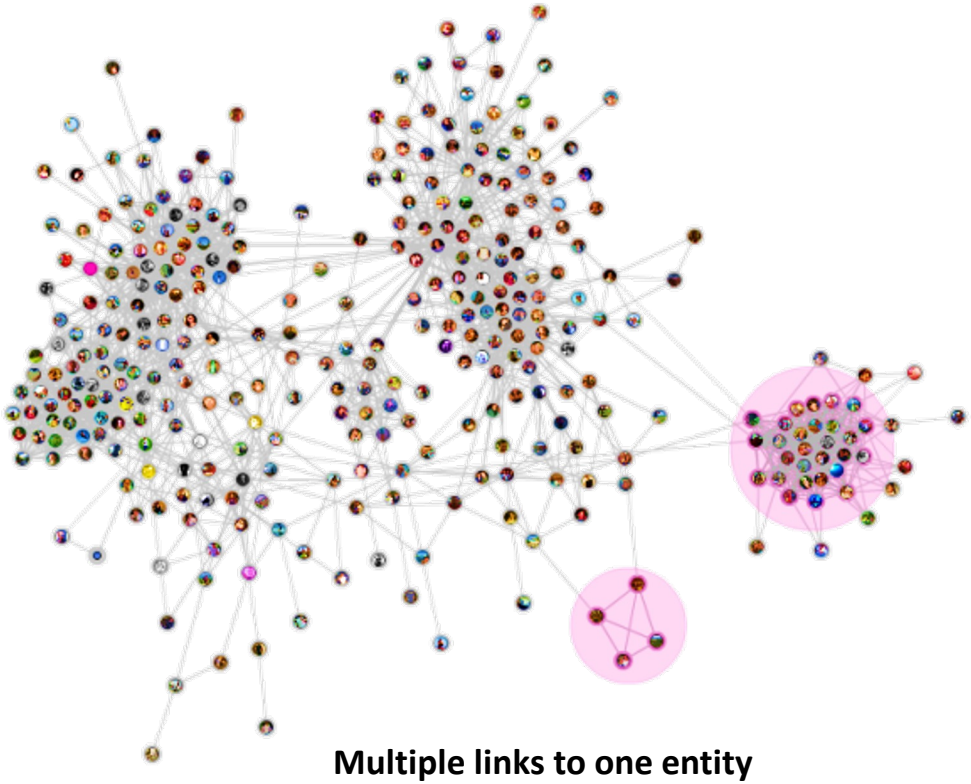
Our goal is to facilitate a guide for analyzing SNs (as derived from online social media, telecommunications, surveys, etc.) within geographic space by combining the mature fields of social network analysis (SNA) and GISystems. First, we describe why modeling socialization in geographic space is essential for understanding human behavior. We then outline best practices and techniques for embedding SN nodes and edges in



Andris C (2016) Integrating Social Network Data into GISystems. *International Journal of Geographical Information Science*. 31(1): 2009-2031. [PDF] and other stuff is here: https://friendlycities.gatech.edu/publications/

# Problem: Social network models and physical infrastructure models are very different.

**Graph Structure**



**Multiple links to one entity**

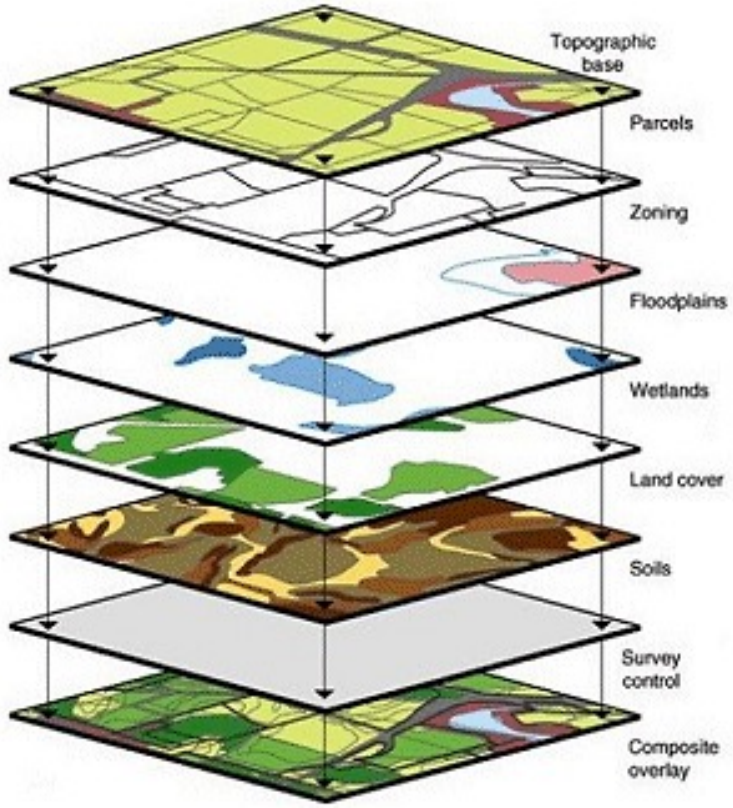
Links to entities

Agent-based social features

Discrete space

**Measured in network distance**

**Cartesian Structure**




Contiguous space

**Boundaries**

Paths to entities

Top-down physical features

**Measured in Euclidean distance**

Image source: ESRI

# How do we pin down nodes?

**Table 1.** Types of anthrospaces.

| Scope | Description | Example sources of volunteered information |
|---|---|---|
| I Daily | Home/work activity space | Mobile phone activity, in-car GPS, commuter flows*, e-mail or internet IP addresses, WiFi hot-spot log in locations, transit (subway) card records, personal surveys. |
| II Short term | Out-of-city travel trajectory | Volunteered travel itineraries, frequent flyer and traveler programs, a user's travel activity derived from I. |
| III Long term | Migration trajectory | Census records and tax data*, personal surveys, long term (6+ month) data from I or II. |
| IV Real-time | Capture of a user's location | Volunteered location using GPS traces, cell tower triangulation, or check-in sites. |
| V. Domain assignment | Mayor to a city, land parcel to owner, or agent's work address | Historical records, public or government records, self-report |
| VI. Cognitive | Places of interest to an individual, memories, thoughts | Shared recollections, perception surveys, psychological studies of marketing; online radio station IP access, accessed literature by library location. |

* These typically appear as aggregate flows, not as an individual's behavior.

# Data

**Table 2.** Example for location-based social network (LBSN) data records.

| Caller | Receiver | Caller location | Receiver location | Time | Duration (minutes) |
|---|---|---|---|---|---|
| A | B | 73.2, 43.0 | 71.2, 43.3 | 5:10 | 13 |
| B | A | 71.2, 43.3 | 73.2, 43.0 | 5:30 | 1 |
| C | B | 74.4, 43.9 | 71.2, 43.3 | 6:10 | 15 |
| D | A | 72.4, 41.8 | 73.2, 43.0 | 6:12 | 120 |

## DERIVED DATASETS

### 3.1 Commonly derived datasets

3.1.1 Social network

3.1.2 Individual spatial communication or movement patterns

3.1.3 Aggregate spatial communication or movement patterns

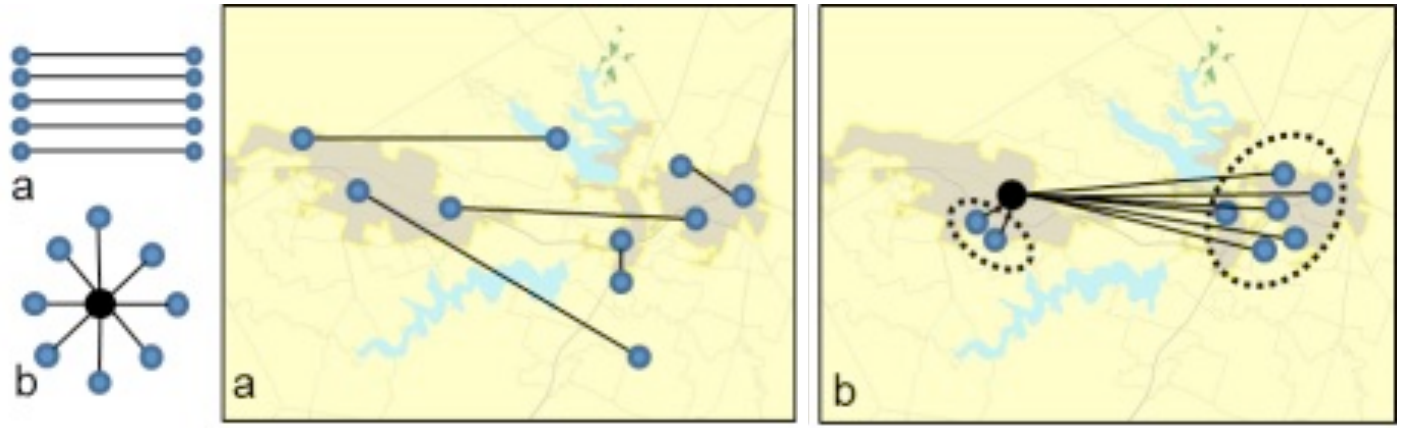
### 3.2 Complex derived datasets

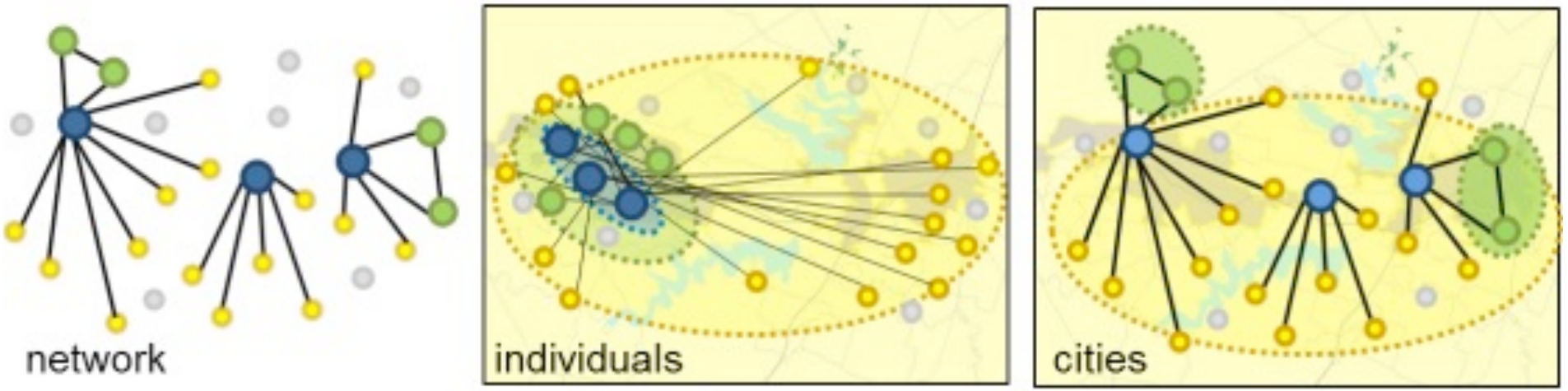
3.2.1 Spatial distribution of social connections

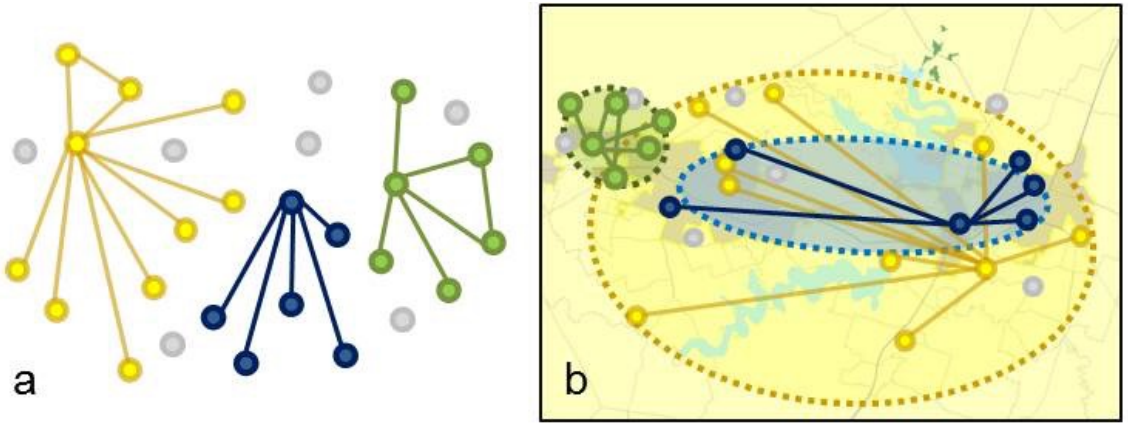
3.2.2 Dynamics of spatially distributed social connections

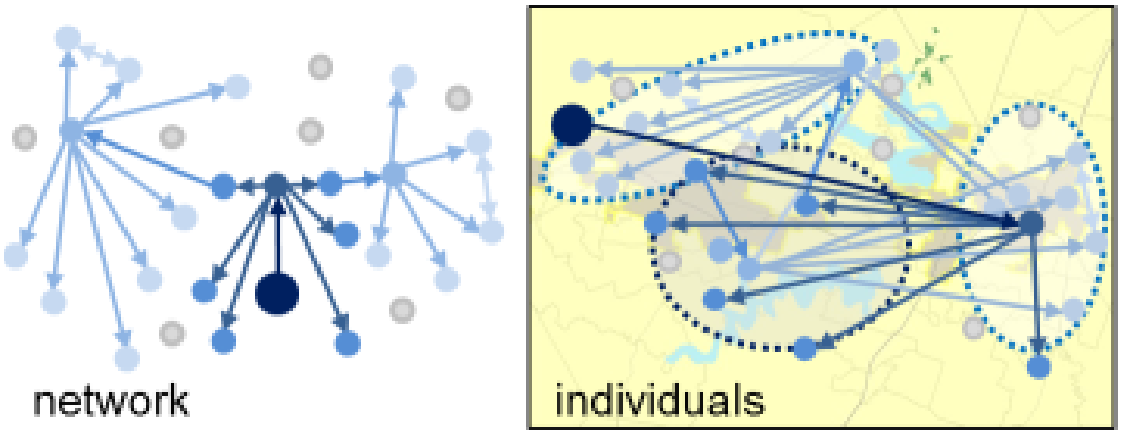
**Table 3.** Case studies and classes of data, anthrospaces, resultant network, and analysis methods.

| Location | Nodes/edges | Data | Anthrospace | Resultant network | Model |
|---|---|---|---|---|---|
| Santa Fe, U.S.A. | Mentors and proteges/ mentorship | Stated relationships | Domain assignment | Spatial distribution of social connections | Disaggregate dyadic |
| Singapore | Mobile phone subscribers/mobile phone calls | Telecommunications, movement | Daily activity space | Spatial distribution of social connections | Disaggregate ego-based |
| Bolivia | Households/friendships | Stated relationships | Domain assignment | Spatial distribution of social connections | Disaggregate modularity |
| U.K. | Telephone exchange areas/landline phone calls | Telecommunications | Domain assignment | Aggregate telecommunications | Aggregate modularity |
| Jiamusi, China | Mobile phone subscribers/mobile phone calls | Telecommunications, movement | Daily activity space | Individual spatial movement patterns | Disaggregate node roles |
| Abidjan, Côte d'Ivoire | Mobile phone towers/ mobile phone calls | Telecommunications | Domain assignment | Aggregate telecommunications | Aggregate node roles |
| U.S.A. | Congressional representatives/voting agreements | Stated relationships | Domain assignment | Spatial distribution of social connections | Disaggregate transitivity |

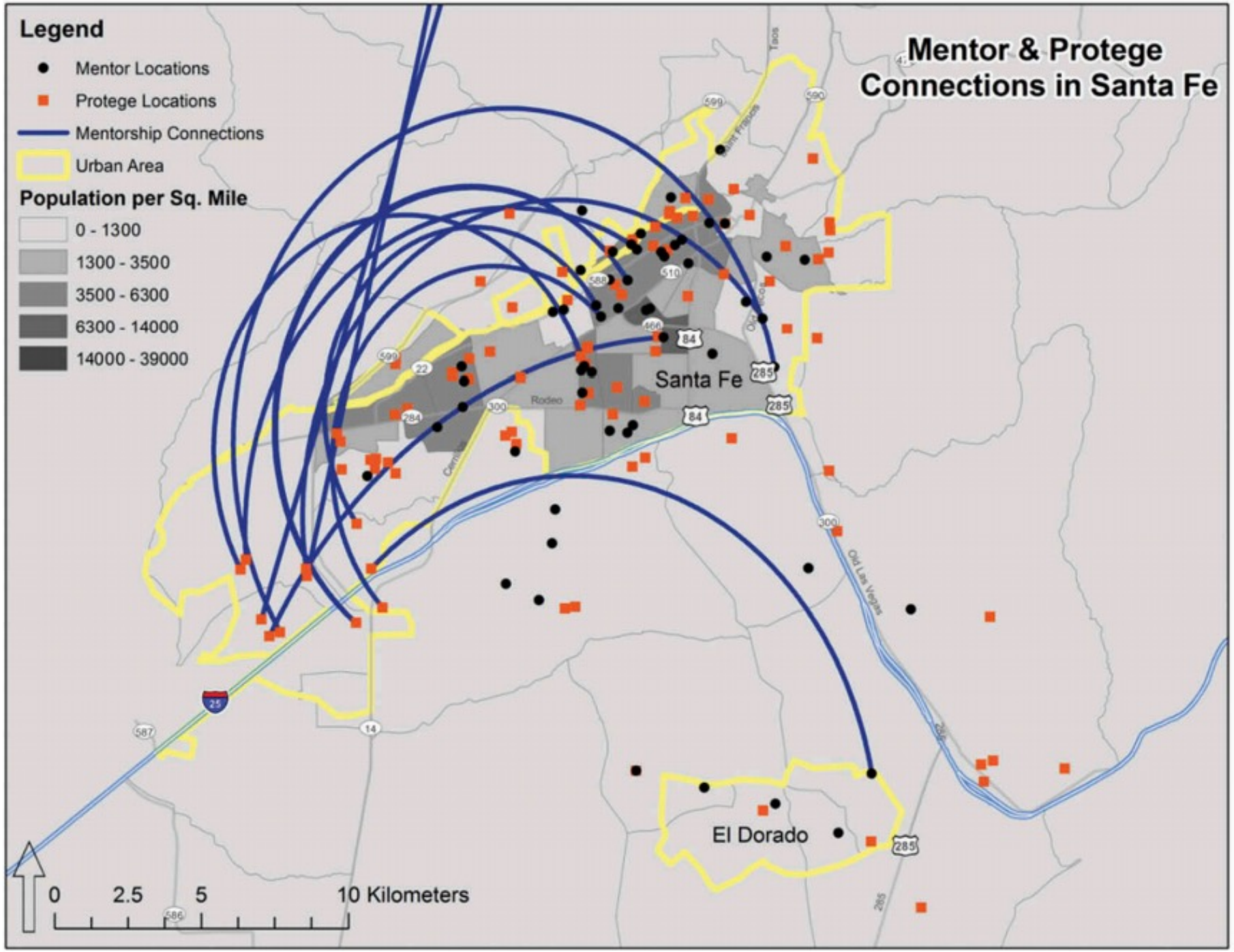

a
b
a
b

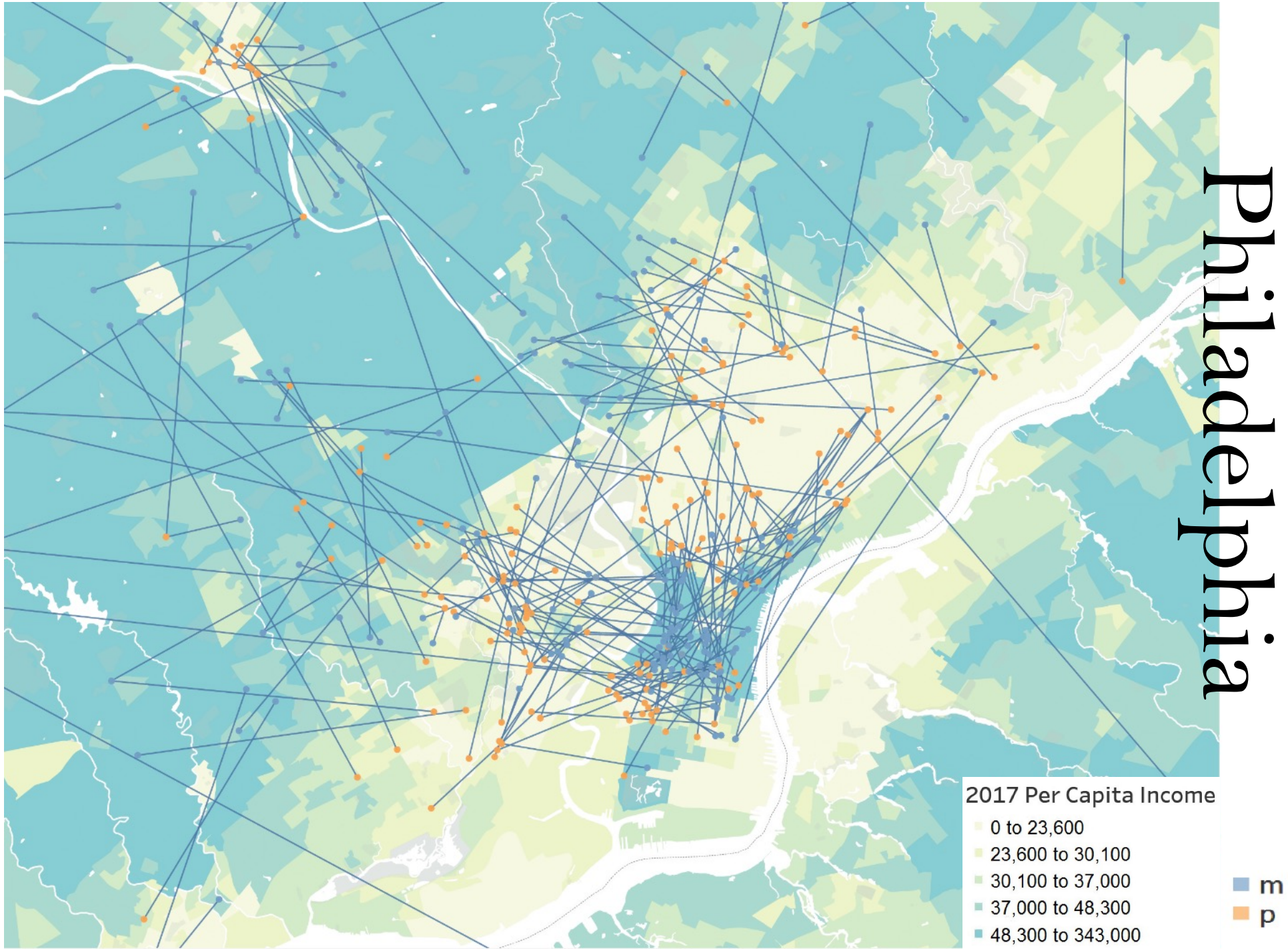

network
individuals
cities

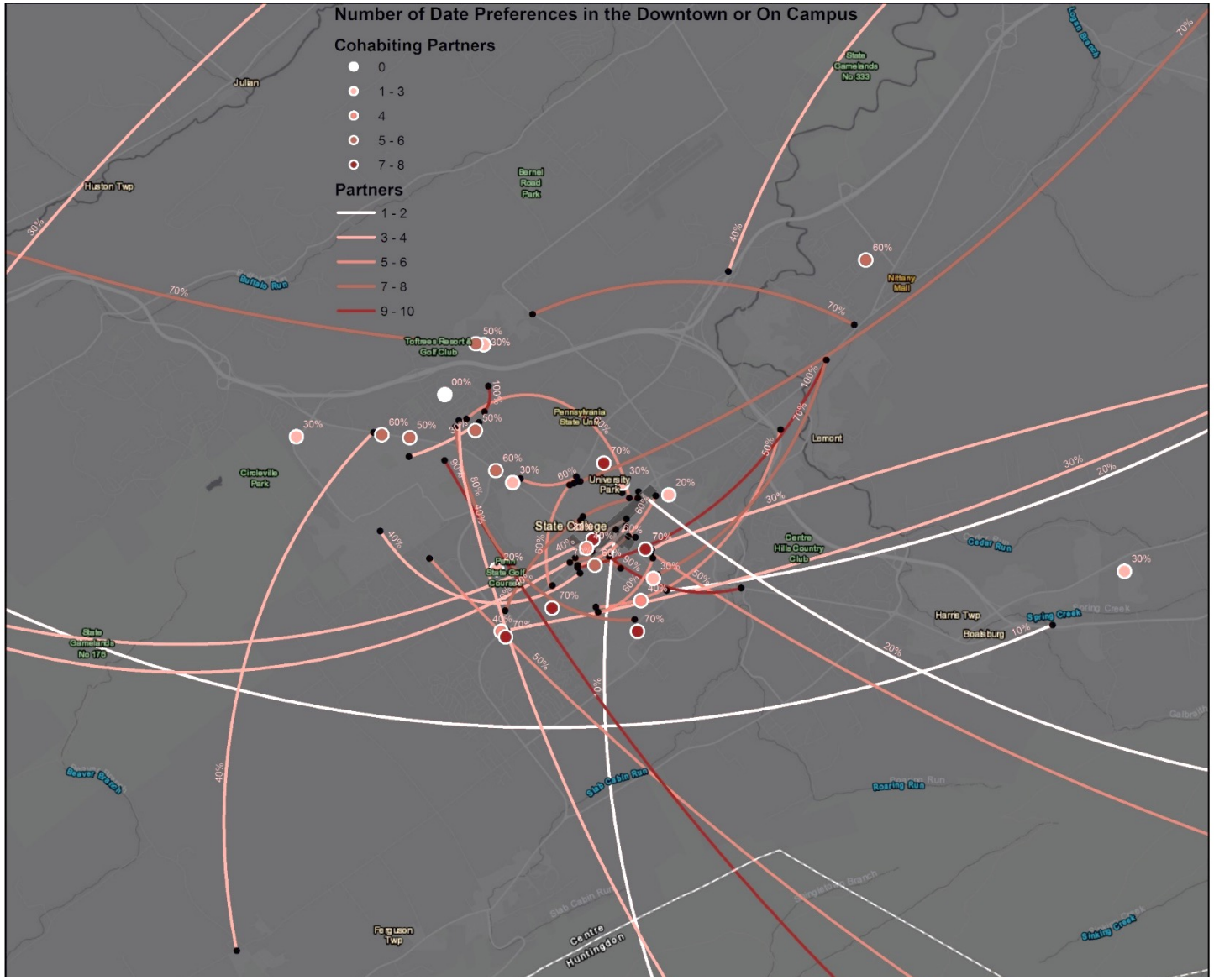

a
b


network
individuals

# Dyadic Relationships

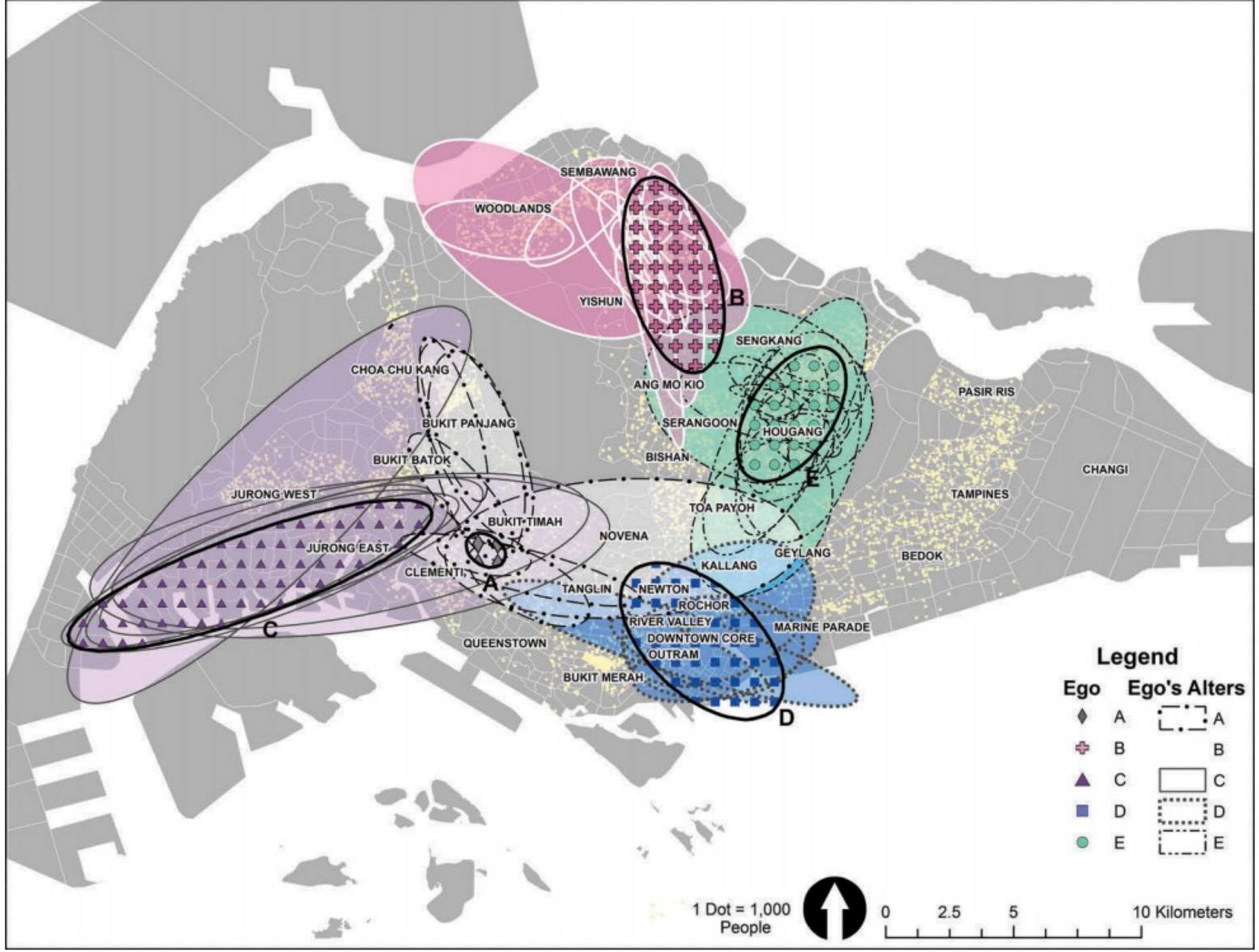



Philadelphia
2017 Per Capita Income
0 to 23,600
23,600 to 30,100
30,100 to 37,000
37,000 to 48,300
48,300 to 343,000
m
p

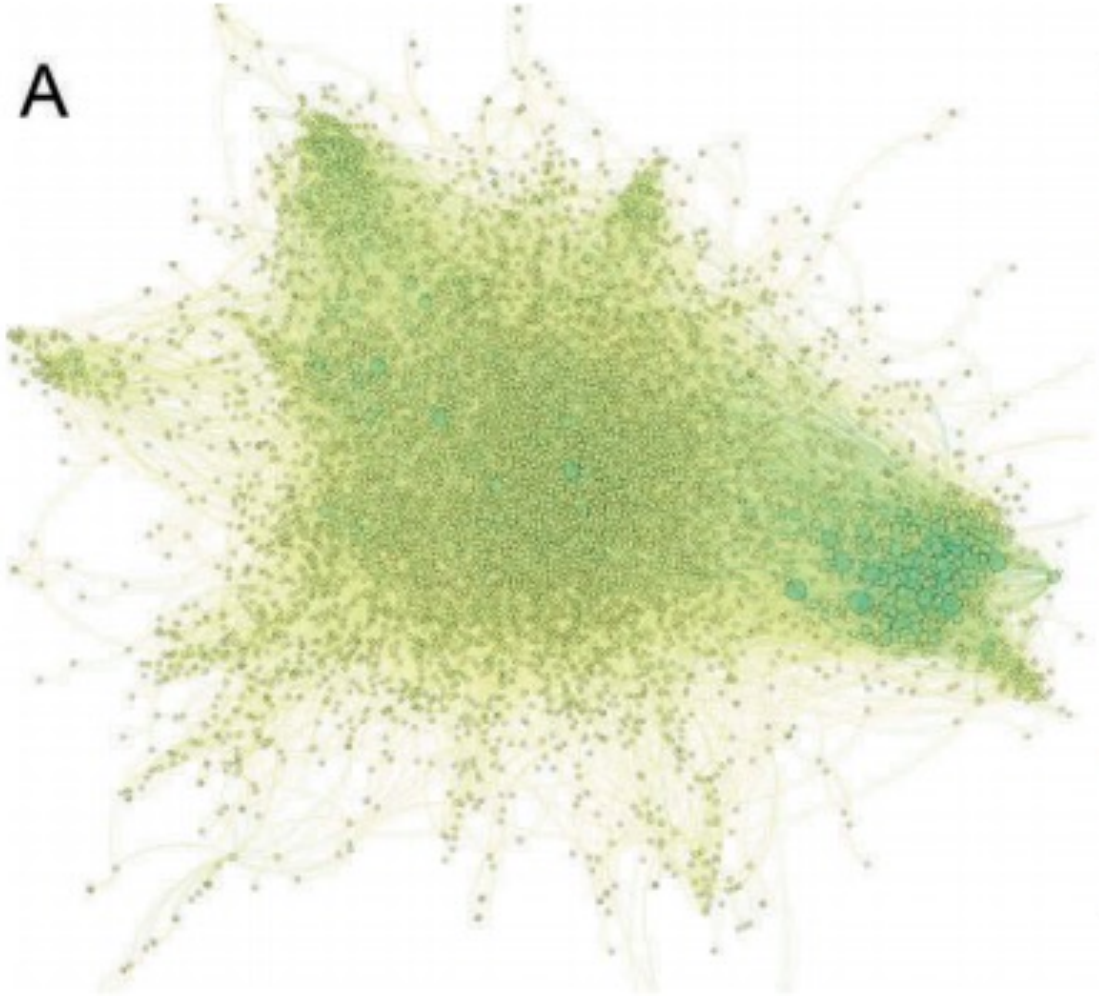


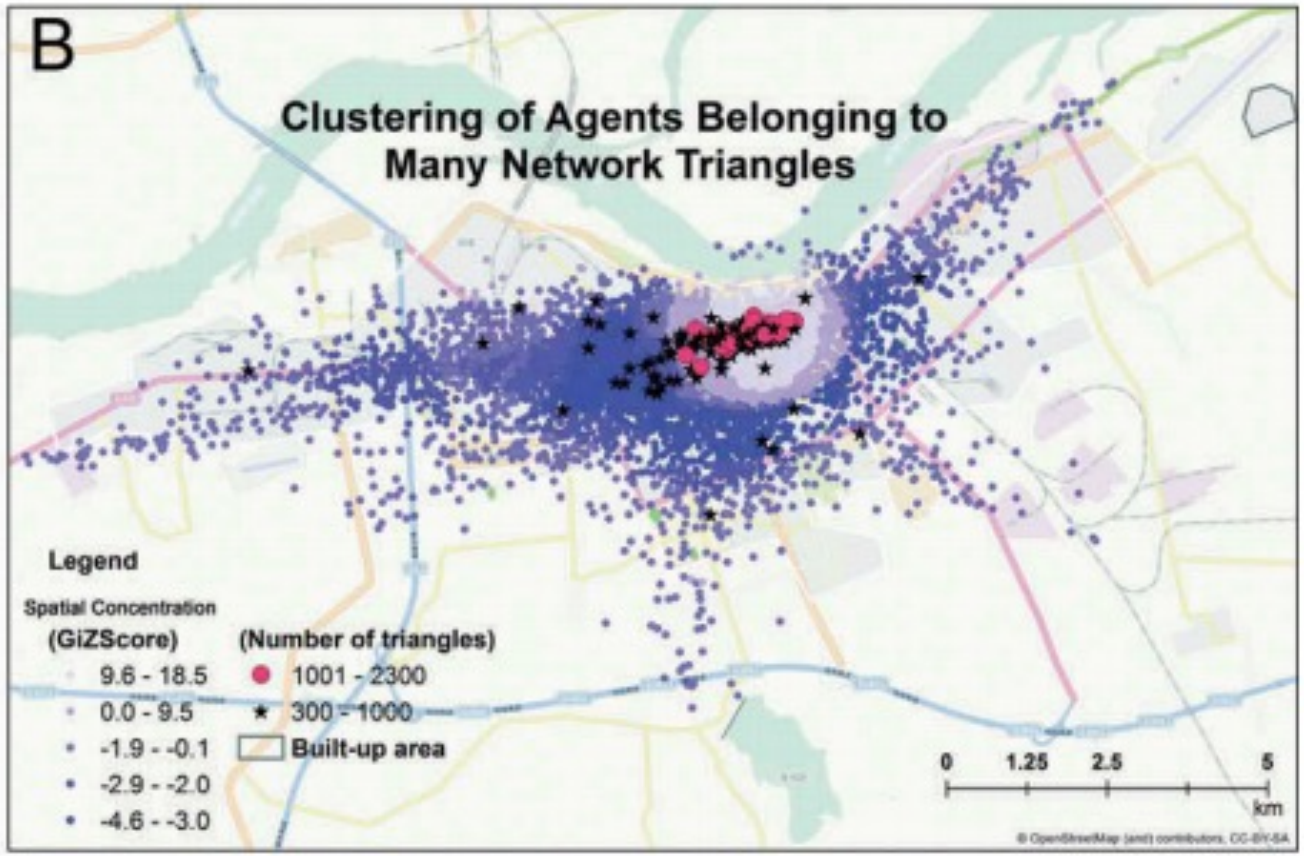

Andris C and Lee S (2021) Romantic Relationships and the Built Environment: A Case Study of a US College Town. *Journal of Urbanism: International Research on Placemaking and Urban Sustainability*, 1-22. [PDF] and [Supplementary Information]

# Ego Alter Relationships

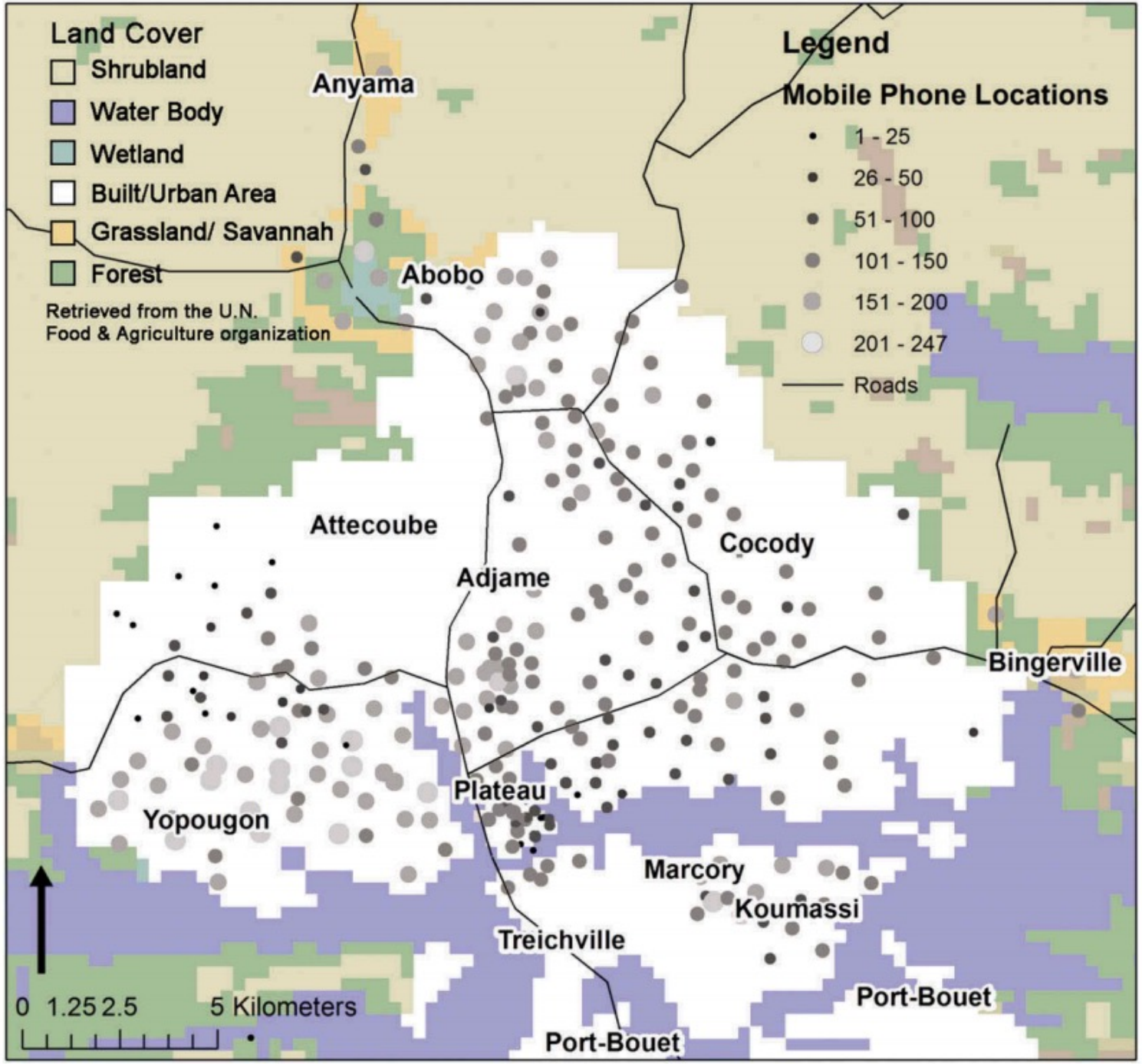


# Disaggregate Node Roles

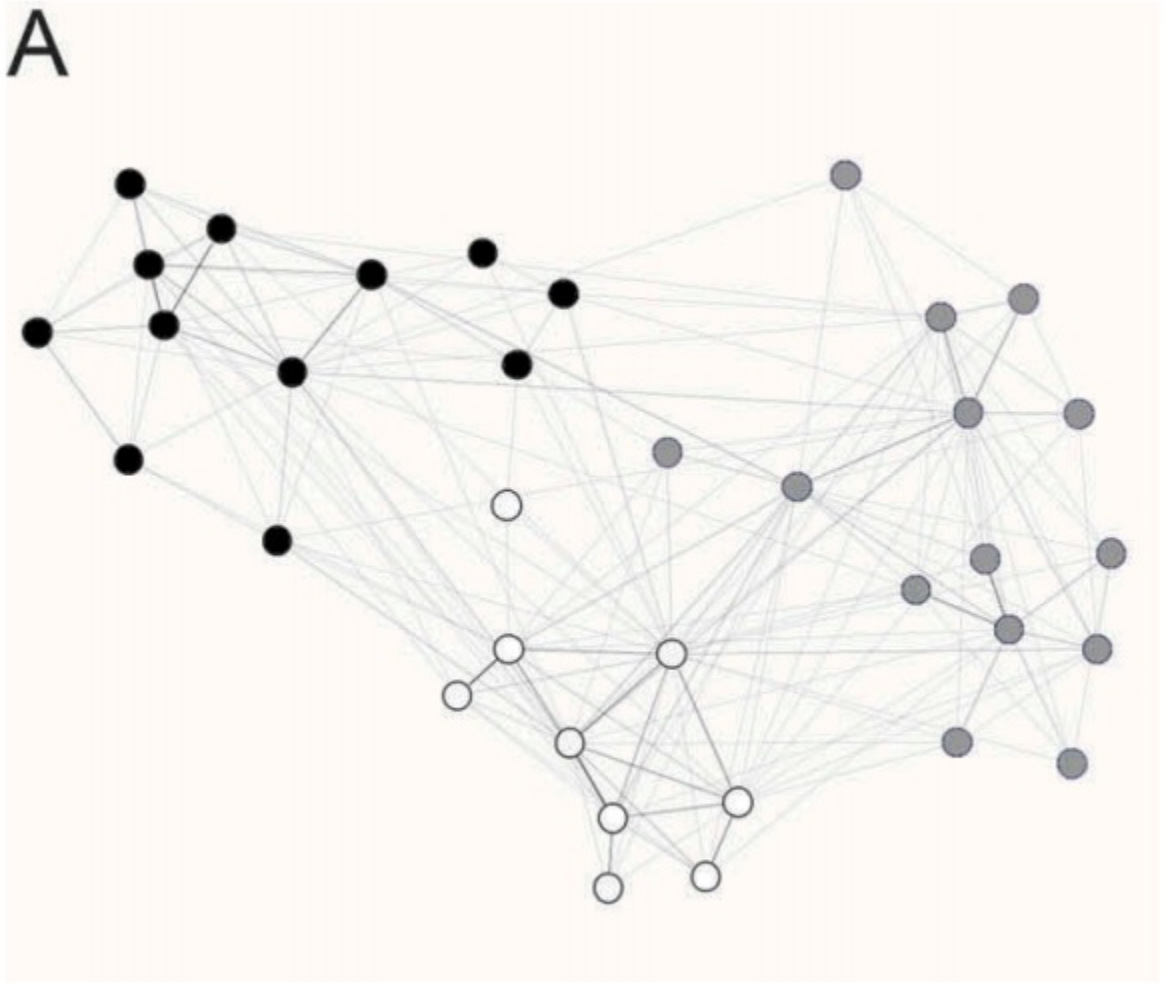


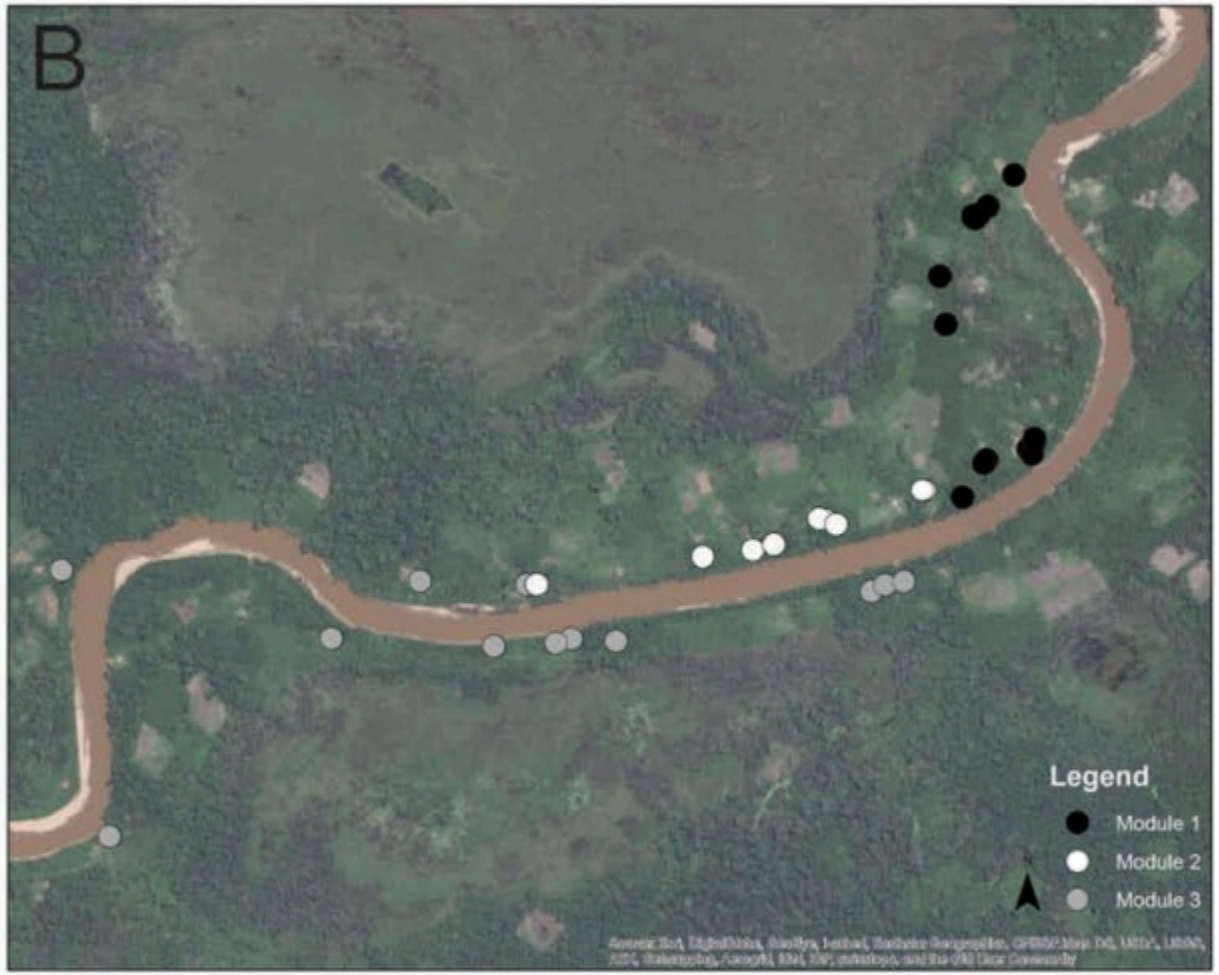



# Aggregate Node Roles

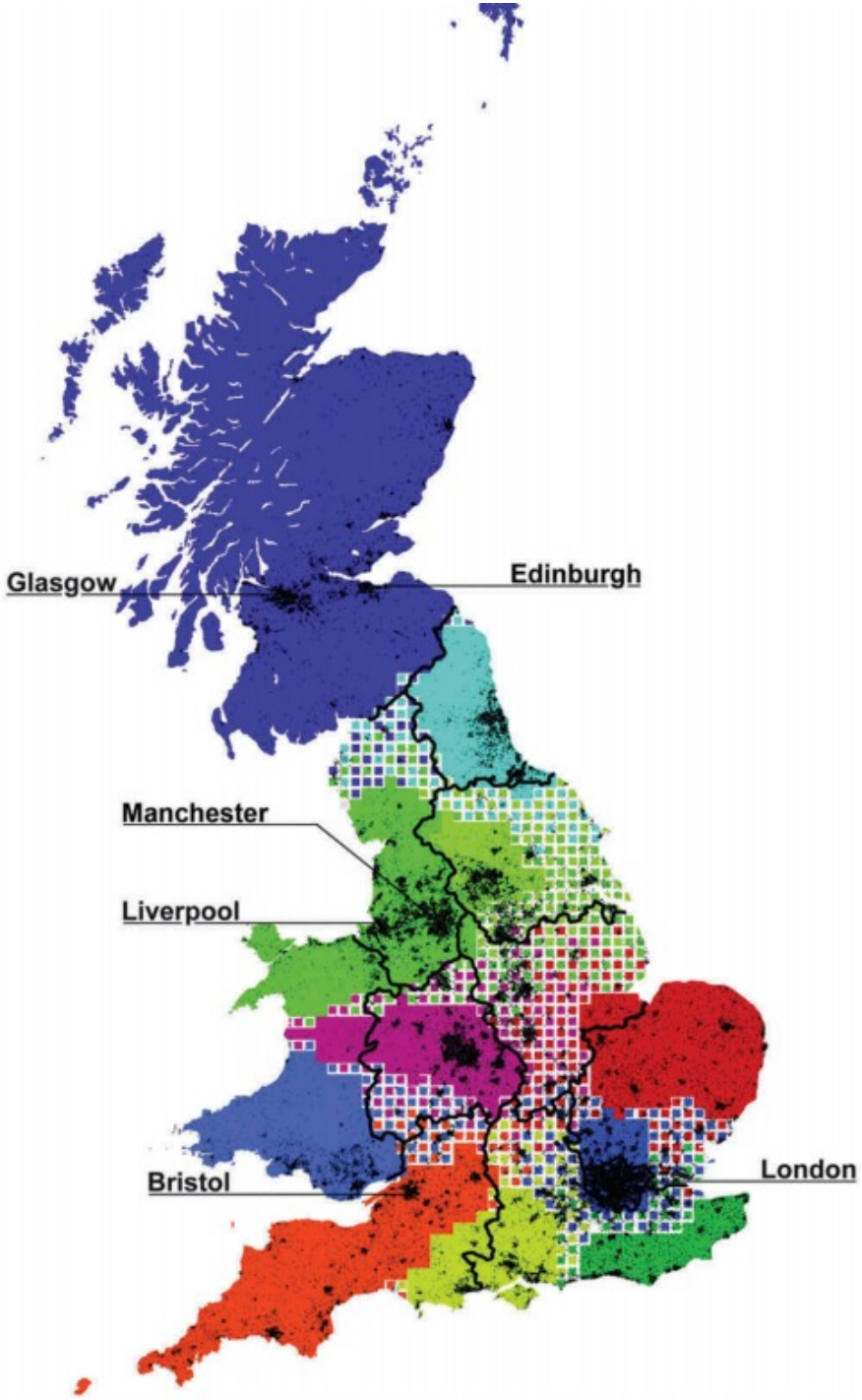


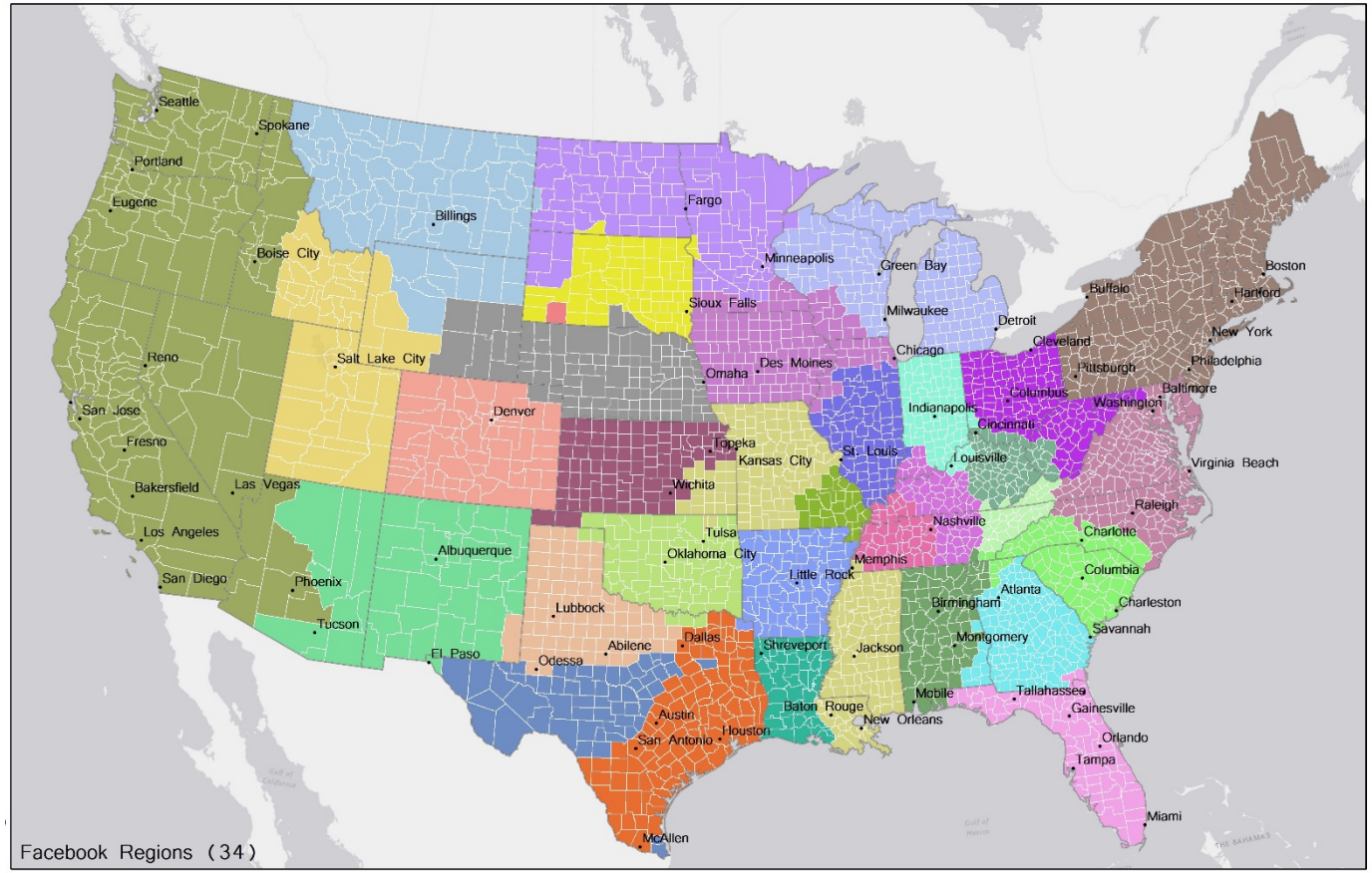
# Disaggregate Modularity



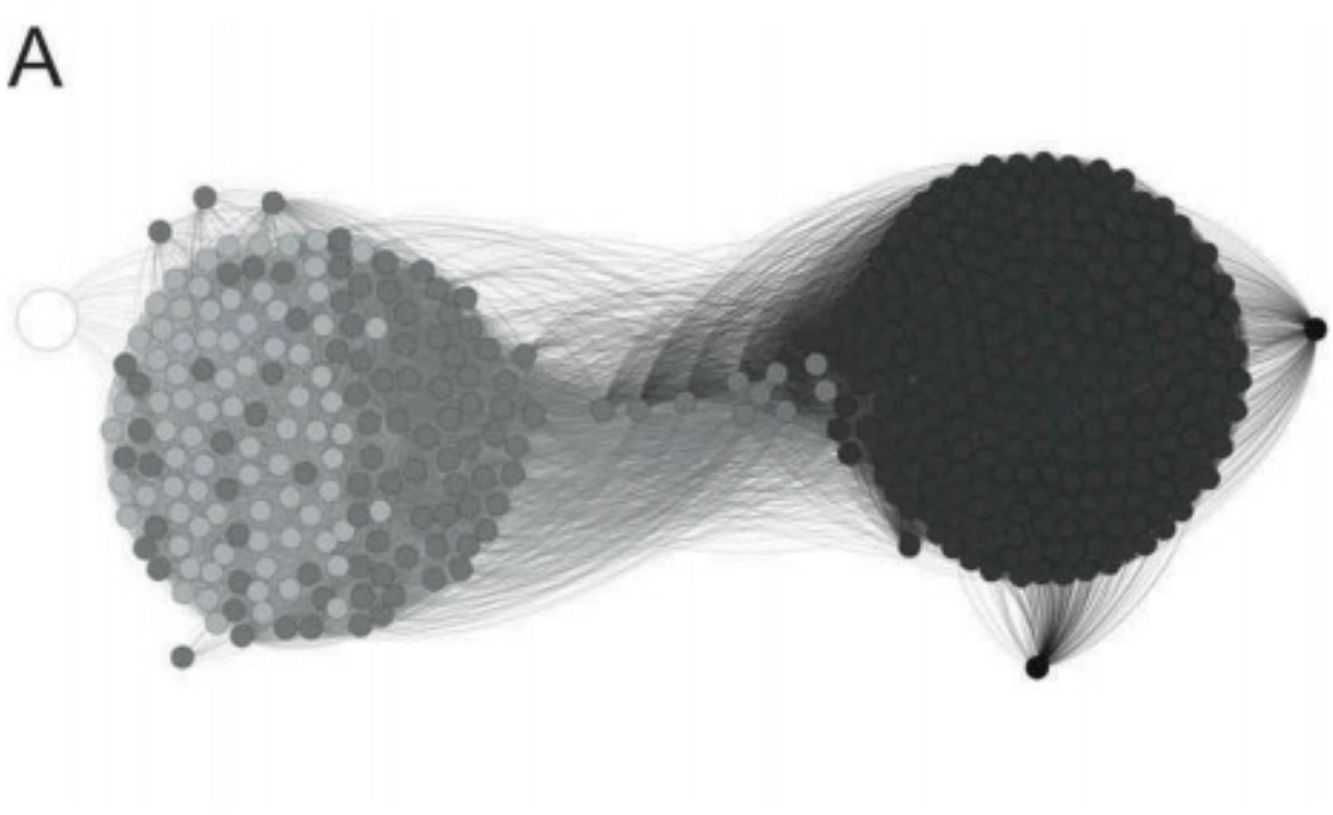



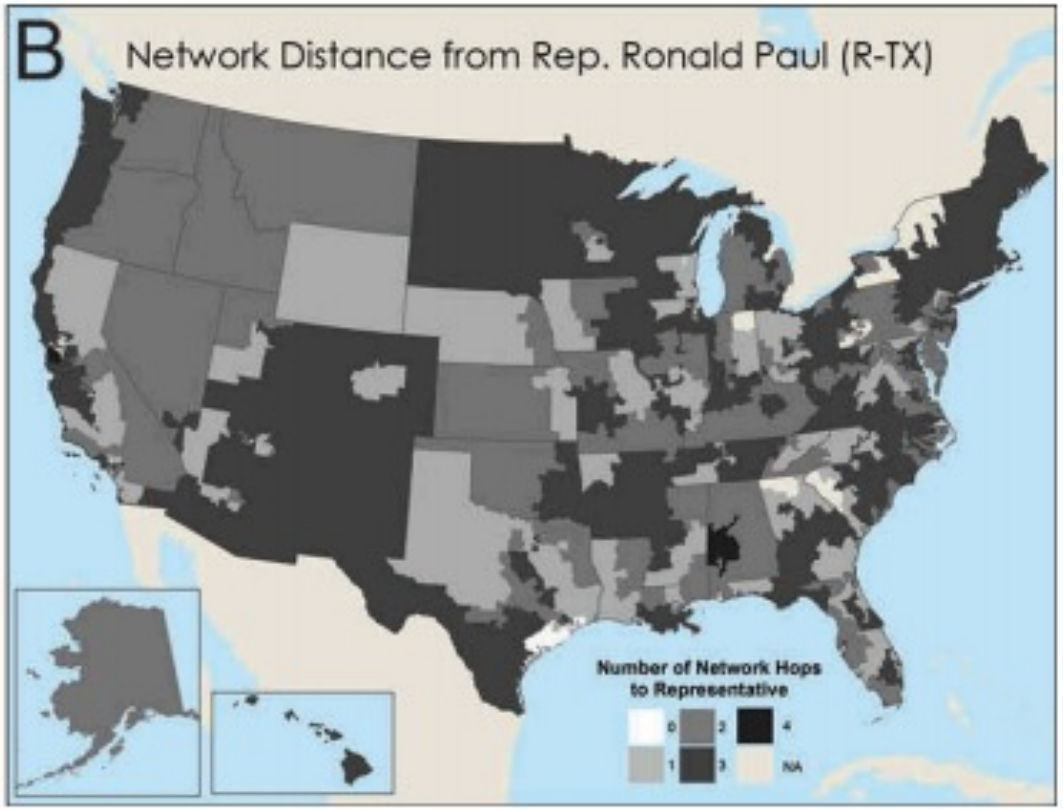
# Aggregate Modularity



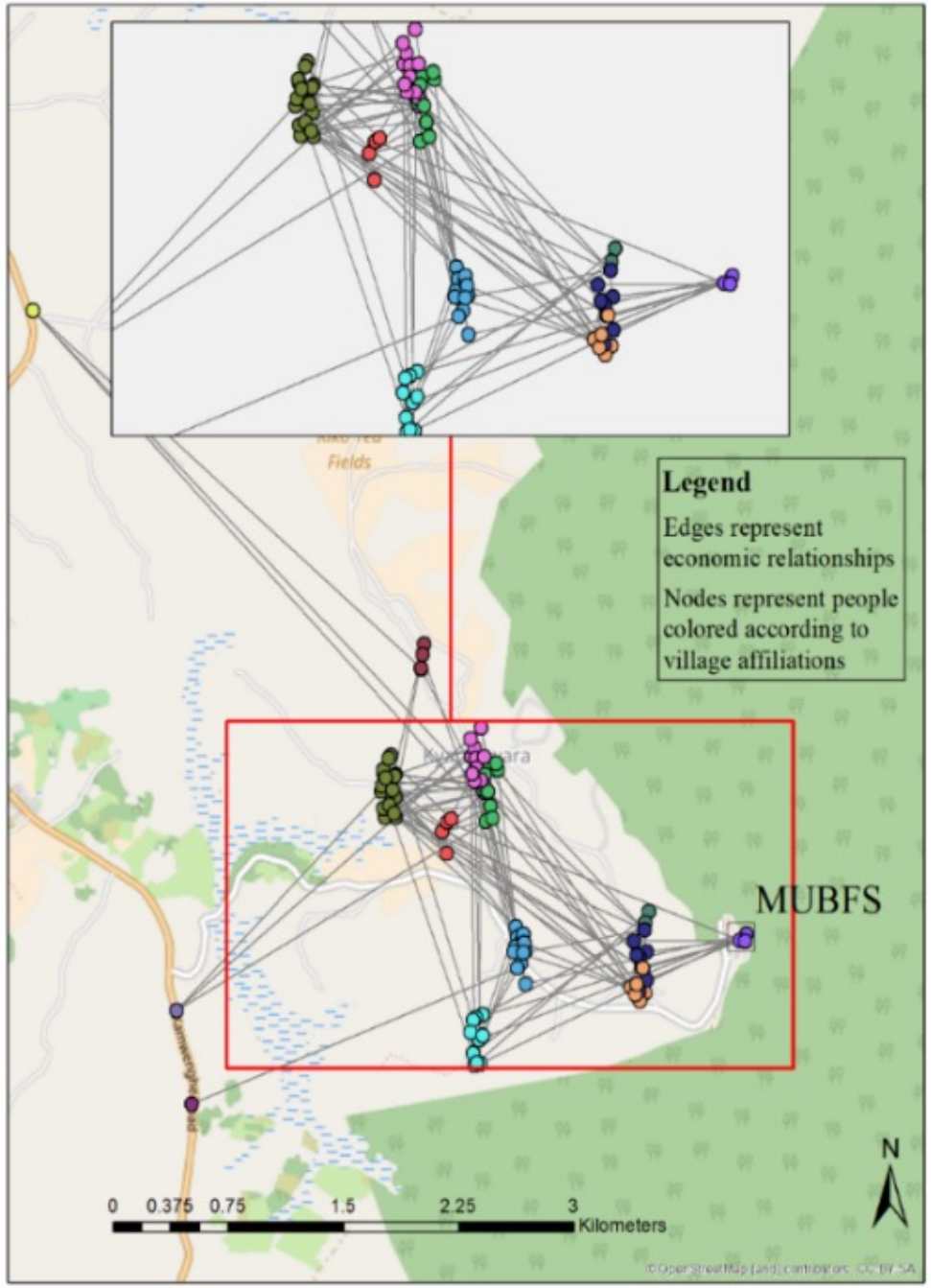



# Disaggregate Diffusion



# Villagers in Uganda and job referrals to Kibale National Park

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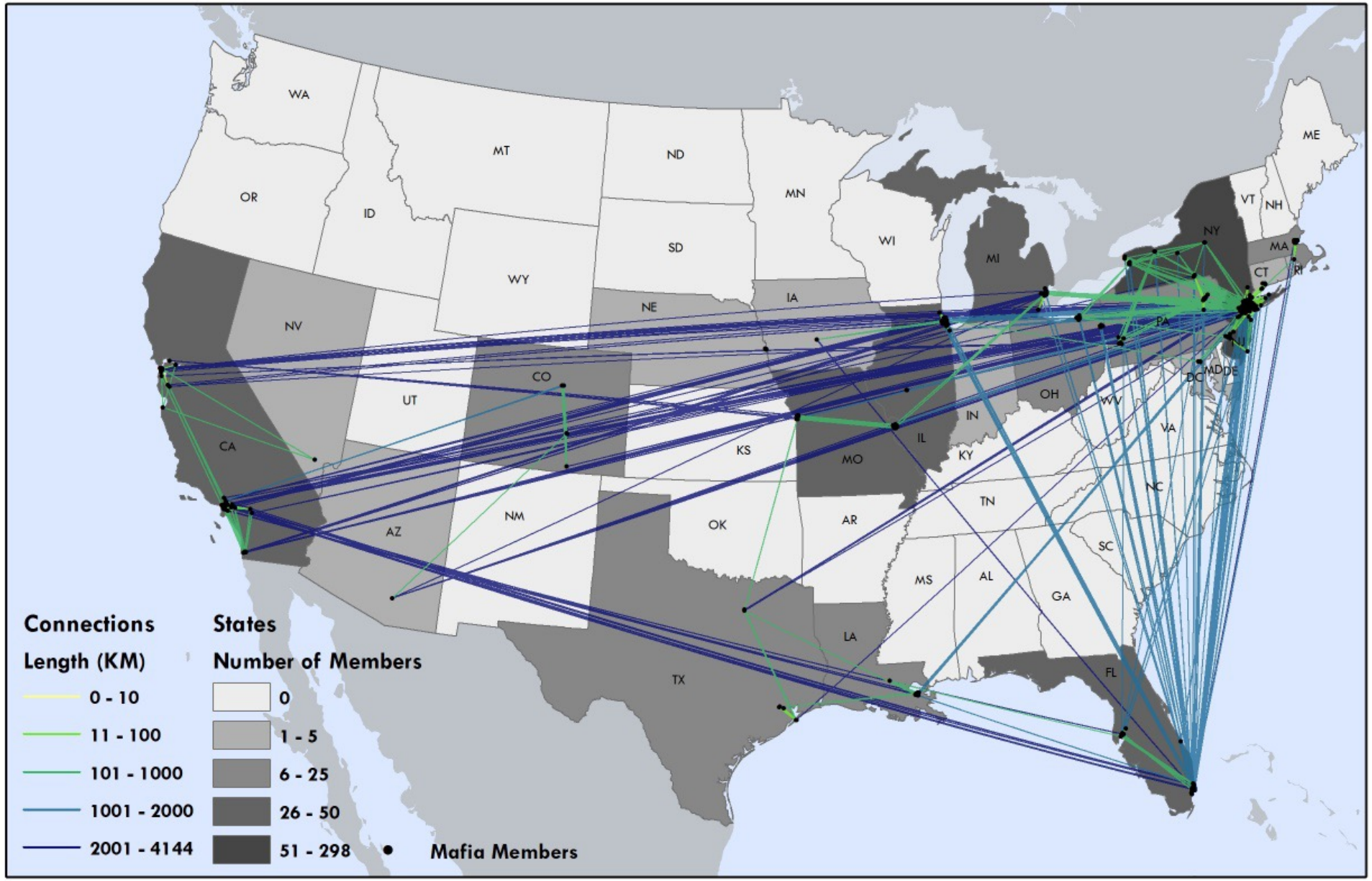
# Members of the Mafia and their connections in the 1960s.

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# Food sharing in Virginia