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A Macroscopic Framework to Spatially Model Gang Location

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Article

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Abstract

Few studies model gang locations spatially, and even fewer attempt to understand their interconnectivity. Fundamental to this method is “mapping” an object to better understand how it influences or is influenced by other locations. This study aims to provide a macroscopic framework for spatially modeling gang locations using Twitter data and to examine the connections between cities and states. The data is modified from Ryan Roberts (2021), which uses a four-step process: detection, validation, REST API search, and network building. The results show geospatial diversity among cities, with variation in population density, and in their connections to other cities. State connections, on the other hand, exhibit small-world properties. The findings have significant policy implications and identify areas for future non-metropolitan ecological research.

Introduction

Gangs are frequently framed as neighborhood groups, keeping spatial models geographically narrow. Thus, few attempts have been made at a macroscopic analysis of gangs. The reason for this is partly due to data limitations (Huff & Barrows, 2015; National Gang Intelligence Center, 2015) and partly to the rejection of formal gang connections that extend beyond the local context (Decker et al., 2013). However, empirical evidence suggests the latter might be overstated. For example, leaders in gangs like the Gangster Disciples, who originated in Chicago, appoint regional governors in other states, and several outlaw motorcycle gangs have (trans)national connections, with chapters holding regional and national conferences. Regardless of size, gang members have increasingly relied on social media to coordinate and form connections outside their immediate proximity. This study aims to contribute to our understanding of gang interconnectivity by using Twitter (now known as X) data to spatially model gangs by city and state. The data, borrowed from Ryan Roberts (2025), used a four-step iterative process: detecting gang member profiles, validating their gang affiliation using exemplar documents, searching the REST API to verify their locations, and building the network dataset.

This paper is divided into six sections. The first section summarizes spatial modeling in gang research, highlighting the dearth of attention to the interconnectivity of gang locations between cities and states. Section two provides a literature review on gangs and social media to distinguish this study's contribution. In the third section, I discuss the data collection methodology that was used to build the network data. The data has been modified to focus on gang connections by location. The results, discussed in the fourth section, show geographic clusters and a range of connections between gang members in different cities and states. Section five explains the significance of the results as well as the challenges and limitations of this study. The conclusion details the utility of macroscopic analysis in spatially modeling gangs.

Spatial Modeling in Gang Research

Spatial modeling is the formal process of representing, analyzing, and simulating phenomena in geographic space. Models are constructed so that the attributes or behaviors of an object at one location are allowed to influence, or be influenced by, those at other locations. This is typically achieved by defining a spatial structure and then embedding that structure within statistical or process-based equations (Anselin, 2010). John Hipp and Seth Williams (2020) argue that criminal offenders and targets move through space, necessitating models that account for spatial behavior, awareness, and scale. Geographic profiling, a specialized branch of spatial modeling in criminology, uses the locations of a connected series of crimes to generate a probability surface area that estimates an anchor point of offender activity (Rossmo, 2000). Fundamental to this approach is establishing where, in space, an object is to "map" its location. Gangs exhibit an inherent geographic orientation, as evidenced by their use of graffiti to claim territory in addition to adopting neighborhood names (Bloch, 2022).

Scholarship by George Tita includes several studies that model gangs spatially. In one ethnographic study, Tita et al. (2005) conduct interviews with gang members in Pittsburgh who map the locations where they congregate in what the authors refer to as "set spaces," which tend to be much smaller than the neighborhood territory they claim. Using a logit model, they estimate that the presence of set space in census block groups shows that diminished social control, manifested in the absence of capable guardians and physical abandonment of place, together with underclass structural features, significantly elevates the likelihood of gang set-space formation. A later study in which Tita was involved, Brantingham et al. (2012), applies formal spatial Lotka–Volterra competition models to analyze 563 shootings between thirteen rival gangs. They find that violent competition among gangs correlates with stable territorial partitions. George Tita and Steven Radil (2011) model the spatial distribution of gang violence by simultaneously accounting for gangs' relative geographic locations and their positions within adversarial networks in Los Angeles. They find that the socio-spatial dimensions of these rivalries (i.e., territorial positioning and network relations) explain observed patterns of violence more effectively than conventional adjacency-based measures of spatial autocorrelation. This work is an extension of Steven Radil et al. (2010), who integrate social networks with spatial analysis to examine gang rivalries and violence in Los Angeles. Addressing critiques that network methods often neglect geographic context, the authors use the concept of structural equivalence to link gangs' positions in both territorial space and rivalry networks. By comparing the geography of inter-gang rivalries with the spatial distribution of gang-related violence, the study shows that gangs similarly embedded in both geographic and network spaces share related patterns of conflict, thereby accounting for the socio-spatial context of urban gang violence. Similar to Tita and Radil, Andrew Papachristos et al. (2013) consider the role of network embeddedness and spatial proximity in generating gang violence. Their analysis of fatal and non-fatal shootings in Boston and Chicago supports Tita and Radil's assessment of network patterns in explaining gang violence. However, Papachristos et al. attest that turf adjacency and prior conflict also help predict future violence. Subsequent work in Papachristos et al. (2015) suggests an "epidemic-like diffusion pattern" of gang-related gun violence that further supports Tita and Radil in emphasizing spatial proximity of turf and relational processes. Both model the probability of violent ties between gangs as a function of territorial adjacency *and* network structures such as reciprocity.

While many of these studies emphasize geographic profiling to better understand patterns of gang violence, spatial modeling in gang research has received little attention in terms of macroscopic analysis targeting specific gangs and the interconnectedness of their locations. Ryan Roberts (2021) collects spatial data on gang members from Twitter (X) to examine location homophily using an exponential random graph model and assess the extent to which location influences gang member connections. A modified version of that network data is used in this study. His research was inspired by earlier work conducted by Julian Way and Robert Muggah (2016). They used social media analytics to collect Twitter data to examine human trafficking clusters at the U.S. southern border. The authors inadvertently discovered a network that extended throughout Latin America and the United States. One of the most comprehensive attempts to spatialize gangs appears in the 2011 gang assessment published by the National Gang Intelligence Center (NGIC). Participating law enforcement agencies reported the gangs operating in their state. However, the report did not indicate the extent to which gangs in each state were connected. Although the NGIC's gang assessments provided insight into gang trends, the agency discontinued publishing its reports after 2015.

Social Media as a Source for Gang Data

Gang data accessibility suffers from two significant issues. One is a disconnect in inter-agency data sharing (Huff & Barrows, 2015). The other is the barriers to obtaining gang data that make it prohibitive. Some city and state agencies do not collect gang data (NGIC, 2011), while others are reluctant to make it publicly available. A 2017 administrative memorandum from the Los Angeles Police Department reinforces the latter point. It states, "access is restricted to gang officers or personnel who have met the "right to know and need to know" criteria" (p. 5). In fact, lawsuits have been filed to compel city officials to release spatial gang data (*State ex rel. Toledo Blade Co. v. Toledo*, 2013). However, courts have been divided on whether gang data should remain confidential or publicly accessible (Stephan, 2018).

Social media provides an alternative to circumvent gang data accessibility issues. Relevant to this study is online socialization and the extent to which it influences offline behavior. Ariadna Fernández-Planells et al. (2021) systematically review 73 academic publications on gangs and social media. According to their synthesis, the foci of gang researchers are criminal and deviant uses of social media platforms and the connections between online activity and offline violence. Platforms such as Facebook, Twitter, and YouTube have been used to varying degrees for posturing, provocation, and projecting group power, with online actions frequently generating offline consequences for violence and criminal activity (Pyrooz & Moule Jr., 2019).

Desmond Patton et al. (2013) were among the first studies to address the connection between gangs and social media. In their seminal work, they introduce the term "cyber banging" to describe the phenomenon in which gang-affiliated individuals use social media to exchange insults, issue threats, and display violence in ways that can escalate into offline victimization. Forrest Stuart (2020) contextualizes Patton et al. by establishing parameters that contribute to the likelihood that online conflict leads to offline violence. He divides this interaction into three domains aimed at targeting and undermining rival

gang members through “context collapse.” One is ‘cross-referencing’ content to undermine claims of toughness and expose inconsistencies in a rival’s online persona. Another, ‘calling bluffs,’ involves daring a rival to act on their online threats, thereby invoking offline violence. The third, referred to as ‘catching lacking,’ involves recording an attack on a rival and uploading the video to denigrate the gang. Stuart acknowledges that the initial act of violence is not attributed to online interaction. However, the provocation is an affront to the target gang, necessitating retaliation to defend its reputation (Leverso & Matsueda, 2019). Yuan Hsiao et al. (2023) add to Stuart’s observations by adopting a multiplex network to frame online and offline relationships between gang rivals as mutually constitutive. Their study incorporates Facebook data, territorial gang maps, and recorded shootings of Latino gangs in Chicago to demonstrate that online conflicts are not random, but form structured, targeted network ties. These online relationships systematically depend on offline geographic proximity and prior shooting histories between gangs, consistent with the findings of Papachristos et al. (2013).

Other research aims to understand how gangs utilize social media. Andrew Whittaker et al. (2020) distinguish between “traditionalist” and “digitalist” gangs. The former tend to be older and avoid social media to minimize the risk of exposure. Digitalist gangs, on the other hand, are younger and embrace social media as a tool for branding, building their reputation, expanding territory, and recruiting. Lakshika Balasuriya et al. (2016) detect gang members on Twitter to analyze their digital footprint. They systematically identify patterns in language use, profile and cover images, YouTube links (often related to gang-affiliated music), and emoji usage. In their bivariate analysis of St Louis middle schools, Timothy McCuddy and Finn-Aage Esbensen (2020) find that youth gang members seek similar online peer groups compared to non-gang youths. These results are reinforced by Roberts (2021), who found that gang affiliation was a strong predictor of Twitter connections. Approximately 82.04% of the observed connections were members of the same gang, suggesting online gang-affiliated congruence that mirrors offline peer groups. Another 64.3% were from the same set or coalition.

Despite the nuanced approaches to understanding gang member social media activity, the studies discussed in this section exemplify social media as an intelligence-gathering tool. Publicly available data from platforms such as X (formerly Twitter), YouTube, and Meta (formerly Facebook) can be systematically extracted, processed, and analyzed to generate actionable insights for security and intelligence purposes. Because these platforms host large volumes of free-form user-generated textual content in near real time, they function as distribution centers for public discourse, group dynamics, and potential threats. Thus, mining social media content enables analysts to capture the online activity of a target population (Agarwal et al., 2015). Within the security domain, social media analytics have been used to detect hate and extremist groups (Agarwal & Sureka, 2015), prevent gang violence (Blandtfort et al., 2019), and link individual profiles to drug-related criminal organizations (Park et al., 2026), among other intelligence-related applications.

Methodology

This study modifies Twitter (X) data collected by Ryan Roberts (2025) to spatialize gang member connections across cities and states. Compared with other social media platforms, Twitter (X) is less restrictive regarding data collection and is a proven tool for “gang activity identification and monitoring” (Wijerante et al., 2015, p. 96). At present, Twitter (X) is the preferred source for gang research (Fernández-Planells et al., 2021). The following iterative four-step process was used to collect gang data on Twitter (X) and build the spatial model:

Step 1: Gang Member Detection

Step 1 involved finding initial seeds and detecting gang members using four different methods. A language algorithm coded in R, an open-source programming platform, was used to capture streaming API data. One method of identifying gangs is through language and other idiomatic expressions. Street verbiage known to be distinct to specific gangs (e.g., Bloods, Crips, Gangster Disciples, etc.) and general terminology were used. Table 1 provides a small language sample used to capture the streaming API. The Twitter search function was another method for detecting gang members. Searching for different gangs by name generated profiles that matched the query. As part of the iterative process, Twitter provided profile recommendations based on my search history. Additionally, as gang member profiles were detected, their follower lists were consulted to discover other gang member profiles.

Table 1
Language Sample to Capture Twitter (X) Streaming API

Gang	Language	Meaning
Folk Nation	All is one	We're all together and OK
	GD, 74	Gangster Disciples
	LLLWUK	Love, Life, Loyalty, Wisdom, Understanding, Knowledge
	Vicky Lous	Disrespectful name for Vice Lords
People Nation	(G)DK	(Gangster) Disciple Killer
	5 in the sky, 6 must die	Revenge against Folk
	Eleven Pointed Pancake	Vice Lord who became a Disciple
Crips	Slob, Sloob	Disrespectful name for Bloods
	Adidas	All Day I Destroy a Slob (Blood)
	BKAD	Blood Killing All Day
	What it C Like	Crip greeting
Bloods	Crab	Disrespectful name for Crip
	CKAD	Crip Killing All Day
	Snoovers	Insult to Hoover Street Crips
	Krab	Insult to Crips
Latin Kings	ALKN	Almighty Latin King's Nation (a member of the People Nation)
	La Vida Loca	The Crazy Life
	Amor de Rey	"Love of the King" greeting
Outlaw Motorcycle Gangs	1%	One Percenters
	AFFA	Angels Forever, Forever Angels (Hells Angels)
	BFFB	Bandidos Forever, Forever Brothers
White Power Gangs	88	Heil Hitler
	(10%) Ten Percent And Out	10% of the country be reserved for whites only
	White Laces	White power, White pride, Hatred of Jews

Gang	Language	Meaning
Source: Flores (2015)		

Step 2: Gang Member Validation

Once a gang member profile was detected, a manual inspection of the profile was conducted and compared to exemplar documents to validate the profile as a gang member using the following ten criteria: self-admission, language, hand signs, tattoos, gang media, gang colors/apparel, associates, hashtags, emojis, and external news sources. Members who satisfied two or more criteria were included in the dataset. Those that did not meet the minimum criteria were discarded.

Step 3: Search REST API

A search of the REST API in step 3 was used to verify a gang member's location. User statements, references, and other information in each profile were consulted. Profiles on which the location could not be verified were discarded. Step 3 also involved a random snowball sampling of the follower list, which was reviewed to further detect and validate gang members (see steps 1 and 2).

Step 4: Build the Spatial Network

The final step involved building the network. Profiles that were validated as gang members and whose locations could be verified were used to build the spatial network, which was divided into two graphs. Graph 1 is the network connections of gang members by city, and Graph 2 is the network connections of gang members by state. The nodes in each graph represent the respective location, and the edges represent pairwise connections. An undirected, unweighted network was used to represent connections in each graph.

Results

The data collection method revealed 23 gangs across 88 U.S. cities and 7 international cities (combined and represented as INTL in the figures below). The network of 89 cities is connected by 233 edges. The state network includes 26 different gangs in 29 U.S. states and 7 international states/provinces (combined and represented as INTL in the figures below). Within the state network, the 30 nodes are connected by 272 edges. Table 2 describes the spatial network dataset by city and state.

Table 2
Description of the Spatial Network Dataset

U.S. Cities	**88**	**U.S. States**	**29**
International Cities	7	International States	7
Nodes	89	Nodes	30
Edges	233	Edges	272
Gangs	23	Gangs	26

Figure 1 illustrates the spatial connections of gang members by city in Graph 1. Node size indicates degree centrality for each city (i.e., the larger the node, the more connections it has). In Graph 1, Los Angeles, Atlanta, Chicago, and Compton have the most connections, represented by inter- and intra-city ties. Respectively, 113, 33, 39, and 36 gang members are represented in each city. They are connected to a range of small and large cities, both within and outside their state. For example, in addition to connections to other California cities such as Compton and Long Beach, gang members in Los Angeles have ties to Murfreesboro, TN, Houma, LA, and Phoenix, AZ, among other cities. The same is true for gang members in Chicago with ties to Reno, NV, Baltimore, MD, Kansas City, MO, and Kokomo, IN. Graph 1 also consists of several disconnected subgraphs from the larger network. The Gotti Gang has members in Pemberton, NJ, Georgetown, NJ, and New Orleans, LA. Another subgraph consists of Cleveland, OH, Miami, FL, and Highland Beach, FL, represented by the Latin Kings. A third disconnected network includes members of the Folk Nation in Flint, MI, and Little Rock, AR. Other connections appear to be more localized, with the Bloods in Jacksonville, FL, and the Crips in Macon, GA.

Figure 2 illustrates gang member connections by state in Graph 2. Node size indicates degree centrality by state (i.e., the larger the node, the more connections it has). In Graph 2, the detected gang members are primarily concentrated in California, Georgia, Illinois, Tennessee, North Carolina, and South Carolina, each with its own configuration of connections to other states. Unlike Graph 1, there are no strictly localized connections. Rather, the graph represents a combination of inter- and intra-state connections with all states connected through various paths. The diameter of the graph is 4, meaning the longest shortest path between any two states is four steps away. A few states, like Georgia and Texas, are connected to international gang members having ties to Indonesia and South Africa, respectively.

Discussion

Spatial modeling can be applied to macroscopic studies of gang locations that are not available through conventional data sources or have limited geographic scope. Moreover, it provides an opportunity to identify new areas beyond the urban foci that have been featured prominently in gang research. Although the data used for this study show gang member clusters in large cities, it also identifies less densely populated cities such as Laurens, South Carolina, and Houma, Louisiana. As of the 2020 U.S. Census, the populations of these two cities were approximately 9,300 and 33,000, respectively. In fact, a member of

the Insane Gangster Disciples (IGD) residing in Laurens was convicted along with 39 other members in a 2023 RICO (Racketeer Influenced Corrupt Organizations) case that involved an inter-city drug trafficking operation. Other members charged in the case were primarily from South Carolina cities, including Lexington, Gaffney, Greenville, Easley, Williamston, West Columbia, and York, with a couple members from Gastonia, North Carolina (U.S. Attorney's Office, District of South Carolina, 2023). The IGD themselves originated in Chicago and belong to the Folk Nation alliance.

As an intelligence tool, spatial modeling allows researchers to proactively track gang diffusion. Similar to the IGD, which migrated from Chicago to other cities and states, the Gotti Gang, a relatively new set affiliated with the Bloods, originated in the Sunbury Village neighborhood of Pemberton Township in Burlington County, New Jersey. Their activity was first documented in the area in 2014 after one of their members shot at a patrol officer. They have since been validated in New York (Brooklyn District Attorney's Office, 2024) and Virginia (Edwards, 2017). The data from this study also suggests that they have a presence in New Orleans, Louisiana. Additionally, the results show that some gangs in the sample population appear more diffuse than others. The Grape Street Crips are concentrated in the Los Angeles area where they originated, while the Gangster Disciples and Five Percenters are more spread out. Understanding the conditions that explain this disparity is another area identified in this study that would benefit from location-based research.

Geospatial modeling identifies location patterns and interconnectivity. However, online socialization does not guarantee offline interaction. Studies by Forrest Stuart (2020) and Ryan Roberts (2021) indicate that gang members tend to connect with similar others. Whether they coordinate extraterritorially is beyond the scope of this paper. Stuart also highlights that gang members create online personas that may not reflect who they are offline. The same is true for "wannabes." That is to say, people on social media can falsely represent themselves as being a gang member despite having no gang affiliation. In addition to active gang members, the Office of Juvenile Justice and Delinquency Prevention (2009) identifies "associates" as those affiliated with gang members but not active participants, and "wannabes" as those who pretend to be gang members. They also acknowledge that the three are similar in appearance and difficult to distinguish from one another. In fact, gang members will victimize wannabes the same as they would a gang member if they share identifiers with rival gangs. The data used for this study gives equal weight to a "wannabe" and an active gang member for two reasons. One is the inherent challenge of distinguishing between gang member and wannabe profiles. Perhaps more significant is that both promote and disseminate gang culture. Related to profile verification, another challenge is distinguishing between human users and "bots." Lynnette Hui Xian Ng and Kathleen Carley (2025) define social media bots as "An automated account that carries out a series of mechanics on social media platforms, for content creation, distribution, and collection and processing, and/or for relationship formation and dissolutions" (p. 4). The authors continue by contrasting bot and human accounts to provide several diagnostic signs. For example, the timeline for bots tends to include an exorbitant number of hashtags, mentions, and retweets, whereas human accounts reply, quote, use first-person language, and attach media. In addition to collecting data from the REST API, the manual profile

inspections were conducted to mitigate this issue. Bot accounts that exhibited recognizable patterns were discarded.

Conclusion

Rather than studying gangs as geographically isolated, macroscopic geospatial modeling treats gangs as patterned phenomena across neighborhoods, cities, counties, states, and regions. As territorial organizations, geography remains a defining gang feature that can distinguish durable turf from a more fluid or symbolic presence. However, spatial gang data is limited to agencies willing and able to share it. In many cases, gang data is altogether inaccessible or limited in scope. Data mining on social media represents an innovative method for collecting gang data to model spatial connections among gangs beyond local contexts. While gang research has historically framed gangs as local actors, the findings of this study highlight gang member connections across various cities and states. City connections are spatially diverse, with some being localized and others spanning multiple cities. When considering state connections, gang members have connections to at least one other state. Although online socialization is not indicative of offline interaction or behavior, it is important to spatially model gang member connections for several reasons. Foremost, there is a spillover effect of gang-related activity (Valasik et al., 2023). Geospatial models help identify territorial concentrations, their stability over time, and their relationship to adjacent areas. They also allow researchers to test ecological theories, such as social disorganization, and assess whether urban explanations are applicable to non-metropolitan areas. Several small-density cities were identified in this study. A gang presence in these areas is likely to exacerbate the limited training and resources available. Moreover, individual-level analyses often neglect regional heterogeneity. Gang problems in rural and small towns tend to be more transitory and organized differently than those in large cities. Comparisons across the urban–rural continuum prevent urban templates from being applied uncritically. As one law enforcement observer explains, “the problem is significant for us, but I suppose if you were comparing it to an urban environment it would be minimal” (Weisheit & Wells, 2001, part 2, p. 13). When left unchecked, their presence can become permanent, allowing them to proliferate and claim new territory. Across space and time, longitudinal spatial models track the extent to which gangs persist, diffuse, contract, or disintegrate. Finally, social networks and geography are mutually constitutive. Alliances, rivalries, and co-offending networks occur across both proximate and distant spaces. To operate outside their territory, gangs need connections with others familiar with the area (McLean et al., 2019). Otherwise, they risk being detected by law enforcement or attacked by rival gangs. The implications of which are significant for gang prevention, intervention, and suppression strategies.

Declarations

All aspects of the study conception and design were completed by Ryan J. Roberts. There were no other authors involved.

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The author has no conflicts of interest to declare.

Author Contribution

All aspects of study conception and design were completed by R.R. No other authors were involved.

Data Availability

The network data is publicly available in the Kaggle repository. A reference has been cited in the manuscript and can also be accessed at the following URL: https://doi.org/10.34740/kaggle/dsv/13659491.

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Figures

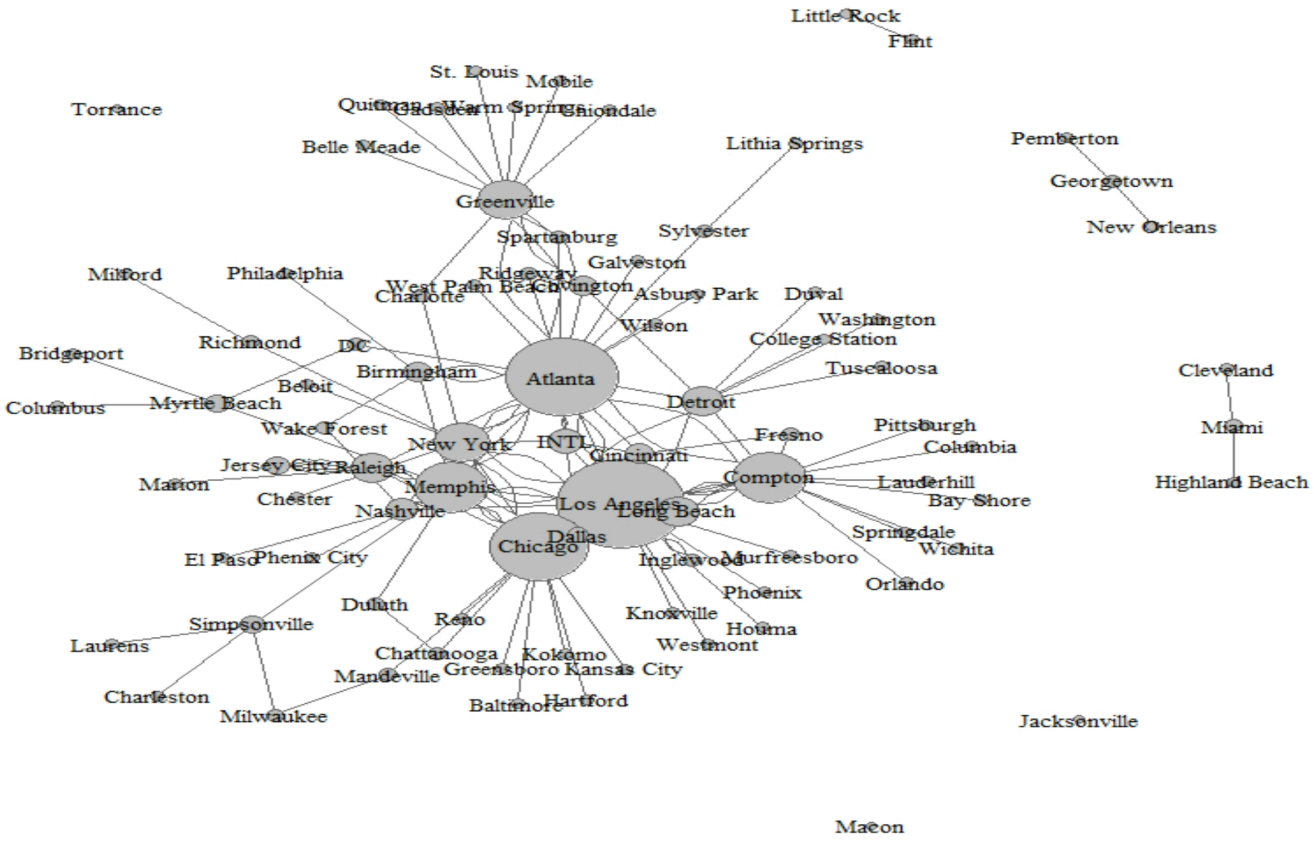


Figure 1

illustrates the spatial connections of gang members by city in Graph 1. Node size indicates degree centrality for each city (i.e., the larger the node, the more connections it has). In Graph 1, Los Angeles, Atlanta, Chicago, and Compton have the most connections, represented by inter- and intra-city ties. Respectively, 113, 33, 39, and 36 gang members are represented in each city. They are connected to a range of small and large cities, both within and outside their state. For example, in addition to connections to other California cities such as Compton and Long Beach, gang members in Los Angeles have ties to Murfreesboro, TN, Houma, LA, and Phoenix, AZ, among other cities. The same is true for gang members in Chicago with ties to Reno, NV, Baltimore, MD, Kansas City, MO, and Kokomo, IN. Graph 1 also consists of several disconnected subgraphs from the larger network. The Gotti Gang has members in Pemberton, NJ, Georgetown, NJ, and New Orleans, LA. Another subgraph consists of Cleveland, OH, Miami, FL, and Highland Beach, FL, represented by the Latin Kings. A third disconnected network includes members of the Folk Nation in Flint, MI, and Little Rock, AR. Other connections appear to be more localized, with the Bloods in Jacksonville, FL, and the Crips in Macon, GA.

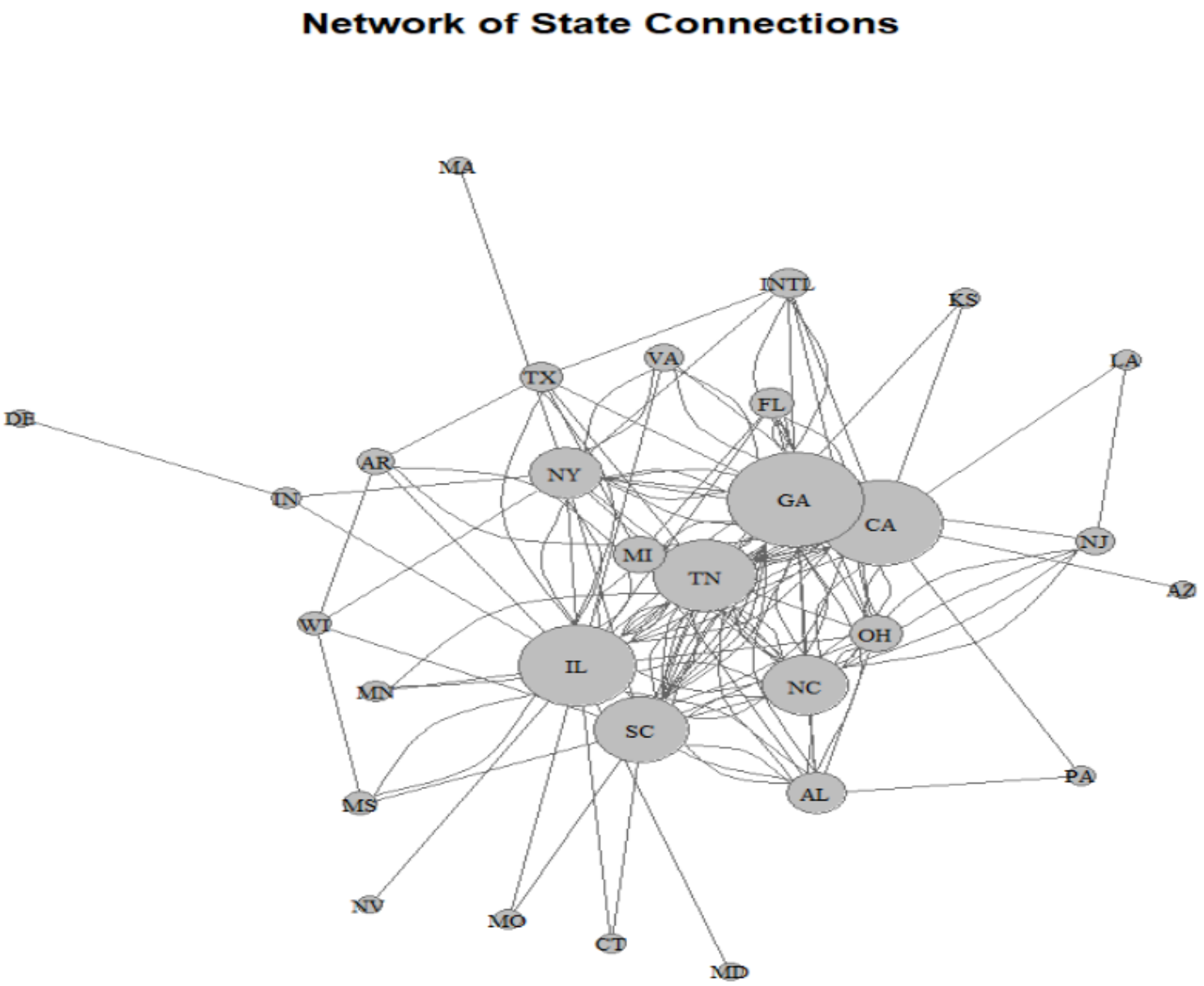


Figure 2

illustrates gang member connections by state in Graph 2. Node size indicates degree centrality by state (i.e., the larger the node, the more connections it has). In Graph 2, the detected gang members are primarily concentrated in California, Georgia, Illinois, Tennessee, North Carolina, and South Carolina, each with its own configuration of connections to other states. Unlike Graph 1, there are no strictly localized connections. Rather, the graph represents a combination of inter- and intra-state connections with all states connected through various paths. The diameter of the graph is 4, meaning the longest shortest path between any two states is four steps away. A few states, like Georgia and Texas, are connected to international gang members having ties to Indonesia and South Africa, respectively.