MEASURING SOCIAL INTERACTION POTENTIAL IN OKLAHOMA CITY AND TULSA

By

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2012

Submitted to the Faculty of the
Graduate College of the
Oklahoma State University
in partial fulfillment of
the requirements for
the Degree of
MASTER OF SCIENCE
July, 2014

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IN OKLAHOMA CITY AND TULSA

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Date of Degree: JULY, 2014

Title of Study: MEASURING SOCIAL INTERACTION POTENTIAL IN OKLAHOMA CITY AND TULSA

Major Field: GEOGRAPHY

Abstract: Social degradation is now a serious problem in cities in the United States. People are interacting with their neighbors, families, and those within their community less frequently. Some major causes of this are central city decline, urban sprawl, and suburbanization. People within cities are now farther away from each other and from activity locations, making social interaction more difficult. Recently, time geography has researchers rethinking traditional approaches to these topics along with studies in transportation, accessibility, and mobility. This subdiscipline of geography is based on an individualized approach that incorporates the constraints that all humans face on a day-to-day basis. In my thesis I evaluate the social interaction potential (SIP) of working populations in the urbanized areas of Oklahoma City and Tulsa, focusing on coupling constraints that limit the opportunities for individuals to meet face-to-face at certain activity locations and interact with each other. Using restaurants as activity locations, I calculate the amount of time that can potentially be spent interacting with others at activity locations based on different combinations of work locations and home locations within the two cities. Several variables strongly affect the calculation of SIP such as the population within each zone, the driving time to activity locations, and the distance from all other zones. While Oklahoma City and Tulsa are similar in terms land area, population, restaurant location distribution, and recent capital improvement projects, the two have different urban forms which affect the patterns of SIP. While there is generally more SIP near the center of both cities, Oklahoma City shows a more dispersed and sectoral pattern with "fingers" of SIP extending from the downtown area, while Tulsa shows a more central city phenomenon with high concentration of SIP in the center and a steep drop off in SIP away from the center.

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CHAPTER I

INTRODUCTION

1.1 Problem statement

Social degradation is a serious problem in many cities across the United States (Putnam, 2001). Today, many people do not frequently interact with their neighbors or families in physical space, and this has led to a loss of social cohesion in cities (Putnam, 2001). While some of this is surely due to changes in communication technology, changes in metropolitan structures due to urban renewal and suburbanization are also largely responsible. To counter these problems, planners in many cities are now attempting to implement principles of smart growth and new urbanism which allow people to interact face-to-face on a more regular basis. While these programs have shown some positive effects, measuring the degree of social improvement is a difficult task. To measure social interaction and study issues related to urban form and transportation, geographers are now tapping into a subdiscipline of geography called “time geography.” Recent studies (Delfontaine et al., 2011; McQuoid and Dijst, 2012; Neutens et al., 2012a) have demonstrated vast potential in using time geography to examine the relationships between urban form and the potential for people to interact with others in a metropolitan area. In this study, I will implement a time geographic approach in measuring social interaction potential in Oklahoma’s two largest cities, investigating how their urban forms and transportation systems contribute to the patterns of social interaction potential present.

1.2 Time geography

Time geography was developed in the late 1960s and became well-known to the research community when Hagerstrand published the seminal paper *What about people in regional science?* This piece engendered an entirely new perspective from which to study human activities, but many of the concepts were left unused in real-world studies due to lack of technology and methodology. Recent advancements in geographic information systems (GIS) and improvements in computational power have made it possible and feasible to implement the time-geographic framework in real world cases. Miller (1991, 2003) made great efforts to computationalize the time-geographic framework for real world cases. This has opened the door for many others to adopt and employ the time-geographic framework in their studies (for example: Delfontaine et al., 2011; Farber et al., 2012; Neutens et al., 2012a; Neutens et al., 2012b; Neutens et al., 2012c; Scott and He, 2012). Urban and transportation geographers are seeking ways to reverse the loss of social cohesion in US cities, and many consider time geography a new and promising approach to better address these issues. Noticeably, Farber et al. (2012) have created powerful methods to study social interaction potential (SIP), which can be defined as the potential for two or more people to interact face-to-face in physical space.

This research will explain how a city's urban form and transportation network either encourages or inhibits social interaction on a day-to-day basis using methods similar to those presented by Farber et al. (2012). Farber et al. (2012) use many theoretical city models with various residential and employment distributions to determine the SIP of living and working in different zones within the city (Farber et al., 2012). SIP is computed by calculating the amount of time citizens can spend interacting with others based on a given after-work time budget.

Studies measuring SIP differ from other studies in time geography in a few ways. Most notably, travel diaries are not necessary and are rather impractical for this type of study because the research is theoretical. It is based on the potential for people to interact, and data are collected from sources available to the public, such as the US Census Bureau and Yellopages.com. Since an aggregated approach without travel diaries is often exhaustive and still incorporates the three constraints of time geography (capability, coupling, and authority constraints), it is still considered a valid method within this subdiscipline.

It is important to note that social interaction potential does not equate to social interaction realization (Farber et al., 2012). The goal of time geographic studies in SIP is not to measure how humans actually interact but to observe how the transportation networks and urban characteristics of cities affect the potential to interact. This is a key component of studying SIP with a time geographic framework and can lead to positive policy change with proper interpretation. Most application studies utilizing time geographic concepts (Delfontaine et al., 2011; Farber et al., 2012; Neutens et al., 2012a; Neutens et al., 2012b; Neutens et al., 2012c; Scott and He, 2012) make a strong case for cities to increase population density and incorporate mixed land use.

1.3 Research questions

This research will attempt to explain the spatial patterns of SIP in Tulsa and Oklahoma City based on each city's transportation network, urban form, and zoning policies. A recent practical application of this method was implemented by Neutens et al. (2012c) on the region of Flanders, Belgium. However, this research will focus on smaller areas – Oklahoma City and Tulsa – in a comparative case study and will delve deeper than previous studies in several ways. Instead of using only zonal centroids and studying one urban area, this research implements the use of actual activity locations to create an SIP index for employment locations, residential locations, and clusters of sit-down restaurants and compares these measures both within and between the two cities. Since this project is concerned with social interaction and not simply accessibility, sit-down restaurants are chosen since there is a much greater chance for social interaction at these locations as opposed to fast food locations, which often implement a drive through; carryout restaurants; convenience stores; or grocery stores (Oldenburg, 1989). Also, only those locations at which residents can spend a meaningful amount of time are considered.

This study reveals differences in the SIPs of the two cities and uncovers areas of disparity within each city. This project addresses the following research questions:

- What spatial patterns of SIP are present within the two cities?
- How do these spatial patterns relate to the urban form of each city?
- Which city shows more disparity in accessibility and to what degree is this disparity present?
- What factors contribute to high or low SIP in specific zones?

1.4 Study areas

The study areas for this project are the 2010 US Census urbanized areas (UAs) of Oklahoma City and Tulsa (see Figure 1.1). According to the US Census, urbanized areas "comprise a densely settled core of census tracts and/or census blocks that meet minimum population density requirements, along with adjacent territory containing non-residential urban land uses as well as territory with low population density included to link outlying densely settled territory with the densely settled core" (US Census, 2013). These two cities are chosen for their relative proximity to each other and their comparability in terms of both land area and population. Despite these similarities, the two cities have differing urban forms and population densities. According to the US Census (2010), the population density of Oklahoma City is roughly 959 people per square mile, and the population density of Tulsa is much higher at approximately 1990 people per square mile. Historically, Tulsa has been thought of as a polycentric city. Today, according to Sarzynski et al. (2005), Tulsa takes on a "dispersed" city form with a relatively low percentage of employment in core centers as compared to other cities in the United States. Although dispersed, the city does have several distinct centers (Sarzynski et al., 2005). Oklahoma City, on the other hand, has been traditionally considered a monocentric city with several suburbs (Brueckner, 1979). Today, due to further suburbanization Oklahoma City has become more dispersed but retains its general monocentric structure. I will investigate how these forms affect the outcome of the SIP calculation and explain the spatial pattern of SIP within the two cities.

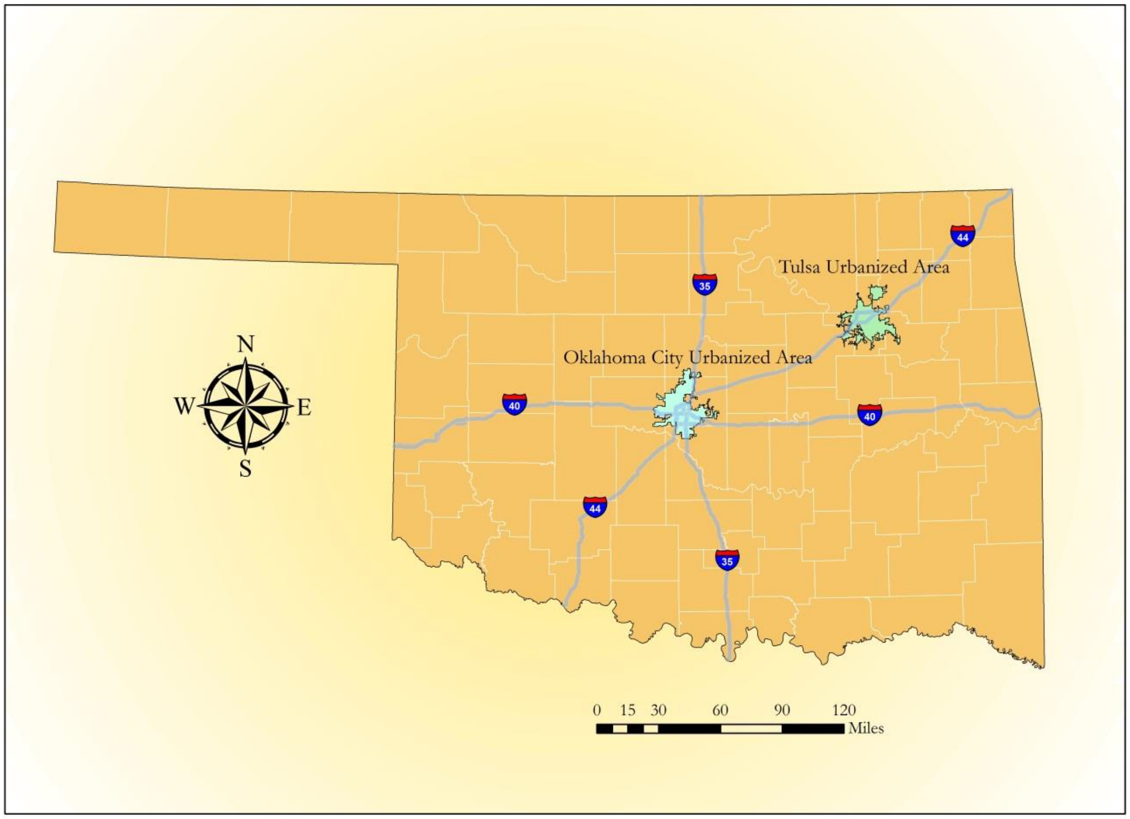

Figure 1.1: Study areas

Both Oklahoma City and Tulsa have undergone projects to revitalize downtown areas and the central city in general within recent years. Oklahoma City enacted its initial Metropolitan Area Projects (MAPS) in 1993 and continued the program until 2004 (City of Oklahoma City, 2014). Funded by a one cent sales tax, the project raised $309 million over 66 months and was largely successful (City of Oklahoma City, 2014). Since the completion of MAPS, a continuation in MAPS2 was implemented and completed, and MAPS3 has been implemented and is still underway. These projects have included nine capital improvement programs targeting facilities used for recreation, education, sports, entertainment, and conventions (City of Oklahoma City, 2014). The government of Oklahoma City claims that it may have been the first program of its type ever implemented in the United States (City of Oklahoma City, 2014). Notable projects under the MAPS programs include Bricktown Ballpark, completed in 1998; renovations to the Cox Convention Center, completed in 1999; Chesapeake Energy Arena, completed in 2002; the transformation of the Oklahoma River, completed in 2004; and the Ronald J. Norick Downtown Library, completed in 2004 (City of Oklahoma City, 2014). Aside from MAPS, private companies have also been investing in downtown Oklahoma City. The Devon Tower, now the largest building in Oklahoma, was completed in 2012 in downtown and employs over 2,000 people (Devon Energy Center, 2014).

Tulsa has implemented similar projects in program titled Vision2025: Foresight for Greater Tulsa. This plan focuses more on the whole of the metropolitan area but nevertheless improves the central city as well. It was started in 2003 and is projected to be completed by 2025, as the name suggests (Vision2025, 2014). Noteworthy projects under this plan include the BOK center, completed in 2008; OSU – Tulsa, completed in 2011; OU – Tulsa, completed in 2007; Northeast State University – Broken Arrow, completed in 2007; and improvements to American Airlines facilities, which is an ongoing project (Vision2025, 2014). So far, the program has raised over $556 million through taxes (Vision2025, 2014).

The characteristics of Oklahoma City and Tulsa allow for an interesting comparative case study on SIP. I first describe the developments in time geography and their applications in measuring SIP. I then discuss the methods employed in calculating SIP and show how I use computer programs to execute this calculation. Next, I transition into describing the sources of data used, how spatial data are aggregated, and how the data are prepared. I then present my results and offer analyses both within and between the two cities. Finally, I conclude by discussing the limitations of this study and suggest avenues for future research along the lines of the methods used.

CHAPTER II

REVIEW OF LITERATURE

2.1 Overview

Accessibility and transportation are topics that became popular during the quantitative revolution because they could be modeled mathematically. Recently, time geography has researchers rethinking traditional approaches to studies in transportation, accessibility, and mobility. Along with this, geographers are now using time geography to explore social exclusion, social interaction, and urban form. Time geography is a relatively new field that has the potential for vast expansion due to recent technological improvements and the introduction of geographic information systems (GIS). In this literature review, I first discuss why social interaction is important along with the theoretical developments in time geography. Next, I discuss the methodological improvements in time geography and mention studies that apply time geographic concepts to measure SIP. I conclude with thoughts on how time geography can be applied to study urban form.

2.2 Social interaction, ICT, and time geography

The concept of social interaction has been studied by psychologists, sociologists, and geographers alike. Social contact is a fundamental human need (Maslow, 1943; Jacobs, 1961; Oldenburg, 1989; Putnam, 2001), and Maslow (1943) was one of the first to show this in scientific research. In his "hierarchy of needs," love and belonging rank only behind physiological and safety needs (Maslow, 1943). These social needs can, of course, be realized within the home, but they can also be fulfilled in public locations as well. Oldenburg (1989), a sociologist, has studied locations like bars, cafes, coffee shops, community centers, and beauty parlors finding that the social element of these places makes them attractive to people. Putnam (2001) and Jacobs (1961) have discussed the role of urban form in shaping social interaction and how suburbanization has led to the disintegration of communities through a decrease in social cohesion. This degradation has largely been caused by the introduction of the automobile into the American society, but more generally by improvements in information and communication technologies (ICT) which have enabled people to live farther away from each other. Modern methods of ICT enable people to communicate more freely, but this has resulted in a decrease in social time spent face-to-face which is essential for strong community.

Due to the rapid changes in ICT, the effect of distance on travel is changing, and the nature of social interaction is constantly evolving (Yu, 2006; Knowles, 2006; Kwan et al., 2007). For example, Knowles (2006) explains the changes in transportation and how this has caused a “time-space convergence.” He notes that although transportation methods have improved, these improvements have been uneven, both globally and within countries (Knowles, 2006). This has resulted in large geographic disparities even within single cities. The structure within cities is changing due to the effect of distance becoming increasingly complex. This is exhibited by that fact that people can now travel to locations faster than ever before (Knowles, 2006), but Kwan et al. (2007) point out that telecommuting enables people to not have to be present in physical space for social interaction to occur. The ever increasing complexity in social interaction and transportation have raised the need for alternative approaches to studying these topics, and time geography presents a new approach that improves on traditional methods.

The discipline of time geography was introduced to the research community when Hagerstrand delivered his seminal presidential address titled *What about people in regional science?* to the European Congress of the Regional Science Association (1970). In this piece, he insists that geographers look at issues in geography from an individual perspective and defines three constraints that limit human behavior (Hagerstrand, 1970): (1) capability constraints refer to biological limitations, such as the need to eat, drink, and sleep, as well as physical and economic limitations, such as those that restrict mobility; (2) coupling constraints are understood to be the restrictions that people have based on locations where they must meet with others or places that they are required to go such as work, school, or home; and (3) authority constraints refer to the restrictions imposed on people by outside sources such as retail businesses with limited opening hours. In his work, Hagerstrand (1970) coins the term ‘space-time prism,’ which defines the locations that a person can reach in a given time period based on his/her constraints. He explains how the size of the space-time prism is largely the result of a person’s capability constraints, or more specifically, their method of transportation (Hagerstrand 1970). Traditional studies (for example, Eckert and Shetty, 2011) in transportation planning and location analysis look at issues from the perspective of the network or facility to the general population, whereas methods in time geography look from the perspective of the individual to these locations (Delfontaine et al., 2011; Neutens et al., 2012a; Neutens et al., 2012b; Neutens et al., 2012c; Scott and He, 2012). Using these three constraints along with the concept of the space-time prism in a theoretical framework provides a unique individualized viewpoint different from traditional, aggregated models.

Other geographers have added to the theoretical development of time geography since Hagerstrand presented the concepts in 1970. Kwan and Hong (1998) focus on the types of activities available to people and how people decide on visiting certain locations. They coin the term ‘feasible opportunity set’ (FOS), which refers to the activity locations that a person could reach within a given time period. Related to this is the ‘cognitive opportunity set’ (COS), which is the term for all of the locations a person is aware of. The intersection of the COS and the FOS is the ‘cognitive feasible opportunity set’ (CFOS) which explains the locations that a person can reach and that they are aware of. Later, Ellegard (1999) introduces the terms ‘series’ and ‘group.’ A ‘series’ is a meeting between people who are partaking in some activity but do not know each other (Ellegard, 1999). A ‘group’ refers to people that know each other and are meeting for a specific purpose, with a goal in mind. Along with these terms, Ellegard (1999) also recommends using real-time use instead of added-time use to appropriately describe how people organize their activities throughout the day. After this, Yu (2006) clarifies and describes Miller’s classification of the types of social interaction that are now available due to changes in ICT. Miller (2003) creates four categories: ‘synchronous presence’ – physically meeting face-to-face, ‘asynchronous presence’ – physical communication in which two people are not present at the same time, ‘synchronous telepresence’ – virtual communication in which people are communicating at the same time, and ‘asynchronous telepresence’ – communication conducted in neither the same time or space (Miller, 2003). All communication and activity types can be categorized using these four groups including those carried out through electronic sources like cell phones or computers (Yu, 2006). The definitions of the types of social contact, the types of activities available to a person, and the new types of interactions available due to changes in ICT have all strengthened time geography’s theoretical framework. They allow researchers to better understand how individual humans interact on a day-to-day basis, which is fundamental in studying SIP and is the essence of time geography.

2.3 Methodological improvements

Even with a strong theoretical framework, time geography initially lacked the means for application due to limitations in technology and methodology. Since applications in time geography are mostly quantitative, many researchers have focused on improving the subdisipline’s methods (Miller, 1991; Miller, 2003; Yu and Shaw, 2008; Delfontaine et al., 2011; Scott and He, 2012; Neutens et al., 2012a; Farber et al., 2012). Miller (1991) was one of the first to explicitly state how a space-time prism could be used to measure accessibility. He creates the concept of the potential path area (PPA) which is the two-dimensional projection of the three-dimensional space-time prism (Miller, 1991). When the methods were presented, geographic information systems (GIS) were very limited, but improvements in GIS have allowed researchers to use the concepts in a more efficient manner. Although ArcGIS does not have an explicit space-time prism function, Yu and Shaw (2008) have created such a method for making space-time prisms within ArcGIS. The overlap of multiple prisms can be used to show where people meet in time and space (Yu and Shaw, 2008).

Other geographers (Delfontaine et al., 2011; Scott and He, 2012; Neutens et al., 2012a; Neutens et al., 2012b; Neutens et al., 2012c; Farber et al., 2012) have been applying these concepts and creating new methods through case studies. Delfontaine et al. (2011) use travel diary data to determine all the locations that citizens of Ghent, Belgium could feasibly reach. Using maximum distance traveled by each person and by using the locations and opening hours of public libraries within these distances, they create three approaches to reallocate the opening hours of the libraries: the utilitarian approach, the egalitarian approach, and the distributive approach (Delfontaine et al., 2011). After using these approaches, they measure the new levels of accessibility with Theil's inequality index (Delfontaine et al., 2011). Similarly, Neutens et al. (2012b) use travel diaries to conduct a study on the accessibility to government offices in Ghent, Belgium using each office's actual opening hours, and they measure the accessibility of sampled households to these facilities. The results of the study conducted by Delfontaine et al. (2011) reveal that the current method of opening hours of libraries is satisfactory, but Neutens et al. (2012b) show that a small percentage of the population does not have any feasible access to the government facilities. It is unlikely that this would have been discovered without using a time-geographic approach, especially since traditional models do not take into account capability constraints that are critically restricting. Taking a broader approach, researchers also measure accessibility to social options in general (Neutens et al., 2012c, Farber et al., 2012). This thesis implements methods similar to Neutens et al. (2012c) and Farber et al. (2012), therefore these two studies will be evaluated in further detail in the next section.

2.4 Measuring social interaction

Farber et al. (2012) conducted a landmark study in measuring SIP in *The social interaction potential of metropolitan regions: A time-geographic measurement approach using joint accessibility*. They created many theoretical city models with different residential and employment distributions to determine the SIP of living and working in different zones with the city (Farber et al., 2012). After completing the analysis using the theoretical city models, they conducted a short study using the Salt Lake City area (Farber et al., 2012). While the methods presented are indeed powerful, the article has several limitations, some of which the authors acknowledge. These limitations are in part due to the assumptions in the study; the authors assume a ninety minute time budget for conducting an activity, and they use multiple friction of distance coefficients on the entire study area to simulate the negative effect of distance on travel (Farber et al., 2012). Since the study was mostly theoretical, they leave out the "true" effect of distance due to individual capability constraints and congestion within the traffic network.

Neutens et al. (2012c) conduced a more practical study measuring SIP in the entire region of Flanders, Belgium, and the results reveal various patches of high SIP, some of which are close to city centers while others remain in the periphery. Like Farber et al. (2012), they assume a ninety minute time budget for conducting after work activities and use network travel times. Conversely, Scott and He (2012) use traffic analysis zones (TAZs) as an independent variable in their constrained destination choice model to simulate average travel times and how this affects the choice of certain locations over others. Likewise, Fang et al. (2012) focus on traffic patterns in evaluating bridge traffic in Wuhan, China using travel diary data. While Fang et al. (2012) seek to simply explain traffic flows and recommend alternative routes rather than measure SIP, their study also shows the immense effect of traffic on the ability to reach certain locations.

On one hand, the studies conducted by Farber et al. (2012) and Neutens et al. (2012c) go against the philosophy of time geography because they measure SIP for aggregated zones rather than for individuals. On the other hand, it would not be possible to conduct a study of such magnitude without some sort of aggregation. Nevertheless, the results of these studies reveal phenomena that would not have been discovered in traditional approaches to transportation and accessibility. For example, it has been shown that people can lack accessibility due to authority and coupling constraints while living relatively close to a facility. The methods presented by Farber et al. (2012) and Neutens et al. (2012c) are explained in more detail in the methods section of this thesis.

2.5 Time geography and urban form

As stated earlier, it is important to note that social interaction potential does not equate to social interaction realization (Farber et al., 2012). Time geographic studies do not necessarily explain how much people interact but how urban form and transportation structure inhibit or encourage social interaction. The results of most case studies in time geography make a strong case for high density and mixed land use, which has been recommended in urban planning for many years (Jacobs, 1961). Farber et al. (2012) suggest that a time geographic study could be implemented to find an ideal urban form enabling the highest levels of social interaction, but since land in cities is being intensely used already, it is doubtful that city structure could be greatly altered to fit a theoretical model. However, questions still remain on how the SIP of individual cities is affected by urban planning and policy. The next section describes the methods put forth by Farber et al. (2012) and how these methods are used.

CHAPTER III

METHODOLOGY

3.1 SIP Equations

The calculation of SIP is a measure of joint accessibility based on two individuals' work locations and home locations. It is the amount of time that two individuals can spend interacting at an activity location and still return home within a given time budget, and these results are summarized for work locations and home locations. Similarly, the equations are also used to find the most accessible activity locations given these constraints. The equations used in this thesis are those developed by Farber et al. (2012). The calculation of SIP for each zone is primarily dependent upon population, driving time to various home locations and work locations, and driving time to activity locations. These factors differ for each city based upon the distribution of work, home, and activity locations as well as that city's transportation network.

In the following equations, *i* represents the home location of one individual, *j* represents the work location of one individual, *q* represents the home location of a second individual, *r* represents the work location of a second individual, and *k* represents an activity location. Farber et al. (2012, 5) first define the amount of time that two individuals can spend at an activity location given limited time budgets:

$$A_{ij}^{k} = \begin{cases} t_{b_{ij}} - \left(t_{jk} + t_{ki}\right) & \text{if } t_{jk} + t_{ki} < t_{b_{ij}} \\ 0 & \text{otherwise} \end{cases}$$

Where A_{ij}^{k} = the amount of time spent in an activity at location
$t_{b_{ij}}$ = the time available for an activity
t_{jk} = the time it takes to travel from work to the activity location
t_{ki} = the time it takes to travel from the activity location back home

The function is defined piecewise, so if the amount of commuting time to and from an activity location exceeds the amount of time available for the activity, the value is set to 0. Since social interaction requires two individuals, the time spent conducting an activity between two people must be defined as shown below (Farber et al., 2012, 5):

Let $A_{ij}^{k_S} = t_{b_{ij}} + t_{jk}$ be the start time of the time window A_{ij}^{k}
$A_{ij}^{k_E} = t_{h_{ij}} + t_{ki}$ be the last moment of time an individual can be at location k before needing to begin his or her return trip home
$A_{qr}^{k_S} = t_{w_{qr}} + t_{rk}$ be the start time for A_{ij}^{k} at location k
$A_{qr}^{k_E} = t_{h_{qr}} + t_{kq}$ be the end time for A_{ij}^{k} at location k for an individual living at q and working at r

With these equations defined, the amount of time two individuals can spend in an activity is defined as follows (Farber et al., 2012, 5):

$$A_{ijqr}^{k} = \begin{cases} \min\left(A_{ij}^{k_E}, A_{qr}^{k_E}\right) - \max\left(A_{ij}^{k_S}, A_{qr}^{k_S}\right) \\ if \ \min\left(A_{ij}^{k_E}, A_{qr}^{k_E}\right) > \max\left(A_{ij}^{k_S}, A_{qr}^{k_S}\right) \\ \\ 0 \qquad\qquad\qquad otherwise \end{cases}$$

With the amount of activity time for two individuals to conduct an activity defined, the total amount of time two individuals can spend at G locations is (Farber et al., 2012, 5):

$$A_{ijqr} = \sum_{k \in G} A_{ijqr}^{k}$$

Now let $R = \sum_{i,j} r_{ij}$

Where R = the working population
r_{ij} = the number of workers living in zone i and working in zone j

Let $P_{ij} = \frac{r_{ij}}{R}$ be the percentage of workers in the metropolitan region that travel from zone i to zone j

$P_{qr} = \frac{r_{qr}}{R}$ be the percentage of workers in the metropolitan region that travel from zone q to zone r

The metric showing the SIP of an entire metropolitan region c is as follows (Farber et al., 2012, 5):

$$M_c = \sum_i \sum_j \sum_q \sum_r (A_{ijqr} P_{ij} P_{qr})$$

Using this metric with the other equations written above, Farber et al. (2012, 6) create four other metrics useful in measuring SIP:

$$M_{ci} = \sum_j \sum_q \sum_r (A_{ijqr} P_{ij} P_{qr})$$
$$M_{cj} = \sum_i \sum_q \sum_r (A_{ijqr} P_{ij} P_{qr})$$
$$M_{cij} = \sum_q \sum_r (A_{ijqr} P_{ij} P_{qr})$$
$$M_{ck} = \sum_i \sum_j \sum_q \sum_r (A_{ijqr}^k P_{ij} P_{qr})$$

M_{ci} represents the SIP of living in zone i of city c, M_{cj} represents the SIP of working in zone j of city c, M_{cij} represents the SIP of living in zone i and working in zone j, and M_{ck} represents the SIP "demand" at location k (Farber et al., 2012). Farber et al. (2012) use theoretical friction of distance coefficients to simulate the capability constraints of the general population through a doubly constrained gravity model. To capture individual differences that may occur, they settle on five different coefficients on which they conduct the entire study: 0.35, 0.25, 0.15, 0.05, and 0.01 (Farber et al., 2012).

Since this project is concerned with social interaction and an application of the above methods presented, only social meetings in which the individuals can spend a significant amount of time are considered. After experimentation with different time budgets and considering the size of the two urbanized areas, only if A_{ijqr}^{k} is equal to or greater than 45 minutes is the meeting between two individuals considered. The metric, when used in this way, does not merely count the number of locations that two individuals can reach. Neither does it sum up all possible meetings between two people including insignificant meetings of very short time. Only locations in which the two individuals can spend a significant amount of time are considered, but spending more time at a location is beneficial and taken into consideration in this model.

3.2 Commute-flow estimation

Since calculating SIP requires the percentage of workers traveling from each zone into every other zone, commute-flows must be calculated or collected. The Census Transportation Planning Products contain census tract-to-tract commute flows, but the 2010 data have not yet been released and 2000 data is outdated. Both Oklahoma City and Tulsa have undergone large changes in the transportation structure and have seen considerable construction in their urban areas.

Because of the lack in reliable data, commute-flows are estimated using a doubly constrained gravity model developed by Haider (2011). In this, commute flows are estimated based on the known origin and destination vectors (employment and residential populations) along with a set friction of distance coefficient. For both cities, the suggested value from *Travel Demand Modeling with TransCAD Version 5.0 User's Guide* (Caliper, 2008) is used: -0.123. Using known values for residential and employment population, the commute flows are calculated using an iterative algorithm in the statistical program "R." Numbered lines are inserted for reference purposes, and the code executed is shown below:

```
1.  x1<-matrix(c(),20,byrow=T); x1
2.
3.  aij<-matrix(c(),20,byrow=T) ; aij
4.
5.  beta<-0.123
6.  fij<-exp(beta*aij); fij
7.
8.
9.  of<-matrix(c(),20); of
10. df<-matrix(c(),1); df
11.
12.
13. o1<-rowSums(x1); print(o1)
14. d1<-colSums(x1); print(d1)
15.
16. dk<-df
17.
18. i=1
19.
20.
21. print(i)
22.
23. while (i<6)  {
24.
25. od.1<-of%*%dk; print(od.1)
26. odf.1<-od.1*fij; print(odf.1)
27. den.1<-rowSums(t(matrix(apply(fij, 1, "*", dk), nrow=nrow(x1),
28. ncol=ncol(x1)))); print(den.1)
29.
30. tij.1<-odf.1/den.1; print(tij.1)
31.
32. o2<-rowSums(tij.1); print(o2)
33. d2<-colSums(tij.1); print(d2)
34.
35. rj.1<-df/d2; print(rj.1)
36. rjf.1<-abs(rj.1-1); print(rjf.1*100)
37. d3<- dk*rj.1;    print(d3)
38. dk<-d3
39. i<-i+1
40. }
```

In line 1, the origin-destination matrix (the distance between work and home locations in miles) is entered and declared as *x1*. This matrix is obtained using the OD-Cost Matrix function within Network Analyst in ArcGIS. In line 3, the origin-destination travel times are entered and declared as variable *aij*. Likewise, this matrix is obtained using the OD-Cost Matrix function within Network Analyst in ArcGIS.

Line 5 is the declaration of *beta*, the friction of distance coefficient; the value 0.123 is selected for both Tulsa and Oklahoma City. In line 6, the variable *fij* is the result of the exponential function using *beta*. The variables *of* and *df* in lines 9 and 10, respectively, represent the origin and destination vectors (the work and residential populations). Subsequent lines execute the model using different matrix functions which are all based on the original data and the declared friction of distance coefficient. The “while” loop runs six times, ending when there is negligible change from one iteration to the next.

The end result is a matrix which is imported into Microsoft Excel using the Text Import Wizard. The values in the matrix are the predicted commute flows in number of people. Since the SIP model is concerned with percentage commute flows, each value in the matrix is divided by the total employment population for each city. These matrices are shown in the appendix.

3.3 SIP calculation

Microsoft Excel and other spreadsheet programs are not sufficient for executing the iterative calculations necessary for this project. Therefore the scripting language Python is used to calculate SIP. Like the sample in the previous section from “R,” line numbers are included below for reference. In this section and subsequent sections, the letters *r*, *w*, and *h* are used in combination with a number to represent restaurant locations, work locations, and home locations, respectively, with their corresponding locations. While variables shown below have lengthy and seemingly cumbersome names, these are used to keep the nomenclature consistent with the equations used by Farber et al. (2012). This script runs separately for Oklahoma City and Tulsa using each city’s respective data.

```
import numpy
from numpy import *

tkj_original_ = [()]

tki_original_ =[()]

P_ = [()]


tkj_original = numpy.matrix(tkj_original_)
tqk_original = tkj_original
tki_original = numpy.matrix(tki_original_)
tkr_original = tki_original
```

```
P = numpy.matrix(P_)

t = 90
list = []
homelist = []
worklist = []
homelist2 = []
worklist2 = []
counter1 = 0
counter2 = 0
AijqrPijPqr = 0

for u in range(50):
  tkj = (tkj_original[u])
  tqk = (tqk_original[u])
  tki = (tki_original[u])
  tkr = (tkr_original[u])
  AKSij = tkj
  AKSqr = tqk
  AKEij = numpy.array(t - tki)
  AKEqr = numpy.array(t - tkr)
  for x in range(20):
        for y in range(20):
            for z in range(20):
                for w in range(20):
                    val1 = max(AKSij[0, x], AKSqr[0, y])
                    val2 = min(AKEij[0, z], AKEqr[0, w])
                    AKijqr = val2 - val1
                    if AKijqr > 45:
                        AijqrPijPqr = ((P[x,z]) * (P[y,w]) * AKijqr)
                        list.append(AijqrPijPqr)
                        AijqrPijPqr = 0
                    counter1 = counter1 + 1
        print ("RESTAURANT", u, "\n", "Location:", "w", x)
        print ("SIP:", sum(list))
        print ("\n")
        worklist.append(sum(list))
        worklist2.append(sum(list))
        list = []
    for z in range(20):
        for y in range(20):
            for x in range(20):
                for w in range(20):
                    val1 = max(AKSij[0, x], AKSqr[0, y])
                    val2 = min(AKEij[0, z], AKEqr[0, w])
                    AKijqr = val2 - val1
                    if AKijqr > 45:
                        AijqrPijPqr = ((P[x,z]) * (P[y,w]) * AKijqr)
                        list.append(AijqrPijPqr)
                        AijqrPijPqr = 0
                    counter2 = counter2 + 1
       print ("RESTAURANT", u, "\n", "Location:", "h", z)
       print ("SIP:", sum(list))
       print ("\n")
       homelist.append(sum(list))
       homelist2.append(sum(list))
       list = []

print ("OKC WORK SIP:", sum(worklist))
print ("OKC HOME SIP", sum(homelist))
```

```
75. print ("WORK LIST LENGTH:", len(worklist2))
76. print ("WORK LIST:", worklist2)
77. print ("HOME LIST LENGTH:", len(homelist2))
78. print ("HOME LIST:", homelist2)
79. print ('Count1:', counter1)
80. print ('Count2:', counter2)
81. print ("\n")
82. print ("END")
```

Lines 1 and 2 import the Numpy module that is used to make the SIP calculation since Python alone does not have does not have the capability to execute matrix multiplication. Line 4 declares an array that contains driving times from work locations to restaurant locations, and line 6 declares an array that contains driving times from restaurant locations to home locations. These arrays are, in effect, lists containing lists with each value separated by a comma and each list denoted with parentheses. The values are listed in sets based on the restaurant location number, so in *tkj_original_*, the first value is the driving time from *w1* to *r1*, the second value is the driving time from *w2* to *r1*, the third value is the driving time from *w3* to *r1*, and so on. Likewise, the twenty-first value is the driving time from *w1* to *r2*, the twenty-second value is the driving time from *w2* to *r2*, the twenty-third value is the driving time from *w3* to *r2*, and so on. In *tki_original_*, the correspondence is the same except that the driving times are from restaurant locations to home locations. The full arrays used in lines 4 and 6 are not listed here since these arrays both have an extensive number of elements.

Line 8 declares an array that represents the commute flows from each work location to each home location described previously. It is also a list within a list with each value separated by a comma and each list denoted with parentheses. These values are very small, since the total one hundred percent is divided up between many possible combinations. The first value in the list represents the percentage of the population commuting from *w1* to *h1*, the second value in the list represents the percentage of the population commuting from *w1* to *h2*, and so on.

In lines 11, 13, and 15 arrays are converted to matrices using Numpy. Lines 11 and 13 each produce a true matrix, as opposed to simply arrays containing lists. This prepares the data for the actual SIP calculation. Lines 12 and 14 are variable declarations that simply copy the matrices of the driving times from work locations to restaurant locations and the driving times from the restaurant locations to home locations. This is carried out since the calculation involves two individuals, and the possible work, home, and restaurant locations are the same for both individuals.

Line 17 is the declaration of *t*, the time budget for after-work activity and travel. Lines 18 – 22 declare the lists used in the nested "for" loops and sets them as empty. Lines 23 and 24 declare the variables *counter1* and *counter2* which are used in the nested "for" loops to count how many times the loops run. Line 25 is the declaration of variable *AijqrPijPqr* which holds each calculated SIP value in the nested "for" loops.

Lines 27 – 71 are used to calculate SIP. Lines 36 – 53 calculate and summarize the results for work locations, and lines 54 – 71 calculate and summarize the results for home locations. Line 27 starts the nested "for" loops. By running the loop for each element in range(50), the loop is executed once for each restaurant location. Lines 28 – 33 reference the matrices containing driving time from work locations to restaurant locations and from restaurant locations to home locations. Since these are matrices, referencing the [*u*] element refers to the first row in the matrix, and every row represents the driving time from each work location to a single restaurant location or from a single restaurant location to each home location.

Lines 34 and 35 declare the variables *AKEij* and *AKEqr*, the time budget, *t*, minus the travel time from work locations to restaurant locations and from restaurant locations to home locations, respectively. In lines 36 – 39, *x* represents the work location of individual 1, *y* represents the work location of individual 2, *z* represents the home location of individual 1, and *w* represents the home location of individual 2. Since this project takes into account joint accessibility, four nested "for" loops are created to account for all possible work-home location combinations between the two individuals. In line 40, *val1* is computed by selecting the greater value between *AKSij* and *AKSqr*. Since these two are actually matrices, the elements in the (0, *x*) and (0, *y*) positions are compared, selecting the greater driving time from the work locations to the restaurant location. In line 41, *val2* is computed by selecting the lesser value between *AKEij* and *AKEqr*. Likewise, these are also matrices, and the elements in the (0, *z*) and (0, *w*) positions are compared, selecting the lesser driving time from the restaurant location to the home locations. In each comparison, the work and home locations can vary, but the restaurant cluster location will remain the same until the original "for" loop (started in line 27) is complete.

In line 42, *AKijqr* is computed by subtracting *val1* from *val2*. This value represents the amount of time that a pair of individuals can interact at a given restaurant cluster location. In the next line, line 43, unfeasible meetings are ruled out. If potential interaction time is greater than 45 minutes, the interpreter proceeds to lines 44 – 46. In line 44, *AijqrPijPqr* is computed by multiplying *AKijqr* by the percentage of the working population commuting from *x* to *z*, *Pij*, and by the percentage of the working population commuting from *y* to *w*, *Pqr*. Since *Pij* and *Pqr* are matrices, the elements in the (*x, z*) and (*y*, *w*) positions are selected. After this computation, the value for *AijqrPijPqr* is stored in a list in line 45. The value for *AijqrPijPqr* is reset in line 46.

In line 47 the value for *counter1* is increased by one. Lines 48 – 50 are then executed outside of the three previous three "for" loops and prints a summary of the results for each work location. A sample of three consecutive, printed results for Oklahoma City are shown below, and an exhaustive summary is available in the appendix:

```
RESTAURANT 2
 Location: w 15
SIP: 0.0


RESTAURANT 2
 Location: w 16
SIP: 0.000473826429853


RESTAURANT 2
 Location: w 17
SIP: 0.000271779142183
```

The result for r*2 - w15* shows a value of 0, meaning that none of the home combinations with this work location are reachable with all of the possible work-home location combinations of the second individual. The SIP values for *r2 – w16* and *r1 – w17* are very small, which is typical in this study, since many of the values in the commute flows matrix are small. Multiplying two of these small values together often produces a negligible amount of SIP, and this is especially common for zones on the periphery of the urbanized areas of the two cities.

Even though line 48 is already used to summarize and reduce the total number of records (from 8,000,000 to 1,000), the number of records is still fairly large. To reduce this number for further summarization, line 51 stores the sum of the SIP for each work location in *worklist*. This is still executed within the original “for” loop, so each value in this list gives the specific SIP for each restaurant cluster – work location combination. Lines 36 – 53 and 54 – 71 run through the same basic processes, except that lines 54 – 71 summarize results for home locations as opposed to work locations. After these two sections run, lines 73 – 82 print the results from the list created in lines 48 and 69. In lines 73 and 74, the total SIP for the urbanized area is computed by adding all of the values in both *worklist* and *homelist*. Every time the program runs, these two values should be equal. This check is used to ensure that the program has run accurately, and in order to further ensure accuracy, the lengths of the *worklist* and the *homelist* are printed in lines 75 and 78. Along with this, the two counters, *counter1* for work locations and *counter2* for home locations, are printed and compared to the total possible number of combinations.

Once the script has run, the results for work locations, home locations, and restaurant locations are summarized in Excel and then mapped and compared in both cities. Along with this, the patterns within the two cities are compared. Moran’s *I*, a measure of spatial autocorrelation, is used along with standard deviation to discuss issues of disparity within the two cities. Moran’s *I* is an index of global spatial autocorrelation, so each feature type returns only index value. These values range between -1 and 1, where -1 indicates a perfect juxtaposition of high and low values (like a checkerboard), 1 indicates a perfect positively correlated pattern, and a zero value indicates a random pattern. The null hypothesis in Moran's *I* is that the pattern is perfectly random. A small *p*-value indicates a small chance of committing a type-I error, meaning that the pattern is statistically dispersed or spatially correlated. With these methods established and the necessary safeguards in place within Python, SIP can effectively be calculated with the proper dataset. The next section describes how data are collected, aggregated, and prepared.

CHAPTER IV

DATA COLLECTION AND PREPARATION

4.1 Overview

Data for this project are collected in several categories: boundary lines for spatial units, transportation network, population and employment information, and restaurant data. First, the boundary lines for spatial units provide base layers for maps as well as the spatial data used in the project. Second, since the SIP calculation takes into account driving time, network datasets must be created and used. Along with this, the doubly-constrained gravity model requires both driving time and distance, which the network datasets are used for as well. Third, population and employment information is required for the calculation of SIP, not to mention that population is a significant determinant of SIP in any zone. Last, the calculation of SIP requires activity locations. Since one of the purposes of this project is to introduce more realism into the calculation of SIP, actual activity locations are used. The activity location chosen for this project are restaurants. These data provide a solid basis for the execution of the methods in this project.

4.2 Boundary lines for spatial units

The boundary lines for spatial units in this project come from a variety of sources. The state, county, urbanized area, census tract, and zip code shapefiles are obtained through the USCensus TIGER files. The state of Oklahoma shapefile is obtained from the “States and Equivalent” layer type, Oklahoma is selected with the pointer, and a new layer is created. The counties in Oklahoma are obtained from the "County and Equivalent" layer type, counties in Oklahoma are selected by using the Select by Attribute function, and a new layer is created.

Due to improvements in transportation and the subsequent suburbanization of cities in the United States, central cities are not separate, isolated units that independent from suburbs. Rather, metropolitan areas in the United States are complex intertwined units with central cities relying on suburbs and vice versa (Hollar, 2011). This is exhibited in part by the number of people who live and work in different regions within metropolitan areas. Because of this, the whole urbanized areas of Tulsa and Oklahoma City are considered under this study. These areas are obtained from the "Urban Areas" layer type in the US Census TIGER files, the urban areas of Oklahoma City and Tulsa are selected using the pointer, and an individual layer is created for both cities. Census tracts are obtained from the "Census Tract" layer type, and only census tracts in Oklahoma are considered. Census tracts serve as the basis for residential locations in this study. These tracts are then modified by using the "Clip" tool in ArcGIS. Using census tracts as the Input Features and the Urban Area as the clip features, the census tracts are clipped so that only those within the urbanized boundary are considered. This is essential because including all of the full census tracts that touch the urbanized boundary nearly doubles the size of the study area, which would include many residential locations that would not have much association with the central city. This would also greatly exaggerate driving times to outside zones, resulting in a very small or even zero-value SIP in many peripheral zones, further increasing the SIP of zones near the center of the city.

Since daytime employment information is not available at the census tract level, zip codes are used as the basis for employment locations in this study. Zip code data are typically not ideal for research since they vary greatly in size and frequently change, but in this case, the smaller zip codes actually have higher employment levels, and daytime employment information is only available at this level of aggregation. With the size and shape of census tracts and zip codes being much different, the residential locations and employment locations are not the same in this study. However, this difference does not hinder the model, and the interpretation of the results is the only aspect that needs modification. Because of the size and shape of zip codes around the urbanized area, only zip codes with a centroid lying within the urbanized area are considered. The centroid is created by first creating a field for latitude and a separate field for longitude in ArcGIS. Both are computed using the "Calculate Geometry" feature, selecting decimal degrees as units. This layer is exported, and the .dbf of the layer is saved as a Microsoft Excel Worksheet (.xlsx). This table is then added to the ArcMap document, and the *x-y* data of this file is added to the map. With this layer overlaying the urbanized boundary and zip codes of each city, the centroids are filtered out using the "Select by Location" feature, and zip codes are filtered out using the "Select by Location" feature again.

In the original dataset, there are 292 census tracts in the Oklahoma City urbanized area and 209 census tracts in the Tulsa urbanized area. In Oklahoma City there are 37 zip codes in the urbanized area and in Tulsa there are 31 zip codes in the urbanized area. Using all of these observations is an option, but many observations will lead to lengthy calculations. Since this project is concerned with joint accessibility, the problem of having many observations is compounded. With 292 residential locations (census tracts), 37 employment locations (zip codes), and 1,633 activity locations (the restaurant locations described below), in Oklahoma City this would require 292 x 292 x 37 x 37 x 1,633 calculations for a total of 190,614,237,328. Calculations of this magnitude are not feasible without a super computer.

In order to reduce the number of residential locations and employment locations and allow for easy comparison, the dataset is reduced to 20 residential locations and 20 employment locations in both Oklahoma City and Tulsa. For each census tract and zip code, two fields are created titled "latitude" and "longitude." Using the calculate geometry feature, the *y* centroid and *x* centroid of each polygon is computed and placed in the latitude and longitude fields, respectively. These latitude and longitude fields are used as criteria in the ArcGIS Grouping Analysis, grouping locations based on Euclidean distance. The "K_NEAREST_NEIGHBORS" option is selected, ensuring that each point is a feature of at least one other point. After this, boundaries are dissolved using the ArcGIS Dissolve function, and the population values from the table are added together. The original census tracts in the urbanized areas are shown in Figures 4.1 and 4.3 for Oklahoma City and Tulsa, respectively, and the aggregated home locations are shown in Figures 4.2 and 4.4. Original zip codes in the urbanized areas are shown in Figures 4.5 and 4.7, and aggregated employment zones are shown in Figures 4.6 and 4.8.

4.3 Transportation network

A person's ability to interact with others after working hours is largely dependent upon his/her commute time. Cities in the United States have varied mean commute times varying from less than 15 minutes – like in Great Falls, Montana and Lewiston, Idaho – up to around 35 minutes, like in New York City (US Census, 2011). Citizens of Oklahoma City and Tulsa have very comparable figures for mean travel time to work at 20.2 minutes and 18.3 minutes, respectively (US Census, 2014). In this project, network datasets and the Network Analyst function in ArcGIS are used to calculate commute times. The network datasets are compiled using the US Census's TIGER files. The "All roads" shapefile is available at the county level only, and the urbanized areas of Oklahoma City and Tulsa both span multiple counties. All the roads in Oklahoma County, Logan County, Cleveland County, and Canadian County are used for the network dataset of the Oklahoma City urbanized area, and all the roads in Tulsa County, Waggoner County, Creek County, Osage County and Rogers County are used for the network dataset of the Tulsa urbanized area. All of the surrounding counties' roads are merged into one shapefile for Oklahoma City and one shapefile for Tulsa.

In order to properly execute the model, the SIP calculation requires driving time between each location, and the doubly-constrained gravity model requires both driving time and distance. Distance is calculated for each road segment by creating a new field and using the ArcGIS "calculate geometry" option. Distance is calculated in miles. ArcGIS cannot directly calculate

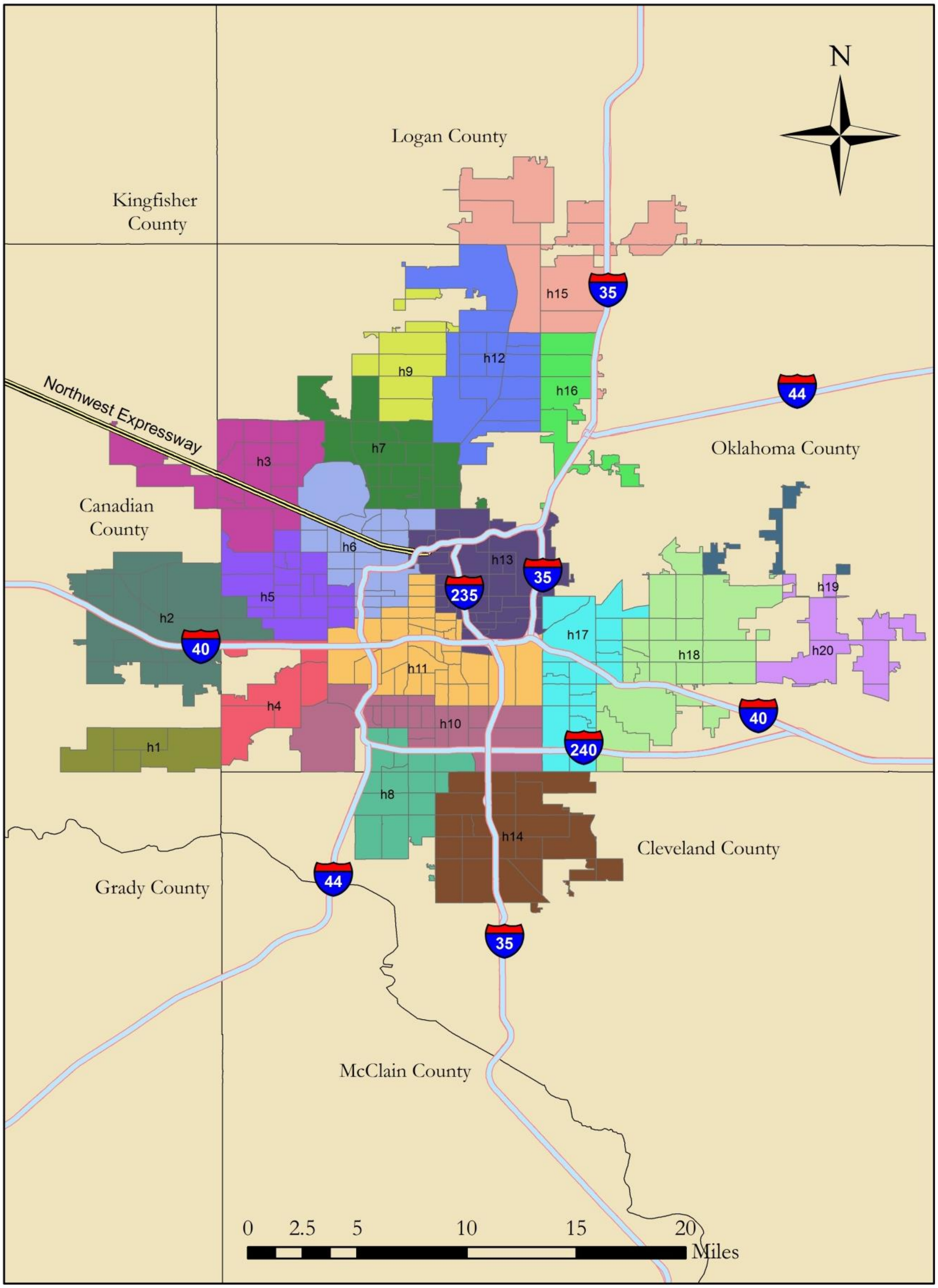

Figure 4.1: Grouped census tracts in the Oklahoma City urbanized area

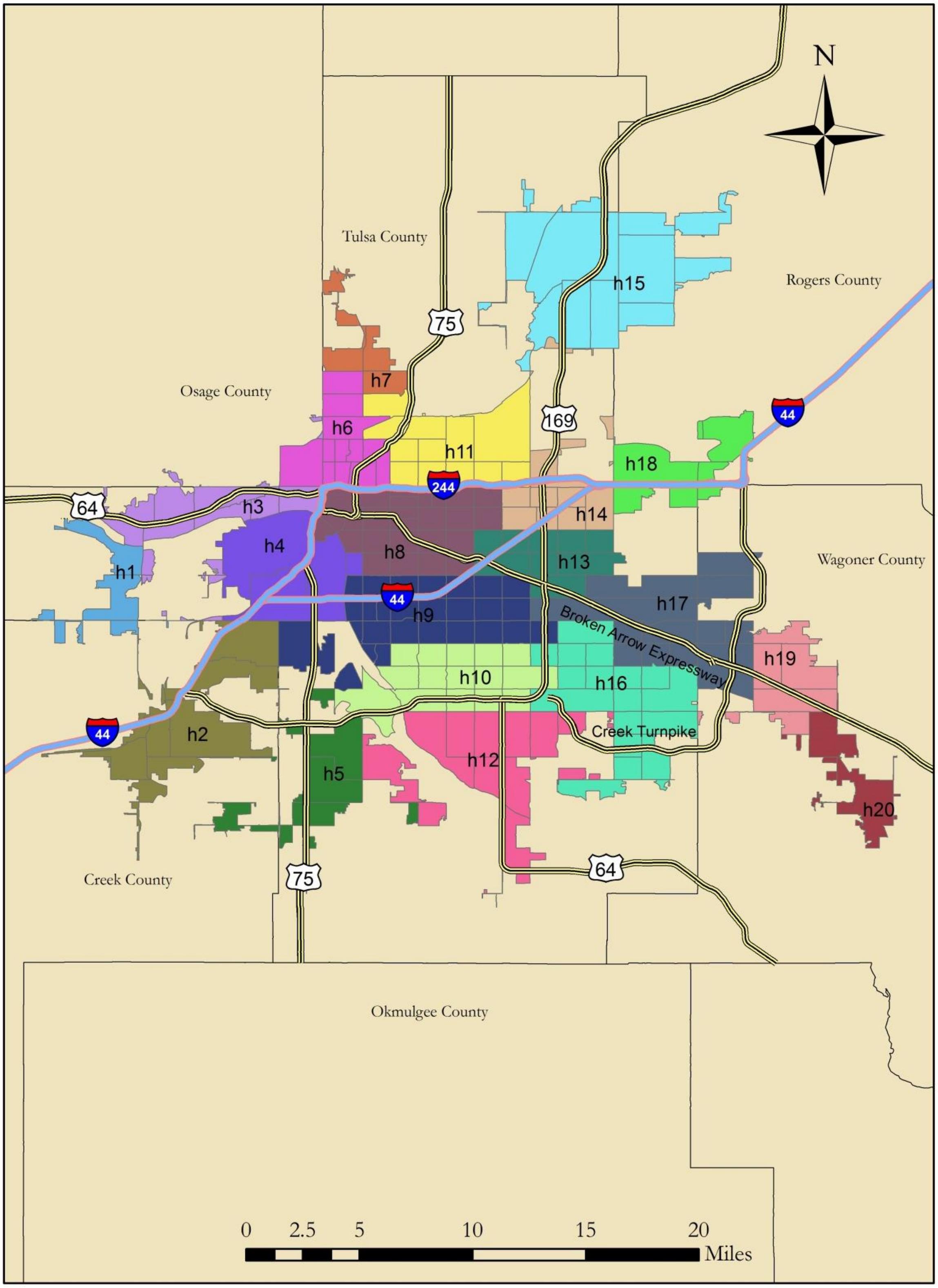

Figure 4.2: Grouped census tracts in the Tulsa urbanized area

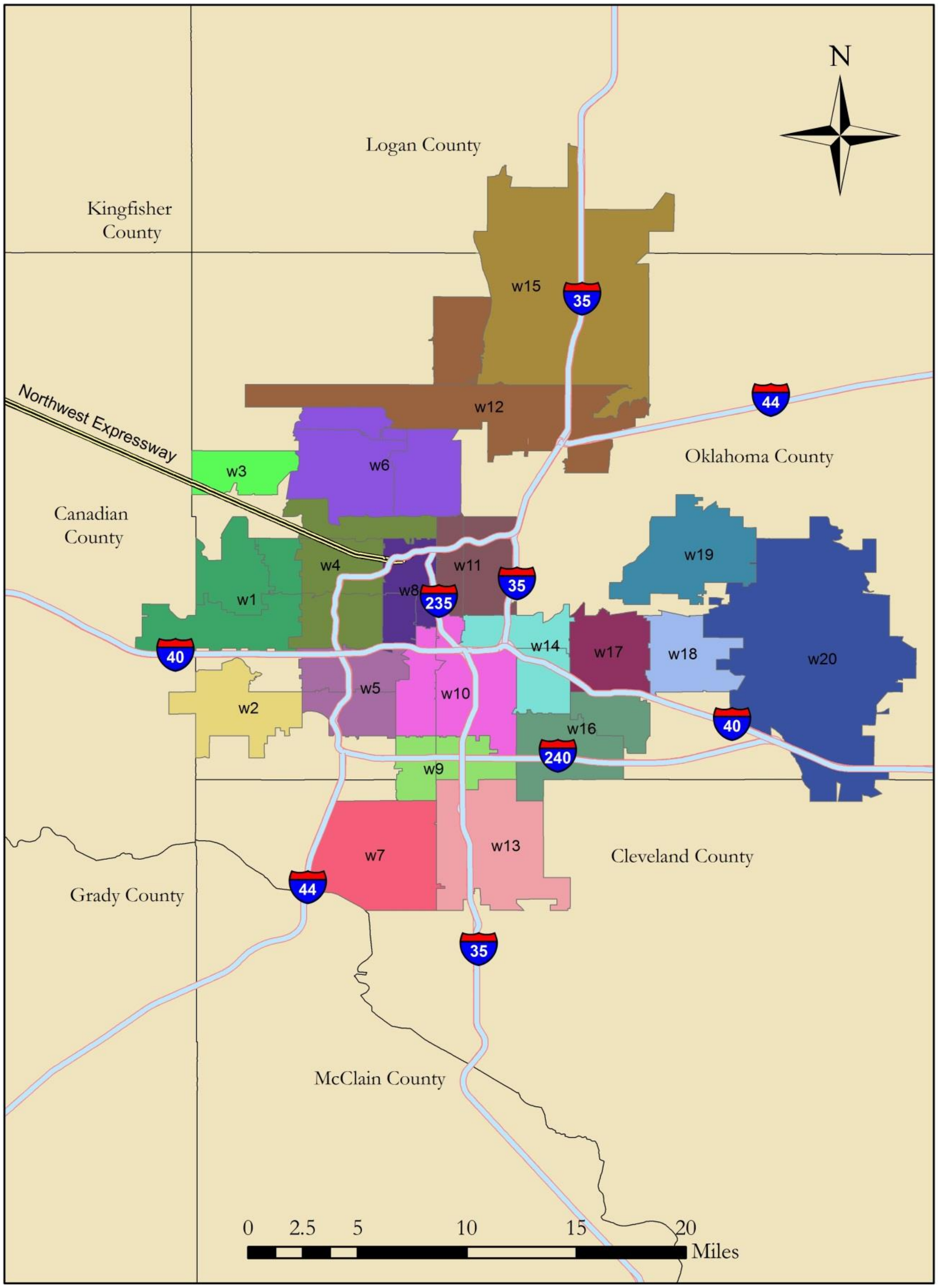

Figure 4.3: Grouped zip codes in the Oklahoma City urbanized area

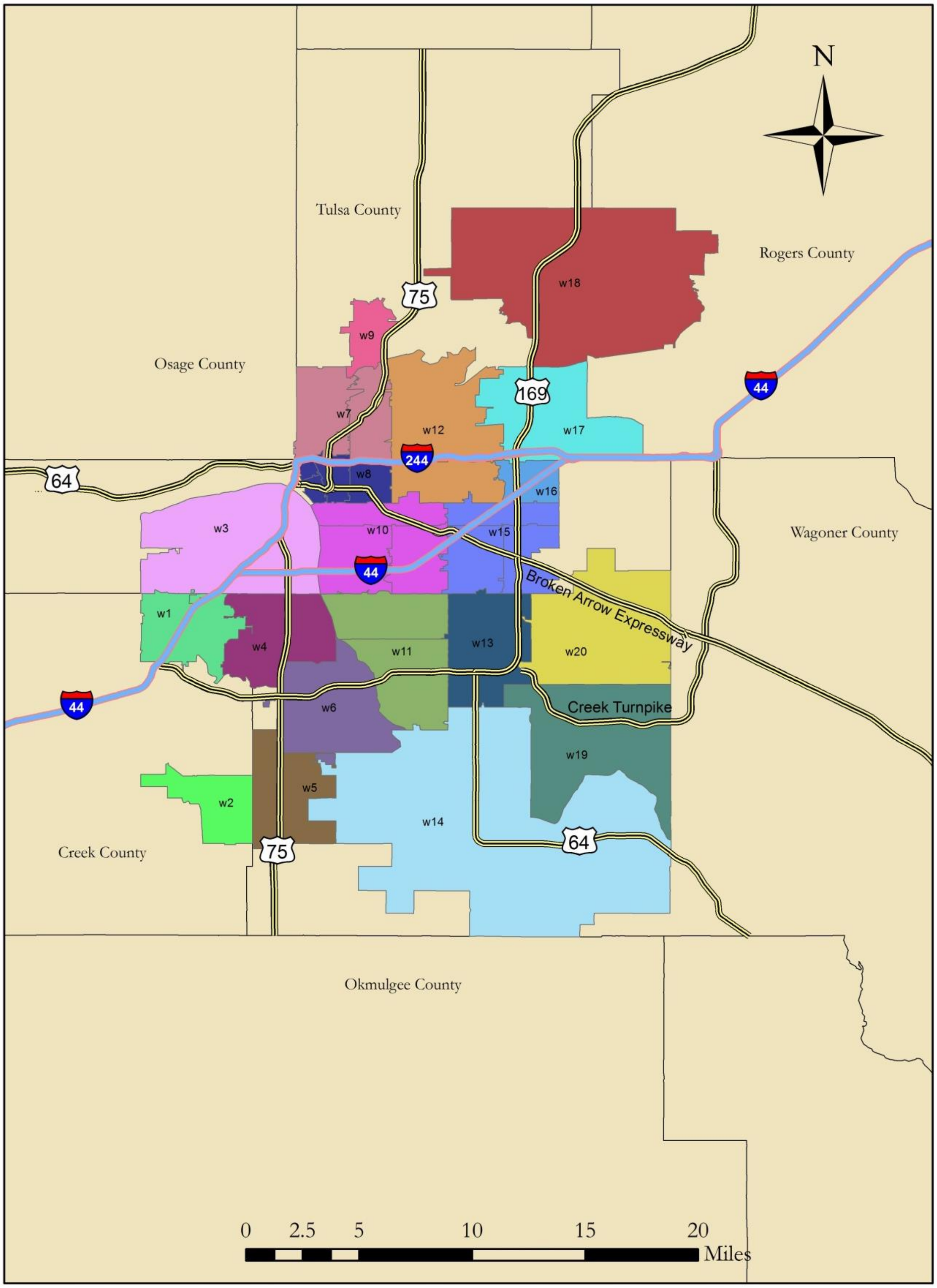

Figure 4.4: Grouped zip codes in the Tulsa urbanized area

driving time, but each segment has a letter indicating road type listed under the “RTTYP” column in the .dbf table. Table 4.1 shows the various coded listing of each road type and its assumed speed.

RTTYP	Road Type	Assumed Speed Limit (MPH)
I	Interstate	60
U	US Highway	50
S	State Highway	45
C	County Road	40
M	Local Street	25
Blank	Local Street	25

Table 4.1: Road types in network datasets

A number of segments are listed as blank under “RTTYP.” Most of these are very short segments, much less than one mile. Many are located close to neighborhoods and other streets listed as “M” (local streets), so these blank listings are assumed to have the same speed as local streets.

The speeds assumed are less than most actual listed speed limits because several items are not accounted for in the network dataset calculations such as time spent stopped in traffic, time spent stopped at traffic lights, excess time making turns, and other forms of impedance. For a project calculating theoretical values of SIP, these rough assumptions are sufficient. Numerous test calculations were performed and compared with Google Maps driving directions, and the results of the two methods proved very comparable.

The network datasets used in calculating SIP are created by using “time” as the impedance. Turns are modeled, segments are connected using “any vertex,” elevation is ignored, and driving directions are not produced. Since the doubly-constrained gravity model accounts for both time and distance, another network dataset is created designating “distance” as impedance.

4.4 Population and employment

Population and employment information come from two sources: (1) the 2012 American Community Survey 5-year estimate “Total Population” table at the census tract level is used for residential population, and (2) the 2011 Zip Code Business Patterns from the US Census is used for employment population. Since the purpose of these values is to predict commuting patterns from each employment zone into each residential zone, the alternative is to bypass residential and employment information and use the 2000 Census Transportation Planning Products for tract-to-tract commute flows (Farber et al., 2012). This would remove the need to use any zip code data, but these data from 2000 are outdated; both Tulsa and Oklahoma City have undergone extensive changes in their transportation and employment structure over the last fourteen years as mentioned earlier. The 2010 Census Transportation Planning Products tract-to-tract commute flows would be another alternative, but these have not yet been released. Since predicting trip generation is not the main purpose of this study, census tract population information and zip code employment information are sufficient. This information is joined to both census tract and zip code shapefiles.

Before executing the gravity model, either the origin or destination vectors must be adjusted since reported employment populations in Oklahoma City and Tulsa are much different than the residential populations as shown in Table 4.2 below:

City	Residential Population	Employment Population
Oklahoma City	963,181	319,844
Tulsa	742,912	284,078

Table 4.2: Population figures

This is due to a number of reasons. First, not all of the residential population is of working age. Second, some of those in the working age population either stay at home to work or do not work. Third, some of those in the urbanized population commute outside of the urbanized area for work. Since this project is concerned with after-work trips, the employment population levels are used to adjust the residential population values. For both cities, the total employment population is the new assumed total residential population, and the individual residential population values are adjusted based on each zone's percentage of total residential population as shown in Tables 4.3 and 4.4.

Zone No.	Residential Population	% of Residential Population	Adjusted Residential Population
h14	80,559	0.0858	27,435
h3	70,695	0.0753	24,076
h11	69,018	0.0735	23,505
h12	64,991	0.0692	22,133
h2	61,386	0.0654	20,905
h6	59,963	0.0638	20,421
h8	59,957	0.0638	20,419
h18	58,284	0.0621	19,849
h5	56,657	0.0603	19,295
h7	56,425	0.0601	19,216
h10	54,811	0.0584	18,666
h17	51,089	0.0544	17,399
h15	40,470	0.0431	13,782
h13	40,294	0.0429	13,722
h9	33,218	0.0354	11,313
h20	26,626	0.0284	9,068
h16	21,712	0.0231	7,394
h1	17,395	0.0185	5,924
h19	7,383	0.0079	2,514
h4	5,248	0.0056	1,787

Table 4.3: Oklahoma City residential population adjustment

Zone No.	Residential Population	% of Residential Population	Adjusted Residential Population
h1	16,969	0.0228	6,489
h2	30,253	0.0407	11,568
h3	30,875	0.0416	11,806
h4	16,685	0.0225	6,380
h5	26,597	0.0358	10,170
h6	45,974	0.0619	17,580
h7	9,852	0.0133	3,767
h8	80,111	0.1078	30,633
h9	78,740	0.1060	30,109
h10	57,651	0.0776	22,045
h11	32,173	0.0433	12,302
h12	43,189	0.0581	16,515
h13	50,334	0.0678	19,247
h14	21,482	0.0289	8,214
h15	57,426	0.0773	21,959
h16	61,298	0.0825	23,439
h17	41,172	0.0554	15,744
h18	12,294	0.0165	4,701
h19	10,980	0.0148	4,199
h20	18,857	0.0254	7,211

Table 4.4: Tulsa residential population adjustment

4.5 Restaurant data

Restaurants are used as activity locations in this project because they are commonly used for social interaction, their locations are numerous in urban areas, and their authority constraints are generally not restrictive for day-to-day interaction. Many restaurants stay open until 9:00 PM or 10:00 PM, allowing for the working population to reach them with plenty of time available for social interaction. According to YellowPages.com, there are roughly 2,553 restaurants in the vicinity of the Oklahoma City urbanized area and 1,859 restaurants in the vicinity of the Tulsa urbanized area. Extracting restaurant information manually would be a difficult task, especially considering that latitude and longitude are not visible on the web site; locational information is stored in the underlying HTML. A web scraping program called “Yello” is used in this project to extract information about each restaurant such as the business name, address, latitude, longitude, and restaurant category.

Yello automatically extracts information that spans multiple webpages on YellowPages.com based on set criteria. This is advantageous to a researcher because it allows for the inclusion of much more realism in the study. As opposed to using only zonal centroids, this web scraper allows for inclusion of all activity locations of a particular type. However, when searching for restaurants in each urbanized area, there are many locations that are left out due to the limited area of the search. For example, when retrieving restaurant locations in Oklahoma City proper, the web scraper will extract all of the restaurants within the city limits of Oklahoma City but only a handful of restaurants in the surrounding suburbs. Likewise, when retrieving restaurants by searching for Yukon, the web scraper will extract all of the restaurants in Yukon but only a handful of restaurants in Mustang, Oklahoma City, and other townships. Because of this, separate queues are created for each suburb within the urbanized areas.

In the Oklahoma City area, restaurant information is collected for Bethany, Edmond, Jones, Midwest City, Moore, Mustang, Nichols Hills, Nicoma Park, Oklahoma City, Piedmont, Spencer, and Yukon. In the Tulsa area, restaurant information is collected for Bixby, Broken Arrow, Catoosa, Claremore, Jenks, Oakhurst, Owasso, Sand Springs, Sapulpa, Tulsa, and Turley. As stated earlier, retrieving restaurant information in a town also produces results for some restaurants in neighboring towns. This creates significant overlap in the data. Compiling the results from each suburb with the central city produces 22,302 locations in the vicinity of the Oklahoma City area and 13,957 locations in the vicinity of Tulsa.

Given the overlap of locations and the sheer volume of data, duplicates must be removed efficiently. Due to the fact that there are many chain restaurants within both cities, duplicates cannot be removed based on restaurant name alone. Removing duplicates is completed in Microsoft Excel using the "Remove Duplicates" feature based on a concatenation of latitude, longitude, and full address. Despite the removal of many duplicates, some locations still had to be removed manually. Occasionally the same restaurant is listed with two different addresses or one component such as latitude or longitude is missing.

Next, the dataset is delimited to sit-down restaurants. On YellowPages.com, each restaurant contains up to three categories. Those restaurants labeled as "Take Out Restaurants" and/or "Fast Food Restaurants" are removed, and a list is compiled of those that were taken out. Any obviously similar restaurants to those in the list are also removed. For example, Taco Bell is listed as a "Restaurant," "Mexican Restaurant," and "Fast Food Restaurant," but Taco Mayo is only listed as a "Restaurant" and "Mexican Restaurant." Since the two serve a similar purpose and offer very similar menu items, Taco Mayo restaurants are also removed from the study area. Likewise, since Subway restaurants are removed, Quiznos restaurants are also removed. For consistency, any restaurant that is removed from the Oklahoma City area is also removed from the Tulsa area and vice versa.

4.6 Restaurant aggregation

The restaurant extractions using YellowPages.com yield many results outside of the study area. The restaurant locations outside the study area are not considered with the exception of those located within 5 miles of the edge of each study area in order to account for the "edge effect." In order to build a strong model, the locations just outside of the study need to be considered, since these are feasible activity locations, especially for those living on the edge of the urban areas. Using the buffer function in ArcGIS and selecting only those restaurants falling within the buffer and the urbanized area reduces the number of sit-down restaurants in the Oklahoma City area to 1,633 (see Figure 4.5) and reduces the number of sit-down restaurants in the Tulsa area to 1,213 (see Figure 4.7).

Because of the large number of possible activity locations, the difficulty these numbers create in massive calculations, and the fact that the model is very sensitive to the number of activity locations (Farber et al. 2012), the number of restaurant locations are reduced to an equal

50 restaurant clusters in each city again with the ArcGIS Grouping Analysis using latitude and longitude of each restaurant as criteria (see Figures 4.6 and 4.8). Since there is a greater number of restaurant locations than zip codes or census tracts, more restaurant clusters are used than employment and residential locations. After this, the average latitude and longitude of each group is computed in Excel, yielding one latitude-longitude coordinate for each group. While individual clusters have different frequencies of restaurants, this aggregation is required for comparison between the two cities. Therefore, each cluster counts as only one location. In Figures 4.5 and 4.7, the color of each restaurant indicates its assigned group from the Grouping Analysis. Restaurants in close proximity should be colored the same.

With these data collected and prepared, the model is ready for implementation. The network dataset is used to calculate driving times and distances needed for the doubly constrained gravity model. Using this information with population and employment data in R yields the percentage commute-flow estimations. These values are used in Python along with driving times from work locations to restaurant cluster locations to home locations, and the results are summarized within the program as described in the *Methods* chapter. Once these results are derived, they are summarized within charts in Excel. These charts are used in the next chapter along with a number of maps and statistical calculations to describe the patterns of SIP.

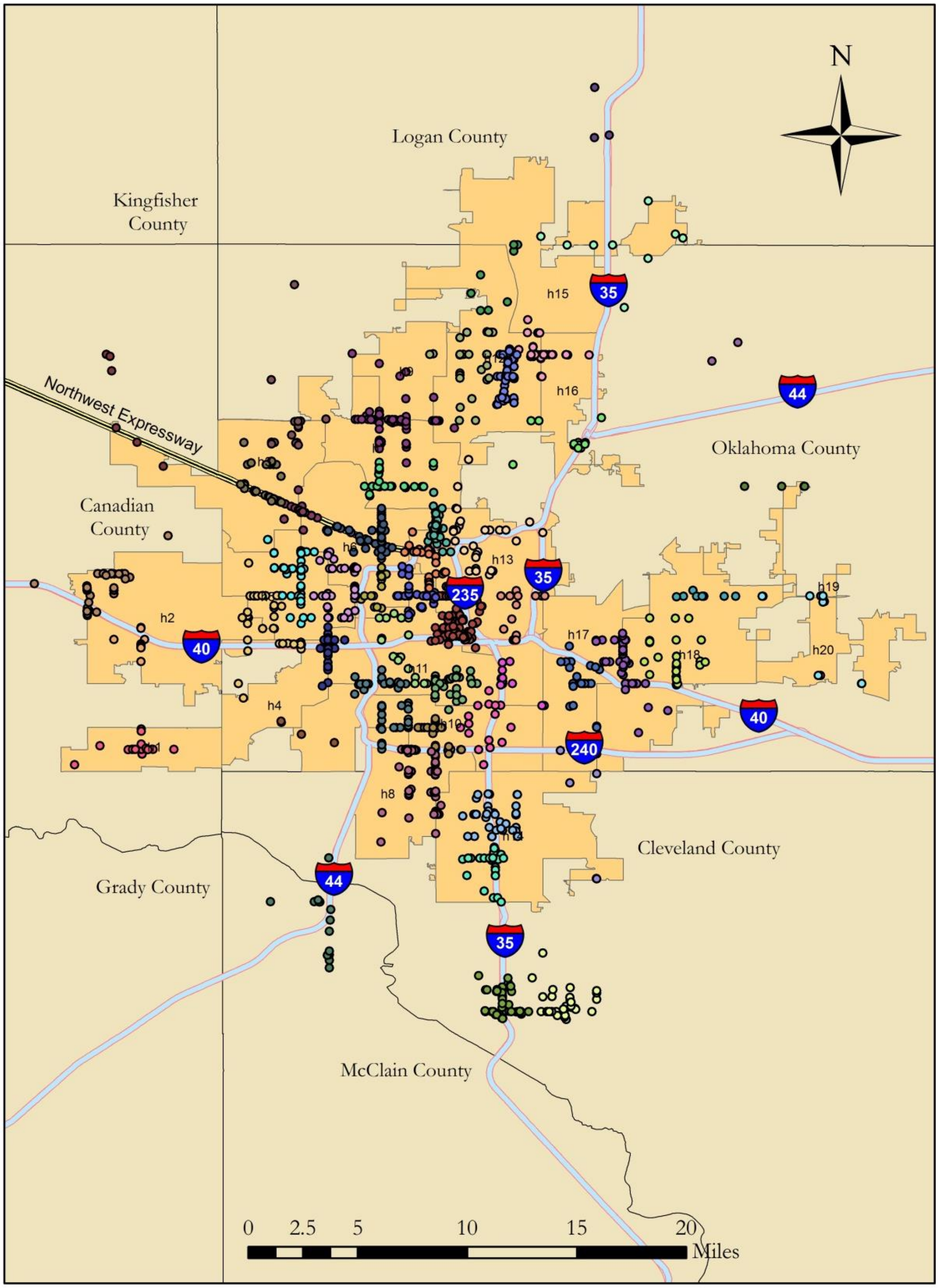

Figure 4.5: Locations of grouped sit-down restaurants in Oklahoma City

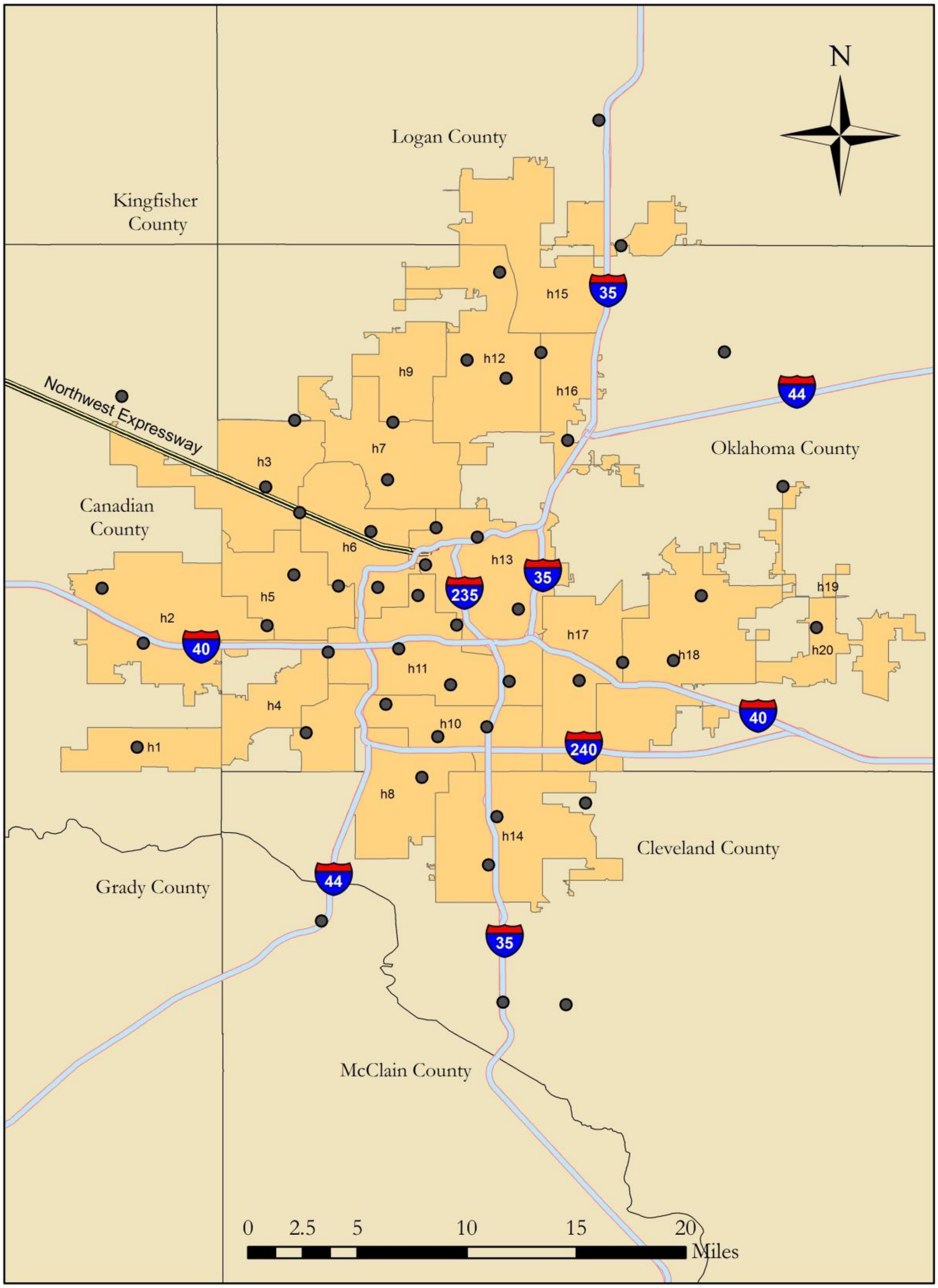

Figure 4.6: Locations of restaurant clusters in Oklahoma City

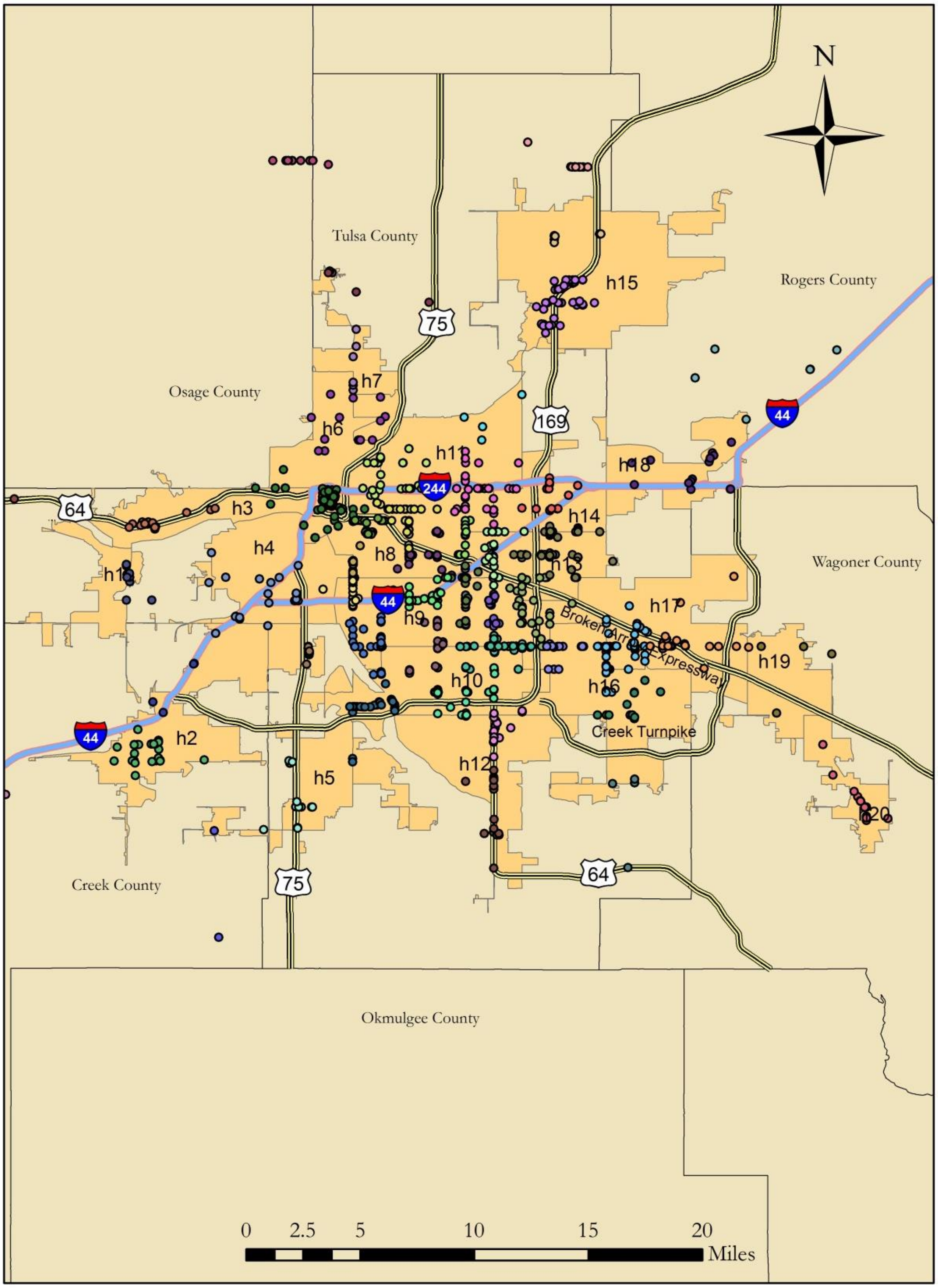

Figure 4.7: Locations of grouped sit-down restaurants in Tulsa

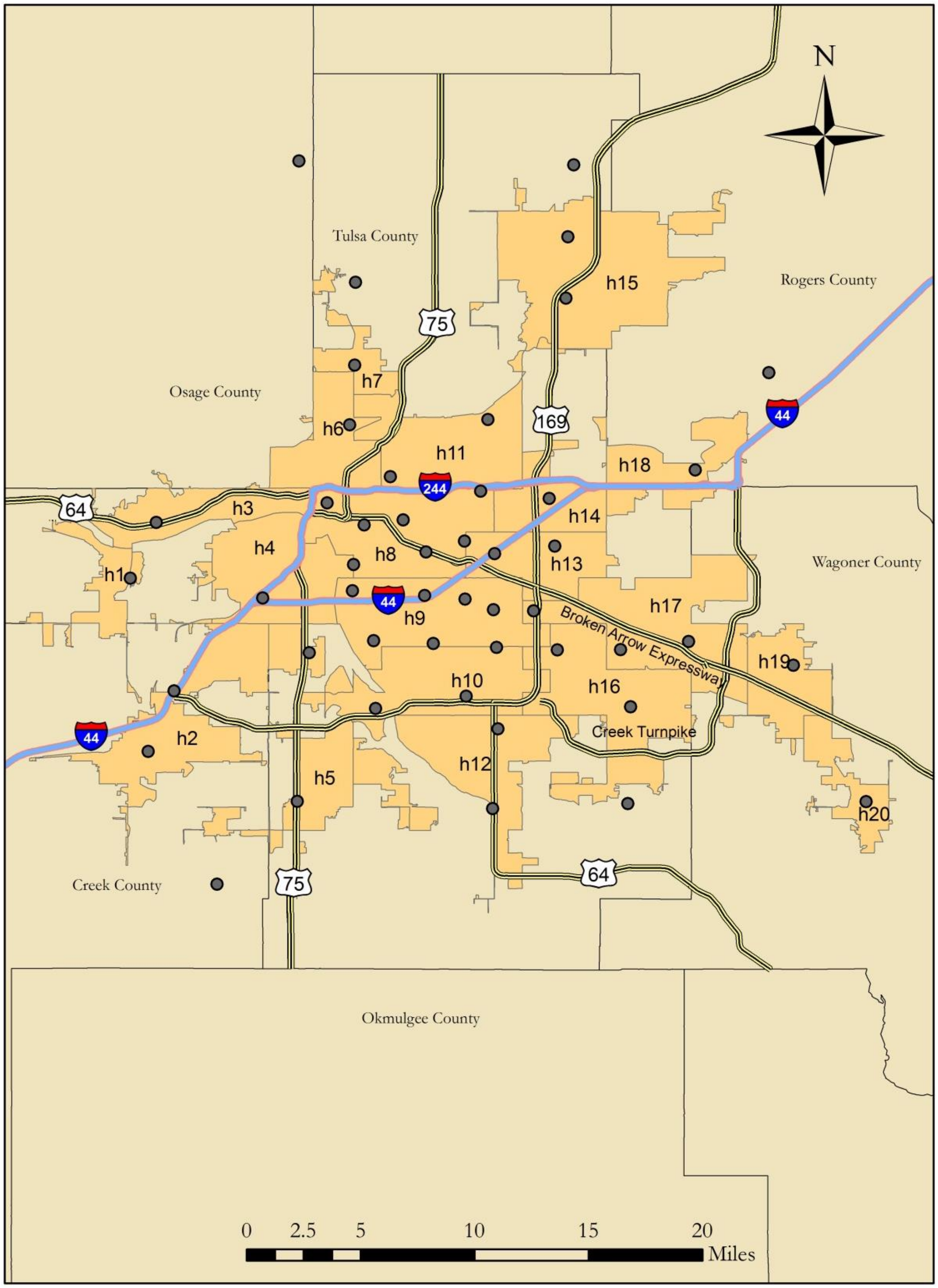

Figure 4.8: Locations of restaurant clusters in Tulsa

CHAPTER V

RESULTS AND DISCUSSION

5.1 Overview

Using the data described in the previous section, the scripts are executed in R and Python. The results are described in detail in this chapter. In general, there is greater SIP near the center of the city, and lesser SIP around the periphery of the city. Even without knowing the distribution of activity locations in each city, this pattern is expected, since driving time to all work and home locations is a significant factor in the calculation of SIP, and the zones in the center of the each will have the least amount of driving time to all other zones. However, this pattern does not hold true in every area of the two cities, and the overall pattern of SIP is not ubiquitous. Meaningful patterns exist in both cities.

The maps (Figures 5.1, 5.3, 5.5, and 5.7) show SIP expressed as a percentage of each zone's contribution to the urbanized area's overall SIP. Since the calculation of SIP is partially dependent upon the population in each zone, population maps (Figures 5.2, 5.4, 5.6, and 5.8) using adjusted residential population are shown along with maps of SIP. All of the maps also show each urbanized area's interstate highways, major roadways, and restaurant clusters, and each map shows five equal interval classes. Along with these maps, the standard deviation of SIP and Moran's I is computed for Oklahoma City work locations, Oklahoma City home locations, Tulsa work locations, and Tulsa home locations. In the following sections, the pattern of SIP is first described individually within each city and location type. After this, the SIP of restaurant clusters for each city is discussed. Lastly, the overall patterns of the two cities are compared.

5.2 Residential locations in Oklahoma City

As shown in Figure 5.1, residential locations in Oklahoma City generally show high SIP in the center of the city with pockets of high SIP emanating from the center. SIP gradually (as opposed to sharply) decreases away from the center of the city. Two zones touching the outer edge of the city fall into the highest class of SIP; in fact, one of these zones, *h14*, actually returns the highest percentage value of SIP in Oklahoma City, as shown in Table 5.1. In this table and subsequent tables, darkened lines are used to separate each equal interval class shown on the table's corresponding map(s).

Residential Locations				Employment Locations			
Location	SIP	% of SIP	Working Population	Location	SIP	% of SIP	No. of Employees
h14	121.92	9.13	80,559	w4	228.83	17.13	47,361
h11	120.95	9.05	69,018	w10	215.23	16.11	46,000
h6	104.11	7.79	59,963	w8	162.21	12.14	34,009
h3	100.91	7.55	70,695	w6	144.49	10.82	38,845
h8	92.10	6.89	59,957	w5	95.26	7.13	19,672
h2	90.82	6.80	61,386	w1	87.77	6.57	21,393
h5	90.48	6.77	56,657	w12	67.99	5.09	19,517
h10	89.17	6.67	54,811	w9	57.90	4.33	12,832
h17	82.72	6.19	51,089	w13	46.95	3.51	12,033
h18	78.98	5.91	58,284	w11	44.45	3.33	9,902
h7	78.20	5.85	56,425	w17	37.62	2.82	10,834
h12	76.16	5.70	64,991	w2	35.60	2.67	8,870
h13	69.11	5.17	40,294	w14	27.47	2.06	5,995
h9	34.08	2.55	33,218	w15	25.52	1.91	13,746
h16	28.86	2.16	21,712	w16	23.58	1.76	6,534
h15	25.74	1.93	40,470	w7	15.65	1.17	4,187
h1	21.52	1.61	17,395	w3	12.51	0.94	3,876
h20	15.78	1.18	26,626	w18	5.34	0.40	2,378
h4	8.24	0.62	5,248	w20	0.91	0.07	1,494
h19	6.08	0.46	7,383	w19	0.61	0.05	366

Table 5.1: Oklahoma City SIP

For residential locations in Oklahoma City, four zones fall into the highest (fifth) class: *h14, h11, h6* and *h3.* Zone *h11* is located in the heart of the city, in the downtown area, so this result is

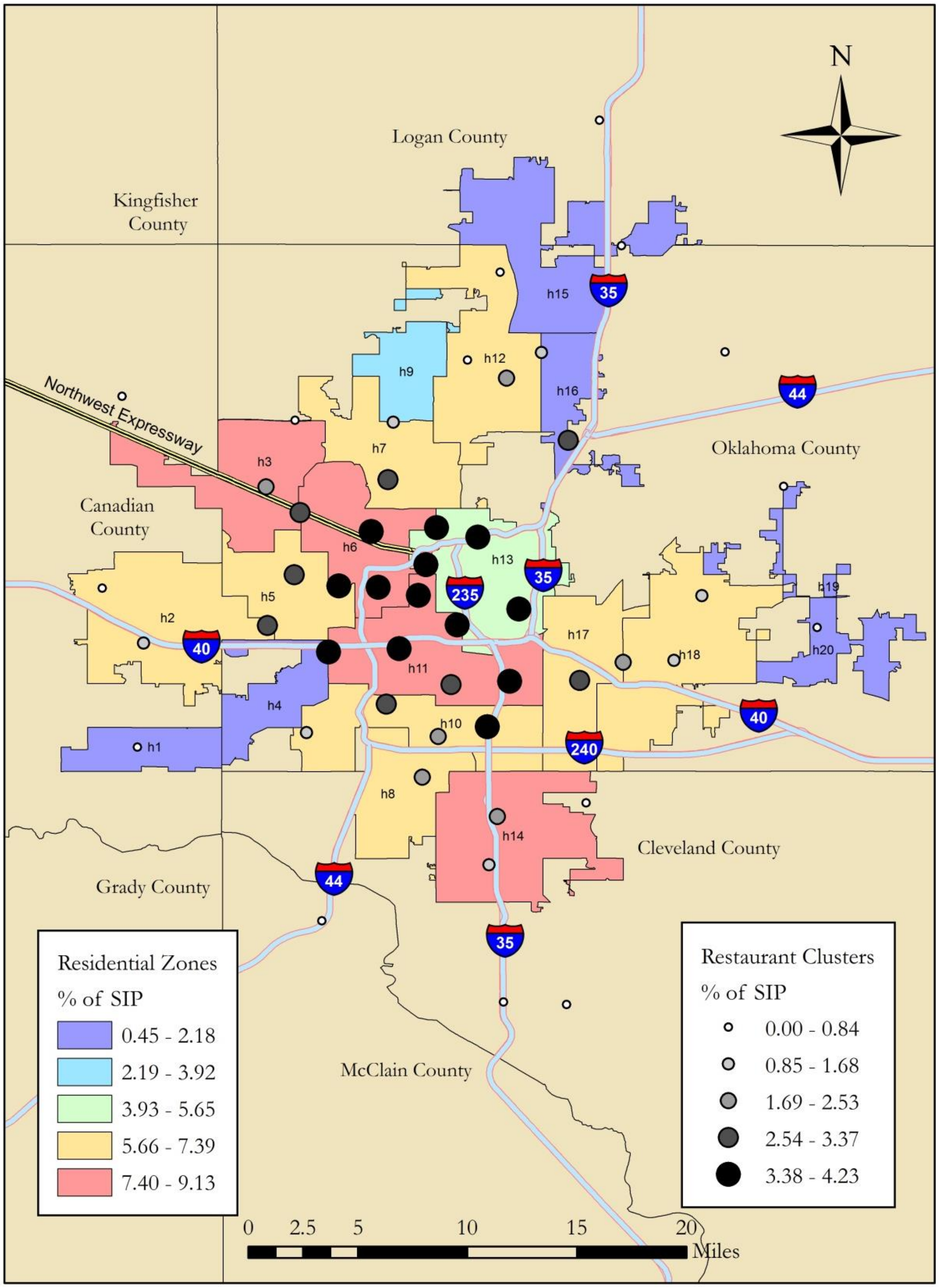

Figure 5.1: SIP of residential zones in Oklahoma City

expected. Oklahoma City University is located within this zone, boosting the residential population of these aggregated census tracts. The area bounded by I-40, I-44, and I-235 is shared by *h11* and *h6* and seems to form the hearth of SIP for residential locations in Oklahoma City, as shown by the highly accessible restaurant clusters and the high SIP of these two residential zones. Zone *h6* returns a high value for SIP because it is fairly centrally located and lies along I-44 and Northwest Expressway. Many of the highly accessible restaurant clusters lie within this zone or close to it, and it is also the fifth largest zone in terms of population (as shown in Figure 5.2).

At first glance it is surprising that the SIP of *h14*, near Moore, is the largest in the group since this zone lies on the periphery of the city; however, this zone also has the largest population in the Oklahoma City area. Along with this, Zone *h14* is situated on I-35, a major transportation corridor, and because of this, most of the restaurant clusters in the downtown area are easily accessible. In order to account for the edge effect, there are two restaurant clusters located in Norman – which lies outside the urbanized area – that are included in the dataset. These two clusters are closer to *h14* than any other zone, and there are two other restaurant clusters located close to *h14* that are also outside of the urbanized area and far away from many other zones. These factors result in a large value of SIP for zone *h14*.

Zone *h3* also appears to be an anomaly since it is located on the periphery of the city. It is the only zone that falls into the highest class without a major interstate passing through it. However, *h3* has the second highest population of all zones, and the Northwest Expressway provides access to many of the restaurant clusters near downtown, similar to the way I-44 enables residents of *h14* to access many restaurant clusters.

Zones falling into the lowest class and returning low values of SIP are *h15*, *h1*, *h20*, *h4*, and *h19*. Comparatively, these zones have low populations and are all located on the outskirts of the urbanized area. Despite the relatively high income of residents in Edmond (which lies in *h15* and *h16*) and Mustang (which lies in *h1*), these zones have low values of SIP. The populations and population densities are low and the driving time to restaurant clusters and to other zones are

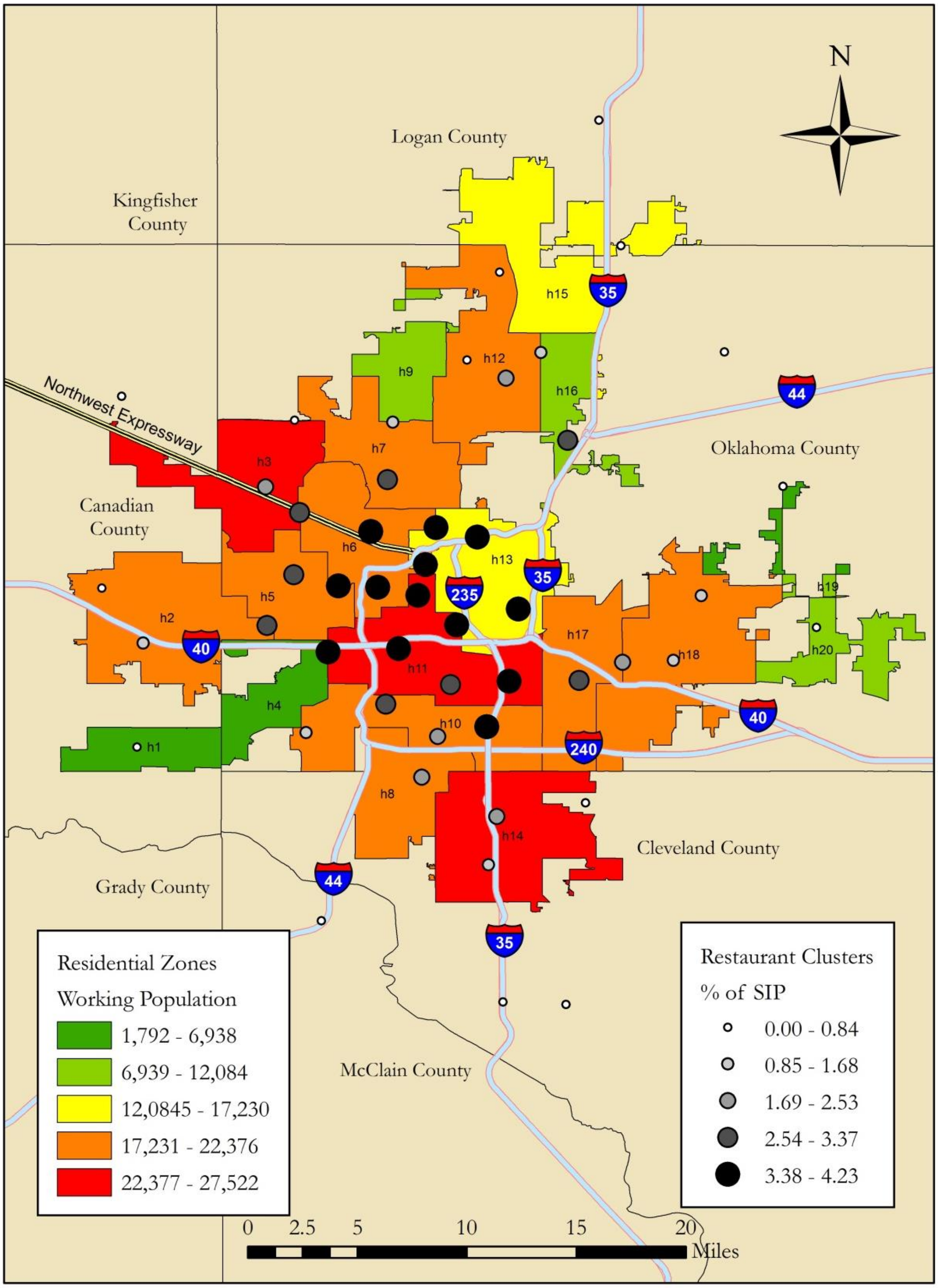

Figure 5.2: Working population in residential zones in Oklahoma City

high. These greatly factors inhibit the ability to interact with others on a day to day basis. Interestingly, *h13* returns a relatively low SIP value despite being fairly centrally located and bordering *h11*, the zone with the second highest SIP value in Oklahoma City. This is likely due to the fact that no restaurant clusters are located directly north or east. Likewise, there are neither employment zones nor residential zones contiguous to the north or east, and the population of *h11* is lower than the population of all its other bordering zones.

5.3 Employment locations in Oklahoma City

Like the pattern of SIP in Oklahoma City residential zones, employment zones in Oklahoma City (Figure 5.3) show a gradual decrease in SIP away from the center of the city. However, pockets of high SIP outside of the center of the city are not present.

Two employment locations fall into the highest class: *w10* and *w4*. Zone *w4* contains the largest employment population of all zones (see Figure 5.4 and Table 5.1) and is fairly centrally located. Chesapeake Energy is a major employer in the Oklahoma City area, and although a small portion of the Chesapeake Energy campus lies in *w8*, most lies within *w4*. Zone *w10* contains the core of employment centers in the downtown area including the headquarters of three large employers in the Oklahoma City area: Devon Energy, Continental Energy, and SandRidge Energy. Also, Bricktown, which contains many shops and restaurants, lies within *w10*. Although outside of the downtown area, OU Medical Center, another major employer for the state, also lies within *w10*. While *w8* encompasses more of the downtown area than *w10*, most of the large employers are located in *w10* as shown in Figure 5.4.

Eleven zones fall into the lowest class of SIP, and all border the outside of the city. Zones *w20*, *w19*, *w18*, and *w3* are isolated from the major interstates, and these zones also have very low employment populations. Zone *w16* has low SIP despite containing the third largest employer in state, Tinker Air Force Base (Oklahoma Commerce, 2008). The employment population

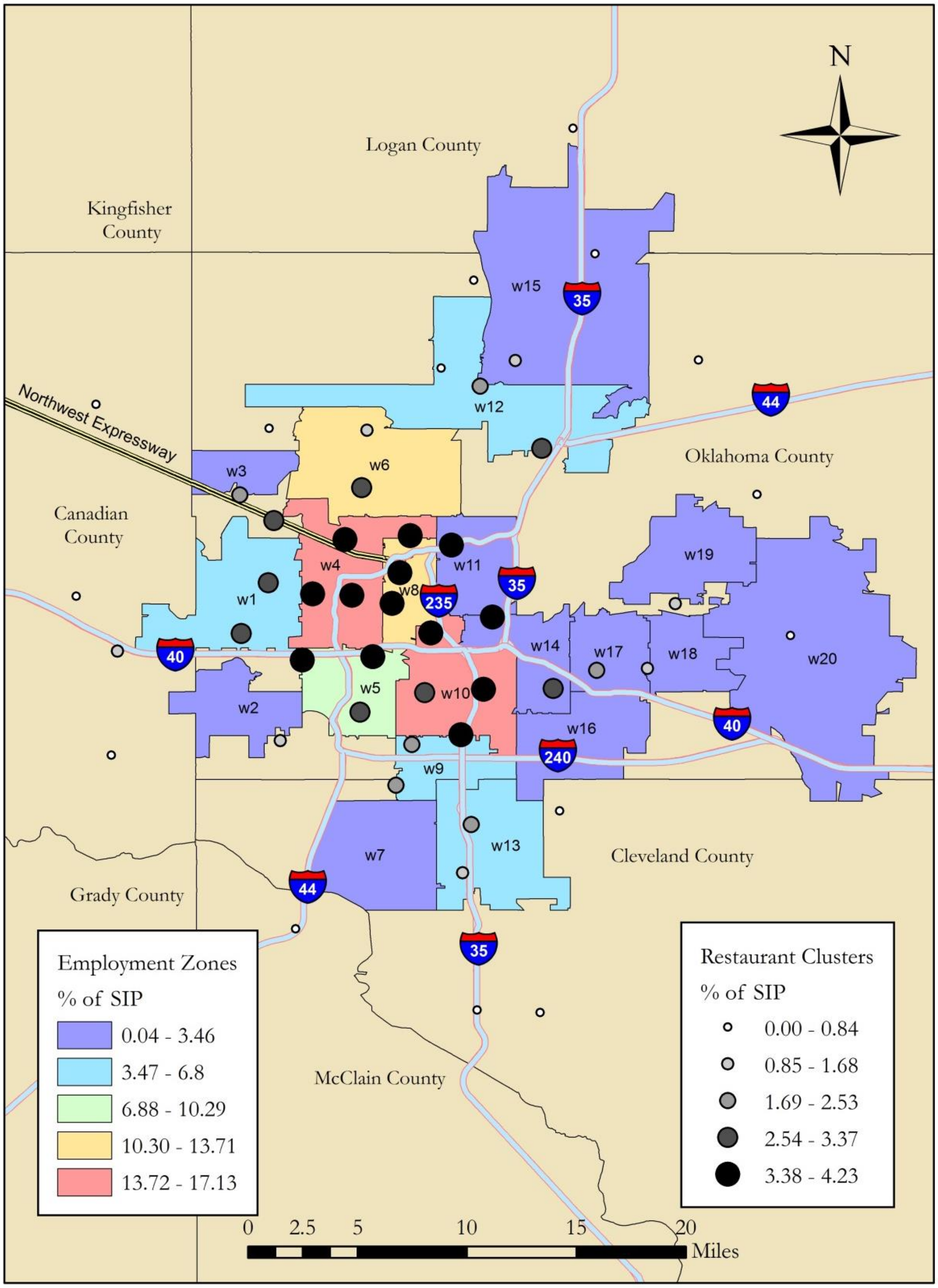

Figure 5.3: SIP of employment zones in Oklahoma City

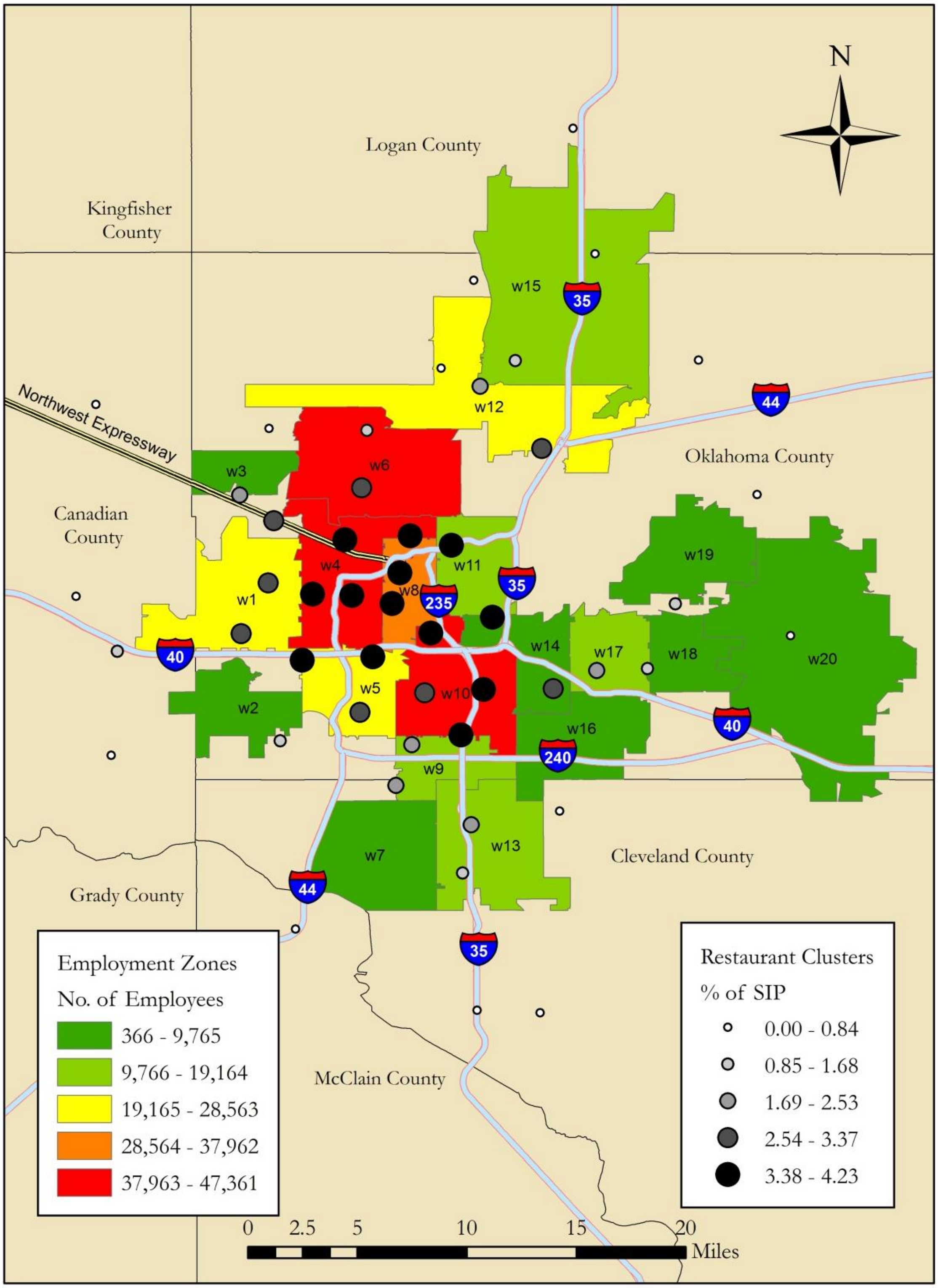

Figure 5.4: Working population in employment zones in Oklahoma City

density of this zone is low, and the distance from this zone to other zones is great. All of these factors demonstrate that central location is crucial to high SIP of employment locations.

5.4 Residential locations in Tulsa

The residential locations in Tulsa (Figure 5.5) show a sharp decrease in SIP away from the center; in fact, no zones fall within the fourth class. While an empty class is not ideal when mapping, five equal interval classes are kept for the sake of consistency and to illustrate the noteworthy disparity of SIP in Tulsa (also see Table 5.2). These locations only show two zones

Residential Locations				Employment Locations			
Location	SIP	% of SIP	Working Population	Location	SIP	% of SIP	No. of Employees
h8	187.77	13.22	26751	w15	240.49	16.93	42,948
h9	177.86	12.52	26293	w8	226.96	15.97	40,407
h10	114.47	8.06	19251	w11	169.34	11.92	34,267
h13	112.65	7.93	16808	w10	167.86	11.81	29,980
h16	104.30	7.34	20469	w13	138.51	9.75	28,386
h6	95.83	6.74	15352	w17	107.35	7.56	21,689
h15	81.34	5.73	19176	w12	90.07	6.34	17,482
h17	80.30	5.65	13748	w20	86.40	6.08	20,622
h12	70.59	4.97	14422	w3	50.56	3.56	10,236
h11	67.99	4.79	10743	w7	29.18	2.05	5,942
h3	60.09	4.23	10310	w18	27.84	1.96	10,104
h2	50.19	3.53	10102	w16	19.57	1.38	3,483
h14	48.07	3.38	7173	w6	15.25	1.07	3,876
h5	46.89	3.30	8881	w1	13.96	0.98	3,005
h4	36.39	2.56	5572	w4	13.84	0.97	2,778
h1	25.08	1.77	5666	w14	10.26	0.72	4,200
h18	24.30	1.71	4105	w5	5.78	0.41	1,609
h7	17.21	1.21	3290	w19	5.76	0.41	2,518
h19	12.90	0.91	3667	w9	1.07	0.08	269
h20	6.58	0.46	6297	w2	0.72	0.05	277

Table 5.2: Tulsa SIP

within the highest class of SIP: *h8* and *h9.* These two zones border each other, and the downtown area lies within *h8*. These two zones are also the only two zones that fall in the highest class of

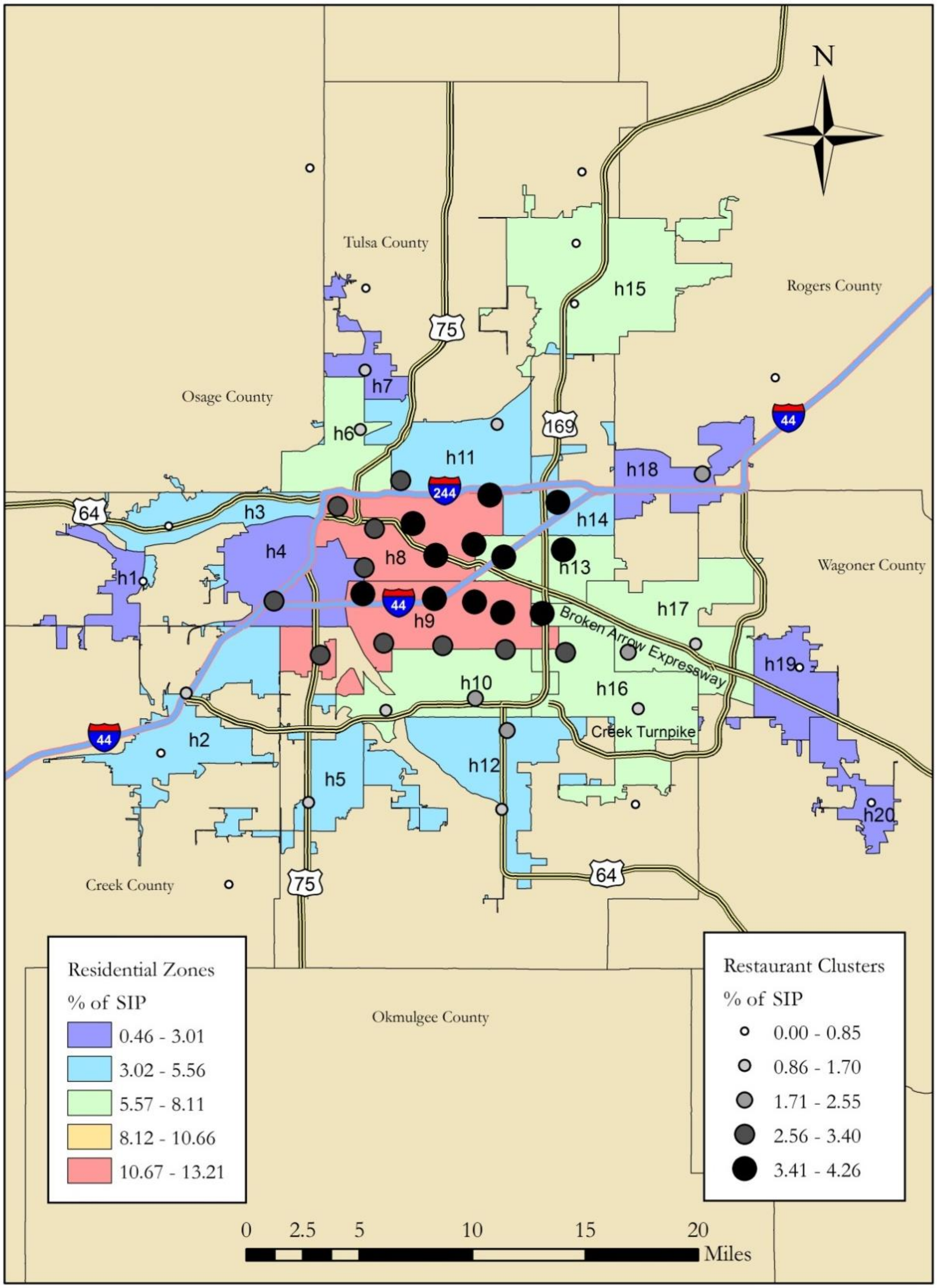

Figure 5.5: SIP of residential zones in Tulsa

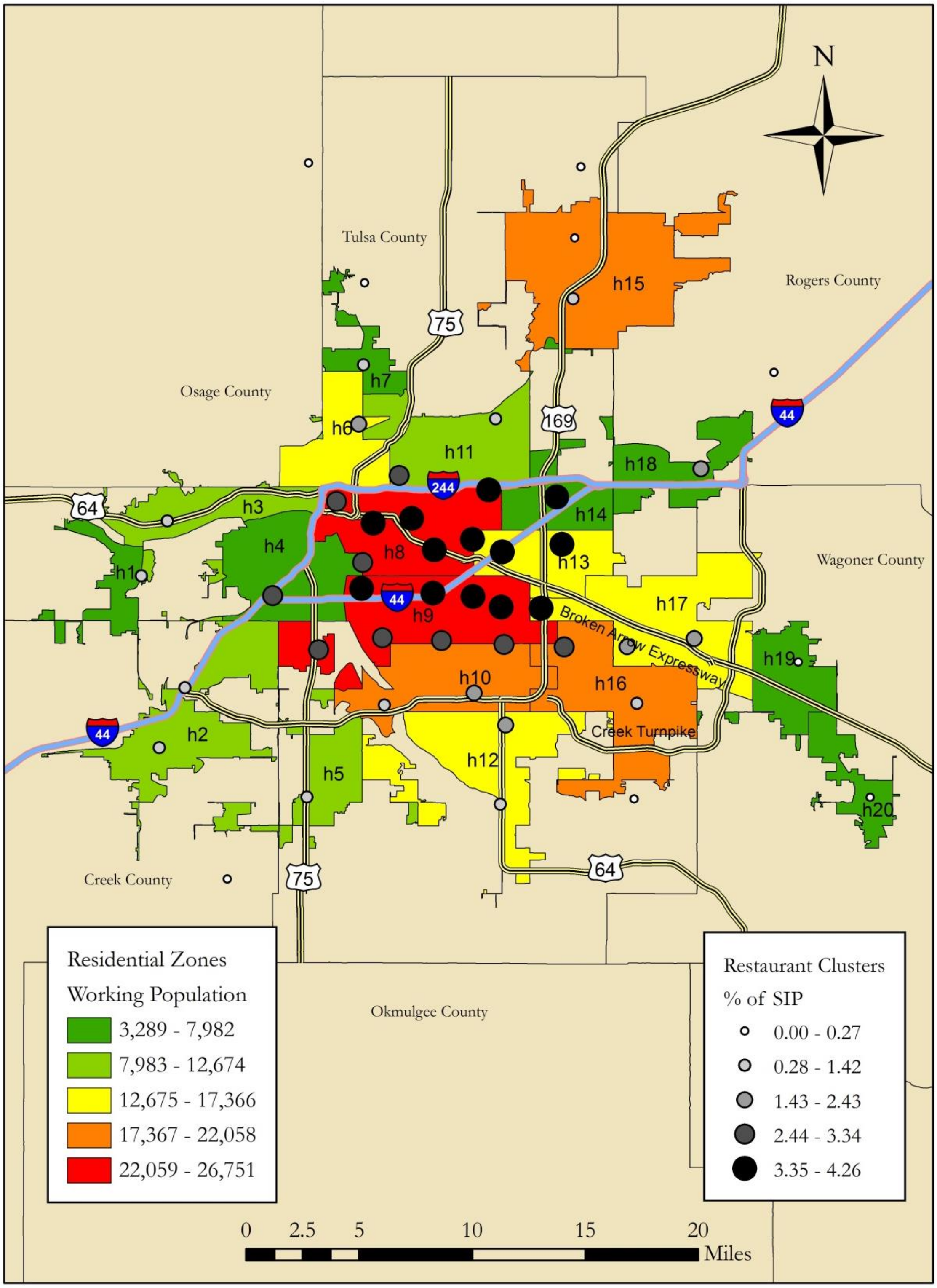

Figure 5.6: Working population in residential zones in Tulsa

population (shown in Figure 5.6). The main interstate highways in Tulsa pass through these zones; I-244 passes through *h8*, and I-44 passes through *h9*. US-64/Broken Arrow Expressway also passes through *h8*. Zone *h9* contains Oral Roberts University, and *h8* contains the University of Tulsa. Both universities are large sources of population. These factors result in a very high SIP for these two zones.

Other residential zones with fairly high SIP in Tulsa, falling into the third class, are *h10*, *h13*, *h16*, *h6*, *h15*, and *h17*. With the exception of *h13*, these zones do not have a major interstate that passes through. However, similar to Northwest Expressway passing through zones *h3* and *h6* in Oklahoma City, these zones still contain a major transportation corridor. Highway 169, the Broken Arrow Expressway, and the Creek Turnpike are major roadways that pass through these zones.

Interestingly, *h15*, which encompasses Owasso, returns a high value of SIP, despite being isolated on the periphery of the city. Two restaurant clusters lie within *h15*, which is more than most of the other peripheral zones. Along with this, several restaurant clusters outside of the urbanized area can feasibly be reached from *h15*. This zone also has a fairly large population, compared to other zones in Tulsa.

5.5 Employment locations in Tulsa

For employment locations in Tulsa (Figure 5.7), only two zones fall into the highest class: *w15* and *w8*. Despite *w8* encompassing the downtown area, *w15* slightly edges out *w8* for the highest value of SIP. Zone *w15* also possesses the largest employment population (shown in Figure 5.8) and contains 5 of the 13 restaurant clusters in the highest class. While the restaurant clusters are used as activity locations in this study, they certainly also act as employment locations that contribute to the high employment population of this zone and positively affect its SIP. Zone *w15* contains Tulsa Technology Center and one of the St. Francis hospital locations, one of the largest employers in the state of Oklahoma (Oklahoma Commerce, 2008). While this is

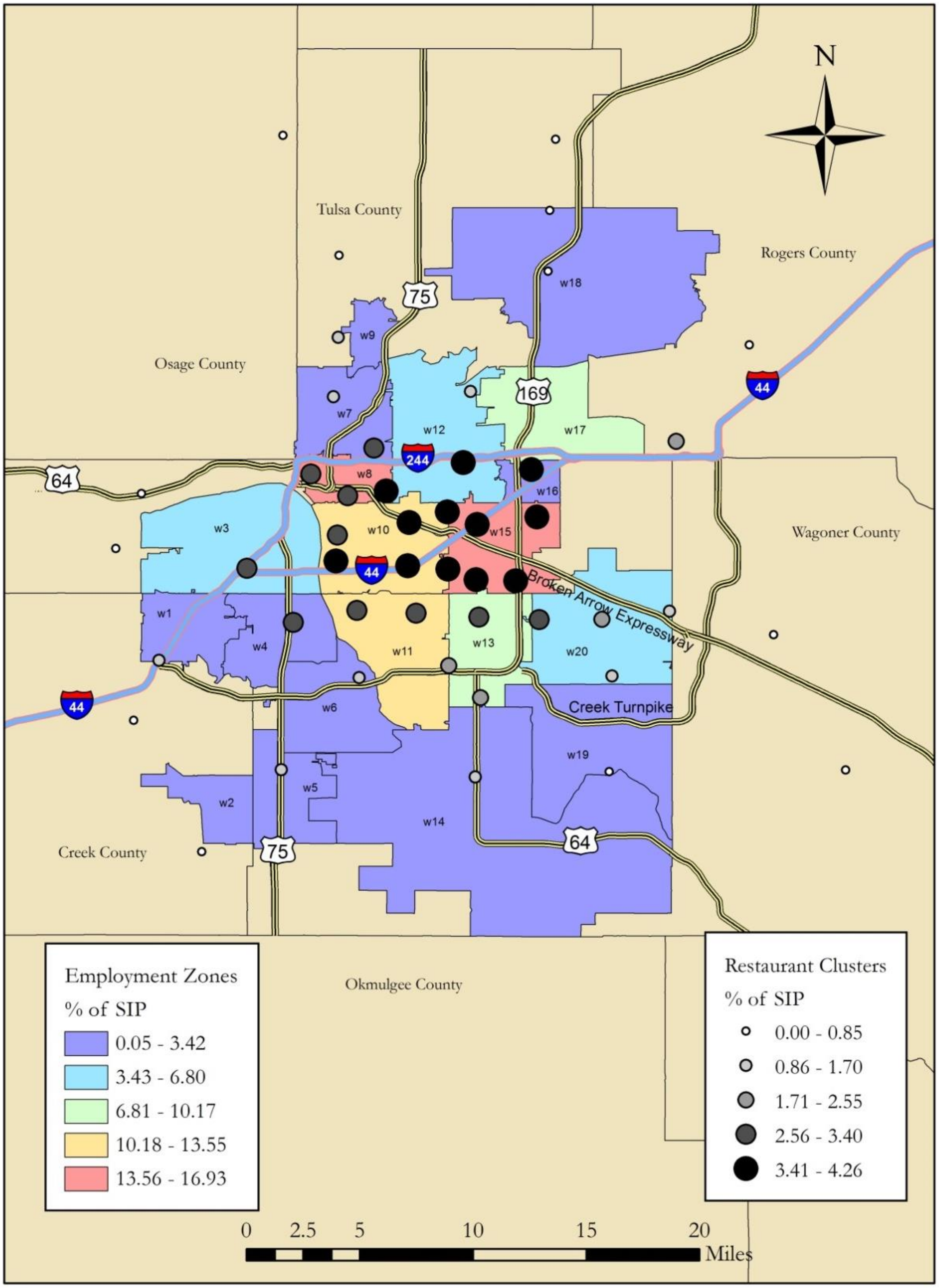

Figure 5.7: SIP of employment zones in Tulsa

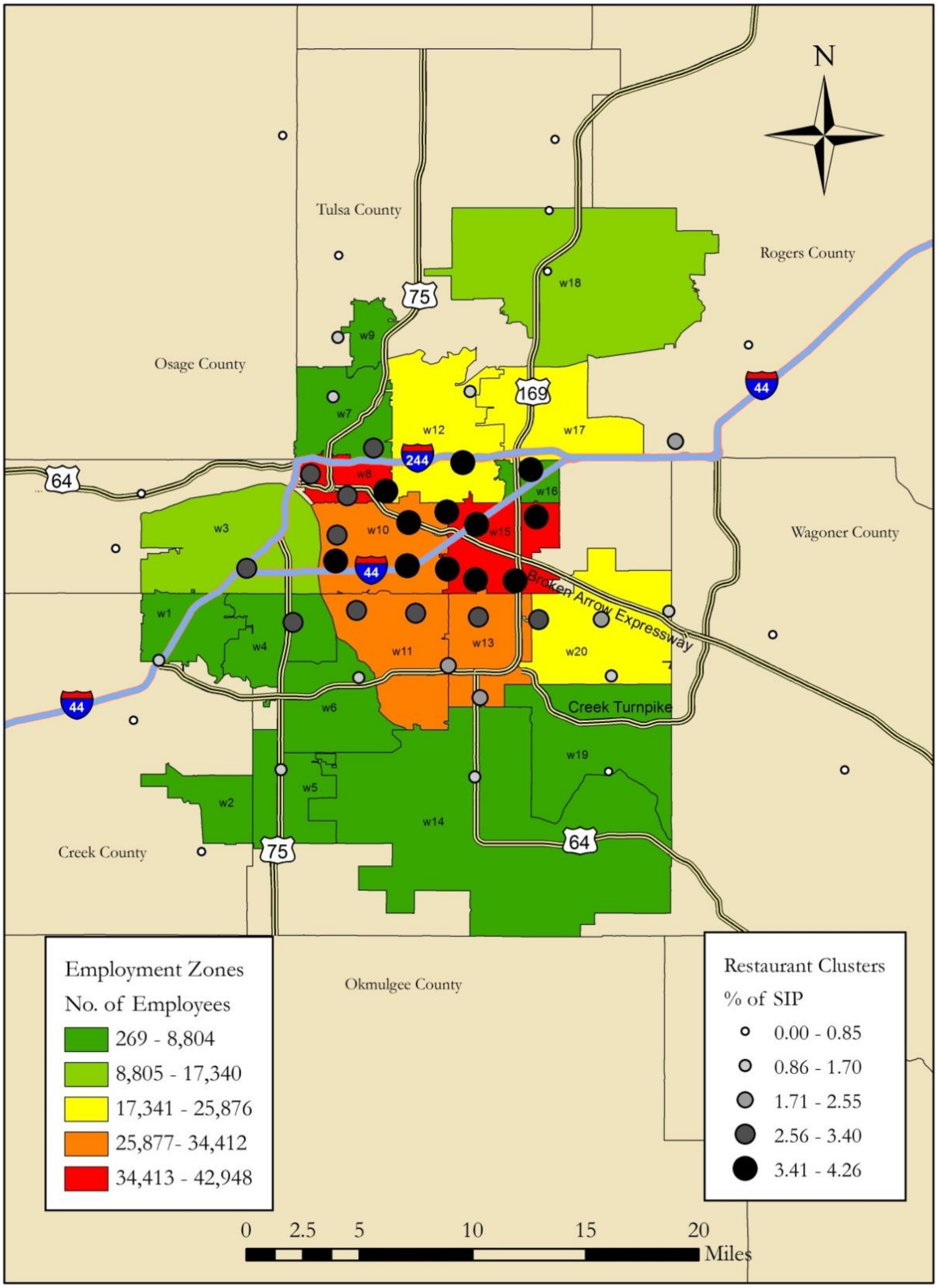

Figure 5.8: Working population in employment zones in Tulsa

not the largest branch of St. Francis hospital, it is nevertheless a significant employer in the city. Zone *w15* also contains corporate locations for Quiktrip, Mazzio's, and State Farm. Besides several major employers being located in this zone, *w15* is centrally located exhibited by the centroid for the urbanized area lying within it, increasing its SIP.

Zone *w8* also contains several of the major employers in the Tulsa urbanized area including OSU – Tulsa, OU – Tulsa, AEP/Public Service Company of Oklahoma, AT&T, Hillcrest HealthCare System, University of Tulsa, ONEOK, OSU Medical Center, and Williams Companies (Tulsa Metro Chamber, 2012). This zone's high employment and close proximity to major highways and interstates leads to its large SIP.

5.6 SIP per person

Since SIP is very dependent upon population, the amount of SIP per person or SIP divided by the working residential population is useful measure. Along with this, the SIP per person measure adheres to the foundation of time geography and its individualized approach. This measure of SIP per person was completed for residential zones in Tulsa and Oklahoma City, since these two produce very different results when mapping SIP without adjusting for population. This measure creates very similar patterns in both Oklahoma City (Figure 5.9) and Tulsa (Figure 5.10). Both show a heavy concentration of SIP per person near the center of the city and a decreasing amount away from the center.

This measure also shows interesting results when comparing each zone's SIP rank to its SIP per person rank (see Tables 5.3 and 5.4). In both cities, most zones do not show a great change in rank, but a select few show a large change. In Oklahoma City, two zones show a large rank increase in SIP: *h13* and *h4*. In the unadjusted SIP maps, *h13* appears to be an anomaly since it is fairly centrally located and lies in close proximity to many restaurant clusters. However, its population is very low, and there are no zones adjacent to the north or east. Zone *h4* experiences a similar phenomenon since its population is very low and it lies on the periphery of the city as

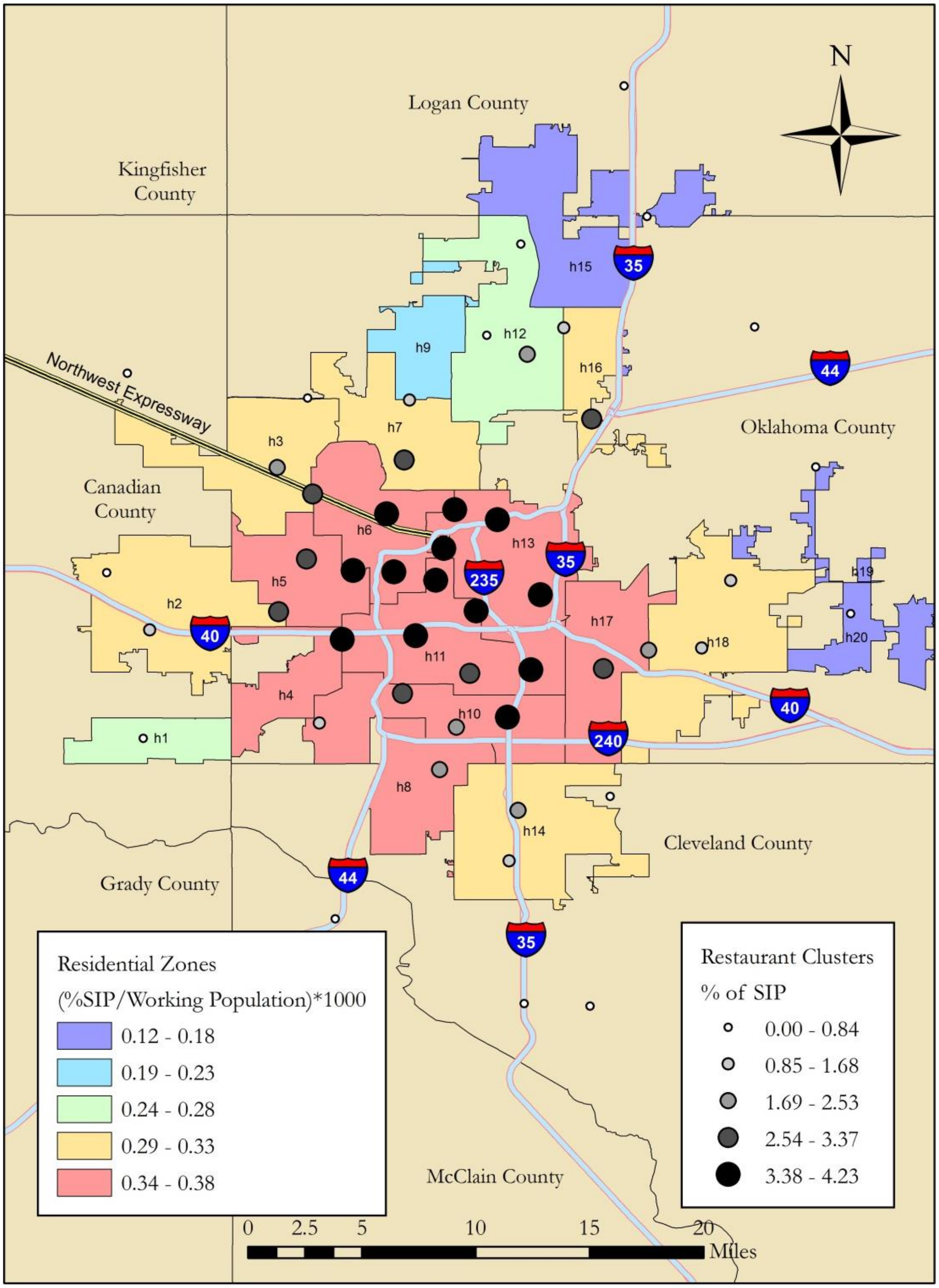

Figure 5.9: SIP per person in residential zones in Oklahoma City

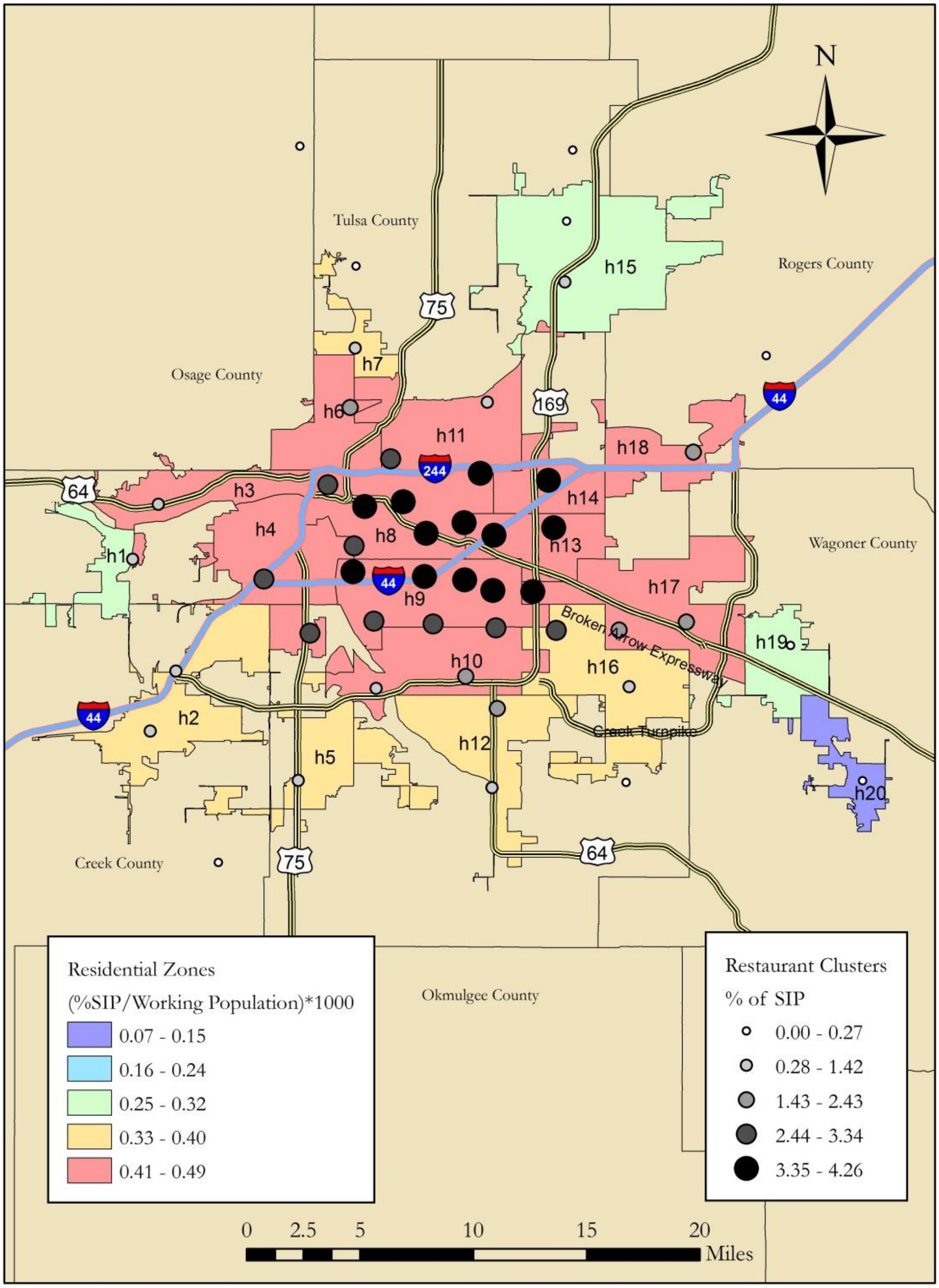

Figure 5.10: SIP per person in residential zones in Tulsa

Location	% of SIP	% SIP Rank	Working Population	SIP Per Person	SIP Per Person Rank	Rank Change
h11	9.05	2	69,018	0.38	1	+1
h6	7.79	3	59,963	0.38	2	+1
h13	5.17	13	40,294	0.38	3	+10
h10	6.67	8	54,811	0.36	4	+4
h17	6.19	9	51,089	0.35	5	+4
h5	6.77	7	56,657	0.35	6	+1
h4	0.62	19	5,248	0.34	7	+12
h8	6.89	5	59,957	0.34	8	-3
h14	9.13	1	80,559	0.33	9	-8
h2	6.80	6	61,386	0.32	10	-4
h3	7.55	4	70,695	0.31	11	-7
h7	5.85	11	56,425	0.30	12	-1
h18	5.91	10	58,284	0.30	13	-3
h16	2.16	15	21,712	0.29	14	+1
h1	1.61	17	17,395	0.27	15	+2
h12	5.70	12	64,991	0.26	16	-4
h9	2.55	14	33,218	0.22	17	-3
h19	0.46	20	7,383	0.18	18	+2
h15	1.93	16	40,470	0.14	19	-3
h20	1.18	18	26,626	0.13	20	-2

Table 5.3: Oklahoma City residential SIP per person

well. In Table 5.4, several zones in Tulsa experience a similar rank increase when SIP is divided by population, notably *h4* and *h18*. These two zones lie on the outskirts of the Tulsa urbanized area and have low populations. While all four of these zones, *h13* and *h4* in Oklahoma City and *h4* and *h14* in Tulsa, have several disadvantages, all have a high level of accessibility to the restaurant clusters. Several zones in both cities experience large rank decreases when dividing SIP by population including *h14* and *h3* in Oklahoma City and *h15* and *h16* in Tulsa. All four of these have fairly large populations and also long driving times to the bulk of the restaurant clusters in the urbanized area.

Location	% of SIP	% SIP Rank	Working Population	SIP Per Person	SIP Per Person Rank	Rank Change
h8	13.22	1	26751	0.49	1	0
h9	12.52	2	26293	0.48	2	0
h13	7.93	4	16808	0.47	3	+1
h14	3.38	13	7173	0.47	4	+9
h4	2.56	15	5572	0.46	5	+10
h11	4.79	10	10743	0.45	6	+4
h6	6.74	6	15352	0.44	7	-1
h10	8.06	3	19251	0.42	8	-5
h18	1.71	17	4105	0.42	9	+8
h17	5.65	8	13748	0.41	10	-2
h3	4.23	11	10310	0.41	11	0
h5	3.30	14	8881	0.37	12	+2
h7	1.21	18	3290	0.37	13	+5
h16	7.34	5	20469	0.36	14	-9
h2	3.53	12	10102	0.35	15	-3
h12	4.97	9	14422	0.34	16	-7
h1	1.77	16	5666	0.31	17	-1
h15	5.73	7	19176	0.30	18	-11
h19	0.91	19	3667	0.25	19	0
h20	0.46	20	6297	0.07	20	0

Table 5.4: Tulsa residential SIP per person

5.7 Restaurant clusters

The SIP of restaurant clusters is highly dependent upon location, even more so than the work locations or home locations as shown in the Moran's *I* indices and *p*-values (see Table 5.5). With high index values (0.674 and 0.622) and negligible *p*-values (0.000 for both cities' restaurant clusters), the activity locations are highly clustered with respect to SIP in both cities. This is to be expected, since the restaurant clusters (activity locations) are the middle ground between home locations and work locations. In this study, individuals start from work, always travel to activity locations second, and lastly travel home. Along with this, both individuals must be able to arrive at the activity location and spend 45 minutes interacting before returning home.

Location Type	St. Dev.of SIP	Moran's I - Inverse Distance	
		Index	p-value
Oklahoma City Employment Locations	5.040	0.324	0.005
Oklahoma City Residential Locations	2.770	0.270	0.099
Oklahoma City Restaurant Clusters	1.480	0.674	0.000
Tulsa Employment Locations	5.381	0.361	0.002
Tulsa Residential Locations	3.454	0.202	0.013
Tulsa Restaurant Clusters	1.442	0.622	0.000

Table 5.5: Spatial autocorrelation of SIP

Also, population is not a factor in the SIP of restaurant clusters. Because of these facts, the SIP of restaurant clusters is more dependent upon location. Despite this, there are distinct patterns in the SIP of restaurant clusters in both Oklahoma City and Tulsa.

5.8 Restaurant clusters in Oklahoma City

In Oklahoma City, the highest ranking restaurant cluster is located at the intersection of I-44 and Northwest Expressway as exhibited in Figure 5.11. The Penn Square Mall is located in this cluster and contains many restaurants, and outside of the mall along Northwest Expressway there are many restaurants as well. Aside from this, most of the highly accessible restaurant clusters are located close to the downtown; many of them surround the downtown area with a slight skew to the west. Several of these fall within *h11*, which is the second highest populated residential zone in the urbanized area. Part of the reason why many of these are located close to the downtown is because of the metric’s dependence upon distance for activity and that the downtown area of Oklahoma City is approximately equidistant from the edges of the urbanized area.

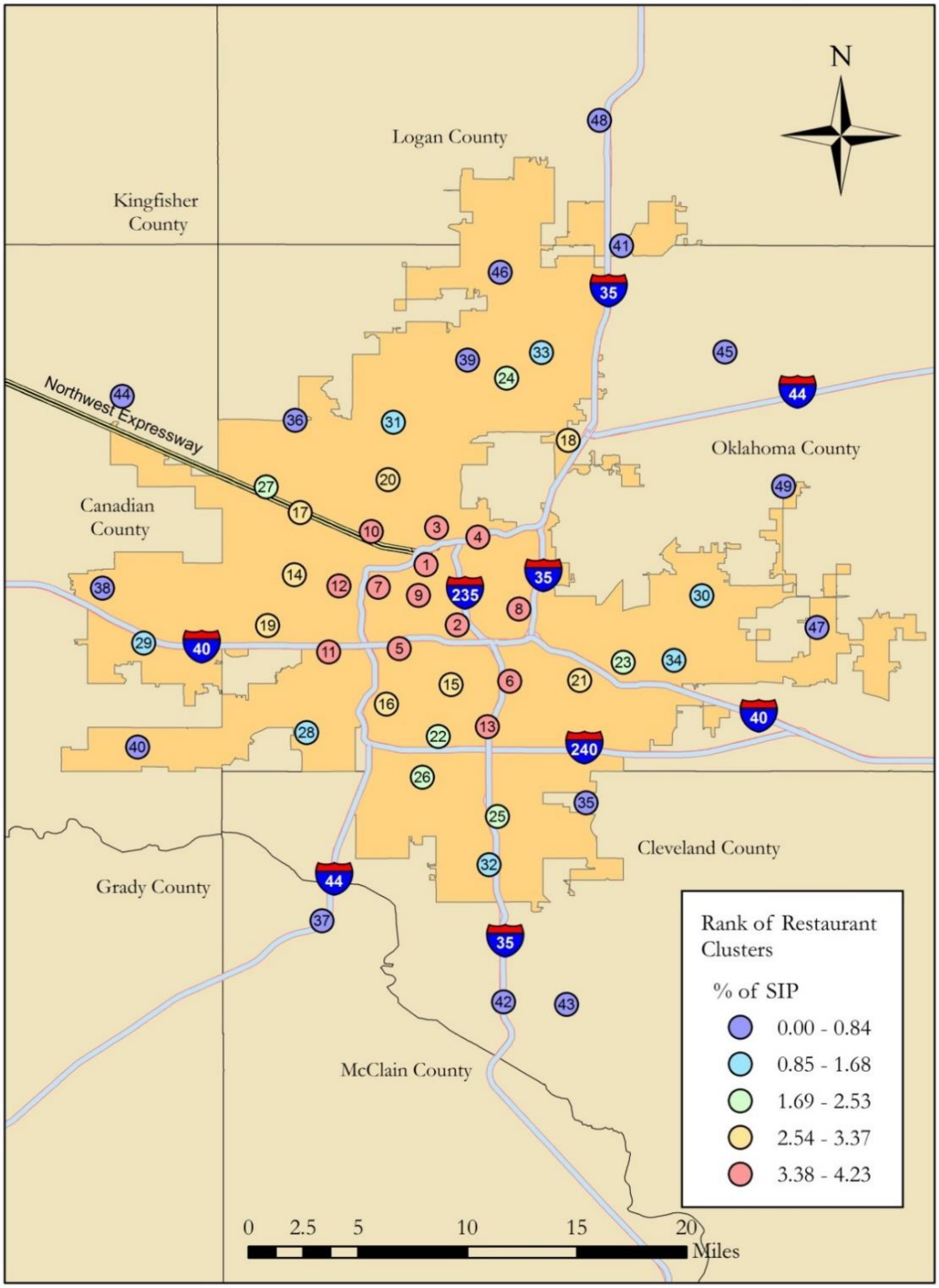

Figure 5.11: Social interaction demand at restaurant clusters in Oklahoma City

Two of restaurant clusters in the highest class, those ranked 6th and 13th, are located south of the downtown area along I-35, similar to the finger of residential zones with high SIP in which Northwest Expressway passes through.

5.9 Restaurant clusters in Tulsa

An obvious factor in the placement of restaurant locations is the presence of residential population. Many of the restaurants in the Tulsa area are located in the zones of highest residential population, and most of the highly accessible clusters are located within these zones as well. An interesting phenomenon in Tulsa is the presence of clusters lying in apparent horizontal lines as pictured in Figure 5.12. While this has to do more with the location of restaurants and their aggregation into clusters, each "line" of clusters falls mainly within only one class. This is apparent in the clusters ranked 12, 3, 5, 11, and 2 (from west to east) and also in clusters 21, 22, 14, 17, and 15 (from west to east). On this first line, the clusters lie mainly along I-44 and 51st Street. On the second line, the clusters lie along 71st Street.

5.10 SIP comparison

The urbanized area of Oklahoma City returns a total SIP value of 1335.92, and Tulsa returns a total SIP value of 1420.78. At first glance it seems that Tulsa has slightly higher SIP than Oklahoma City, but even though the two cities in this study have an artificially imposed identical number of work locations, the identical number of home locations, and identical number of restaurant clusters, the SIP of the two cities cannot truly be compared. One major reason for this is that the calculation for SIP is highly dependent upon the spatial configuration of work locations, home locations, and activity locations. While the method for selecting these locations in the two cities was the same, it is still not wise to go so far as to say that citizens in Tulsa truly have a greater potential to interact with others than those in Oklahoma City. This same study

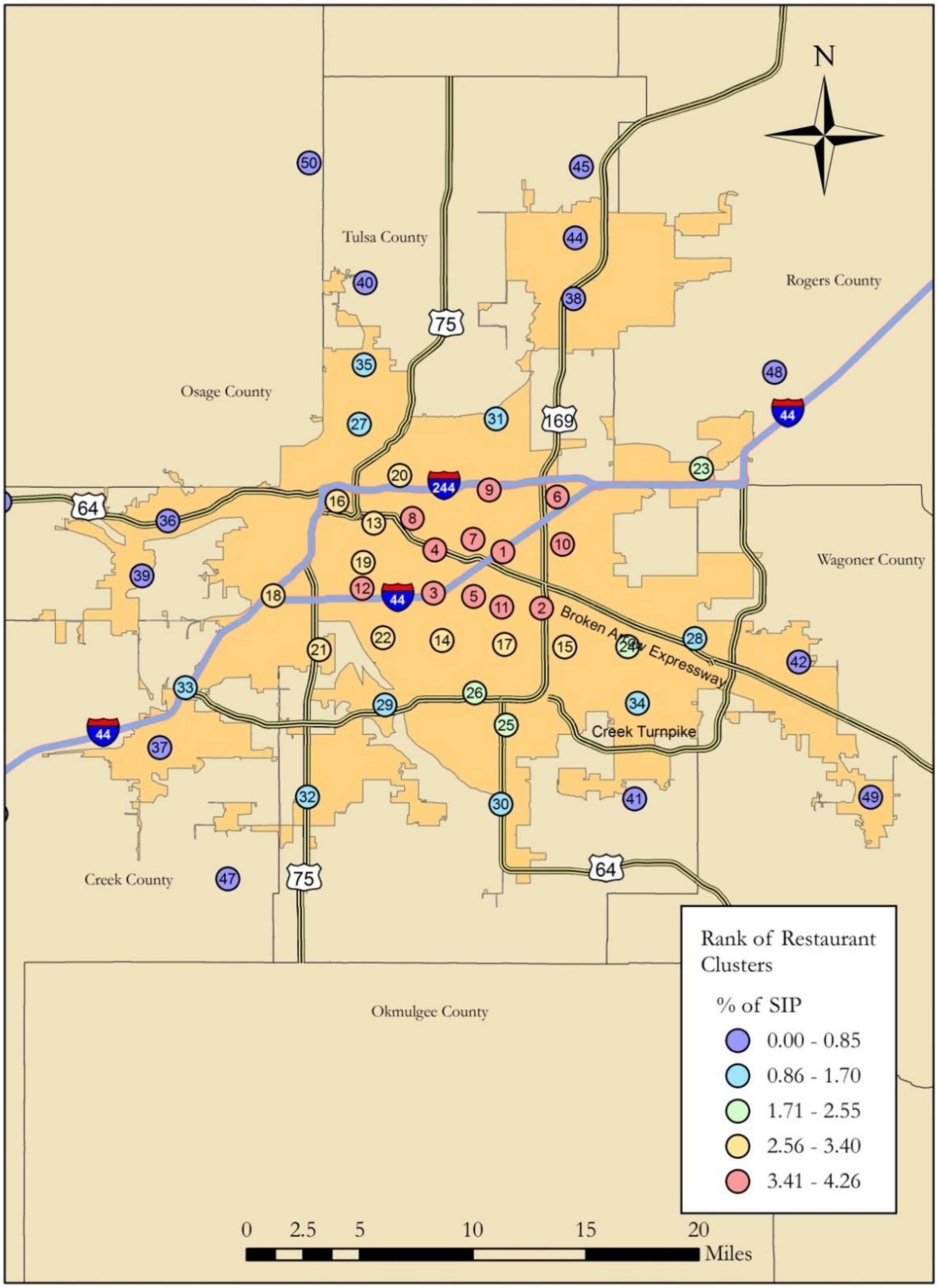

Figure 5.12: Social interaction demand at restaurant clusters in Tulsa

could produce different results if work or home locations were chosen in an alternative way. Similarly, if the activity locations were chosen differently, the results could vary greatly. Despite the inability to compare the overall SIPs of the two cities, comparison can still be conducted through comparing the percentage of SIP that each zone contributes to the urbanized area's overall SIP value and by comparing the patterns of SIP within the two cities.

The residential locations of Oklahoma City have the lowest standard deviation of SIP between the four SIP maps with a value of 2.770, shown in Table 5.5. These residential locations in Oklahoma City also have the lowest value of Moran's *I* at 0.270 with a p-value of 0.099, meaning that the pattern of SIP is roughly random. This relates to the idea that Oklahoma City is dispersed. Oklahoma City employment locations have a much higher standard deviation than residential locations with a value of 5.040 (as compared to 2.770). These employment locations also return a larger value for Moran's *I* at 0.324 with a *p*-value of 0.005, indicating that they are statistically clustered. This is evident from a visual inspection of the map since nearly all of the zones east of I-35 fall within the lowest SIP class. Historically, there are more employment opportunities in near the core of cities in the United States, so this pattern is easily explainable. Comparing the maps of population and SIP of employment locations in Oklahoma City suggests a strong correlation between population and SIP.

Similar to the pattern of residential SIP in Oklahoma City, residential locations in Tulsa show greater SIP values near the center of the city, but this pattern is much more defined in Tulsa. As shown in the map of population of residential zones in Tulsa (Figure 5.6) the centrally located zones have larger populations than those in Oklahoma City (Figure 5.2), comparatively. The standard deviation of SIP is greater for residential zones in Tulsa than in Oklahoma City: 3.454 compared to 2.770. The Moran's *I* value is actually lower (0.202 compared to 0.270), but the *p*-value is smaller (0.013 compared to 0.099) indicating that SIP is still statistically clustered in Tulsa. The maps of SIP per person show very similar patterns. When population is no longer a factor, driving time to the activity locations and other zones throughout the city becomes a more dominant factor.

Unlike residential locations in Oklahoma City, only two residential zones in Tulsa fall within the highest class of SIP (*h8* and *h9*) and no zones fall within the fourth class. In this, Tulsa exhibits a central city phenomenon in regards to residential SIP. There is a high concentration of SIP in the central core of the city with a sharp decrease away from the center. Oklahoma City shows a more dispersed pattern than Tulsa with fingers of high SIP extending out from the center.

Tulsa employment locations show the largest standard deviation of SIP at 5.381, the highest value for Moran's *I* at 0.361, and the lowest Moran's *I p*-value at 0.002; SIP is highly clustered at these locations. Interestingly, the maps of SIP of employment zones in Tulsa and Oklahoma City look very similar. In both maps, two zones fall within the highest class of SIP, and both of these zones are near the center of the city. However, in neither city are the two zones contiguous. Both maps also show two zones in the second highest class, three zones in the third highest class, and the majority of zones in the lowest class.

Table 5.5 indicates that there is greater spatial autocorrelation of SIP in restaurant clusters in Oklahoma City than in Tulsa. While visually it appears that the restaurant clusters are in Tulsa are more compact than those in Oklahoma City, there is a greater standard deviation among those in Oklahoma City. Since the time budget is the same for the two urbanized areas, and the land area of Oklahoma City is greater than Tulsa, driving time plays a more important factor in accessibility in Oklahoma City.

One notable difference between the two cities' restaurants clusters is that in Tulsa the highly ranking restaurant clusters are not located nearly as close to the downtown area as the clusters in Oklahoma City. This is because the downtown area of Tulsa is located in the Northwest portion of the urbanized area away from the centroid. The centroid of the Tulsa urbanized area is located approximately 5.89 miles from the downtown area as opposed to Oklahoma City, whose urbanized area covers a larger land area but whose centroid is only 2.26

miles from downtown. Since the urbanized area of Oklahoma City spans a larger land area than Tulsa, proportionally the downtown area of Tulsa is much farther from its centroid and from the outskirts of its urbanized area. The restaurant clusters in the highest class for Tulsa are located in a more compact group. A finger of high SIP clusters does not appear outside of the central portion of the city as seen in Oklahoma City.

CHAPTER VI

CONCLUSION

6.1 Summary

The social interaction potentials (SIPs) of Oklahoma City and Tulsa were measured and compared in this research. In general, the SIP of residential and employment locations is dependent upon population, distance to other zones, and distance to activity locations, while the SIP demand of activity locations is more dependent upon distance from the centroid of the city. The location of major employment centers in the two cities produce very similar patterns of employment zone SIP, but overall, Tulsa shows more disparity in SIP and greater spatial autocorrelation, especially in residential zones. Though the two cities are both considered dispersed, and Oklahoma City more so than Tulsa (Sarzynski, 2005), Tulsa has traditionally been thought of as a polycentric city, and Oklahoma City has been considered a monocentric city. While SIP is not a direct indicator of urban form, potential social interaction patterns are in part determined by a city's urban form. In this study, Tulsa shows a more central city phenomenon with high SIP in the center and a steep drop off in SIP away from the center, and Oklahoma City shows a more dispersed pattern with fingers of high SIP extending from the downtown. This may indicate that the urban forms of the two cities are changing in several ways.

Tulsa's core of SIP in the center of the city shows that the multiple centers in the city may be coalescing due to increased urban development, although the absence of a second core could also be due to a lack of spatial resolution in the study. Also, Oklahoma City may be more polycentric than what geographers have previously thought. While Oklahoma City did show its expected dispersed pattern of SIP, one would expect a monocentric city like Oklahoma City to show concentric zones of SIP instead of showing sectors extending from the downtown. Instead, Tulsa shows more of a concentric zonal pattern.

6.2 Limitations

There were several limitations in this study. First, different units of aggregation were used for residential and employment locations. It would be ideal if the same unit of aggregation could be used for both residential and employment locations as opposed to using census tracts and zip codes. This would allow for an easier comparison between a city's SIP of work locations and home locations given the distribution of residential and employment populations. Also, with this sort of aggregation, the SIP of living and working within same zone could be mapped. With this, the SIP of individual work-home pairs could be mapped and explained.

This project dealt with joint accessibility – observing how two individuals could meet up for social interaction. An interesting extension to this project would be to observe the SIP with respect to three individuals. However, this would create very extensive calculations, much larger than those used in this project. The "for" loops in this thesis ran 8 million times with 20 work locations, 20 home locations, and 50 activity locations; overall, it takes about 10 minutes to run. Including a third individual into the research project increases the number of calculations to 3.2 billion, an increase of four hundredfold. Using the same computer, if the increased calculation time is linear, this calculation would take about 66 hours. A high powered super computer would be required for calculations of this magnitude. The absence of computing restraints would allow for this extension as well as allow for more activity locations, residential locations, and employment locations to be studied, producing a higher spatial resolution and removing the need for aggregation of census tracts and zip codes.

6.3 Future research

One of the goals of this project was to introduce more realism into the calculation of SIP as suggested by Farber et al. (2012) by using actual activity locations. This was achieved, but more realism could be introduced in several ways.

One way to introduce more realism would be to use the 2010 Census Transportation Planning Products' tract-to-tract commute flows once they are released. But in the absence of this, the friction of distance coefficients could be calculated for each city individually. By multiplying the results of the doubly constrained gravity model (the percentage of people commuting from each zone to every other zone) by the respective travel time from each zone to every other zone and taking an average of all of these values, the estimated average commute time for citizens in the region is easily found. Conveniently, the US Census provides data for "mean travel time" for citizens commuting to work, so the average commute times produced by the model can be compared to the actual data reported by the census, and the researcher can, in a way, calibrate a more applicable friction of distance coefficient.

This project used the network analyst extension in ArcGIS to calculate travel times. These are theoretical calculations that do not account for traffic. Though difficult, it would be interesting to observe how SIP changes when accounting for realistic traffic congestion, especially along major highways.

In effect, this project only measured the SIP for one type of individual living in urbanized areas: those who commute to work by vehicle. While this is rather large portion of the population, it would be interesting to measure SIP with respect to different modes of commuting such as biking, walking, or public transit. The difficulty in this would be accurately predicting the friction of distance and applying this to an entire residential or employment zone. The friction of distance would most likely be greater for those using alternative modes of transit but would not apply to every person living within a certain zone. The model would probably have to be applied individually to a single mode of transportation.

Similar to the issue described above, this study only assumes social interaction can take place at sit-down restaurants. Again, while these are popular social meeting places, they certainly are not exhaustive. This study does not account for social interaction with both family and friends that takes place within a person's home, which is a major source of interaction for many people. Also, people can effectively interact at fast food restaurants (although there is much greater chance for social interaction at sit-down restaurants, especially for the working population commuting by vehicle), but other activity locations such as parks, recreation/community centers, book stores, or music venues could be studied as well.

Originally, the intent was to compare SIP with income through correlation and linear regression. However, the variable SIP did not adhere to the regression assumptions in the slightest – nearly all were heavily skewed in some way. Also, an informal inspection showed that SIP did not strongly correlate with income. Despite this, another interesting extension to this project would be to compare SIP (or a modification to SIP, such as *log*(SIP)) with other variables such as population density, housing characteristics, age, or race. Despite the limitations, this thesis effectively computed SIP for two cities, compared SIP patterns, and provided a platform for future research in time geography.

6.4 Concluding thoughts

One of the most important applications of studies in SIP is how the urban form of cities can be altered to allow for more social interaction (Farber et al., 2012). In this study, the residential zones with high population (and high population density) have noticeably higher SIP. In both cities, these zones contain a combination of single family and multiple family homes along with a mix in land uses. These mixed land uses offer citizens an opportunity for very high SIP because residential, office, and retail locations are located close together in mixed land use areas. These are the same types of locations factored into SIP in this study only labeled as residential, employment, and restaurant cluster locations. People who live and work within the same zone have a short commute leading to more time available for interaction. Since mixed land use areas offer close proximity to retail locations, activity locations are easily accessible. These factors lead to high SIP with the possibility for a more close-nit, integrated community.

The information in this thesis could be used by a number of groups of people to reverse social degradation in these two cities. It could be used by urban planners to create communities that allow for more social interaction by observing the characteristics of zones with high SIP and emulating these characteristics in other parts of the city. It could also be used by businesses looking to construct facilities with high accessibility for all of the working population in these urbanized areas. This research may also be of interest to new residents moving to Tulsa or Oklahoma City who desire to live in areas with ample social opportunities. Future research in time geography will provide more insight into urban environments and will enable urban planners, businesses, and individuals to decrease social degradation and create more close-knit communities.

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APPENDICES

A.1 Exhaustive SIP calculation sample

```
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r 3 w 19 - h 18 , w 19 - h 1 : 3.0795774682e-07
r 3 w 19 - h 18 , w 19 - h 2 : 8.54516782068e-07
r 3 w 19 - h 18 , w 19 - h 3 : 5.54241266737e-07
r 3 w 19 - h 18 , w 19 - h 4 : 3.98160263742e-07
r 3 w 19 - h 18 , w 19 - h 5 : 1.89873479386e-06
r 3 w 19 - h 18 , w 19 - h 6 : 2.03879985325e-07
r 3 w 19 - h 18 , w 19 - h 7 : 1.87429619802e-06
r 3 w 19 - h 18 , w 19 - h 8 : 5.43253542409e-07
r 3 w 19 - h 18 , w 19 - h 9 : 2.2039395912e-06
r 3 w 19 - h 18 , w 19 - h 10 : 7.77756058785e-07
r 3 w 19 - h 18 , w 19 - h 11 : 1.52444690834e-06
r 3 w 19 - h 18 , w 19 - h 12 : 6.75800806112e-06
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r 3 w 19 - h 18 , w 19 - h 14 : 8.69399083885e-06
r 3 w 19 - h 18 , w 19 - h 15 : 2.23332539496e-06
r 3 w 19 - h 18 , w 19 - h 16 : 2.65761693208e-06
r 3 w 19 - h 18 , w 19 - h 17 : 7.37421829818e-07
r 3 w 19 - h 18 , w 19 - h 18 : 3.29762405168e-05
r 3 w 19 - h 18 , w 19 - h 19 : 2.34922117038e-06
r 3 w 19 - h 19 , w 19 - h 0 : 1.33182102484e-07
r 3 w 19 - h 19 , w 19 - h 1 : 2.19388519454e-08
r 3 w 19 - h 19 , w 19 - h 2 : 6.08756147888e-08
r 3 w 19 - h 19 , w 19 - h 3 : 3.94840435693e-08
r 3 w 19 - h 19 , w 19 - h 4 : 2.83648622805e-08
r 3 w 19 - h 19 , w 19 - h 5 : 1.35265509493e-07
r 3 w 19 - h 19 , w 19 - h 6 : 1.45243717973e-08
r 3 w 19 - h 19 , w 19 - h 7 : 1.33524508524e-07
r 3 w 19 - h 19 , w 19 - h 8 : 3.87012801554e-08
r 3 w 19 - h 19 , w 19 - h 9 : 1.57008241836e-07
r 3 w 19 - h 19 , w 19 - h 10 : 5.54071953036e-08
r 3 w 19 - h 19 , w 19 - h 11 : 1.08601310946e-07
r 3 w 19 - h 19 , w 19 - h 12 : 4.81439222847e-07
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r 3 w 19 - h 19 , w 19 - h 16 : 1.89328130247e-07
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r 3 w 19 - h 19 , w 19 - h 18 : 2.34922117038e-06
r 3 w 19 - h 19 , w 19 - h 19 : 3.02184244006e-07
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r 4 w 0 - h 0 , w 0 - h 1 : 2.30448483387e-05
r 4 w 0 - h 0 , w 0 - h 2 : 7.73989016341e-05
r 4 w 0 - h 0 , w 0 - h 3 : 1.91807841556e-05
r 4 w 0 - h 0 , w 0 - h 4 : 1.34106800632e-05
r 4 w 0 - h 0 , w 0 - h 5 : 7.48189484537e-05
r 4 w 0 - h 0 , w 0 - h 6 : 8.4257857781e-06
r 4 w 0 - h 0 , w 0 - h 7 : 5.12271829311e-05
r 4 w 0 - h 0 , w 0 - h 8 : 1.8968745747e-05
r 4 w 0 - h 0 , w 0 - h 9 : 2.3702185383e-05
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r 4 w 0 - h 0 , w 0 - h 11 : 1.16551542732e-05
r 4 w 0 - h 0 , w 0 - h 12 : 2.25393826191e-05
r 4 w 0 - h 0 , w 0 - h 13 : 3.72327391793e-05
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r 4 w 0 - h 2 , w 0 - h 15 : 3.70261106064e-06
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r 4 w 0 - h 3 , w 0 - h 11 : 1.46585494863e-06
r 4 w 0 - h 3 , w 0 - h 12 : 4.10140585968e-06
r 4 w 0 - h 3 , w 0 - h 13 : 7.53893825864e-06
r 4 w 0 - h 3 , w 0 - h 14 : 7.51946465006e-06
r 4 w 0 - h 3 , w 0 - h 15 : 9.17570948257e-07
r 4 w 0 - h 3 , w 0 - h 16 : 2.43699758237e-06
r 4 w 0 - h 3 , w 0 - h 17 : 1.09350649391e-06
r 4 w 0 - h 3 , w 0 - h 18 : 1.1724644566e-07
r 4 w 0 - h 4 , w 0 - h 0 : 1.34106800632e-05
r 4 w 0 - h 4 , w 0 - h 1 : 2.17049438919e-06
r 4 w 0 - h 4 , w 0 - h 2 : 6.80600419264e-06
r 4 w 0 - h 4 , w 0 - h 3 : 1.686645348e-06
r 4 w 0 - h 4 , w 0 - h 4 : 1.26309383358e-06
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r 4 w 0 - h 4 , w 0 - h 5 : 6.57913828379e-06
r 4 w 0 - h 4 , w 0 - h 6 : 7.40914045565e-07
r 4 w 0 - h 4 , w 0 - h 7 : 4.50461717731e-06
r 4 w 0 - h 4 , w 0 - h 8 : 1.66799993743e-06
r 4 w 0 - h 4 , w 0 - h 9 : 2.2324061165e-06
r 4 w 0 - h 4 , w 0 - h 10 : 9.43293158504e-07
r 4 w 0 - h 4 , w 0 - h 11 : 1.09774846783e-06
r 4 w 0 - h 4 , w 0 - h 12 : 1.98198074348e-06
r 4 w 0 - h 4 , w 0 - h 13 : 3.27402810127e-06
r 4 w 0 - h 4 , w 0 - h 14 : 3.26557105606e-06
r 4 w 0 - h 4 , w 0 - h 15 : 6.8714991447e-07
r 4 w 0 - h 4 , w 0 - h 16 : 1.82501711009e-06
r 4 w 0 - h 4 , w 0 - h 17 : 6.12709169807e-07
r 4 w 0 - h 4 , w 0 - h 18 : 8.7803439353e-08
r 4 w 0 - h 5 , w 0 - h 0 : 7.48189484537e-05
r 4 w 0 - h 5 , w 0 - h 1 : 1.13055596908e-05
r 4 w 0 - h 5 , w 0 - h 2 : 5.73909261692e-05
r 4 w 0 - h 5 , w 0 - h 3 : 1.51494476475e-05
r 4 w 0 - h 5 , w 0 - h 4 : 6.57913828379e-06
r 4 w 0 - h 5 , w 0 - h 5 : 8.08722875283e-05
r 4 w 0 - h 5 , w 0 - h 6 : 9.10748659505e-06
r 4 w 0 - h 5 , w 0 - h 7 : 4.40080804437e-05
r 4 w 0 - h 5 , w 0 - h 8 : 1.13576333378e-05
r 4 w 0 - h 5 , w 0 - h 9 : 1.16280423161e-05
r 4 w 0 - h 5 , w 0 - h 10 : 1.08234335615e-05
r 4 w 0 - h 5 , w 0 - h 11 : 5.71789583532e-06
r 4 w 0 - h 5 , w 0 - h 12 : 1.59984529888e-05
r 4 w 0 - h 5 , w 0 - h 13 : 2.94744509133e-05
r 4 w 0 - h 5 , w 0 - h 14 : 4.01411537497e-05
r 4 w 0 - h 5 , w 0 - h 15 : 3.57919118026e-06
r 4 w 0 - h 5 , w 0 - h 16 : 9.50605538426e-06
r 4 w 0 - h 5 , w 0 - h 17 : 4.26546721645e-06
r 4 w 0 - h 5 , w 0 - h 18 : 4.57346045034e-07
r 4 w 0 - h 6 , w 0 - h 0 : 8.4257857781e-06
r 4 w 0 - h 6 , w 0 - h 1 : 1.27318314445e-06
r 4 w 0 - h 6 , w 0 - h 2 : 6.46311742549e-06
r 4 w 0 - h 6 , w 0 - h 3 : 1.70606515023e-06
r 4 w 0 - h 6 , w 0 - h 4 : 7.40914045565e-07
r 4 w 0 - h 6 , w 0 - h 5 : 9.10748659505e-06
r 4 w 0 - h 6 , w 0 - h 6 : 1.26346174246e-06
r 4 w 0 - h 6 , w 0 - h 7 : 4.95599932887e-06
r 4 w 0 - h 6 , w 0 - h 8 : 1.27904745293e-06
r 4 w 0 - h 6 , w 0 - h 9 : 1.30949974036e-06
r 4 w 0 - h 6 , w 0 - h 10 : 1.21888818885e-06
r 4 w 0 - h 6 , w 0 - h 11 : 6.43924652853e-07
r 4 w 0 - h 6 , w 0 - h 12 : 1.80167645297e-06
r 4 w 0 - h 6 , w 0 - h 13 : 3.3192849466e-06
r 4 w 0 - h 6 , w 0 - h 14 : 4.6246478745e-06
r 4 w 0 - h 6 , w 0 - h 15 : 4.03073001786e-07
r 4 w 0 - h 6 , w 0 - h 16 : 1.07053076684e-06
r 4 w 0 - h 6 , w 0 - h 17 : 4.80358435291e-07
r 4 w 0 - h 6 , w 0 - h 18 : 5.15043298731e-08
r 4 w 0 - h 7 , w 0 - h 0 : 5.12271829311e-05
r 4 w 0 - h 7 , w 0 - h 1 : 7.74071256533e-06
r 4 w 0 - h 7 , w 0 - h 2 : 3.92945307869e-05
r 4 w 0 - h 7 , w 0 - h 3 : 1.03725532366e-05
r 4 w 0 - h 7 , w 0 - h 4 : 4.50461717731e-06
r 4 w 0 - h 7 , w 0 - h 5 : 4.40080804437e-05
r 4 w 0 - h 7 , w 0 - h 6 : 4.95599932887e-06
r 4 w 0 - h 7 , w 0 - h 7 : 3.01315379851e-05
r 4 w 0 - h 7 , w 0 - h 8 : 7.77636645106e-06
r 4 w 0 - h 7 , w 0 - h 9 : 7.96151059547e-06
r 4 w 0 - h 7 , w 0 - h 10 : 6.30972011998e-06
r 4 w 0 - h 7 , w 0 - h 11 : 3.9149400251e-06
r 4 w 0 - h 7 , w 0 - h 12 : 1.09538518626e-05
r 4 w 0 - h 7 , w 0 - h 13 : 2.01806242929e-05
r 4 w 0 - h 7 , w 0 - h 14 : 2.18435162069e-05
r 4 w 0 - h 7 , w 0 - h 15 : 2.45060756835e-06
r 4 w 0 - h 7 , w 0 - h 16 : 6.50862446194e-06
r 4 w 0 - h 7 , w 0 - h 17 : 2.92048837761e-06
r 4 w 0 - h 7 , w 0 - h 18 : 3.13136578313e-07

A.2 Gravity model commute flow results

Tulsa Gravity Model Results

	[h1,]	[h2,]	[h3,]	[h4,]	[h5,]	[h6,]	[h7,]	[h8,]	[h9,]	[h10,]	[h11,]	[h12,]	[h13,]	[h14,]	[h15,]	[h16,]	[h17,]	[h18,]	[h19,]	[h20,]
[w1,]	0.0031	0.0005	0.0016	0.0004	0.0003	0.0015	0.0002	0.0011	0.0004	0.0006	0.0002	0.0005	0.0005	0.0008	0.0008	0.0003	0.0005	0.0001	0.0001	9E-05
[w2,]	0.0041	0.0005	0.0008	0.0005	0.0004	0.0036	8E-05	0.0006	0.0002	0.0006	0.0003	0.0003	0.0004	0.0011	0.0007	0.0002	0.0002	7E-05	0.0001	8E-05
[w3,]	0.0133	0.0016	0.008	0.0033	0.0012	0.0103	0.0022	0.0136	0.005	0.0066	0.0018	0.007	0.0055	0.0033	0.0091	0.0035	0.006	0.0018	0.0014	0.001
[w4,]	0.0067	0.0005	0.0047	0.0014	0.0005	0.0044	0.0004	0.003	0.001	0.0023	0.0008	0.0013	0.0016	0.0013	0.0027	0.0008	0.0011	0.0004	0.0004	0.0003
[w5,]	0.0094	0.0082	0.004	0.0062	0.0099	0.0479	0.0005	0.0035	0.0011	0.0043	0.0031	0.0015	0.0046	0.0256	0.005	0.0015	0.0018	0.0005	0.003	0.0006
[w6,]	0.0065	0.0005	0.0039	0.0016	0.0006	0.005	0.0031	0.0078	0.0056	0.0037	0.0009	0.0048	0.0031	0.0018	0.005	0.002	0.0035	0.0011	0.0008	0.0006
[w7,]	0.0006	5E-05	0.0004	0.0002	6E-05	0.0005	0.0004	0.0009	0.0027	0.0004	9E-05	0.0009	0.0004	0.0002	0.0006	0.0003	0.0006	0.0003	0.0001	8E-05
[w8,]	0.0055	0.0004	0.0033	0.0014	0.0005	0.0043	0.001	0.0094	0.0023	0.0075	0.0015	0.0042	0.0063	0.0038	0.0104	0.0032	0.0038	0.0011	0.0016	0.0012
[w9,]	0.0094	0.0008	0.0043	0.0028	0.001	0.0101	0.0005	0.0047	0.0012	0.0108	0.0068	0.0028	0.0119	0.0056	0.0134	0.0041	0.0049	0.0014	0.002	0.0015
[w10,]	3E-05	6E-06	1E-05	1E-05	8E-06	0.0002	2E-06	2E-05	5E-06	4E-05	9E-05	1E-05	0.0002	0.0002	6E-05	2E-05	2E-05	6E-06	4E-05	1E-05
[w11,]	0.0068	0.0005	0.0041	0.0017	0.0006	0.0053	0.0031	0.0097	0.0102	0.0046	0.0015	0.0203	0.0087	0.0052	0.0118	0.0069	0.0121	0.0037	0.0022	0.0016
[w12,]	0.0001	0.0002	7E-05	9E-05	0.0002	0.0014	2E-05	0.0001	4E-05	0.0002	0.0004	0.0001	0.0019	0.005	0.0007	0.0002	0.0002	6E-05	0.0011	0.0002
[w13,]	4E-05	4E-06	2E-05	1E-05	4E-06	4E-05	5E-06	4E-05	2E-05	5E-05	2E-05	5E-05	0.0001	9E-05	0.0002	7E-05	9E-05	2E-05	4E-05	3E-05
[w14,]	0.0034	0.0003	0.0017	0.001	0.0004	0.0032	0.0007	0.0045	0.0021	0.004	0.0014	0.0059	0.0079	0.0047	0.0107	0.0076	0.0108	0.0029	0.002	0.0015
[w15,]	0.0009	8E-05	0.0005	0.0003	0.0001	0.0009	0.0002	0.0015	0.0018	0.0011	0.0004	0.0019	0.0022	0.0013	0.003	0.0018	0.0046	0.0124	0.0006	0.0004
[w16,]	0.0002	4E-05	7E-05	5E-05	5E-05	0.0005	2E-05	0.0002	5E-05	0.0002	0.0002	0.0001	0.0016	0.0013	0.0007	0.0002	0.0002	6E-05	0.0024	0.0007
[w17,]	0.0008	8E-05	0.0004	0.0003	9E-05	0.0008	9E-05	0.0009	0.0002	0.001	0.0004	0.0007	0.0031	0.0018	0.0039	0.001	0.0012	0.0003	0.0019	0.0019
[w18,]	0.0005	4E-05	0.0002	0.0001	5E-05	0.0004	8E-05	0.0006	0.0003	0.0005	0.0002	0.0008	0.0011	0.0006	0.0015	0.001	0.0018	0.0004	0.0003	0.0002
[w19,]	0.0058	0.0005	0.0027	0.0017	0.0006	0.0055	0.0006	0.0058	0.0017	0.0068	0.0024	0.0047	0.021	0.0125	0.027	0.0069	0.0082	0.0023	0.0213	0.0132
[w20,]	0.0001	2E-05	5E-05	3E-05	2E-05	0.0001	1E-05	0.0001	3E-05	0.0001	5E-05	9E-05	0.0004	0.0013	0.0005	0.0001	0.0002	5E-05	0.002	0.0003

Oklahoma City Gravity Model Results

	[h1,]	[h2,]	[h3,]	[h4,]	[h5,]	[h6,]	[h7,]	[h8,]	[h9,]	[h10,]	[h11,]	[h12,]	[h13,]	[h14,]	[h15,]	[h16,]	[h17,]	[h18,]	[h19,]	[h20,]
[w1,]	0.002	0.0131	0.0034	0.0004	0.0065	0.0023	0.0046	0.0035	0.0028	0.0036	0.0033	0.0017	0.0029	0.0056	0.0006	0.0017	0.0034	0.0036	0.0004	0.0013
[w2,]	0.0014	0.0021	0.0025	0.0002	0.0024	0.0013	0.0012	0.002	0.0007	0.0019	0.0018	0.0009	0.0007	0.0031	0.0003	0.0004	0.0019	0.002	0.0002	0.0007
[w3,]	0.0002	0.0001	0.0065	8E-05	0.0004	0.0008	0.0002	0.0007	0.0001	0.0003	0.0008	0.0004	0.0001	0.0005	0.0001	7E-05	0.0003	0.0003	5E-05	0.0001
[w4,]	0.0027	0.0309	0.0076	0.0008	0.0144	0.0051	0.0102	0.0078	0.0063	0.008	0.0073	0.0037	0.0065	0.0124	0.0013	0.0037	0.0074	0.0081	0.001	0.0029
[w5,]	0.0052	0.0021	0.0093	0.0007	0.0035	0.0045	0.0017	0.0066	0.0011	0.0027	0.0063	0.0032	0.0011	0.0045	0.0012	0.0006	0.0027	0.0029	0.0004	0.0011
[w6,]	0.0025	0.0027	0.0207	0.0014	0.0065	0.0137	0.0032	0.0129	0.002	0.0054	0.0139	0.007	0.002	0.009	0.0026	0.0013	0.0054	0.0058	0.0009	0.0025
[w7,]	0.0001	0.0002	0.0019	8E-05	0.0004	0.0049	0.0002	0.0007	0.0001	0.0003	0.0008	0.0014	0.0001	0.0005	0.0004	8E-05	0.0003	0.0004	5E-05	0.0001
[w8,]	0.001	0.0046	0.0041	0.0004	0.0078	0.0027	0.0212	0.0046	0.0067	0.0085	0.0045	0.002	0.0095	0.0089	0.0009	0.0039	0.0054	0.0058	0.0007	0.0031
[w9,]	0.0003	0.0003	0.005	0.0002	0.0008	0.0103	0.0004	0.0017	0.0003	0.0009	0.0024	0.0093	0.0004	0.0016	0.0034	0.0002	0.0009	0.001	0.0002	0.0004
[w10,]	0.0015	0.0068	0.006	0.0006	0.0116	0.0041	0.0115	0.0075	0.011	0.014	0.0074	0.0033	0.0113	0.0147	0.0015	0.0065	0.0088	0.0096	0.0011	0.005
[w11,]	0.0004	0.0008	0.0015	0.0002	0.0019	0.001	0.0009	0.0029	0.0009	0.0031	0.0024	0.0011	0.0011	0.0046	0.0005	0.0007	0.0028	0.003	0.0004	0.001
[w12,]	0.0004	0.0004	0.0022	0.0002	0.001	0.0065	0.0005	0.0034	0.0006	0.0018	0.0048	0.0209	0.0007	0.0031	0.0083	0.0004	0.002	0.0023	0.0004	0.0011
[w13,]	0.0003	0.0004	0.0018	0.0002	0.0009	0.0019	0.0007	0.0041	0.0007	0.0022	0.0089	0.002	0.0008	0.004	0.0008	0.0006	0.0025	0.003	0.0005	0.0014
[w14,]	8E-05	0.0004	0.0003	4E-05	0.0006	0.0004	0.0027	0.0008	0.0011	0.0016	0.0008	0.0004	0.0042	0.0017	0.0002	0.0007	0.001	0.0011	0.0001	0.0006
[w15,]	0.0002	0.0002	0.001	1E-04	0.0005	0.002	0.0003	0.0016	0.0003	0.0011	0.0033	0.0066	0.0004	0.0026	0.0176	0.0004	0.0016	0.0019	0.0004	0.0009
[w16,]	0.0001	0.0001	0.0007	7E-05	0.0003	0.0016	0.0002	0.0011	0.0002	0.0007	0.0023	0.0045	0.0003	0.0018	0.0029	0.0002	0.0011	0.0013	0.0002	0.0006
[w17,]	0.0002	0.0003	0.0007	7E-05	0.0009	0.0008	0.0006	0.0018	0.0007	0.0021	0.0023	0.0008	0.0008	0.0067	0.0005	0.0015	0.0054	0.0059	0.0004	0.0015
[w18,]	2E-05	3E-05	7E-05	7E-06	8E-05	8E-05	6E-05	0.0002	7E-05	0.0002	0.0002	8E-05	8E-05	0.0007	5E-05	0.0002	0.0015	0.003	0.0002	0.0007
[w19,]	2E-06	4E-06	1E-05	1E-06	1E-05	1E-05	7E-06	2E-05	8E-06	3E-05	4E-05	1E-05	1E-05	6E-05	1E-05	9E-06	0.0001	0.0003	0.0002	0.0003
[w20,]	3E-06	6E-06	1E-05	1E-06	1E-05	2E-05	1E-05	3E-05	2E-05	3E-05	6E-05	2E-05	2E-05	8E-05	1E-05	3E-05	0.0002	0.0008	8E-05	0.0032

A.3 Restaurant cluster SIP

Restaurant Cluster SIP					
Oklahoma City			Tulsa		
Rank	Location	% of SIP	Rank	Location	% of SIP
1	r50	4.22	1	r35	4.26
2	r25	4.22	2	r16	4.05
3	r31	4.18	3	r44	3.95
4	r6	4.17	4	r26	3.94
5	r18	4.02	5	r11	3.90
6	r14	3.97	6	r14	3.84
7	r8	3.97	7	r21	3.83
8	r46	3.93	8	r32	3.64
9	r42	3.90	9	r39	3.59
10	r44	3.83	10	r43	3.57
11	r13	3.77	11	r31	3.55
12	r34	3.65	12	r23	3.52
13	r26	3.47	13	r47	3.39
14	r22	3.20	14	r6	3.34
15	r43	3.11	15	r25	3.21
16	r27	3.01	16	r7	3.10
17	r32	2.96	17	r45	3.09
18	r23	2.79	18	r15	2.95
19	r41	2.65	19	r20	2.91
20	r9	2.56	20	r37	2.84
21	r39	2.54	21	r36	2.69
22	r11	2.50	22	r38	2.66
23	r29	2.35	23	r30	2.43
24	r36	2.01	24	r33	2.30
25	r45	1.94	25	r22	2.24
26	r16	1.87	26	r42	2.13
27	r48	1.82	27	r13	1.59
28	r28	1.60	28	r12	1.59
29	r17	1.54	29	r17	1.42
30	r7	1.47	30	r10	1.40
31	r35	1.26	31	r18	1.27
32	r10	1.14	32	r48	1.18
33	r30	1.12	33	r27	1.07
34	r49	0.99	34	r40	1.07
35	r19	0.82	35	r49	0.95
36	r5	0.71	36	r41	0.84
37	r4	0.65	37	r50	0.75
38	r21	0.56	38	r29	0.67
39	r37	0.51	39	r34	0.61
40	r33	0.21	40	r19	0.27
41	r47	0.19	41	r24	0.10
42	r24	0.18	42	r8	0.10
43	r12	0.12	43	r3	0.08
44	r2	0.10	44	r9	0.05
45	r1	0.08	45	r46	0.03
46	r15	0.07	46	r1	0.02
47	r40	0.03	47	r4	0.02
48	r38	0.02	48	r2	0.01
49	r20	0.00	49	r28	0.00
50	r3	0.00	50	r5	0.00

VITA

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