APPROVAL SHEET

Title of Thesis: A Nation of Neighborhoods: A Quantitative Understanding of US Neighborhoods and Metropolitan Areas

Name of Candidate: D.W. Rowlands
Master of Science, 2021

Thesis and Abstract Approved: Dillon Mahmoudi
Dillon Mahmoudi
Assistant Professor
Geography and Environmental Systems

Date Approved: April 20, 2021

D.W. Rowlands

d.w.rowlands@gmail.com **dwrowlands.net**

EDUCATION

University of Maryland, Baltimore County (UMBC) **May 2021**
M.S. in Human Geography *Catonsville, MD*
• Research Advisor: Professor Dillon Mahmoudi *GPA: 4.0/4.0*
• Thesis Topic: GIS-Based Typology of US Metro Areas and Neighborhoods

Massachusetts Institute of Technology (MIT) **September 2015**
M.S. in Physical Chemistry *Cambridge, MA*
• Research Advisor: Professor Sylvia Ceyer *GPA: 4.7/5.0*
• Thesis Topic: etching and oxidation of silicon by molecular beams in ultra-high vacuum

California Institute of Technology (Caltech) **June 2009**
B.S. with Honors in Chemistry with Minor in History *Pasadena, CA*
• Research Advisor: Professor Daniel Weitekamp *GPA: 3.7/4.0*
• Thesis Topic: NMR hyperpolarization

WORK EXPERIENCE

Brookings Institution Metropolitan Policy Program **Jun 2020–Present**
Research Intern and Research Assistant *Washington, DC*
- Performed GIS analyses of jobs and economic data for studies of US metro areas.
- Authored reports and blog posts for publication on the Brookings website.

University of Maryland, Baltimore County (UMBC) **Aug 2016–Aug 2019**
Visiting Lecturer in Physical and Analytical Chemistry *Catonsville, MD*
- Taught general chemistry lab and lecture with flipped-classroom techniques.
- Taught analytic chemistry lab and lecture for juniors, focusing heavily on error analysis and wetlab technique, and instrumental analysis lab for seniors.
- Taught a two-semester physical chemistry lab course with lecture component for juniors, focused on instrumentation techniques, MATLAB, and formal report-writing.
- Helped organize mentor students in the SCIART undergrad summer research program.

Anne Arundel Community College **Sep 2015–May 2016**
Adjunct Professor of Physical Science *Arnold, MD*
- Taught remedial physics, covering algebra, trigonometry, and Newtonian mechanics.
- Taught introductory physical science lab and general chemistry lecture.

Massachusetts Institute of Technology (MIT) **Jan 2010–Jan 2015**
Graduate Research Assistant in Chemistry Department, Ceyer Lab *Cambridge, MA*
- Repaired and operated an ultra-high vacuum molecular beam set-up.
- Repaired and maintained electronics and power supplies.
- Rebuilt an Auger electron spectrometer and repaired its control electronics.
- Designed and programmed a classical dynamics simulation in Python.

TECHNICAL PUBLICATIONS

D.W. Rowlands (2021). *A Nation of Neighborhoods: A Quantitative Understanding of US Neighborhoods and Metropolitan Areas*. MS Thesis, University of Maryland, Baltimore County, Catonsville, MD.

D.W. Rowlands and T.H. Loh (2020). "Retail Revolution: The New Rules of Retail Call for Small Business Empowerment." Research Report, Brookings Institution Metropolitan Policy Program, Washington, DC.

D.W. Rowlands (2020). "Understanding Walkable Density." Research Report, City Observatory, Portland, OR.

D.W. Rowlands (2015). *Xenon Difluoride Etching and Molecular Oxygen Oxidation of Silicon by Reactive Scattering*. MS Thesis, Massachusetts Institute of Technology, Cambridge, MA.

D.W. Rowlands (2009). *Producing Safe Spin-Polarized Metabolites for Magnetic Resonance Imaging*. BS Thesis, California Institute of Technology, Pasadena, CA.

NON-ACADEMIC WRITING EXPERIENCE

Greater Greater Washington **Jun 2016–Present**
Contributor and Former Member of Elections Committee *Washington, DC*

- Five articles on the Prince George's County library system history, Nov–Dec 2020.
- Three articles on 1940's subway proposed for the DC region, April–May 2019.
- Seven-article series (w/David Alpert) proposing DC bus improvements, Sep–Oct 2018.
- Nine articles on the history of rail transit in Baltimore and DC, 2016–2018.
- Seven articles on historical and current place names in the DC region, 2017–2018.
- Eight-article series (w/Tracy Hadden-Loh), discussing problems with Prince George's County's TheBus bus service, and proposing improvements, April–June 2018.
- Analyzed DC Metro to show why express tracks would not make sense, June 2016.
- Reviewed candidates, voted on endorsements, and drafted endorsement articles for the Greater Greater Washington Elections Committee during the 2018 elections cycle.
- All articles online at https://ggwash.org/contributors/drowlands/.

DC Policy Center **Jan 2017–Present**
Fellow *Washington, DC*

- Article on 2020 Census self-response rates in the DC region, May 2020.
- Article on the history of regional transit proposals in the DC region, February 2020.
- Four-article series on the demographic history of the DC area, July 2019–January 2020.
- Seven-article series on circumferential transit in the DC area, discussing possibilities for improved service and capital investment, February–March 2019.
- Five-article series on DC-area transit fares and service cuts, with comparisons to other transit systems nationwide, March–May 2017.
- All articles are online at https://www.dcpolicycenter.org/people/dw-rowlands/.

AWARDS AND HONORS

MIT Teaching and Learning Lab Graduate Student Teaching Certificate (2014)

MIT Chemistry Department Outstanding Teaching Award (2012-2013)

MIT Energy Initiative Fellowship (2010-2011)

Dow-Corning Foundation Fellowship (2010)

MIT Presidential Fellowship (2009-2010)

Arthur A. Noyes Summer Research Fellowship, Caltech (2008)

James A. Michener NASA College Scholarship (2006-2009)

Robert and Phyllis Henigson Scholarship, Caltech (2006-2008)

LEADERSHIP AND SERVICE

UMBC All-Gender Restrooms Steering Committee **Feb 2019–Present**
Faculty and then Grad Student Committee Member *Catonsville, MD*
- Participated in planning and implementing a strategy to open an all-gender restroom in every building on campus.

PG County Advocates for Community-Based Transit **Sep 2015–Sep 2017**
Member of the Advisory Board *Hyattsville, MD*
- Work on advertising/awareness building and social media for a transit advocacy group.
- Provided advice and recommendations to the director as member of the advisory board.

MIT Graduate Student Council (GSC) **Oct 2013–Jan 2015**
General Council Representative and Member of the Funding Board *Cambridge, MA*
- Represented the Chemistry Department and served on the GSC Housing and Community Affairs committee and the GSC Transportation subcommittee.
- Represented the GSC on the MIT Campus Activities Complex Advisory Board.
- Served as the General Council's representative on the six-member GSC Funding Board

MIT Science Fiction Society **Jan 2010–Jan 2015**
President, Vice President, and Secretary *Cambridge, MA*
- Co-ordinated a major rearrangement of a 60,000-book library to increase shelf space with fixed floor space and improve the organization and navigability of the collection.
- Arranged author visits and talks and organized the annual post-elections retreat.

MIT Association of Student Activities (ASA) **Oct 2011–Oct 2013**
Treasurer and Student Member at Large *Cambridge, MA*
- Chaired the Large Events Fund and Cultural and Diversity Events Funding Board, and prepared allocations totaling $175,000 to student-run events over the course of a year.
- Served on all student group funding boards and represented the ASA to administration.
- Organized the reallocation of office space to student groups.
- Chaired the ASA committee in charge of recognizing new student groups.

SKILLS AND TECHNICAL EXPERIENCE

Programming and Computer Proficiency:

- Geographic Information System (GIS) mapping and analysis using QGIS and ArcGIS.
- Geographic Information System (GIS) mapping and analysis using R and R Markdown.
- Data analysis and plotting in Microsoft Excel
- Document production in Microsoft Word
- Document production in LaTeX
- Raster image editing in GIMP

Programming and Computer Experience:

- Data analysis and plotting in IgorPro
- Computer-aided design and drafting in VectorWorks
- Programming in Labview
- Programming in Matlab
- Programing in Python

Ultra-High Vacuum Experience:

- Leak-checking and internal repairs on UHV systems
- Repairing and rebuilding mechanical vacuum pumps
- Repairing and rebuilding ionization vacuum pumps
- Repairing and rebuilding oil diffusion pumps.

Spectrometry Experience:

- Repairing a differentially-pumped, TOF-capable quadrupole mass spectrometer
- Performing time-of-flight and thermal desorption mass spectrometry experiments
- Performing He diffraction experiments with a mass spectrometer
- Repairing and rebuilding an Auger electron spectrometer
- Performing Auger electron spectrometry experiments

General Laboratory Experience

- Working with toxic chemicals, including F_2 and HF gas
- Working with cryogens, particularly liquid N_2
- Working and performing repairs in confined spaces

ABSTRACT

Title of thesis: A NATION OF NEIGHBORHOODS:
A QUANTITATIVE UNDERSTANDING OF
US NEIGHBORHOODS AND METROPOLITAN AREAS

D.W. Rowlands, Master of Science, 2021

Directed by: Professor Dillon Mahmoudi
Department of Geography and Environmental Systems

While pedestrian-oriented urban places have been identified as beneficial in a number of fields, including public health and climate change, there is a shortage of quantitative studies of such places covering large geographic areas. This study characterizes neighborhoods in US metropolitan areas based on built environment and density variables derived from the American Community Survey, Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics, National Land Cover Database, and OpenStreetMaps datasets. Neighborhoods and metropolitan areas as a whole are typologized based on this data using k-means analysis. The resulting neighborhood and metro area types are analyzed in connection with metro area history, the distributions of residents by race and jobs by income, and qualitative perceptions of density. Finally, the implications of these results for public transportation are discussed, and it is shown that transit commute share in US metro areas is strongly correlated with the number of jobs in dense central business districts.

A NATION OF NEIGHBORHOODS: A QUANTITATIVE UNDERSTANDING OF US NEIGHBORHOODS AND METROPOLITAN AREAS

by

D.W. Rowlands

Thesis submitted to the Faculty of the Graduate School of the
University of Maryland, Baltimore County, in partial fulfillment
of the requirements for the degree of
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Advisory Committee:
Prof. Dillon Mahmoudi (UMBC), Chair/Advisor
Prof. Matthew Fagan (UMBC)
Prof. Ashanté Reese (University of Texas at Austin)
Prof. Eric Stokan (UMBC)

Preface

Like the majority of Americans of my generation, I was raised a child of car-oriented suburbia. With the exception of a couple of friends' houses and occasional trips to the library when I couldn't convince my parents to drive me, I never traveled anywhere on foot, and I only rode public transportation a few times a year, when my mom and I took the Washington Metro downtown to see the Smithsonian museums.

My only real experience with walkable urbanism as a child, perhaps surprisingly, was in Detroit. Several times a year, my family traveled to Hamtramck, Michigan, a streetcar suburb that forms an enclave surrounded by Detroit, to visit my grandparents in the house where my mother grew up. While I enjoyed walking to the bakery to get pumpernickel bread and to small grocery stores to buy *pierogi* and *gołąbki*, the experience never really felt like "real life." Instead, I filed this sort of walkable urbanism in my brain as an exotic and somewhat outdated way of life, as unrelated to my everyday existence as my mother's stories of growing up in Hamtramck and helping out in her father's store were.

However, while my childhood in Prince George's County, Maryland was thoroughly car-oriented, I spent the ten years after I graduated high school living without a car in much more urban environments. My four years living without a car in Los Angeles while I was an undergraduate at Caltech were my first real experience with urban living, though Caltech's Pasadena, California campus is really a border condition between urban and suburban living. This was enough to make me realize that I wanted to go to graduate school somewhere walkable and with good public transportation if at all possible.

My next six years, pursuing a PhD in physical chemistry at MIT and living in Boston really cemented my love of public transportation and vital, urban places. Life in Boston, along with travel to visit college friends in a large number of American cities helped me develop an intuitive sense of how urban life and public transportation worked, a sense that I began to supplement with reading on these topics.

By the time I left MIT with a Master's degree, I was more interested in transit and urbanism in chemistry but, as I returned home to Prince George's County, I pursued a career teaching chemistry because it was, after all, what I was qualified for. It was only thanks to Les Henderson's efforts to get me involved in running Prince George's Advocates for Community-Based Transit (PG-ACT) and then Dan Reed, David Alpert, and Jonathan Neeley's efforts to get me involved in writing for *Greater Greater Washington* that I realized that I had something to contribute to conversations about transportation and the built environment. And it was only thanks to Dan Reed and Tracy Hadden Loh's efforts to convince me to take advantage of free tuition as a visting lecturer in the chemistry department to start taking geography classes at UMBC.

My path to this Master's degree has been indirect and as much a result of accident as intention, but I am very glad that it has brought me here. I have greatly enjoyed getting to work on this project for the past year-and-a-half, and I hope that I will be able to continue this research in the future.

D.W. Rowlands

16 April 2021

College Park, Maryland

In memory of three dear friends

who did not live to see this work completed:

Caroline Mitter, DVM

(10 December 1987 – 24 September 2019)

Karl C. Ramm

(15 February 1973 – 28 June 2020)

Izzy Vivian Dupree

(17 August 1988 – 2 December 2020)

Acknowledgments

My first thanks go to my advisor, Professor Dillon Mahmoudi. He convinced me to enter the Master's program when I took my first GIS class from him in Fall 2018, and he has been an essential source of guidance throughout my time in the geography department at UMBC. He has also been incredibly helpful in dealing with the logistical and administrative complications of completing a Master's program in a global pandemic. Among other things, he allowed me to take laboratory computers home to perform calculations, which made it possible for me to complete this thesis while working remotely for the past year due to the COVID-19 pandemic.

The other members of my committee provided invaluable help as well. Professor Matthew Fagan helped me design my *k*-means analyses, and Professor Ashanté Reese provided assistance with placing my quantitative work in a qualitative context, even after she had left UMBC to take a job at the University of Texas in Austin. Professor Eric Stokan's willingness to join my committee on short notice this winter, when it became clear that I needed an additional committee member, is much appreciated.

I would also like to thank Professors Erle Ellis, Maggie Holland, and David Lansing, along with my classmates in GES 700, 701, and 702—particularly Bergren Cliff, Julian Holman, Nicati Robidoux, and Kirk Saylor—for their help with developing the literature reviews in Chapters 1 and 4 of this thesis. In addition, my labmate Alicia Sabatino provided a very helpful sounding board throughout this project, as well as providing help with my R coding.

Kirk Saylor brought the Geofabrik OpenStreetMap data dumps used in my street network analysis to my attention and Professor Geoff Boeing of the University of Southern California provided significant assistance in understanding the limitations of this data and why my node analysis was not producing the results I expected. (My decision not to use the node results in my typologization was partly based on his advice and my too-late realization that additional data-cleaning would have been necessary to get accurate results.)

My neighborhood cluster results were validated with the help of input from a number of friends who are well-acquainted with metro areas across the United States: Sarah Emrys, Autumn Florek, Ellie Fullerton, Felix Knutson, Blair Lorenzo, Fedor Manin, Sean McKenna, and Sky Rose. Alon Levy and Nilo Cobau helped me understand the East Stroudsburg, Pennsylvania MSA's high transit usage. And Professors Jamal Green of the University of Pennsylvania and Colin V. Parker of Georgia Tech, along with Alon Levy and Blair Lorenzo, provided invaluable advice and discussion on a number of aspects of this project.

I particularly appreciate Stephanie Diederich and Tegan Sutherland's efforts in proofreading this entire thesis during the last few days before it was due to my committee. They both caught an impressive number of typographic errors and stylistic inconsistencies; any that remain are, of course, not their responsibilities.

Dr. Tracy Hadden Loh, my mentor at the Brookings Institution, provided invaluable advice over the course of this project. In addition, by extending my internship at Brookings and then converting it into a temporary position as a research assistant, she has provided me with the opportunity to acquire more experience doing research on US metro areas.

In particular, she has taught me about a number of potential resources for characterizing neighborhoods, and the study we did together at Brookings on the history of sprawl in US metro areas (Rowlands and Loh, 2021) provided the basis for some of my analysis in Chapter 3.

My return to graduate school, and thus this project, would not have been possible without substantial financial support from my parents, David Rowlands and Peggy Kwik. I greatly appreciate their willingness to provide this assistance.

Finally, I want to thank my friends and chosen family for being a huge source of emotional support while I completed this Master's program during a pandemic: Shelby and Jamie Anfenson-Comeau, Sara Bowerman, Ember Bricault, Stephanie Diederich, Cathy Douglass, Ruthanna and Sarah Emrys, Sam Friedman, Ellie Fullerton, Deepthi Gopal, Les Henderson, Beth Hocking, Zoe Jones, Blair Lorenzo, Alex Malz, Noor Pervez, Emily Prince, Dan Reed, Kedron Silsbee, Tegan Sutherland, Nora Tempkin, Shulin Ye, and many others.

Table of Contents

List of Tables

List of Figures

List of Abbreviations

ACI	Area-Based Centralization Index
ACS	American Community Survey (Census Bureau program)
ADC	Weighted Average Distance from CBD
BTS	United States Bureau of Transportation Statistics
CBD	Central Business District
CBSA	Core-Based Statistical Area (OMB-defined geography), referred to as “metropolitan areas” herein
CONUS	Contiguous United States
CRS	Coordinate Reference System
CSA	Combined Statistical Area (OMB-defined geography)
DHS	United States Department of Homeland Security
EPA	United States Environmental Protection Agency
EPSG	European Petroleum Survey Group (Geodetic Parameter Dataset)
EUA	Extended Urban area (Wolman et al., 2005)
FHA	Federal Housing Administration
HIFLD	Homeland Infrastructure Foundation-Level Data (DHS program)
HISDAC-US	Historical Settlement Data Compilation for the United States
HOLC	Home Owners’ Loan Corporation
LEHD	Longitudinal Employer-Household Dynamics (Census Bureau program)
LODES	LEHD Origin-Destination Employment Statistics
MAUP	Modifiable Areal Unit Problem
MSA	Metropolitan Statistical Area (OMB-defined geography)
μSA	Micropolitan Statistical Area (OMB-defined geography)
MWI	Modified Wheaton Index
NAICS	North American Industry Classification System
NLCD	National Land Cover Database (USGS program)
NOAA	United States National Oceanic and Atmospheric Administration
NTAD	National Transportation Atlas Database (BTS program)
NWI	National Walkability Index (EPA Program)
OMB	United States Office of Management and Budget
OSM	OpenStreetMap
UA	Urbanized Area (Census Bureau geography)
UC	Urban Cluster (Census Bureau geography)
USGS	United States Geologic Survey
UTM	Universal Transverse Mercator

Chapter 1: Introduction

Cities are as old as history. Older, actually: the earliest written records date from around 3200 BCE in Egypt, 2900 BCE in Mesopotamia, 1200 BCE in China, and 200 CE in Mesoamerica (Trigger, 2003, Ch. 25), while the earliest cities date from around 3600 BCE in the Middle East, 2000 BCE in China, and 100 BCE in Mesoamerica (Smith, 2002; Trigger, 2003). Throughout nearly this five-thousand-year history, as the vast majority of urban transportation was on foot, the scale and structure of cities was shaped by the needs and convenience of pedestrians and they were largely made up of closely-packed neighborhoods of a few hundred or few thousand residents (Talen, 2019, Ch. 1).

Today, however, most American cities have been completely reshaped into places fundamentally hostile to people traveling on foot. Historic urban cores have been cut apart by wide freeways; major roads have become wide barriers that pedestrians cross at significant risk of death; and residential and commercial uses have become separated enough that it is common to have to drive several miles to buy a gallon of milk.

Traditional urban environments that would be recognizable to an American from 1900 have become rare outside of a few major cities. However, the goal of identifying and classifying these environments is not only of interest to urban theorists interested in living fossils of lost urban past: it has significant practical implications for other fields, and for society as a whole.

Walkable, non-automobile-oriented urban spaces have been a subject of interest in the urban planning field at least since Jane Jacobs valorized them in her 1961 classic *The Death and Life of Great American Cities* (Jacobs, 2011). More recently, they have become a matter of interest in the studies of public health, options for reducing greenhouse gas emissions, and gentrification (Talen and Koschinsky, 2013, 2014).

Research into US urban form has generally consisted of two separate streams: one localized and qualitative, and the other broad-brushed but quantitative. The former stream, strongly associated with Jane Jacobs' *The Death and Life of Great American Cities* (2011), is based on case studies and on-the-ground observation of specific neighborhoods. While this approach gives the best possible view of specific locales and is responsible for much of our understanding of what it means for a place to be walkable and traditionally urban, it requires a large time investment for each study site, and so makes broad comparisons across metro areas and the identification of similar neighborhoods in different regions very difficult.

The latter stream uses statistics and quantitative data—usually collected by government agencies—to classify neighborhoods, cities, and metropolitan areas, usually in order to understand how specific variables affect specific outcomes of concern. In order to create a typology based on this approach—using largely-quantitative data collected across the US and automated data analysis—that can identify walkable, amenable to public transportation, Jacobsian urban places, it is necessary to understand features of urban places that the first stream of work has recognized as important. Only once such features have been understood and quantified can they be analyzed using the techniques of the second stream.

While Jacobsian urban neighborhoods are commonly recognized as important, there has been relatively little work done on identifying them consistently on a national scale. No detailed, empirical, and automated typology of urban or suburban neighborhoods has been developed with public data. While commercial tools such as Walk Score are available for measuring walkability, they use proprietary algorithms and are not well-designed for distinguishing between types of built environment (Goodyear, 2012).

This research aims to fill that gap by addressing three fundamental questions. First, how can we build land-use typologies that center vital, walkable urban places? Entwined in that question is a second, more fundamental, question: what properties make neighborhoods and metro areas vital and walkable? Finally, what can we learn from such typologies about making cities more transit-friendly?

A consistent, national typology of urban places will have a number of potential uses. From an academic standpoint, it can serve as a jumping-off point for studies of the geography of socioeconomic phenomena in American cities by providing examples of similar places for comparison. For planners and, in particular, transit planners, it will help provide an understanding of where resources and initiatives may be most likely to be effective by allowing more useful comparisons between different cities' neighborhoods. And, from a personal standpoint, it should provide a resource for people interested in cities and urbanism to help them find places in other metro areas similar to those they enjoy in their home metros. Likewise, a national typology of metro areas based on this typology of urban places will provide a similar resource for recognizing similarities and bases for comparison between metro areas seen as wholes.

In this chapter, I will begin by discussing the factors that create walkable urban places and attempts to systematically identify urban and suburban neighborhood types in general (Section 1.1). I will then review the history of American urban centers in the 20^{th} Century and how it has influenced the structure of American metro areas today (Section 1.2) and consider several approaches that have been used to typologize metro areas (Section 1.3).

Chapter 2 will present a new method for characterizing neighborhoods in US urban places and the results of this method as applied to all 926 Core-Based Statistical Areas (CBSAs) in the United States. In Chapter 3, I will use the neighborhood characterizations developed in Chapter 2 to typologize neighborhoods and the CBSAs themselves and present some initial results following from this typologization. Finally, in Chapter 4, I will review the literature on conditions that contribute to effective and equitable public transportation and perform some initial analysis of the relationship between public transportation ridership in major US metro areas and the types developed in Chapter 3.

1.1 Urban Vitality and the Built Environment

Pedestrian- and transit-friendly urban environments are of interest to scholars studying food access and public health because living and working in them may provide significant health benefits. Work by scholars such as Widener and Shannon (2014) on the temporality of food access shows potential benefits to neighborhoods where low-income individuals—who tend to have more constrained time-budgets—have access to more needed resources such as grocery stores near where they live, work, or go about other errands without making separate trips.

Walkable urban neighborhoods, and environments that promote public transit and active transportation modes, have repeatedly been shown to provide public health benefits, in particular by increasing physical activity and leading to a larger share of the population meeting physical activity recommendations, (Lachapelle and Frank, 2009; Lachapelle et al., 2011; Freeland et al., 2013; Riggs and Gilderbloom, 2016). Public health benefits have also been used to support the construction of improved transit infrastructure (Stokes et al., 2008), although the effects depend strongly on a built environment that supports walking to transit.

As well as being healthier for people, Jacobsian urban environments in which people use public transportation and active transport modes rather than driving are healthier for the planet, as they reduce the large carbon emission costs of automobile transportation and reduce the need for large areas of impervious surface for parking that contribute to damaging storm-water run-off.

A number of workers, including Lehmann (2016); Lee and Lee (2014); Schwanen et al. (2012) and others have observed the need for more of the population to live in walking-friendly, dense urban areas to help reduce carbon emissions that contribute to global warming. However, Rice et al. (2020) has found that the limited supply of these neighborhoods can create a paradoxical situation where the gentrification of dense urban neighborhoods raises carbon emissions by replacing low-income populations with more affluent ones with more carbon-intensive habits.

The gentrification of vital urban places has become a national phenomenon because, after decades of neglect, the market has begun to value them highly. As Loh et al. (2019) described in their report *Foot Traffic Ahead*, these areas have become linked to the "knowledge economy" and associated with higher commercial as well as residential rents and with significantly higher GDP per capita than other urban areas.

The severe gentrification that has resulted from the resurgence of interest in these areas, besides the climatic consequences noted by Rice et al. (2020), is pushing low-income and minority residents into areas where their mobility is significantly decreased, even in "shrinking" cities such as Buffalo (Knight et al., 2018). Together, these factors—the push for more-walkable neighborhoods for health, economic, and climate change reasons, and the displacement problems caused by the limited supply of such neighborhoods—necessitate a better understanding of the types of walkable, Jacobsian urban form in the United States, and of urban and suburban form in the United States in general.

In the next three sections, I will discuss three of these factors—a fine-grained mixture of residential and commercial uses, a walkable street network, and density—in more detail, along with more recent research on their importance to walkable, public-transportation friendly urban places. Then, in a fourth section, I will discuss previous attempts to classify types of urban and suburban places.

1.1.1 Density: The Defining Trait of Cities

In a study in the *Journal of Monetary Economics* on the concentration of employment in cities, Chatterjee and Carlino (2001) noted that "In 1990, the state of Nebraska had roughly the same population as the San Francisco metropolitan area. The difference, of course, is that San Francisco's population is crammed into a land area that is 1/80th that of Nebraska." Although the San Francisco metropolitan area has grown substantially in the past thirty years, their point still stands: much of what differentiates a great city from a rural area, both economically and socially, is due to having large numbers of people living and working in close proximity.

Density is so significant because people's ability to interact—positively and negatively—is strongly influenced by proximity. Jacobs (2011, 276) argued that the health of cities fundamentally depends on their maintaining relatively high population densities: she suggested that a minimum of 100 dwellings per net acre were necessary for a healthy city.

Even authors such as Hawley (1972) who favor the reduction in city and metropolitan population density brought about by the automobilization of American life have tended to consider density important and, indeed, the mid-20th Century urban renewal planners Jacobs railed against considered density a defining feature of the “slums” they sought to eliminate (Jacobs, 2011, 14-15)

As studied by Angel and Blei (2016a); Brown et al. (2017); Glaeser and Ponzetto (2007); Rosenthal and Strange (2020) and others, concentration of workers and firms can lead to increased economic productivity, even on as small a scale of individual buildings. This increased productivity is what motivates businesses to locate in expensive-to-build skyscrapers on expensive land in major central business districts rather than spreading out to cheaper locations. In addition, Glaeser and Maré (2001) found that working in cities builds workers’ human capital, resulting in a wage premium that persists even when they move elsewhere.

The social effects of density can be seen in voting patterns: as reported by Lang et al. (2008), by the early years of this century, denser suburbs had begun to vote more in line with central cities than with lower-density suburbs that were otherwise more similar in urban form. More recently, a study by Gimpel et al. (2020) found that, controlling for age, race, education, and other demographic factors, population density still played a substantial role in determining Americans’ voting patterns. Whether, as suggested by Wilkinson (2019), this effect is due to urbanizing involving self-sorting based on personality traits, or whether the social effects of living at higher densities affect people’s political outlooks, it is clear that density plays a major role in what makes urban places socially distinct.

Since people tend to live and work in different neighborhoods or districts in modern American cities, looking at residential population alone—a practice encouraged by the fact that residential population is the factor most consistently reported by censuses worldwide—does not tell the whole story. The number of employees in a given area is now often reported by national censuses or workers' insurance agencies, including the US Census's Longitudinal Employer-Household Dynamics program (LEHD), so considering the summed density of residents and employees is a natural extension of using simple population density.

Newman and Kenworthy (2006) evaluated data from a number of world cities found that a density of activity units (jobs plus residents) of about 35 per hectare (14 per acre or 9,000 per square mile) correlates with a significant reduction in automobile dependence. They then attempted to develop a theoretical model for understanding the physical constraints that lead to this threshold. This estimate of a density threshold for the transition from automobile-based to transit-based mobility was not entirely novel: although Levinson and Kumar (1997) were working solely with American population density data, they came up with a similar density threshold.

However, residential density and employment density are more complements than substitutes: people need to be able to travel between home and work easily and, unlike with shopping or other errand destinations, they cannot generally simply rely on commuting to the closest employment district. As a result, calculating the "activity" of a neighborhood by adding the number of jobs and residents in a neighborhood is overly simplistic.

1.1.2 Fine-Grained Mixtures of Uses

A mixture of uses, with residential, employment, and shopping destinations in close proximity—the first of the factors that Jacobs (2011, Ch. 8) identified as essential to urban vitality—seems intuitively likely to promote walking and other non-automobile transportation modes by shortening the distances traveled for many errands. Indeed, this conclusion has been supported by a number of empirical studies.

Sarzynski et al. (2006) found that job-housing proximity (which is related to mixing of uses) was inversely related to commute time, while density and housing centrality were not. However, they did not specifically consider transportation mode. Likewise, a meta-analysis of studies in the literature by Ewing and Cervero (2010) found that land use diversity was somewhat important to increasing non-automobile transportation modes, while population and job densities alone were relatively unimportant. On the other hand, Seskin et al. (1996, Ch. 2) suggested that land use diversity, while useful, was less important than job and population densities in driving transit ridership.

Also relevant to the issue of mixtures of uses is the distinction made by Anas et al. (1998, 1441-1442) between sub-centers being complements and substitutes. In a metropolitan area with sub-centers that all contain similar mixtures of uses, they may largely be substitutes, with most trips to or within the nearest sub-center rather than between sub-centers: trips that walking can more easily serve. However, if sub-centers specialize in different uses, they will be complements and there will be more significant travel between them.

Mixed-use environments may be particularly important for facilitating non-automobile travel by women. As early as the 1980's, researchers noted that employed women's travel patterns differed from employed men's, and that the former tended to have more time-pressure on their travel and the need to make more multi-destination trips (Michelson, 1988).

More recently, Schwanen et al. (2008) found that women's schedules tended to contain more fixed-point obligations in time and space because they, even when they work, tend to be responsible for a disproportionate fraction of household errands. Plyushteva and Schwanen (2018) found similar obligation patterns in the context of inter-generational caring relationships. As a result, the opportunity to perform multiple errands on foot in the same neighborhood—and ideally, near their home or place of work—is likely to particularly benefit women and others who perform these traditionally-gendered-as-feminine activities.

1.1.3 Walkable Street Networks

As discussed at length by Marshall (2005), urban and suburban street networks tend to fall into several distinct patterns, largely dependent on when and for what transportation technology they were developed. Much modern American development takes the form of cul-de-sac residential and commercial developments designed to avoid through traffic while, consequentially, forcing all traffic to follow a few major arterial routes.

Such an arterial-and-cul-de-sac street network may be optimal for automobile-oriented suburbia, but it is not amenable to walkability or pedestrian street life. In fact, as noted by Jacobs (2011, 499), "actual physical cut-offs to foot traffic in particular are destructive in cities." She argued in Chapter 9 of the same work that street networks with small blocks that encourage pedestrian through-traffic promote urban vitality by encouraging mixture of uses as well as increasing urban safety.

A number of factors influence the safety and comfort of walking in cities, including the condition of pedestrian infrastructure such as sidewalks and crosswalks, traffic speeds, and the presence of amenities such as street trees and varied building fronts that provide visual interest rather than monotony. In addition, street network structure is important to walkability because it can have a large influence on how many destinations are within walking distance of a given location.

Several studies, including Sandalack et al. (2013), have shown that certain types of street networks tend to result in significantly larger walksheds (areas accessible within a certain walking distance of a location). Recently, I did preliminary work (Rowlands, 2020) showing significant differences in walkshed size within different sorts of neighborhoods in large American metro areas.

The benefits of well-connected street networks for walkability are consistent with studies on how street networks affect transit ridership. In their meta-analysis of studies on factors that promote transit ridership, Ewing and Cervero (2010) found that the most important features for increasing transit usage, after distance to transit, were the density of streets and intersections and the percentage of intersections that were four-way rather than three-way. Seskin et al. (1996, Ch. 2) also suggested that street and sidewalk connectivity are important for transit ridership, but found the effects hard to quantify.

In addition, Grosvenor and O'Neill (2014) explicitly positioned themselves in opposition to researchers who focus on the importance of density to public transportation, arguing that a focus on density to the exclusion of location, accessibility, and other design characteristics may actually be leading to poorly-located and designed transit-oriented developments that actually encourage car use. The authors develop an alternative typology of urban structure and form that they believe better leads to sustainable development.

1.1.4 Classifying Urban and Suburban Neighborhood Types

While theorists such as Jacobs (2011) have long attempted to identify the properties of ideal urban neighborhood, a number of more recent empirical studies have attempted to classify neighborhood types within metropolitan areas. In many cases, the first step in such an analysis was simply to determine how to distinguish rural areas from the increasingly low-density fringes of cities that have come to be known as exurbs.

Nelson (1992) summarized attempts to define "exurban" and found little consistency, beyond that efforts tended to focus on commuting to a central county—which is problematic given that much commuting in fact occurs within exurbs—and that they generally focused on defining counties, rather than places, as exurban, which is a particular problem in western states with very large counties. He focused at length on the question of the urban/rural divide and noted that the Census Bureau first defined "urbanized areas" in 1950, at which point a density criterion of 2,000 people or 500 housing units per square mile was used. Since then, the required density has dropped to 1,000 people per square mile (US Census Bureau, 1994, Ch. 12). However, as pointed out by Theobald (2001), the Census's defined urbanized areas exclude a significant amount of land settled at this density because of discontinuity from the urban core, even if it is still part of the central city's commute shed.

Cohen and Debbage (2004) attempted to resolve the issue with defining the rural-urban distinction at the county level by instead measuring it at the minor civil division (MCD) / census county division (CCD) level. Rather than using a constant density cut-off, though, they used an adjusted percentile rank for each MCD or CCD consisting of the average of the percentile rank of its density in the country and within its census division. The upper third of these, which they classified as "densely settled" had an average population density of 1,000 people per square mile.

Distinguishing between the types of exurban and suburban places that make up the vast majority of land in American metropolitan areas has posed a complex problem as well. Mikelbank (2004) specifically studied suburban incorporated places and used a number of demographic and economic variables to identify 2-cluster, 4-cluster, and 10-cluster typologies of these municipalities. He found distinct clusters primarily based on income, race, and age, but with relatively little consideration of land use factors likely to be relevant from the context of transportation. Between this issue, and the fact that the study focuses solely on incorporated places and does not consider variations within them, Mikelbank's approach is probably of limited applicability here.

Berube et al. (2006) reviewed and discussed the literature on exurban places with a focus on their definition and distinction from suburbs. While most of the studies cited focused on counties rather than census tracts or block groups, there was a rough consensus that "exurban" referred to areas with a commuting tie to a central city but outside of a UA, and thus with a density of less than 1,000 people per square mile. Rate of growth was also often considered important: exurban areas were expected to be fast-growing, compared to low-density rural or rural-commuter areas. However, as noted by Fulton et al. (2001), faster-growing metropolitan areas tend to have less exurban growth (in terms of increase in land compared to increase in population) than slow-growing or declining metropolitan areas.

Unfortunately, studies of exurbia seem to focus more on what sort of people live in exurbs than in coming up with a durable definition of what exurbia is. However, there has been some work on characterizing different sorts of exurban land use. Clark et al. (2009) studied the patterns of exurban growth in American metropolitan areas. They determined an index for measuring patterns of exurban development and found correlations to other properties of metro areas, including polycentricity.

Brinkley (2018) considered the "rugosity" of cities, defined as the ratio of the urban-rural interface to the area of the urbanized region. This is potentially a useful measure for the connectivity of exurban places, but it is less clear that it is directly relevant to a broader understanding of suburban and exurban geography. However, a rugosity-based measure of areas meeting some threshold density considered necessary for effective transit service could potentially be a useful approach for measuring the connectivity of transit-servable places.

It is not only exurbia that can be hard to define: the definition of "suburb" can be elusive as well and, unlike the urban-rural distinction, the Census Bureau does not attempt to distinguish between suburb and city. US Census Bureau (1994, Ch. 12) divides Census tracts into "urban" and "rural" categories using a definition of "urban" that includes all but the most far-flung and low-density suburbs. Even within suburbia, Lang and LeFurgy (2007); Lang et al. (2008) have noted a class of suburbs they call "boomburbs" that seem to be an intermediate between traditional urban centers and more traditional small, primarily-bedroom suburban communities.

A review of definitions of "suburb" in planning and urban geography literature by Forsyth (2012) suggested that it may be impossible to give a single definition to the term that applies universally. She suggests two alternative solutions to this problem. First, one may abandon the term entirely and either insist on more specific terminology for each type of metropolitan environment—as per Hayden (2003)—though this may prove a problem when focusing on especially general topics of suburban development, or else focus on specific features of interest for a given study without using the term "suburb," as has become common in urban studies. Second, Forsyth (2012) observes, it may be possible to preserve the term suburb so long as precise definitions are given of the type of suburb of interest in a particular study.

Walkable urban places have also proved difficult to define and identify. One approach, not uncommon in studies of specific metro areas and sometimes seen even in broader surveys—such as Leinberger (2007)—is an appeal to local expert knowledge. This is the approach that that the Census Bureau has used to identify central business districts in US metro areas, as discussed at length in Section 1.3.2. However, it leaves much to be desired, since it does not scale without an increasing pool of experts familiar with different metropolitan areas and since it is not reproducible enough to support rigorous analysis of differences in the quantity or quality of such places in multiple metro areas.

In a follow-up to Leinberger (2007)'s expert-knowledge identification of walkable urban places in major US metro areas, Leinberger and Alfonzo (2012) developed a more-systematic methodology for identifying such places in the Washington metro area. While their method was more reproducible, and allowed for a comparison of the economic performance, transportation costs, and socioeconomic equity of walkable urban places in the Washington area, the complex scoring system it used would be very time-consuming to apply to a large number of metro areas. Furthermore, their technique depended on the proprietary Walk Score tool, which potentially raises replicability issues..

Loh et al. (2019) refined this approach for a study of walkable urban places—which they referred to as "WalkUPs" in the thirty largest US metros by requiring that such places have either 1.4 million square feet of leasable office space or 340,000 square feet of leasable retail space[1] and a Walk Score value of 70 or greater at the most-walkable intersection. They also excluded candidate locations dominated by automobile-oriented land use as determined by visual inspection of satellite images for surface parking lots.

Discussion with Tracy Hadden Loh of the Anne T. and Robert M. Bass Center for Transformative Placemaking at the Brookings Institution Metropolitan Policy Program in Washington, DC confirmed that the Loh et al. (2019) approach still depended on expert judgment. While the criteria for identifying WalkUPs depended on office and retail space

[1] For comparison, Garreau (1992)'s classic *Edge Cities: Life on the New Urban Frontier* defined an "edge city" as having five million square feet of leasable office space and 600,000 square feet of retail space.

thresholds from the CoStar commercial real estate database, the initial boundaries of the places—and thus the area over which this office and retail space was distributed—were drawn by hand based on commercial real estate clusters with high Walk Score values according to a Walk Score point dataset covering the United States.

An alternate approach, used by Fan (2010) to create a factor ecology model of the Raleigh-Durham-Chapel Hill "Triangle Region" of North Carolina[2], involves using moving-window kriging (Gaussian process regression) to estimate both built-environment and social factors . In addition to publicly available land-use and Census Bureau data, Fan used data from a telephone interview survey of travel patterns. It is notable that her analysis included quite detailed social data on residents as well as information about street grid connectivity and transit service. However, the dependence on a survey of local residents would make this approach quite expensive and time-consuming to expand to a significant number of metro areas.

More recently, a series of papers by Krehl of the Leibniz Institute of Ecological Urban and Regional Development in Dresden have taken a somewhat different approach in creating a typology of types of urban centers in four German metropolitan areas: Cologne, Frankfurt, Stuttgart, and MuniCh. Her initial approach involved using a local Moran's I statistic to identify job clusters (both of all jobs and of service-sector jobs) and clusters of built-up areas (Krehl, 2015).

[2]This area, the Raleigh-Durham-Cary, NC Combined Statistical Area, is made up of the Raleigh-Cary, NC Metropolitan Statistical Area, the Durham-Chapel Hill, NC Metropolitan Statistical Area, and the Henderson, NC Micropolitan Statistical Area.

More recent work by Krehl on typologizing land use types in these cities have involved the use of remote sensing data as a proxy for built densities to take advantage of its higher granularity (Krehl et al., 2016); the possibility of using a locally-weighted regression model derived from job concentrations to identify urban centers and subcenters (Krehl, 2018); and a combined analysis based on employment and population data, built-up-volume, and history of development (Krehl and Siedentop, 2019).

1.2 The History of American Urban Centers in the 20th Century

Although it has become commonplace to explain the US's low urban densities and low transit ridership by noting that many European cities are centuries older than American ones and predate the automobile, American cities were just as much walking cities as the cities of Europe and nearly as much so as cities had been for millennia. The first two stages in the classic Borchert (1967) periodization of American metropolitan evolution—up until roughly 1870—predated the introduction of mechanized street cars (the technology that Americans originally meant when they spoke of "rapid transit") and, in many cities, even predated the significant growth of horse-pulled streetcar networks (Cudahy, 1995; Warner, 1962).

Although steam railroads were used for intercity travel and by a few rich businessmen to commute and animals were used to move cargo and occasionally for riding, nearly everyone got around the cities of the mid-19th Century United States on foot. This finally changed with the expansion of horse-pulled and cable-drawn streetcar networks in the 1870's and 1880's, along with and the introduction of the practical electric streetcar in 1888 (Cudahy, 1995; Lorenzo, 2014; Vuchic, 1999).

These transportation innovations made it possible to travel more quickly within cities and allowed even low-wage industrial workers to easily commute several miles to work. This, in turn, led metropolitan areas to expand outward significantly between 1870 and 1930 with new "streetcar suburbs" built around public transportation for suburbanites commuting to work in the urban core, as discussed by Warner (1962) in his classic study *Streetcar Suburbs: The Process of Growth in Boston, 1870-1900*.

Streetcars brought workers and shoppers from the suburbs to city centers, but these suburbanites still had to complete the last stage of their trips on foot, so the increasingly-commercial urban cores remained structured around the needs of pedestrians. Suburban residential areas that developed along streetcar lines tended to have less resemblance to traditional neighborhoods, with non-residential uses strung out along the streetcar tracts, but the ability of suburbanites to easily walk to stores, to church, and to the streetcar stop remained essential (Warner, 1962, Ch. 7). In particular, places where circumferential and radial streetcar lines crossed, significant commercial districts developed, though they were not large enough to pose a threat to downtown central business districts (Lorenzo, 2014).

However, while American cities in 1910 were still largely oriented toward pedestrian life and walkable neighborhoods, within two decades nearly every city in the country was on the path toward a very different type of urban form, one not previously seen in human history. Much of the the 20th Century history of American urban planning is the history of the destruction of walkable neighborhoods and their replacement with pedestrian-unfriendly, car-oriented development patterns. This new dispensation had become so ingrained in the American understanding of cities that, by the time Jacobs (2011) wrote her 1962 rallying cry for traditional urbanism, *The Death and Life of Great American Cities*, she had to devote six chapters to describing the four factors she considered essential to maintaining traditional urban vitality: mixed primary uses, small blocks, aged buildings, and concentration.

1.2.1 The Revolution of 1910-1930

How did walkable neighborhoods go from being the normal state of affairs in cities throughout history to an endangered species in the United States over the course of the 20th Century? The answer begins with a pair of changes in the way American culture and law understood public space and land ownership between 1910 and 1930.

Automobiles began to reshape American cities shortly after the introduction of the Ford Model T, the first mass-produced automobile, in 1908. Public transportation ridership in the United States reached its peacetime peak in 1926 and began to fall (Cudahy, 1995) while, by 1925, there were already seventeen cars for every hundred Americans (Jones, 2008, 12).

This explosion of driving led to fundamental changes in the relationship between Americans and the public sphere in a way that the rise of streetcar suburbs had not. As documented by Norton (2007, 2008), the 1910's and 1920's saw a massive spike in pedestrian deaths at the hands of motorists. Initially, as cars were rare and seen as toys of the rich, these deaths led to public outrage and efforts to force cars to conform to the pre-automobile understanding that pedestrians had a right to use the entire width of the road for travel, to cross mid-block, and even to play in the street. As late as 1923, a petition signed by more than ten percent of the population of Cincinnati placed a referendum on the November ballot to require mechanical governors limiting the top speed of all cars entering the city to 25 miles per hour.

However, a massive advocacy and advertising campaign by automobile manufacturers and motorists' clubs in the 1920's led to cultural and legal shifts in who was understood to have a right to the road: the word "jaywalker" was popularized as part of this campaign to refer to pedestrians who exercised what had been traditional rights in ways that inconvenienced motorists by crossing streets mid-block or entering the roadway when a car was approaching (Norton, 2007). Soon, traffic engineers begin to widen and redesign city streets to increase street parking while allowing for faster passage of more automobiles (Norton, 2008). Even citizens' rights not to be stopped or searched in public places without probable cause were reshaped and restricted in response to the shift to an automobile-based society (Seo, 2019).

At the same time as cars were reshaping American public space, the spread of zoning laws was leading to a fundamental change in American land tenure that rendered the fine-grained, heterogeneous land use that had been traditional in cities illegal in most of the country. From their beginning, zoning laws in American cities were often motivated by racism, and it is notable that they became common just as the beginning of the Great Migration led to the rise of substantial Black populations in Northern cities.

As long as white Americans had been able to keep their Black neighbors enslaved—first as chattel and then as effective debt-slaves in the Jim Crow South—they did not necessarily mind living near them or even having live-in Black servants. However, when Black Americans began to move to cities and to find industrial jobs that gave them more economic freedom, they quickly found numerous barriers rapidly rising up to keep them from living in the same areas as white people—unless they were living in the homes of white families as servants (Pietila, 2010; Rothstein, 2017).

The charge to use zoning-like laws to limit the spread of Black neighborhoods began in 1910 with the passage of a Baltimore law banning the purchase of houses on city blocks by members of a race that was not in the majority on a given block. This led to a host of similar laws across the country until, in its 1917 *Buchanan v. Warley* decision, the Supreme Court overturned a Louisville law based on the Baltimore one: not on the basis of the rights of racial minorities, but as an infringement of the rights of landowners to sell their land to whomever they wished (Pietila, 2010, Ch. 1-2).

Because the *Buchanan v. Warley* decision was based on the rights of landowners, however, the courts held that it did not prevent landowners from voluntarily creating restrictive covenants: private agreements included in land deeds that banned the land from being sold to Black or other minority buyers, prevented Black renters from living on it, and often prevented high-density housing or commercial uses, all of which were claimed to lower property values. Unlike racial zoning, restrictive covenants had to be separately added to every lot in a neighborhood to be effective which, in practice meant they could only easily be applied to land in newly-built subdivisions by the developer[Ch. 5](Rothstein, 2017).

Restrictive covenants were soon added to nearly all new suburban developments by developers who hoped to increase sale prices by promising white, middle-class buyers that Black neighbors would not be moving in. This meant that, as the Black populations of cities rapidly grew in the first half of the 20_{th} Century, these new residents were crowded into older housing in the denser urban cores where restrictive covenants could not easily be added to the already-fragmented plots of land.

During the same period when racial zoning was being implemented and then replaced with restrictive covenants, land-use zoning was introduced in American cities. While nuisance industries such as slaughterhouses and tanneries had long been restricted to certain neighborhoods in many cities, building codes mandating brick or stone construction were a common response to urban fires at least as early as the 1666 Great Fire of London, and some cities restricted building heights after the introduction of safety elevators made much taller buildings practical, urban landowners had long been largely free to build whatever sort of buildings they wanted on their land and to use them as they wished.Starting in the 1910's, however, much more detailed land-use zoning codes were introduced. These codes generally mandated complete separation of residential and commercial land uses and banned multi-family dwellings and small lots in most residential areas, effectively mandating an end to high-density and mixed-use development in many areas (Hirt, 2014, Ch 6.).

The introduction of land-use zoning to "protect" suburban single-family homes on large lots from "encroachment" by denser housing or commercial uses was another response to the fears of middle-class white homeowners that Black and immigrant residents would move into their neighborhoods. Although these laws, which restricted the types of buildings and activity permitted on private land, were initially criticized as authoritarian and even "Communist," they were upheld by the Supreme Court in its 1926 *Euclid v. Ambler* decision on the basis that they were a legitimate use of the state's police power to increase the value of land (Hirt, 2014, Ch. 6).

By 1930, the fight had largely been won by the advocates of what became known as “Euclidean” zoning, and the American City Planning Institute described the promotion of “health, safety, morals, convenience, prosperity, and the general welfare” (Hirt, 2014, 133)—a set of options broad enough to easily cover racist motivations—as legitimate uses of zoning. The era of what Ross (2014) has called “suburban land tenure”—in which the rights of landowners are to prevent their neighbors from using their land in non-standardized ways largely eclipsed the rights of landowners to make land-use decisions based on market pressures or personal preferences—had begun.

As a result, by the 1930’s, American metro areas were increasingly divided into dense, mixed-use cores of older buildings with Black and low-income immigrant residents and rings of low-density suburbia where neither mixed land use nor Black residents were allowed.

1.2.2 1930-2000: Redlining, White Flight, and Urban Renewal

The pattern that had been set in place by 1930 largely continued for the next sixty to seventy years, albeit by different means as time went on. New developments, government funding, and transportation infrastructure were directed to the suburbs while the denser, historically-walkable neighborhoods in urban cores were encouraged to decay and sometimes actively destroyed by government action. At the same time government policy and elite practice also helped to ensure that the growing suburbs remained largely white, while Black residents of metro areas were kept contained in the decaying cores. This process formed a self-reinforcing cycle: as urban cores became associated primarily with

Black Americans, the logic of white supremacy produced political and economic pressures against investment in historically walkable, urban places and promoted suburbia and car-based lifestyles as better and more properly "American."

Although the phenomena of white flight and complete divestment from urban areas did not fully come into being until the 1950's, Federal programs began to encourage these processes during the New Deal. One major component of this was the loan policies mandated by the Federally-created Home Owners' Loan Corporation (HOLC), which are commonly referred to as "redlining."

In the early 20th Century, mortgage loans to individuals for home construction or purchase generally had very high interest rates and short terms—always less than a decade—because of the high risk of default. Furthermore, these mortgages were not amortized, meaning that the entire principal was due for repayment at the end of the term, rather than being paid off over the course of the loan and thus reducing the total interest owed. This effectively limited home-ownership to relatively well-off Americans who could save a substantial portion of the price before building or buying a home (Warner, 1962, Ch. 6).

The HOLC was created by the Franklin Roosevelt administration in 1933 as a response to large numbers of home-owners who had taken out mortgages in the economic boom years of the 1920's and who were now at risk of default. It purchased mortgages at risk of default and replaced them with loans at much more generous terms: 15 and then 25 years, with amortization. In order to assess risk and decide whether and at what rate to issue loans, the HOLC created color-coded maps of neighborhood "risk"—effectively, a prediction of the likelihood that a house would lose value during the course of the loan, meaning that the government would lose money if it had to foreclose (Rothstein, 2017, Ch. 4).

Unsurprisingly, given the prevailing belief in the real estate industry that racial mixing and the presence of Black or other minority residents lowered housing values, the racial makeup of neighborhoods was a major factor in how they were assessed. All neighborhoods with predominantly Black residents were placed in riskiest category, red—the origin of the term "redlining"—meaning that if loans were issued to buyers of houses in these neighborhoods at all, they would be at significantly higher interest rates. This made it difficult for Black buyers to purchase homes in what were often the only neighborhoods where they were allowed to purchase them; it also made it difficult for Black homeowners to sell their homes or get loans for major repair work, creating a self-fulfilling prophecy that housing stock would decay and land values would fall in Black neighborhoods (Rothstein, 2017, Ch. 4).

Although the HOLC was dissolved in 1954, similar practices—also often included in the broader meaning of "redlining"—were implemented by the Federal Housing Administration (FHA), which was created in 1934 to insure privately-issued mortgages against default. The FHA required the loans it insured to have relatively generous policies, making home ownership more attainable for the the families eligible for them. However, it also required that insured mortgages be in whites-only neighborhoods and strongly discouraged banks from making loans in urban neighborhoods or in areas that were even near Black or low-income neighborhoods. Furthermore, FHA policies discouraged well-connected, grid-like street networks and neighborhoods that allowed commercial land uses or multi-family housing (Rothstein, 2017, Ch. 4).

The effect of redlining and other FHA policies was two-fold. These policies helped white families build generational wealth through home ownership while denying the same benefits to Black family. And they funneled private capital into car-oriented, non-walkable suburban developments while keeping it from being invested in maintenance and improvements to dense, walkable traditional urban cores.

Initially, New Deal programs did not produce a rapid change in the American built environment because, during the Great Depression, there was little private capital available for new developments. However, in the years after World War II, the Federal policies established during the New Deal shaped how the postwar economic boom and the response to a decade's worth of unmet demand would be translated into the American built environment.

Huge, entirely car-oriented suburban developments of single-family home monocultures in the model of Levittown, New York (built 1947-1951) sprang up on the rural fringes of metropolitan areas. These developments, heavily subsidized by Federal policy and open only to white home buyers acted as one of the driving forces of the flight of white residents from urban areas.

At the same time, urban housing stock continued to decay and neighborhood retail. Even white homeowners and entrepreneurs found it impossible to get loans to buy housing, make repairs, or start businesses in urban cores and older, inner-ring streetcar suburbs (Jacobs, 2011, Ch. 16); the situation was even worse for Black homeowners and in neighborhoods that were majority-Black or were perceived as likely to become so in the future. These structural forces acted as a second driving force, pulling white residents and entrepreneurs into the new suburbs.

Furthermore, the cultural disconnect between the increasingly large corporations that increasingly fulfilled roles—such as operating grocery stores—that were essential to maintaining functional urban environments and the low-income, Black residents of those communities tended to prevent investment even when capital was available. White workers and managers perceived urban areas as unsafe and crime-ridden while Black residents perceived white retail workers as arrogant if not actively racist, a combination that discouraged businesses from providing even essential retail services in these areas (Jones, 1967).

The speed and scale of the demographic transition of American urban cores in the second half of the 20th Century was incredible. As documented by Rowlands and Loh (2021), roughly half of the US population lived in the metro areas of the nation's fifty largest cities in 1950. Just over half of this population lived within the city limits of central cities, and both the central cities and the suburbs were, on average, 90% white. In 2018, almost exactly the same share of the US population lived in these metro areas, but only a fifth of it lived within the 1950 boundaries of those central cities. That fifth of the population was about 35% white in 2018, while the four-fifths of the population that lived outside the 1950 central city borders was 60% percent white.

Many central cities saw much more intense declines. Detroit and St. Louis each lost 63% of their population between 1950 and 2018, while Buffalo and Pittsburgh lost 55%. Even metro areas that were economically successful and saw large population growth overall had major declines in central city populations. There are four times as many people living in the counties that make up the current Atlanta metropolitan area today as there were in 1950, but 37% fewer people living within the 1950 city limits (Rowlands and Loh, 2021).

The massive loss of population and businesses that urban cores saw after 1950 meant a reduced tax base. Rusk (2006, 2013) has described how this was a disaster for cities that were unable to expand their boundaries to capture the new suburbs, as they lost revenue but were still responsible for maintaining infrastructure built for a larger population and for paying the pensions of the larger workforces they had needed before population loss.

Yinger (2010) has noted that the legacy expenses that older municipalities primarily populated by people of color and especially Black Americans may be contributing to a form of bond rating redlining, where municipal bonds issued by minority communities are rated lower and these municipalities face higher borrowing costs, compounding the difficulty of a reduced tax base. In addition, as Randall et al. (2018) discuss, the decentralization of employment and businesses in US metro areas has also caused "race to the bottom"-type issues in some regions, as central cities and suburban jurisdictions compete to offer the largest tax breaks to convince corporations to locate in their part of the region.

Furthermore, in those cases where cities were able to annex surrounding suburbs, it often came at the cost of political independence. A good example of this is the consolidation of the City of Indianapolis with Marion County, Indiana to form an entity called "Unigov" in 1970. Unigov was established at the behest of white, suburban politicians who wanted to retain control over a city that was rapidly becoming majority Black. It ensured that government resources remained in the hands of leaders who cared little about the plight of the crumbling core of Indianapolis that they had abandoned and the Black population who lived there. At the same time—as has been common in cases of urban annexations in the US—the city and suburban school districts were not merged, allowing white suburbanites to continue to send their children to effectively segregated schools and avoid paying taxes to support majority-Black schools (Hammar, 2012; Poletika, 2019).

More recently, the 2003 merger of Louisville with Jefferson County, KY largely resulted from a push by the business community, which hoped to increase the city's profile. As in the Indianapolis-Marion County merger, the governments of suburban municipalities were left intact, while the old city of Louisville and unincorporated Jefferson County were put under county-level governance. And, as with Indianapolis, the merger seems to have benefited suburban areas more the central city and to have largely increased suburban control over policy decisions (Savitch et al., 2010).

When Federal or state funding was available for urban cores, it often came in the form of what Jacobs (2011, 383) called "cataclysmic money": large amounts of money for mega-projects planned by and often intended to serve the needs of a governing elite that no longer had personal experience with urban life or connections to those who lived in the places the projects were intended to serve.

These projects, which were commonly marketed as "urban renewal" were intended to make up for years of disinvestment and to correct conditions of poverty and decline. However, they often made matters worse through a failure to understand the needs of the communities they were intended to serve or even to understand the basics of how vital urban places function. Huge empty plazas, civic centers of questionable utility, and high-rise public housing designed in ways that discouraged social interaction were often consequences of cataclysmic money (Jacobs, 2011, Ch. 16).

Cataclysmic money also built freeways through urban cores—the Federal government paid for 80% of the cost of Interstate highways—often intentionally destroying dense, Black neighborhoods perceived by planners as "slums" while speeding suburban commuters to downtown jobs (Jones, 2008). These freeways, as was recognized at the time by Shipler (1975), served to form the structure for the new suburban geography of American metro areas.

Furthermore, because money for urban renewal projects came and went with the whims of outsiders and was rarely sustained unless, like the freeways, they served suburban residents—especially since the political will to spend money on programs that white voters saw as primarily benefiting Black people was hard to maintain—the infrastructure produced by urban renewal that did benefit urban communities often decayed rapidly due to neglect (Jacobs, 2011, Ch. 16).

1.2.3 2000-Present: Gentrification and the Re-evaluation of Urbanism

The past twenty years have seen a major change in the economic conditions of cities and how academic, government, and business elites perceive them. Today, walkable urban places have become some of the most in-demand environments in American metro areas (Loh et al., 2019) and some central cities, especially those with many high-paying service jobs, are seeing a resurgence (Short and Mussman, 2014). Unfortunately, though, the decades of government policy and private actions that worked together to eliminate vital urban environments through a mixture of neglect and active destruction while essentially prohibiting more of them from being built have left the US with a very small stock of such places.

This mismatch of supply and demand has become a disaster for many of the long-term residents of urban neighborhoods, who are being displaced by rapid increases in prices as new populations with higher incomes move in (Knight et al., 2018; Short and Mussman, 2014). It is also a disaster for the environment in an era where climate change has made it essential that we rapidly decrease our fossil fuel use, something that can only be done by having the population as a whole—not only the few people who can move into the few walkable urban cores that currently exist—adopt less car-dependent lifestyles Lehmann (2016); Lee and Lee (2014); Rice et al. (2020); Schwanen et al. (2012).

The growing recognition that Jacobsian urban places are valuable is an important change but, as is to be expected of the repudiation of nearly a century of policy and dogma, it is moving slowly. Meanwhile, American society is in a race against time to retrofit our built environment to make walkable, Jacobsian, vital places available more widely before the nation's relatively few such places become inaccessible to all but the very rich and before our current national lifestyle destroys the planet.

1.3 Typologizing Metro Areas

As available computational power has increased over the past two decades, it has increasingly been possible to apply computational techniques to the typologization of metro areas based on relatively-complex representations of their population and job distributions. Several distinct approaches have developed, using data of varying complexity, but much of the work has particularly focused on job distribution as the determining factor of urban form.

Although the phrase “urban sprawl” is perhaps most strongly associated with low-density residential subdivisions, employment in American metropolitan areas has also largely moved to the suburbs. While in 1950, the majority of workers in the typical American metropolitan area worked in the downtown core, as of 1996, in the one hundred largest metropolitan areas in the country, only 22% of people worked within three miles of the city center, while 35% of people worked more than ten miles from the city center (Glaeser et al., 2001).

This increased sprawl is not only a consequence of manufacturing jobs, which require large amounts of space, moving to low-density areas, and of retail moving outward to follow customers: Lang (2000) studied the distribution of office space in metropolitan areas and found that from 1979 to 1999, the share of office space found in the core city of the average metropolitan area dropped from 74% to 58%.

While jobs in large American metropolitan areas remain more concentrated in urban cores than population does, the sprawl of jobs into suburban office parks is perhaps an even larger problem for a metropolitan area's amenability to public transit than residential sprawl. This is because it requires significant suburb-to-suburb service, along with suburb-to-city and intra-city service.

1.3.1 Centralization and Concentration of Population and Jobs

Density provides a simple, one-dimensional measure of how concentrated a metropolitan area is, but it does not really provide enough information to characterize population or job distribution. For transportation, and particularly public transit, it makes a significant difference whether the dense neighborhoods of a city form a single compact cluster, or are spread out among many smaller clusters separated by low-density areas, a distinction that a region-wide average cannot make.

One solution to this problem is to treat the population or job distribution of a metropolitan area as a simple exponential decay with distance r from the downtown core. In this case, the density at distance r from the core is

$$d(r) = d_0 e^{-\gamma r}$$

where d_0 is the density in the downtown core and and γ is a positive constant called the *density gradient*, the proportional rate that density falls with distance. Anas et al. (1998, 1436-1438) discussed this model at some length and tabulated values of γ for a number of world cities in the 19^{th} and 20^{th} Centuries as evidence of the consistent pattern of cities becoming increasingly sprawling over time.

However, this model does not accurately describe the distribution of density in American cities, as it assumes radial symmetry—that metro areas are roughly circular with the same distributions in each direction from the core—and neglects the existence of population clusters outside a metropolitan area's primary downtown.

A related approach, suggested by Manin (2010) and used by Walker (2012, Ch. 9) in his discussion of the need to consider the densities at which most people actually live, rather than the overall population density in transit planning, is to plot the fraction of a metro area's population living in Census tracts or other small geographies as a function of their densities, producing a curve that represents the density distribution of residents. This method is essentially an extension of Craig (1984)'s population-weighted density measure, which will be discussed further in Section 3.3.2. Like population-weighted density, it does not take into account the spatial relationship between the geographies used to bin the data and so cannot identify the scale of population clustering. As a result, more complex models are needed to fully describe residential sprawl.

Another approach to describing the distribution of jobs in a metropolitan area is the two-dimensional model proposed by Anas et al. (1998, 1431), consisting of *centralization*—the extent to which employment is concentrated in a single central business district—and *concentration*—the extent to which employment is locally clustered or dispersed evenly. This model potentially leads to three types of cities:

- *monocentric cities*, with high levels of centralization and concentration.
- *polycentric cities*, with a low level of centralization and a high level of concentration.
- *dispersed cities*, with low levels of centralization and concentration.

(A low level of concentration seems to imply a low level of centralization, so the two dimensions are not fully independent, and there is no fourth category of low-concentration, high centralization cities.)

Having established this model, Anas et al. (1998, 1439-1444) discuss early attempts to measure the polycentricity of employment in individual American metropolitan areas by identifying job clusters. While these studies consistently found subcenters, it proved much more difficult to precisely quantify them.

In both newer cities that developed alongside the automobile and older pre-automobile cities, the number and boundaries of these subcenters was very sensitive to the exact employment density and total employment cut-offs used in defining them. These subcenters were also often arranged in corridors that, with the right choice of density cut-off, could become a single, very long sub-center. Furthermore, they note that even in cities with significant numbers of employment clusters, a large fraction—and often a majority—of employment exists outside clusters.

Glaeser and Kahn (2001, 9-10) attempted to approximate the centralization and concentration of American metropolitan areas relatively simply, by fitting employment density to an exponential function and calculating employment density gradients. They found that job centralization and job concentration were relatively strongly correlated. They also, (pp. 21-25) found that population centralization was generally (but not always) less than but correlated with job centralization, and that, with the exception of the oldest and newest metropolitan areas, there was little correlation between city age and centralization. In addition, decentralization of jobs increased with increasing political fragmentation of the metropolitan area.

Glaeser and Kahn (2003, 7-11) then expanded their previous work by calculating employment and population density gradients, confirming that job centralization and population centralization are strongly correlated in American metropolitan areas. In addition, they measured the percentage of residents living and workers working within three and ten miles of the central business district (CBD) as defined by the 1982 Census Economic Survey (see Section 1.3.2) for each city. To characterize concentration, they used the arithmetic mean population-weighted population densities and employment-weighted employment densities of these cities.

A correlation matrix of their results showed a strong correlation ($r^2 = 0.77$) between the percentage of employment and population within three miles of the central business district and an even stronger one ($r^2 = 0.89$) between the median worker's and the median person's distance in miles from the CBD. Both of these results suggest that employment and population centralization are correlated.

Likewise, they found a correlation with $r^2 = 0.90$ between population-weighted average population density and employment-weighted average employment density, suggesting that employment and population concentration are correlated as well. On the other hand, there was little to no correlation between their measures of concentration and centralization.

More recent work by Angel and Blei (2016b) indicates that job distributions in US metro areas are largely neither centralized nor concentrated. They found that three-quarters of jobs in the average metro area are dispersed outside of CBDs and non-CBD employment clusters, in areas with low job density. Furthermore, this does not necessarily lead to short commute distances: only one out of twelve workers live within two kilometers of their workplace. This largely comports with Lang (2003), who found that the majority of US jobs were in dispersed "edgeless city" rather than in CBD or "edge city" job clusters.

1.3.2 Defining the Central Business District

One complication in measuring metro area density gradients, and in applying some of the more complex models of population and job density discussed below is the need to identify the location of a metro area's central business district (CBD) or "downtown." For a simple density gradient calculation, one could in many cases simply select the Census tract with the highest population or job density and declare it to be the metro area's downtown. This may not always work, however, especially in smaller metro areas where a large hospital may contain as many jobs as the central business district without being central or having the diversity of employers associated with a normal central business district.

As Federal agency responsible for geographic statistics, the Census Bureau would theoretically be an ideal source for definitions of central business districts. However, the Census Bureau last defined CBDs nearly forty years ago, in 1982[3], and its guidelines for defining them—

> A CBD was defined as an area of very high land valuation characterized by a high concentration of retail businesses, offices, theaters, hotels, and service businesses, and by a very high traffic flow. It was delineated to follow existing census tract boundaries i.e. to consist of one or more whole census tracts, except in 14 cities where CBD tracts crossed corporate limits. In those instances, only the part of the census tract that lay within the limits was considered to be in the CBD. (US Census Bureau, 1987, 201-202)

—are more subjective than quantitative (Limehouse and McCormick, 2011; Brown et al., 2017). A related, though perhaps unavoidable, issue with the Census CBD definitions is that their boundaries were determined by committees of local stakeholders, which increases the likelihood that they are not defined consistently nationwide (US Census Bureau, 1987, 201-202; US Census Bureau, 1994, Ch. 3). In any case, forty-year-old CBD boundaries must be considered too outdated to accurately represent cities today.

Glaeser et al. (2001) and Cortright (2015) attempted to account for the outdated CBD boundaries provided by the Census definition by defining CBD employment as all employment within three miles of the center of the Census-defined CBD. While it is un-

[3] These definitions, from the 1982 Economic Census, comprise 456 CBDs for 455 cities in 315 metropolitan statistical areas (Brown et al., 2017).

likely that many metro areas' CBDs migrated by several miles in the past few decades, boundaries generated this way are far too large to usefully characterize the dense core of employment that constitutes a central business district.

One alternative approach used by a number of researchers is to define CBDs centered on the city halls of the principal cities of each metropolitan area. However, in many large cities, city hall is not actually located near the current center of employment: consider the distance between New York City Hall and Midtown Manhattan, or Boston's Government Center and financial district. Despite these shortcomings, an analysis by Holian (2019) found this method to be the best available option for developing a catalog of CBD locations for modern metropolitan areas. For comparison, one of the other methods they considered, the Census Bureau Gazetteer files providing what purport to be "representative latitude and longitude coordinates," identified the center of San Francisco in the Farallon Islands which, although legally part of the City and County of San Francisco, are thirty miles west of the mouth of San Francisco Bay.

Recently, Brown et al. (2017) made a rather thorough attempt to define CBDs for major metro areas using a machine-learning algorithm based on employment density, transportation links, and the share of employment in occupations that particularly benefit from agglomeration. This sort of approach seems likely to be the most effective, as a simple density cut-off uniformly applied will either fail to identify CBDs at all in many smaller and less dense metro areas, or else will define very large swaths of cities like New York and Chicago as central business district.

1.3.3 Typologizing Metropolitan by Polycentricity

Lee (2007) analyzed movement of jobs in six American metro areas between 1980 and 2000 and found three distinctive patterns of employment distribution: traditional monocentric metro areas (New York and Boston), polycentric metro areas (Los Angeles and San Francisco), and metro areas with dispersed employment (Philadelphia and Portland). These results are consistent with the typology used by Anas et al. (1998), but Lee considered a number of indices of centralization and concentration beyond the limited ones used by Glaeser and Kahn (2003).

Lee (2007) measured centralization of jobs by census tract using three measures. First, the *modified Wheaton index* (MWI), (Wheaton, 2004)

$$\text{MWI} = \frac{(\sum_i E_{i-1}d_i) - (\sum_i E_i d_{i-1})}{d_{max}}$$

where tracts are sorted by increasing distance from the CBD, E_i is the cumulative proportion of employment in tracts 0 to i, d_i is the distance of tract i from the CBD, and d_{max} is the distance of the outermost tract from the CBD. Second, the *area-based centralization index* (ACI), (Massey and Denton, 1988)

$$\text{ACI} = \left(\sum_i E_{i-1}A_i\right) - \left(\sum_i E_i A_{i-1}\right)$$

where tracts are sorted by increasing distance from the CBD, E_i is the cumulative proportion of employment in tracts 0 to i, and A_i is the cumulative proportion of area in tracts 0 to i. And, third, the *weighted average distance from CBD* (ADC), (Galster et al., 2001)

$$\text{ADC} = \sum_i \frac{e_i d_i}{E}$$

where e_i is the number of employees in tract i, d_i is the distance of tract i from the CBD, and E is the total employment in the metropolitan area.

Lee (2007)'s two measures of concentration were the *Gini Coefficient*, (Gordon et al., 1986; Small and Song, 1994)

$$\text{Gini} = \left(\sum_i E_{i-1} A_i\right) - \left(\sum_i E_i A_{i-1}\right)$$

where tracts are sorted by employment density, E_i is the cumulative proportion of employment in tracts 0 to i, and A_i is the cumulative proportion of area in tracts 0 to i, and the *Delta Coefficient*, (Massey and Denton, 1988; Small and Song, 1994)

$$\Delta = \frac{1}{2} \sum_i \left| \frac{e_i}{E} - \frac{a_i}{A} \right|$$

where e_i and a_i are the employment in and area of tract i and E and A are the total employment in and area of the metropolitan area.

The MWI and ACI indices measure how fast cumulative proportion of metropolitan employment increase as one moves away from the CBD and vary from -1 (perfect decentralization) to 1 (perfect centralization). A Gini or Δ value of 0 indicates complete equality of employment density between tracts, while one of 1 indicates complete inequality. Because their measures of centralization and, to a lesser degree, concentration, are sensitive to the presence of large, low-population census tracts at the edge of the metropolitan area, Lee limited their analysis to the tracts closest to the CBD that contained 95% of the MSA's population.

Lee also attempted to identify employment sub-centers in metropolitan areas both by using a minimum density cut-off of the 90th percentile employment density in the region and by using geographically weighted regression (GWR). They found that the minimum-density approach tended to primarily identify a region surrounding the CBD while GWR was more effective at identifying many regional sub-centers.

A more general survey of the spatial distribution of employment in American metropolitan areas was performed by Hajrasouliha and Hamidi (2017). After an extended review of past attempts to describe and typologize the spatial structure of employment in American metro areas, the authors discuss their efforts to develop a useful typology of the employment distributions in 356 Metropolitan Statistical Areas (MSAs) in the contiguous United States.

Because they wish to analyze such a large number of metro areas, they focus on definitions of urban employment "cores" that can be calculated algorithmically from employment data without in-depth analysis. After an extended, and very useful, description of their efforts to define measures of employment distribution, they propose a typology of five types of MSA based on employment distribution and discuss differences between the metro areas in each category. Notably, they used 1983 Census-defined central business districts, because this is the last year the Census defined this.

Having established their typology, the authors go on to compare the mean population densities and population sizes of the MSAs in each of their five categories. However, in doing this, they do not take into account the very different size categories of the metro areas in their sample. It is notable that the mean population densities of the categories track quite well with the mean populations of the categories. Since it is well-known that larger metropolitan areas tend to be denser, it is very unclear whether there is actually a pattern of different job distributions being related to different population densities, or whether this is solely a size effect: it would be very interesting to see this same comparison for MSAs within the same rough size category.

More generally, given that the MSAs spanned a range of sizes from nearly twenty million residents to under two hundred thousand residents—a difference of a factor of one hundred—the authors should have considered several different size classes separately in discussing the differences between metro areas in their different categories. For example, the apparent tendency of polycentric MSAs to be large might be a consequence of the largest MSAs to be polycentric, or it might be a consequence of the fact that nearly half of the MSAs studied have under two hundred thousand residents and may be too small to support identifiable secondary job clusters. These two effects would look the same as their data is presented, but would actually correspond to very different statements about the nature of polycentricity.

1.3.4 More-Complex Typologies of Metro Area Sprawl

Over the past two decades, a group of researchers, mostly based at Wayne State University in Detroit, have been developing methods to measure and classify sprawl in American urbanized areas. In the first study in this series, Galster et al. (2001) performed a literature review of definitions of sprawl and found many inconsistent definitions of it. They then developed a set of eight quantitative dimensions of sprawl based on laying half-mile-square and mile-square grids over a UA and and applied six of them to the distribution of housing units in thirteen urbanized areas across the US to determine whether they matched intuitive definitions of "sprawl." They found that the six dimensions tested were independent but seemed to all yield results relatively consistent with their intuitive understandings.

Wolman et al. (2005) continued this work by evaluating the issue of what land should be counted in measuring sprawl. While water areas are clearly not part of the land area of a city, various other types of non-developable land should potentially also be excluded. The authors use satellite imagery and the National Land Cover Database (NLCD) to measure sprawl in several major metro areas and to argue that the choice of what land to include strongly influences the results.

However, while they could find no theoretical justification for a specific choice of land to include, they proposed a unit they refer to as the *Extended Urban Area* (EUA) of a metropolitan area: "the Census Bureau-defined urbanized area, modified to follow census tract boundaries, as well as additional 'outlying' one mile square grid cells that contain

60 or more dwelling units (identified using data at the census block level), and are located in a census tract from which at least 30 percent of the workers commute to the urbanized area."

Using EUAs as their unit of analysis, Cutsinger et al. (2005) evaluated Galster et al.'s indices of sprawl for residential and employment sprawl in fifty of the one hundred largest American MSAs. They then analyzed the correlations between the indices and performed a factor analysis to identify seven independent dimensions of land use:

- *density/continuity*, a combination of the area-weighted averages of jobs and housing units, the percentage of square-mile units within the EUA in which 50% or more of developable land has been developed, and the share of the EUA that is within the Census UA.

- *proximity*, the ratio of the average distance among centroids of the square-mile cells in the EUA to the weighted average distance among housing units in the EUA plus the ratio of the average distance among centroids of the square-mile cells in the EUA to the weighted average distance among housing and jobs in the EUA.

- *mixed-use*, a combination of the average number of housing units in the same square-mile cell as a job and the average number of jobs in the same square-mile cell as a housing unit.

- *housing centrality*, the ratio of the average distance to city hall of the cells in the EUA to the average distance to city hall of a housing unit in the EUA.

- *housing concentration*, the percentage of housing units that would need to move to produce an even distribution of housing units within square-mile cells in the EUA.
- *job distribution*, the job equivalents of the housing centrality and concentration dimensions plus the ratio of the average distance among centroids of the square-mile cells in the EUA to the weighted average distance among jobs in the EUA.
- *[job] nuclearity*, the ratio of jobs in the CBD to all jobs in any job cluster.

Among the fifty urbanized areas they studied, they found that there were a number of variations of type of sprawl in terms of which of these axes they were higher or lower on. This suggests that there is not a single type of sprawl or sprawling city, but a wide variety of different sorts of sprawl.

In a follow-up study, Cutsinger and Galster (2006) performed a cluster analysis on the same fifty metropolitan areas and came up with four clusters or “types” of cities based on land-use patterns in 1990:

- *dense, deconcentrated*, with high job and housing density, high continuity of developed land, low proximity of jobs and housing, low concentration of jobs in the CBD, and high mixed use. These cities have a mixture of traits generally seen as sprawling and non-sprawling.
- *leapfrog*, with high job concentration but low housing and job density, low continuity, mixed use, and housing centrality, concentration, and proximity. Although they have concentrated job clusters, they generally are very sprawling and have larger gaps of vacant land between development.

- *compact, core dominant*, which have high job nuclearity and housing and job centrality, concentration, and proximity. Despite these non-sprawl-like features, they are much less dense and have low levels of continuity than the dense, deconcentrated metropolitan areas.

- *dispersed*, which are not statistically distinguishable from the cities studied as a whole, but which have a generally dispersed distribution of jobs and housing.

Sarzynski et al. (2014a) continued this line of analysis on all 257 United States metropolitan areas as of the 1990 and 2000 Decennial Censuses. They found that the EUAs studied became more employment-dense, but jobs became more dispersed and less concentrated. This deconcentration of metropolitan employment has been an ongoing pattern of American urban areas since the 1950's, as documented by Chatterjee and Carlino (2001).

While population distribution changed less, it followed the same basic pattern: while employment and population density increased from 1990 to 2000, they found that every other index of sprawl they measured became more sprawl-like over the period. In addition, the differences between metropolitan areas generally became less distinct.

In a companion article, Sarzynski et al. (2014b) essentially repeated Cutsinger and Galster (2006)'s analysis, but this time using 2000 Deccenial Census data. They also analyzed a number of geographic, historical, economic, demographic, and transportation variables as the basis of an exploratory analysis between these variables and land use characteristics.

As with Cutsinger and Galster (2006), Sarzynski et al. (2014b) found four distinct clusters of metropolitan areas based on land-use patterns. However, their clusters were somewhat different:

- *Ascendants* (most-intensive, least-compact, least-mixed, more-monocentric) was the largest cluster, consisting largely of large, young, and fast-growing areas. Nearly half were located in the South census region.

- *Insulars* (less-intensive, most-compact, less-mixed, less-monocentric) consisted of small, young, slow-growing metro areas below one million residents with locally oriented economies. They tended to be inland, have disproportionately high Black populations and low immigrant populations. About half were in the South census region.

- *Redevelopers* (least-intensive, less-compact, most-mixed, most-monocentric) consisted of smaller, older, predominantly white areas with central cities that have declined. The plurality of them were located in the Northeast census region.

- *Cosmopolitans* (more-intensive, more-compact, more-mixed, polycentric) consisted of, on average, the oldest and largest metropolitan areas, had the strongest economic indicators and highest population of Latinx and foreign-born residents. They also tended to have relatively good transit, including rail.

Sarzynski et al. (2014b) also noted that, while the clusters were distinctive in terms of Black and non-Latinx white percentages of the population, percentage of Latinx residents did not appear to be distinctive, and suggested that this might be due to sprawl being driven by forces related to Black-white segregation. This is consistent with Galster and Cutsinger (2007)'s more detailed study of the connection between sprawl and segregation.

1.3.5 Analyzing Street Networks

An alternative to the traditional approach of typologizing metropolitan areas based on their distributions of population and jobs is to base one's analysis on the structure of the street networks along which these populations and jobs are distributed.

Because, as noted by Marshall (2005) in his detailed study of street networks from an urbanist, architectural perspective, the basic structure of street networks changed with the introduction of the automobile, analyzing it can potentially be an effective proxy for a fuller measurement of the pedestrian-friendliness of a neighborhood.

Marshall explains that while traditional (pre-automobile) cities were designed with the same streets serving as the most central urban "places" and as the primary arteries for travel, modernist attempts to redesign the city for cars inverted this relationship, centering primary arteries for travel that would discourage or forbid pedestrians and street-fronting businesses while making urban places into tranquil backwaters accessed by side roads or long driveways. This has led many governments' roadway agencies to organize streets into hierarchies where the highest-level streets are dedicated to fast car movement and only the lowest-level consider pedestrians and street-fronting uses.

Marshall (2005, 83-89) attempts to establish a typology of four forms of street networks that correspond to different technological and planning eras:

- *A-type* street networks have irregular, fine-scale angular streets, most of which are short or crooked, varying in width and going in all directions. They have a mixture of T- and X-junctions and some cul-de-sacs, with moderate connectivity.
- *B-type* street networks have regular, rectilinear streets of consistent width with continuous cross-roads and X-junctions, and have high connectivity.
- *C-type* street networks have a mixture of regularity and irregularity, with streets largely of consistent width. Roads have curved or rectilinear formations, but largely meet at right angles, and have a mix of T- and X-junctions with some cul-de-sacs and moderate connectivity.
- *D-type* street networks are based on consistent road geometry and arterial roads. They have curvilinear or rectilinear formations and mostly meet at right angles, with mostly T-junctions, many cul-de-sacs, and generally tree-like low-connectivity formations.

A-type street networks are the result of unplanned pedestrian-area development, and are mostly only found in the US in a few colonial-era historic cores, such as downtown Boston. B-type networks are associated with planned cities from the pedestrian and sometimes streetcar eras, while C-type networks are associated with the public transportation and early car eras and D-type networks with the later car era.

While Marshall's typology is fundamentally qualitative, the past fifteen years have seen a number of attempts to develop more quantitative typologies of street networks. Lämmer et al. (2006) studied of road networks in German cities taking into account road speeds to show that the shortest driving time between two points is particularly likely to pass through a few major arterials and intersections. This can potentially be used to develop an understanding of the hierarchy of the road network. However, it is perhaps less useful for assessing walkability and amenability to transit: for those purposes, road speeds are likely unimportant except as a means of excluding highways from one's model of the walkable grid.

Another approach, taken by Cardillo et al. (2006) is to analyze street grids by counting the number of nodes (intersections and dead-ends), the number of block edges, total length of edges, and average length of edges. They studied districts of several world cities and found significant variation among cities and also among neighborhoods in the one city where they looked at multiple neighborhoods. They also measured the "efficiency" of the street grids, effectively defined as the average ratio between Euclidean distance and grid distance between any two nodes on the grid:

$$E = \frac{1}{N(N-1)} \sum_{i,j,i \neq j} \frac{d_{ij}^{\text{Euclidean}}}{d_{ij}}$$

where d_{ij} is the network distance between nodes i and j, $d_{ij}^{\text{Euclidean}}$ is the Euclidean distance between those two nodes, and N is the total number of nodes. While this paper is very mathematical and focused on describing methods of analysis, it does not discuss connections to demographics or the walkability of a given sort of street grid.

Some researchers have attempted to include these sorts of measures as part of larger models of urban environments. For example, Fan (2010) used miles of sidewalks and the "percentage of intersections that are not dead-ends," which I take to be the percentage of nodes that are not dead-ends, as components in her study of regions of the "Research Triangle" metropolitan area in North Carolina.

A more explicit attempt to identify types of street grid that coexist *within* American cities was made by Talen et al. (2018), who used the street grid and aerial photograph data on the built environment to typologize types of built environment in Census blocks in several American cities, coming up with roughly thirty types. They then looked at how these types of built environment correlated with demographic factors and particularly with racial diversity.

The authors found that there is generally a consistent ordering of types of built environment by density between cities, but the density of a given environment could vary significantly between cities. They also found that more sprawling types of environment consistently correlated with lower diversity and more-traditional family structures. However, their technique requires the investigators to classify built environment by hand, and so may not be applicable to a study of a large number of cities.

In the last decade, a group of researchers led by Barthelemy at the Center of Social Analysis and Mathematics of the Ecole des Hautes Etudes en Sciences Sociales in Paris have been working on an alternate approach, analyzing street networks based on the shapes and sizes of city blocks. In Barthelemy et al. (2013), they introduced their approach of analyzing block sizes and shapes rather than street segment lengths. This method was motivated by an attempt to understand how Baron Haussmann's redesign of Paris during the French Second Empire fundamentally changed the street network, despite not significantly changing the results of a nodal analysis of the street network. They showed that Haussman's redesign did significantly change the *centrality* of the street network: the set of nodes that show up on a disproportionate number of the shortest paths between pairs of other nodes. They also analyzed the change to the *form factor* of blocks (Lämmer et al., 2006), defined as the ratio of the area of the block and the area of a circumscribed circle:

$$\phi = \frac{4A}{\pi D^2}$$

where D is the maximum distance between two points on the circumference of the block and A is the area of the block.

In Louf and Barthelemy (2014b), the method is elaborated on: using both ϕ and A to classify blocks, the authors defined the "fingerprint" of a street grid as the conditional probability distribution $P(\phi|A_{\text{bin}})P(A_{\text{bin}})$ with A_{bin} an area bin. They found that two cities have visually similar street networks if the shape distributions for each area bin are very similar between the two cities.

Since the vast majority of city blocks (though not necessarily the vast majority of land in the city), have areas between 10^3 and 10^5 m^2, they neglected blocks outside of this range and used only two bins,

$$\alpha_1 = \{\text{blocks } | A \in [10^3 \text{ m}^2, 10^4 \text{ m}^2]\}$$

and

$$\alpha_2 = \{\text{blocks } | A \in [10^4 \text{ m}^2, 10^5 \text{ m}^2]\}$$

They then defined $f_\alpha(\phi)$ as the ratio of cells in bin α that have form factor ϕ to the total number of cells in the city. With two bins, this gave a fingerprint consisting of two functions $f_\alpha(\phi)$ for a given city.

Using this analysis, the authors found several "types" of cities, and typological differences between most American and essentially all European cities. They also found differences between boroughs in New York City. Unfortunately, they do not draw any direct connections between these types and "on the ground" urban environment.

Barthelemy (2017) extends the method in Louf and Barthelemy (2014b) and defines a *simplicity index*, defined as the average ratio of the lengths of the simplest to shortest route and finds that for artificial networks, it generally has a maximum at an intermediate scale, with one peak in simplicity index as a function of distance for monocentric networks and multiple peaks for polycentric networks, which might pose an interesting way to analyze street grids for polycentricity. This approach is not limited to Barthelemy's group, however: Riascos (2017) performed a similar analysis using lot size rather than block size.

One difficulty in performing street network analyses is sourcing high-quality, accurate street network shapefiles. This is particularly important for some sorts of analyses: for example, a road network shapefile that represents single X-junction intersections as pairs of T-junction intersections will frustrate attempts to analyze street networks by intersection type. The OSMnx Python package developed by Boeing (2017a,b) provides a method to simplify street network shapefiles downloaded from the OpenStreetMap open-source worldwide road-mapping project.

Further work by Boeing (2018, 2019a,b,c, 2020a,b,c) has identified patterns between different measures of street network order, found difference between driving and walking networks in American cities, identified temporal patterns in American street network design—including a return to more gridded street networks in the past two decades—and compiled measures of street networks at the Census tract level throughout the US.

Chapter 2: Characterizing Neighborhoods

The first step in developing a typology of metropolitan areas by neighborhood types is to define and characterize the neighborhoods themselves. This requires making choices about the definition of metropolitan area to work with and dealing with the slippery question of what counts as a "neighborhood." It also involves selecting data sources to quantify the land-use, economic, transportation, and social conditions that determine the feel and vitality of a place. To be useful, these data sources need to be available at a national level, so that comparable data will be available in all metro areas studied.

In this chapter, I discuss several options for defining metropolitan areas (Section 2.1) and my choice to use the US Office of Management and Budget's Core-Based Statistical Area definitions (Section 2.2). I then discuss my choice to establish grids of hexagonal cells as the spatial units for my neighborhood analysis (Section 2.3) and the process of selecting data for use in characterizing these neighborhoods (Section 2.4). Finally, I cover the process of aggregating this data into the neighborhood cells (Section 2.5) and the results of characterizing them (Section 2.6).

A list of the metropolitan areas analyzed can be found in Appendix A; details on the data sources used are given in Appendix B; and details on methodology used in analysis can be found in Appendix C. The source code for the R scripts used is available in UMBC's online ScholarWorks repository.

2.1 Options for Defining Metropolitan Areas

A fundamental problem with studying American metropolitan areas is that there is significant ambiguity in what "metropolitan area" means. Whether the car-driven reduction in metropolitan area density is a good or a bad thing, as Bryan et al. (2007, 342-346) notes, the population density of a city or metropolitan area depends strongly on where the city's boundaries are drawn. In the United States, there are three real options for defining the boundaries of a metropolitan area: the legal boundaries of the primary city, the *Urbanized Area* (UA) as defined by the Census Bureau based on a minimum density criterion (US Census Bureau, 1994, Ch. 12), and the *Metropolitan Statistical Area* (MSA), a collection of counties defined by the Office of Management and Budget based on commuting to the central city (US Office of Management and Budget, 2010).

While city boundaries are important for understanding issues of governance, they are often arbitrary in what areas they include, and their expansiveness varies significantly between metropolitan areas, due to differences in local politics and state regulatory regimes that make it easier or harder for cities to annex their suburbs. Furthermore, enough of the population and jobs in metropolitan areas are outside the central cities that a study of public transportation which excludes suburbs would be effectively useless.

2.1.1 Urbanized Areas

One alternative to using legal city limits is defining metropolitan areas as the *Urbanized Areas* (UAs) and *Urban Clusters* (UCs) established by the Census Bureau based on a minimum density criterion. Although a new set of boundaries for UAs is defined after each Decennial Census, the basic rules for establishing them reached their current form in 1990 (US Census Bureau, 1994, Ch. 12).

Urbanized areas and urban clusters are defined as collections of Census block groups consisting of an urban core with a population density of at least 2,500 people per square mile and a contiguous fringe with a density of at least 1,000 people per square mile. There are special exceptions allowing for jumps, non-residential urban land use such as parks and industrial development, and non-developable areas such as open water, swamps, and steep slopes. The only distinction between urbanized areas and urban clusters is population: urbanized areas must have populations of at least 50,000 residents and urban clusters must have populations between 10,000 and 49,999 residents.

In regions of the country with relatively continuous settlement, UAs and UCs can provide a relatively good description of built-up areas. However, in other areas, particularly where development is geographically constrained by steep hills or surface water, the continuity requirement can lead to the division of areas with deeply integrated economies into multiple distinct UAs and UCs. For example, the Concord, California urbanized area is separated from the San Francisco-Oakland, California urbanized area by the steep and largely undeveloped Berkeley Hills, but the Concord UA largely consists of suburbs of San Francisco and Oakland and is served by two lines of San Francisco's BART rapid transit system.

In addition, using UAs and UCs raises another issue: the fact that an increasing fraction of the population and jobs in metropolitan areas are found in exurban areas beyond UA boundaries, and not all metropolitan areas have the same fraction of their residents and jobs within their UA or UC. This is a consequence of the tendency of American land use to progress toward greater and greater sprawl and lower-density settlement, and excluding part of a city's commuter-shed from its metropolitan area based on a density cut-off would defeat the purpose of measuring the density distribution and sprawl of population and jobs.

2.1.2 Core-Based Statistical Areas

A more useful way to construct metropolitan areas is to examine economic integration and commuter flows. The Census Bureau began defining metropolitan districts using this technique for the 1910 Decennial Census. However, these early definitions were not commonly used by government agencies or organizations outside the Census Bureau and in 1949, the Bureau of the Budget (predecessor to the current Office of Management and Budget, OMB) defined *Standard Metropolitan Areas* for use by all Federal government agencies. An updated version of these areas, now called *Core-Based Statistical Areas* (CBSAs) and divided into *Metropolitan Statistical Areas* (MSAs) and *Micropolitan Sta-*

tistical Areas (µSAs), are still defined by the OMB after each Decennial Census (US Census Bureau, 2019b). The OMB notice that gives the current criteria for defining CBSAs describes their purpose as:

> The general concept of a metropolitan statistical area is that of an area containing a large population nucleus and adjacent communities that have a high degree of integration with that nucleus. The concept of a micropolitan statistical area closely parallels that of the metropolitan statistical area, but a micropolitan statistical area features a smaller nucleus. (US Office of Management and Budget, 2010, 37246)

Core-based statistical areas are defined based on urbanized areas and urban clusters and consist of *central counties* that have at least 50% of their population in UAs and UCs or a population of at least 5,000 people located in a single UA or UC and *outlying counties* where either 25% of the workers living in the county work in the central counties of the CBSA or 25% of the jobs in the county are held by workers from the central counties of the CBSA. A CBSA containing at least one urbanized area is a metropolitan statistical area, while a CBSA containing only urban clusters is a micropolitan statistical area.

Since MSAs and μSAs are defined as collections of counties, they contain both rural and urban areas and may vary greatly in the amount of outlying land they contain, depending on the geographic size of counties in the states where they are located. For example, the Riverside–San Bernardino–Ontario MSA consists of Riverside and San Bernardino

Counties in southern California. Nearly all of the MSA's 4 million people live in the far western portion of these counties, but the counties themselves extend roughly 200 miles across the Mojave Desert to the state's border with Arizona and Nevada.

Furthermore, in areas of the country with a high level of urbanization, they often border each other along county borders, despite these being essentially arbitrary. Two MSAs or μSAs are merged if the central county or counties of one of them qualify as outlying counties for the other; this means it is possible for quite a large number of people to commute between two distinct μSAs, particularly if both have large, similarly-sized core areas.

2.1.3 Combined Statistical Areas

In addition to Metropolitan Statistical Areas, OMB also defines *Combined Statistical Areas* (CSAs), consisting of multiple adjacent MSAs and μSAs with employment interchange of at least 15%. Not all MSAs and μSAs are included in a CSA but, for those that are, these provide a broader model of metropolitan area sprawl.

One difficulty with using CSAs, however, is that not all metropolitan areas are within one, and the US Office of Management and Budget (2018) recommends against comparing them with individual MSAs: "Because combined statistical areas represent groupings of metropolitan and micropolitan statistical areas (in any combination), they should not be ranked or compared with individual metropolitan and micropolitan Statistical Areas."

A case can be made that combining them specifically with those MSAs that are not part of any MSA may make sense, since MSAs not in any CSA are those metropolitan areas without any outlying metropolitan sprawl that would qualify for delineation as a CSA. However, it is possible that a MSA not in a CSA could have potential outlying counties that would qualify for inclusion by the 15% employment interchange standard used for CSAs, but not the 25% standard used for MSAs.

An additional difficulty, which cuts both ways, is the case of CSAs which contain two arguably distinct metropolitan areas. Boston and Providence, which are historically distinct and significant metropolitan areas, and which are separate MSAs, are combined in the same CSA. Baltimore and Washington, which perhaps have even stronger claims to be separate metropolitan areas, are also separate MSAs combined into one CSA. On the other hand, the two largest CSAs in California both combined pairs of large MSAs that probably should be thought of as part of the same metropolitan area: Los Angeles and the Inland Empire and, more arguably, San Francisco and San Jose.

2.1.4 Other Approaches

While most researchers studying American metropolitan areas use either urbanized areas or core-based statistical areas, a collection of papers by researchers at Wayne State University use what Wolman et al. (2005) called *Extended Urban Areas* (EUAs). These authors used satellite imagery and the National Land Cover Database (NLCD) to measure sprawl in several major metro areas and to argue that the choice of what land to include strongly influenced the results.

However, while they could find no theoretical justification for a specific choice of land to include, they proposed a unit they refer to as the extended urban area of a metropolitan area:

> The Census Bureau-defined urbanized area, modified to follow census tract boundaries, as well as additional 'outlying' one mile square grid cells that contain 60 or more dwelling units (identified using data at the census block level), and are located in a census tract from which at least 30 percent of the workers commute to the urbanized area. (Wolman et al., 2005, 96)

This definition, with its focus on a grid pattern of cells, was designed to be compatible with their use of raster land cover data as a major part of their analyses, and their conversion of demographic data to rasters to simplify computations. However, the basic idea of allowing lower-density land to be included if it meets a commuting standard seems reasonably sound.

2.2 Using CBSAs to Study Metropolitan Areas

While using a special-purpose definition of metropolitan areas, as done by Wolman et al. (2005), has significant benefits in a study specifically aiming to measure sprawl, it has significant downsides as well. It requires an initial pre-processing step to establish metropolitan area boundaries before further analysis can be done. Furthermore, and more seriously, an analysis done with non-standard metropolitan area definitions will be less comparable with results from other studies.

Because of these issues, I decided to use the core-based statistical areas established by the US Office of Management and Budget as my basic units for studying US metropolitan areas. For the purposes of this study, “metropolitan areas” will mean the 926 core-based statistical areas (both MSAs and μSAs) in the United States excluding Puerto Rico as established by US Office of Management and Budget Bulletin No. 18-04 in September 2018.

It should be noted that these definitions were superseded by updated definitions issued in March 2020. However, the changes are minor: the March 2020 definitions add one new micropolitan statistical area, the Bluffton, IN Micropolitan Statistical Area, consisting of Wells County, Indiana and add this μSA to the Fort Wayne-Huntington-Auburn, IN Combined Statistical Area (US Office of Management and Budget, 2020).

2.2.1 Exclusion of Puerto Rican Metropolitan Areas

In addition to the core-based statistical areas in the incorporated United States, consisting of the fifty states and the District of Columbia, the Office of Management and Budget also defines eight metropolitan statistical areas and four micropolitan statistical areas in Puerto Rico. These metropolitan areas were excluded from this study for two reasons.

First, I was uncertain about the comparability of Puerto Rican and mainland American metropolitan areas. Puerto Rico has significantly lower income than even the poorest of US states, which is likely to have a significant impact on land use and development patterns. Furthermore, the commonwealth's distinct legal and cultural history, and limited migration from the mainland US, make it unclear whether the rather unique American approach to land-use planning described by Hirt (2014) extends there.

A second, and more important, concern is that many of the data sources I used are not available for Puerto Rico. The most recent National Land Cover Database land cover data for Puerto Rico available for download is from 2001, while 2005 data is available for Hawaii, 2011 data is available for Alaska, and 2016 data is available for the contiguous United States. Furthermore, the Census Bureau's Longitudinal Employer-Household Dynamics program's LODES job location data, which I used to characterize land use, is not available for Puerto Rico for any year.

2.2.2 Selecting Coordinate Reference Systems for Metro Areas

A number of the steps in characterizing neighborhoods require accurate area and distance measurements. These measurements are needed to calculate population densities, measure walksheds, and so forth, and require a choice of planar coordinate reference system (CRS) that does not distort distances locally.

While it was obvious that separate CRS projections would be necessary for Hawaii, Alaska, and the contiguous US, I had initially hoped that a single choice of CRS would provide sufficiently little distortion to allow for accurate measurements, particularly for walkshed calculations.

After determining that a contiguous US Lambert Conformal Conic projection had too much variation, I used state plane CRS systems for my earlier walkshed work (Rowlands, 2020). However, state planes were not a viable option for this project, because there is no easy way to automate the process of identifying which state plane to use for each of the 926 metropolitan areas studied. In addition, larger CBSAs can span multiple state planes.

Universal Transverse Mercator (UTM) projections provide a good solution to these problems: the UTM system divides Earth into sixty zones, each of which is 6° wide and assigned a transverse Mercator projection based on its central meridian. Transverse Mercator projections are fairly robust and provide an accuracy of better than 1% even several degrees outside their assigned UTM zone, which means that metro areas that cross UTM zone borders do not pose an issue.

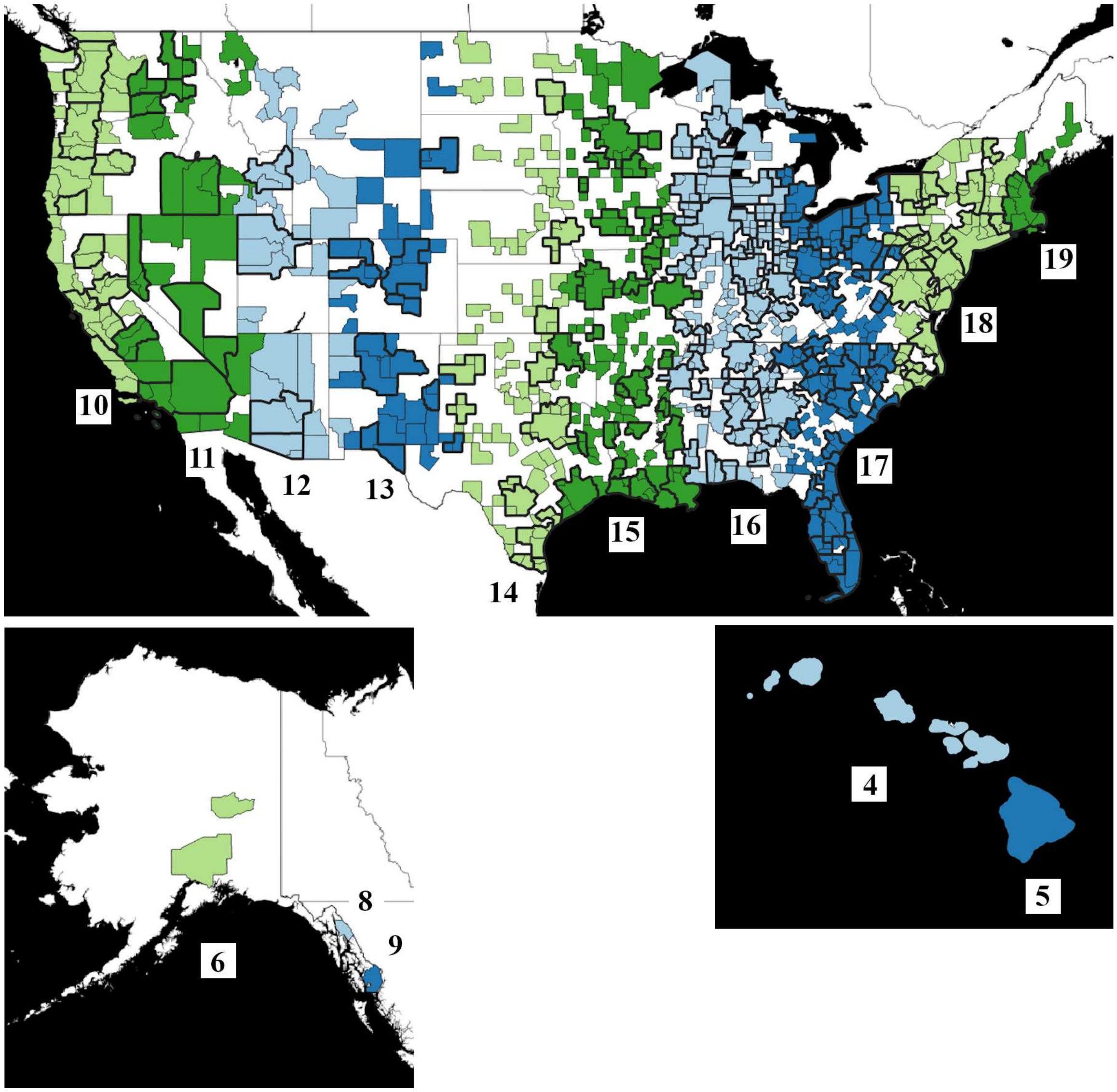

Figure 2.1: A map of core-based statistical areas color-coded by the UTM zone they were assigned. Combined statistical areas (outlined in bold) are kept in the same UTM zone even when this leads to non-optimal placement of some of their CBSAs.

Core-based statistical areas were assigned to the UTM zone in which their center of population or primary city was located. To allow for consistent mapping of entire combined statistical areas, all CBSAs in the same combined statistical area were assigned the same UTM projection. These assignments are shown in Figure 2.1 on page 70 and listed in Appendix A.

2.3 Establishing Standard Neighborhoods for Study

While it is a commonplace that nearly every major city is described from time to time as "a city of neighborhoods," these neighborhoods are often more matters of local geographic understanding than formally defined and named areas. Even in those cities where they are given official borders, the standards for what qualifies as a neighborhood vary between cities. Furthermore, as noted by Taylor (2012), residents' perceptions of neighborhoods often have overlapping borders, and different scales of proximity are relevant for different purposes.

To usefully typologize neighborhoods nationally, however, the neighborhoods need to be disjoint, comparable entities similarly defined between metropolitan areas. Furthermore, since the goal is to identify and classify walkable, urban, non-automobile-dominated places, the neighborhoods used need to be small enough that they can easily be crossed on foot and are likely to be reasonably thought of as unified places by pedestrians.

2.3.1 Choice of Spatial Units for Neighborhood Analysis

The most obvious choice for comparing neighborhood-sized areas across metropolitan areas is to use Census tracts or block groups. Census tracts are intended to be relatively stable geographic entities, though many of them are divided or merged for each new Decennial Census. Tracts are generally constructed to have between 2,500 and 8,000 residents, which means that their physical size varies substantially between urban, suburban, and exurban areas. Block groups are subdivisions of tracts intended to be more homogeneous in use, and they suffer from the same issue of vastly different sizes in areas with different population densities (US Census Bureau, 1994, Ch. 10-11).

Using the large tracts and block groups in suburban and exurban areas as "neighborhoods" would defeat the purpose of using higher-resolution data sources, such as the National Land Cover Database—which presents data in 30-meter by 30-meter pixels—to characterize neighborhoods. It would also be problematic from the point of view of a study of neighborhood walkability, since such areas are much larger than the areas pedestrians typically cover on foot even in very walkable environments.

An additional issue with using Census tracts or block groups for spatial analysis is that the results of spatial analysis can depend strongly on the choice of analysis units, an effect known as the Modifiable Areal Unit Problem (MAUP). This problem really consists of two separate issues: the scale effect and the zoning effect. Using larger-scale spatial units for analysis can disguise heterogeneity at smaller scales and can turn small negative spatial correlations into positive correlations. Furthermore, the choice of zoning—where to draw the borders of spatial units—can significantly alter results if the underlying phenomenon being measured has a non-random spatial distribution (Wong, 2009).

Since the boundaries of these Census geographies are fundamentally arbitrary, and vary in size with the sort and density of the area they cover, they are a particularly poor choice for spatial analysis. Using a grid of identically-sized units for neighborhood analysis reduces the scale-effect issue to the choice of the best scale for studying the effects of interest.

Previous studies of commute patterns and travel mode choice have found that relatively small-scale analysis units are preferable. In work on commute patterns in Boise, Idaho, Horner and Murray (2002) argued for aggregating data at the smallest level possible. A much more detailed analysis of the MAUP in the context of urban form, however, was conducted by Zhang and Kukadia (2005).

Zhang and Kukadia found significant MAUP effects in measures of urban form and mode choice, and concluded that spatial units be selected based on behavior-based properties. In particular, grids of cells with radii approximating 400-m—the radius of the conventionally-used "transportation impact area"—and reflecting the size of area where pedestrian travel dominates. This is also the size, Talen (2019, 55-56) notes, that New Urbanists and earlier Twentieth Century planners considered the maximum size for a walkable neighborhood.

Based on these findings, I chose a hexagonal grid with a hexagon radius of 400 meters as the spatial unit for my neighborhood analysis. A hexagonal grid, rather than the more common square grid, was chosen to better approximate the circular transportation impact area.

2.3.2 Creating Hexagonal Cell Neighborhoods

Once the decision to use hexagonal (hex) cells as the spatial analysis unit for neighborhoods was made, it was necessary to actually create the cells. The process for doing so is described in broad strokes in this section, but more technical details and the R scripts used can be found in Appendix C, Section C.1.

Ideally, several offset sets of cells would have been created and analyzed separately to account for the zoning effect of the MAUP. However, the amount of computation time needed to perform the analysis made it impractical to repeat it several times for offset hex cells.

Census Bureau shapefiles for each CBSA in the US were downloaded and divided up by UTM zone as discussed in Section 2.2.2. All CBSAs in a given UTM zone were transformed to that zone's UTM coordinate system and a single hexagonal grid with a side length and radius of 400 meters. The grids were then divided into separate files for each CBSA, with hexagons split by a CBSA boundary divided into two partial hexagons, one for each CBSA.

Once the hex cell grids were created, one additional step was needed before data could be aggregated into them to characterize them: water areas needed to be removed, as the CBSA definition shapefiles used include major bodies of water, including rivers, bays, and the Great Lakes.

However, the question of *which* water features should be removed is somewhat more complicated, since the Census-provided water area shapefiles which were used contain small streams and ponds as well as larger water features. While cropping the hex grids to the boundaries of major bodies of water should not seriously effect the analysis, removing all small water features potentially raises the observed density of development in cells by lowering their measured area without reducing the total area that they encompass.

In addition, the Census water shapefiles seem to be inconsistent in their representation of small bodies of water: in some counties, many small bodies of water are shown, while almost none are shown in neighboring counties with similar underlying geology

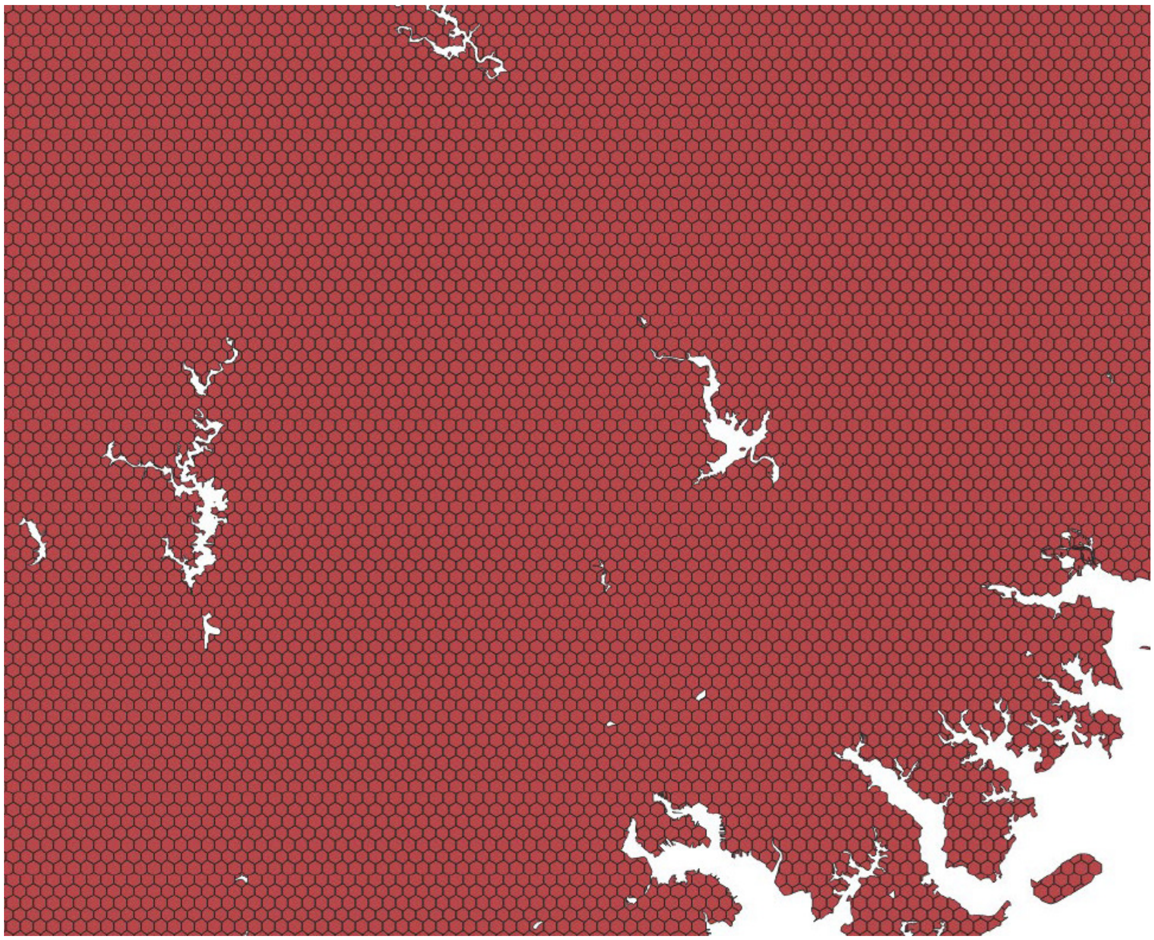

Figure 2.2: A map the hexagonal cells in part of the Baltimore-Columbia-Towson, MD Metropolitan Statistical Area with water features removed.

and topography.[1] To take into account both these issues, all water features with areas of less than 100,000 square meters—roughly one quarter of the area of one of the hexagonal cells—were removed from the water shapefiles before water features were removed from the hex cells.

Finally, to avoid either saving very small residual cells, which would be too small for useful statistics, or wasting processing time and memory space on the removal of very small areas from cells, the processing of the cells was handled differently depending on the amount of water to be removed from a cell. If 85% or more of the area of a cell was water, the cell was completely deleted, while if 15% or less of the cell was water, no water area was removed from the cell. However, water areas were removed from cells if between 15% and 85% of their area was water. An example of the results of this process can be seen in Figure 2.2 on page 76.

[1] For example, a large number of small ponds are shown in Prince George's County, Maryland on the west side of the Patuxent River, while none are shown in Anne Arundel County, Maryland on the eastern side.

2.4 Review of Available Data Sources

Directly measuring the vitality and walkability of a neighborhood would likely require surveys of residents or direct observation by researchers, neither of which is a viable option at a national scale. Instead, data sources covering the entire United States were selected to measure the traits most generally believed to be essential for walkable, vital neighborhoods: density, mixture of use and building types, and pedestrian-friendly street networks. Five data sources were chosen to provide a fairly basic characterization of neighborhoods, although others (discussed in Section 2.4.4) have potential merit for inclusion in further work.

Density was measured in terms of activity units—number of residents plus jobs, as per Newman and Kenworthy (2006)—using data from the Census Bureau's American Community Survey (ACS) and Longitudinal Employer-Household Dynamics (LEHD) programs. Mixture of use was measured using ratios of residents and jobs in different industries from these same sources. Mixture of building types, and building types in general, could not be directly measured, but numbers of housing units in different building types—also from the ACS—and percentage of developed land—from the USGS National Land Cover Database (NLCD)—were used as proxies. And, for road network connectivity, measurements were derived from street networks reported by the OpenStreetMap (OSM) project.

2.4.1 Census Bureau Data

The largest source of data for characterizing neighborhoods was the US Census Bureau, which also provided the TigerLine shapefiles of Census geographies (blocks and block groups), water areas, and core-based statistical areas used in data processing and the creation of maps. Datasets from two major Census programs were used: the American Community Survey (ACS) and the Longitudinal Employer-Household Dynamics (LEHD) program.

The ACS, which began in 2006, is a continuous program conducted by the Census Bureau to collect more detailed data than is included in the Decennial Census every ten years. This data, which was traditionally collected via the long-form questionnaire sent to a fraction of households each Decennial Census, was moved to a separate program for two reasons: to allow for more continuous data collection, and to prevent lower response rates to the long-form questionnaire from suppressing Decennial Census responses.

Unlike the Decennial Census, ACS results are produced by statistical sampling. Surveys are sent to approximately three million households each year, and the highest-precision results, the five-year samples, estimate values for the reported year based on that year's sample and samples from the four previous years. Because of the statistical nature of the results, they are not available at the Census block level (US Census Bureau, 2014).

Block-group-level 2018 ACS five-year estimates were used as a source for several datasets used to characterize neighborhoods. Total population and number of housing units by type of structure (i.e. detached single-family homes, attached single-family homes, mobile homes, and various sizes of apartment building) were used in the initial characterization and to develop neighborhood clusters.

In addition, data on population by race, median household income, transportation modes for commuting to work, and available cars per household were collected for potential use in typologizing metropolitan areas by the demographics of different neighborhood types. More details on the ACS data collected can be found in Appendix B, Section B.1.

Demographic data was excluded from the initial neighborhood and metro area typologies because the goal of these typologies is to understand the built environments available in different neighborhoods and metro areas independent of demographics. Keeping the built environment typologies independent of demographics allows for later study of the demographics with access to different neighborhood types and to similar neighborhood types in different metropolitan areas.

The Longitudinal Employer-Household Dynamics is a program of the Census Bureau's Center for Economic Studies that combines Federal and state data on employers and employees with Census data to produce datasets related to employment and economics. One of these datasets, LEHD Origin-Destination Employment Statistics (LODES), contains data on the locations of jobs (US Census Bureau, 2021a).

Although the LODES dataset has some weaknesses—it excludes national-security-related Federal jobs; available data is somewhat less recent than ACS data; and there are errors in location assignment for some jobs—it is a relatively accurate source on the density of jobs and their distribution by income and industrial sector at the Census block level (US Census Bureau, 2019c).

LEHD data on the number of jobs in two-digit North American Industry Classification System (NAICS) industrial sectors was used in the initial characterization and typologization of neighborhoods. Data on the number of jobs in three income bands was also collected for potential use in the development of demographic-based metro area typologies. Appendix B.2 contains technical information about this data.

2.4.2 Other Sources of Federal Data

Although the Census Bureau is the best known source of Federal government data on the built environment, two other Federal data sources were used to supplement the Census's ACS and LODES datasets: the National Land Cover Database (NLCD) and the National Transportation Atlas Database (NTAD).

The NLCD is a project of the US Geological Survey (USGS), with assistance from several other Federal agencies, to produce an atlas of land cover types in the United States derived from remote-sensing imagery from the Landsat constellation of satellites. Although the project primarily focuses on identifying different types of natural and agricultural land cover, developed land is also identified with relatively high accuracy. NLCD data is provided as rasters with a 30-meter by 30-meter pixel size, which offers significantly higher resolution than the Census block group and block geographies available for ACS and LEHD data (Yang et al., 2018; Homer et al., 2015).

Figure 2.3 on page 83 shows raw NLCD data for Baltimore, color-coded in the NLCD's default color scheme, with developed land indicated in shades of red. The urban core is nearly continuously coded as developed, while major radial roads are visible as long, narrow strands of developed land.

NLCD data was used for two purposes in this project: to characterize the built form of neighborhoods in terms of their fraction of developed land, and to increase the effective resolution of the ACS and LEHD data. Pixels containing at least 20% developed land were coded as developed and used to calculate the fraction of developed land in each neighborhood hex cell.

Large tracts of undeveloped land identified in the NLCD data were also removed from the Census block and block group geometries for the Census data. This was intended to correct for the fact that suburban and exurban Census blocks and block groups often contain large areas of empty land, lowering the apparent density of their developed portions. More details on the specific NLCD datasets used can be found in Appendix B.3

The United States Bureau of Transportation Statistics (BTS) maintains the NTAD, a set of several dozen nationwide GIS databases of "transportation facilities, transportation networks, and associated infrastructure" (US Bureau of Transportation Statistics, 2021). Although this data mostly consists of transportation infrastructure and administrative boundaries, it also contains a dataset (US Bureau of Transportation Statistics, 2019) of borders of military bases and related Department of Defense facilities.

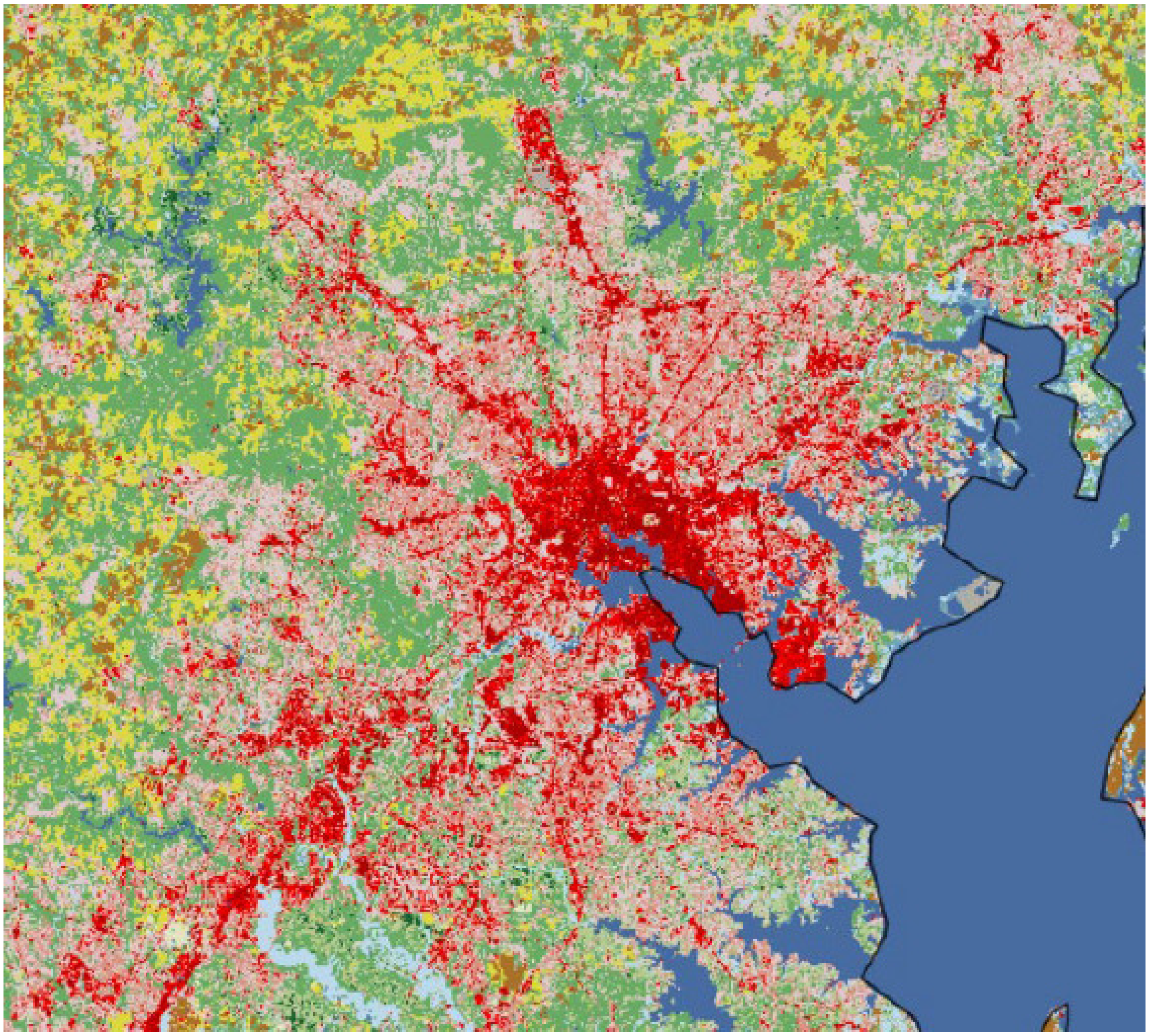

Figure 2.3: A map of raw National Land Cover Database data for part of the Baltimore-Columbia-Towson, MD Metropolitan Statistical Area. Developed land is shown in shades of red.
(US Geologic Survey, 2020)

The NTAD military base data was used to remove hex cells located on military bases from analysis. These cells were removed due to two concerns: first, that the exclusion of military and national-security jobs from LEHD data meant that density and use-type calculations for these areas would necessarily be inaccurate and, second, that the high security of and exclusion of the general public from military bases make them inherently non-urban facilities. Details on the use of this data can be found in Appendix B.4.

2.4.3 Road Network Shapefiles

The structure of the road network is an important component of walkable, vital urban places. As such, it is important to characterize the street network in neighborhoods as part of characterizing the neighborhoods. While numerous methods have been developed to characterize street networks (Boeing, 2019b), all of them require GIS data on road networks as a starting point.

Furthermore, for the purpose of characterizing walkability, what we actually care about is the network of walkable paths, which includes some things that are not roads—off-road shared-use trails and paths in pedestrianized areas—but excludes roads along which it is illegal—i.e. the Interstate Highway System—or unsafe—i.e. high-speed roads without sidewalks—to walk.

While the Census Bureau does produce TigerLine shapefiles of the US road network, they are missing many pedestrian-only paths, and they provide only very limited options for eliminating non-walkable roads. Fully grade-separated freeways can be identified, but not largely-but-not-entirely grade-separated highways or other high-speed roads that are very unlikely to have sidewalks.

The open-source web-mapping project OpenStreetMap (OSM) provides a better alternative for mapping the road networks in US cities. Its US road network is based on 2005 Census TigerLine shapefiles (Boeing, 2019b), but additional pedestrian paths have been added in many metropolitan areas and freeways and freeway-like roads have been identified and removed, as seen in Figure 2.4 on page 86.

Road network characterization of neighborhoods for this project was based on Geofabrik GmbH (2020) data-dumps of the OSM road network for the US. Details on the OSM data imported and the choice of road types to include in analyses are given in Appendix B.5.

2.4.4 Other Possible Data Sources

Characterization of neighborhoods for this project was limited to the five data sources discussed in the preceding pages. However, there are a number of other data sources of potential interest for similar work that seem worth mentioning here.

Figure 2.4: The OpenStreetMap street network in part of the Baltimore-Columbia-Towson, MD Metropolitan Statistical Area. Roads identified as non-walkable are highlighted in red.

In addition to Census, NLCD, and NTAD data, other Federal agencies produce datasets relevant to the characterization of neighborhoods: the US Department of Homeland Security (DHS)'s Homeland Infrastructure Foundation-Level Data (HIFLD) datasets and the US Environmental Protection Agency (EPA)'s Smart Locations Database datasets are of particular interest.

The HIFLD is a collection of datasets of point data on the locations of public facilities, including schools, college, hospitals, and other infrastructure, much of which is publicly available and free to use. In many cases, this data includes information on staff size or other data that can be used to quantify the size of facilities, and it could potentially be used to correct for inaccuracies in LODES data on the location of education and other government jobs. It also potentially provides for greater ability to distinguish between different sorts of amenities not distinguishable in the LODES data.

The US Environmental Protection Agency's (2021) Smart Locations Database is a collection of indicators associated with the built environment selected for relevance to environmental efficiency, tabulated by Census block group. Many of these indicators, including the National Walkability Index (NWI), which attempts to quantify walkability in a single number, are potentially quite useful for characterizing urban neighborhoods. However, the Smart Locations Database appears to have last been updated in 2013.

The OpenStreetMap project also has additional potentially useful data beyond the road networks that were sourced from it for this project. In particular, the Geofabrik GmbH (2020) OSM datasets contain shapefiles of building footprints that—for the areas they cover—are potentially very useful for measuring built form since they, unlike NLCD data, distinguish between building footprints and paved non-building surface such as roads and parking lots.

While this data does not give as much detail as the LIDAR-based "built-up volume" data used by Krehl et al. (2015, 2016, and 2019) in studying the spatial structure of German cities, it is potentially incredibly useful. However, while the dataset covers up most downtowns and significant portions or all of many major metropolitan areas, it is too incomplete to be used for a complete national survey such as this one. It may, however, be useful for a more targeted study of major metropolitan areas, or may be extended to cover larger areas in the future.

Analyzing street networks is one of the most computationally-intensive components of characterizing neighborhoods, since it requires processing very large datasets and performing complex calculations on them. As such, the repository of already-processed street network data with a number of calculated measures created by Boeing (2019b) is potentially a useful source for future projects.

Another academic database of potential interest is Leyk et al.'s (2018 and 2020) Historical Settlement Data Compilation for the United States (HISDAC-US). This database consists of 250-meter resolution rasters of intensity of settlement covering much of the contiguous United States back to 1810. It is based on surveying and real estate data collected by the real estate company Zillow Group, but the raster-level data is freely available to researchers.

Since, as discussed in Chapter 1, the nature of the American urban environment has changed substantially since the advent of automobiles and the Interstate highway system, being able to identify areas that were built up before these changes could be useful in characterizing urban neighborhoods. However, it is important to note that an area having been initially developed as a pedestrian-and-streetcar city does not mean that "urban renewal" and the construction of urban freeways has not completely changed the built environment.

While the previously-discussed data sources are free and available to the public, a large quantity of proprietary data exists which would be quite useful for characterizing neighborhood. Of particular note are "point of interest" datasets—which list businesses and related locations which are of interest to pedestrians—and travel data—often derived from cell phone location data—from companies such as SafeGraph and Replica. This data, which is largely intended for marketing firms, is quite expensive, but could be of value if sufficient budget was available.

2.5 Processing Data to Characterize Neighborhoods

The final, and most time-consuming, step in characterizing neighborhoods was the process of taking the raw data discussed in Section 2.4 and importing it into the hexagonal cell neighborhoods described in Section 2.3.

For the three main data sources—NLCD data, Census data, and OSM road network data—importing the data was a two-step process, as preliminary processing (discussed in Sections 2.5.1, 2.5.2, and 2.5.3 respectively) was needed before the data could be extracted into the hex cells. In addition, NLCD data was used in this initial processing of Census data.

A general outline of the procedure of processing the raw data and importing it into the hex cells is shown in Figure 2.5 on page 91. More technical details on this process, and the R code used, can be found in Appendix C.

2.5.1 Processing NLCD Data

National Land Cover Database data was downloaded from the USGS as rasters made up of 30-meter pixels with roughly a dozen values corresponding to different types of land cover, as seen in Figure 2.3 on page 83. However, for the purposes of this project, only one land-use distinction was used: "developed" versus "undeveloped" land. Land reported by the NLCD as "low-intensity developed" (20%-49% of land covered with impervious surfaces), "medium-intensity developed" (50%-79% of land covered with impervious sur-

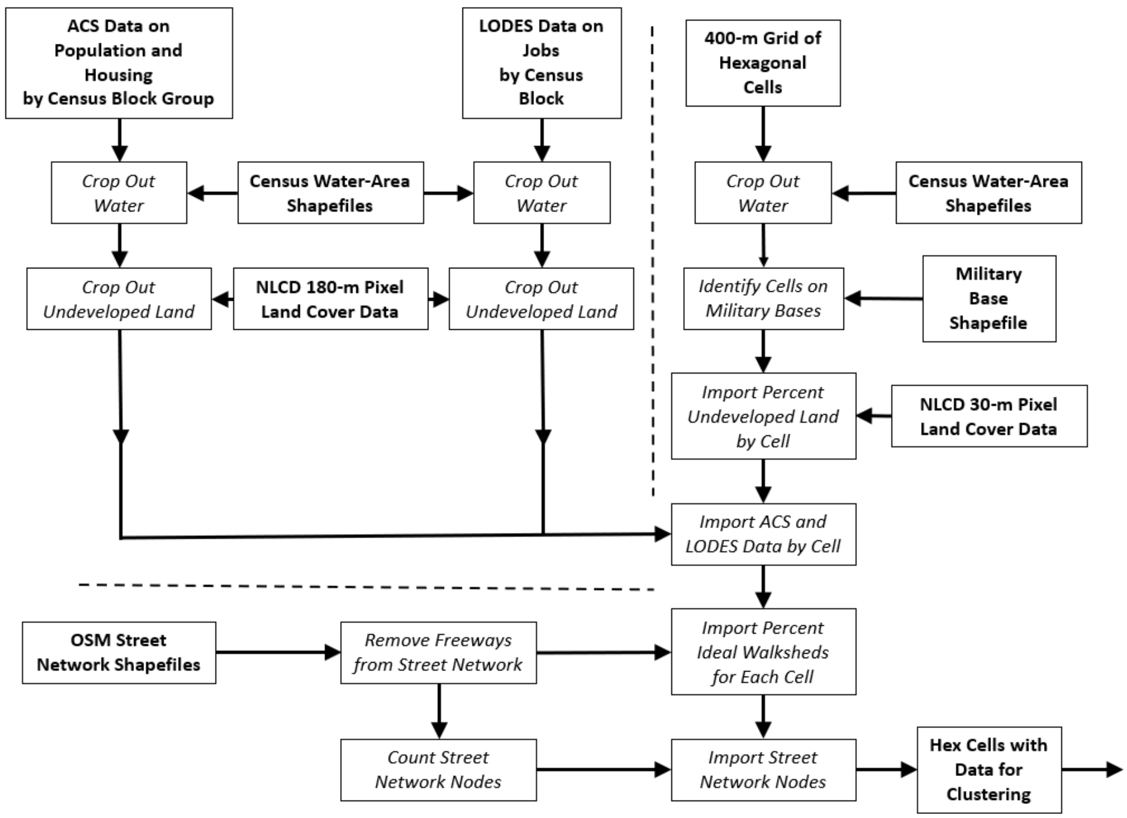

Figure 2.5: A flowchart showing the procedure for processing raw data and using it to characterize the 400-meter hexagonal cells for clustering analysis. Text in bold indicates data sources and the final hex cell neighborhoods, while text in italics indicates processes. With the exception of calculating percent ideal walksheds (done with the service area analysis tool in QGIS) and converting NLCD 180-meter pixel land cover data to vector objects for use in cropping out undeveloped land (done with a GDAL Python script), all steps were performed with R scripts.

faces), or “high-intensity developed” (at least 80% of land covered with impervious surfaces) was binned together as developed land, while all other pixel values were binned as undeveloped land.

This pixel reclassification produced the raster shown in Figure 2.6(a) on page 93. In the central cores of cities, almost all land except for parks registered as developed, while suburban areas are dappled with individual developed and undeveloped pixels at a scale much smaller than the hexagonal neighborhood grid.

Calculating the fraction of pixels in each hex classified as developed produces the more continuous gradient seen in Figure 2.6(b), with suburban hexes having intermediate values between the completely developed hexes in the urban core and the completely undeveloped hexes in parkland such as Patapsco Valley State Park to the left of the image.

The 30-meter pixel developed/undeveloped rasters of the sort shown in Figure 2.6(a) are sufficient to calculate the percent of developed land in each hex cell. However, NLCD data was also needed for a second purpose: improving the resolution of ACS and LODES Census data. This data is reported at the block group and block levels respectively and, especially in suburban and exurban areas, these geographies are large enough to often include large tracts of undeveloped land in the same geometry as a concentration of jobs and residents.

The correlation between developed land—in effect, land that is at least 20% covered in impervious, artificial surfaces—and density is not absolute. Airport runways and freeways, for example, register as developed land even though they are not the locations

(a)

(b)

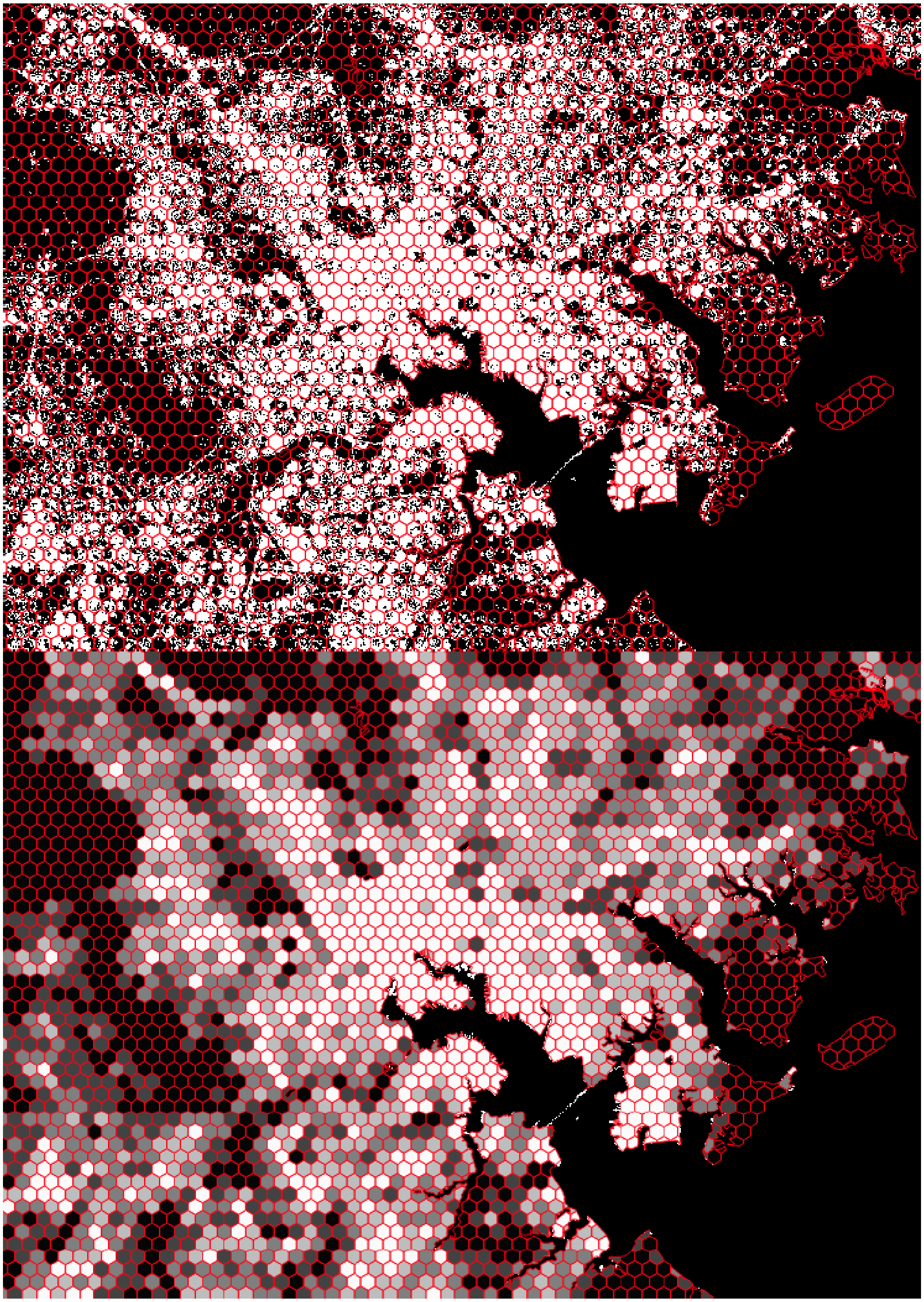

Figure 2.6: Two views of NLCD data with the hex cell grid overlaid in part of the Baltimore-Columbia-Towson, MD Metropolitan Statistical Area. In (a), developed pixels are white. In (b), hexes are shaded by percent developed land, with black completely undeveloped.

of jobs and residents. However, removing undeveloped areas from the block groups and blocks used to tabulate Census data should give a more accurate sense of the locations where jobs and residents are actually located.

Rather than cropping the Census geographies with the developed pixels in the rasters used to classify neighborhoods based on their percent developed land, however, a new set of rasters with 180-meter pixels were created for use in cropping Census geometries. These rasters—an example of which is shown in Figure 2.7 on page 95—were created by reducing the resolution of the classification rasters and by assigning a pixel in the new raster a value of developed if *any* of the thirty-six 30-meter pixels covering the same area as one 180-meter pixel were developed.

This reclassification serves two purposes. First, lowering the resolution in this way ensures that undeveloped pixels represent large areas of undeveloped land, such as parks, and not simply large backyards in suburban areas. Second, lowering the resolution makes the cropping process much more computationally tractable, as it reduces the graininess of the rasters and thus the complexity of the Census geometry vector objects that remain after cropping.

As can be seen in Figure 2.7, the 180-meter resolution cropping rasters do seem to only crop out large parks in urban and inner-suburban areas, but become more dappled in outer suburban and exurban areas, and in large parks such as Patapsco Valley State Park on the left of the image, which do contain roads, parking lots, and occasional structures.

Unfortunately, one technical issue with the cropping procedure was discovered: due to undocumented behavior of the R functions used for the cropping procedure, a small number of Census block groups were reduced to tiny residual features, resulting in their

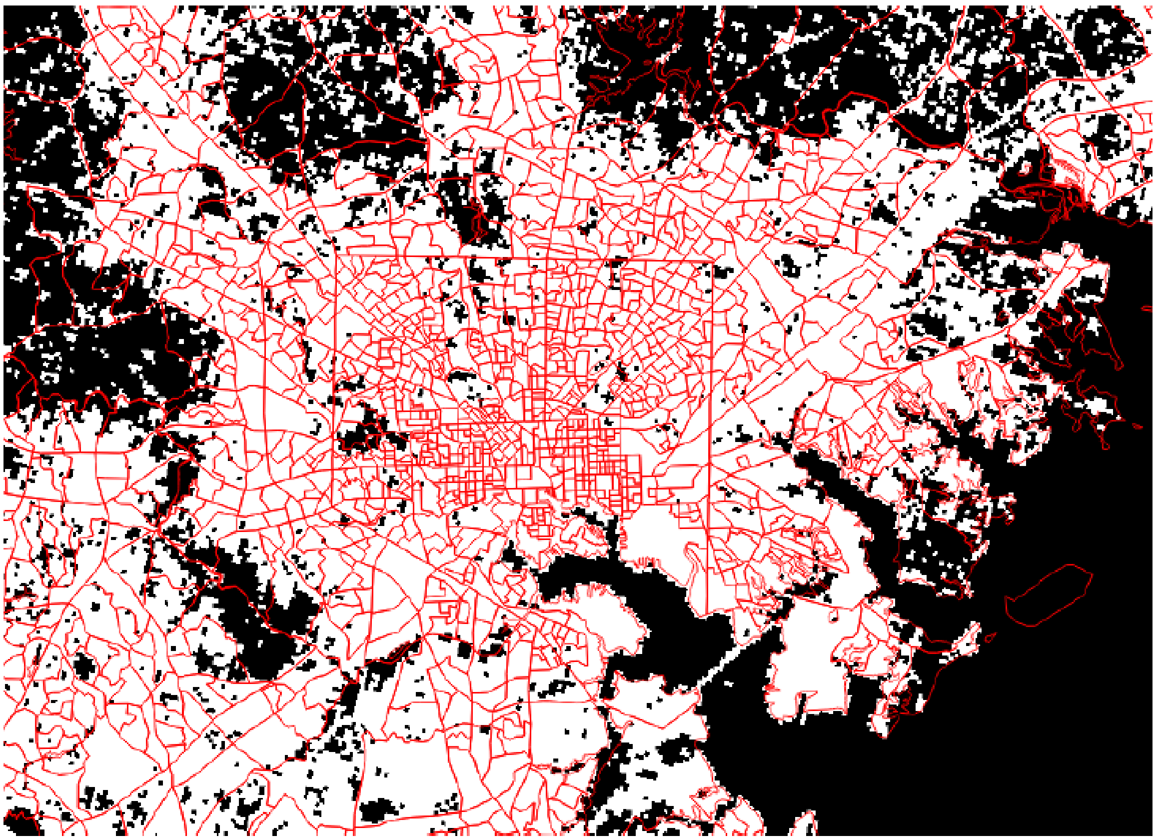

Figure 2.7: Census block groups (outline in red) in part Baltimore-Columbia-Towson, MD Metropolitan Statistical Area. Black areas have been identified as completely undeveloped based on NLCD data and will be cropped from the block groups and blocks used for ACS and LEHD data.

population data being transferred to a single hex cell. This problem was discovered too late to redo the analysis, so the resulting invalid hexes (recognizable due to their implausibly high densities) were removed from consideration. For details on this issue, see Appendix C, Section C.3

2.5.2 Processing Census Data

The pre-processing of Census data primarily consists of cropping the TigerLine Census geographies to remove water and undeveloped land. Unlike with the other data sources, Census data and geographies were downloaded within the R scripts used to process them using the R packages `tidycensus`, `lehdr`, and `tigris`, which directly access the Census Bureau's data APIs.

Census geographies with no population and no jobs were immediately dropped to save disk space and computation time and were cropped with the same Census water features used to remove water areas from hex cells, as discussed in Section 2.3. However, while water features with areas of less than 100,000 square meters were still discarded before cropping, Census geometries were kept regardless of the fraction of their areas that were removed by cropping.

After water areas were cropped out of the Census geographies, undeveloped land was removed using the 180-meter resolution NLCD data discussed in the previous section. While these cropping procedures were relatively straightforward, they did produce one complication.

All GIS operations on the Census and NLCD data polygons were performed using the R package `sf`, which stores spatial features as sets of points. Unfortunately, cropping an `sf` polygon feature can, at times, leave a remainder containing only one point or a pair of points called a linestring instead of a new polygon feature. These features cannot be stored in the ESRI Shapefile format used to save files to disk, as it only allows a single geometry type in a given file, so it was necessary to strip out lone points and linestrings from the cropped Census geometries before they could be saved to disk.

2.5.3 Processing Roads Data

The most computationally intensive part of characterizing the hex cell neighborhoods was processing the OSM road network data. This data was used in two separate ways to create measures of the road network. First, percent ideal walkshed values (Rowlands, 2020) were calculated for the centroids of each neighborhood hex cell. Second, and separately, the road network nodes in each hex cell were analyzed.

In both cases, the road network data needed to be pre-processed to remove non-walkable roads. Unfortunately, while OSM does contain some information on speed limits and the presence of sidewalks, this information is unreliable and missing for a large fraction of roads. As a substitute, road types corresponding to limited-access and partially grade-separated roads were removed from the road networks before calculations were performed.

Percent ideal walkshed is a measure of the ratio between measured density and the density actually experienced by pedestrians in an urban environment. It is based on the concept of a walkshed: the area reachable by walking a given distance from a given starting point. In an ideal world, this would simply be the area of a circle with the specified radius but, since pedestrians are generally limited to sidewalks and footpaths, it can be much smaller depending on how well- or poorly-connected the street network is.

The procedure for calculating the percent ideal walksheds of hex cells, shown in Figure 2.8 on page 99, involves the calculation of an 800-meter (roughly ½-mile) walkshed for the point on the road network closest to the centroid of the hex cell. This distance was chosen because it is roughly the distance that transit planners generally assume that people will walk to transit. The ratio of the area of this walkshed to the area of a circle with an 800-meter radius is then the percent ideal walkshed.

Some hex cells—particularly in rural areas—have no roads crossing them, which means that the point on the road network closest to the centroid of these hex cells is not within them. Since this would make the percent ideal walkshed measure not particularly useful, these hex cells were removed from analysis completely on the justification that a 400-meter radius hex cell with no roads passing through is inherently non-urban.

The second measure used to characterize the road networks of neighborhoods is the numbers of dead-ends, three-way intersections, and four-way intersections (collectively, nodes) in the street network of each hex cell. These values are important as measures of connectivity and it has been suggested, at least since the 1960's (Jacobs, 2011, Ch. 9) that small blocks and frequent intersections improve urban walkability and vitality.

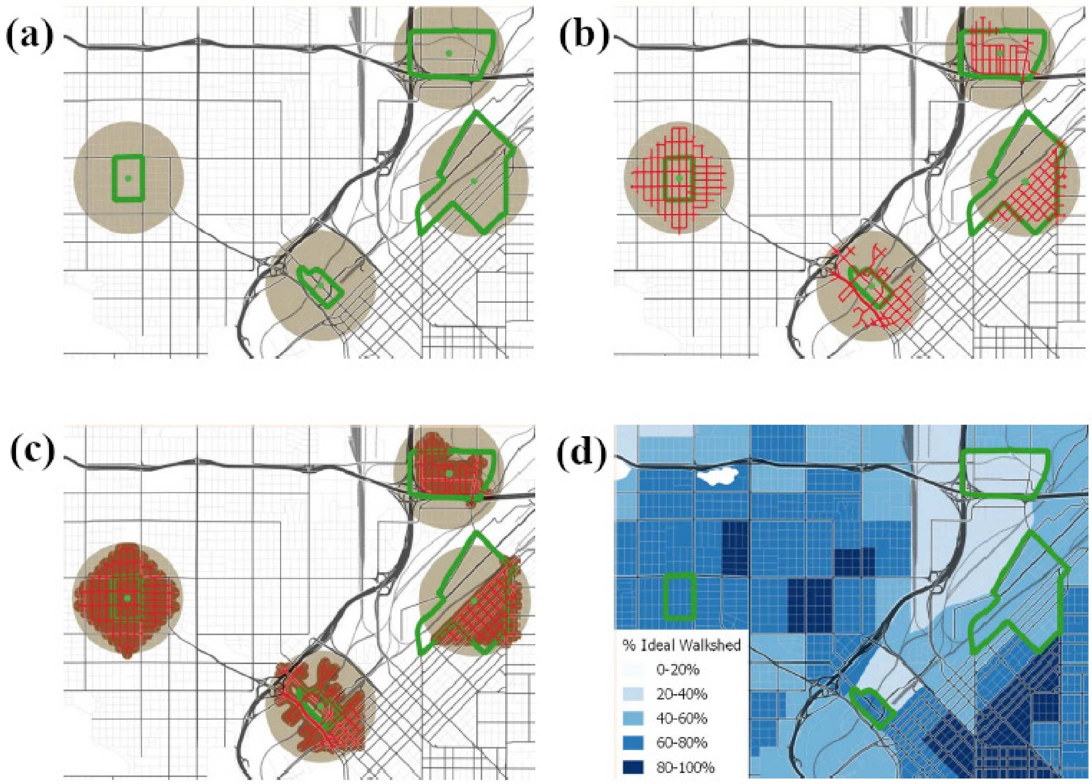

Figure 2.8: The process for calculating percent ideal walksheds.
Figure from Rowlands (2020).
(a) Centroids and 800-meter ideal (circular) walksheds are calculated.
(b) The portion of the road network within 700-meter road distance of the centroid of each cell is identified.
(c) A 100-meter buffer is created around each cell's road network section. This is the actual walkshed.
(d) Percent ideal walkshed is calculated from the ratio between the actual and ideal walksheds.

Street network nodes were counted by converting each metropolitan area's street network to a topological graph, identifying the order (number of connections) at each node of the graph, and then counting the number of nodes of each order in each hex. The main complication was the need to avoid multiply-counting intersections in areas where sidewalks are included in the OSM datasets.

While the OSM road networks are generally very complete as far as roads go, sidewalks are shown as separate features alongside roads in some but not all areas where they are actually present. These sidewalk features can make a single four-way intersection appear to consist of nine closely-spaced four-way intersections as the sidewalks cross each other and the road beds. In order to achieve better consistency between areas where sidewalk features are and are not present, and in order to to avoid this intersection duplication, sidewalks and related features were removed from the road networks before nodes were counted.

2.5.4 Extracting Data to Hex Cells

For the collected data to be useful in characterizing the hex cell neighborhoods, it needs to be associated with them. This was the simplest in the case of the road network data, which was initially calculated on the level of hex cells. For the other datasets, it was somewhat more complicated.

The NTAD data on the location of military bases was simply used to determine which cells were located on military bases. To simplify calculation, the centroids of the cells were used: any hex cell with a centroid in a feature in the military base shapefile was deemed to be located on a base and was dropped from the analysis.

Calculating the percentage of developed land in each hex cell was somewhat more complicated, as it required counting the number of pixels in a raster within the boundaries of each cell, which was defined as a vector object. The R package `raster` does have a tool for this, but it runs extremely slowly. Instead, the R package `velox`, which was developed specifically for this purpose, was used.

Extracting ACS and LODES data posed a slightly different problem: the need to redistribute variables from one set of geometries (the cropped Census geographies) to another (the hex cells). This was done with an area-weighted integration R package called `areal`, based on the assumption that all variables were distributed evenly over each cropped Census geography.

Area-weighted integration works well for extensive variables, such as population, but not for the one intensive variable being handled, median household income. This is because the weighting of two block groups' contributions to a cell's median income should be based on their population contributions to the cell, not their relative areas of overlap. To resolve this issue, the median income variable was made extensive by multiplying it by population before the area-weighted integration.

Once all the data sources had been imported into the hex cells, hex cells with activity densities of less than 100 activity units (jobs plus residents) per square mile were removed on the basis that they were too low in density to qualify as urban.

Table 2.1: Neighborhood Characterization Variables

Variable	**Description**
AREA_mi	Area of the hex cell in square miles
DEVEL_ct	Count of developed 30-meter NLCD pixels
UNDEVEL_ct	Count of undeveloped 30-meter NLCD pixels
DEVEL_fr	Fraction of 30-meter NLCD pixels that are developed
POP_total	Total population
HU_htot	Total number of housing units
HU_h1d	Number of detached single-family housing units
HU_h1a	Number of attached single-family housing units
HU_h2	Number of housing units in duplexes
HU_h34	Number of housing units in triplexes and quadruplexes
HU_h59	Number of housing units in buildings of 5-9 units
HU_h1019	Number of housing units in buildings of 10-19 units
HU_h2049	Number of housing units in buildings of 20-49 units
HU_h50	Number of housing units in buildings of 50 or more units
HU_hmobl	Number of mobile homes and vehicles used as homes
JOBS_total	Total number of jobs
JOBS_11	Number of jobs in NAICS sector 11
JOBS_21	Number of jobs in NAICS sector 21
JOBS_22	Number of jobs in NAICS sector 22
JOBS_23	Number of jobs in NAICS sector 23
JOBS_3133	Number of jobs in NAICS sectors 31-33
JOBS_42	Number of jobs in NAICS sector 42
JOBS_4445	Number of jobs in NAICS sectors 44-45
JOBS_4849	Number of jobs in NAICS sectors 48-49
JOBS_51	Number of jobs in NAICS sector 51
JOBS_52	Number of jobs in NAICS sector 52
JOBS_53	Number of jobs in NAICS sector 53
JOBS_54	Number of jobs in NAICS sector 54
JOBS_55	Number of jobs in NAICS sector 55
JOBS_56	Number of jobs in NAICS sector 56
JOBS_61	Number of jobs in NAICS sector 61
JOBS_62	Number of jobs in NAICS sector 62
JOBS_71	Number of jobs in NAICS sector 71
JOBS_72	Number of jobs in NAICS sector 72
JOBS_81	Number of jobs in NAICS sector 81
JOBS_92	Number of jobs in NAICS sector 92
PER_WALK	Percent ideal walkshed (as a fraction, not a percent)
NODES_D1	Number of dead ends in the street network
NODES_D3	Number of 3-way intersections in the street network
NODES_D4	Number of 4-or-more-way intersections in the street network

For the purposes of developing a neighborhood typology (discussed further in Chapter 3), a single file was saved containing all the hex cells from all 926 CBSAs studied, with the variables shown in Table 2.1 on page 102. These variables were specifically selected to characterize built environment while leaving more distinctly demographic variables, such as race and income, out of the neighborhood typology so that the demographics of similar neighborhoods can be compared in the metropolitan area typologies in Chapter 3.

As a final step, the neighborhood characterization variables were simplified by combining them into larger groups, reducing the number of variables to a smaller set that was easier to work with. The variables, shown in Table 2.2 on page 104, are divided into four groups: activity, housing units, percent ideal walkshed, and percent developed land.

Total activity units and activity density are defined as the sum and density of the sum of all jobs and residents in a hex. The fractions of activity units consisting of residents and of four job types—retail (including entertainment), education/medical, office (including research), and industrial—are then broken out into separate variables.

Retail and education/medical jobs were separated from office and industrial jobs because the former tend to provide services to their local neighborhoods and to be non-tradable, as calculated by Jensen (2011), between metro areas while the latter are largely tradable and less often provide local services or direct benefits to their neighborhoods. Industrial and office jobs were broken out separately because of their different land-use impacts, while retail and education/medical jobs were broken out because location data on the latter are less reliable in the LODES dataset used for determining employment locations.

Table 2.2: Simplified Neighborhood Characterization Variables

Variable	Description
ACT_TOTAL	Total number of activity units (jobs plus residents)
ACT_DENSE	Density of activity units
ACT_RESID	Residents as a fraction of all activity units
ACT_RETAIL	Jobs in NAICS sectors 44–45, 71–72, and 81 as a fraction of all activity units
ACT_EDMEDS	Jobs in NAICS sectors 61–62 as a fraction of all activity units
ACT_OFFICE	Jobs in NAICS sectors 51–56 and 92 as a fraction of all activity units
ACT_INDUST	Jobs in NIACS sectors 11–23, 42, and 48–49 as a fraction of all activity units
HU_TOTAL	Total number of housing units
HU_SFH	Detached single-family housing units as a fraction of all housing units
HU_SMALL	Housing units in row houses and apartments of $<$10 units as a fraction of all housing units
HU_LARGE	Housing units in apartments of $\geq$10 units as a fraction of all housing units
HU_MOBILE	Housing units in mobile homes and vehicles as a fraction of all housing units
PER_DEV	Percent developed land (as a fraction, not a percent)
PER_WALK	Percent ideal walkshed (as a fraction, not a percent)

The total number of housing units was recorded, along with the fractions of housing units in four categories: detached single-family homes, row houses and small apartment buildings, large apartment buildings, and mobile homes and vehicles. The goals of these categories was to provide a general metric for the sort of built environment predominating in a neighborhood. Ideally, row houses would have been separated from duplexes and other small apartment buildings, but it was decided to group them to reduce the number of variables used in clustering.

The percent developed land (from NLCD data) and percent ideal walkshed variables were not changed in this step. However, I decided not to use the street network node data because it appeared to be unreliable. While it does produce aesthetically pleasing and potentially useful maps of street networks, as shown in Figure 2.9 on page 106, the number of nodes counted per hex was inconsistent.

Discussion with Geoff Boeing of the University of Southern California in Los Angeles provided a likely explanation for this issue. It seems that both OSM and Census road network shapefiles contain topological errors in the representation of complex intersections, many of which are represented as larger numbers of simpler intersections. Boeing (2020a) has attempted to solve this problem with the OSMnx package, which consolidates road network topologies, but there was not time to attempt to integrate this approach into my analysis.

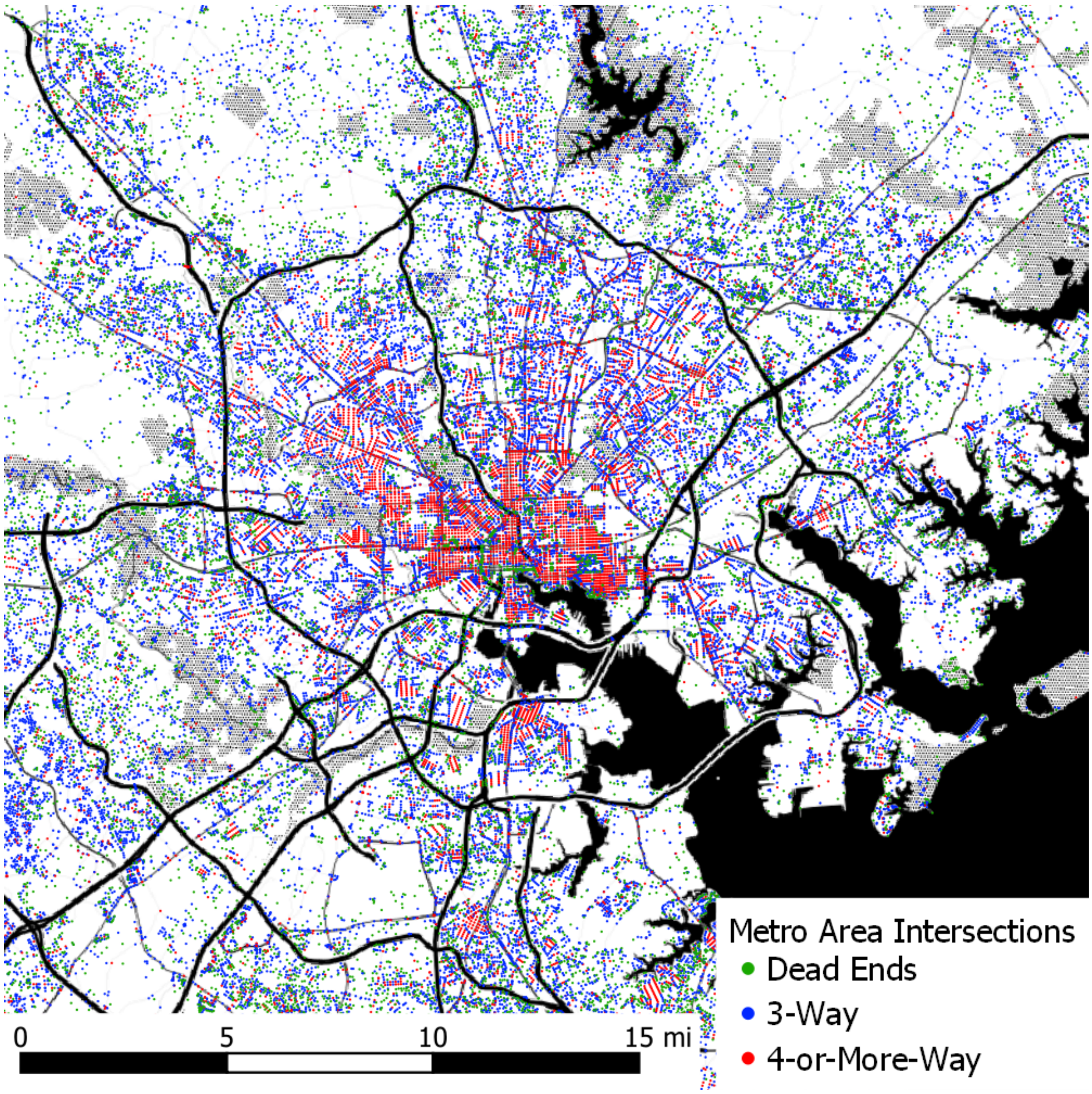

Figure 2.9: Intersections in the Baltimore metro area. Figure from Rowlands (2021).

2.6 Results

Although the primary goal of the neighborhood characterization discussed in this chapter is to provide data for the k-means cluster analyses in Chapter 3, the data can also be used to directly describe the neighborhood hex cells. In this section, I describe the breakdown of neighborhoods nationally by activity density, street network connectivity, land use types, and housing types, and then draw some preliminary conclusions about differences in metropolitan areas and the rarity of dense urban form.

2.6.1 Density and Connectivity

The activity density and street network connectivity of urban areas are both closely related to walkability and public transportation, as they determine the number of people, whether residents or workers, who will be within walking distance of any given location. Furthermore, while each can be considered separately, they can also be combined in the measure walkshed-adjusted density (Rowlands, 2020), which multiplies density by percent ideal walkshed to determine the experienced density of a neighborhood, which will be lowered if poorly-connected streets reduce the area—and thus number of people—within a short walk of a given location.

Table 2.3 on page 108 shows the breakdown of population and jobs nationally into seven activity density categories, each twice the density of the one before. Particularly notable binning boundaries are the ones at 40,000 activity units per square mile—the rough density at which either public transportation or expensive multi-level parking garages become essential, as noted by various authors including Garreau (1992)—and 10,000 activity

Table 2.3: Distribution of Population and Jobs by Activity Density

Density (/ sq. mi.)	Hexes	% of Hexes	Population (millions)	% of Population	Jobs (millions)	% of Jobs
> 80,000	485	0.02%	3.47	1.2%	7.60	6.5%
40,000 – 80,000	1,295	0.07%	5.53	1.9%	5.20	4.4%
20,000 – 40,000	5,966	0.3%	13.4	4.6%	10.90	9.3%
10,000 – 20,000	26,581	1.5%	33.4	11.5%	21.88	18.6%
5,000 – 10,000	90,711	5.2%	67.5	23.2%	30.27	25.7%
2,500 – 5,000	155,105	8.9%	64.8	22.3%	21.54	18.3%
< 2,500	1,466,542	84.0%	102.2	35.2%	20.31	17.3%

units per square mile—the density at which, according to Newman and Kenworthy (2006), public transportation can begin to break down automobile dependence with good land use choices.

It is immediately obvious from this table that lower-density neighborhoods—particularly those with densities below 10,000 activity units per square mile—dominate residential areas of American metro areas, with 80% of metropolitan populations located in such neighborhoods. This effect is significantly less pronounced for job distribution, but 60% of jobs in metropolitan areas are also located in such neighborhoods.

The distribution of population and jobs by neighborhood street network connectivity is a bit more balanced, however. Table 2.4 on page 109 shows the distribution of population and jobs by percent ideal walkshed in bins 10% wide from greater than 65% ideal walkshed to less than 15% ideal walkshed.

Since the ratio of the area of a square to that of a circle circumscribed around it is $^2/_\pi$, an ideal square street grid with small blocks would have a percent ideal walkshed of 64%. Actual street grids vary widely, and while blocks are ideally around 100 meters or shorter

Table 2.4: Distribution of Population and Jobs by Percent Ideal Walkshed

Percent Ideal Walkshed	Hexes	% of Hexes	Population (millions)	% of Pop.	Jobs (millions)	% of Jobs
> 65%	10,941	0.6%	17.5	6.0%	11.5	9.7%
55% – 65%	47,357	2.7%	41.3	14.2%	18.6	15.8%
45% – 55%	88,678	5.1%	47.2	16.3%	21.2	18.0%
35% – 45%	175,465	10.0%	52.5	18.1%	22.5	19.1%
25% – 35%	443,334	25.4%	59.7	20.6%	21.8	18.5%
15% – 25%	774,798	44.4%	56.5	19.5%	16.8	14.3%
< 15%	206,112	11.8%	15.6	5.4%	5.32	4.5%

for pedestrian convenience (Siksna, 1997) they can be significantly longer in US cities: even east-west blocks in Manhattan approach 300 meters long. This can potentially reduce percent ideal walkshed significantly by increasing the walk from a random starting point to the nearest intersection but, even so, percent ideal walkshed in areas with pedestrian-friendly grids is generally at least 55%. Such areas contain roughly 20% of population and 25% of jobs in metro areas nationally.

Finally, Table 2.5 on page 110 combines these measures to show the numbers and percentages of jobs and residents in neighborhoods at different walkshed-adjusted density levels. Since the median percent ideal walkshed for both jobs and residents is less than 50%, the bin sizes are shifted down by one from the activity densities given in Table 2.3.

Unsurprisingly, there is significant variation between metropolitan areas in the density and connectivity of their neighborhoods. Appendix D has maps and tables of population and job distribution by neighborhood activity density and connectivity for the twenty largest metropolitan areas in the country, as well as for ten other medium-sized metropolitan areas of interest. An example map for Baltimore is given in Figure 2.10 on page 111,

Table 2.5: Distribution of Population and Jobs by Walkshed-Adjusted Activity Density

Walkshed-Adjusted Density (/ sq. mi.)	**Hexes**	**% of Hexes**	**Population (millions)**	**% of Pop.**	**Jobs (millions)**	**% of Jobs**
> 40,000	731	0.04%	5.15	1.8%	8.46	7.2%
20,000 – 40,000	1,609	0.09%	5.90	2.0%	5.12	4.3%
10,000 – 20,000	6,432	0.4%	13.7	4.7%	9.70	8.2%
5,000 – 10,000	23,439	1.3%	29.0	10.0%	17.5	14.9%
2,500 – 5,000	64,761	3.7%	51.1	17.6%	23.6	20.1%
1,250 – 2,500	100,854	5.8%	51.4	17.7%	20.0	17.0%
< 1,250	1,548,859	88.7%	134.0	46.2%	33.3	28.3%

which shows that density and connectivity are relatively correlated, with a dense and well-connected core in the center and higher connectivity in suburban areas with some density. However, dense suburban areas tend to only reach the medium connectivity range, while areas within the urban core are almost all more highly-connected.

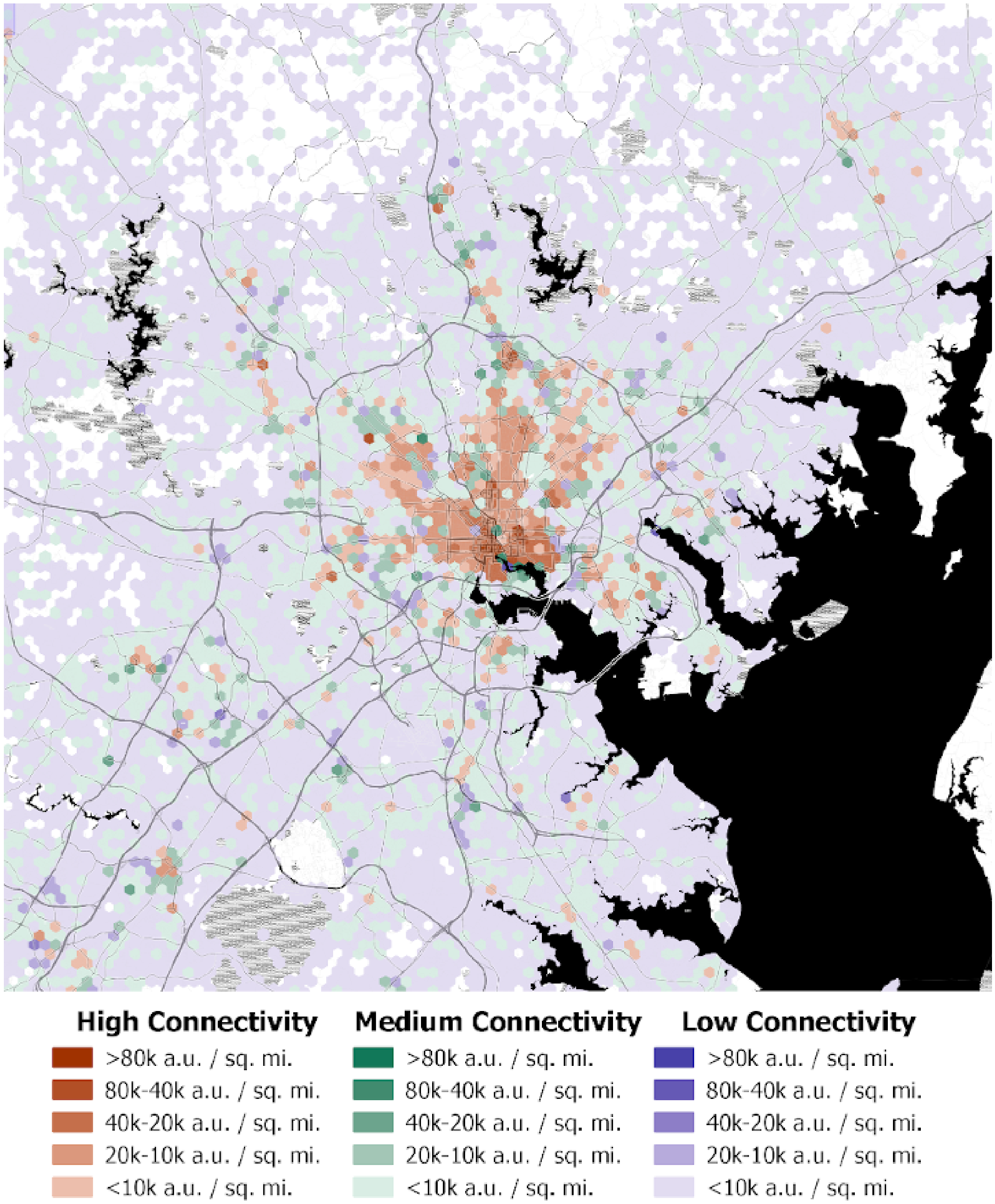

Figure 2.10: Baltimore-Columbia-Towson, MD MSA activity-connectivity neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

2.6.2 Land Use Types

Land use was measured based on the fractions of activity units consisting of residents and jobs in the four categories listed in Table 2.2 on page 104. Despite the attempts of zoning policies in much of the country, land use is in the US is not fully Euclidean (Sutherland, 1926), and almost all neighborhood hexes do have some mixture of uses.

I divided land use into the twelve categories shown in Table 2.6 on page 113 via a two-step process. First, neighborhoods were classified as residential or non-residential based on whether a majority of activity units were residents or jobs. Residential neighborhoods were classified as either "Pure Residential" or "Residential" depending on the fraction of activity consisting of residents, and non-residential neighborhoods were classified by their plurality job type and whether this job type was a majority of all activity units.

Finally, I created two categories for specifically walkable neighborhoods. "Walkable Residential" neighborhoods are any residential neighborhoods meeting a threshold of walkshed-adjusted density of retail jobs selected to identify streetcar suburb-type neighborhoods with enough retail that residents can carry out most errands on foot. "Mixed Use" neighborhoods have to meet the same retail job cut-off but are non-residential neighborhoods without a dominant job type.

Table 2.7 on page 116 shows the distribution of jobs and population among the twelve land-use categories. It is evident that population is nearly entirely concentrated in residential neighborhoods, though this may partly because 90% of neighborhoods are classified as residential. On the other hand, over a quarter of jobs are located in neighborhoods

Table 2.6: Use Type Definitions

Use Type	Definition
Pure Residential	population is $\geq$ 90% of total activity units
Residential	population is between 50% and 90% of total activity units
Walkable Residential	all residential areas with a walkshed-adjusted density of at least 400 retail jobs
Mixed Use	all non-residential areas with a walkshed-adjusted density of at least 400 retail jobs and where no job type is $\geq$ 40% of total activity units
Retail	retail jobs are $\geq$ 50% of total activity units
Retail Mix	total jobs are $\geq$ 50% of total activity units and retail jobs are a plurality of jobs
Education / Medical	education and medical jobs are $\geq$ 50% of total activity units
Education / Medical Mix	total jobs are $\geq$ 50% of total activity units and education and medical jobs are a plurality of jobs
Office	office jobs are $\geq$ 50% of total activity units
Office Mix	total jobs are $\geq$ 50% of total activity units and office jobs are a plurality of jobs
Industrial	industrial jobs are $\geq$ 50% of total activity units
Industrial Mix	total jobs are $\geq$ 50% of total activity units and industrial jobs are a plurality of jobs

classified as non-walkable residential. This is likely partially due to the rather large choice of neighborhood size and Lang's (2003) "edgeless city" observation: that most jobs, and even most office jobs, are distributed at low density throughout metro areas rather than being clustered in downtowns or edge cities.

Only 11% of the population nationally lives in walkable residential areas, while 52% lives in neighborhoods where at least 90% of the activity units are residents. Honestly, it's hard to say if this is a large or a small number, given the wide range of values among metropolitan areas: 25% of San Franciscans but only 5% of Pittsburghers residents live in such neighborhoods. (41% of New Yorkers do, but in this, as in most of the data, New York is an outlier.)

Appendix E has maps and tables of population and job distribution by neighborhood use type for the same thirty metro areas included in Appendix D. The map for Baltimore is presented as an example in Figure 2.11 on page 115. Most of the map is pure residential, with strips of mixed residential and commercial uses along major roads, and with walkable residential areas mostly concentrated to the north and southeast of downtown Baltimore. Large industrial tracts are visible, mostly associated with Baltimore/Washington International Thurgood Marshall Airport and port facilities in Baltimore.

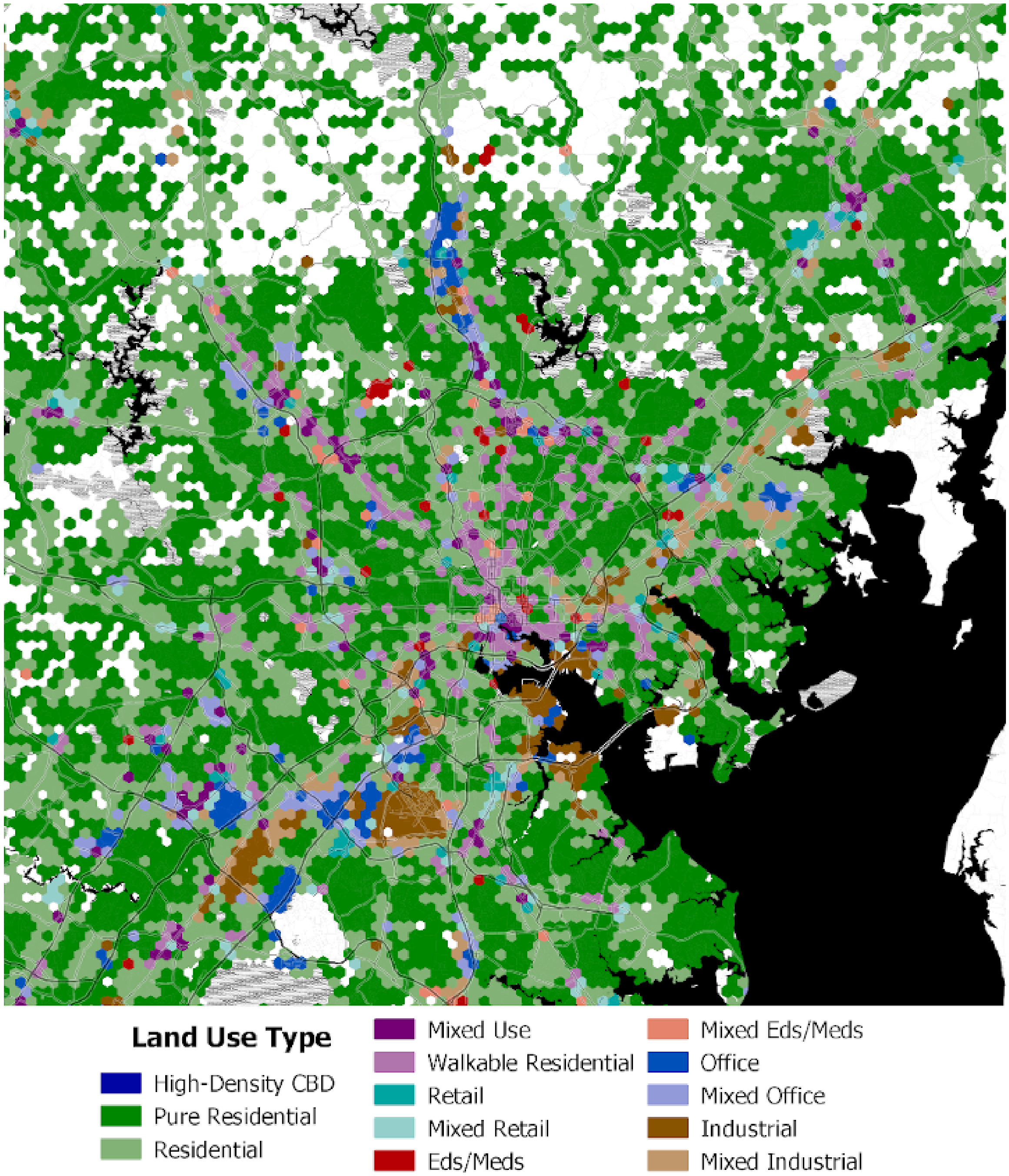

Figure 2.11: Baltimore-Columbia-Towson, MD MSA use type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table 2.7: Distribution of Population and Jobs by Use Type

Use Type	Hexes	% of Hexes	Population (millions)	% of Population	Jobs (millions)	% of Jobs
Pure Residential	1,101,068	63.0%	152.1	52.4%	5.91	5.0%
Residential	467,439	26.8%	80.9	27.9%	26.1	22.1%
Walkable Residential	23,916	1.4%	32.1	11.1%	12.1	10.3%
Mixed Use	11,134	0.6%	6.06	2.1%	11.4	9.7%
Retail	18,368	1.1%	2.18	0.7%	7.44	6.3%
Retail Mix	16,419	0.9%	2.73	0.9%	5.17	4.4%
Education / Medical	7,674	0.4%	1.74	0.6%	6.93	5.9%
Education / Medical Mix	6,926	0.4%	1.58	0.5%	2.83	2.4%
Office	9,779	0.6%	1.96	0.7%	13.5	11.5%
Office Mix	11,625	0.7%	2.76	1.0%	7.20	6.1%
Industrial	49,053	2.8%	2.90	1.0%	12.7	10.8%
Industrial Mix	23,284	1.3%	3.20	1.1%	6.43	5.5%

2.6.3 Housing Types

Like use types, housing types—based on the type of housing units present—are generally mixed at the neighborhood level, though hexes consisting solely of single-family homes do exist, unsurprisingly. I classified neighborhoods into nine categories based on the types of housing present: three for majority-detached-single-family-home neighborhoods, three for majority-apartment (including row house) neighborhoods, and three for other types of neighborhoods. The resulting categories are listed in Table 2.8 on page 118.

The three majority-single-family-housing categories are simply divided up by the percentage of housing units that are single-family homes: this is in part a response to the predominance of this this housing type, which makes up 63% of housing units in the US (Hirt, 2014, 20) and a much larger fraction of the land devoted to housing: 85% of hexes nationally are majority detached-single-family-home.

The three multifamily housing categories, on the other hand, are differentiated by the type of multifamily housing present: whether the majority of all housing is row houses and buildings with less than ten units, buildings with more than ten units, or whether neither type has an absolute majority. The goal of this differentiation is largely to serve as a metric for overall building form factor in neighborhoods that do not consist of detached single-family homes.

While multifamily housing is expected to be the most common form of housing in denser urban areas, the remaining three categories are not expected to be significant sources of housing. The "Few Housing Units" category is intended to catch neighborhoods

Table 2.8: Housing Type Definitions

Housing Type	Definition
Pure Single-Family	$\geq$ 90% of housing units are detached single-family
Single-Family	between 75% and 90% of housing units are detached single-family
Mixed Single-Family	between 50% and 75% of housing units are detached single-family
Multifamily: Small Building	$\geq$ 50% of housing units are row houses or apartments in buildings of less than 10 units
Multifamily: Large Building	$\geq$ 50% of housing units are apartments in buildings of more than 10 units
Multifamily: Mixed Types	$\geq$ 50% of housing units are row houses or apartments, but does not qualify for other multifamily categories
Mobile Homes	$\geq$ 40% of housing units are mobile homes, even if the hex qualifies for another category
Mixed Housing Types	all other cases
Few Housing Units	$<$ 2 housing units per hex

where the total number of housing units is too low—purely commercial or industrial hexes and hexes made up entirely of group quarters—for housing unit characterization to be a useful distinction. In practice, this mostly identifies some, but not all, airports.

Hexes are identified as "Mobile Homes" if as many as forty percent of their housing units are vehicles or mobile homes/trailers. This potentially overrides other categories: a hex that consisted of 55% detached single-family homes and 45% mobile homes would be classified as a mobile homes hex. This choice was made based on the relatively low number of hexes where mobile homes predominate and a desire to be able to identify areas where they are and are not present at all.

Finally, the "Mixed Housing Types" category is a catch-all for hexes that don't fit into any of the other categories: it makes up only 1.7% of hexes nationally and does not really correspond to a particular built environment type, so far as I can tell.

Table 2.9 on page 120 shows the distribution of jobs and population among the nine housing-type categories nationally. Although the vast majority of hexes are majority detached single-family homes, there is significant variation in how large a majority it is. Meanwhile, all three types of multifamily neighborhood seem to be similarly common. Although mobile home neighborhoods are rare nationally, mapping the data shows significant regional variation: large tracts of hexes that are majority mobile homes do exist on the outskirts of many Southeastern cities, while they are less common in other regions.

Appendix F has maps and tables of population and job distribution by neighborhood use type for the same thirty metro areas included in Appendices D and E. An example map for Baltimore is presented in Figure 2.12 on page 122 and shows that most of Baltimore

Table 2.9: Distribution of Population and Jobs by Housing Type

Housing Type	Hexes	% of Hexes	Population (millions)	% of Population	Jobs (millions)	% of Jobs
Pure Single-Family	430,320	24.6%	57.9	20.0%	11.3	9.6%
Single-Family	560,142	32.1%	65.6	22.6%	18.3	15.6%
Mixed Single-Family	499,284	28.6%	78.5	27.0%	31.0	26.3%
Multifamily: Small Building	28,433	1.6%	23.6	8.1%	9.12	7.7%
Multifamily: Large Building	19,105	1.1%	18.6	6.4%	21.2	18.0%
Multifamily: Mixed Types	66,757	3.8%	33.9	11.7%	20.2	17.2%
Mobile Homes	96,377	5.5%	6.02	2.1%	1.98	1.7%
Mixed Housing Types	30,104	1.7%	5.91	2.0%	3.04	2.6%
Few Housing Units	16,163	0.9%	0.35	0.1%	1.54	1.3%

City is made up of small apartments and rowhouses while large swaths of suburban areas consist of more than 90% single-family homes. Notably, large apartment buildings are found both in the core of the city and in significantly less-dense suburban areas.

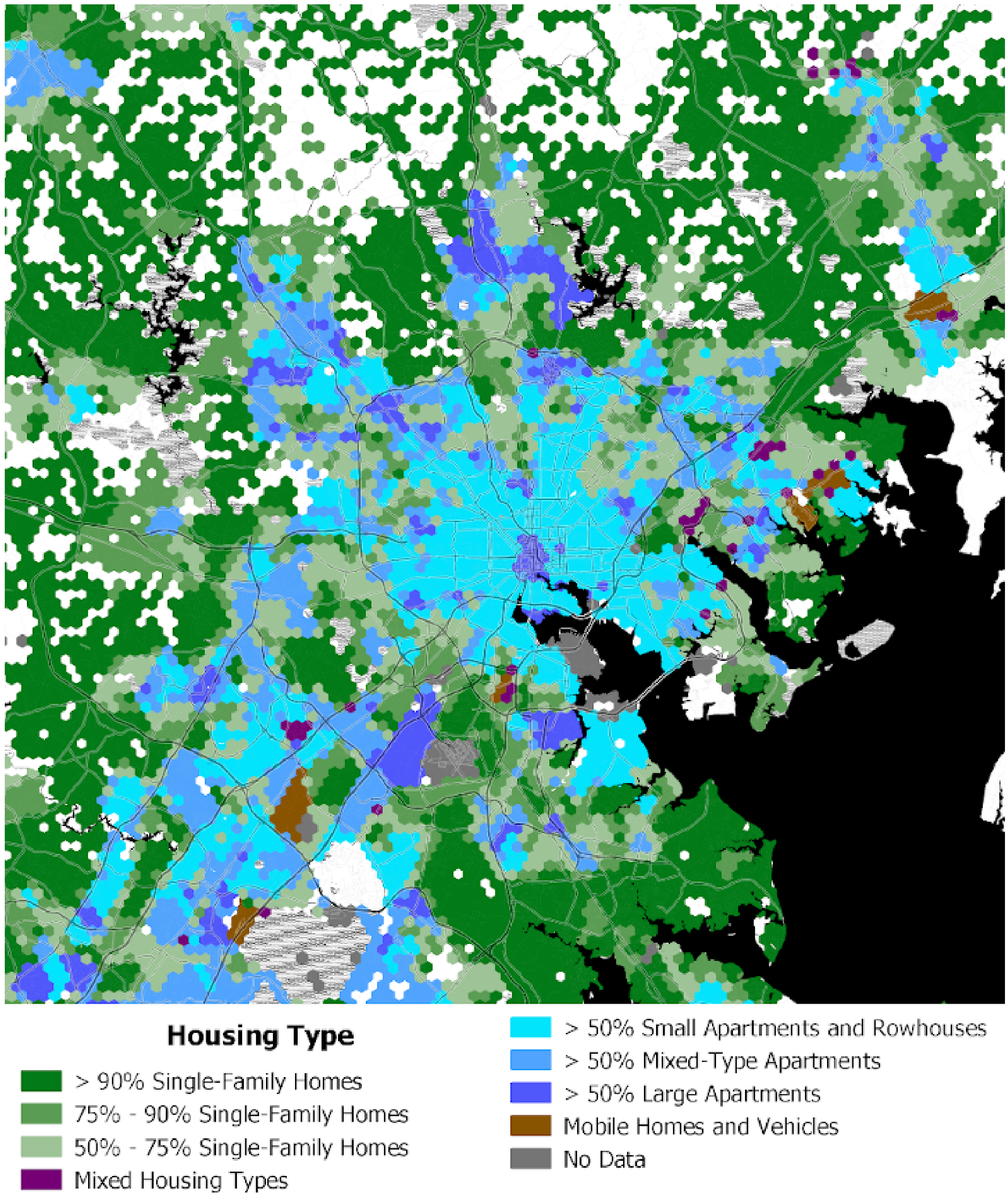

Figure 2.12: Baltimore-Columbia-Towson, MD MSA housing type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

2.6.4 Are there only eight cities in the US?

Table 2.10 on page 124 shows the twenty US metro areas with at least 20,000 residents living in hex cells with a density of 40,000 activity units per square mile, roughly the density where either expensive multi-story parking garages or public transportation is necessary.

Notably, there is a 40% drop from the last two metro areas—Denver and San Diego—which have populations of 24,000 in hexes with a density of 40,000 activity units per square mile to the first city not shown in the table—Milwaukee—with a population of only 14,000 at this density. Furthermore, while the table contains the nine largest metro areas in the US, it is missing the tenth—Phoenix—which has only 11,000 residents in hexes at the cut-off density. The other eleven metro areas included in the table range from number Boston (11^{th}) and San Francisco (12^{th}) to Honolulu (56^{th}) and Madison, WI (89^{th}).

Looking over Table 2.10, it is immediately obvious just how much of an outlier New York is in terms of density: assuming that the vast majority of the neighborhoods with densities of at least 40,000 activity units per square mile are in CBSAs, the 2.8 million residents of the New York metro area who live at densities of at least 80,000 activity units per square mile make up 80% of Americans living at this density. Likewise, the 6.4 million New Yorkers who live at densities of at least 40,000 activity units per square mile are 70% of the Americans who live this density nationally.

Table 2.10: Top 20 Metro Areas by Population in High-Activity Hexes

Metro Area	MSA Population Rank	Population in 40k Activity Units Per Sq. Mi. Hexes	Population in 80k Activity Units Per Sq. Mi. Hexes
New York	1	6,376,000	2,816,000
Los Angeles	2	466,000	73,000
San Francisco	12	358,000	117,000
Chicago	3	327,000	97,000
Boston	11	243,000	82,000
Washington	6	231,000	58,000
Philadelphia	8	160,000	42,000
Seattle	15	114,000	51,000
Honolulu	56	89,000	9,000
Miami	7	79,000	16,000
Atlanta	9	39,000	8,000
Minneapolis	16	38,000	13,000
Houston	5	36,000	4,000
Dallas	4	29,000	7,000
Baltimore	21	29,000	4,000
Portland, OR	25	28,000	7,000
Madison, WI	89	27,000	0
Pittsburgh	27	26,000	8,000
Denver	19	24,000	6,000
San Diego	17	24,000	2,000

Another 15% and 20% of Americans living at densities of 80,000 and 40,000 activity units per square mile live in the next seven cities on the list—San Francisco, Chicago, Boston, Los Angeles, Washington, Seattle, and Philadelphia—meaning that 95% and 90% of Americans living at these densities live in just eight metro areas.

While jobs are generally more concentrated than population, Table 2.11 on page 126 shows that the same eight cities also have the most jobs in hexes of at least 40,000 and at least 80,000 activity units per square mile.

Public transportation analyst and advocate Alon Levy is known for asserting that only eight US cities “have public transportation” (Levy, 2019), based on their commute to work transit mode-shares. Other than the substitution of Honolulu (ninth in order of population in 40,000 activity unit per square mile hexes) for Los Angeles, their list of cities with significant public transit is identical to my list of cities with substantial populations living at high densities.

One might make a case based on the evidence in table 2.10 that, although the US has over fifty metro areas with a million or more residents, it really only has eight cities and the others should be seen as some new and different type of human habitation, built fundamentally around the automobile and lacking the concentration that has historically been present in cities. The fact that the list contains some of the most expensive and rapidly gentrifying metro areas in the country potentially supports this interpretation: as traditional urban lifestyles have become popular with high-income groups over the past two decades, the limited supply of traditionally urban neighborhoods has funneled them into the few metro areas where these are available.

Table 2.11: Top 25 Metro Areas by Jobs in High-Activity Hexes

Metro Area	MSA Population Rank	Jobs in 40k Activity Units Per Sq. Mi. Hexes	Jobs in 80k Activity Units Per Sq. Mi. Hexes
New York	1	3,577,000	2,782,000
Los Angeles	2	995,000	411,000
Chicago	3	753,000	586,000
Washington	6	739,000	453,000
San Francisco	12	626,000	425,000
Boston	11	571,000	409,000
Seattle	15	437,000	332,000
Philadelphia	8	340,000	253,000
Atlanta	9	339,000	152,000
Dallas	4	330,000	124,000
Houston	5	286,000	156,000
Minneapolis	16	196,000	136,000
Miami	7	182,000	37,000
Orlando	23	150,000	98,000
Phoenix	10	149,000	32,000
San Jose	35	148,000	55,000
Pittsburgh	27	147,000	105,000
Honolulu	56	135,000	62,000
Las Vegas	28	123,000	40,000
Denver	19	119,000	67,000
Baltimore	21	117,000	56,000
Portland	25	115,000	65,000
Detroit	14	108,000	61,000
Cleveland	34	103,000	92,000
St. Louis	20	99,000	42,000

However, the interpretation that there are only eight cities in the US seems like an oversimplification, and certainly premature to make on the basis of these two charts: the more-detailed typologies developed by k-means clustering in Chapter 3 should provide a more-nuanced view.

Chapter 3: Developing Neighborhood and Metro Area Typologies

The work in Chapter 2 characterizing neighborhoods in the form of hex cells is preliminary to the main goal of this project: typologizing neighborhoods and metro areas and identifying types that correspond to walkable urbanism and are potentially amenable to improved public transportation.

In Section 3.1 of this chapter, I discuss the creation of neighborhood typologies developed based on the characteristics measured in Chapter 2. I then present a pair of typologies of metro areas based on the distributions of population and of jobs in these neighborhood types in Section 3.2. These neighborhood and metro area types and their potential applications are then discussed in further detail in Section 3.3.

Neighborhood and metropolitan area typologies were developed using the k-means clustering technique, which divides a dataset into k clusters of similar features by partitioning it to minimize the distance between features within each cluster. A k-means analysis begins with initial seed clusters, which may be random or selected based on theoretical considerations. These clusters are defined by centroid vectors and each data point is assigned the cluster with the shortest (usually Euclidean) distance between its data values and those of the cluster centroid. Cluster centroids are then recalculated and data points are reassigned based on the distances to the new centroid vectors. This process is continued until the clusters converge (Steinley, 2006, 2-6).

The two major limitations of this approach are that it requires the investigator to select the value of k—the number of clusters to be obtained—and that the clusters obtained will generally depend on the choice of initial seed clusters. This latter feature is a consequence of the fact that the algorithm converges when it reaches a local optimum, but cannot verify whether this local optimum is in fact a global optimum. Although various methods have been proposed to select starting seeds, repeating the algorithm with a large number of random initial seeds has been found to give comparably-good results (Steinley, 2006, 6-7).

A number of methods have been proposed for identifying the optimal number of clusters to use for a given dataset; there is no consensus on the best method (Steinley, 2006; Sugar and James, 2003; Tibshirani et al., 2001). However, most of the possible methods involve performing repeated analyses for a variety of k values and analyzing various statistical measures of the resulting clusters. Because of the very large datasets used for the neighborhood clustering—nearly four million hexes and roughly a dozen variables—the calculations for even a single value of k with a relatively small number of random seeds could take more than a day, and a simpler method was needed.

As discussed in more detail in Appendix G, k values were selected in part based on the rule of thumb discussed by Royall and Wortmann (2015) that k should be roughly the square root of half the number of data points and, for the metro area typologies, where calculations were less time-consuming, based on a goal of having 80-90% of variation between clusters, balanced with the need to have a small enough number of clusters to make analysis of the resulting clusters meaningful. In addition, the k-means clusters used in this project were computed using Euclidean distances, the MacQueen k-means algorithm, and random seeds.

Details on methodology used in the analyses in this chapter can be found in Appendix G. The source code for the R scripts used is available in UMBC's online ScholarWorks repository. The full results of my metro area typology are given in tables in Appendix I and maps and tables of additional data on selected metro areas are provided in Appendices H and J. In addition, tables associated with the analysis in Section 3.3.3 can be found in Appendix K

3.1 Neighborhood Clusters

Both neighborhood-type and metro area-type clusters were found using variables normalized by calculating z-scores: subtracting the mean value of the variable from each variable and dividing the results by the standard distribution. While this procedure is generally effective at re-scaling variables so that differences in each variable will have a similar effect on the distances between data points and their assignment to clusters, it runs into a significant difficulty with the activity density data.

The problem is that the most-dense cells have densities of nearly one million activity units per square mile, while the least-dense cells considered have activity densities of one hundred activity units per square mile: a difference of four orders of magnitude. Meanwhile, the other variables used in the analysis are percentages and vary significantly less broadly. As a result, differences in activity density tend to swamp variation in other variables in producing cluster assignments.

This effect is particularly pronounced at the highest densities, since relatively few hexes have high activity densities, while far, far more hexes have densities close to the 100 activity units per square mile lower bound. Since higher-density hexes are also of more interest from the perspective of assessing walkability and urban vitality, this poses a serious difficulty.

One option, not attempted here, would simply be to set a very high cut-off density and remove all hexes with lower densities. Eliminating all neighborhoods with densities of less than 10,000 activity units per square mile, for example, would retain neighborhoods with truly urban densities and reduce the range of activity density values to two orders of magnitude. However, while these are the primary neighborhoods of interest in the context of walkability and amenability to public transportation, they consist of a very small fraction of neighborhoods in American metro areas and a typology that focused solely on them could not reasonably be called a typology of US metropolitan neighborhoods in general.

3.1.1 Activity Density and Connectivity Neighborhood Clusters

One potential approach to resolving this issue is a two-step clustering procedure. If clusters are first found based on density, and then the density clusters are broken up into sub-clusters based on other variables, it is possible to isolate density from variables with smaller ranges. However, performing clustering in two steps adds an additional level of arbitrariness into the results, since it requires selections of k for the initial clustering and each sub-cluster. As a result, the single-step clustering procedure using a very large number of clusters discussed in Section 3.1.2 was eventually settled on.

However, a preliminary attempt at a two-step neighborhood clustering approach was made, and the results from its first step are of potential interest. Three variables were used: activity density, percent ideal walkshed, and percent developed land. These variables are not fully independent: there is a 64% correlation between percent ideal walkshed and percent developed land, a 53% correlation between activity density and percent developed land, and 40% correlation between activity density and percent ideal walkshed.

Table 3.1: Activity Density / Connectivity Clusters

Cluster Name	Cluster Size	Median Activity Density	Median % Developed Land	Median % Ideal Walkshed
CBD (High Density)	19	510,000	93%	68%
CBD (Medium Density)	65	230,000	96%	68%
CBD (Low Density)	340	110,000	96%	65%
Urban (High Density)	1,339	54,000	97%	63%
Urban (Mid-Density)	7,562	23,000	97%	57%
Urban (Low Density, High Connectivity)	27,263	10,000	95%	58%
Urban (Low Density, Low Connectivity)	27,477	8,900	87%	35%
Suburban (High Density, High Connectivity)	66,711	4,700	83%	54%
Suburban (High Density, Low Connectivity)	77,107	3,400	71%	38%
Suburban (Mid-Density, High Connectivity)	67,892	2,000	42%	45%
Suburban (Mid-Density, Low Connectivity)	61,627	2,800	65%	21%
Suburban (Low Density, High Connectivity)	113,928	1,500	37%	30%
Suburban (Low Density, Low Connectivity)	122,471	1,000	28%	19%
Exurban 1	150,853	450	9%	34%
Exurban 2	395,283	240	4%	25%
Exurban 3	471,913	190	3%	18%
Exurban 4	154,861	240	5%	11%

As seen in Table 3.1 on page 133, the resulting clusters are strongly density-based: in the seventeen-cluster solution shown, roughly eleven distinct activity density levels are seen among the clusters. At low and intermediate densities, pairs of clusters with higher and lower connectivity are visible as well, though there is also clearly a trend toward higher connectivity, as measured by percent ideal walkshed, at higher densities. Above roughly 10,000 activity units per square mile, all clusters are at the high end of the percent ideal walkshed range.

The very small number of hexes in the high-density clusters is also quite notable: while the clusters with median densities less than 2,000 activity units per square mile have at least one hundred thousand hexes each, the highest-density cluster has only 19 hexes, and there are only 424 hexes in clusters with median densities above 100,000 activity units per square mile.

3.1.2 Comprehensive Neighborhood Clusters

After preliminary work with clusters based solely on activity density, percent developed land, and percent ideal walkshed, the next step was to develop a typology based on the full set of land-use and built form variables developed to characterize neighborhoods in Chapter 2. Ten variables, representing density, connectivity, land use type, and housing type were used to create clusters.

Using three times as many variables as were used for the density-and-connectivity clusters posed a significant computational challenge, as the larger number of variables and the need for far more clusters to represent the variation in so many variables both increased the time needed to complete a k-means clustering run. To make it possible to complete clustering analyses in a reasonable time, hex cells with activity densities less than 500 activity units per square mile—the density cut-off the Census Bureau uses for allowing jumps across low-density areas in the fringes of urban areas and urban clusters (US Census Bureau, 1994, Ch. 12)—were excluded from the analysis, leaving 765,085 hex cell neighborhoods to typologize.

Even with this reduction in the number of neighborhoods included, a k-means analysis with fifty random seeds still took several days to complete, so doing a thorough comparison of the results with different numbers of clusters was difficult. However, the rule of thumb presented by Royall and Wortmann (2015) that k should be $\sqrt{n/2}$ where n is the number of data points works well in this case, as $\sqrt{765085/2}$ is 618.49. Using 600 clusters both approximated the number recommended by the rule of thumb and resulted in a typology that both seemed to accurately reflect the diversity of neighborhoods in metro areas and that had a workable number of clusters to analyze individually.

Along with the activity density, percent developed land, and percent ideal walkshed variables used in the preliminary analysis in the previous section, four variables representing types of land use and three representing types of built environment were included. Since nearly all hexes contain at least some housing units, the housing unit data was judged to be useful even for primarily-commercial hexes as a measure of the built form and building sizes in an area.

For land use, the percentages of activity units consisting of jobs in the retail, education and medical, office, and industrial sectors were included, with the difference between the sum of these percentages and 100% representing the percentage consisting of popu-

Table 3.2: Cluster Density Type Definitions

Density Type	Average Activity Units per Square Mile
Extremely High	>160,000
Very High	40,000–160,000
High	20,000–40,000
Low	10,000–20,000
Very Low	5,000–10,000
Minimal	<5,000

lation. For housing type, fractions of housing units consisting of single-family homes, apartments in small buildings and row houses, and apartments in large buildings were included, with the difference between the sum of these percentages and 100% representing the percentage of housing units in mobile homes and vehicles. More detailed descriptions of these variables can be found in Table 2.2 on page 104.

While a very large number of clusters is necessary to fully describe the variations of urban form in the United States, it is impractical to attempt to characterize each cluster type independently. Instead, clusters were classified into types based on their average density and connectivity and based on their dominant activity type and housing type.

Six activity density categories, shown in Table 3.2 on page 136 were defined with density levels motivated by theoretical and practical concerns. Two important density levels for urbanism are 10,000 activity units per square mile, at which Newman and Kenworthy (2006) and others have noted that automobile dependency first starts to break down and 40,000 activity units per square mile, at which Garreau (1992) noted that, in the absence of well-used transit, expensive, multi-level parking garages start to become necessary.

Table 3.3: Cluster Connectivity Type Definitions

Connectivity Type	Average Percent Ideal Walkshed
Very High	>55%
High	45%–55%
Low	35%–45%
Very Low	25%–35%
Minimal	<25%

The density levels chosen were selected primarily with a focus on these density levels, but the cut-off of 160,000 activity units per square mile for "Extremely High" was chosen for more practical reasons related to the clusters themselves. Due to the low number of neighborhoods this dense and the fact that almost all of them are central business district office space, the clustering algorithm failed to distinguish between use types for them, although some residential neighborhoods in New York and educational and medical campuses in several cities also attain this density.

Clusters were also sorted into five connectivity types, shown in Table 3.3 on page 137 based on their average percent ideal walkshed values. Boundaries for these categories were spaced by 10% and were selected based on the fact that very few neighborhoods had values above 65% or below 15%.

In addition, for mapping purposes, clusters were sorted into intensity types by walkshed-adjusted activity density, with boundaries between types set at half the densities used for the density categories, as shown in Table 3.4 on page 138. These boundaries were chosen based on the fact that high-connectivity clusters have percent ideal walksheds of roughly 50% and thus have walkshed-adjusted densities roughly half their unadjusted densities.

Table 3.4: Cluster Intensity Type Definitions

Intensity Type	**Average Walkshed-Adjusted Activity Units per Square Mile**
Extremely High	>80,000
Very High	20,000–80,000
High	10,000–20,000
Low	5,000–10,000
Very Low	2,500–5,000
Minimal	<2,500

Classifying clusters by use type is more challenging because, unlike density and connectivity, it is not one-dimensional. Instead, five variables—the percentages of activity units consisting of population and of workers in four industry categories—are involved. As shown in Table 3.5 on page 139, the clusters are divided into eight categories: three types of residential, four types of commercial based on the four industrial categories, and a "mixed use" commercial category.

Clusters are first classified as residential or commercial based on whether the majority of activity units in them were residents or jobs. The choice of a 50% cut-off is fairly arbitrary, but the exact value is not particularly important as relatively few neighborhoods are that closely mixed. At least partly as a consequence of the fact that the residential-commercial distinction is the most basic and strongly-enforced distinction in American zoning codes (Hirt, 2014), either residential or commercial uses tend to dominate in a given area.

Table 3.5: Cluster Use Type Definitions

Use Type	Definition
Pure Residential	population is $\geq$ 90% of total activity units
Residential	population is between 50% and 90% of total activity units
Walkable Residential	all residential areas with a walkshed-adjusted density of at least 400 retail jobs
Mixed Use	all non-residential areas with no job type $\geq$ 50% and with a walkshed-adjusted density of at least 400 retail jobs
Retail	non-residential areas where retail jobs are plurality of total jobs
Education / Medical	non-residential areas where education and medical jobs are a plurality of total jobs
Office	non-residential areas where office jobs are a plurality of total jobs
Industrial	non-residential areas where industrial jobs are a plurality of total jobs

Residential clusters are then divided into "pure residential" for areas that are at least 90% residents, a general residential category, and "walkable residential" for all residential that have walkshed-adjusted densities of at least 400 retail jobs per square mile. This last cut-off was selected based on the densities of retail jobs in known walkable residential areas in Boston, San Francisco, and New York that developed before the rise of the automobile along transit lines.

Commercial clusters are similarly subdivided, with four categories based on plurality job types, plus a mixed-use category for areas with no majority job type that meet the same walkshed-adjusted density cut-off of at least 400 retail jobs per square mile. This category was intended to capture more modern, New Urbanist mixed-use areas, as opposed to the historic streetcar suburbs largely identified by walkable residential cluster.

Table 3.6: Cluster Housing Type Definitions

Housing Type	Definition
Pure Single-Family	$\geq$ 90% of housing units are detached single-family
Single-Family	between 50% and 90% of housing units are detached single-family or, if there is no majority housing type, SFH and mobile homes together comprise a majority and SFH outnumber mobile homes
Multifamily: Small Building	$\geq$ 50% of housing units are row houses or apartments in buildings of less than 10 units or, if there is no majority housing type, row houses and apartments together comprise a majority and row houses and apartments in buildings of less than ten units outnumber apartments in large buildings
Multifamily: Large Building	$\geq$ 50% of housing units are apartments in buildings of more than 10 units or, if there is no majority housing type, row houses and apartments together comprise a majority and row houses and apartments in buildings of more than ten units outnumber row houses and apartments in small buildings
Mobile Homes	$\geq$ 50% of housing units are mobile homes or, if there is no majority housing type, SFH and mobile homes together comprise a majority and mobile homes outnumber SFH
Few Housing Units	housing percentages sum to less than 90%, indicating that many hexes lack housing units entirely

A similar approach is used for housing type categories, but without the initial residential/commercial split. As shown in Table 3.6 on page 140, four basic types were used based on plurality housing type, with an additional category for clusters with at least 90% of dwelling units single-family homes—included because of the preponderance of single-family home neighborhoods in the US—and a category for clusters that consisted of areas with very few housing units.[1]

[1]It is worth noting that these areas cannot be identified by low population alone, because some high-population areas consist almost entirely of residents in housing that the Census classifies as "group quarters," such as dormatories, barracks, prisons, and health care facilities.

Classifying clusters in this way made it possible to effectively map them, as demonstrated in Figure 3.1 on page 142, which shows neighborhoods in Baltimore coded by use type and intensity of activity. Due to the limited number of colors available, the two non-walkable residential use categories are combined, as are the walkable residential and mixed use categories.

The map shows that the city has a walkable core centered on high-intensity office and medical areas, and that this core is surrounded by a belt of relatively high-intensity but non-walkable residential development, much of which consists of areas that originally developed as streetcar suburbs but which currently lack significant retail. Moderate-intensity neighborhoods of various use types are also visible in suburban areas, including Bel Air, Laurel, Columbia, and Timonium. Similar maps are provided for a number of metropolitan areas in Appendix H.

3.1.3 Simplifying Cluster Types for Metro Area Typology

Although the cluster classifications discussed in the previous section are useful for mapping metro areas and for characterizing specific clusters, the large number of potential neighborhood types—six density types, five connectivity types, eight use types, and six housing types produce 1,440 possible combinations, more than twice the number of neighborhood clusters.

This profusion of neighborhood types does not lend itself to use in a clustering analysis, as it would require an unreasonable number of variables, comparable to the total number of metro areas to be clustered. Instead, as shown in Table 3.7 on page 144, clusters are

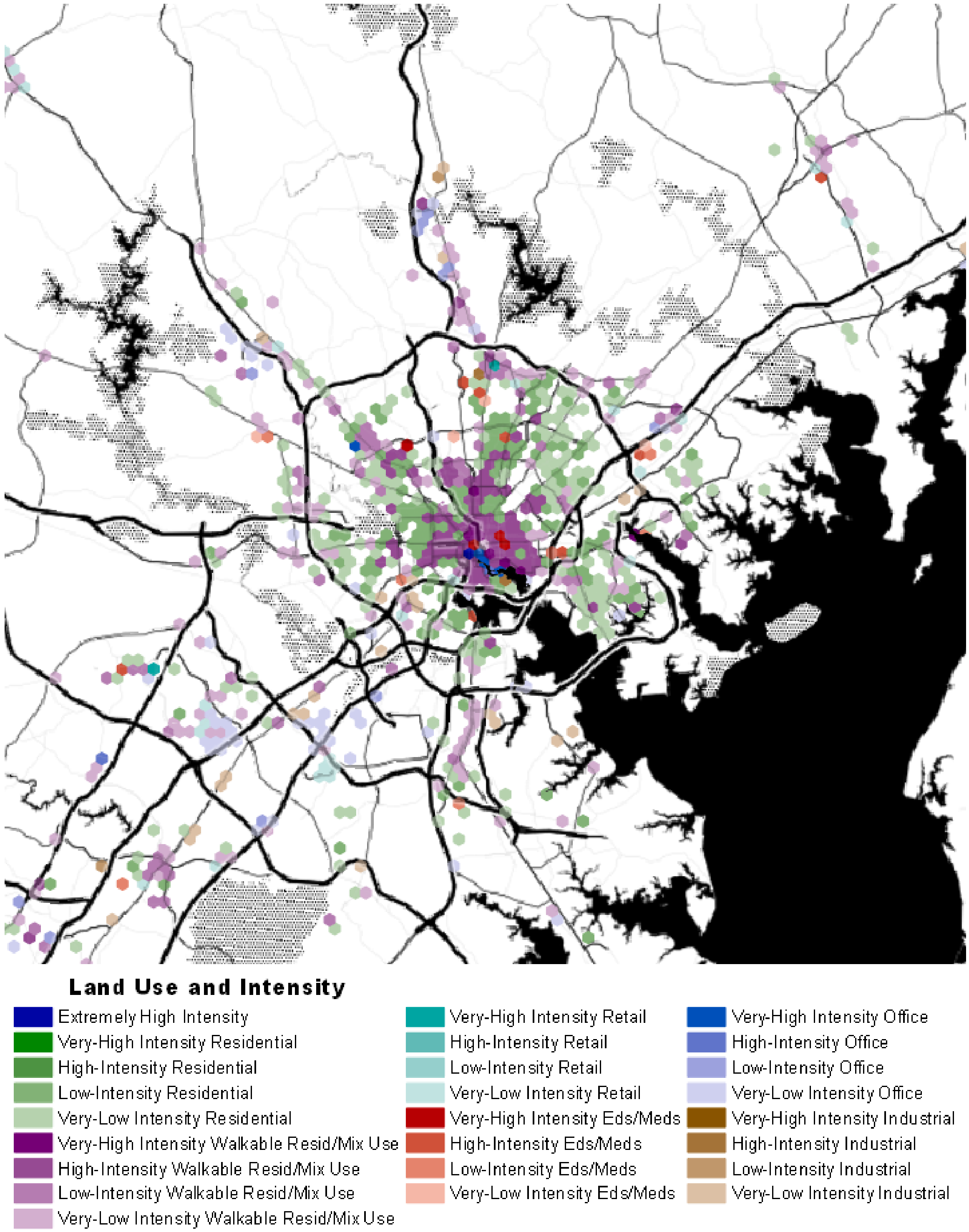

Figure 3.1: Baltimore-Columbia-Towson, MD MSA map of land use and intensity, measured by walkshed-adjusted density. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

grouped into a smaller number of types for use in metro area clustering. These types are created based around the more common combinations of density, connectivity, use, and housing, with a particular focus on high-density and otherwise urban areas.

In addition, to reduce the number of types, clusters with less than roughly 3,000 activity units per square mile are simply grouped together as "very-low density residential" and "very-low density non-residential." Since areas with densities below this are unlikely to be effectively served with transit or to be otherwise traditionally walkable, there is no need to distinguish them further.

As well as use types, activity densities, and—for some residential neighborhood types—housing type, neighborhood types are identified as walkable or non-walkable, based on the same 400 retail jobs per square mile walkshed-adjusted density cut-off used previously.

As noted above, however, the clustering algorithm struggled to deal with high-density neighborhoods because of their relative paucity. To correct for this, every hex with a density above 30,000 activity units per square mile was checked by hand to confirm that the neighborhood type matched the criteria for assigning types to clusters. This resulted in significant reassignments, particularly in New York, where a large number of residential districts were misclassified as central business district based on density alone. The resulting distributions of jobs and populations into each of the 22 neighborhood types are shown in Table 3.8 on page 146.

Table 3.7: Neighborhood Types for Metro Area Clustering

#	Description	10^{th}–90^{th} Percentile Activity Density per Square Mile	Use Type	Walkable
00	Major Central Business District	150,000 – 485,000	Major CBD	✓
01	Non-Walkable Residential	3,000 – 11,000	Residential	
02	Very-High Density Residential	56,000 – 115,000	Residential	✓
03	High Density Residential	33,000 – 50,000	Residential	✓
04	Medium-Density Large Apartments	15,000 – 30,000	Residential	✓
05	Medium-Density Small Apartments	13,000 – 28,000	Residential	✓
06	Low-Density Large Apartments	4,000 – 15,000	Residential	✓
07	Low-Density Small Apartments	4,000 – 15,000	Residential	✓
08	Low-Density Single-Family Homes	3,000 – 12,000	Residential	✓
09	Medium-Density Mixed Use	14,000 – 40,000	Mixed Use	✓
10	Low-Density Mixed (High Connectivity)	3,000 – 16,000	Mixed Use	✓
11	Low-Density Mixed (Low Connectivity)	3,000 – 15,000	Mixed Use	✓
12	High-Density Retail	30,000 – 55,000	Retail	✓
13	Low-Density Retail	3,000 – 13,000	Retail	✓
14	High-Density Eds/Meds	13,000 – 58,000	Eds/Meds	✓

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Table 3.7 – *Continued from previous page*

#	Description	10^{th}–90^{th} Percentile Activity Density per Square Mile	Use Type	Walkable
15	Low-Density Eds/Meds	4,000 – 16,000	Eds/Meds	
16	High-Density Office	33,000 – 110,000	Office	✓
17	Medium-Density Office	11,000 – 33,000	Office	✓
18	Low-Density Office	3,000 – 15,000	Office	
19	Low-Density Industrial	3,000 – 14,000	Industrial	
20	Very-Low Density Residential	0 – 1,000	Very Low Density	
21	Very-Low Density Non-Residential	0 – 4,000	Very Low Density	

It is notable how much more concentrated jobs are relative to population: 64% of the population of metropolitan areas nationally is in very-low density residential hexes, with another 4% in very-low density non-residential hexes, while roughly 22% of jobs are found in each of very-low density residential and non-residential hexes. Despite this, jobs also seem to be less concentrated in commercial hexes than population is concentrated in residential hexes: in fact, a larger fraction of jobs than population is found in the low-density small apartments cluster.

These patterns seem likely to be due to two factors: the effects of zoning on the American built environment and agglomeration effects that encourage the co-location of businesses. Zoning policies that favor large tracts of low-density, purely residential land lead to low residential densities and most of the population living in residential areas, while small job concentrations are likely to be surrounded by primarily residential areas.

Table 3.8: Population and Jobs by Neighborhood Type

#	Description	Population (millions)	% of Pop.	Jobs (millions)	% of Jobs
00	Major Central Business District	0.7	0.2%	4.0	3.4%
01	Non-Walkable Residential	44.1	14.7%	7.7	6.5%
02	Very-High Density Residential	5.0	1.7%	1.3	1.1%
03	High-Density Residential	3.8	1.3%	0.9	0.7%
04	Medium-Density Large Apartments	3.5	1.2%	0.9	0.8%
05	Medium-Density Small Apartments	10.6	3.5%	2.0	1.7%
06	Low-Density Large Apartments	4.1	1.4%	1.6	1.3%
07	Low-Density Small Apartments	3.3	1.1%	1.9	1.6%
08	Low-Density Single-Family Homes	7.6	2.5%	3.2	2.7%
09	Medium-Density Mixed Use	1.5	0.5%	3.6	3.1%
10	Low-Density Mixed (High Connectivity)	3.5	1.2%	5.0	4.2%
11	Low-Density Mixed (Low Connectivity)	2.1	0.7%	5.5	4.7%
12	High-Density Retail	0.1	0.04%	0.5	0.4%
13	Low-Density Retail	1.0	0.3%	3.2	2.7%
14	High-Density Eds/Meds	0.8	0.3%	4.0	3.4%

Continued on next page

Table 3.8 – *Continued from previous page*

#	Description	Population (millions)	% of Pop.	Jobs (millions)	% of jobs
15	Low-Density Eds/Meds	1.1	0.4%	2.3	2.0%
16	High-Density Office	0.6	0.2%	4.1	3.4%
17	Medium-Density Office	0.4	0.1%	2.6	2.2%
18	Low-Density Office	1.7	0.6%	5.3	4.5%
19	Low-Density Industrial	1.7	0.6%	5.7	4.8%
20	Very-Low Density Residential	191.1	63.6%	26.6	22.5%
21	Very-Low Density Non-Residential	11.2	3.7%	26.3	22.2%

As Lang (2003) noted, even two decades ago, the majority of jobs in American metropolitan areas were spread out in relatively small, low-density clusters embedded in largely residential areas. This effect appears to have, if anything, become more pronounced over time (Angel and Blei, 2016b). However, the concentration of more jobs than population in large, dense clusters makes economic sense. Research on human capital and firm agglomeration (Wheaton and Lewis, 2001; Rosenthal and Strange, 2004, 2008, 2020) has shown that there are significant benefits to firm agglomeration on a number of scales, including neighborhoods and even single buildings.

3.2 Metro Area Job and Population Clusters

With the typologization of neighborhoods complete, the next step was the creation of a typology of metropolitan areas. However, the list of twenty-two neighborhood types proposed in the previous section proved far too large for useful k-means clustering of the 926 CBSAs studied. As a result, it was necessary to trim the set of variables further. In doing so, I focused on two major considerations.

First, the distributions of jobs and of population in metropolitan areas are both important, but they are relatively independent. Some metropolitan areas, such as Los Angeles, have relatively high population densities without relatively high job densities, while others—particularly smaller ones with a single major employer, such as Rochester, MN[2]—have high job densities with very dispersed populations. Because of this, I decided to create two separate typologies: one based on job distributions and one based on population distributions.

Second, given the large number of possible combinations of variables, it makes more sense to try to develop a typology for a specific purpose, rather than a general-purpose one. In this light, variables were chosen specifically based on amenability to public transportation and vital, walkable urban environments. For this purpose, the neighborhood types from the previous section were condensed into the six shown in Table 3.9 on page 149.

These six neighborhood types cover densities above roughly 10,000 to 15,000 activity units per square mile—the density at which transit service can start to break down automobile dependence according to Newman and Kenworthy (2006)—and distinguish densities above around 30,000 activity units per square mile, where providing parking in the absence of public transportation begins to become significantly more expensive.

[2]Rochester, MN is the home of the Mayo Clinic

Table 3.9: Neighborhood Types Used in Metro Area Typology

Neighborhood Type	Component Types
Central Business District	00–Major Central Business District
High-Density Commercial	12–High-Density Retail 14–High-Density Ed/Meds 16–High-Density Office
Medium-Density Commercial	09–Medium-Density Mixed-Use 17–Medium-Density Office
High-Density Residential	02–Very-High Density Residential 03–High-Density Residential
Medium-Density Residential (Large Apartments)	04–Medium-Density Large Apartments
Medium-Density Residential (Small Apartments)	05–Medium-Density Small Apartments

Commercial and residential neighborhoods are distinguished because the agglomeration benefits of businesses locating near each other are presumably more present when businesses are located in commercial areas, and very-high density central business districts are distinguished because they are relatively unique environments and have been suggested by Levy (2018) to be essential for high transit ridership in US cities.

Ideally, central business districts would be distinguished regardless of density, due to their importance in the context of radial transit networks as discussed by Walker (2012), but since my model considers only density and not spatial relationships between neighborhoods, they can only be identified in the cases of CBDs at densities that no non-CBD areas (outside of New York) reaCh. Large-apartment and small-apartment medium-density areas are distinguished because they predominate in different cities and have different effects on the streetscape. In particular, small-apartment medium-density largely corre-

Table 3.10: National Prevalence of Dense Neighborhood Types

Neighborhood Type	# of Hexes	Population (millions)	% Population	Jobs (millions)	% Jobs
Central Business District	109	0.7	0.2%	4.0	3.4%
High-Density Commercial	1,586	1.5	0.5%	8.8	7.4%
Medium-Density Commercial	2,149	1.9	0.6%	6.2	5.3%
High-Density Residential	1,237	8.8	2.9%	2.1	1.8%
Medium-Density Residential (Large Apartments)	1,430	3.5	1.2%	0.9	0.8%
Medium-Density Residential (Small Apartments)	9,977	10.6	3.5%	2.0	1.7%

sponds to older, pre-World War II row house and duplex/triplex neighborhoods, while large-apartment medium-density neighborhoods tend to be more recently built and sometimes more car-oriented.

The distributions of population and jobs in these six neighborhood types is shown in Table 3.10 on page 150. While these neighborhood types contain 9% of the population and 20% of jobs across the metropolitan areas studied, there is significant variation between metropolitan areas, as can be seen in the tables in Appendix J.

These tables, giving distributions of population and jobs among the six neighborhood types for thirty-five metropolitan areas, are accompanied by maps, such as the map of Baltimore presented in Figure 3.2 on page 152 showing the geographic distribution of these neighborhood types in the metro areas.

The pattern seen in Baltimore is reminiscent of that seen in other Rust Belt cities, albeit with a somewhat stronger center. A relatively small dense commercial core, with only one hex cell of central business district density, is surrounded by a large area of medium-density small-apartment, largely consisting of pre-War rowhouses. Interestingly, some patches of high-density residential are visible in gentrifying areas on the edge of the commercial core: Mount Vernon and Fells Point. Outside of the pre-War city, occasional high- and medium-density commercial areas are seen, but virtually no dense residential.

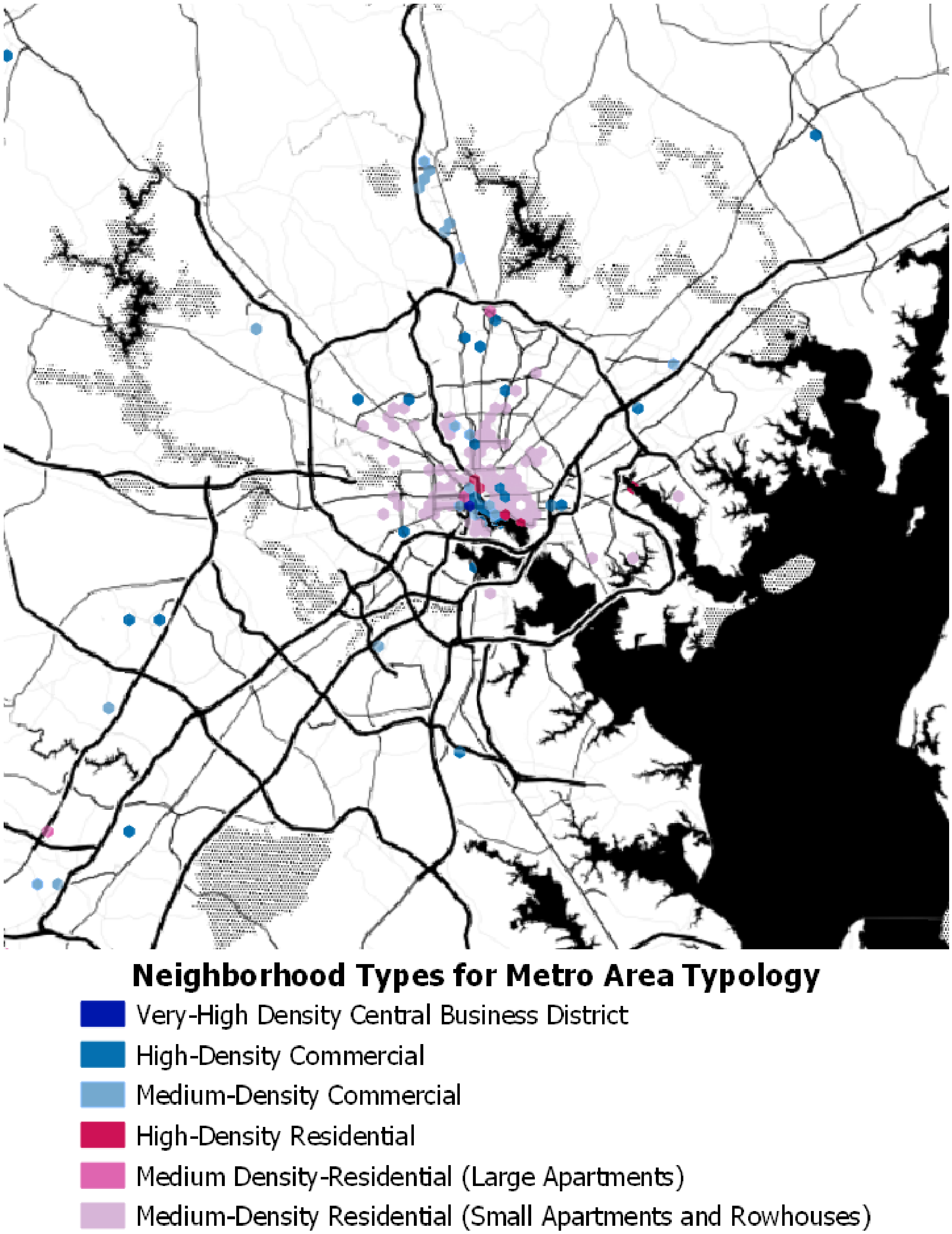

Figure 3.2: Baltimore-Columbia-Towson, MD MSA map of dense neighborhoods used in my metro area typology. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

3.2.1 Job-Distribution Clusters

Job-distribution clusters were constructed in two steps: first, a k-means analysis based only on jobs in CBD and high-density commercial hexes produced six clusters. Then, the clusters were divided into sub-clusters using k-means analyses that took into account the distributions of jobs in CBD, high-density commercial, and medium-density commercial hexes, as well as all jobs in any residential hexes of at least medium density. Perhaps not surprisingly, the resulting clusters and sub-clusters vary significantly in size, with higher-density clusters containing significantly fewer metro areas.

The clusters are numbered in order of decreasing job density and cluster 1 consists of only one metro area, New York, which has 24% of its jobs in CBD hexes, twice as many as any other metro area in the country. Cluster 2 contains six metro areas—Chicago, Washington, Boston, San Francisco, Seattle, and Honolulu—and cluster 3 contains 10. Meanwhile, Cluster 4 contains 52 metros, cluster 5 contains 165, and cluster 6—consisting of metros with no CBD hexes and very few if any jobs in high-density commercial hexes—contains 692 metro areas, more than two-thirds of the CBSAs in the United States.

The metro areas in the first three clusters, which are shown in Table 3.11 on page 154, are of the most potential interest from the standpoint of public transportation and an urban environment, as they have at least 2% of their jobs in high-density job clusters. Still, there is a lot of variation between these metro areas.

The six metro areas of cluster 2 have CBD employment shares by American standards—between 7.2% and 13.9%—and even by European standards, as Levy (2018) calculated that Paris's CBD has roughly 7% of the jobs in Ile-de-France. These metro areas divide up

Table 3.11: Metro Areas in Job Clusters 1, 2, and 3

CBSA Name	**Total Jobs**	**Cluster**	**CBD Jobs**	**HD Jobs**	**MD Jobs**	**HD / MD Residential Jobs**
New York	8,034,000	**1**	24.4%	5.0%	3.3%	21.8%
Honolulu	362,000	**2a**	8.2%	13.9%	6.2%	25.8%
Chicago	4,104,000	**2b**	12.5%	5.3%	5.7%	8.6%
Boston	2,419,000	**2b**	7.8%	12.4%	5.5%	10.5%
San Francisco	2,140,000	**2b**	13.9%	10.3%	11.6%	12.8%
Washington	2,723,000	**2c**	8.2%	17.6%	11.7%	5.2%
Seattle	1,697,000	**2c**	7.2%	11.0%	10.3%	4.8%
Philadelphia	2,587,000	**3a**	4.7%	8.6%	3.8%	7.3%
Pittsburgh	1,048,000	**3a**	4.2%	9.8%	3.3%	2.1%
Los Angeles	5,599,000	**3b**	3.0%	11.7%	11.7%	14.5%
San Jose	997,000	**3b**	2.5%	12.4%	15.0%	5.5%
Minneapolis	1,695,000	**3c**	3.3%	10.0%	7.8%	2.0%
Denver	1,300,000	**3c**	1.8%	12.1%	9.9%	1.7%
Baltimore	1,156,000	**3c**	2.0%	10.4%	5.4%	4.0%
Houston	2,608,000	**3d**	2.9%	7.9%	10.0%	2.2%
Charlotte	1,071,000	**3d**	2.6%	4.8%	4.8%	0.0%
Austin	837,000	**3d**	3.1%	6.1%	11.8%	0.5%

fairly clearly into three groups. Honolulu (cluster 2a) is particularly distinguishable from the mainland metro areas in that its jobs are particularly intermixed in residential areas: nearly 26% of jobs in Honolulu are located in medium- or high-density residential areas. Only New York, at 22%, is comparable in this: the next highest values for metro areas nationally are 15% for Los Angeles and 13% for San Francisco.

The three metro areas of cluster 2b—Chicago, Boston, and San Francisco—can all be characterized as legacy industrial cities that, unlike the industrial cities of the Rust Belt, have managed to hold onto substantial job concentrations in their cores. Both Chicago and San Francisco have over 10% of metro area jobs in CBD hexes and Boston's value of 8% would probably be in a similar range if several hexes in the CBD area were not just below the density cut-off for the CBD-density cluster, as seen in the map of Boston in Figure 3.3 on page 156.

Washington and Seattle—cluster 2c—have somewhat weaker central business districts, with 7–8% of metro area employment (and without the boundary effect Boston has), and substantially fewer jobs in medium- and high-density residential areas, in part because these metro areas, which do not have the same history as major pre-automobile industrial cities, do not have nearly as large pre-zoning dense mixed-use neighborhoods. It is notable that Washington, which includes Tysons Corner, one of the country's largest edge cities, and the one that Garreau (1992) particularly focused on in developing the concept, has the highest fraction of its jobs in high-density-but-not-CBD-density hexes among US metro areas with populations over 500,000.

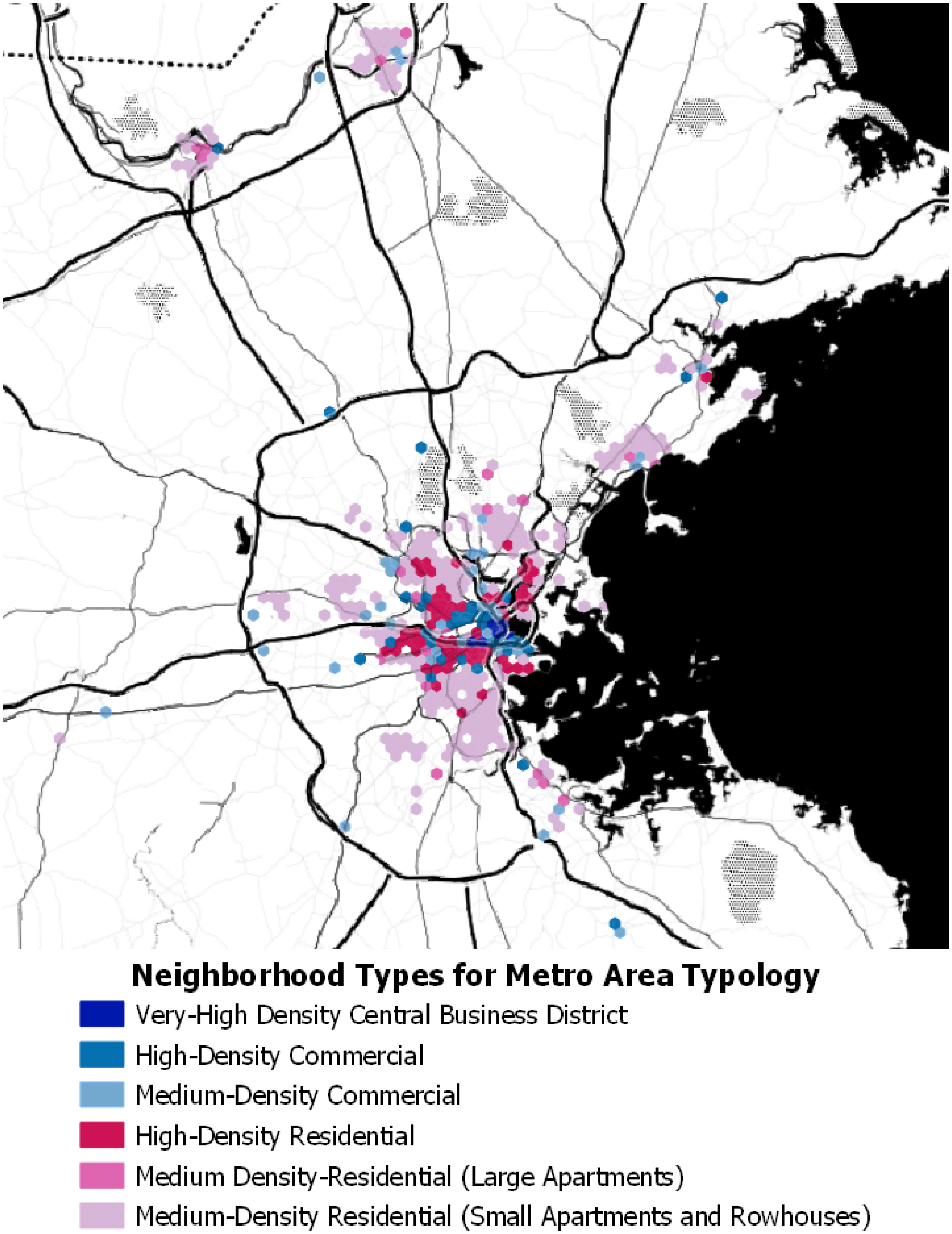

Figure 3.3: Boston-Cambridge-Newton, MA-NH MSA map of dense neighborhoods used in my metro area typology. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

The ten metro areas of cluster 3 are significantly more weakly-centered, with 2–5% of their jobs at CBD densities. Within this cluster, the two metro areas in cluster 3a—Philadelphia and Pittsburgh—stand out as having the highest percentages of their jobs at CBD densities, though in Pittsburgh these are divided between downtown Pittsburgh and the university and cultural center of Oakland about three miles to the east.

Clusters 3b—Los Angeles and San Jose—and 3c—Minneapolis, Denver, and Baltimore—have similarly weak CBDs, with 2–3% of metro area jobs and have 10–12% of metro area jobs in high-density commercial clusters. The main difference seems to be that Los Angeles and San Jose have relatively high levels of jobs in medium-density commercial and medium- and high- density residential areas. However, a closer examination of the map of clusters in San Jose shown in Figure 3.4 on page 158 shows that the apparent CBD-density clusters in San Jose do not actually constitute a central business district, but major campuses of technology companies such as Apple, suggesting that San Jose is perhaps closer in structure to the metro areas in cluster 4.

The three metro areas in cluster 3d—Houston, Charlotte, and Austin—are all in the Sunbelt, unlike those in cluster 3c. They have similar percentages of jobs in their CBDs, but somewhat lower percentages of jobs in high-density commercial areas and in residential areas, which seems consistent with their more recent growth.

In general, the metro areas of cluster 3 have job distributions that are rather less amenable to effective public transit service than those in clusters 1 and 2, but they do still have dense cores, and it seems plausible that improved transit service combined with plan-

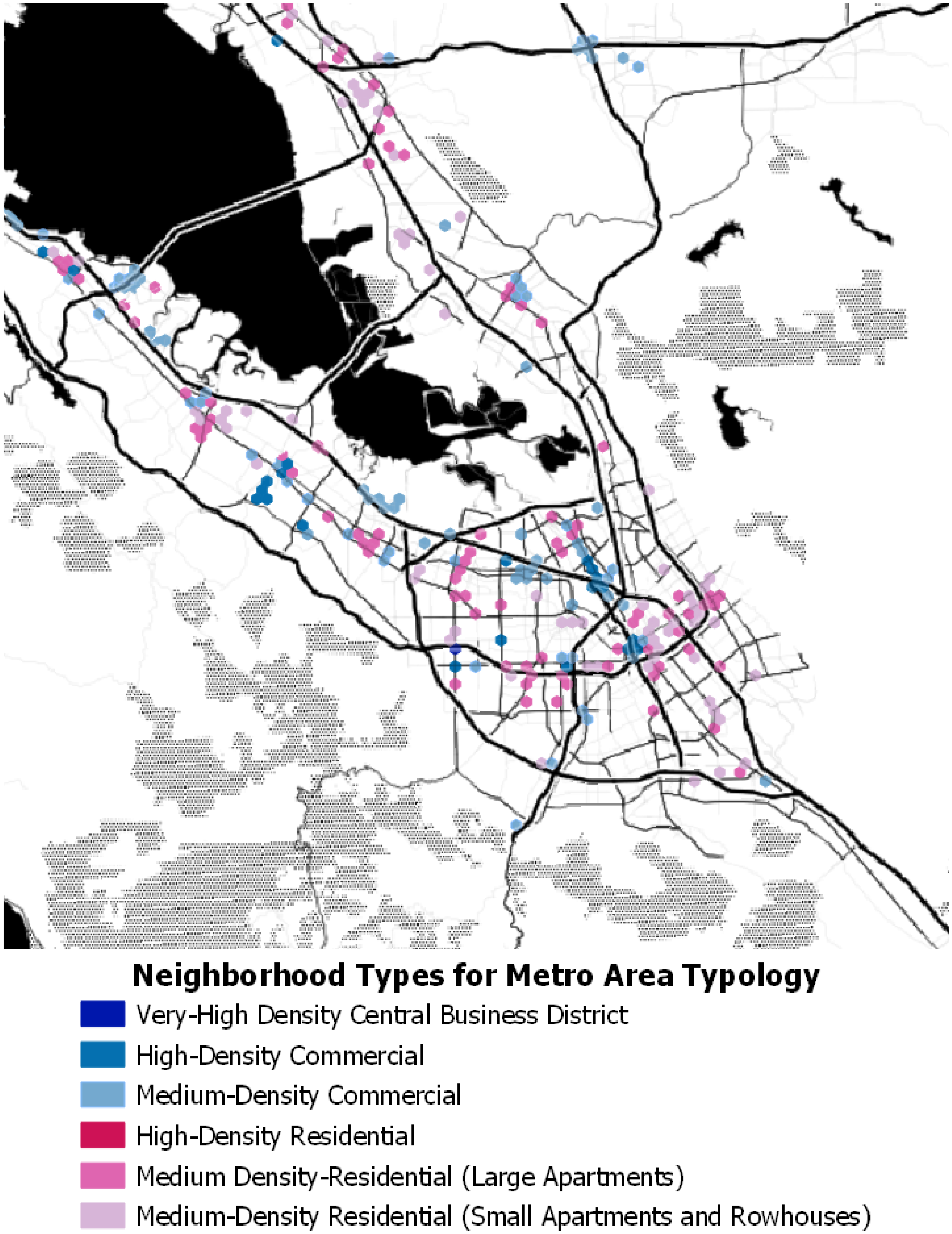

Figure 3.4: San Jose-Sunnyvale-Santa Clara, CA MSA map of dense neighborhoods used in my metro area typology. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

ning policies intended to increase the concentration of jobs could be effective in increasing their transit ridership. The metro areas in clusters 4, 5, and 6, on the other hand, are largely lacking in dense central business districts.

The sub-clusters of cluster 4, shown in Table 3.12 on page 160 do have substantial fractions of their jobs in high-density, but not CBD-density commercial neighborhoods. With the exception of cluster 4b, which consists of small metro areas with a dominant university or—in the case of the Mayo Clinic in Rochester, MN—medical employer, which have on average a quarter of their jobs in high-density commercial hexes, these clusters have roughly the same fractions of jobs in high-density commercial hexes as the metro areas in cluster 2.

The main distinction between these metro areas that is visible in my data is differences in the fractions of jobs in medium-density commercial areas: 9% in Dallas, which is alone in cluster 4a; 6% in cluster 4d, which contains famously-sprawled cities such as Atlanta and Phoenix; 3% in cluster 4c, which contains Las Vegas and Milwaukee, and 1% in cluster 4e, containing Cleveland and Louisville. However, viewing the maps of these metro areas in Appendix J shows another distinction that does not match up entirely well with the clusters: some of the metro areas, such as Atlanta and Dallas, are quite polycentric with significant edge city job clusters, while others are much less so.

With the exception of cluster 5a, consisting of Miami and Jacksonville, the metro areas in clusters 5 and cluster 6, shown in Table 3.13 on page 162, have no hexes with CBD-level densities. The main difference between the two clusters is that metro areas in cluster 5 have 4–8% of their jobs in high-density commercial neighborhoods, while metro areas in cluster 6 have far fewer jobs in such neighborhoods.

Table 3.12: Sub-Clusters of Job Cluster 4

Cluster	# of Metros	Mean CBD Jobs	Mean HD Jobs	Mean MD Jobs	Mean HD / MD Residential Jobs	Example Metros
4a	1	1%	11%	9%	1%	Dallas, TX
4b	5	0%	24%	1%	0%	Rochester, MN Bloomington, IL Bloomsburg, PA Wisconsin Rapids, WI Sayre, PA
4c	10	0%	13%	3%	3%	Las Vegas, NV Milwaukee, WI New Orleans, LA Hartford, CT Rochester, NY New Haven, CT Syracuse, NY
4d	13	0%	12%	6%	0%	Atlanta, GA Phoenix, AZ St. Louis, MO Orlando, FL Portland, OR Indianapolis, IN Nashville, TN Des Moines, IA Durham, NC Spokane, NC
4e	23	0%	12%	1%	0%	Cleveland, OH Louisville, KY Winston-Salem, NC

While the majority of metro areas in these clusters are relatively small, not all of them are: cluster 5d, in particular, contains ten metro areas of over a million people, including Detroit, with over four million, and Tampa, with over 3 million. Perhaps the most impressive example of a large metro area without job concentration, however, is Riverside, CA, which has a population of nearly four-and-a-half million people and less than 3% of its jobs in high-density commercial neighborhoods.

Riverside's particular paucity of high-density jobs can partly be explained by its specialization in the warehousing and logistics industries, which are traditionally relatively low-density, and partly by the fact that a significant fraction of the metro area serves as a bedroom community for Los Angeles. As Loh and Goger (2020) note, the Riverside-San Bernardino-Ontario, CA MSA is likely to be merged into the Los Angeles-Long Beach-Anaheim, CA MSA in the next round of CBSA redefinitions by the Office of Management and Budget.

Table 3.13: Sub-Clusters of Job Clusters 5 and 6

Cluster	# of Metros	Mean CBD Jobs	Mean HD Jobs	Mean MD Jobs	Mean HD / MD Residential Jobs	Example Metros
5a	2	1%	8%	6%	3%	Miami, FL Jacksonville, FL
5b	15	0%	6%	10%	1%	Sacramento, CA Grand Rapids, MI Omaha, NE
5c	17	0%	7%	4%	5%	San Diego, CA Providence, RI Buffalo, NY
5d	28	0%	8%	5%	0%	Detroit, MI Tampa, FL San Antonio, TX Kansas City, MO Columbus, OH
5e	40	0%	7%	0%	0%	Memphis, TN Tulsa, OK
5f	63	0%	4%	2%	0%	Virginia Beach, VA Raleigh, NC Tucson, AZ
6a	37	0%	2%	2%	1%	Riverside, CA Stockton, CA
6b	25	0%	0%	10%	0%	El Paso, TX Fayetteville, AR Boulder, CO
6c	3	0%	0%	3%	11%	State College, PA Rexburg, ID Butte, MT
6d	14	0%	0%	1%	4%	Salinas, CA Hagerstown, MD
6e	613	0%	0%	0%	0%	Bakersfield, CA Oxnard, CA

3.2.2 Population-Distribution Clusters

Population-distribution clusters were constructed in two steps: first, a k-means analysis based only on population in CBD and high-density hexes, treated as a single variable, produced four clusters. Then, the clusters were divided into sub-clusters using k-means analyses that took into account the concentration of population in high-density and CBD hexes, medium-density large-apartment hexes, medium-density small-apartment hexes, and medium-density commercial hexes. Because, outside of New York, only a very small fraction of the population is present in CBD and high-density commercial hexes, it did not make sense to distinguish between population in high-density commercial and residential hexes.

Perhaps not surprisingly, the resulting clusters and sub-clusters vary significantly in size, with higher-density clusters containing significantly fewer metro areas. The clusters are numbered in order of decreasing job density and cluster 1 consists of only one metro area, New York, which has 36% of its population in high-density hexes, more than three times the fraction for any other metro area in the county.

Cluster 2 contains seven metro areas—Los Angeles, Chicago, Washington, Philadelphia, Boston, San Francisco, and Honolulu—and cluster 3 contains 65. Meanwhile, Cluster 4 contains 853 metro areas with half a percent or less of their population in high-density hexes of any kind.

Table 3.14: Metro Areas in Population Clusters 1 and 2

CBSA Name	Total Population	Cluster	HD Pop.	MD Large Apt. Pop.	MD Small Apt. Pop.	MD Comm. Pop.
New York	19,274,000	**1**	35.9%	2.7%	10.9%	0.7%
Los Angeles	13,242,000	**2a**	5.6%	7.6%	16.3%	1.8%
San Francisco	4,654,000	**2a**	9.8%	3.6%	14.8%	2.0%
Honolulu	893,000	**2b**	11.5%	5.0%	4.7%	0.9%
Chicago	9,511,000	**2c**	6.0%	1.3%	13.8%	0.8%
Philadelphia	6,030,000	**2c**	5.1%	0.2%	15.2%	0.4%
Boston	4,795,000	**2c**	7.8%	1.0%	13.9%	1.4%
Washington	6,081,000	**2d**	4.6%	2.8%	3.1%	2.2%

The metro areas in the first two clusters, which are shown in Table 3.14 on page 164, are of the most potential interest from the standpoint of public transportation and an urban environment, as they have over 4% of their populations in high-density neighborhoods.. Still, there is a lot of variation between these metro areas.

As with jobs, New York is a substantial outlier, with 36% of its population in high-density hexes and another 14% in medium-density hexes. Honolulu gets its own sub-cluster again, cluster 2b, but it is less obviously distinct from other metro areas, though it has a higher fraction of its population in high-density hexes than the other cluster 2 metros and only 5%, as opposed to 14–16% of its population in medium-density small-apartment neighborhoods.

Los Angeles and San Francisco in cluster 2a and Chicago, Philadelphia, and Boston in Cluster 2c have quite similar population distributions, with 5–10% of their populations in high-density neighborhoods and 14–16% in medium-density small-apartment neighborhoods. The separate sub-cluster for the California metros seems to be due to their larger fraction of the population, 3–8% versus 0–1%, in medium-density large-apartment neighborhoods.

Washington, DC, which gets its own sub-cluster, cluster 2d, is as much of an outlier as Honolulu, and the least population-dense of the eight metro areas in clusters 1 and 2. At 4.6%, it has the lowest fraction of its population in high-density neighborhoods, albeit by a small margin, and its 3.1% in medium-density small-apartment neighborhoods is ten percentage points smaller than any other cluster 2 metro area except Honolulu.

The sixty-seven metro areas in Cluster 3 have significantly lower fractions of their population in high- and medium- density neighborhoods, but are distinguishable from those in Cluster 4 by having 1-3% of their populations in high-density neighborhoods, rather than less than half a percent.

Of the sub-clusters of cluster 3, shown in Table 3.15 on page 166, clusters 3a, 3b, and 3c are both the smallest and most similar. These metro areas—Miami, San Diego, San Jose, Seattle, Madison, and four smaller college towns—are notable for having significant fractions of their populations in medium-density large-apartment neighborhoods.

Cluster 3d, on the other hand, which consists almost entirely of Rust Belt metro areas, is made up of cities with significant fractions of their population in medium-density small-apartment neighborhoods. Clusters 3e and 3f, on the other hand, have very small fractions of their populations in such areas, and mostly consist of cities with less substantial pre-War industrial histories. Cluster 3e is notable because it consists of five college towns and four metro areas—Minneapolis, Denver, Portland, and Austin—which have

Table 3.15: Sub-Clusters of Population Cluster 3

Cluster	# of Metros	Mean HD Pop.	Mean MD Large Apt. Pop.	Mean MD Small Apt. Pop.	Mean MD Comm. Pop.	Example Metros
3a	4	1%	5%	3%	1%	San Diego, CA San Jose, CA Ann Arbor, MI Iowa City, IA
3b	3	3%	2%	3%	2%	Seattle, WA Madison, WI Santa Barbara, CA
3c	3	3%	5%	1%	0%	Miami, FL Urbana-Champaign, IL State College, PA
3d	15	1%	0%	7%	1%	Baltimore, MD Milwaukee, WI Hartford, CT Worcester, CT Bridgeport CT Albany, NY
3e	9	1%	1%	1%	2%	Minneapolis, MN Denver, CO Portland, OR Austin, TX
3f	33	1%	0%	0%	0%	Dallas, TX Atlanta, GA Orlando, FL Pittsburgh, PA Indianapolis, IN

good reputations with urbanists and budding transit networks, but relatively low transit ridership. These metro areas have 3-5% of their populations in high- or medium-density neighborhoods.

The metro areas of cluster 4 are distinguished by having very few if any of their residents in high-density neighborhoods. Despite this, there is some notable variation among the sub-clusters, shown in Table 3.16 on page 168. Cluster 4a consists of three college towns with roughly 5% of their residents in medium-density large-apartment neighborhoods; one suspects that these residents are largely college students. Cluster 4c, on the other hand, which has closer to 2% of metro populations in this neighborhood type, consists mostly of larger college towns, but also contains Houston and Las Vegas.

Cluster 4b, on the other hand, is notable primarily for its large fraction—on average, roughly 5%—of metro areas' populations living in medium-density small apartments. As with the other clusters notable for this neighborhood type, it primarily consists of metro areas that were industrial centers before World War II, such as Providence, New Orleans, and Buffalo.

The remaining two sub-clusters of cluster 4 have very small fractions of their populations at high or medium density. Cluster 4e consists of a mix of sunbelt sprawl—Phoenix, Riverside, Tampa, and Charlotte—and Rust Belt cities with especially hollowed-out cores—Detroit and St. Louis. Cluster 4f, which contains two-thirds of the metro areas in the country, consists of small metros of less than a million people: Greenville, SC and Bakersfield, CA are the largest in the cluster.

Table 3.16: Sub-Clusters of Population Cluster 4

Cluster	# of Metros	Mean HD Pop.	Mean MD Large Apt. Pop.	Mean MD Small Apt. Pop.	Mean MD Comm. Pop.	Example Metros
4a	3	0%	4.6%	0%	0%	Corvallis, OR Mt. Pleasant, MI Butte, MT
4b	17	0.2%	0.1%	4.8%	0.4%	Providence, RI New Orleans, LA Buffalo, NY
4c	12	0.2%	1.8%	0.7%	0.4%	Houston, TX Las Vegas, NV Lansing, MI Fort Collins, CO Boulder, CO
4d	22	0.1%	0%	0.3%	1.2%	Salt Lake City, UT Omaha, NE Durham, NC Spokane, WA Anchorage, AK
4e	126	0.3%	0.1%	0.2%	0.2%	Phoenix, AZ Riverside, CA Detroit, MI Tampa, FL St. Louis, MO Charlotte, NC
4f	671	0%	0%	0%	0%	Greenville, SC Bakersfield, CA McAllen, TX

3.3 Discussion

The primary products of this project are the neighborhood typology developed in Section 3.1 and the metro area typologies developed in Section 3.2. However, these typologies are not intended so much as ends in themselves as means to a better understanding of the US urban environment and metropolitan areas.

In this section, I will discuss several interesting results based on my initial analysis, along with possibilities for future work. Further discussion of the possible applications of these typologies to public transportation can be found in Chapter 4.

In Section 3.3.1, I note a correlation between metro areas with relatively large percentages of their populations living in medium-density neighborhoods consisting of row houses and small apartment buildings and cities—especially in the Northeast—with histories as significant industrial centers before World War II. I then consider the possibility that more detailed analysis of housing type and density might reveal more about historical types of American neighborhood development.

Section 3.3.2 explores what features of the urban environment lead a city to be perceived as "dense" or "sprawling" in the context of the paradoxical observation that Los Angeles is generally perceived as a sprawling, low-density metro area despite rating highly on most metrics of density. In Section 3.3.3, I investigate the differences in the densities experienced by residents of different races and employees of different income levels in large American metro areas.

3.3.1 Housing Type and Neighborhood History

The population-distribution-based clusters of metro areas introduced in Section 3.2.2 are based on four variables: the fraction of a metro area's population in high-density neighborhood types and the fractions of its population in each of three types of medium-density neighborhood: commercial neighborhoods—those where jobs outnumber residents—and what I call "large apartment" and "small apartment" residential neighborhoods.

These last two categories are distinguished based on housing type: large-apartment neighborhoods have the majority of their housing in multi-family buildings of at least ten units while small-apartment neighborhoods have the majority of their housing in row houses or multi-family buildings of less than ten units. The choice to set the cut-off at ten units rather than, for example, eight or twelve was somewhat arbitrary and partially dictated by the building-size bins that ACS housing unit counts are provided in.

However, the distinction between row houses and small apartment buildings—a category which also includes duplex houses and the traditional New England "triple-decker"—on one hand and larger apartment buildings with dozens of residents on the other is not especially arbitrary. When density and land use are held constant, smaller buildings may be preferable from an urban vitality standpoint because their residents are closer to the street and thus perhaps more likely to make more, shorter trips around their neighborhood and more able to participate in what Jacobs (2011, 66) referred to as the "sidewalk ballet."

The type of housing found in a neighborhood can also provide a clue to the time and context in which it was built. One example of this can be seen in the distribution of medium-density small-apartment neighborhoods among American metro areas. The percentage of the population living in this neighborhood type in population-distribution clusters 2a, 2c, 3d, and 4b (see Tables 3.14–3.16 on pages 164–168) reveals a pattern that cuts across clusters and thus across the population-density distributions of these metro areas.

Table 3.17 on page 172 lists metro areas over 500,000 residents with at least 3% of their residents in medium-density small-apartment neighborhoods, sorted by the percentages of their populations in this neighborhood type. Of the 28 metro areas included, 17 are former industrial cities in the Northeast, three—Chicago, Milwaukee, and New Orleans—are former industrial cities in the Midwest or South, seven are cities in the West of varying industrial histories, and one is Washington, DC, which has relatively little industrial history.

Besides geography, there are several other ways to break these metro areas up into groups. One is to consider the ratios of metro areas' populations in medium-density large-apartment and medium-density small-apartment neighborhoods. Of the 28 metros, three—San Jose, San Diego, Honolulu—have higher fractions of their populations in medium-density large-apartment than medium-density small apartment neighborhoods and another two—Washington and Los Angeles—have 90% and 45% as many residents in medium-density large-apartment neighborhoods than in medium-density small apartment neighborhoods.

Table 3.17: Metro Areas with High Medium-Density Small-Apartment Populations

CBSA Name	Population	High Density Pop.	Medium Density Large Apt. Pop.	Medium Density Small Apt. Pop.	Medium Density Comm. Pop.
Los Angeles, CA	13,242,000	5.6%	7.6%	16.3%	1.8%
Philadelphia, PA	6,030,000	5.1%	0.2%	15.2%	0.4%
San Francisco, CA	4,654,000	9.8%	3.6%	14.8%	2.0%
Boston, MA	4,795,000	7.8%	1.0%	13.9%	1.4%
Chicago, IL	9,511,000	6.0%	1.3%	13.8%	0.8%
Providence, RI	1,607,000	0.6%	0%	13.3%	0.4%
New York, NY	19,274,000	35.9%	2.7%	10.9%	0.7%
Milwaukee, WI	1,572,000	0.8%	1.5%	9.4%	1.0%
Bridgeport, CT	931,000	1.4%	1.5%	8.4%	1.2%
Baltimore, MD	2,758,000	1.6%	0.1%	6.7%	0.7%
Buffalo, NY	1,123,000	0.3%	0%	6.7%	0.6%
Lancaster, PA	533,000	0.8%	0%	6.3%	1.0%
Allentown, PA	821,000	2.0%	0%	5.5%	0%
Springfield, MA	692,000	0.7%	0%	5.3%	0.7%
Worcester, MA	931,000	0.7%	0.2%	5.1%	0%
Scranton, PA	549,000	0.4%	0.0%	5.0%	0.7%
San Jose, CA	1,980,000	0.8%	6.3%	4.9%	1.4%
San Diego, CA	3,211,000	1.4%	5.1%	4.7%	1.0%
Honolulu, HI	893,000	11.5%	5.0%	4.7%	0.9%
New Orleans, LA	1,248,000	0.6%	0.4%	4.6%	0.9%
Albany, NY	864,000	1.1%	0.2%	4.4%	0.5%
Oxnard, CA	838,000	0.1%	0.3%	4.4%	0%
Hartford, CT	1,204,000	0.9%	0.2%	4.0%	0.5%
New Haven, CT	855,000	1.6%	0.4%	3.8%	0.4%
Provo, UT	598,000	0.2%	0%	3.4%	0.5%
Poughkeepsie, NY	660,000	0.2%	0%	3.3%	0.4%
Washington, DC	6,081,000	4.6%	2.8%	3.1%	2.2%
Harrisburg, PA	553,000	0.1%	0%	3.1%	0.1%

Unlike these five metro areas—none of which have particularly strong histories as pre-World War II industrial towns and all of which other than Washington are located in California or Hawaii—the remaining 23 metros each have at least four times as meant residents in medium-density small-apartment neighborhoods as in medium-density large-apartment neighborhoods. Furthermore, the remaining 23 metro areas were all significant industrial or port cities in the late-19th and early-20th Centuries with the exception of two—Oxnard, CA and Provo, UT—that are both relatively small (under a million residents) and have less than 5% of their populations in medium-density small apartment neighborhoods[3].

It is notable that the remaining 23 metro areas include all of the major and several of the more minor late-19th and early-20th Century industrial centers east of the Alleghenies while containing only five—Buffalo, Chicago, Milwaukee, New Orleans, and San Francisco—west of them. It is possible that the medium-density small-apartment built environment was primarily a phenomenon of Northeastern cities and that the four cities west of the Alleghenies are simply outliers.

However, a recent study by Rowlands and Loh (2021) makes it possible to test an alternative hypothesis: that the fraction of a former industrial metro area's population in medium-density small-apartment neighborhoods is related to how much its core hollowed out during the white flight and urban disinvestment of the second half of the 20th Century. This seems plausible since a large population loss in a metro area's urban core would

[3]One possible explanation for Provo's unusually high fraction of its population in medium-density small-apartment neighborhoods is that it is notably home to both Brigham Young University and the Mormon Missionary Training Center. Particularly relevant to this is that Brigham Young University only allows unmarried students to live off-campus in apartments with landlords who commit to ensuring their tenants obey the University's rules against certain mixed-gender socialization, a rule which in practice may require smaller buildings where landlords can more easily monitor their tenants.

naturally depopulate its late-19th–early-20th Century housing stock, resulting in lower populations in these neighborhoods and in many of these neighborhoods no longer qualifying as medium-density.

Rowlands and Loh (2021) calculated the 1950 and 2018 populations of the 44 present-day CBSAs that contain what were the 50 largest US cities in 1950, the last Decennial Census year before urban populations began to decline. More relevantly at present, they also calculated the 1950 and 2018 populations within the 1950 city limits of the principal cities of the 1950 Standard Metropolitan Areas contained in these present-day CBSAs. This data makes it possible to quantify how much population the cores of these cities lost over the past sixty-eight years.

Table 3.18 on page 175 shows the present-day fraction of metro area population in medium-density small-apartment neighborhoods for the twenty-three metro areas identified above. It also includes the 1950–2018 population change within 1950 city limits for the ten of these metro areas included in Rowlands and Loh (2021)'s dataset.

The fact that only three of the metro areas with between 3% and 9% of their populations in medium-density small-apartment neighborhoods are included in Rowlands and Loh (2021)'s dataset makes it hard to determine if there is a correlation. However, with the addition of several Midwestern Rust Belt metro areas in their dataset that have lower fractions of their populations in medium-density small-apartment neighborhoods—Pittsburgh, Columbus, Cincinnati, Detroit, St. Louis, and Kansas City—it becomes possible to plot a set of metro areas spanning population changes from –63% to +13% and fractions of metro area population in medium-density small-apartment neighborhoods from 0.2% to 15.2%.

Table 3.18: Selected Metro Areas with Medium-Density Small-Apartment Populations

CBSA Name	2018 Metro Area Population	2018 Metro Area Medium-Density Small-Apartment Population	1950–2018 Population Change in 1950 City Limits
Philadelphia, PA	6,030,000	15.2%	–24%
San Francisco, CA	4,654,000	14.8%	+13%
Boston, MA	4,795,000	13.9%	–6%
Chicago, IL	9,511,000	13.8%	–23%
Providence, RI	1,607,000	13.3%	–22%
New York, NY	19,274,000	10.9%	+5%
Milwaukee, WI	1,572,000	9.4%	–35%
Bridgeport, CT	931,000	8.4%	-
Baltimore, MD	2,758,000	6.7%	–35%
Buffalo, NY	1,123,000	6.7%	–55%
Lancaster, PA	533,000	6.3%	-
Allentown, PA	821,000	5.5%	-
Springfield, MA	692,000	5.3%	-
Worcester, MA	931,000	5.1%	-
Scranton, PA	549,000	5.0%	-
New Orleans, LA	1,248,000	4.6%	–31%
Albany, NY	864,000	4.4%	-
Oxnard, CA	838,000	4.4%	-
Hartford, CT	1,204,000	4.0%	-
New Haven, CT	855,000	3.8%	-
Provo, UT	598,000	3.4%	-
Poughkeepsie, NY	660,000	3.3%	-
Harrisburg, PA	553,000	3.1%	-

While the resulting plot does show a positive correlation between metro area population change and fraction of population in medium-density small-apartment neighborhoods, the R^2 value is only 0.60. Understanding why this neighborhood type seems to correlate particularly with Northeastern and not Midwestern industrial cities likely requires research into the history of streetcar suburbs and pre-World War II workforce housing in these cities.

However, the general approach introduced here seems promising for identifying neighborhoods with similar histories in different metro areas, especially if one breaks housing types down into smaller categories. Measuring housing unit density rather than population density could potentially also help with correcting for the effects of population movement since a neighborhood was built.

3.3.2 Resolving the Paradox of Los Angeles

One of the properties of a built environment that people tend to form intuitive opinions of when they spend time in it is density. Nearly everyone has an opinion of the relative densities of the places they live and work, and often even of places they visit on vacation or see on television.

What these opinions are based on, however, is not always as clear, even to the people forming them, and they do not always correspond particularly well with population, job, or activity density. For example, it is common for people to complain of tall buildings as indicating "too-high" a density for their neighborhood, even though they may actually have less usable floor space and house fewer residents or jobs than shorter buildings that cover more of the ground.

Los Angeles provides an interesting example of this effect: the city's name has become a byword for low-density sprawl in American culture and its reputation for low density is near-universal, except for a relatively few contrarians who point out a paradoxical fact: by most simple measures of population density, Los Angeles is one of the densest metro areas in the United States!

Measuring the density of metropolitan statistical areas directly is relatively meaningless, since MSAs are defined in terms of county boundaries and so often contain large tracts of nearly-uninhabited land that may have little connection to the city whose metro area they are technically part of. However, as discussed in Section 2.1.1, Census-defined urbanized areas (UAs) are specifically intended to characterize continuous areas of urban and suburban density. Their lower-density cut-off excludes the outer reaches of exurbia along with rural and uninhabited areas, but they do include most areas that would reasonably be considered "urban."

Despite Los Angeles's reputation for sprawl, the Los Angeles urbanized area has the highest population density in the country, followed by San Francisco and San Jose. New York—justifiably the American standard of a big, dense city—comes in fourth among urbanized areas of at least 100,000 residents. It is strange enough that these three coastal Californian urbanized areas—two of them with reputations for sprawl—are denser than New York, but Table 3.19 on page 178—which shows the twenty-five highest-population-density urbanized areas with populations of at least 800,000 residents—demonstrates that the situation is even more counter-intuitive.

Table 3.19: Major Urbanized Areas with Highest Population Densities

Rank	**Urbanized Area**	**Population Density (/ sq. mi.)**
1	Los Angeles	7,000
2	San Francisco	6,300
3	San Jose	5,800
4	New York	5,300
5	Honolulu	4,700
6	Las Vegas	4,500
7	Miami	4,400
8	San Diego	4,000
9	Fresno	3,800
10	Salt Lake City	3,700
11	Sacramento	3,700
12	Denver	3,600
13	New Orleans	3,600
14	Washington	3,500
15	Chicago	3,500
16	Portland	3,500
17	Riverside	3,500
18	Phoenix	3,200
19	Baltimore	3,100
20	Seattle	3,000
21	Houston	3,000
22	Albuquerque	3,000
23	San Antonio	2,900
24	Dallas	2,900
25	Virginia Beach	2,800

While several of the nation's reputedly-densest metro areas—New York, Chicago, San Francisco, and Washington, and Honolulu, all of which were in my my population distribution clusters 1 and 2—make the top twenty-five, Boston and Philadelphia are completely missing and most of the list, including at the highest ranks, are made up of Sunbelt metro areas with reputations for being sprawling and car-oriented.

A similar result is achieved if we take the population density of those parts of metro areas included in my hex cells, which include all land with densities of at least 100 activity units per square mile: a threshold significantly lower than the Census Bureau uses for urbanized areas, and without the requirement that urbanized areas be contiguous. Table 3.20 on page 180 shows the twenty-five major metro areas with the highest population densities by this standard.

The results here are relatively similar: Tampa, Philadelphia, Bridgeport, Boston, Orlando, Detroit, and Milwaukee have replaced Fresno, New Orleans, Portland, Albuquerque, San Antonio, Dallas, and Virginia Beach, but the other eighteen metro areas are still present in a similar order. Metro area population density brings several generally-understood-as-dense metro areas into the top twenty-five, but it also brings two definite Rust Belt metros—Detroit and Milwaukee—in.

What appears to be going on is that, for the most part, the major urbanized areas with the highest population densities are simply the most geographically constrained major urban areas because, regardless of how low-density their cores may be, they are unable to form the vast tracts of very-low-density exurbia that surround most American metro areas.

Table 3.20: Major Metro Areas with Highest Population Densities

Rank	**Metro Area**	**Population Density (/ sq. mi.)**
1	Los Angeles	5,100
2	New York	3,700
3	San Francisco	3,700
4	Miami	3,600
5	Honolulu	3,200
6	San Jose	3,000
7	Las Vegas	2,700
8	San Diego	2,200
9	Salt Lake City	1,800
10	Tampa	1,700
11	Philadelphia	1,700
12	Chicago	1,600
13	Denver	1,600
14	Bridgeport	1,600
15	Phoenix	1,600
16	Boston	1,600
17	Washington	1,600
18	Baltimore	1,500
19	Seattle	1,500
20	Orlando	1,500
21	Sacramento	1,400
22	Houston	1,400
23	Detroit	1,300
24	Riverside	1,300
25	Milwaukee	1,200

Los Angeles, San Francisco, San Jose, Honolulu, and San Diego are all crowded into relatively narrow patches of flat land between the Pacific Ocean and steep mountains. Likewise, Salt Lake City is bounded to the east by mountains and to the west by the Great Salt Lake and Riverside is nestled in a valley between two mountain ranges, while Miami is bounded to the west by swamp and to the east by the Atlantic Ocean and New Orleans is surrounded by swamp and Lake Pontchartrain. Orlando is also surrounded by swampy land for the most part, and the Tampa metro area is significantly constrained from expanding by Tampa Bay and the Gulf of Mexico.

Although they are less constrained by physical geography, Las Vegas, Portland, and Sacramento are constricted by legal and economic factors. Las Vegas is hemmed in by large tracks of Federally-owned wilderness on nearly all sides, while Portland is partly constrained by an urban growth boundary. As for Sacramento, it is located in the Central Valley of California, perhaps the most economically productive agricultural area in the US. As a result, the high value of the farmland surrounding the city makes it unlikely to be subdivided for low-density housing. Supporting this theory, other Central Valley urbanized areas too small to appear in Table 3.19—Stockton, Modesto, Fresno, and Bakersfield—have very similar population densities to Sacramento.

Denver and Phoenix both have at least one direction in which they can expand relatively unimpeded, but they—like many of the other metro areas in the previous two tables—are in quite dry areas. Lang (2002)'s distinction between wet and dry sunbelt cities—also discussed in Lang (2003, 108-110)—may come into play here. In the wet climates of the Northeast, South, much of the Midwest, and the Pacific Northwest east of the Cascades, suburban and exurban developments can use wells and septic tanks to avoid the expensive of extending water and sewer connections, and the land on the fringes of metro areas is generally privately owned. On the other hand, in the dryer climates of much of the West, water is a very limited resource that is piped in from hundreds of miles away and many metro areas are surrounded by large tracts of Federally-owned land that is not available for development.

The appearance of Detroit and Milwaukee on the high-population-density metro areas list is a bit harder to explain, but it may be a function of the fact that both metro areas have stagnant populations and are located in states with small counties, which may have prevented the development of sufficient exurban sprawl to bring outlying counties into their metro areas. Many of the densest metropolitan areas, it seems, do not actually have particularly dense cores. Instead, they have high population densities because they are lacking the large tracts of very low density suburban and exurban land that surround most American cities: land that is home to relatively little of most metro areas' populations despite taking up the vast majority of their area.

When we speak of population density, however, what we are really interested is the densities that most people live at and experience regularly. The existence of a belt of very-low-density exurbia on the edge of a metro area is not particularly significant to most of the metro area's residents and visitors; indeed, they may not even be aware of it, since it is unlikely to contain many destinations of interest to them.

One way to assess the local densities that most people in a metro area actually experience is to take a population-weighted average of the densities of smaller, walking-distance-sized districts:

$$d_{weighted} = \frac{\sum_i d_i p_i}{\sum_i p_i}$$

where d_i is the density and p_i is the population of the i^{th} district. Using a population-weighted average effectively calculates the population density of the district containing the average resident, rather than the population density of the average district (Craig, 1984; Wilson et al., 2012).

Table 3.21 on page 184 is a list of the twenty-five major metropolitan areas with the highest population-weighted densities, using my quarter-mile radius hex cells as the districts for the weighted average. This has two advantages over Wilson et al. (2012, 21-32)'s calculation of population-weighted densities using Census tracts: all the hex cells are roughly the same size, and their size was specifically selected to approximate a pedestrian-scale neighborhood.

With this analysis, some order seems to have been restored to the universe: unlike with the two pure population-density measures, New York decisively has the highest population-weighted density density of any major metropolitan area in the US. However, Los Angeles is still in third place and San Jose is in fifth. While calculating a population-weighted density instead of a normal population density does increase the rankings of the strongly-centered metro areas in population-distribution clusters 1 and 2, geographically-constrained sunbelt metros still rank well and we are still faced with the fact that Los Angeles comes in in third place.

Table 3.21: Major Metro Areas with Highest Population-Weighted Densities

Rank	**Metro Area**	**Population-Weighted Density (/ sq. mi.)**
1	New York	29,300
2	San Francisco	12,500
3	Los Angeles	11,400
4	Honolulu	11,400
5	San Jose	9,100
6	Chicago	8,800
7	Boston	8,400
8	Miami	8,300
9	Philadelphia	8,100
10	San Diego	7,800
11	Washington	7,200
12	Las Vegas	7,100
13	Seattle	5,900
14	Baltimore	5,700
15	Bridgeport	5,700
16	Denver	5,600
17	Sacramento	5,300
18	Milwaukee	5,200
19	Providence	5,200
20	Salt Lake City	5,200
21	Phoenix	5,200
22	Houston	5,200
23	Riverside	5,200
24	Portland	5,100
25	New Orleans	5,100

In fact, an examination of the land use and intensity map of Los Angeles in Figure 3.5 on page 186 suggests that this result may not be as ridiculous as it first seems. Los Angeles's high population-weighted population density is not solely the result of the absence of very-low-density exurban sprawl. The city actually contains rather large areas of relatively-high density residential areas. Many of these areas even have enough retail to be classified as walkable in my neighborhood typology.

Why, then, is it commonly accepted wisdom that Los Angeles is not dense? The only reasonable conclusion, I think, is that population density—the number of people per square mile—is not actually what most people are evaluating when they judge a place as "dense" or "sprawling." This makes sense on a practical and psychological level. Residents—unless they are people one knows or has reason to interact with—are not particularly relevant to how one experiences a place.

Outside of the fairly limited vital urban places with an active sidewalk life, the presence of a high residential density is only likely to be apparent to the causal observer in terms of building height or automobile traffic. And automobile traffic does not register to people as "density" so much as "congestion": something that interferes with getting places, rather than the presence of a large number of destinations.

If the presence of numerous nearby destinations is the main thing besides building height that registers as density to most people, then one would expect employment density to be a relatively good proxy for it. Not all destinations involve employees, to be sure—parks, plazas, and what Jacobs (2011, 89-90) calls "public characters" qualify, though public characters often are retail workers—but many of them do.

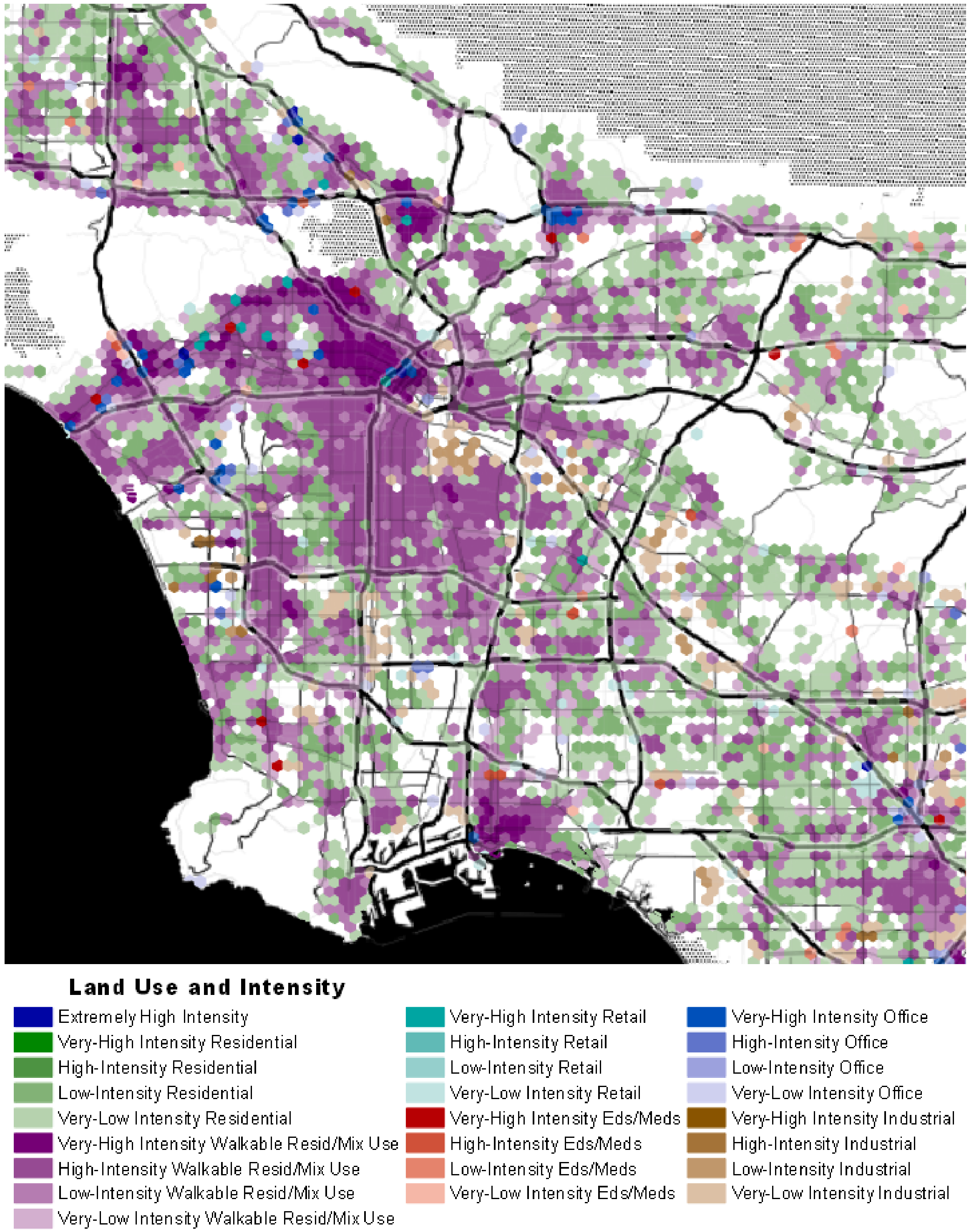

Figure 3.5: Los Angeles-Long Beach-Anaheim, CA MSA map of land use and intensity, measured by walkshed-adjusted density. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

This model of how people perceive urban density would be expected to yield a lower perceived density for Los Angeles, a city which Wachs (1984) notes, had an unusually weak downtown core even before the advent of mass automobile ownership. This core weakness was originally due to height limits downtown, the long distance between downtown and the port facilities in Long Beach and San Pedro, and an interurban streetcar system—the Pacific Electric ”red cars” (Hilton and Due, 2000)—that was one of the country’s most extensive, but it has been magnified greatly by over half a century of freeway-and-automobile-oriented development (Wachs, 1984).

A simple test of this hypothesis is to consider the metro areas in my job-density clusters 1, 2, and—to a lesser extent—3 (shown in Table 3.11 on page 154), which contain the metro areas with the largest fractions of their jobs in high and very-high density neighborhoods. This model seems to do a better job of representing the common understanding of metro area density than the population density measures discussed above.

As a check on this test, one can also calculate job-weighted job densities in place of population-weighted population densities. The list of the twenty-five major metro areas with the highest job-weighted densities given in Table 3.22 on page 188 is, unsurprisingly, fairly similar to the set of metro areas in clusters 1, 2, and 3.

Notably only the seven metro areas with the highest job-weighted densities—New York, Chicago, San Francisco, Boston, Seattle, Honolulu, and Washington—have densities near or above 40,000 jobs per square mile, the approximate value that makes transit or parking structures necessary. This is consistent with Lang (2000, 2003)’s observation that, even twenty years ago, a large fraction or even majority of office jobs—the type of

Table 3.22: Major Metro Areas with Highest Job-Weighted Densities

Rank	**Metro Area**	**Job-Weighted Density (/ sq. mi.)**
1	New York	124,000
2	Chicago	65,200
3	San Francisco	56,200
4	Boston	41,100
5	Seattle	39,500
6	Honolulu	36,200
7	Washington	35,900
8	Philadelphia	26,300
9	Minneapolis	22,900
10	Los Angeles	22,900
11	San Jose	19,800
12	Pittsburgh	19,600
13	Houston	19,100
14	Orlando	18,800
15	Cleveland	16,900
16	Denver	16,400
17	Las Vegas	16,200
18	Atlanta	15,800
19	New Orleans	15,200
20	Portland	14,700
21	Dallas	14,000
22	Austin	14,000
23	Baltimore	13,900
24	Charlotte	13,400
25	Indianapolis	12,600

jobs that is most often found at high densities due to agglomeration economies—in most metro areas were found in low-density "edgeless city" corridors and office parks rather than traditional downtowns or relatively dense "edge city" developments.

To be clear, the fact that the common perception of urban density does not track particularly well with population density does not mean that population density is unimportant: for many purposes, including the potential ridership for transit and the presence of a sufficient customer base to support neighborhood retail such as grocery stores, it can be essential. However, developing a better understanding of the factors that lead to perceived density than the crude proxy of employment density used here would be a potentially interesting line of research.

3.3.3 Is Density Demographics?

Another potential use case for the neighborhood characterization data collected in Chapter 2 and the typologies developed in Sections 3.1 and 3.2 is the study of how density relates to various demographic traits. The fact that the neighborhood characterization data is tabulated by relatively-consistently-sized hex cells that are roughly the size of a walkable neighborhood makes it more useful than data tabulated by Census tract or block group for this purpose. This is because because the use of a consistently-sized tabulation geography mitigates that modifiable areal unit problem—discussed in Section 2.3.1—and because the hex cell tabulation geographies can reasonably be expected to represent the actual experienced environment of residents of a given neighborhood.

Given the complicated and problematic history of racism in the United States, and the degree to which racism and racial segregation are fundamental to the history of American urban areas over the past century—discussed in Section 1.2—the different population densities experienced by residents of different races in American metro areas is a particularly interesting topic. While the relationship between race and density is a subject large enough to easily fill a thesis as long as this one, I have calculated the median activity densities at which non-Hispanic white, non-Hispanic Black, Latin, non-Hispanic Asian, and non-Hispanic other race residents live in the sixty largest US metro areas.

Table 3.23 on page 191 lists the ratios between the median activity density experienced by residents of each race and the overall median activity density for each of the ten metro areas where white residents live at the highest and lowest densities compared to residents overall. The same ratios are given for the each of the ten metro areas where Black residents live at the highest and lowest densities in Table 3.24 on page 192, and a full list for the sixty largest metro areas is given in Table K.1 on page 683.

While this is a very preliminary analysis, some recognizable patterns immediately jump out from these tables. In each of the sixty largest metro areas in the United States, white residents live at a median activity density lower than the overall median activity density for all residents and lower than the median activity density for members of any other race. And in each of these metros, Black residents live at a median activity density higher than the overall median activity density for all residents; in nine of them—Rochester, Worcester, Boston, Philadelphia, Providence, Grand Rapids, Bridgeport, and Hartford—they live at median activity densities more than twice the overall median activity densities for all residents.

Table 3.23: Metro Areas With White Residents at Elevated and Reduced Densities

Metro Area	**Median Activity Density of Residents (/ sq. mi.)**	**White Median / Overall Median**	**Black Median / Overall Median**	**Latin Median / Overall Median**	**Asian Median / Overall Median**	**Other Median / Overall Median**
Albuquerque	4,900	97%	121%	101%	107%	91%
Salt Lake City	6,300	95%	125%	118%	110%	112%
Portland	5,900	94%	139%	122%	118%	110%
Tampa	4,400	93%	126%	110%	102%	105%
Kansas City	3,200	91%	117%	128%	131%	104%
Seattle	5,500	91%	127%	115%	113%	106%
Denver	6,300	91%	132%	122%	104%	104%
Austin	4,100	91%	114%	110%	112%	102%
Fresno	5,900	91%	128%	104%	101%	97%
Las Vegas	8,000	90%	109%	115%	97%	100%
...	...	...	...	...	...	...
Hartford	2,600	74%	221%	268%	115%	126%
Birmingham	1,700	73%	151%	111%	137%	105%
Memphis	3,100	73%	119%	138%	91%	92%
San Antonio	4,900	73%	104%	114%	106%	91%
Philadelphia	5,400	73%	262%	195%	114%	113%
Providence	4,200	72%	259%	301%	142%	190%
Boston	5,300	68%	311%	324%	202%	144%
Milwaukee	5,200	65%	177%	190%	114%	136%
Bridgeport	4,500	58%	237%	235%	120%	131%
New York	17,700	44%	174%	186%	142%	143%

Table 3.24: Metro Areas With Black Residents at Elevated and Reduced Densities

Metro Area	**Median Activity Density of Residents (/ sq. mi.)**	**White Median / Overall Median**	**Black Median / Overall Median**	**Latin Median / Overall Median**	**Asian Median / Overall Median**	**Other Median / Overall Median**
Rochester	2,600	81%	347%	281%	134%	144%
Worcester	1,900	78%	324%	347%	156%	138%
Boston	5,300	68%	311%	324%	202%	144%
Philadelphia	5,400	73%	262%	195%	114%	113%
Providence	4,200	72%	259%	301%	142%	190%
Grand Rapids	2,500	80%	251%	222%	140%	153%
Bridgeport	4,500	58%	237%	235%	120%	131%
Hartford	2,600	74%	221%	268%	115%	126%
Pittsburgh	2,600	87%	219%	151%	198%	155%
Minneapolis	3,700	87%	194%	156%	143%	129%
...	...	...	...	...	...	...
Los Angeles	13,000	77%	113%	116%	92%	89%
Riverside	5,300	74%	113%	117%	102%	94%
San Jose	10,800	85%	112%	112%	103%	100%
New Orleans	5,800	84%	110%	122%	107%	94%
Las Vegas	8,000	90%	109%	115%	97%	100%
Houston	4,900	80%	107%	118%	106%	96%
Dallas	5,100	83%	107%	119%	111%	102%
Miami	8,200	77%	105%	117%	88%	91%
San Antonio	4,900	73%	104%	114%	106%	91%
Honolulu	9,900	81%	100%	97%	116%	89%

Latin and Asian residents also usually live at elevated activity densities: Latin residents only live at reduced densities in Honolulu and Raleigh and Asian residents live at reduced densities in eight of the sixty metro areas: Phoenix, Detroit, Las Vegas, Orlando, Baltimore, Los Angeles, Memphis, and Miami. In no case do members of either race live at median activity densities below 88% of the overall metro area median activity density while white residents do so in forty-five of the sixty metro areas considered.

In addition, the ten metro areas where white residents live at median activity densities closest to the metro area median activity density are all—except for Kansas City—located in cities in the West, Southwest, or South Florida and have no more than 10% Black residents. These are, for the most part, metro areas that did not experience particularly severe white flight or severe core population collapses (Rowlands and Loh, 2021) during the second half of the 20th Century, as well as being metro areas where, as discussed in Section 3.3.2, physical, economic, and legal factors prevented the development of a large band of very-low-density exurbs.

Mirroring this phenomenon, ten metro areas where white residents live at median activities densities the furthest below the metro area median activity density are—except for San Antonio—all located in former industrial cities in the Northeast, Midwest, or South. However, the latter metro areas have significantly larger variations in the sizes of their Black populations: the Memphis metro area is 47% Black and the Birmingham metro area is 47% Black while the Providence and San Antonio metro areas are 5% and 6% Black, respectively.

The tendency of white residents of former industrial cities that experienced substantial white flight to the suburbs to have white populations living at particularly reduced activity densities is consistent with the histories of these metro areas and the fact that many of them lost almost the entire white populations of their dense urban cores to the suburbs (Rowlands and Loh, 2021). Even in metro areas such as New York and Boston that have recently experienced a significant influx of white residents to denser neighborhood in their cores as a result of gentrification over the past two decades, the presence of a large white population in highly-segregated, low-density suburbia and exurbia is keeping the median white resident at a much lower activity density than non-white residents.

Likewise, the ten metro areas where Black residents live at median activity densities the furthest above the median activity density for all residents are all former industrial cities in the Northeast or Midwest. These metro areas all also—except for Philadelphia, at 20%—have relatively low Black populations, which presumably means that Black residents living at high median population densities have a relatively small effect on the overall median population densities of these metro areas.

There is clearly the possibility for much more interesting analysis of data related to race and density using this data. One obvious opportunity provided by the neighborhood characterization data tabulated by hex cells is the calculation of segregation indices based on them. Since the cells are roughly equal in size and roughly the size of walkable neighborhoods, such an analysis would give a useful impression of the relationship between levels of fine-grained racial segregation and the differences between the activity densities that residents of different races live at.

Likewise, a fuller analysis would need to take into account threefold relationship between race, income, and density, as well as other factors such as differences in the densities at which workers of different residents work and racial differences in commuting patterns.

While I did not collect the necessary data to investigate racial differences in workplaces and commuting patterns during the neighborhood characterization process in Chapter 2, I did collect information on workplace by income level. This data, from the LODES dataset, divides all jobs into three income categories: low-income (earning less than \$1,250 per month), middle-income (earning \$1,251–\$3,333 per month), and high-income (earning more than \$3,333 per month). As with the racial data above, I have calculated the median activity densities at which high-income, middle-income, and low-income jobs are located the sixty largest US metro areas.

Table 3.25 on page 196 lists the ratios between the median activity densities at which jobs in each income band are located and the overall median activity densities for each of the ten metro areas where low-income jobs are located at the highest and lowest densities compared to jobs overall. The same ratios are given for the each of the ten metro areas where high-income jobs are located at the highest and lowest densities in Table 3.26 on page 197, and a full list for the sixty largest metro areas is given in Table K.1 on page 683.

In general, high-income jobs tend to be located at somewhat-higher densities than low-income jobs. This is likely a consequence of the fact that the highest-income jobs are mostly in industries that benefit from agglomeration and are commonly found in central business districts, while low-income jobs are often in the service sector and frequently found in retail strips across low-density suburbia.

Table 3.25: Metro Areas With Low-Income Jobs at Elevated and Reduced Densities

Metro Area	**Median Activity Density of Jobs (/ sq. mi.)**	**Low-Income Median / Overall Median**	**Middle-Income Median / Overall Median**	**High-Income Median / Overall Median**
Grand Rapids	6,300	108%	94%	97%
Los Angeles	17,000	105%	92%	105%
Fresno	8,000	103%	98%	99%
Riverside	7,100	103%	100%	99%
San Antonio	8,000	100%	94%	104%
Memphis	5,700	100%	92%	107%
Tulsa	5,400	100%	98%	102%
Oklahoma City	5,400	100%	98%	101%
Milwaukee	7,300	100%	96%	103%
New Orleans	8,900	100%	100%	100%
...	...	...	...	...
Pittsburgh	6,000	88%	92%	113%
Hartford	5,400	86%	87%	116%
San Jose	15,700	85%	85%	113%
San Francisco	19,600	85%	80%	119%
Nashville	6,800	84%	87%	127%
Atlanta	6,900	83%	85%	129%
Seattle	12,500	81%	81%	134%
Boston	12,200	80%	82%	122%
New York	25,900	79%	84%	142%
Washington	15,200	70%	73%	138%

Table 3.26: Metro Areas With High-Income Jobs at Elevated and Reduced Densities

Metro Area	Median Activity Density of Jobs (/ sq. mi.)	Low-Income Median / Overall Median	Middle-Income Median / Overall Median	High-Income Median / Overall Median
New York	25,900	79%	84%	142%
Washington	15,200	70%	73%	138%
Seattle	12,500	81%	81%	134%
Atlanta	6,900	83%	85%	129%
Nashville	6,800	84%	87%	127%
Boston	12,200	80%	82%	122%
Dallas	9,000	89%	89%	121%
St. Louis	6,500	89%	94%	119%
San Francisco	19,600	85%	80%	119%
Tampa	7,500	90%	93%	119%
...	...	...	...	...
Milwaukee	7,300	100%	96%	103%
Providence	6,300	95%	98%	103%
Albuquerque	7,500	100%	99%	102%
Tulsa	5,400	100%	98%	102%
Salt Lake City	8,800	99%	98%	101%
Oklahoma City	5,400	100%	98%	101%
New Orleans	8,900	100%	100%	100%
Fresno	8,000	103%	98%	99%
Riverside	7,100	103%	100%	99%
Grand Rapids	6,300	108%	94%	97%

High-income jobs are particularly concentrated at high densities in some of the cities with the most job concentration—New York, Washington, and Seattle in particular—while they are actually found at lower median activity densities than jobs overall in three dispersed metro areas with industrial or agricultural economies: Fresno, Riverside, and Grand Rapids. This pattern is mirrored by low-income jobs, which are found at higher median activity densities than jobs overall in Grand Rapids, Los Angeles, Fresno, and Riverside and at much lower median activity densities than jobs overall in Washington, New York, Boston, and Seattle.

The relatively low densities at which low-income jobs are found and the relatively high densities at which high-income jobs are found in more sprawling metro areas, such as Atlanta and Nashville, is more surprising, though in the case of Atlanta it may be related to the fact that, as Lang (2003, Ch. 6) notes, Atlanta has several of the nation's largest edge cities, which—while they are much less dense than traditional CBDs—are still significantly dense than the "edgeless city" office parks and office strips where a significant fraction or even majority of office jobs are found in most American metro areas.

Significant care must be used in interpreting these results, though, because what counts as a high-income or low-income job in practice varies significantly between metro areas. In eight high-income and high-cost-of-living metro areas, the majority of jobs fall into the high-income band of the LODES data: San Jose (64%), San Francisco (57%), Washington (57%), Seattle (56%), Boston (55%), Bridgeport (54%), Hartford (52%), and Minneapolis (51%). While the fact that this data is only divided into three income bands poses a significant limitation, it is still possible that interesting results may be gleaned from it.

Chapter 4: Implications for Public Transportation

A major potential use of my neighborhood and metro area typologies—and the use case that originally motivated them—is the comparison between neighborhoods that are and are not served by high-quality public transportation in American metro areas. The properties that my typologies are based around were selected to measure urban vitality and walkability, traits that are also essential to supporting high transit ridership. This chapter is an exploration of the potential for further research based on my work on typologizing American urbanism.

I begin in Section 4.1 with a review of the literature on what makes metropolitan areas and neighborhoods within them particularly amenable to public transportation. Section 4.2 reverses the question with a review of the traits of high-quality public transportation. Section 4.3 continues with a discussion of the literature on several equity issues in American public transportation. And, finally, Section 4.4 presents a preliminary analysis of major American public transportation networks based on my data.

4.1 What Makes Metropolitan Areas Amenable to Transit?

While the exact mix of urban properties that make a metropolitan area tend toward high transit ridership and low private automobile use are still under debate, there are several traits that seem to clearly make a significant difference: density, clustering of destinations, mixture of land use, and walkable street networks.

4.1.1 Density of Population and Jobs

The idea that high population density is the main requirement for an urban area to be amenable to transit is both traditional and simple. It fits well with the fact that American cities generally had decreasing densities over the course of the 20$^{\text{th}}$ Century (Anas et al., 1998, 1436-1438) as cars supplanted public transit outside of a few older cities, and with the pro-density approach to understanding urban vitality promoted by Jane Jacobs in Chapter 11 of *The Death and Life of Great American Cities*. (Jacobs, 2011, Ch. 11)

Residential population density is frequently regarded by transit planners as one of the most useful metrics for determining how much transit service it is practical to supply to an area, since higher density means that more people will live within walking distance of each transit stop (Walker, 2012, 109-116). However, since this is principally a concern about the number of people within walking distance—at most a mile—of a given location, the overall density of the city or metropolitan area is not as relevant as the density of smaller units such as census tracts.

Density has consistently been found to drive transit ridership, though the size of the effect seems to depend on the type of transit. Seskin et al. (1996, Ch. 2)'s meta-analysis found that ridership of light rail systems had an elasticity of 0.59 with respect to residential density near stations, but only 0.40 with respect to employment density near stations, while commuter rail systems had elasticities of 0.25 with respect to residential density but 0.71 with respect to employment density. These values are averages of system-wide figures, though, and the elasticity of station ridership with density near that station can be greater than unity. Seskin et al. (1996, Ch. 2) also reported that walking environment around transit stations is important, but that studies have suggested that few people are willing to walk half a mile to transit, while most are willing to walk at least 500 feet.

In addition to general suggestions about density required for transit, Seskin et al. (1996, Ch. 2) cite suggestions, including from a report by the Institute of Transportation Engineers (1989), for density thresholds for different levels of transit service. However, these studies are likely overly simplistic and do not take into account the wide non-density variation in environments.

The importance of density was reaffirmed by Holtzclaw et al. (2002), who studied Chicago, Los Angeles, and San Francisco, and found that car ownership was a function of three factors: residential density, per capita income, and the availability of public transit. Likewise, Ewing et al. (2003), studying a large number of metropolitan areas, found that density—of population and jobs—had a very large effect in determining transit ridership and mode-share (the fraction of all commuters who commute by transit).

Analysis of transit ridership and density in a number of metro areas by Levinson and Kumar (1997); Newman and Kenworthy (2006) found that transit ridership was strongly correlated to activity (job plus population) density, with a particular upturn in ridership at densities of around 9,000 activity units per square mile. However, work by Schwanen and Mokhtarian (2004) suggests that some of the relationship between density and transit ridership may be more a consequence of people who prefer to ride transit choosing to live in denser relationships, rather than density directly driving people to choose transit. The same study did find (Schwanen and Mokhtarian, 2005), though, that the physical structure of neighborhoods does influence mode choice to some degree, even controlling for residents' preferences.

The relative importance of density versus broader descriptions of urban form is still in dispute. Ewing et al. (2014) examined the merits of compact cities versus sprawl as a spatial solution to a number of problems, including automobile dependence. The authors began with a literature review on the nature of sprawl and disagreed on whether multi-dimensional sprawl indices or density form a better measure of sprawl. They conclude, however, that increasing density and the mixing of uses are probably worthwhile.

4.1.2 Clustering of Destinations

While density is clearly important, relative concentration of destinations can be as well. A city where everyone only travels from their home to a single downtown core is much simpler to serve by transit than one where residents make many trips in all directions from their homes. While no real city is perfectly monocentric, and people commute to destinations other than work, it seems plausible that having jobs concentrated in a few dense clusters—a polycentric city—would be easier to serve by transit than one in which they are broadly dispersed throughout the metropolitan area.

Barnes (2001) found that having a large fraction of a region's jobs in high-density areas and the concentration of a relatively large fraction of the metropolitan population in a relatively small fraction of its land area were the main drivers of transit mode share for commute trips. Likewise, Schwanen et al. (2001) found that movement of jobs to suburbs generally reduced transit mode share in Dutch cities.

These results suggest that urban monocentricity—the concentration a metro area's jobs and population in a single, dense core—may be optimal, but polycentricity is still far better than dispersion—in which jobs and population are spread roughly evenly across an area—for encouraging transit ridership, even at the same overall densities.

This is consistent with the study by Yang et al. (2012) discussing the effect of development densities and sprawl on commute travel times, which found that the density of suburban centers relative to the region and the spatial distribution of high-density nodes are important to reducing travel times. More recently, Knaap et al. (2016) studied the role of polycentric development in the Baltimore-Washington area in the Maryland transportation network and found that this development promoted both economic growth and transit ridership.

However, while polycentricity may make a city easier to serve with transit, the type of transit still matters. Louf and Barthelemy (2014a) modeled city congestion in polycentric cities and concluded that congestion can't be resolved without transit that is not constrained by traffic: buses running in mixed traffic, the primary form of transit in most American cities, are not sufficient.

In addition, the significance of employment centralization may depend on the city: Merlin (2016) studied changes in transit and automobile accessibility of neighborhoods in four American metro areas between 2000 and 2010 and found that in some cities, changes in employment centralization made little difference, while in others, both centralization and decentralization sometimes correlated with transit accessibility. Another study, by Brown and Neog (2012), found no relationship between the strength of CBDs and transit ridership in metropolitan areas of greater than 500,000 people after controlling for other factors.

Residential density and employment density are more complements than substitutes: people need to be able to travel between home and work easily and, unlike with shopping or other errand destinations, they cannot generally simply rely on commuting to the closest employment district. However, by allowing work commutes to be served more easily by transit, job clustering can encourage a less automobile-dependent lifestyle.

It is important to keep in mind, though, that trips to work are not the only important type of transit trip, and that American public transportation providers have a history of neglecting other types of trips, such as travel for shopping and education. Because of the importance of non-work destinations, calculating the activity density of a neighborhood by adding the number of jobs and residents in a neighborhood without considering the shares of residential and various commercial uses—the mixture of uses called for by Jacobs and others—is overly simplistic for understanding walkability.

4.1.3 Mixed Land Uses and Walkable Street Networks

In addition to density, mixed land uses and walkable street networks also play an important role in encouraging public transportation use. A particularly detailed study in of Washington Metrorail stations in Montgomery County, Maryland by Cervero (2001, 2002) found that land-use diversity had the largest positive impact on transit ridership of the factors studied, followed by density, and well above measures of the street network's amenability to walking. However, Cervero also found that the presence of continuous sidewalks and the dimensions of streets played a major role in determining whether reached particular stations on foot or not.

On the other hand, Seskin et al. (1996, Ch. 2) suggested that land use diversity, while useful, was less important than job and population densities in driving transit ridership. They also suggested that street and sidewalk connectivity are important for transit ridership, but found the effects hard to quantify.

A meta-analysis by Ewing and Cervero (2010) found that the most important features for increasing transit usage, after distance to transit, were the density of streets and intersections and the percentage of intersections that were four-way rather than three-way. In addition, Grosvenor and O'Neill (2014) explicitly positioned themselves in opposition to Newman and Kenworthy (2006), arguing that a focus on density to the exclusion of location, accessibility, and other design characteristics may actually be leading to poorly-located and designed developments that encourage car use.

4.2 What is good transit service?

No matter how well-suited a metropolitan area may be for public transportation, its transit ridership also depends on the existence and quality of the public transportation that is actually provided. While there is no simple definition of what constitutes good or sufficient public transportation, a review of recent transit planning literature suggests three particular traits as important: long hours of operation, high frequencies, and rapid speeds with good reliability of travel time.

4.2.1 Hours of Operation

At the risk of stating the obvious, transit service is only useful when it is available. While some American transit systems—most famously, the New York City Subway, but more often bus networks—do operate twenty-four hours a day, it is much more common for service to be limited to times when higher ridership is anticipated. At a minimum, service during commuting peaks for "nine-to-five" office workers is nearly always provided, while mid-day, evening, and weekend services are less often available.

However, while peak-only transit service may help get commuters off of roads at the most-congested times of day, it cannot provide a complete alternative to driving and car ownership. Furthermore, even if we limit our consideration to work trips, non-peak service is particularly important for the economically disadvantaged.

Legrain et al. (2015) observed that transit availability outside of peak periods is essential, and often not considered in studies measuring transit ridership. In particular, they found that low-wage workers have very different transit needs from their higher-wage counterparts, and are more likely to need non-peak transit service and service to locations other than the downtown core, results that are echoed by Lubitow, Rainer, and Bassett (2017).

In addition to work journeys, transit is essential for errands, shopping, and care-related journeys: journeys that are more likely to happen during evenings and weekends, or at mid-day on weekdays. Furthermore, these sorts of journeys are particularly commonly performed by women (Galicia, Higueros, and Khanna, 2019; Lubitow, Rainer, and Bassett, 2017; Plyushteva and Schwanen, 2018). Although some transit agencies have recently suggested that "ride-sharing" companies such as Uber and Lyft can substitute for transit during these lower-ridership periods, Jin et al. (2019) found that they were not effective substitutes for low-income and minority riders, and that their presence actually worsens transportation inequity.

Leaving aside equity concerns, a number of authors have noted that providing non-peak service results in significant ridership increases. Evans (2004) found that increasing on hours of operation generally has a significant effect on ridership. In particular, they noted that adding later evening service can increase ridership at other times of days by offering riders a guarantee that they will not be stranded.

A more-detailed study carried out in Australia by Currie and Loader (2009) found very large ridership increases from adding additional service: the addition of weekend hours showed elasticities of more than 0.8 and the addition of evening service led both to large ridership increases in evening hours and to equal increases in daytime ridership. They also found that weekends in particular need late-evening service, with significant fractions

(6-7%) of outbound trips before 5pm resulting in return trips after 11pm and concluded that service absolutely needs to last until at least 8pm, though there is significant value to continuing it at least until midnight.

Although adding hours of service does of course cost money, it can sometimes reduce the cost per rider, even if the added hours have lower ridership. This is because, as noted by Walker (2012, 80-83), peak-only service sharply increases costs, since the size of the fleet scales with peak service and since because peak service requires operators to work split shifts, which generally require higher pay. Increasing non-peak service requires more operator hours, but will generally not require more vehicles or other capital expenses.

Providing overnight service on at least the most important routes is a good goal for transit networks in major metropolitan areas. However, this can lead to some complications: while studying the unhoused in Santa Clara County, California, Nichols and Cazares (2011) found that in areas where 24-hour transit is available, many houseless people regularly use buses as overnight shelters. This was often an active choice despite knowing about other options, and women in particular often said they rode the bus overnight for safety. Awkwardly, other passengers—especially women—have reported (Galicia et al., 2019) that the use of buses as de-facto shelters for the unhoused makes them feel less safe using them, especially at night.

4.2.2 Frequency

The need to wait for a transit vehicle is one cost of using public transit that does not have a clear mirror in either automobile or active (walking and cycling) transport. Besides the direct addition waiting time makes to travel time, it is a particular concern because passengers tend to weigh it particularly heavily in making mode-choice decisions, overestimating wait time (especially if it is unpredictable), while accurately estimating in-vehicle travel time (Fan et al., 2016a,b).

Besides its effects on ridership, Lubitow, Rainer, and Bassett (2017) and Galicia et al. (2019) have noted that low frequency can be a particular issue for female transit users, both because women are more likely to “trip-chain,” riding to several destinations before returning home, and because low frequency at night can mean long waits at dark and isolated bus stops. Fan et al. (2016b) found that women in particular do overestimate wait times by especially large amounts at night and in perceived unsafe locations.

A number of studies Dziekan and Kottenhoff (2007); Gooze et al. (2013); Watkins et al. (2011) have shown that the presence of real-time arrival time information at transit stations can significantly reduce passengers’ perceived wait times. However, it is essential that this information be reliable—a particular difficulty for buses running in mixed traffic—as *inaccurate* real-time arrival time information significantly *increases* perceived waiting time above no arrival time information.

The costs of wait time can be multiplied by the need for transfers, since passengers have to wait for a vehicle at each transfer location. Jansen et al. (2002) and (Walker, 2012) note that transfers are generally unpopular with riders because they cost time (both wait time and often travel time caused by having to go out of one's way), but they are essential for designing functional transit networks.

As a result, it is important to design systems to reduce the costs of transfers for riders. This can include optimizing stations and schedules to ease transfers and should involve fare structures that do not penalize them. However, higher frequencies are also an important part of this, since they ensure that even if a connection is missed, another vehicle will be coming soon.

Although techniques such as improving station amenities by adding seats, shelters, lights, and real-time arrival time estimates can make transit riders more willing to endure waits (Fan et al., 2016b), the only way to actually reduce wait time is to provide service with shorter headways (waits between vehicles) and higher frequency. As detailed by Grosfeld-Nir and Bookbinder (1995) headways have historically been set to reduce congestion, with a goal of ensuring that transit vehicles are never so overcrowded that passengers are left behind at stations.

Because operation costs tend to be directly related to frequency, especially for bus service, there has been a tendency to assume that the optimal frequency for transit is the lowest frequency that does not lead to severe overcrowding. However, a number of studies have found that ridership elasticity for frequency is quite high, *particularly* on low-frequency routes where wait times are long.

Forty years ago, Lago et al. (1981a,b) reviewed the literature on calculations of frequency elasticities on bus routes and found values as high as 0.7 on low-frequency routes. More recently, Evans (2004) found elasticities between 0.3 for urban transit and 1.03 for regional rail with lower frequencies and Brown and Neog (2012) reported an elasticity of between 0.76 and 0.91 between commuter mode share and average system-wide frequency for transit in US metropolitan areas of at least 500,000 people.

While an avoiding-overcrowding approach would focus primarily on supplying higher frequencies during weekday rush hour, when crowding is most often an issue, Paulley et al. (2006) reported that studies in Europe have found higher frequency elasticities on weekends, when frequency is lower. A study of ridership on Minneapolis-St. Paul's MetroTransit by Totten and Levinson (2016) found an elasticity of 0.39 between rush hour ridership and frequency and mid-day ridership and frequency on weekdays, but with little or no connection between the two. The authors also reported that ridership on weekends was more interconnected, with increased frequency on either Saturday or Sunday increasing ridership on both days.

Although frequency elasticity studies confirm that increasing frequency, especially on low-frequency routes, will have a significant effect on increasing ridership, they do not provide a clear answer to the question of *how* frequent a transit line needs to be to reasonably qualify as "good." Two recent studies of urban rail transit in Europe may give a hint of this, though. Both Luethi et al. (2007) in Zurich and Ingvardson et al. (2018) on the Copenhagen Metro analyzed how much before the next train passengers arrived at stations.

Luethi et al. (2007) found that, for lines with headways as short as 5 minutes, half of passengers still arrived based on the schedule, rather than than at random, while Ingvardson et al. (2018) estimated this threshold as occurring at a headway of 10 minutes. In either case, this suggests that rather short headways are needed to encourage passengers to discount concern about wait time completely. However, it should be noted that both studies found that the fraction of riders who did not take the schedule into account increased on weekends, suggesting that spontaneous travel, as opposed to regularly scheduled commutes, have somewhat higher thresholds.

Furthermore, both studies were performed on European rapid transit systems with very high on-time reliability. On systems, such as urban buses running in mixed traffic, with lower schedule reliability, passengers may be less inclined to make travel decisions based on scheduled arrival times.

Surveys of American bus riders (Higashide and Accuardi, 2016; Higashide and Buchanan, 2019) corroborate the idea that headways of roughly 10 minutes are significantly more appealing to riders than longer headways: after a halving of ride length, the most popular transit improvement for bus service was a reducting in headway from 20 minutes to 10 minutes. Although 15 minute headways are the most common definition of "frequent service" for American transit networks (Spieler, 2018, 26-27), Higashide (2019, 23-27) argues that this is insufficient, and should be treated as a floor for frequency.

High frequencies that make transit always available without consulting a schedule may be particularly important to help local transit avoid losing ridership to ride-hailing services, which have recently served as a replacement for transit for an increasing number of riders, especially on social/leisure trips where short wait time is particularly valued because riders are less likely to be following a regular, fixed schedule. It is also notable that ride-sharing is particularly heavily used during evening hours when many transit systems operate at lower frequencies, making the wait time difference more pronounced (Clewlow and Mishra, 2017; Gehrke et al., 2018, 2019; Rayle et al., 2016).

The loss of transit ridership to ride-hailing services reduces fare-box revenue and makes it more difficult for transit agencies to maintain high frequencies for the benefit of those riders who cannot afford to use ride-hailing services. Furthermore, these services are leading to a substantial increase in vehicle miles traveled with negative consequences for both congestion and climate change (Erhardt et al., 2019; Wu and MacKenzie, 2021).

4.2.3 Speed and Reliability of Travel

While increasing the frequency of public transportation service reduces the time passengers have to wait for a transit vehicle, it is not the full story: to make public transportation competitive with driving for most passengers, the transit vehicles themselves need to travel quickly. Ideally, they would be able to travel significantly faster than automobile traffic, since the need to wait for a transit vehicle and to walk from one's origin and then to one's final destination are time costs that drivers do not need to deal with.

While very high speeds for transit vehicles are possible in some cases, particularly regional rail trains with long stops between stations, the need to have frequent stops constrains the maximum speed of most urban transit. On the other hand, large metropolitan areas tend to have significant road congestion, especially during peak travel times, so transit modes, such as rapid transit, that do not share road space with automobiles can have a significant speed advantage (Vuchic, 1999, Ch. 2).

An additional advantage of transit modes that are completely grade-separated from automobiles, or at least have their own travel lanes, is greater reliability, since travel time is not dependent on unpredictable road congestion. This can, itself, be quite important, as noted by Bowman and Turnquist (1981), who found that schedule reliability was more important for passengers than frequency on services with longer headways. Once-every-half-hour service is much less inconvenient on a regional train that consistently keeps its schedule than on a bus with travel times that depend on how much traffic it gets stuck in.

As for the question of how fast transit needs to be, that depends on a city's level of traffic congestion, the sorts of trips that it is used for, and the distances riders need to travel to make these trips. For commuting trips, Schwanen and Dijst (2002) found that Dutch commuters averaged half an hour each for travel to and from work, consistent with Marchetti (1994)'s work on daily travel times across cultures. The acceptable time for other sorts of trips depends, among other things, on how frequently they are made: people will readily make more time available for a trip if it happens monthly or yearly than if it is a daily or weekly necessity.

Since travel time often seems fixed by infrastructure or by factors, such as traffic, outside a transit agency's control, there have not been many studies on the elasticity of ridership with respect to travel time for public transit. However, literature reviews by Lago et al. (1981a,b) found speed elasticities as high as 0.85 for bus service, with lower values for (generally more reliable and faster) rapid transit service.

However, while building new grade-separated rapid-transit or light rail with its own right-of-way is very expensive and generally only an option for the highest-potential routes, the construction of bus lanes and the use of transponders to give buses priority at intersections provide cheap options to increase the speed and reliability of bus service by making it no longer constrained to the speed of general automobile traffic. Speeding boarding by having off-board fare collection and proof-of-payment fare enforcement rather than making each passenger pay the driver as they board can also help with this (Danaher et al., 2007; Spieler, 2018).

Improving the speed and reliability of bus service has the additional benefit that, unlike running more buses to increase frequency or period of service, it can actually lower operational costs, since fewer vehicles are needed to maintain the same level of service if they can complete a route more quickly. The need to improve bus service in this way by building many more bus lanes and speeding boarding has been the focus of a major push in transit planning recently, and is discussed in detail by Walker (2012, 97-107) and Higashide (2019, 39-58).

4.3 What is Needed for Transit Service to be Equitable?

While high frequency, long hours of service, and rapid speed of travel are all important considerations in determining whether transit service is "good," they are not always sufficient to ensure equitable service for all members of the community. For this reason, it is important to consider what features a public transportation network needs to have to ensure that it effectively serves more-vulnerable members of the community.

4.3.1 Access for the Disabled

Public transit access is particularly important for people with disabilities, both because many disabilities make it more difficult or impossible to drive, and because being disabled tends to correlate with a lower income and higher expenses (Imrie and Wells, 1993) that make it more difficult to own a car. Unfortunately, though, many transit systems have features that make them inaccessible to disabled populations, including a lack of step-free access to vehicles and insufficient space for both mobility devices and strollers in vehicles (Lubitow, Rainer, and Bassett, 2017).

Transit agencies in the United States have made significant improvements in accessibility for people with mobility impairments in recent years, including the replacement of high-floor buses with low-floor buses with ramps that make it possible to use wheelchairs without a special lift. Many of these improvements have been beneficial to abled passengers as well: for example, low-floor buses lower general passenger boarding and alighting time by about 15%, thus reducing bus dwell time at stops and speeding up overall service (Levine and Torng, 1994). On the other hand, other potential improvements, such as reducing the distance between bus stops to give disabled people shorter walks to destinations, reduce service quality for other passengers, in this case by slowing down bus service.

For rail systems, however, replacing rolling stock is not enough: stations often need to be renovated to add elevators and ensure level boarding from platform to train. Unfortunately, these renovations are expensive and larger systems such as New York often do not perform complete retrofits. Ferrari et al. (2014) found that even the fairly ambitious retrofit of the London Underground performed by Transit for London from 2006 to 2014 left riders who could not climb stairs with trips that were often twice as long as available to other users.

It is also important to keep in mind that mobility impairments are not the only disabilities that can limit a person's ability to use transit, and that can be accommodated by improvements to vehicle and transit facility design (Levine, 1997). For example, Jones and Jain (2006) discussed a variety of barriers that make it more difficult for visually impaired passengers to use rail stations in the United Kingdom.

In the United States, the Americans with Disabilities Act of 1990 requires accessibility for people with certain impairments in all new and renovated transit facilities, and also requires the provision of paratransit service (point to point shuttle service provided on demand with small vans) for all individuals who are unable to use regular transit service because of their disabilities. The high cost of providing paratransit service provides one motivation for transit agencies to make their regular transit service as accessible to people with disabilities as possible (Levine, 1997).

Despite the high costs of provision noted by Fei and Chen (2015), Nguyen-Hoang and Yeung (2010) found that paratransit service is essential, as it is often the *only* means of transportation available to a significant fraction of the population. Still, as noted by Levine (1997), making regular transit accessible to more riders is beneficial both because it reduces the costs of providing paratransit in the long term and because paratransit's requirements for trips to be scheduled in advance impose a significant downside for paratransit users.

4.3.2 Affordability

People with low incomes are another group that benefit disproportionately from public transit, since automobile-based transportation is often too expensive for them to access. However, high fares can pose a significant barrier to their use of transit. Furthermore, low-income commuters often make different types of trips—in terms of times of day and destinations—than higher-income commuters, and so transit service optimized to the needs of the latter may not effectively serve the former. Unfortunately, government efforts to alleviate these problems have been sporadic and inconsistent (Sanchez, 2008).

Since no transit system in the US serves the entirety of its metropolitan area with high-quality service, part of the price of riding transit is the price of living and working in neighborhoods that are well-served by transit. For a transit system to be truly affordable, it is essential that it provide good service to low-income residential areas, and to low-income jobs.

Ironically, improvements to transit can feed gentrification, producing a situation where attempts to improve transit for low-income riders actually prices them out of areas with good transit. Besides the obvious economic harm this causes, it is also socially harmful (Sandoval, 2018) and may actually increase carbon release as richer people with more energy-intensive lifestyles move into dense areas (Rice et al., 2020). This does not mean that providing transit to low-income areas is unimportant, but it does mean that efforts need to be made to ensure that these areas remain affordable.

In addition to serving low-income areas, transit systems need to adopt fare policies that do not make transit inaccessible for substantial portions of the population. This means funding transit sufficiently that basic fares can remain low, and it also means avoiding charging excessively high fares for certain services—as is common with American commuter rail services—that essentially turn them into a parallel transit system for the well-off.

Many transit systems provide discounted fares for certain groups perceived to be low-income—students, disabled people, and the elderly, in particular—but, as pointed out by Lipscombe (2016, 44-48), these mechanisms do not always effectively target low-income riders. An alternative would be reduced fares for low-income people, but this would potentially require a significantly larger bureaucracy for verification.

One method that many transit systems use to reduce costs for regular riders is to sell weekly or monthly unlimited ride passes at a cost lower than many riders would pay if they made all their trips at full fare. However, Lubitow, Rainer, and Bassett (2017) and others have noted that these passes disadvantage the lowest-income riders, who are often unable to save up enough cash to pay for these passes in advance, and so have to purchase single-trip tickets, even though the overall cost is higher.

One alternative, described by Streeting and Charles (2006) and Lipscombe (2016, 43-44), is the "fare-capping" system introduced for public transit in London in 2005. Rather than purchasing a pass in advance, riders use a farecard that caps the total fare paid for trips in a one-day, one-week, or one-month period at a maximum level, no matter how many trips are made. Another technique, described by Chalabianlou et al. (2015), is to cap payment at a certain number of trips, regardless of the total fare paid.

Such a system avoids the need for a lump-sum payment in advance, and also eliminates the requirement that passengers predict in advance how much they will use transit in the future, a prediction that is especially difficult for those with more precarious and unpredictable income and work schedules. Furthermore, since women are more likely to own transit passes than men (Vance and Peistrup, 2012), making transit passes more easily affordable in this manner could be of particular value to low-income women. However, a combination of inertia and the fact that it requires a significantly more complex ticketing system has slowed its spread.

A final, and concerning, issue is the response of some public transit systems to the rise of "ride-sharing" services like Uber and Lyft. There have been arguments made that these services improve transportation equity and can be used to justify eliminating low-ridership services. However, Jin et al. (2019) found that, in New York City, Uber provides no significant equity benefit and the distribution of Uber services is highly unequal.

4.3.3 Fare Enforcement and Racial Injustice

One obvious racial justice concern for US transit agencies, given the high level of segregation in American cities, is the degree to which they do or do not effectively serve minority neighborhoods. Disinvestment in transit over the course of the 20th Century often left cities with transit that primarily served low-income communities with low rates of car ownership, while avoiding higher-income neighborhoods where transit was seen as bringing in undesirable elements.

However, recent attempts to improve transit networks, such as the construction of the Los Angeles Metrorail system, have raised objections that new improvements are primarily targeted at richer, white areas while leading to disinvestment in existing service to minority neighborhoods (Mann, 1997). In their survey of transit-dependent riders in Portland, Oregon, Lubitow, Rainer, and Bassett (2017) observed similar concerns: a number of the riders interviewed reported that bus stops have more amenities on routes that white commuters tend to use than ones black commuters tend to use, and that transit often fails to serve minority and low-income residential areas and employment sites at the hours needed to allow commutes to work.

Lubitow, Rainer, and Bassett (2017) also recorded significant concerns about racial profiling by transit employees, and particularly transit police, as well as difficulties caused by the transit agency (TriMet) not providing important information in minority languages and not having employees able to communicate in these languages.

A particular issue is raised by proof-of-payment fare collection, where passengers do not have their tickets checked at the start of a journey, but are instead subject to random fare inspections while on-board vehicles or in a "proof-of-payment" zone at stations. This approach is increasingly popular with transit agencies because it dispenses with the need for expensive fare gates and allows for faster boarding and shorter dwell times than having drivers check all fares on entry (Cummins et al., 2012; Currie and Reynolds, 2016). Furthermore, switching from payment-at-entry to all-door boarding with proof-of-payment does not seem to increase fare evasion on bus networks (Lee and Papas, 2015).

While proof-of-payment systems have practical benefits, it is important to recognize that their requirement for random fare inspections does pose a risk of racial profiling and of creating a hostile environment for people of color, who often feel less safe with law enforcement and civilian security agents (Camacho, 2017; Lubitow, Rainer, and Bassett, 2017; Renauer, 2018).

In recent years, some transit agencies have recognized that having an overly-punitive approach to fare evasion can lead to both employee stress and passenger fear, and have looked to having a broader understanding of why passengers evade fares (Delbosc and Currie, 2019). On the other hand, there has been a recent spurt of American transit agencies focusing on fare evasion as a major concern and cracking down on it just as Black Lives Matter protests have brought concerns about police brutality and bias into the public eye.

In addition to these issues, and complicating them, Liévanos et al. (2019) noted that public input surveys from US transit systems often get disproportionately low response rates from people of color, leading to a situation in which transit agencies may be unaware of the degree to which they are failing these riders.

4.3.4 Safety for Women and the LGBT Community

Riding public transit potentially raises one's exposure to harassment or violence for the simple reason that it increases one's contact with other people compared to traveling by private automobile. This can pose a particular concern to women and members of the LGBT community because these groups tend to be at particular risks of violence and harassment in public places.

The majority of women, but not men, reported that safety was a top concern for them in deciding whether to ride transit in Los Angeles, and only 20% of women reported feeling safe riding the system after dark. However, women and men who do not ride transit generally perceive it as less safe than those who do ride it (Galicia et al., 2019).

Some of the safety issues often noted by women can be fixed with improved infrastructure: both Galicia et al. (2019) and Lubitow, Rainer, and Bassett (2017) noted that lack of lighting and shelter at bus stops led to safety concerns for riders, and particularly women, at night. Likewise, long wait times reduced the perception of safety, providing an additional argument for higher frequency, especially in the evenings. Furthermore, the fact that many bus routes do not run late at night often forces riders to walk longer distances to bus stops at exactly those times of day when it is least safe for them to do so.

Low frequencies can be a safety problem during the day as well. Besides potential issues of safety waiting for the bus, routes run with insufficient frequency during the day can be overcrowded and, as noted by Lubitow, Rainer, and Bassett (2017), crowding on buses and trains can increase the risk of theft, harassment, and sexual assault.

Participants in Galicia et al.'s study of transit riders in Los Angeles expressed concern that transit system employees do not intervene when they observe harassment, and also observed that the lack of resources for those experiencing houselessness and mental illness can lead to transit serving as shelters-of-last-resort and being the sites of unpredictable and unsafe behavior. Increased police presence on transit was also suggested by many riders, and particularly female riders, two-thirds of whom felt that too few police officers are present on transit vehicles and in stations.

The same safety issues that are present for women on transit are often serious concerns for lesbian, gay, bisexual, and particularly transgender transit riders. Lubitow, Carathers, Kelly, and Abelson (2017) interviewed transgender people who ride transit in Portland, Oregon and found that trans people—particularly trans people of color—experience, and so anticipate, higher rates of harassment, discrimination, and violence on public transit.

The authors recommended that transit agencies needed to provide more training to employees about sensitivity towards the transgender community, and about the importance of responding to harassment and not treating trans people as presumed sources of "disruption." On the other hand, the trans people, and particularly trans women of color, they interviewed were strongly opposed to increased police presence as a way to potentially improve safety. Additionally, both Lubitow, Carathers, Kelly, and Abelson (2017) and Benner (2016) recommended that gender identity and expression be explicitly included in transit agency non-discrimination policies.

4.4 Preliminary Public Transportation Analysis

Properly studying the differences between public transportation ridership and service in US metropolitan areas, and the sorts of neighborhoods that do and do not require high-quality service would be a research project at least as ambitious as this one. However, I have performed a preliminary analysis of the relationship between the results of my metro area and neighborhood typologies and the largest American public transportation systems.

In Section 4.4.1, I discuss the difficulty of measuring transit ridership at a metropolitan and neighborhood level and identify thirty-eight metropolitan areas with at least 4% of their workforce commuting by public transportation. I find that these metro areas fall into four main categories: college towns, very small tourist towns, commuter suburbs, and major metropolitan areas.

Next, in Section 4.4.2, I analyze and discuss one of the categories—the sixteen major metropolitan areas with relatively high transit ridership—with a focus on the relationship between transit ridership and job concentration. I continue this line of inquiry in Section 4.4.3 with a discussion of the relationship between transit ridership and residential concentration.

In Section 4.4.4, I explore public transportation in several of these high-ridership metro areas in more detail by comparing maps of their rail transit service to the maps of high-density neighborhoods that I developed and used for my metro area clustering analysis in Section 3.2. Finally, in Section 4.4.5, I briefly investigate the median densities at which carfree households and workers who use of transit to commute to work live.

Maps associated with the discussion in Section 4.4.4 can be found in Appendix L while additional tables associated with the analysis in Section 4.4.5 can be found in Appendix K

4.4.1 Types of Metro Area with High Transit Ridership

In most of the United States, a car and a driver's license are *de facto* requirements for full participation in society. Public transportation, when available, operates infrequently, during limited hours of service, and along relatively indirect, winding routes. There are three main exceptions to this rule: college towns where campus shuttles or public buses provide service to a large population of students without cars, a few small towns in rural areas with mostly tourism-focused economies, and a handful of major metropolitan areas, most of which are located on the coasts.

The simplest and most common approach to identifying such metro areas and comparing their transit usage—as well as for identifying the neighborhoods whose residents make the most use of transit—is to use American Community Survey (ACS) data on the fraction of the workforce that uses public transportation to commute to work. This approach has two major shortcomings, however. First, it does not clearly distinguish commuters who drive to a park-and-ride station before taking a commuter train or bus to work from those whose entire commute is conducted by public transportation.

Second, and more seriously, it privileges commutes to work—the commute type that US transit agencies tend to serve the best—while neglecting travel for other purposes that plays an essential role in a carfree lifestyle. This can also pose a gender equity problem since, as Lubitow, Rainer, and Bassett (2017) and Galicia et al. (2019) both note, women are particularly likely to be responsible for shopping, errands, and other care trips that are excluded by measuring transit ridership solely in terms of commutes.

For a more-complete study of transit ridership patterns in American metro area and neighborhood types, it would be useful to construct more complete measures of transit ridership based on transit agency system-wide and route or station-specific ridership data. This would, however, be a necessarily piecemeal approach, with data collected and processed separately for each metro area under consideration. For the purposes of this preliminary survey, ACS commute share data will have to suffice.

According to 2018 American Community Survey data, thirty-eight metropolitan areas have at least 4% of their workforce commute by public transportation on a regular basis. Of these, ten are medium or small metro areas dominated by a college or, in the case of Rochester, MN, by the Mayo Clinic; the largest such metro area is Ann Arbor, MI with 366,000 residents. Besides being special cases due to a single dominant employer, these metro areas are difficult to study based on my LODES-based jobs data, since many state university jobs seem to be missing from or misclassified in the LODES datasets.

Another seven of the metropolitan areas with relatively high transit commuter shares are small metro areas that appear to have economies largely driven by tourism: none have over 80,000 residents and four have 40,000 or fewer. While it is why this sort of metro area would be prone to high transit usage, their small populations may make statistical data less reliable.

Table 4.1: Minor Metro Areas with ≥4% Transit Commute Share

Metro Area	**Population**	**% Transit Commuters**	**Type**
Bridgeport, CT	944,000	10.0%	Commuter
Bremerton, WA	262,000	8.9%	Commuter
Trenton, NJ	369,000	7.6%	Commuter
Atlantic City, NJ	269,000	6.2%	Commuter
East Stroudsburg, PA	168,000	4.3%	Commuter
New Haven, CT	859,000	4.1%	Commuter
Elko, NV	54,000	13.8%	College
Ames, IA	97,000	6.5%	College
Ithaca, NY	103,000	6.5%	College
Champaign-Urbana, IL	239,000	5.6%	College
State College, PA	161,000	5.4%	College
Ann Arbor, MI	366,000	5.2%	College
Iowa City, IA	169,000	4.9%	College
Boulder, CO	321,000	4.7%	College
Pullman, WA	49,000	4.7%	College
Rochester, MN	216,000	4.3%	College
Winnemucca, NV	17,000	12.4%	Tourism
Clewiston, FL	40,000	7.6%	Tourism
Glenwood Springs, CO	76,000	6.9%	Tourism
Edwards, CO	54,000	5.1%	Tourism
Juneau, AK	32,000	5.0%	Tourism
Breckenridge, CO	30,000	4.9%	Tourism

Finally, five of the high-transit metro areas are commuter rail or ferry suburbs of New York, Philadelphia, and Seattle, and have transit ridership that is significantly driven by commutes to these adjacent metro areas[1]. Since their transit commutes largely consist of travel to another metro area, these metro areas' transit commute shares cannot be explained in terms of their job and population density characteristics alone. The college-town, tourist-town, and commuter-suburb metro areas with transit ridership above 4% are shown in Table 4.1 on page 230.

After these metro areas are removed from consideration, there remain sixteen major metro areas—shown in Table 4.2 on page 232—with transit commute shares over 4% that are not largely the result of single large employers or employment in nearby metro areas. However, there is significant variation in the transit commute shares of these metro areas. At the high end, New York has nearly twice as large a faction of workers commuting to work by public transportation (31%) as the second-place metro area, San Francisco (17%). The next three metro areas—Washington, Boston, and Chicago—have transit commute shares between 12% and 14%, roughly three quarters of the commuter share in San Francisco. These five metro areas, along with the following three—Seattle (9.8%), Philadelphia (9.5%), and Honolulu (8.4%)—make up the set of eight metro areas that Levy (2019) has described as having significant public transportation; the next highest transit commute shares, 6.5% in Portland and 6.3% in Baltimore, are only three-quarters of the transit commuter share in Honolulu.

[1] East Stroudsburg, Pennsylvania is something of a special case, as it does not have a direct transit link to New York. Historically, the metro area—which is located in the Poconos—had a tourism-driven economy. However, the population increased by 70% from 1990 to 2010 and many of the new residents commute to New York via New Jersey Transit commuter rail lines that reach most of the way to the Delaware River. Roughly 5% of workers living in the East Stroudsburg MSA work in New York City—more than the fraction of workers living in East Stroudsburg who commute by transit.

Table 4.2: Major Metro Areas with $\geq$4% Transit Commute Share

Metro Area	% Transit Commuters	CBD Jobs	High Density Jobs	CBD and High Density Population	Medium Density Population
New York	31.0%	24.4%	5.0%	35.9%	14.3%
San Francisco	17.1%	13.9%	10.3%	9.8%	20.4%
Washington	13.6%	8.2%	17.6%	4.6%	8.2%
Boston	13.3%	7.8%	12.4%	7.8%	16.3%
Chicago	12.1%	12.5%	5.3%	6.0%	15.9%
Seattle	9.8%	7.2%	11.0%	2.7%	5.2%
Philadelphia	9.5%	4.7%	8.6%	5.1%	15.8%
Honolulu	8.4%	8.2%	13.9%	11.5%	10.6%
Portland	6.5%	0.0%	10.8%	1.1%	2.8%
Baltimore	6.3%	2.0%	10.4%	1.6%	7.6%
Pittsburgh	5.6%	4.2%	9.8%	1.1%	2.4%
Los Angeles	5.1%	3.0%	11.7%	5.6%	25.8%
Minneapolis	4.7%	3.3%	10.0%	1.1%	4.0%
Madison	4.4%	0.0%	2.9%	3.5%	2.5%
San Jose	4.2%	2.5%	12.4%	0.8%	12.6%
Denver	4.2%	1.8%	12.1%	1.1%	3.9%

4.4.2 Transit Commute Share and Job Density

At a first glance, it is impressive how well the list of metro areas in Table 4.2 matches with my job-distribution clusters from Section 3.2.1. Transit ridership is the highest by far in the one cluster 1 metro area, New York, which also has nearly twice the CBD-density job concentration of any other metro area. The next five highest transit commute shares are in my five cluster 2b and cluster 2c metro areas—San Francisco, Chicago, Boston, Washington, and Seattle—with the one cluster 2a metro area—Honolulu—taking seventh place.

The remaining nine metro areas, with transit commuter shares between 6.5% (Portland, Oregon) and 4.2% (Denver), are made up of my seven cluster 3a, 3b, and 3c metro areas, plus Portland and Madison, Wisconsin. The only metro areas from clusters 1, 2, and 3 that do not make the list in Table 4.2 are the three cluster 3d metros—Austin, Houston, and Charlotte—which have lower total CBD and high-density job shares than any of the metro areas on the list. They are also the only metro areas with more than 1.8% of metro area jobs at CBD densities on the list.

Furthermore, among the sixteen major metro areas with greater than 4% transit commuter share and the six additional major metro areas with at least some jobs at CBD densities, plotting the percentage of workers who commute by public transit as a function of the percentage of jobs at CBD densities gives a linear fit with an elasticity of 1.12 and $R^2 = 0.885$, as seen in Figure 4.1 on page 235. This suggests that in cities with strong central business districts, every new job added to the central business district will add a new transit commuter: a result that makes sense given that these metro areas tend to have very congested CBDs with no room for additional parking or for more traffic at rush hour.

This is consistent with Levy's (2018) observation about the dependence of transit ridership in American cities on CBD strength, but contradicts the claim by Brown and Neog (2012) that there is no relationship between CBD strength and transit ridership. A likely explanation for this inconsistency is that Brown and Neog (2012) included all metro areas of at least 500,000 residents in their analysis and also separately considered small and medium, but not large, metro areas. Their explanation is that doing so was necessary to get large enough samples to be statistically valid. However, this means that the vast majority of the metro areas in their samples had very little job density and minimal transit ridership: the opposite of the conditions I am considering.

Furthermore, the definition of "CBD" used by Brown and Neog (2012)—the problematic 1982 Census Bureau definition discussed in Section 1.3.2—also seems to be deeply at odds with mine, as they report that New Orleans had the strongest CBD in the country in 2000, with 10.75% of MSA employment, followed by Austin (10.03%), Louisville (9.48%), Jacksonville (8.44%), and Columbia, South Carolina (8.26%). While this is 2000 data, it seems very inconsistent with my results, given I found that that none of these metro areas except Jacksonville had any CBD-density neighborhoods at all. Given that the CBDs used by Brown and Neog (2012) are not necessarily particularly dense, their results say little about the connection between job concentration and transit ridership.

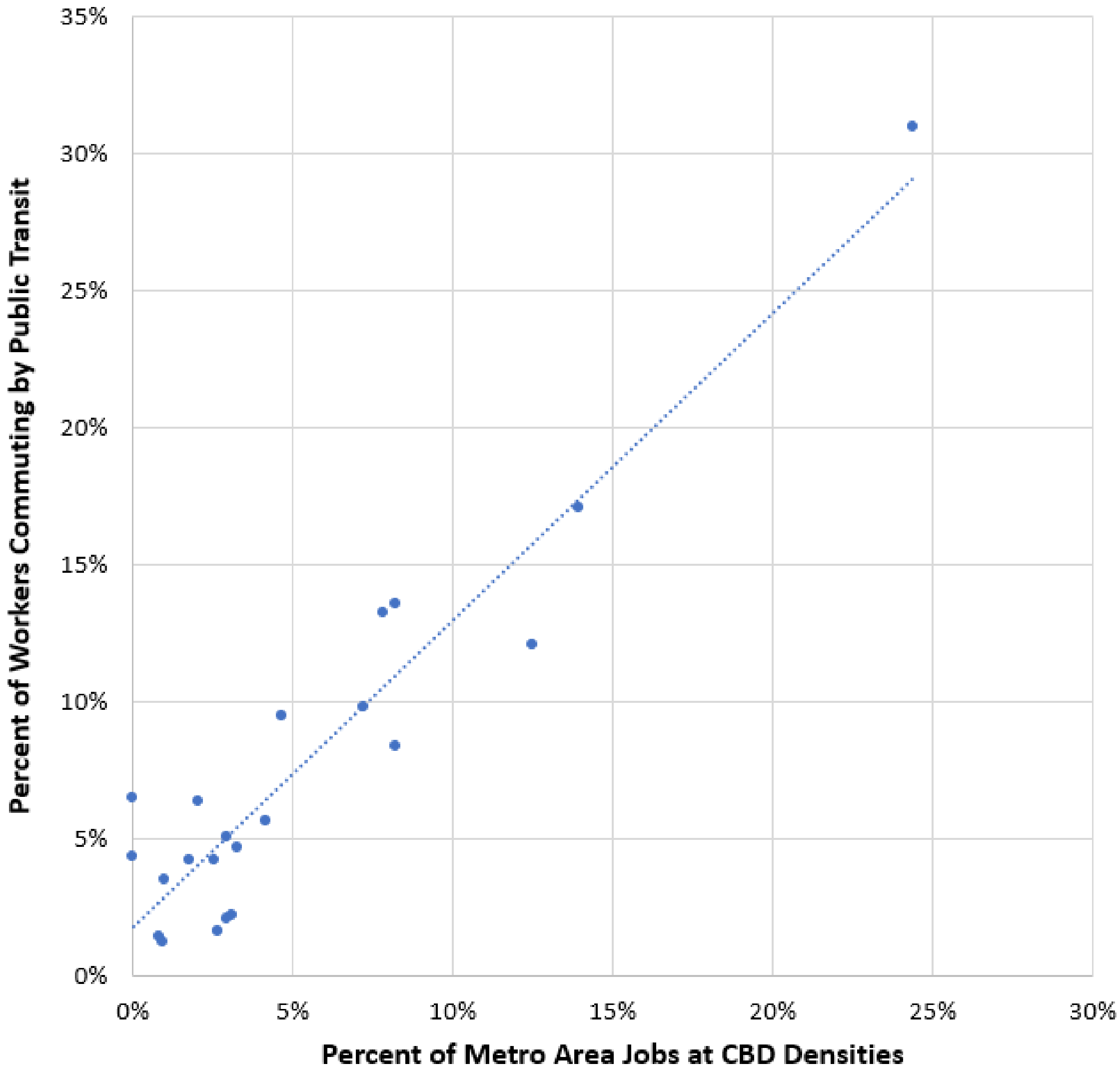

Figure 4.1: Transit commute share versus fraction of jobs in the central business district for major US metro areas with either at least 4% transit commute share or at least some jobs at CBD densities.

A significant part of the reason that very high job densities promote transit use is that at high densities, there simply isn't enough space for everyone to drive to work. Roughly four hundred square feet of paring lot space are needed to park each car; as density increases it first becomes much more expensive to provide this space (when multi-level parking garages become necessary) and then becomes essentially impossible in the densest urban districts (Garreau, 1992, 466).

Whether this price is passed on to workers—through parking fees—or covered by employers who provide free parking, significantly increases the cost of driving to a dense central business district and is part of the reason that downtown LA is able to have parking spaces for roughly one out of two workers, while the Chicago Loop has one parking space for every seven workers and Midtown Manhattan has roughly one for every seventeen (Moser, 2012). Limited parking, along with the traffic congestion when large numbers of office workers arrive and depart their jobs at the same times, essentially requires a large share of workers in dense CBDs to commute to work while the less-dense CBDs in most American metro areas contain plentiful parking and road space, allowing workers to drive to work with little added cost or inconvenience.

While having a large fraction of a metro area's jobs in a dense central business district clearly promotes transit ridership, it is clearly not the whole story behind Table 4.2. Among other things, Madison and Portland have no CBD-density neighborhoods, and Madison only has three percent of its employment in high-density neighborhoods. However, Madison is somewhat of a special case, as it has a relatively small population—

640,000 residents—and its major employers are the state government and a large public university, both employer types that are often inaccurately recorded in LEHD employment data.

4.4.3 Transit Commute Share and Population Density

Population density is perhaps the most common statistic used to explain why some cities are more suited to public transportation than others, so it makes sense to investigate if it could explain some of the pattern in transit ridership among the sixteen major metro areas discussed in Section 4.4.2.

A comparison of Table 4.2 on page 232 to my population-density clusters from Section 3.2.2 shows that transit ridership does not seem to correspond with these clusters as well as it does with the job-density clusters. Unsurprisingly, New York is again in a cluster of its own, cluster 1, with 36% of its population in high-density neighborhoods. However, while cluster 2 contains seven metros with between 4.6% and 11.5% of their populations in high-density neighborhoods, only six of these—Honolulu (11.5%), San Francisco (9.8%), Boston (7.8%), Chicago (6.0%), Philadelphia (5.1%), and Washington (4.6%)—are in the top eight major metros by transit ridership.

Seattle, which has a higher transit commute share than Philadelphia or Honolulu, is in cluster 3 with only 2.7% of its population in high-density neighborhoods. Nor can this be explained by a large population in medium-density neighborhoods: only 5.2% of Seattle's population lives in such neighborhoods, while the cluster 2 metro areas—with the exception of Washington, at 8.2%—have at least twice as large a share of their populations in medium-density neighborhoods. It is worth noting, as well, that Washington has the third-highest transit commuter share among the major metropolitan areas despite having the lowest shares of its population in both high-density and medium-density tracts among the seven cluster 2 metro areas.

On the other hand, Los Angeles—which, as discussed in Section 3.3.2, has one of the highest population densities in the country on a metro-area level—has a transit commuter share of only 5.1%, lower than Portland, Baltimore, and Pittsburgh. While Los Angeles only has 5.6% of its population in high-density neighborhoods—lower than Honolulu, San Francisco, Boston, and Chicago—this is higher than the fractions in Philadelphia (5.1%) and Washington (4.6%). Furthermore, a full 26% of Los Angeles's residents live in medium-density neighborhoods, the highest fraction in the United States.

The pattern that high- and medium-density population is relatively uncorrelated with transit commute share is visible at lower densities as well. Portland (6.5%) and Pittsburgh (5.6%) have moderately-high transit commuter shares even though the fractions of their population living at high or medium densities are 3.9% and 3.5% respectively. In comparison, San Diego and Miami have roughly half their transit commute shares (2.9% and 3.5%) despite having three times the population—11% to 12%—living at high or medium densities and having significant rail transit systems.

4.4.4 Public Transit Service and Neighborhood Types

One important factor influencing transit ridership that cannot be identified in metro area-wide job and population distribution data is the quality of the public transportation in a given metropolitan area. As discussed in Section 4.2, this has a number of components, including the hours of operation, frequency, and reliability of transit lines. While these factors are important and need to be carefully considered in a more complete study of the topic, they are too complex to treat here.

One component of the quality of transit service that can be addressed relatively briefly is the characteristics of the specific neighborhoods served. To that end, I have plotted rapid transit and light rail lines, along with a few significant bus rapid transit lines—using GIS shapefiles sourced from transit providers and local governments—on the neighborhood type maps discussed in Section 3.2.

Rapid transit and light rail lines were included, while commuter rail and bus services were generally excluded[2] because rapid transit and light rail lines usually operate with the highest frequencies and longest hours of service in metro areas, and so can be assumed to provide relatively good service. While some bus lines also operate with high frequencies and long hours of service in most or all of the metro areas under consideration, distinguishing these bus lines from others that do not in each metro area is a relatively large project.

[2] Denver's commuter rail lines are included because they—uniquely in the United States—operate at the same frequencies with the same hours of service and charging the same fares as the city's light rail lines.

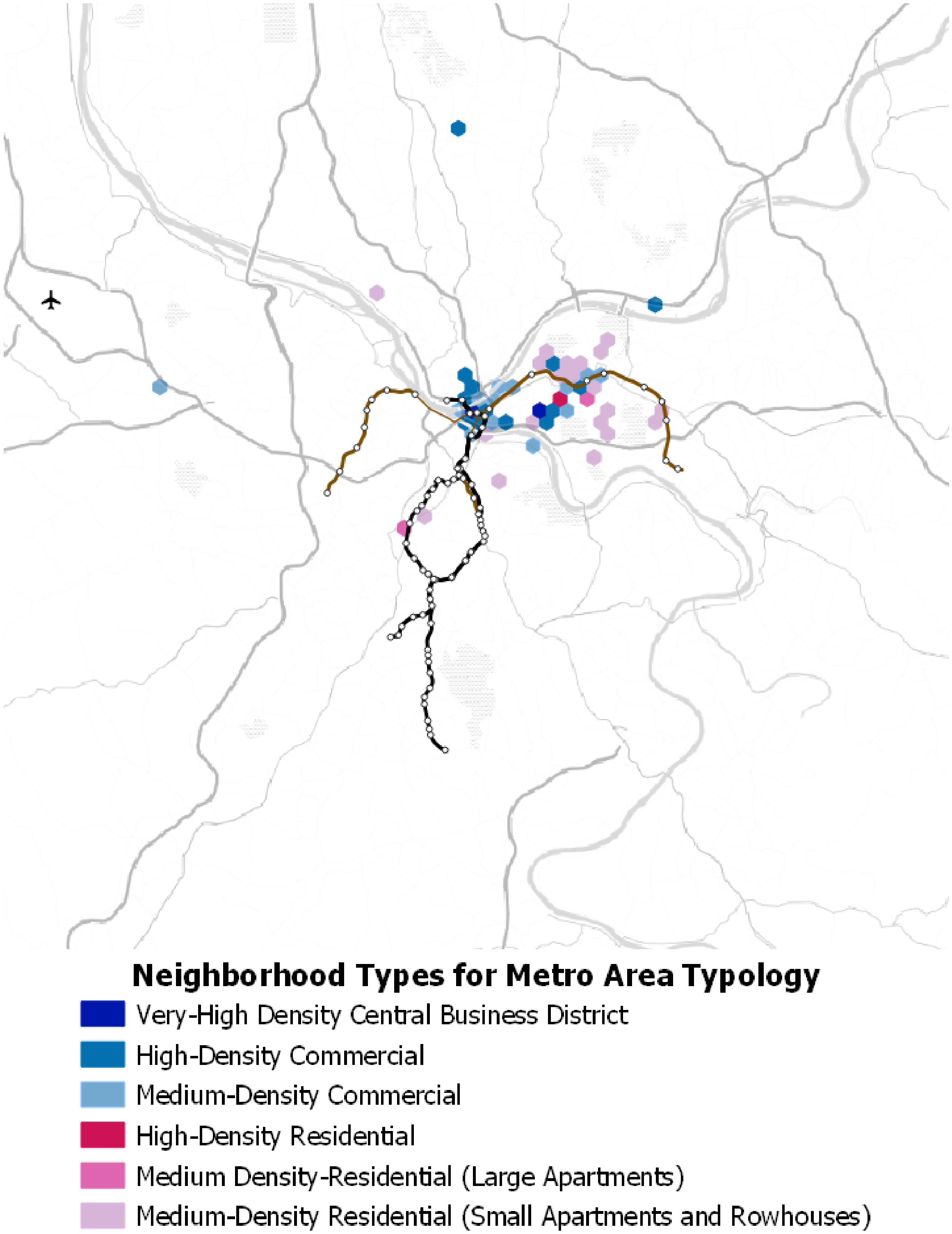

Figure 4.2: Light rail and bus rapid transit in the Pittsburgh metro area. Light Rail lines are shown with black lines; the West, South, and East Busways with brown lines. Note that all busways connect downtown via street running. The area shown is a 30-mile by 30-mile square.

Maps for the fourteen major metro areas with transit commute shares over 4% that have rail transit—Honolulu and Madison do not at present, though a light metro line is under construction in Honolulu—are presented in Appendix L. Here, I will discuss some specific examples that are particularly illustrative.

Pittsburgh (see Figure 4.2 on page 240) is an interesting metro area to consider for these purposes because it has a significantly lower transit commuter share than would be expected from the fraction of metro area jobs in its CBD. Pittsburgh has only slightly fewer jobs—4.2% versus 4.7%—at CBD densities than Philadelphia (see Figure 4.3 on page 242), and has more jobs—9.8% versus 8.6% at non-CBD high densities. Despite this, Pittsburgh has a transit commute share of 5.6% while Philadelphia's transit commute share is 9.5%. While part of this may be explained by population density—Philadelphia has roughly five times as large a share of its population living at medium or high population densities—the structure of Pittsburgh's employment distribution and transit network likely also plays a role.

Pittsburgh's two light rail lines and its West and South Busways serve low-density suburbs and, while the East Busway does pass through medium-density areas, its stops largely seem to be located just on their edges. Even more problematically, while Pittsburgh's light rail and bus rapid transit network converges on on the historic downtown at the confluence of the Monongahela and Allegheny Rivers, it fails to serve the city's densest employment cluster: the uptown neighborhood of Oakland, home to Carnegie Mellon University, the University of Pittsburgh, and technology companies such as Google that have located in proximity to the universities.

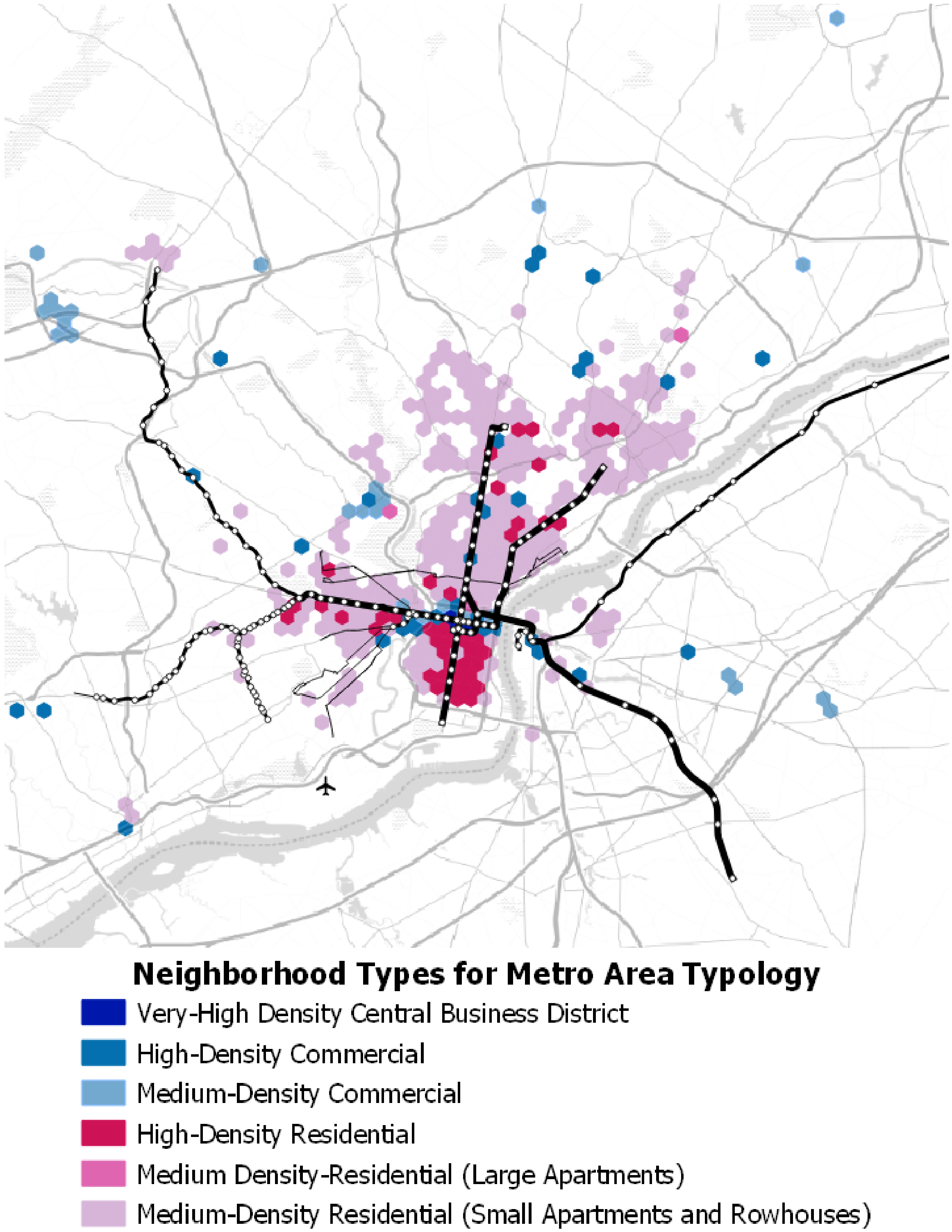

Figure 4.3: Rapid transit and light rail in the Philadelphia metro area. The Market-Frankford Line, Broad Street Subway, PATCO Speedline, and Norristown High-Speed Line are shown with thick lines; SEPTA and New Jersey Transit light rail lines are shown with thin lines. Stops on street-running portions of SEPTA light rail lines are closely spaced and not shown. The area shown is a 30-mile by 30-mile square.

Philadelphia's rail transit, on the other hand, does a good job of serving the metro area's two largest job clusters: the central business district of Center City and the University City area around the University of Pennsylvania and Drexel University campuses, both of which are served by the subway tunnel carrying the Market-Frankford Line rapid transit line and the Subway-Surface light rail lines.

Much of the city's core of medium- and high-density residential areas is also served by rapid transit and light rail lines, although the high-density residential area to the south of Market Street stands out as relatively under-served. It is also worth noting that Philadelphia's high-quality transit service area could be significantly improved if better service was provided by the SEPTA Regional Rail commuter rail lines. This network, which covers the built-up portion of the city fairly densely and extends relatively far into the suburbs is entirely electrified and served by a four-track dedicated tunnel through the city center that was built in the 1980's. However, decades of proposals to provide frequent, through-running rapid-transit-style service on some of the city's regional rail lines have so far amounted to nothing (Vuchic and Kikuchi, 1985; DeGraw, 1994; Johnston, 2016).

Baltimore (see Figure 4.4 on page 244) and Los Angeles (see Figure 4.5 on page 246) are two other metro areas that, like Pittsburgh, have relatively dense job and population clusters that their rail lines manage to fail to serve.

While Baltimore's one-line Metro Subway rapid transit and its light rail line both serve the city's central business district to some degree—while, famously, failing to have a direct transfer—they miss Baltimore's main dense residential districts and—with the exception of the Johns Hopkins University Medical Campus—most of its main job clusters outside of the central business district.

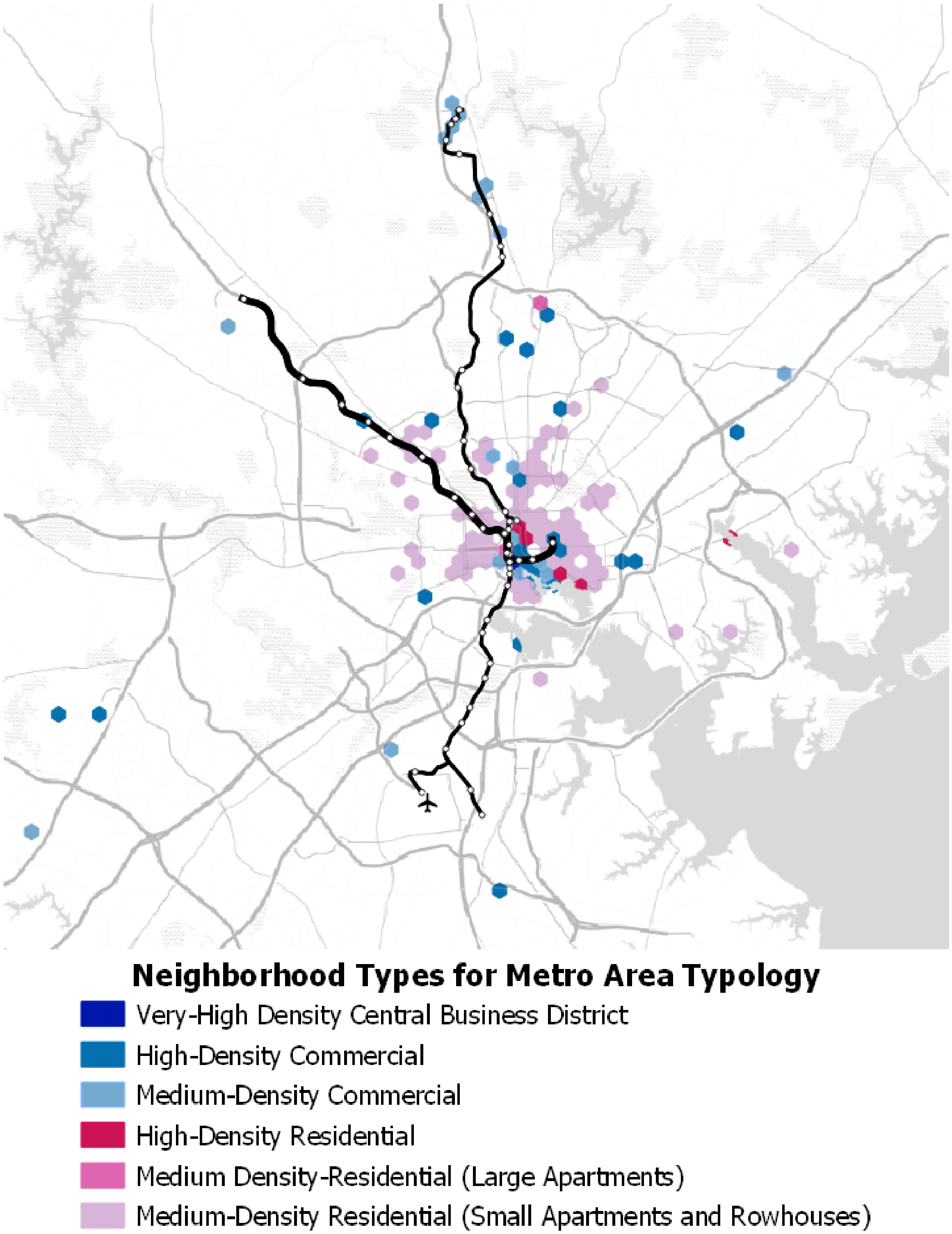

Figure 4.4: Rapid transit and light rail in the Baltimore metro area. The Baltimore Metro Subway is shown with a thick line; the Baltimore Light Rail is shown with thin lines. The area shown is a 30-mile by 30-mile square.

This situation is, to a large degree, the product of racism-driven opposition to public transit. Baltimore's Metro Subway was originally intended to be the first line of a six-line system. Early plans called for the line expected to have the highest ridership—a north-south line through downtown and some of the highest-density residential districts, connecting to BWI Thurgood Marshall Airport and potentially the state capital in Annapolis in the south and to the mall and major college at Towson in the north—to be built first.

However, racially-tinged opposition from residents of Baltimore's southern suburbs led these plans to be canceled and a line to the northwest, running along a rail line and a freeway median in much less-dense areas to be built instead. When a north-south line was eventually built, it was constructed on a much more limited budget, resulting in a light rail line that runs slowly on surface streets (and was originally single-tracked) through downtown and that misses residential and commercial districts north of downtown because it runs along an old mainline rail right-of-way in a river valley.

Los Angeles began building rail transit at roughly the same time as Baltimore and, although its system is rather more extensive, it also manages to miss or run just to the edge of a number of significant high-density areas, as seen in Figure 4.5. Unlike Baltimore, though—where the one recent attempt to build a new rail line, the Red Line, was canceled by the governor after it had received Federal funding and was ready to begin construction—Los Angeles is currently in the construction or planning stages of building a number of new rail lines, some of which, such as the under-construction Purple Line Extension, will serve a number of the most significant missed destinations.

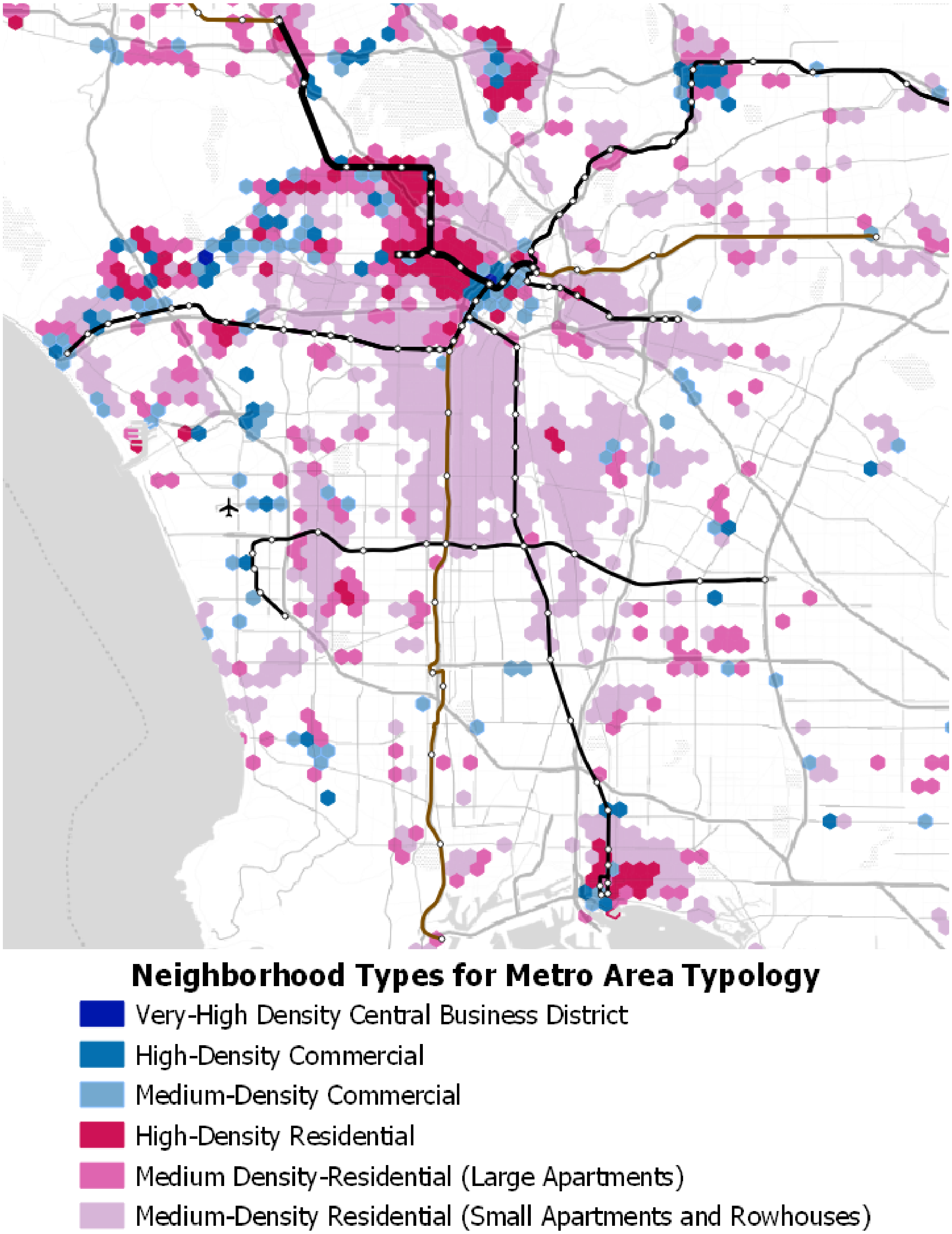

Figure 4.5: Rapid transit, light rail, and bus rapid transit in the Los Angeles metro area. The Red and Purple Lines are shown with thick lines; the Blue, Expo and, Gold, Lines are shown with thin lines; the Orange and Silver Lines are shown with brown lines. The area shown is a 30-mile by 30-mile square.

Portland (see Figure 4.6 on page 248) is an opposite case to Pittsburgh, as it has a significantly higher transit commuter share than would be expected for its relatively weak, low-density CBD. This high transit share cannot be explained by a high population density, either: only 3.9% of Portland residents live in high- or medium-density neighborhoods.

Unfortunately, it is not evident from the map in Figure 4.6 why Portland's transit is relatively successful in comparison to the city's low job and population density. Part of the answer may be that it does do a very good job of fully covering the large but low-density commercial core. Portland also generally has a good reputation for transit-oriented development: it is possible that dense but relatively small developments located at transit stations provide a significant number of riders despite being too small to bring the hexes containing them up to the density cut-off to appear on the map.

This considered, Portland is a good place to close this thesis, since it demonstrates the limitations of the techniques discussed herein for fully identifying the factors that contribute to transit ridership in US metro areas, and thus shows the need for future work on this topic.

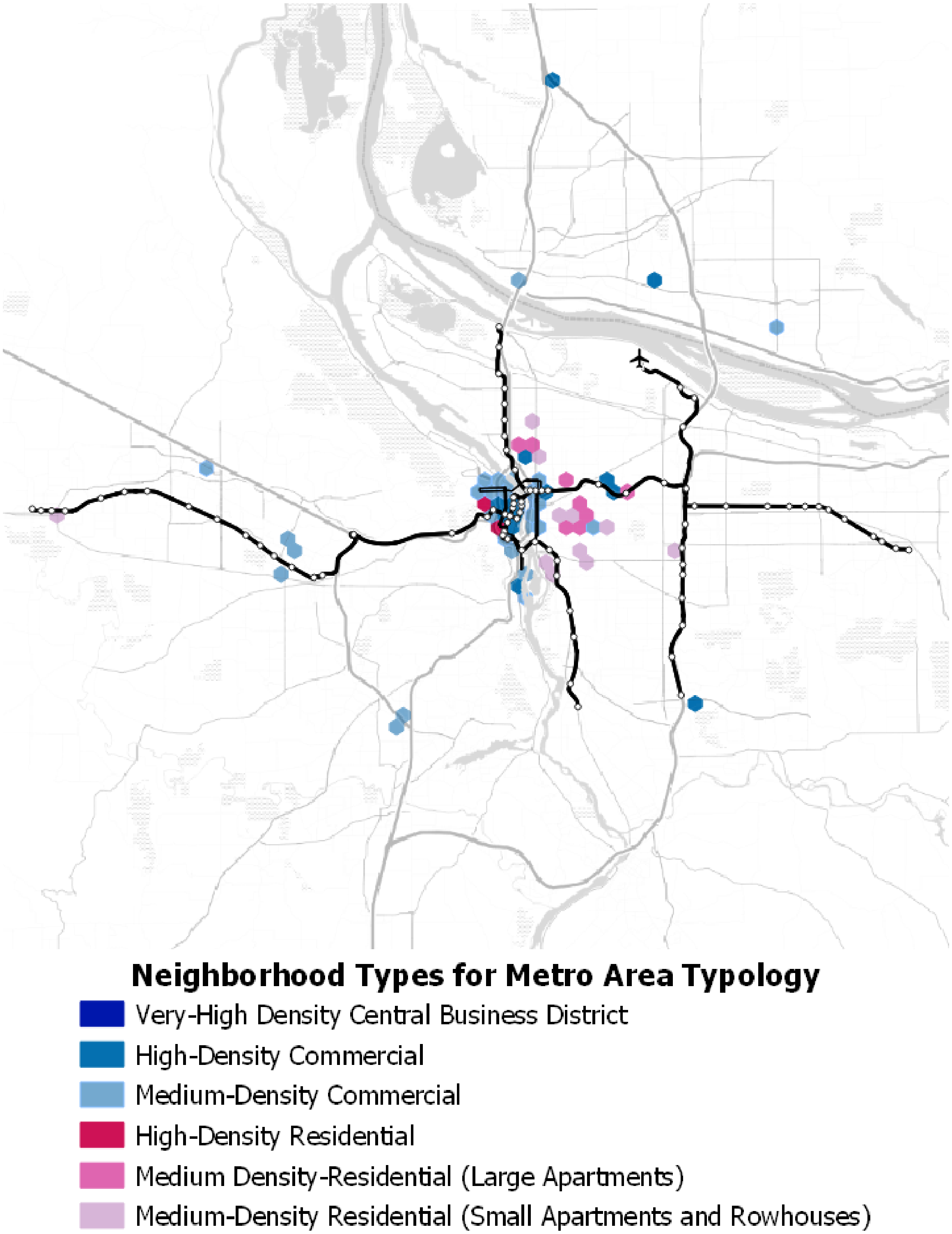

Figure 4.6: Light rail and streetcars in the Portland metro area. The MAX Light Rail is shown with thick lines; the Portland Streetcar is shown with thin lines. Stops on the streetcar are closely spaced and not shown. The area shown is a 30-mile by 30-mile square.

4.4.5 Density, Transit Commuters, and Carfree Households

Another issue which may deserve further examination is the question of what densities transit commuters and carfree households—households that do not own or lease any motor vehicles—live at in various metro areas. One would expect such commuters and households to live at higher densities than average given the structure of American metro areas and transit networks.

In the lower-density portions of US metro areas, it is generally simply impossible to commute entirely by transit—these areas are not served by transit—although some residents do drive to park-and-ride lots and take commuter trains, buses or (occasionally) ferries the rest of the way to work. Likewise, the lack of transit and long distances make it nearly impossible to go about daily tasks without a car in these low density areas, even if one does not need to commute regularly.

While the densest portions of American metro areas usually have at least some public transportation and, in some cities, have very good public transportation, not everyone who lives in these neighborhoods commutes by transit and lives without a car, either. In particularly dense areas, it is often easy to walk or bike to work rather than using transit. Furthermore, the fact that most of the land and many or most of the jobs, stores, and residents of even the best-served US metro areas are effectively or entirely out of reach of public transportation means that residents of dense urban neighborhoods often have an incentive to own a car if they can afford one.

To investigate the relationship between density and commuting by transit, I tabulated the percentages of workers who commute by transit, the median activity densities that transit commuters and workers overall live at, and the ratios of these median densities for each of the the ten major metro areas with the highest and lowest ratios in Table 4.3 on page 251. A complete tabulation of this data for the sixty largest metro areas in the country can be found in Table K.3 on page 689.

Interestingly, it appears that at least four separate phenomena are involved in the relative densities that transit commuters and workers overall live at. The cites with relatively small differences in the densities that these groups live at are largely dispersed metro areas without strong cores of dense residential neighborhoods but also, as discussed in Section 3.3.2, without the bands of very-low-density exurban development that surrounds most American metro areas. Two of them—Omaha and Oklahoma City—also have transit commute shares of less than 1%, which may indicate especially low-quality transit networks that even residents of dense areas are strongly incentivized to find alternatives to using.

The major metro area with the lowest difference between the densities at which transit commuters and workers overall live, however, is an example of a completely different phenomenon. Bridgeport has one of the highest transit commute shares in the country—10%—but the majority of its transit commuters use Metro-North commuter rail to commute to jobs in New York City. Although some Metro-North commuter rail stations are located in the historic cores of smaller cities, most of its ridership drives to park-and-ride lots before taking the train into the city.

Table 4.3: Metro Areas Where Transit Commuters Live at Elevated Densities

Metro Area	% of Workers Who Commute by Transit	Median Activity Density of Workers (/ sq. mi.)	Median Activity Density of Transit Commuters (/ sq. mi.)	Transit Commuter Median / Overall Median
Rochester	2.3%	2,600	9,200	355%
Boston	13.3%	5,500	18,200	331%
New York	31.9%	17,000	55,200	324%
Philadelphia	9.5%	5,100	16,100	316%
Hartford	2.8%	2,500	7,000	284%
Chicago	12.1%	6,500	17,500	269%
Pittsburgh	5.7%	2,600	6,800	259%
Grand Rapids	1.5%	2,500	6,500	258%
Milwaukee	3.3%	4,800	10,000	210%
Buffalo	3.3%	4,400	9,100	208%
...	...	...	...	...
Dallas	1.4%	5,200	6,900	133%
Las Vegas	3.8%	8,000	10,600	132%
Riverside	1.4%	5,500	7,100	129%
Denver	4.2%	6,400	8,200	128%
Omaha	0.9%	4,500	5,700	127%
Oklahoma City	0.4%	3,600	4,600	126%
Salt Lake City	3.7%	6,400	7,800	121%
San Jose	4.2%	11,100	13,100	118%
Sacramento	2.4%	6,300	7,300	117%
Bridgeport	10%	4,800	5,300	110%

Furthermore, the extreme traffic congestion and expense of parking in Manhattan and the fact that the highest concentration of jobs in the entire US is located within walking distance of Grand Central, Metro North's New York terminal, mean that almost all Bridgeport residents commuting to jobs in New York find it worthwhile to take commuter rail even if they have to drive a significant distance to a station. As a result—as with residents of the other commuter-rail suburbs discussed in Section 4.4.1—there is little difference between the densities at which these workers live and the densities at which workers in the metro area overall live.

As for the metro areas with large differences between the densities that transit commuters and workers overall live at, these also seem to fall into two categories. Several of them—New York, Chicago, Boston, Philadelphia, and to some extent Pittsburgh—have high transit commuter shares and relatively effective transit service, which means that people who live in dense parts of these metro areas are likely to find commuting by transit convenient. In addition, the densest areas of New York and Boston have gentrified rapidly in recent years and it is likely that being able to commute by transit is part of what attracts residents to these areas despite the cost premium.

It is worth noting that San Francisco and Washington—with the second- and third-highest transit commute shares in the nation—does not have a especially high differences in the median densities that transit commuters and workers overall live at. This likely reflects that—unlike the pre-World War II rapid transit systems in New York, Chicago, Boston, and Philadelphia and the still-under-construction light rail system in Seattle—BART in San Francisco and Metrorail in Washington extend far into relatively-low density suburbs and have numerous stations located at park-and-rides. Because these metro areas also have very dense CBDs with many jobs and where driving and parking inconvenient, many residents of low-density areas commute by driving to a park-and-ride station, as in Hartford[3].

Other metro areas with large differences between the densities at which transit commuters and workers overall live, however—Rochester, Hartford, Grand Rapids, Milwaukee, Buffalo, in particular—do not have especially dense cores, particularly large shares of transit commuters. These may, instead, be cases of transit systems that simply do not serve lower-density populations at all—thus requiring that their riders live in the densest parts of the region—or may be evidence of large populations low-income or otherwise involuntarily carfree residents concentrated in denser parts of the regions. The fact that these are—except for Hartford—particularly economically stagnant metro areas supports this hypothesis.

One potential way to determine if the large differences between the densities at which transit commuters and workers overall live in these cities is to consider the number of carfree households that do not commute by transit. Since these metro areas do not have particularly dense cores—and since they generally have relatively unpleasant weather that would discourage biking to work much of the year—these are likely households that cannot afford car ownership or where residents are otherwise unable to use a car, but where transit does not provide a viable commuting option. Buffalo (9.4 percentage points) and Rochester (8.0 percentage points), followed by Detroit, New Orleans, and Cleveland (each 7.5 percentage points) are the top metro areas by this metric.

[3] In the case of San Francisco, this is also, yet again, the phenomenon discussed in Section 3.3.2 cropping up: because San Francisco, like other Californian cities, lacks a substantial belt of low-density exurbia, the densities that workers overall live at are relatively higher than they would be in the Northeastern transit cities, all of which have such belts.

The differences in the activity densities where carfree households are found and the densities where households in general are found in various metro areas also merits some examination. To this end, I tabulated the percentages of carfree households, the median activity densities where carfree households and and households in general are located, and the ratios of these median densities for each of the the ten major metro areas with the highest and lowest ratios in Table 4.4 on page 255. A complete tabulation of this data for the sixty largest metro areas in the country can be found in Table K.4 on page 683.

As expected, carfree households, like transit commuters, are consistently found living in denser areas than households overall. The effect is even larger, in fact: transit commuters lived at median densities between 355% and 110% of the median densities for workers in their metro areas, while carfree households are found at median densities between 390% and 120% of the median densities for households in their metro areas.

The ten metro areas where carfree households live at the most elevated densities relative to households overall again seems to include two populations. Boston, New York, Philadelphia, San Francisco, Washington, and Honolulu have some of the densest residential cores in the country, where car ownership is both especially expensive and unusually easy to get along without[4]. Furthermore, as mentioned above, the dense cores of Boston, New York, San Francisco, and Washington have seen particularly extreme gentrification in recent years, with influxes of populations willing to pay a premium to live in these neighborhoods because they can easily do so without owning a car or driving regularly.

[4]It is particularly noteworthy that San Francisco and Honolulu place sixth and ninth in this ranking, since both metro areas are strongly geographically constrained and so have relatively smaller variations of residential density.

Table 4.4: Metro Areas Where Carfree Households Live at Elevated Densities

Metro Area	**% Carfree Households**	**Median Activity Density of Households (/ sq. mi.)**	**Median Activity Density of Carfree Households (/ sq. mi.)**	**Carfree Household Median / Overall Median**
Boston	13.1%	5,600	21,500	390%
New York	30.7%	19,200	67,800	350%
Philadelphia	13.0%	5,500	17,600	320%
Worcester	9.0%	1,900	6,000	320%
Hartford	9.1%	2,600	7,100	270%
San Francisco	12.2%	11,500	29,800	260%
Washington	9.7%	6,400	16,200	260%
Bridgeport	7.7%	4,600	11,500	250%
Honolulu	10.2%	10,700	26,100	240%
Providence	10.0%	4,300	10,300	240%
...	...	...	...	...
Sacramento	6.3%	6,200	7,900	130%
Detroit	8.9%	4,600	5,700	130%
Salt Lake City	5.2%	6,600	8,300	130%
Omaha	6.0%	4,500	5,600	120%
Memphis	7.8%	3,200	3,900	120%
Oklahoma City	5.0%	3,600	4,500	120%
Dallas	4.8%	5,200	6,300	120%
Kansas City	6.1%	3,300	4,100	120%
San Jose	5.1%	10,800	13,200	120%
Riverside	4.7%	5,000	5,900	120%

The other four metro areas in the top ten—Worcester, Hartford, Bridgeport, and Providence (it is notable that they are all located in southern New England)—seem to fall in a different category altogether. All are relatively small metro areas and Worcester and Providence are both home to relatively large college student populations in their dense cores, and it seems likely that these students make up a non-trivial portion of the high-density carfree households. Beyond this, I am not sure what the cause is likely to be. As for the ten metro areas where carfree households live at densities most similar to the densities where households in general are found, a number of these do seem to be examples of metro areas that have relatively little density variation because they lack both high-density cores and substantial very-low-density exurban belts.

Appendix A: List of CBSAs with Assigned UTM Zones

Table A.1 lists the 926 core-based statistical areas studied, along with the UTM zones they were assigned to, as discussed in Section 2.2.2, and the EPSG Geodetic Parameter Dataset codes for the associated coordinate reference systems.

Table A.1: List of CBSAs with Assigned UTM Zones

CBSA FIPS Code	**CBSA FIPS Code**	**CBSA Name**	**EPSG Code**	**UTM Zone**
-	10100	Aberdeen, SD	32614	14N
-	10140	Aberdeen, WA	32610	10N
-	10180	Abilene, TX	32614	14N
-	10220	Ada, OK	32614	14N
220	10300	Adrian, MI	32617	17N
184	10420	Akron, OH	32617	17N
-	10460	Alamogordo, NM	32613	13N
-	10500	Albany, GA	32616	16N
440	10540	Albany-Lebanon, OR	32610	10N
104	10580	Albany-Schenectady-Troy, NY	32618	18N
172	10620	Albemarle, NC	32617	17N
-	10660	Albert Lea, MN	32615	15N
-	10700	Albertville, AL	32616	16N
106	10740	Albuquerque, NM	32613	13N
388	10760	Alexander City, AL	32616	16N
-	10780	Alexandria, LA	32615	15N

Continued on next page

Table A.1 – *Continued from previous page*

CBSA FIPS Code	CBSA FIPS Code	CBSA Name	EPSG Code	UTM Zone
-	10820	Alexandria, MN	32615	15N
204	10860	Alice, TX	32614	14N
-	10900	Allentown-Bethlehem-Easton, PA-NJ	32618	18N
394	10940	Alma, MI	32616	16N
-	10980	Alpena, MI	32617	17N
107	11020	Altoona, PA	32617	17N
-	11060	Altus, OK	32614	14N
108	11100	Amarillo, TX	32614	14N
-	11140	Americus, GA	32616	16N
218	11180	Ames, IA	32615	15N
104	11220	Amsterdam, NY	32618	18N
-	11260	Anchorage, AK	32606	6N
-	11380	Andrews, TX	32613	13N
258	11420	Angola, IN	32616	16N
220	11460	Ann Arbor, MI	32617	17N
-	11500	Anniston-Oxford, AL	32616	16N
118	11540	Appleton, WI	32616	16N
412	11580	Arcadia, FL	32617	17N
-	11620	Ardmore, OK	32614	14N
-	11660	Arkadelphia, AR	32615	15N
120	11700	Asheville, NC	32617	17N
360	11740	Ashland, OH	32617	17N
184	11780	Ashtabula, OH	32617	17N
-	11820	Astoria, OR	32610	10N
312	11860	Atchison, KS	32615	15N
-	11900	Athens, OH	32617	17N
174	11940	Athens, TN	32616	16N
206	11980	Athens, TX	32614	14N
122	12020	Athens-Clarke County, GA	32616	16N
122	12060	Atlanta-Sandy Springs-Alpharetta, GA	32616	16N

Continued on next page

Table A.1 – *Continued from previous page*

CBSA FIPS Code	CBSA FIPS Code	CBSA Name	EPSG Code	UTM Zone
428	12100	Atlantic City-Hammonton, NJ	32618	18N
426	12120	Atmore, AL	32616	16N
258	12140	Auburn, IN	32616	16N
532	12180	Auburn, NY	32618	18N
194	12220	Auburn-Opelika, AL	32616	16N
-	12260	Augusta-Richmond County, GA-SC	32617	17N
-	12300	Augusta-Waterville, ME	32619	19N
462	12380	Austin, MN	32615	15N
-	12420	Austin-Round Rock-Georgetown, TX	32614	14N
-	12460	Bainbridge, GA	32616	16N
-	12540	Bakersfield, CA	32611	11N
548	12580	Baltimore-Columbia-Towson, MD	32618	18N
-	12620	Bangor, ME	32619	19N
357	12660	Baraboo, WI	32616	16N
350	12680	Bardstown, KY	32616	16N
148	12700	Barnstable Town, MA	32619	19N
162	12740	Barre, VT	32618	18N
538	12780	Bartlesville, OK	32615	15N
464	12860	Batavia, NY	32618	18N
-	12900	Batesville, AR	32615	15N
-	12940	Baton Rouge, LA	32615	15N
310	12980	Battle Creek, MI	32616	16N
474	13020	Bay City, MI	32617	17N
288	13060	Bay City, TX	32615	15N
339	13100	Beatrice, NE	32614	14N
-	13140	Beaumont-Port Arthur, TX	32615	15N
376	13180	Beaver Dam, WI	32616	16N
-	13220	Beckley, WV	32617	17N
144	13260	Bedford, IN	32616	16N
-	13300	Beeville, TX	32614	14N

Continued on next page

Table A.1 – *Continued from previous page*

CBSA FIPS Code	CBSA FIPS Code	CBSA Name	EPSG Code	UTM Zone
198	13340	Bellefontaine, OH	32617	17N
-	13380	Bellingham, WA	32610	10N
-	13420	Bemidji, MN	32615	15N
140	13460	Bend, OR	32610	10N
-	13500	Bennettsville, SC	32617	17N
-	13540	Bennington, VT	32618	18N
-	13620	Berlin, NH	32619	19N
266	13660	Big Rapids, MI	32616	16N
-	13700	Big Spring, TX	32614	14N
-	13720	Big Stone Gap, VA	32617	17N
-	13740	Billings, MT	32612	12N
-	13780	Binghamton, NY	32618	18N
142	13820	Birmingham-Hoover, AL	32616	16N
-	13900	Bismarck, ND	32614	14N
292	13940	Blackfoot, ID	32612	12N
-	13980	Blacksburg-Christiansburg, VA	32617	17N
145	14010	Bloomington, IL	32616	16N
144	14020	Bloomington, IN	32616	16N
146	14100	Bloomsburg-Berwick, PA	32618	18N
-	14140	Bluefield, WV-VA	32617	17N
-	14180	Blytheville, AR	32616	16N
406	14220	Bogalusa, LA	32615	15N
147	14260	Boise City, ID	32611	11N
206	14300	Bonham, TX	32614	14N
-	14380	Boone, NC	32617	17N
108	14420	Borger, TX	32614	14N
148	14460	Boston-Cambridge-Newton, MA-NH	32619	19N
216	14500	Boulder, CO	32613	13N
150	14540	Bowling Green, KY	32616	16N
-	14580	Bozeman, MT	32612	12N

Continued on next page

Table A.1 – *Continued from previous page*

CBSA FIPS Code	CBSA FIPS Code	CBSA Name	EPSG Code	UTM Zone
-	14620	Bradford, PA	32617	17N
-	14660	Brainerd, MN	32615	15N
-	14700	Branson, MO	32615	15N
-	14720	Breckenridge, CO	32613	13N
500	14740	Bremerton-Silverdale-Port Orchard, WA	32610	10N
288	14780	Brenham, TX	32615	15N
120	14820	Brevard, NC	32617	17N
408	14860	Bridgeport-Stamford-Norwalk, CT	32618	18N
298	15020	Brookhaven, MS	32615	15N
-	15060	Brookings, OR	32610	10N
-	15100	Brookings, SD	32614	14N
297	15140	Brownsville, TN	32616	16N
154	15180	Brownsville-Harlingen, TX	32614	14N
-	15220	Brownwood, TX	32614	14N
-	15260	Brunswick, GA	32617	17N
360	15340	Bucyrus-Galion, OH	32617	17N
160	15380	Buffalo-Cheektowaga, NY	32617	17N
-	15420	Burley, ID	32612	12N
161	15460	Burlington, IA-IL	32615	15N
268	15500	Burlington, NC	32617	17N
162	15540	Burlington-South Burlington, VT	32618	18N
-	15580	Butte-Silver Bow, MT	32612	12N
-	15620	Cadillac, MI	32616	16N
174	15660	Calhoun, GA	32616	16N
548	15680	California-Lexington Park, MD	32618	18N
480	15700	Cambridge, MD	32618	18N
198	15740	Cambridge, OH	32617	17N
-	15780	Camden, AR	32615	15N
-	15820	Campbellsville, KY	32616	16N
444	15860	Canon City, CO	32613	13N

Continued on next page

Table A.1 – *Continued from previous page*

CBSA FIPS Code	CBSA FIPS Code	CBSA Name	EPSG Code	UTM Zone
184	15940	Canton-Massillon, OH	32617	17N
163	15980	Cape Coral-Fort Myers, FL	32617	17N
164	16020	Cape Girardeau, MO-IL	32616	16N
-	16060	Carbondale-Marion, IL	32616	16N
-	16100	Carlsbad-Artesia, NM	32613	13N
-	16140	Carroll, IA	32615	15N
456	16180	Carson City, NV	32611	11N
-	16220	Casper, WY	32613	13N
-	16260	Cedar City, UT	32612	12N
168	16300	Cedar Rapids, IA	32615	15N
122	16340	Cedartown, GA	32616	16N
338	16380	Celina, OH	32616	16N
-	16420	Central City, KY	32616	16N
476	16460	Centralia, IL	32615	15N
500	16500	Centralia, WA	32610	10N
548	16540	Chambersburg-Waynesboro, PA	32618	18N
-	16580	Champaign-Urbana, IL	32616	16N
170	16620	Charleston, WV	32617	17N
-	16660	Charleston-Mattoon, IL	32616	16N
-	16700	Charleston-North Charleston, SC	32617	17N
172	16740	Charlotte-Concord-Gastonia, NC-SC	32617	17N
-	16820	Charlottesville, VA	32617	17N
174	16860	Chattanooga, TN-GA	32616	16N
-	16940	Cheyenne, WY	32613	13N
176	16980	Chicago-Naperville-Elgin, IL-IN-WI	32616	16N
-	17020	Chico, CA	32610	10N
198	17060	Chillicothe, OH	32617	17N
178	17140	Cincinnati, OH-KY-IN	32616	16N
-	17220	Clarksburg, WV	32617	17N
-	17260	Clarksdale, MS	32615	15N

Continued on next page

Table A.1 – *Continued from previous page*

CBSA FIPS Code	CBSA FIPS Code	CBSA Name	EPSG Code	UTM Zone
-	17300	Clarksville, TN-KY	32616	16N
-	17340	Clearlake, CA	32610	10N
185	17380	Cleveland, MS	32615	15N
174	17420	Cleveland, TN	32616	16N
184	17460	Cleveland-Elyria, OH	32617	17N
163	17500	Clewiston, FL	32617	17N
209	17540	Clinton, IA	32615	15N
188	17580	Clovis, NM	32613	13N
518	17660	Coeur d'Alene, ID	32611	11N
-	17700	Coffeyville, KS	32615	15N
310	17740	Coldwater, MI	32616	16N
-	17780	College Station-Bryan, TX	32614	14N
-	17820	Colorado Springs, CO	32613	13N
190	17860	Columbia, MO	32615	15N
192	17900	Columbia, SC	32617	17N
194	17980	Columbus, GA-AL	32616	16N
294	18020	Columbus, IN	32616	16N
200	18060	Columbus, MS	32616	16N
-	18100	Columbus, NE	32614	14N
198	18140	Columbus, OH	32617	17N
148	18180	Concord, NH	32619	19N
458	18220	Connersville, IN	32616	16N
-	18260	Cookeville, TN	32616	16N
-	18300	Coos Bay, OR	32610	10N
-	18380	Cordele, GA	32617	17N
539	18420	Corinth, MS	32616	16N
122	18460	Cornelia, GA	32616	16N
236	18500	Corning, NY	32618	18N
204	18580	Corpus Christi, TX	32614	14N
206	18620	Corsicana, TX	32614	14N

Continued on next page

Table A.1 – *Continued from previous page*

CBSA FIPS Code	CBSA FIPS Code	CBSA Name	EPSG Code	UTM Zone
296	18660	Cortland, NY	32618	18N
440	18700	Corvallis, OR	32610	10N
-	18740	Coshocton, OH	32617	17N
525	18780	Craig, CO	32613	13N
294	18820	Crawfordsville, IN	32616	16N
-	18860	Crescent City, CA	32610	10N
-	18880	Crestview-Fort Walton Beach-Destin, FL	32616	16N
-	18900	Crossville, TN	32616	16N
142	18980	Cullman, AL	32616	16N
-	19000	Cullowhee, NC	32617	17N
-	19060	Cumberland, MD-WV	32617	17N
206	19100	Dallas-Fort Worth-Arlington, TX	32614	14N
174	19140	Dalton, GA	32616	16N
-	19180	Danville, IL	32616	16N
-	19220	Danville, KY	32616	16N
-	19260	Danville, VA	32617	17N
380	19300	Daphne-Fairhope-Foley, AL	32616	16N
209	19340	Davenport-Moline-Rock Island, IA-IL	32615	15N
174	19420	Dayton, TN	32616	16N
212	19430	Dayton-Kettering, OH	32616	16N
290	19460	Decatur, AL	32616	16N
-	19500	Decatur, IL	32616	16N
258	19540	Decatur, IN	32616	16N
-	19580	Defiance, OH	32616	16N
-	19620	Del Rio, TX	32614	14N
422	19660	Deltona-Daytona Beach-Ormond Beach, FL	32617	17N
-	19700	Deming, NM	32613	13N
216	19740	Denver-Aurora-Lakewood, CO	32613	13N
217	19760	DeRidder, LA	32615	15N
218	19780	Des Moines-West Des Moines, IA	32615	15N

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Table A.1 – *Continued from previous page*

CBSA FIPS Code	CBSA FIPS Code	CBSA Name	EPSG Code	UTM Zone
220	19820	Detroit-Warren-Dearborn, MI	32617	17N
-	19860	Dickinson, ND	32613	13N
221	19940	Dixon, IL	32616	16N
-	19980	Dodge City, KS	32614	14N
222	20020	Dothan, AL	32616	16N
-	20060	Douglas, GA	32617	17N
428	20100	Dover, DE	32618	18N
-	20140	Dublin, GA	32617	17N
524	20180	DuBois, PA	32618	18N
-	20220	Dubuque, IA	32615	15N
-	20260	Duluth, MN-WI	32615	15N
-	20300	Dumas, TX	32614	14N
-	20340	Duncan, OK	32614	14N
-	20420	Durango, CO	32613	13N
206	20460	Durant, OK	32614	14N
450	20500	Durham-Chapel Hill, NC	32617	17N
-	20540	Dyersburg, TN	32616	16N
-	20580	Eagle Pass, TX	32614	14N
548	20660	Easton, MD	32618	18N
408	20700	East Stroudsburg, PA	32618	18N
232	20740	Eau Claire, WI	32615	15N
233	20780	Edwards, CO	32613	13N
-	20820	Effingham, IL	32616	16N
288	20900	El Campo, TX	32615	15N
-	20940	El Centro, CA	32611	11N
-	20980	El Dorado, AR	32615	15N
545	21020	Elizabeth City, NC	32618	18N
350	21060	Elizabethtown-Fort Knox, KY	32616	16N
-	21120	Elk City, OK	32614	14N
515	21140	Elkhart-Goshen, IN	32616	16N

Continued on next page

Table A.1 – *Continued from previous page*

CBSA FIPS Code	CBSA FIPS Code	CBSA Name	EPSG Code	UTM Zone
-	21180	Elkins, WV	32617	17N
-	21220	Elko, NV	32611	11N
-	21260	Ellensburg, WA	32610	10N
236	21300	Elmira, NY	32618	18N
238	21340	El Paso, TX	32613	13N
-	21380	Emporia, KS	32614	14N
-	21420	Enid, OK	32614	14N
-	21460	Enterprise, AL	32616	16N
240	21500	Erie, PA	32617	17N
-	21540	Escanaba, MI	32616	16N
106	21580	Espanola, NM	32613	13N
-	21640	Eufaula, AL-GA	32616	16N
-	21660	Eugene-Springfield, OR	32610	10N
-	21700	Eureka-Arcata, CA	32610	10N
-	21740	Evanston, WY	32612	12N
-	21780	Evansville, IN-KY	32616	16N
-	21820	Fairbanks, AK	32606	6N
-	21840	Fairfield, IA	32615	15N
-	21860	Fairmont, MN	32615	15N
390	21900	Fairmont, WV	32617	17N
-	21980	Fallon, NV	32611	11N
244	22020	Fargo, ND-MN	32614	14N
378	22060	Faribault-Northfield, MN	32615	15N
476	22100	Farmington, MO	32615	15N
-	22140	Farmington, NM	32612	12N
246	22180	Fayetteville, NC	32617	17N
-	22220	Fayetteville-Springdale-Rogers, AR	32615	15N
-	22260	Fergus Falls, MN	32615	15N
456	22280	Fernley, NV	32611	11N
534	22300	Findlay, OH	32617	17N

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Table A.1 – *Continued from previous page*

CBSA FIPS Code	CBSA FIPS Code	CBSA Name	EPSG Code	UTM Zone
-	22340	Fitzgerald, GA	32617	17N
-	22380	Flagstaff, AZ	32612	12N
220	22420	Flint, MI	32617	17N
-	22500	Florence, SC	32617	17N
-	22520	Florence-Muscle Shoals, AL	32616	16N
-	22540	Fond du Lac, WI	32616	16N
-	22580	Forest City, NC	32617	17N
368	22620	Forrest City, AR	32616	16N
-	22660	Fort Collins, CO	32613	13N
-	22700	Fort Dodge, IA	32615	15N
-	22780	Fort Leonard Wood, MO	32615	15N
161	22800	Fort Madison-Keokuk, IA-IL-MO	32615	15N
-	22820	Fort Morgan, CO	32613	13N
497	22840	Fort Payne, AL	32616	16N
217	22860	Fort Polk South, LA	32615	15N
-	22900	Fort Smith, AR-OK	32615	15N
258	23060	Fort Wayne, IN	32616	16N
320	23140	Frankfort, IN	32616	16N
336	23180	Frankfort, KY	32616	16N
314	23240	Fredericksburg, TX	32614	14N
466	23300	Freeport, IL	32616	16N
420	23340	Fremont, NE	32614	14N
534	23380	Fremont, OH	32617	17N
260	23420	Fresno, CA	32611	11N
-	23460	Gadsden, AL	32616	16N
273	23500	Gaffney, SC	32617	17N
264	23540	Gainesville, FL	32617	17N
122	23580	Gainesville, GA	32616	16N
206	23620	Gainesville, TX	32614	14N
-	23660	Galesburg, IL	32615	15N

Continued on next page

Table A.1 – *Continued from previous page*

CBSA FIPS Code	CBSA FIPS Code	CBSA Name	EPSG Code	UTM Zone
-	23700	Gallup, NM	32612	12N
-	23780	Garden City, KS	32614	14N
456	23820	Gardnerville Ranchos, NV	32611	11N
396	23860	Georgetown, SC	32617	17N
276	23900	Gettysburg, PA	32618	18N
-	23940	Gillette, WY	32613	13N
150	23980	Glasgow, KY	32616	16N
104	24020	Glens Falls, NY	32618	18N
233	24060	Glenwood Springs, CO	32613	13N
104	24100	Gloversville, NY	32618	18N
-	24140	Goldsboro, NC	32618	18N
206	24180	Granbury, TX	32614	14N
-	24220	Grand Forks, ND-MN	32614	14N
-	24260	Grand Island, NE	32614	14N
-	24300	Grand Junction, CO	32612	12N
-	24330	Grand Rapids, MN	32615	15N
266	24340	Grand Rapids-Kentwood, MI	32616	16N
-	24380	Grants, NM	32613	13N
366	24420	Grants Pass, OR	32610	10N
-	24460	Great Bend, KS	32614	14N
-	24500	Great Falls, MT	32612	12N
216	24540	Greeley, CO	32613	13N
267	24580	Green Bay, WI	32616	16N
-	24620	Greeneville, TN	32617	17N
268	24660	Greensboro-High Point, NC	32617	17N
294	24700	Greensburg, IN	32616	16N
-	24740	Greenville, MS	32615	15N
272	24780	Greenville, NC	32618	18N
212	24820	Greenville, OH	32616	16N
273	24860	Greenville-Anderson, SC	32617	17N

Continued on next page

Table A.1 – *Continued from previous page*

CBSA FIPS Code	CBSA FIPS Code	CBSA Name	EPSG Code	UTM Zone
-	24900	Greenwood, MS	32615	15N
273	24940	Greenwood, SC	32617	17N
-	24980	Grenada, MS	32616	16N
-	25060	Gulfport-Biloxi, MS	32616	16N
-	25100	Guymon, OK	32614	14N
548	25180	Hagerstown-Martinsburg, MD-WV	32618	18N
-	25200	Hailey, ID	32611	11N
406	25220	Hammond, LA	32615	15N
260	25260	Hanford-Corcoran, CA	32611	11N
448	25300	Hannibal, MO	32615	15N
276	25420	Harrisburg-Carlisle, PA	32618	18N
-	25460	Harrison, AR	32615	15N
277	25500	Harrisonburg, VA	32617	17N
278	25540	Hartford-East Hartford-Middletown, CT	32618	18N
-	25580	Hastings, NE	32614	14N
279	25620	Hattiesburg, MS	32616	16N
-	25700	Hays, KS	32614	14N
482	25720	Heber, UT	32612	12N
-	25740	Helena, MT	32612	12N
-	25760	Helena-West Helena, AR	32615	15N
450	25780	Henderson, NC	32617	17N
-	25820	Hereford, TX	32613	13N
-	25840	Hermiston-Pendleton, OR	32611	11N
-	25860	Hickory-Lenoir-Morganton, NC	32617	17N
-	25880	Hillsdale, MI	32616	16N
-	25900	Hilo, HI	32605	5N
-	25940	Hilton Head Island-Bluffton, SC	32617	17N
496	25980	Hinesville, GA	32617	17N
-	26020	Hobbs, NM	32613	13N
266	26090	Holland, MI	32616	16N

Continued on next page

Table A.1 – *Continued from previous page*

CBSA FIPS Code	CBSA FIPS Code	CBSA Name	EPSG Code	UTM Zone
-	26140	Homosassa Springs, FL	32617	17N
-	26220	Hood River, OR	32610	10N
-	26260	Hope, AR	32615	15N
284	26300	Hot Springs, AR	32615	15N
-	26340	Houghton, MI	32616	16N
-	26380	Houma-Thibodaux, LA	32615	15N
288	26420	Houston-The Woodlands-Sugar Land, TX	32615	15N
104	26460	Hudson, NY	32618	18N
107	26500	Huntingdon, PA	32617	17N
258	26540	Huntington, IN	32616	16N
170	26580	Huntington-Ashland, WV-KY-OH	32617	17N
290	26620	Huntsville, AL	32616	16N
288	26660	Huntsville, TX	32615	15N
-	26700	Huron, SD	32614	14N
-	26740	Hutchinson, KS	32614	14N
378	26780	Hutchinson, MN	32615	15N
292	26820	Idaho Falls, ID	32612	12N
430	26860	Indiana, PA	32617	17N
294	26900	Indianapolis-Carmel-Anderson, IN	32616	16N
185	26940	Indianola, MS	32615	15N
168	26980	Iowa City, IA	32615	15N
361	27020	Iron Mountain, MI-WI	32616	16N
296	27060	Ithaca, NY	32618	18N
-	27100	Jackson, MI	32616	16N
298	27140	Jackson, MS	32615	15N
-	27160	Jackson, OH	32617	17N
297	27180	Jackson, TN	32616	16N
-	27220	Jackson, WY-ID	32612	12N
300	27260	Jacksonville, FL	32617	17N
522	27300	Jacksonville, IL	32616	16N

Continued on next page

Table A.1 – *Continued from previous page*

CBSA FIPS Code	CBSA FIPS Code	CBSA Name	EPSG Code	UTM Zone
-	27340	Jacksonville, NC	32618	18N
540	27380	Jacksonville, TX	32615	15N
-	27420	Jamestown, ND	32614	14N
-	27460	Jamestown-Dunkirk-Fredonia, NY	32617	17N
357	27500	Janesville-Beloit, WI	32616	16N
142	27530	Jasper, AL	32616	16N
-	27540	Jasper, IN	32616	16N
122	27600	Jefferson, GA	32616	16N
-	27620	Jefferson City, MO	32615	15N
324	27660	Jennings, LA	32615	15N
496	27700	Jesup, GA	32617	17N
304	27740	Johnson City, TN	32617	17N
306	27780	Johnstown, PA	32617	17N
308	27860	Jonesboro, AR	32615	15N
309	27900	Joplin, MO	32615	15N
-	27940	Juneau, AK	32608	8N
-	27980	Kahului-Wailuku-Lahaina, HI	32604	4N
310	28020	Kalamazoo-Portage, MI	32616	16N
-	28060	Kalispell, MT	32611	11N
176	28100	Kankakee, IL	32616	16N
312	28140	Kansas City, MO-KS	32615	15N
-	28180	Kapaa, HI	32604	4N
-	28260	Kearney, NE	32614	14N
-	28300	Keene, NH	32618	18N
258	28340	Kendallville, IN	32616	16N
-	28380	Kennett, MO	32615	15N
313	28420	Kennewick-Richland, WA	32611	11N
314	28500	Kerrville, TX	32614	14N
-	28540	Ketchikan, AK	32609	9N
370	28580	Key West, FL	32617	17N

Continued on next page

Table A.1 – *Continued from previous page*

CBSA FIPS Code	CBSA FIPS Code	CBSA Name	EPSG Code	UTM Zone
545	28620	Kill Devil Hills, NC	32618	18N
-	28660	Killeen-Temple, TX	32614	14N
304	28700	Kingsport-Bristol, TN-VA	32617	17N
408	28740	Kingston, NY	32618	18N
204	28780	Kingsville, TX	32614	14N
272	28820	Kinston, NC	32618	18N
-	28860	Kirksville, MO	32615	15N
-	28900	Klamath Falls, OR	32610	10N
315	28940	Knoxville, TN	32617	17N
316	29020	Kokomo, IN	32616	16N
148	29060	Laconia, NH	32619	19N
-	29100	La Crosse-Onalaska, WI-MN	32615	15N
318	29180	Lafayette, LA	32615	15N
320	29200	Lafayette-West Lafayette, IN	32616	16N
-	29260	La Grande, OR	32611	11N
122	29300	LaGrange, GA-AL	32616	16N
324	29340	Lake Charles, LA	32615	15N
264	29380	Lake City, FL	32617	17N
-	29420	Lake Havasu City-Kingman, AZ	32611	11N
422	29460	Lakeland-Winter Haven, FL	32617	17N
-	29500	Lamesa, TX	32614	14N
-	29540	Lancaster, PA	32618	18N
-	29620	Lansing-East Lansing, MI	32616	16N
-	29660	Laramie, WY	32613	13N
-	29700	Laredo, TX	32614	14N
238	29740	Las Cruces, NM	32613	13N
106	29780	Las Vegas, NM	32613	13N
332	29820	Las Vegas-Henderson-Paradise, NV	32611	11N
279	29860	Laurel, MS	32616	16N
246	29900	Laurinburg, NC	32617	17N

Continued on next page

Table A.1 – *Continued from previous page*

CBSA FIPS Code	CBSA FIPS Code	CBSA Name	EPSG Code	UTM Zone
312	29940	Lawrence, KS	32615	15N
400	29980	Lawrenceburg, TN	32616	16N
-	30020	Lawton, OK	32614	14N
-	30060	Lebanon, MO	32615	15N
-	30100	Lebanon, NH-VT	32618	18N
276	30140	Lebanon, PA	32618	18N
352	30220	Levelland, TX	32614	14N
146	30260	Lewisburg, PA	32618	18N
400	30280	Lewisburg, TN	32616	16N
-	30300	Lewiston, ID-WA	32611	11N
438	30340	Lewiston-Auburn, ME	32619	19N
-	30380	Lewistown, PA	32618	18N
-	30420	Lexington, NE	32614	14N
336	30460	Lexington-Fayette, KY	32616	16N
-	30580	Liberal, KS	32614	14N
338	30620	Lima, OH	32616	16N
522	30660	Lincoln, IL	32616	16N
339	30700	Lincoln, NE	32614	14N
340	30780	Little Rock-North Little Rock-Conway, AR	32615	15N
558	30820	Lock Haven, PA	32618	18N
-	30860	Logan, UT-ID	32612	12N
-	30900	Logansport, IN	32616	16N
-	30940	London, KY	32616	16N
-	30980	Longview, TX	32615	15N
440	31020	Longview, WA	32610	10N
106	31060	Los Alamos, NM	32613	13N
348	31080	Los Angeles-Long Beach-Anaheim, CA	32611	11N
350	31140	Louisville-Jefferson County, KY-IN	32616	16N
352	31180	Lubbock, TX	32614	14N
-	31220	Ludington, MI	32616	16N

Continued on next page

Table A.1 – *Continued from previous page*

CBSA FIPS Code	CBSA FIPS Code	CBSA Name	EPSG Code	UTM Zone
-	31260	Lufkin, TX	32615	15N
246	31300	Lumberton, NC	32617	17N
-	31340	Lynchburg, VA	32617	17N
-	31380	Macomb, IL	32615	15N
356	31420	Macon-Bibb County, GA	32617	17N
260	31460	Madera, CA	32611	11N
-	31500	Madison, IN	32616	16N
357	31540	Madison, WI	32616	16N
-	31580	Madisonville, KY	32616	16N
-	31620	Magnolia, AR	32615	15N
-	31660	Malone, NY	32618	18N
284	31680	Malvern, AR	32615	15N
148	31700	Manchester-Nashua, NH	32619	19N
-	31740	Manhattan, KS	32614	14N
-	31820	Manitowoc, WI	32616	16N
359	31860	Mankato, MN	32615	15N
360	31900	Mansfield, OH	32617	17N
425	31930	Marietta, OH	32617	17N
361	31940	Marinette, WI-MI	32616	16N
-	31980	Marion, IN	32616	16N
120	32000	Marion, NC	32617	17N
198	32020	Marion, OH	32617	17N
-	32100	Marquette, MI	32616	16N
-	32140	Marshall, MN	32615	15N
-	32180	Marshall, MO	32615	15N
-	32260	Marshalltown, IA	32615	15N
362	32280	Martin, TN	32616	16N
-	32300	Martinsville, VA	32617	17N
-	32340	Maryville, MO	32615	15N
-	32380	Mason City, IA	32615	15N

Continued on next page

Table A.1 – *Continued from previous page*

CBSA FIPS Code	CBSA FIPS Code	CBSA Name	EPSG Code	UTM Zone
424	32460	Mayfield, KY	32616	16N
178	32500	Maysville, KY	32616	16N
-	32540	McAlester, OK	32615	15N
365	32580	McAllen-Edinburg-Mission, TX	32614	14N
-	32620	McComb, MS	32615	15N
-	32660	McMinnville, TN	32616	16N
-	32700	McPherson, KS	32614	14N
240	32740	Meadville, PA	32617	17N
366	32780	Medford, OR	32610	10N
368	32820	Memphis, TN-MS-AR	32616	16N
232	32860	Menomonie, WI	32615	15N
488	32900	Merced, CA	32610	10N
-	32940	Meridian, MS	32616	16N
190	33020	Mexico, MO	32615	15N
309	33060	Miami, OK	32615	15N
370	33100	Miami-Fort Lauderdale-Pompano Beach, FL	32617	17N
176	33140	Michigan City-La Porte, IN	32616	16N
-	33180	Middlesborough, KY	32617	17N
474	33220	Midland, MI	32617	17N
372	33260	Midland, TX	32613	13N
-	33300	Milledgeville, GA	32617	17N
376	33340	Milwaukee-Waukesha, WI	32616	16N
508	33380	Minden, LA	32615	15N
206	33420	Mineral Wells, TX	32614	14N
378	33460	Minneapolis-St. Paul-Bloomington, MN-WI	32615	15N
-	33500	Minot, ND	32614	14N
-	33540	Missoula, MT	32611	11N
-	33580	Mitchell, SD	32614	14N
190	33620	Moberly, MO	32615	15N
380	33660	Mobile, AL	32616	16N

Continued on next page

Table A.1 – *Continued from previous page*

CBSA FIPS Code	CBSA FIPS Code	CBSA Name	EPSG Code	UTM Zone
488	33700	Modesto, CA	32610	10N
384	33740	Monroe, LA	32615	15N
220	33780	Monroe, MI	32617	17N
388	33860	Montgomery, AL	32616	16N
-	33940	Montrose, CO	32613	13N
404	33980	Morehead City, NC	32618	18N
318	34020	Morgan City, LA	32615	15N
390	34060	Morgantown, WV	32617	17N
315	34100	Morristown, TN	32617	17N
446	34140	Moscow, ID	32611	11N
393	34180	Moses Lake, WA	32611	11N
-	34220	Moultrie, GA	32617	17N
-	34260	Mountain Home, AR	32615	15N
147	34300	Mountain Home, ID	32611	11N
268	34340	Mount Airy, NC	32617	17N
170	34350	Mount Gay-Shamrock, WV	32617	17N
394	34380	Mount Pleasant, MI	32616	16N
-	34420	Mount Pleasant, TX	32615	15N
336	34460	Mount Sterling, KY	32616	16N
-	34500	Mount Vernon, IL	32616	16N
198	34540	Mount Vernon, OH	32617	17N
500	34580	Mount Vernon-Anacortes, WA	32610	10N
294	34620	Muncie, IN	32616	16N
-	34660	Murray, KY	32616	16N
209	34700	Muscatine, IA	32615	15N
266	34740	Muskegon, MI	32616	16N
538	34780	Muskogee, OK	32615	15N
396	34820	Myrtle Beach-Conway-North Myrtle Beach, SC-NC	32617	17N
-	34860	Nacogdoches, TX	32615	15N
488	34900	Napa, CA	32610	10N

Continued on next page

Table A.1 – *Continued from previous page*

CBSA FIPS Code	CBSA FIPS Code	CBSA Name	EPSG Code	UTM Zone
163	34940	Naples-Marco Island, FL	32617	17N
400	34980	Nashville-Davidson–Murfreesboro–Franklin, TN	32616	16N
-	35020	Natchez, MS-LA	32615	15N
-	35060	Natchitoches, LA	32615	15N
404	35100	New Bern, NC	32618	18N
192	35140	Newberry, SC	32617	17N
294	35220	New Castle, IN	32616	16N
430	35260	New Castle, PA	32617	17N
408	35300	New Haven-Milford, CT	32618	18N
406	35380	New Orleans-Metairie, LA	32615	15N
184	35420	New Philadelphia-Dover, OH	32617	17N
-	35440	Newport, OR	32610	10N
315	35460	Newport, TN	32617	17N
359	35580	New Ulm, MN	32615	15N
408	35620	New York-Newark-Jersey City, NY-NJ-PA	32618	18N
515	35660	Niles, MI	32616	16N
536	35700	Nogales, AZ	32612	12N
-	35740	Norfolk, NE	32614	14N
-	35820	North Platte, NE	32614	14N
412	35840	North Port-Sarasota-Bradenton, FL	32617	17N
294	35860	North Vernon, IN	32616	16N
-	35900	North Wilkesboro, NC	32617	17N
184	35940	Norwalk, OH	32617	17N
278	35980	Norwich-New London, CT	32618	18N
500	36020	Oak Harbor, WA	32610	10N
-	36100	Ocala, FL	32617	17N
428	36140	Ocean City, NJ	32618	18N
372	36220	Odessa, TX	32613	13N
482	36260	Ogden-Clearfield, UT	32612	12N
-	36300	Ogdensburg-Massena, NY	32618	18N

Continued on next page

Table A.1 – *Continued from previous page*

CBSA FIPS Code	CBSA FIPS Code	CBSA Name	EPSG Code	UTM Zone
-	36340	Oil City, PA	32617	17N
-	36380	Okeechobee, FL	32617	17N
416	36420	Oklahoma City, OK	32614	14N
160	36460	Olean, NY	32617	17N
500	36500	Olympia-Lacey-Tumwater, WA	32610	10N
420	36540	Omaha-Council Bluffs, NE-IA	32614	14N
-	36580	Oneonta, NY	32618	18N
147	36620	Ontario, OR-ID	32611	11N
318	36660	Opelousas, LA	32615	15N
192	36700	Orangeburg, SC	32617	17N
422	36740	Orlando-Kissimmee-Sanford, FL	32617	17N
118	36780	Oshkosh-Neenah, WI	32616	16N
218	36820	Oskaloosa, IA	32615	15N
393	36830	Othello, WA	32611	11N
176	36837	Ottawa, IL	32616	16N
312	36840	Ottawa, KS	32615	15N
-	36900	Ottumwa, IA	32615	15N
378	36940	Owatonna, MN	32615	15N
-	36980	Owensboro, KY	32616	16N
-	37060	Oxford, MS	32616	16N
348	37100	Oxnard-Thousand Oaks-Ventura, CA	32611	11N
222	37120	Ozark, AL	32616	16N
424	37140	Paducah, KY-IL	32616	16N
332	37220	Pahrump, NV	32611	11N
300	37260	Palatka, FL	32617	17N
-	37300	Palestine, TX	32615	15N
-	37340	Palm Bay-Melbourne-Titusville, FL	32617	17N
108	37420	Pampa, TX	32614	14N
-	37460	Panama City, FL	32616	16N
308	37500	Paragould, AR	32615	15N

Continued on next page

Table A.1 – *Continued from previous page*

CBSA FIPS Code	CBSA FIPS Code	CBSA Name	EPSG Code	UTM Zone
-	37540	Paris, TN	32616	16N
-	37580	Paris, TX	32615	15N
425	37620	Parkersburg-Vienna, WV	32617	17N
-	37660	Parsons, KS	32615	15N
429	37740	Payson, AZ	32612	12N
484	37770	Pearsall, TX	32614	14N
-	37780	Pecos, TX	32613	13N
218	37800	Pella, IA	32615	15N
426	37860	Pensacola-Ferry Pass-Brent, FL	32616	16N
-	37900	Peoria, IL	32616	16N
316	37940	Peru, IN	32616	16N
428	37980	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	32618	18N
429	38060	Phoenix-Mesa-Chandler, AZ	32612	12N
406	38100	Picayune, MS	32615	15N
-	38180	Pierre, SD	32614	14N
340	38220	Pine Bluff, AR	32615	15N
246	38240	Pinehurst-Southern Pines, NC	32617	17N
-	38260	Pittsburg, KS	32615	15N
430	38300	Pittsburgh, PA	32617	17N
-	38340	Pittsfield, MA	32618	18N
352	38380	Plainview, TX	32614	14N
-	38420	Platteville, WI	32615	15N
-	38460	Plattsburgh, NY	32618	18N
515	38500	Plymouth, IN	32616	16N
-	38540	Pocatello, ID	32612	12N
170	38580	Point Pleasant, WV-OH	32617	17N
-	38620	Ponca City, OK	32614	14N
145	38700	Pontiac, IL	32616	16N
-	38740	Poplar Bluff, MO	32615	15N
188	38780	Portales, NM	32613	13N

Continued on next page

Table A.1 – *Continued from previous page*

CBSA FIPS Code	CBSA FIPS Code	CBSA Name	EPSG Code	UTM Zone
-	38820	Port Angeles, WA	32610	10N
438	38860	Portland-South Portland, ME	32619	19N
440	38900	Portland-Vancouver-Hillsboro, OR-WA	32610	10N
544	38920	Port Lavaca, TX	32614	14N
370	38940	Port St. Lucie, FL	32617	17N
170	39020	Portsmouth, OH	32617	17N
-	39060	Pottsville, PA	32618	18N
408	39100	Poughkeepsie-Newburgh-Middletown, NY	32618	18N
-	39150	Prescott Valley-Prescott, AZ	32612	12N
-	39220	Price, UT	32612	12N
140	39260	Prineville, OR	32610	10N
148	39300	Providence-Warwick, RI-MA	32619	19N
482	39340	Provo-Orem, UT	32612	12N
444	39380	Pueblo, CO	32613	13N
446	39420	Pullman, WA	32611	11N
412	39460	Punta Gorda, FL	32617	17N
448	39500	Quincy, IL-MO	32615	15N
376	39540	Racine, WI	32616	16N
450	39580	Raleigh-Cary, NC	32617	17N
452	39660	Rapid City, SD	32613	13N
154	39700	Raymondville, TX	32614	14N
428	39740	Reading, PA	32618	18N
454	39780	Red Bluff, CA	32610	10N
454	39820	Redding, CA	32610	10N
378	39860	Red Wing, MN	32615	15N
456	39900	Reno, NV	32611	11N
292	39940	Rexburg, ID	32612	12N
458	39980	Richmond, IN	32616	16N
-	40060	Richmond, VA	32618	18N
336	40080	Richmond-Berea, KY	32616	16N

Continued on next page

Table A.1 – *Continued from previous page*

CBSA FIPS Code	CBSA FIPS Code	CBSA Name	EPSG Code	UTM Zone
365	40100	Rio Grande City-Roma, TX	32614	14N
348	40140	Riverside-San Bernardino-Ontario, CA	32611	11N
-	40180	Riverton, WY	32612	12N
-	40220	Roanoke, VA	32617	17N
468	40260	Roanoke Rapids, NC	32618	18N
466	40300	Rochelle, IL	32616	16N
462	40340	Rochester, MN	32615	15N
464	40380	Rochester, NY	32618	18N
466	40420	Rockford, IL	32616	16N
-	40460	Rockingham, NC	32617	17N
204	40530	Rockport, TX	32614	14N
-	40540	Rock Springs, WY	32612	12N
468	40580	Rocky Mount, NC	32618	18N
-	40620	Rolla, MO	32615	15N
122	40660	Rome, GA	32616	16N
-	40700	Roseburg, OR	32610	10N
-	40740	Roswell, NM	32613	13N
-	40760	Ruidoso, NM	32613	13N
-	40780	Russellville, AR	32615	15N
384	40820	Ruston, LA	32615	15N
-	40860	Rutland, VT	32618	18N
472	40900	Sacramento-Roseville-Folsom, CA	32610	10N
-	40940	Safford, AZ	32612	12N
474	40980	Saginaw, MI	32617	17N
378	41060	St. Cloud, MN	32615	15N
-	41100	St. George, UT	32612	12N
312	41140	St. Joseph, MO-KS	32615	15N
476	41180	St. Louis, MO-IL	32615	15N
300	41220	St. Marys, GA	32617	17N
-	41260	St. Marys, PA	32617	17N

Continued on next page

Table A.1 – *Continued from previous page*

CBSA FIPS Code	CBSA FIPS Code	CBSA Name	EPSG Code	UTM Zone
566	41400	Salem, OH	32617	17N
440	41420	Salem, OR	32610	10N
-	41460	Salina, KS	32614	14N
-	41500	Salinas, CA	32610	10N
480	41540	Salisbury, MD-DE	32618	18N
482	41620	Salt Lake City, UT	32612	12N
-	41660	San Angelo, TX	32614	14N
484	41700	San Antonio-New Braunfels, TX	32614	14N
-	41740	San Diego-Chula Vista-Carlsbad, CA	32611	11N
-	41760	Sandpoint, ID	32611	11N
184	41780	Sandusky, OH	32617	17N
246	41820	Sanford, NC	32617	17N
488	41860	San Francisco-Oakland-Berkeley, CA	32610	10N
488	41940	San Jose-Sunnyvale-Santa Clara, CA	32610	10N
-	42020	San Luis Obispo-Paso Robles, CA	32610	10N
488	42100	Santa Cruz-Watsonville, CA	32610	10N
106	42140	Santa Fe, NM	32613	13N
-	42200	Santa Maria-Santa Barbara, CA	32610	10N
488	42220	Santa Rosa-Petaluma, CA	32610	10N
-	42300	Sault Ste. Marie, MI	32616	16N
496	42340	Savannah, GA	32617	17N
-	42380	Sayre, PA	32618	18N
-	42420	Scottsbluff, NE	32613	13N
497	42460	Scottsboro, AL	32616	16N
350	42500	Scottsburg, IN	32616	16N
-	42540	Scranton–Wilkes-Barre, PA	32618	18N
340	42620	Searcy, AR	32615	15N
500	42660	Seattle-Tacoma-Bellevue, WA	32610	10N
370	42680	Sebastian-Vero Beach, FL	32617	17N
-	42700	Sebring-Avon Park, FL	32617	17N

Continued on next page

Table A.1 – *Continued from previous page*

CBSA FIPS Code	CBSA FIPS Code	CBSA Name	EPSG Code	UTM Zone
-	42740	Sedalia, MO	32615	15N
146	42780	Selinsgrove, PA	32618	18N
388	42820	Selma, AL	32616	16N
273	42860	Seneca, SC	32617	17N
464	42900	Seneca Falls, NY	32618	18N
315	42940	Sevierville, TN	32617	17N
294	42980	Seymour, IN	32616	16N
267	43020	Shawano, WI	32616	16N
416	43060	Shawnee, OK	32614	14N
-	43100	Sheboygan, WI	32616	16N
172	43140	Shelby, NC	32617	17N
400	43180	Shelbyville, TN	32616	16N
500	43220	Shelton, WA	32610	10N
-	43260	Sheridan, WY	32613	13N
206	43300	Sherman-Denison, TX	32614	14N
-	43320	Show Low, AZ	32612	12N
508	43340	Shreveport-Bossier City, LA	32615	15N
212	43380	Sidney, OH	32616	16N
-	43420	Sierra Vista-Douglas, AZ	32612	12N
164	43460	Sikeston, MO	32616	16N
-	43500	Silver City, NM	32612	12N
-	43580	Sioux City, IA-NE-SD	32614	14N
-	43620	Sioux Falls, SD	32614	14N
-	43660	Snyder, TX	32614	14N
-	43700	Somerset, KY	32616	16N
306	43740	Somerset, PA	32617	17N
-	43760	Sonora, CA	32610	10N
515	43780	South Bend-Mishawaka, IN-MI	32616	16N
273	43900	Spartanburg, SC	32617	17N
452	43940	Spearfish, SD	32613	13N

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Table A.1 – *Continued from previous page*

CBSA FIPS Code	CBSA FIPS Code	CBSA Name	EPSG Code	UTM Zone
517	43980	Spencer, IA	32615	15N
517	44020	Spirit Lake, IA	32615	15N
518	44060	Spokane-Spokane Valley, WA	32611	11N
522	44100	Springfield, IL	32616	16N
-	44140	Springfield, MA	32618	18N
-	44180	Springfield, MO	32615	15N
212	44220	Springfield, OH	32616	16N
-	44260	Starkville, MS	32616	16N
524	44300	State College, PA	32618	18N
496	44340	Statesboro, GA	32617	17N
277	44420	Staunton, VA	32617	17N
525	44460	Steamboat Springs, CO	32613	13N
-	44500	Stephenville, TX	32614	14N
-	44540	Sterling, CO	32613	13N
221	44580	Sterling, IL	32616	16N
554	44620	Stevens Point, WI	32616	16N
-	44660	Stillwater, OK	32614	14N
488	44700	Stockton, CA	32610	10N
-	44740	Storm Lake, IA	32615	15N
310	44780	Sturgis, MI	32616	16N
-	44860	Sulphur Springs, TX	32615	15N
174	44900	Summerville, GA	32616	16N
-	44940	Sumter, SC	32617	17N
146	44980	Sunbury, PA	32618	18N
-	45000	Susanville, CA	32610	10N
-	45020	Sweetwater, TX	32614	14N
532	45060	Syracuse, NY	32618	18N
-	45140	Tahlequah, OK	32615	15N
142	45180	Talladega-Sylacauga, AL	32616	16N
-	45220	Tallahassee, FL	32616	16N

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Table A.1 – *Continued from previous page*

CBSA FIPS Code	CBSA FIPS Code	CBSA Name	EPSG Code	UTM Zone
-	45300	Tampa-St. Petersburg-Clearwater, FL	32617	17N
-	45340	Taos, NM	32613	13N
522	45380	Taylorville, IL	32616	16N
-	45460	Terre Haute, IN	32616	16N
-	45500	Texarkana, TX-AR	32615	15N
-	45520	The Dalles, OR	32610	10N
422	45540	The Villages, FL	32617	17N
122	45580	Thomaston, GA	32616	16N
-	45620	Thomasville, GA	32617	17N
534	45660	Tiffin, OH	32617	17N
-	45700	Tifton, GA	32617	17N
122	45740	Toccoa, GA	32616	16N
534	45780	Toledo, OH	32617	17N
-	45820	Topeka, KS	32615	15N
408	45860	Torrington, CT	32618	18N
-	45900	Traverse City, MI	32616	16N
408	45940	Trenton-Princeton, NJ	32618	18N
-	45980	Troy, AL	32616	16N
472	46020	Truckee-Grass Valley, CA	32610	10N
536	46060	Tucson, AZ	32612	12N
-	46100	Tullahoma-Manchester, TN	32616	16N
538	46140	Tulsa, OK	32615	15N
539	46180	Tupelo, MS	32616	16N
-	46220	Tuscaloosa, AL	32616	16N
-	46300	Twin Falls, ID	32611	11N
540	46340	Tyler, TX	32615	15N
-	46380	Ukiah, CA	32610	10N
273	46420	Union, SC	32617	17N
362	46460	Union City, TN	32616	16N
212	46500	Urbana, OH	32616	16N

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Table A.1 – *Continued from previous page*

CBSA FIPS Code	CBSA FIPS Code	CBSA Name	EPSG Code	UTM Zone
-	46520	Urban Honolulu, HI	32604	4N
-	46540	Utica-Rome, NY	32618	18N
-	46620	Uvalde, TX	32614	14N
-	46660	Valdosta, GA	32617	17N
488	46700	Vallejo, CA	32610	10N
338	46780	Van Wert, OH	32616	16N
-	46820	Vermillion, SD	32614	14N
-	46860	Vernal, UT	32612	12N
-	46900	Vernon, TX	32614	14N
298	46980	Vicksburg, MS	32615	15N
544	47020	Victoria, TX	32614	14N
-	47080	Vidalia, GA	32617	17N
-	47180	Vincennes, IN	32616	16N
428	47220	Vineland-Bridgeton, NJ	32618	18N
-	47240	Vineyard Haven, MA	32619	19N
545	47260	Virginia Beach-Norfolk-Newport News, VA-NC	32618	18N
-	47300	Visalia, CA	32611	11N
-	47340	Wabash, IN	32616	16N
-	47380	Waco, TX	32614	14N
244	47420	Wahpeton, ND-MN	32614	14N
313	47460	Walla Walla, WA	32611	11N
338	47540	Wapakoneta, OH	32616	16N
356	47580	Warner Robins, GA	32617	17N
-	47620	Warren, PA	32617	17N
312	47660	Warrensburg, MO	32615	15N
515	47700	Warsaw, IN	32616	16N
-	47780	Washington, IN	32616	16N
272	47820	Washington, NC	32618	18N
548	47900	Washington-Arlington-Alexandria, DC-VA-MD-WV	32618	18N

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Table A.1 – *Continued from previous page*

CBSA FIPS Code	CBSA FIPS Code	CBSA Name	EPSG Code	UTM Zone
198	47920	Washington Court House, OH	32617	17N
-	47940	Waterloo-Cedar Falls, IA	32615	15N
-	47980	Watertown, SD	32614	14N
376	48020	Watertown-Fort Atkinson, WI	32616	16N
-	48060	Watertown-Fort Drum, NY	32618	18N
422	48100	Wauchula, FL	32617	17N
554	48140	Wausau-Weston, WI	32616	16N
-	48180	Waycross, GA	32617	17N
-	48220	Weatherford, OK	32614	14N
430	48260	Weirton-Steubenville, WV-OH	32617	17N
-	48300	Wenatchee, WA	32610	10N
-	48460	West Plains, MO	32615	15N
200	48500	West Point, MS	32616	16N
-	48540	Wheeling, WV-OH	32617	17N
376	48580	Whitewater, WI	32616	16N
556	48620	Wichita, KS	32614	14N
-	48660	Wichita Falls, TX	32614	14N
558	48700	Williamsport, PA	32618	18N
-	48780	Williston, ND	32613	13N
-	48820	Willmar, MN	32615	15N
-	48900	Wilmington, NC	32618	18N
178	48940	Wilmington, OH	32616	16N
468	48980	Wilson, NC	32618	18N
548	49020	Winchester, VA-WV	32618	18N
556	49060	Winfield, KS	32614	14N
-	49080	Winnemucca, NV	32611	11N
-	49100	Winona, MN	32615	15N
268	49180	Winston-Salem, NC	32617	17N
554	49220	Wisconsin Rapids-Marshfield, WI	32616	16N
-	49260	Woodward, OK	32614	14N

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Table A.1 – *Continued from previous page*

CBSA FIPS Code	CBSA FIPS Code	CBSA Name	EPSG Code	UTM Zone
184	49300	Wooster, OH	32617	17N
148	49340	Worcester, MA-CT	32619	19N
-	49380	Worthington, MN	32615	15N
-	49420	Yakima, WA	32610	10N
-	49460	Yankton, SD	32614	14N
276	49620	York-Hanover, PA	32618	18N
566	49660	Youngstown-Warren-Boardman, OH-PA	32617	17N
472	49700	Yuba City, CA	32610	10N
-	49740	Yuma, AZ	32611	11N
198	49780	Zanesville, OH	32617	17N
-	49820	Zapata, TX	32614	14N

Appendix B: Data Sources for Characterizing Neighborhoods

This appendix contains technical details on the five sources of data used to characterize neighborhoods as described in Chapter 2: population and housing data from the Census Bureau's American Community Survey (ACS) program, jobs data from the Census Bureau's Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LODES) program, land cover data from the US Geological Survey National Land Cover Database (NLCD), a shapefile of military bases from the Bureau of Transportation Statistics National Transportation Atlas Database (NATD), and road network shapefiles from the OpenStreetMap (OSM) project.

Table B.1: Census Table B03002: Hispanic Or Latino Origin By Race

Variable	**Name**
B03002_001	Total Population
B03002_003	Non-Hispanic White Population
B03002_004	Non-Hispanic Black Population
B03002_005	Non-Hispanic Native American and Alaskan Native Population
B03002_006	Non-Hispanic Asian Population
B03002_007	Non-Hispanic Native Hawaiian and Pacific Islander Population
B03002_008	Non-Hispanic Some Other Race Population
B03002_009	Non-Hispanic Two or More Races Population
B03002_012	Hispanic or Latino of Any Race Population

B.1 Census Bureau American Community Survey

To characterize the population and housing stock of the hex cells, I used 2018 five-year estimate data from the Census Bureau's American Community Survey, acquired through the `tidycensus` library in R. This data was tabulated by census block groups, the smallest geography for which ACS data is available, which were acquired through the `tigris` library in R.

Data was collected from five Census tables `B03002` (Hispanic Or Latino Origin By Race), `B08301` (Means Of Transportation To Work), `B19013` (Median Household Income In The Past 12 Months (In 2018 Inflation-Adjusted Dollars)), `B25032` (Tenure By Units In Structure), and `B25044` (Tenure By Vehicles Available).

Tables B.1-B.5 on pages 290-293 show the Census data that was imported. For the purpose of typologizing hex cells, only the data on total population (from table `B03002`, variable `001`) and on the numbers of housing units of different types (from table `B25032`, with owner-occupied and renter-occupied units consolidated) was used. However, additional data was collected for use in typologizing metropolitan areas based on their land use distributions. The list of variables included in the 2018 ACS are supplied by the US Census Bureau (2021b) on variable definitions are from US Census Bureau (2019a).

Table B.2: Census Table B08301: Means Of Transportation To Work

Variable	Name
B08301_001	Total Workers 16 Years and Over
B08301_003	# of Workers Who Drove Alone
B08301_004	# of Workers Who Carpooled
B08301_010	# of Workers Who Rode Public Transportation
B08301_016	# of Workers Who Used Taxicabs
B08301_017	# of Workers Who Rode Motorcycles
B08301_018	# of Workers Who Rode Bicycles
B08301_019	# of Workers Who Walked
B08301_020	# of Workers Who Commuted by Other Means
B08301_021	# of Workers Who Worked at Home

Table B.3: Census Table B19013: Median Household Income In The Past 12 Months

Variable	Name
B19013_001	Median Household Income In The Past 12 Months (In 2018 Inflation-Adjusted Dollars)

Table B.4: Census Table B25032: Tenure By Units In Structure

Variable	Name
B25032_001	Total Occupied Housing Units
B25032_002	Total Owner-Occupied Housing Units
B25032_003	# of Units: Owner-Occupied, 1 Detached Unit in Structure
B25032_004	# of Units: Owner-Occupied, 1 Attached Unit in Structure
B25032_005	# of Units: Owner-Occupied, 2 Units in Structure
B25032_006	# of Units: Owner-Occupied, 3-4 Units in Structure
B25032_007	# of Units: Owner-Occupied, 5-9 Units in Structure
B25032_008	# of Units: Owner-Occupied, 10-19 Units in Structure
B25032_009	# of Units: Owner-Occupied, 20-49 Units in Structure
B25032_010	# of Units: Owner-Occupied, 50 or More Units in Structure
B25032_011	# of Units: Owner-Occupied, Mobile Home
B25032_012	# of Units: Owner-Occupied, Boat, RV, Van, Etc
B25032_013	Total Renter-Occupied Housing Units
B25032_014	# of Units: Renter-Occupied, 1 Detached Unit in Structure
B25032_015	# of Units: Renter-Occupied, 1 Attached Unit in Structure
B25032_016	# of Units: Renter-Occupied, 2 Units in Structure
B25032_017	# of Units: Renter-Occupied, 3-4 Units in Structure
B25032_018	# of Units: Renter-Occupied, 5-9 Units in Structure
B25032_019	# of Units: Renter-Occupied, 10-19 Units in Structure
B25032_020	# of Units: Renter-Occupied, 20-49 Units in Structure
B25032_021	# of Units: Renter-Occupied, 50 or More Units in Structure
B25032_022	# of Units: Renter-Occupied, Mobile Home
B25032_023	# of Units: Renter-Occupied, Boat, RV, Van, Etc

Table B.5: Census Table B25044: Tenure By Vehicles Available

Variable	Name
B25044_001	Total Occupied Housing Units
B25044_002	Total Owner-Occupied Housing Units
B25044_003	# of Units: Owner-Occupied Units with No Vehicles Available
B25044_004	# of Units: Owner-Occupied Units with 1 Vehicles Available
B25044_005	# of Units: Owner-Occupied Units with 2 Vehicles Available
B25044_006	# of Units: Owner-Occupied Units with 3 Vehicles Available
B25044_007	# of Units: Owner-Occupied Units with 4 Vehicles Available
B25044_008	# of Units: Owner-Occupied Units with 5 or More Vehicles Available
B25044_009	Total Renter-Occupied Housing Units
B25044_010	# of Units: Renter-Occupied Units with No Vehicles Available
B25044_011	# of Units: Renter-Occupied Units with 1 Vehicles Available
B25044_012	# of Units: Renter-Occupied Units with 2 Vehicles Available
B25044_013	# of Units: Renter-Occupied Units with 3 Vehicles Available
B25044_014	# of Units: Renter-Occupied Units with 4 Vehicles Available
B25044_015	# of Units: Renter-Occupied Units with 5 or More Vehicles Available

B.2 Census Bureau LEHD Origin-Destination Employment Statistics

To characterize employment (and thus retail, office, education and medical, and industrial uses) in the hex cells, I used employment data from version 7.4 of the US Census Bureau (2019d) LEHD Origin-Destination Employment Statistics dataset, acquired with the R library `lehdr`. Since this data is tabulated by Census blocks, acquired with the R library `tigris`, I was able to obtain better spatial resolution than was available for the ACS demographic data.

However, version 7.4 of the LODES data—the most recent available when I began this project—does not include 2018 data and I had to use jobs data from three different years:

- Data on federal jobs (excluding military and national-security-related jobs, which are not reported by LEHD) was last reported for 2015.
- Data on non-federal jobs in South Dakota and Alaska was last reported for 2016.
- For non-federal jobs in the other forty-eight states and the District of Columbia, 2017 data was available.

I used "workplace area characteristics" (i.e. data on jobs located in a given Census block, rather than the jobs held by workers living in a given Census block) data for workforce segment `S000`—all workers, regardless of age, income, or industry—and job type `JT02`—all non-federal jobs—for 2017 (and 2016 in Alaska and South Dakota) and job type `JT04`—all federal jobs—for 2015 and summed the federal and non-federal jobs for each Census block. The job variables downloaded are listed in Table B.6 on page 295. (US Census Bureau, 2019c)

Table B.6: LODES Workplace Area Characteristics Data Variables

Variable	**Type of Jobs**
C000	All Jobs
CE01	# of Jobs Earning $\leq$ \$1,250 per Month
CE02	# of Jobs Earning \$1,251 per month to \$3,333 per month
CE03	# of Jobs Earning $>$ \$3,333 per month
CNS01	# of Jobs in NAICS Sector 11 (Agriculture, Forestry, Fishing, Hunting)
CNS02	# of Jobs in NAICS Sector 21 (Mining, Quarrying, and Oil and Gas Extraction)
CNS03	# of Jobs in NAICS Sector 22 (Utilities)
CNS04	# of Jobs in NAICS Sector 23 (Construction)
CNS05	# of Jobs in NAICS Sector 31-33 (Manufacturing)
CNS06	# of Jobs in NAICS Sector 42 (Wholesale Trade)
CNS07	# of Jobs in NAICS Sector 44-45 (Retail Trade)
CNS08	# of Jobs in NAICS Sector 48-49 (Transportation and Warehousing)
CNS09	# of Jobs in NAICS Sector 51 (Information)
CNS10	# of Jobs in NAICS Sector 52 (Finance and Insurance)
CNS11	# of Jobs in NAICS Sector 53 (Real Estate and Rental and Leasing)
CNS12	# of Jobs in NAICS Sector 54 (Professional, Scientific, and Technical Services)
CNS13	# of Jobs in NAICS Sector 55 (Management of Companies and Enterprises)
CNS14	# of Jobs in NAICS Sector 56 (Admin, Support, and Waste Management Services)
CNS15	# of Jobs in NAICS Sector 61 (Educational Services)
CNS16	# of Jobs in NAICS Sector 62 (Health Care and Social Assistance)
CNS17	# of Jobs in NAICS Sector 71 (Arts, Entertainment, and Recreation)
CNS18	# of Jobs in NAICS Sector 72 (Accommodation and Food Services)
CNS19	# of Jobs in NAICS Sector 81 (Other Services except Public Administration)
CNS20	# of Jobs in NAICS Sector 92 (Public Administration)

Table B.7: LODES Industry Groupings Used to Characterize Neighborhoods

Industry	**NAICS Codes Included**
Retail	44-45, 71, 72, 81
Education/Medical	61, 62
Office	51, 52, 53, 54, 55, 56, 91
Industrial	11, 21, 22, 23, 31-33, 42, 48-49

While using federal and non-federal jobs from different years, and using non-federal jobs from a different year for two states, does potentially introduce error, the date range for the data used here is relatively small, and I think that the benefits of being able to include all jobs and all CBSAs in the US with the most recent data available outweigh the downsides of using data from different years.

Although job data by income level was collected for potential use in typologizing metro areas, for the characterization of neighborhoods discussed in 2, jobs were classified into four industry groupings based on North American Industry Classification System (NAICS) codes: retail, education/medical (eds/meds), office, and industrial, as shown in Table B.7 on page 296.

It is, however, worth noting several issues with the LODES workplace location data. For one thing, since the data is collected from a number of sources, including employer reporting of workplace locations, there are a number of mis-located jobs, apparently due to large employers reporting all of their employees as working at a single address even when their workplaces are actually spread over a large location.

Government employers are commonly guilty of this—for example, Fairfax County Public Schools in Virginia reports all of the school system's employees as working at the school system headquarters rather than at the schools where most of them are actually employed—though some private employers, especially temp agencies, do it as well. However, because public school systems are among the largest employers in many areas, fictitious concentrations of education jobs are particularly common.

A separate issue relates to the relatively broad sets of jobs included in the two-digit NAICS codes that LODES data is indexed by. Not all jobs included in a two-digit NAICS code necessarily fall into the same job type as the industry grouping I've assigned the job type to. For example, a large fraction of the jobs in downtown Houston are in NAICS Sector 21 (Mining, Quarrying, and Oil and Gas Extraction). However, these are obviously not industrial-type jobs on oil rigs or in oil refineries: they are in fact jobs in the headquarters of major petrochemical companies that should be classified as office jobs for the purposes of this project. However, because most concentrations of NAICS Sector 21 jobs are industrial facilities, these jobs are classified as "industrial" in characterizing the hex cells containing downtown Houston.

Finally, it is important to note that active-duty military and national-security-related Federal jobs are excluded from the LODES datasets, which means that military bases and other DOD facilities, as well as offices of intelligence agencies, do not show up in the data. This limitation of the data necessitated the decision to exclude neighborhoods located on military bases from analysis, and may also complicate comparisons with the Washington-Arlington-Alexandria, DC-VA-MD-WV metropolitan area.

B.3 USGS and NOAA Land Cover Data

Remote-sensing-based land cover raster data from the US Geological Survey (USGS) and National Oceanic and Atmospheric Administration (NOAA) was used to distinguish between developed and undeveloped land at a higher resolution than US Census Bureau data allowed. In this document, land cover raster data is referred to as National Land Cover Database data throughout this document. However, three separate sources were used for this data:

- For the contiguous US (CONUS), the most recent data was available: a raster of NLCD data from 2016. (US Geologic Survey, 2020) Details of the creation of this dataset have been published by Yang et al. (2018) and Homer et al. (2015).
- For Alaska, a 2011 raster of NLCD data was used, as more recent data was unavailable. (US Geologic Survey, 2020)
- For Hawaii, 2005 NOAA raster was used. (US Geologic Survey, 2020)

Despite the different sources of the data, all land cover raster data consisted of 30-m square pixels. Furthermore, all three data sources used equivalent metrics for defining "developed" land. Pixels with 20% or more coverage by artificial impervious surfaces were classified as "developed". Pixels with less than 20% coverage by artificial impervious surfaces were classified as "undeveloped open space," which I treated as equivalent to undeveloped land for the purposes of my calculations.

However, the 11-year difference in vintage between the data used for Hawaii and that used for the contiguous US may present issues with the comparability of my analysis of Hawaiian CBSAs to those in CONUS. In addition, since my other data on Hawaiian CBSAs is more recent, I have some concern about the applicability of 2005 land-cover data.

B.4 Military Base Shapefile from NTAD

The shapefile `Military_Bases.shp` was downloaded from the National Transportation Atlas Database NTAD maintained by the US Bureau of Transportation Statistics (2019). The version used in this project was last updated on 21 May 2019. The data description is as follows:

> The Military Bases dataset is as of May 21, 2019, and is part of the U.S. Department of Transportation (USDOT)/Bureau of Transportation Statistics's (BTS's) National Transportation Atlas Database (NTAD). The dataset depicts the authoritative boundaries of the most commonly known Department of Defense (DoD) sites, installations, ranges, and training areas in the United States and Territories. These sites encompass land which is federally owned or otherwise managed. This dataset was created from source data provided by the four Military Service Component headquarters and was compiled by the Defense Installation Spatial Data Infrastructure (DISDI) Program within the Office of the Deputy Under Secretary of Defense for Installations and Environment, Business Enterprise Integration Directorate. Sites were selected from the 2010 Base Structure Report (BSR), a summary of the DoD Real Property Inventory. This list does not necessarily represent a comprehensive collection of all Department of Defense facilities, and only those in the fifty United States and US Territories were considered for inclusion. For inventory purposes, installations are comprised of sites, where a site is defined as a specific geographic location of federally owned or managed land and is assigned to military installation. DoD installations are commonly referred to as a base, camp, post, station, yard, center, homeport facility for any ship, or other activity under the jurisdiction, custody, control of the DoD. (US Bureau of Transportation Statistics, 2019)

This dataset was used to identify land that was part of military bases: this land was excluded from further analysis, since military and Department of Defense jobs are excluded from the jobs data used in the analysis, and since military bases are relatively *sui generis* and are not really an urban land use, particularly in the post-9/11 world, where they are generally not open to the general public.

B.5 OpenStreetMap Road Shapefiles

OpenStreetMap data was downloaded from the Geofabrik website (Geofabrik GmbH, 2020) on 11 March 2020. This data is organized by state (with northern and southern California separated) and contains layers named `gis_osm_roads_free_1.shp` for each state that consist of what OpenStreetMap Foundation (2021a) refers to as its "highways" features: actually all roads and pedestrian paths. This model of the road network appears to be more complete than the data provided by the Census Bureau—some comments in the talk pages of the OSM wiki suggest that it is in fact *based* on the roads data provided by the Census Bureau, which would make sense—and certainly includes more details on road types that can be used to identify what is and is not pedestrian-friendly.

The OSM roads data was used to calculate walksheds—and thus percent ideal walksheds—for each hex cell, as well as to calculate the number of dead-ends, three-way intersections, and four-or-more-way intersections in each hex cell. Before these calculations were performed, evidently non-walkable roads were removed based on the values of the `fclass` variable that describes the "type" of roadway (OpenStreetMap Foundation (2021b); OpenStreetMap Foundation (2021c); and OpenStreetMap Foundation (2021d)). Removing roads based on the presence or absence of tags indicating sidewalks, or based on a maximum speed limit (given in the `maxspeed` variable), was considered but determined to be non-viable to to the incompleteness of this data.

Most of the listed road types potentially allow for pedestrians; the four road types that were removed from walkshed calculations are shown in Table B.8 on page 302. Roads with these pedestrian-unfriendly `fclass` values were excluded from the street networks used to count intersections as well. In addition, roads with the `fclass` value `service` were removed because they generally consisted of lanes in parking lots, as well as driveways in rural areas, and were not generally consistently included in the dataset.

Table B.8: OSM Highway fclass Tags Excluded from Walkshed Analysis

Tag	Description
motorway	Limited access freeway with interchanges.
motorway_link	Access ramps for motorways.
trunk	Limited access highway with occasional grade level intersections.
trunk_link	Access ramps for trunks.

Table B.9: OSM Highway fclass Tags Excluded from Intersection Analysis

Tag	Description
motorway	Limited access freeway with interchanges.
motorway_link	Access ramps for motorways.
trunk	Limited access highway with occasional grade level intersections.
trunk_link	Access ramps for trunks.
service	Driveways and parking lots.
footway	Sidewalks and some pedestrian paths.
steps	Steps found within footway paths.

Likewise, “roads” with fclass values of footway or steps were removed because these fclass values were usually used to identify sidewalks. Including sidewalks as well as the roads themselves would produce multiple closely-spaced spurious intersections at each actual intersection. Furthermore, since sidewalks are not consistently included for all neighborhoods in the OSM highways data, including them would introduce a false distinction between neighborhoods based on the completeness of their data. Table B.9 on page 302 shows the full set of OSM highway tags excluded from the street networks used to calculate intersection densities.

Appendix C: Methodology and Scripts for Characterizing Neighborhoods

The most computationally intensive part of this project is the process, discussed in Sections 2.3 and 2.5, of defining and characterizing neighborhoods in metropolitan areas using the data sources detailed in Appendix B.

This appendix discusses the R scripts[1]—run under R version 3.6.2—and technical details of the processes used to characterize the neighborhoods and produce the `hex-final-` shapefiles of characterized hex cells used to typologize neighborhoods and metropolitan areas. It is divided into six sections, each consisting of a prose description of the procedures used by a set of R scripts:

- Section C.1: Generating and Cropping Hex Grids
- Section C.2: Processing NLCD Data
- Section C.3: Processing Census Data
- Section C.4: Extracting Data to Hex Cells
- Section C.5: Processing Roads Data
- Section C.6: Initial Analysis of the Hex Cells

[1]The source code for these R scripts can be found online in UMBC's ScholarWorks repository.

C.1 Generating and Cropping Hex Grids

The initial process of generating and cropping the hex cells involved three R scripts. First, the script `HexGrids-1-GenerateHex.R` is used to generate grids of hex cells for each CBSA. Then, the script `Census-1-DownloadWater.R` is used to download water features for each CBSA. Finally, the script is used `HexGrids-2-CropWater.R` to remove the water features from the hex grids.

The script `HexGrids-1-GenerateHex.R` generates blank hexagonal grids in the appropriate UTM projection for each CBSA in the US. The hexagons generated have side lengths and radius (center to vertices) of 400 m. All hexagons for a given UTM zone are generated in one batch so that they line up between bounding CBSAs and CBSAs in the same CSA in particular. However, hexagons that are split by a CBSA boundary are divided into two partial hexagons, one for each CBSA.

Hexagon grids for each CBSA were saved with the prefix `hex-blank-` and individual hexagons within a given hex grid were given ID numbers in the field `HEXID`. The first action performed on these hex grids after they were saved was the removal of water features, which required that water feature objects be downloaded from the Census.

The first in a series of scripts to download Census data, `Census-1-DownloadWater.R`, uses the `tigris` library to download water area features (by county) for each of the counties in each CBSA, remove water features with areas of less than 100,000 m^2, and, merge all water features within a given CBSA together to simplify future calculations. The resulting objects were saved with the filename prefix `Census-water-`.

Then, to remove water features, the script `HexGrids-2-CropWater.R` loads blank hex grids and Census water features and produces hex grids with the water features removed. Depending on the area of a hex after water is removed, one of three things is done:

1. If the land area of the hex with water removed is 15% or less of the area of a complete hex, the hex is deleted on the assumption that it is too small for statistics on it to be done usefully, and to save space and calculation time.

2. If the land area of the hex with water removed is 85% or more of the area of a complete hex, the non-water-removed hex is used, since the water features are too small to make a significant impact in the nature of the hex. This also saves calculation time and space (since it eliminates an irregularly-shaped hex) and takes into account the fact that small water features are not consistently recorded by the Census for counties: some counties seem to have small ponds and such included and others do not, even when they have similar geography (Prince George's and Anne Arundel Counties on opposite sides of the Patuxent, for example).

3. If the land area of the hex with water removed is between 15% and 85% of the area of a complete hex, the water-removed hex is used.

In cases 2 and 3, the land area of the hex in m^2 is recorded in the variable `AREA_m`. The resulting water-removed hexes are saved with the filename prefix `hex-dry-`.

C.2 Processing NLCD Data

The script `NLCDB-1-ReclassifyPixelCounting.R` imports downloaded rasters for the contiguous US (CONUS), Alaska, and Hawaii and crops them to produce separate rasters for each CBSA in the US. These rasters are kept in the same CRS projections as the original downloaded rasters, to avoid the difficulties involved in reprojecting rasters. However, their pixel values are reclassified to have a value of `1` for all undeveloped land (including water and developed open space) and a value of `4` for low-, medium-, and high-intensity developed land. The output rasters have the filename prefix `NLCDB-raster-` and are intended for use in counting the number of developed and undeveloped pixels in each hexagon.

In the process of extracting ACS and LEHD Census data from the geometries in which they are tabulated (block groups and blocks, respectively) and assigning it to hex cells, the Census geometries are cropped to remove undeveloped land as identified in the NLCD land cover raster data. In order to do this, it is first necessary to create "masking" vectors of undeveloped land from the land cover raster data. This requires a series of four scripts:

- `NLCDB-2-ReclassifyMasking.R` to crop NLCD data to the rectangular bounding box of each CBSA, reclassify the pixels as developed or undeveloped, and reduce the resolution of the rasters.
- `NLCDB-3-GeneratePolygonizeNLCDB.R` to generate a DOS batch script to convert the raster to polygons.
- `NLCDB-4-PolygonizeNLCDB.bat` to use the`gdal_polygonize.bat` GDAL python script to convert the NLCDB rasters to vectors.
- `NLCDB-5-MakeMaskingPolygons.R` (pg. to remove developed land from the vectors, transform them to the correct UTM zones, and crop them to CBSA boundaries.

The `NLCDB-2-ReclassifyMasking.R` reclassification script is very similar to the script—`NLCDB-1-PixelCounting.R`— used to prepare NLCD vectors for the counting of the percentage of developed land in each hex. However, it also uses the `aggregate` function to convert the rasters from 30-m square pixels to 180-m square pixels. These output rasters are also saved with the filename prefix `NLCDB-raster-`, but in a different directory than the rasters produced by the `NLCDB-1-PixelCounting.R` script.

The larger pixels are needed to make the subsequent vectorization and vector subtraction steps more computationally tractable. However, as 180-m square pixels are counted as developed if *any* of the 36 original pixels in them are classified as developed, this also helps to ensure that only large, contiguous tracts of developed land are removed from the Census geometries.

The next step is to convert the rasters output by `NLCDB-2-ReclassifyMasking.R` into vectors. Unfortunately, the `raster` package's script to do this is incredibly slow and not really practical to use, so I decided to instead use the `gdal_polygonize.bat` GDAL python script to do this step. The script can't be called directly from R because it needs to run in the OSGEO4W shell. It is important to note that whenever QGIS is upgraded, it is necessary to reinstall GDAL's command line tools, which are not included in the default QGIS install, and which are lost whenever QGIS is upgraded.

The R script `NLCDB-3-GeneratePolygonizeNLCDB.R` serves to generate the simple DOS batch file `NLCDB-4-PolygonizeNLCDB.bat`, which polygonizes every CBSA raster, taking inputs with the prefix `NLCDB-raster` and producing outputs with the prefix `NLCDB-vector-`.

Finally, the script `NLCDB-5-MakeMaskingPolygons.R` imports these vector files, removes developed land from them, transforms them to the appropriate UTM zone, fixes validity errors caused by the transformation by setting their geometry precision to 1 m with the `st_set_precision` function and using the `st_make_valid` function from the `lwgeom` package to remove validity errors, crops them to the boundaries of their CBSA, and merges all undeveloped area into a single feature to simplify future processing. The output vector objects have the prefix `NLCDB-merged-vector-`.

C.3 Processing Census Data

The R script `Census-2-DownloadACS.R` loops through each county in each CBSA and uses the `tidycensus` package to download ACS data by block group with associated geometries. The resulting `sf` objects are combined with the `rbind` command, transformed to the appropriate UTM coordinate system, and have the water features stored in the `Census-water-` files from Section 2.1 subtracted out. Note that, since not all CBSAs have non-zero water area, it is necessary to test whether the dimension of the water object is zero before subtracting it.

The ACS data is simplified by removing variables for margins of error and combining some related variables into single values. The resulting variables are given somewhat gnomic names to fit within the constraints for variable names set by the ESRI Shapefile format, as seen in Table C.1.

One of the trickier parts of this script is the final export to shapefiles: subtracting water features from block groups occasionally creates “linestring” features when a residue of a polygon is left with only two vertices. Because these features, although allowed in `sf` geometries, can’t be saved in ESRI Shapefiles of polygons, it was necessary to write a small loop to delete any linestring features. Once this process is completed, the geometries are saved with the filename prefix `Census-ACS-`.

The R scripts `Census-3-DownloadLEHD.R` and `Census-4-ProcessLEHD.R` download LEHD data using the `lehdr` package. However, the process by which they do this is somewhat convoluted and non-ideal, both due to practical constraints and the fact that the `Census-4-ProcessLEHD.R` performs some steps that should have been performed by `Census-3-DownloadLEHD.R` but which were omitted in error.

Table C.1: Variables Created by `Census-2-DownloadACS.R`

Variable	Definition
PP_tot	**Total Population**
PP_wht	Non-Hispanic White Population
PP_blk	Non-Hispanic Black Population
PP_ltn	Hispanic or Latino of Any Race Population
PP_asn	Non-Hispanic Asian Population
PP_oth	Non-Hispanic Other or Multiple Race Population
WK_tot	**Total Working Population**
WK_trnst	Workers Who Commute by Transit
WK_car	Workers Who Commute by Car or Motorcycle
WK_carpl	Workers Who Commute by Carpool
WK_activ	Workers Who Commute by Bicycle or Walking
WK_other	Workers Who Work at Home, Commute by Taxi, or Commute by Other Means
INC_MED	**Median Household Income**
HU_htot	**Total Number of Occupied Housing Units**
HU_h1d	Number of One-Unit Detached Housing Units
HU_h1a	Number of One-Unit Attached Housing Units
HU_h2	Number of Housing Units in Two-Unit Buildings
HU_h34	Number of Housing Units in Three- and Four- Unit Buildings
HU_h59	Number of Housing Units in Five- to Nine- Unit Buildings
HU_h1019	Number of Housing Units in 10- to 19- Unit Buildings
HU_h2049	Number of Housing Units in 20- to 49- Unit Buildings
HU_h50	Number of Housing Units in Buildings of 50 or More Units
HU_hmobl	Number of Housing Units in Mobile Homes, Vehicles, and Vessels
HU_vtot	**Total Number of Occupied Housing Units**
HU_b0	Number of Occupied Housing Units with No Vehicles Available
HU_v1	Number of Occupied Housing Units with One Vehicle Available
HU_v2	Number of Occupied Housing Units with Two Vehicles Available
HU_v3	Number of Occupied Housing Units with Three or More Vehicles Available

Downloading LEHD data is complicated by my decision to use Census blocks for this data. Since LEHD is tabulated by blocks, this choice provides the highest possible resolution for the locations of jobs. However, because blocks are the smallest—and most numerous—Census geography, using them leads to difficulties in handling the data.

In particular, the `lehdr` and `tigris` R packages download LEHD data and Census block geometries by entire states. Given the large size of the block shapefiles and the constraints of using a residential internet connection to download the data because of the coronavirus pandemic, it was important to avoid having to download the data for any state more than once.

To solve this problem, the `Census-3-DownloadLEHD.R` script downloads LEHD data and block shapefiles by state and saves them as state shapefiles with filenames of the form `LEHD-blocks-`[State FIPS Code]`.shp` rather than CBSA shapefiles. All blocks not in any CBSA or with no LEHD jobs data are removed before shapefiles are saved. However, water features are not removed, because the water shapefiles are organized by CBSA and the LEHD data was handled at the state level by this script.

Because in writing the `Census-3-DownloadLEHD.R` script, I forgot to acquire jobs by income as well as jobs by two-digit NAICS Code, the `Census-4-ProcessLEHD.R` script begins by acquiring this data and adding it to the data stored in the state Census block shapefiles. Since all blocks with jobs are included in those files, the removed blocks should not pose an issue.

The resulting Census blocks with data are then grouped by CBSA, Federal (from 2015) and non-Federal (from 2017 and 2016 as described in Section 1.5) jobs are combined, and water features are removed. Linestrings produced by this cropping procedure are removed as in `Census-2-DownloadACS.R` and the output is saved in CBSA shapefiles with the prefix `Census-LEHD-`. The data variables added in these files are listed in Table C.2 on page 311

Table C.2: Variables Created by `Census-4-ProcessLEHD.R`

Variable	Type of Jobs
`job_tt`	Total Jobs
`job_linc`	Earnings $1,250/month or less
`job_minc`	Earnings $1,251/month to $3,333/month
`job_hinc`	Earnings greater than $3,333/month
`job_11`	NAICS Sector 11 (Agriculture, Forestry, Fishing, Hunting)
`job_21`	NAICS Sector 21 (Mining, Quarrying, and Oil and Gas Extraction)
`job_22`	NAICS Sector 22 (Utilities)
`job_23`	NAICS Sector 23 (Construction)
`job_313`	NAICS Sector 31-33 (Manufacturing)
`job_42`	NAICS Sector 42 (Wholesale Trade)
`job_445`	NAICS Sector 44-45 (Retail Trade)
`job_489`	NAICS Sector 48-49 (Transportation and Warehousing)
`job_51`	NAICS Sector 51 (Information)
`job_52`	NAICS Sector 52 (Finance and Insurance)
`job_53`	NAICS Sector 53 (Real Estate and Rental and Leasing)
`job_54`	NAICS Sector 54 (Professional, Scientific, and Technical Services)
`job_55`	NAICS Sector 55 (Management of Companies and Enterprises)
`job_56`	NAICS Sector 56 (Admin, Support, and Waste Management Services)
`job_61`	NAICS Sector 61 (Educational Services)
`job_62`	NAICS Sector 62 (Health Care and Social Assistance)
`job_71`	NAICS Sector 71 (Arts, Entertainment, and Recreation)
`job_72`	NAICS Sector 72 (Accommodation and Food Services)
`job_81`	NAICS Sector 81 (Other Services except Pub. Administration)
`job_92`	NAICS Sector 92 (Public Administration)

The scripts described above create shapefiles of ACS and LEHD data in geometries with water areas removed in shapefiles with the prefixes `Census-ACS-` and `Census-LEHD-` respectively. Before the data in these shapefiles can be extracted into hex cells, the geographies need to be clipped to remove the undeveloped land stored in shapefiles with the prefix `NLCDB-masking-vector-`. Unfortunately, this subtraction is a very computationally complex procedure and it took several weeks to perform this cropping for all of the shapefiles.

The cropping procedure, initially performed by `Census-5-CropCensusData.R`, is—in theory—very simple. The three imported shapefiles for each CBSA were first validity-corrected by setting their geometry precision to 1 m with the `st_set_precision` function and using the `st_make_valid` function from the `lwgeom` package to remove validity errors. The `st_difference` function is then used to subtract the undeveloped land masking objects from the ACS and LEHD geometries.

However, this cropping process introduces features with "linestring" geometries, which cannot be saved to ESRI Shapefiles with polygon geometries. As a result, a loop similar to the ones needed to removed linestrings produced when cropping out water features is used to eliminate these linestrings. The resulting geometries are saved with the same two prefixes—`Census-ACS-` and `Census-LEHD-`—but in directories of clipped rather than unclipped data.

For *most* CBSAs, `Census-5-CropCensusData.R` produced the expected cropped ACS and LEHD geometries. However, it fails for some CBSAs due to issues with the validity of imported shapefiles and the presence of linestrings in exported shapefiles. The R script `Census-6-CropCensusData-Careful.R` was written to allow these CBSAs to be handled on a case-by-case basis, with the addition of the `st_snap` command to the initial validity correction. In some cases, it was also necessary to do linestring-removal by hand when the loops failed to do so: I don't fully understand this procedure and haven't figured out how to automate it completely.

Unfortunately, well after data processing was complete, an investigation of anomalies in the variables in used to characterize the hex cells discovered an additional problem with the cropping process. It turns out that in some rare cases, using `st_make_valid` on a polygon feature will yield a non-polygon, "geometry collection" feature containing both polygon and linestring components. Cropping geometry collection features yields unpredictable results and in some cases results in a Census geometry being reduced to a tiny residual feature.

These residual features pose a particular problem because they are sufficiently small that they will almost necessarily fall within a single hex cell, producing a single hex cell that appears to have an absurdly high population density. Unfortunately, by the time this issue was discovered, there was not time to redo the data processing with additional linestring-removal steps. However, twenty-seven such hexes were identified in the final neighborhood characterization data and were removed from the dataset by hand: it is hoped that the effect of this will be small enough to not unduly skew the overall results.

C.4 Extracting Data to Hex Cells

The script `HexGrids-3-ExtractNLCDB.R` is used to extract the fraction of pixels in the NLCD rasters in each hex cell with values of `4`, indicating developed land. The heart of this script is the use of the `velox` package (recently removed from the CRAN package repository) to count the number of developed and undeveloped pixels within the bounds of each hex cell. I turned to the `velox` package once it became clear that the `extract` function in the standard `raster` library performed the task unacceptably slowly.

I have to admit that I don't really understand the syntax for the `velox` package, but I was able to get it to extract a list consisting of a vector of pixel values (`1` for undeveloped land and `4` for developed land) for each hex cell. The resulting hex grid objects are saved with the filename prefix `hex-developed-`. The variables containing the NCLD data were given somewhat gnomic names to take into account the restrictions on variable name length for ESRI Shapefiles:

1. `DEVEL_ct` is an integer variable counting the number of developed 30-m by 30-m pixels are included in the hex cell.

2. `UNDEV_ct` is an integer variable counting the number of undeveloped 30-m by 30-m pixels are included in the hex cell.

3. `DEVEL_fr` is a real variable containing the fraction of pixels in the hex cell that are developed.

4. `UNDEV_b` is a Boolean variable, `TRUE` if the hex cell contains no developed pixels and `FALSE` otherwise.

The process of incorporating data on which hex cells are located on military bases and in Census Urban Areas is relatively simple, and actually only requires a single script, `HexGrids-4-ExtractMilUrb.R`.

This script imports the `hex-developed-` hex cell shapefiles produced by the script `HexGrids-3-ExtractNLCDB.R` , along with the `Military_Bases.shp` shapefile of military bases from the US Department of Transportation and the `tl_2019_us_uac10.shp` shapefile of Urban Areas from the US Census Bureau.

For each CBSA, the `Military_Bases.shp` and `tl_2019_us_uac10.shp` `sf` objects are transformed to the local UTM coordinate system and the centroids of all hexes are determined. Three new variables are then calculated for each hex:

1. `UACE` is an integer variable, set to `0` for hexes whose centroids are not located within the bounds of any Urban Area and to the FIPS code of the Urban Area for hexes whose centroids are located in one.

2. `URBAN_b` is a Boolean variable, set to `TRUE` for hexes whose centroids are located within the bounds of an Urban Area and `FALSE` otherwise.

3. `MILITARY_b` is a Boolean variable, set to `TRUE` for hexes whose centroids are located within the bounds of a military base and `FALSE` otherwise.

Two shapefiles are then exported to disk, both containing the new variables and all variables included in the original `hex-developed-` shapefile. The hex cells are saved with the prefix `hex-milurb-` and the centroids are saved with the prefix `points-milurb-`.

The final step in the process of handling Census data—actually extracting the data from the cropped ACS and LEHD geometries into hex cells—is performed by the script `HexGrids-5-ExtractCensus.R`. This script begins by importing the ACS and LEHD data as well as the hex grids and centroids with filename prefixes `hex-developed-` and `points-milurb-` and performing the now-routine precision-setting and validity-checking of the polygon objects.

The function `aw_interpolate` from the package `areal` is used for area-weighted integration instead of the `st_interpolate_aw` function from `sf` because it is faster and simpler to use. Median household income data was converted to be extensive by multiplying the value for each block group by the number of households in that block group before interpolation: this is important because area-weighted interpolation of extensive population variables is equivalent to population-weighted interpolation, while area-weighted interpolation of intensive population variables is not.

After the interpolation steps were complete the script replaces `NA` values with zeros, divides by number of housing units to recover median household income as a variable, and drops hex cells that have no population, no jobs, and no developed land. The variables are renamed as described in Tables C.3-C.6 on pages 317-319 and the resulting hex cells and centroids are written with filename prefixes `hex-census-` and `points-census-`, respectively.

Tables C.3 and C.4 indicate, along with the variable name, whether it is a string variable, an integer variable, or a real/floating point variable. Since the ESRI Shapefile standard does not allow for Boolean values, Boolean variables are stored as integers with `1` for `TRUE` and `0` for `FALSE`.

Tables C.5 and C.6 do not give variable type because all variables listed in these tables are real/floating point values. (Because of interpolation, even counts of numbers of people and housing units will generally be non-integer values.) These variables generally have the same values as given in Tables C.1 and C.2, but the names have been standardized and—in some cases—lengthened for greater readability while remaining within the constraints of the ESRI Shapefile format.

Table C.3: Cell ID Variables Created by `HexGrids-5-ExtractCensus.R`

Variable	Type	Definition
CSAFP	STRING	FIPS of Combined Statistical Area; 0 if none
CBSAFP	STRING	FIPS/GEOID of Core-Based Statistical Area
UACE	STRING	FIPS of Urban Area; 0 if none
GEOID	STRING	FIPS/GEOID of Core-Based Statistical Area
NAME	STRING	Name of Core-Based Statistical Area
UTMZONE	STRING	UTM Zone Assigned to Core-Based Statistical Area
EPSG	INTEGER	EPSG code associated with UTM Zone
HEXID	INTEGER	ID number for hex; unique within CBSA

Table C.4: Basic Descriptive Variables Created by `HexGrids-5-ExtractCensus.R`

Variable	Type	Definition
AREA_m	REAL/FLOAT	Land area of hex in m^2
AREA_mi	REAL/FLOAT	Land area of hex in mi^2
DEVEL_ct	INTEGER	Number of developed pixels in the hex
UNDEVEL_ct	INTEGER	Number of undeveloped pixels in the hex
DEVEL_fr	REAL/FLOAT	Fraction of pixels in the hex that are developed
URBAN_b	INTEGER	1 if hex is in a Census Urban Area; 1 otherwise
MILITARY_b	INTEGER	1 if hex is in an military base; 1 otherwise

Table C.5: ACS Variables Created by `HexGrids-5-ExtractCensus.R`

Variable	**Definition**
`POP_total`	**Total Population**
`POP_white`	Non-Hispanic White Population
`POP_black`	Non-Hispanic Black Population
`POP_latin`	Hispanic or Latino of Any Race Population
`POP_asian`	Non-Hispanic Asian Population
`POP_other`	Non-Hispanic Other or Multiple Race Population
`WK_total`	**Total Working Population**
`WK_transit`	Workers Who Commute by Transit
`WK_car`	Workers Who Commute by Car or Motorcycle
`WK_carpool`	Workers Who Commute by Carpool
`WK_active`	Workers Who Commute by Bicycle or Walking
`WK_other`	Workers Who Work at Home or Commute by Taxi or Other Means
`INC_MED`	**Median Household Income**
`HU_htot`	**Total Number of Occupied Housing Units**
`HU_h1d`	Number of One-Unit Detached Housing Units
`HU_h1a`	Number of One-Unit Attached Housing Units
`HU_h2`	Number of Housing Units in 2-Unit Buildings
`HU_h34`	Number of Housing Units in 3- and 4- Unit Buildings
`HU_h59`	Number of Housing Units in 5- to 9- Unit Buildings
`HU_h1019`	Number of Housing Units in 10- to 19- Unit Buildings
`HU_h2049`	Number of Housing Units in 20- to 49- Unit Buildings
`HU_h50`	Number of Housing Units in Buildings of 50 or More Units
`HU_hmobl`	Number of Housing Units in Mobile Homes, Vehicles, and Vessels
`HU_vtot`	**Total Number of Occupied Housing Units**
`HU_b0`	Number of Occupied Housing Units with No Vehicles Available
`HU_v1`	Number of Occupied Housing Units with 1 Vehicle Available
`HU_v2`	Number of Occupied Housing Units with 2 Vehicles Available
`HU_v3`	Number of Occupied Housing Units with 3 or More Vehicles Available

Table C.6: LEHD Variables Created by HexGrids-5-ExtractCensus.R

Variable	Type of Jobs
JOBS_total	Total Jobs
JOBS_linc	Earnings $1,250/month or less
JOBS_minc	Earnings $1,251/month to $3,333/month
JOBS_hinc	Earnings greater than $3,333/month
JOBS_11	NAICS Sector 11 (Agriculture, Forestry, Fishing, Hunting)
JOBS_21	NAICS Sector 21 (Mining, Quarrying, and Oil and Gas Extraction)
JOBS_22	NAICS Sector 22 (Utilities)
JOBS_23	NAICS Sector 23 (Construction)
JOBS_313	NAICS Sector 31-33 (Manufacturing)
JOBS_42	NAICS Sector 42 (Wholesale Trade)
JOBS_4445	NAICS Sector 44-45 (Retail Trade)
JOBS_4849	NAICS Sector 48-49 (Transportation and Warehousing)
JOBS_51	NAICS Sector 51 (Information)
JOBS_52	NAICS Sector 52 (Finance and Insurance)
JOBS_53	NAICS Sector 53 (Real Estate and Rental and Leasing)
JOBS_54	NAICS Sector 54 (Professional, Scientific, and Technical Services)
JOBS_55	NAICS Sector 55 (Management of Companies and Enterprises)
JOBS_56	NAICS Sector 56 (Admin, Support, and Waste Management Services)
JOBS_61	NAICS Sector 61 (Educational Services)
JOBS_62	NAICS Sector 62 (Health Care and Social Assistance)
JOBS_71	NAICS Sector 71 (Arts, Entertainment, and Recreation)
JOBS_72	NAICS Sector 72 (Accommodation and Food Services)
JOBS_81	NAICS Sector 81 (Other Services except Pub. Administration)
JOBS_92	NAICS Sector 92 (Public Administration)

C.5 Processing Roads Data

The R script `Roads-1-ExtractRoads.R` extracts CBSA-level street networks from the state-level street network files, removes all roads with the `fclass` variable values `motorway`, `motorway_link`, `trunk`, and, `trunk_link` (which indicate roads that generally do not allow pedestrians), and saves them to disk with filenames with the prefix `streets-`.

The process of extracting street networks for individual CBSAs is complicated by the fact that many CBSAs cross state lines, and the set of all state street network shapefiles is too large to load into memory on the computers I used to do my calculations. To get around this, a number of groups of one or several states were loaded to memory and cropped to the boundaries of those CBSAs located entirely in a given group.

Nine states[2] were treated individually, as no CBSAs cross their state borders. No CBSAs cross the borders of California, either, but since the California road network was provided as two shapefiles (for northern and southern California), it was treated as a group of states.

The `Roads-1-ExtractRoads.R` script begins by defining a vector for the states to be treated as distinct and vectors for the states in each state group. It then imports a shapefile of all CBSAs in the US in which I added a variable, `RoadZone`, to indicate which state cluster each CBSA should be extracted from. Separate `sf` objects are created for the CBSAs in each state cluster, and a vector is created of the `RoadZone` values for CBSAs in the nine states that are treated as distinct.

With this done, the remainder of the script is very repetitive: it consists of a loop through the nine states treated as distinct, followed by nearly-identical code repeated a dozen or so times to process each of the state clusters. The general procedure for each of these processing steps is as follows:

[2] Alaska, Arizona, Colorado, Florida, Hawaii, Maine, Montana, New Mexico, and Nevada

1. A loop is used to load and combine with `rbind` the state road network shapefiles needed for the state cluster.

2. All roads with one of the four `fclass` values associated with non-pedestrian roads are removed.

3. A loop processes each CBSA separately.

   (a) The loop begins by transforming the road network and CBSA boundaries to the appropriate UTM zone.

   (b) The road network is cropped to the boundaries of the CBSA.

   (c) A code block based on the `st_collection_extract` function is used to remove any features that, as a result of cropping, now have point geometries, as these cannot be written to an ESRI shapefile of linestring features.

   (d) The `st_dimension` command is used to remove any features with empty geometries.

   (e) Finally, the resulting roads object is written to disk.

The walkshed analysis was conducted with a combination of 700-m walking paths on the road network and a 100-m buffer around these paths to produce 800-m walksheds. The use of a buffer takes into account that many buildings and destinations are not located exactly on the street grid, but require walking on driveways and through parking lots. This is the approach used in my *City Observatory* article (Rowlands, 2020) on percent ideal walksheds.

To produce and calculated the areas of these walksheds required two scripts and the use of the "service area analysis" tool in QGIS. The first script, `Roads-2-MergeRoads.R`, loops over each CBSA, loading the unmerged roads networks produced by the script

`Roads-1-ExtractRoads.R` and the hex centroids produced alongside the Census-extracted hex cells. It then unions the road network to produce a single merged road network and immediately saves this to disk with the prefix `streets-merged-`.

The script then shifts the locations of the centroids to the nearest points on the merged road network. Centroids that have been shifted by more than 400 m are dropped, since such a large shift would take them outside of their hex cell. These hex cells evidently do not contain any roads, and so it is reasonable to regard them as "non-urban" and to exclude them from our analysis. The remaining centroids are saved in the `Merged CBSA Street Networks` directory with the prefix `centroids-offset-`.

As I haven't been able to find any packages for determining walksheds in R, the next step—actually deriving walksheds—was done with the "service area analysis" tool in QGIS. Using the offset centroids and the merged street networks, and with a 10-m error margin for discontinuities in the street networks, 700-m walksheds were calculated for each centroid and were saved with the prefix `walkshed-lines-`.

Finally, the script `Roads-3-ProcessWalksheds.R` processes the walkshed lines to calculate percent ideal walkshed values. It begins by loading the centroids produced by the previous script and the walkshed lines produced by QGIS. Because a bug in the current version of QGIS scrambles the data tables for geometries while retaining their order, the script immediately transfers the geometries of the walkshed lines to the centroids data frames, ensuring that each walkshed is associated with the correct information.

The geometries are repaired with `st_make_valid` and `st_set_precision` and 100-m buffers are created around the new walkshed lines objects to produce buffered walksheds that roughly correspond to the areas reachable within a half-mile walk of the centroids. The areas of these buffers are then calculated and divided by the area of a 800-m radius circle to calculate fractional ideal walksheds and the walkshed buffers are saved to disk with the prefix `walkshed-buffers-` and the fractional ideal walksheds added.

The script `Roads-4-CountNodes.R` handles the process of counting intersections in the street network, and also produces the final hex cells with all data included. It does this by looping through all 926 CBSAs.

First, the unmerged street network for a CBSA is loaded, duplicate roads with the same `osm_id` value are removed—these seem to be present along the edges of many CBSA road networks, and lead to invalid four-way intersections at every node in the duplicated roads—along with roads with `fclass` values of `footway`, `steps`, or `service`. The `st_cast` function is also used to dis-aggregate any multiline strings.

Next, because the completion time for the process used to analyze the street networks is roughly exponential in the size of the street network, a bounding box for the roads object is created and divided into a ten-by-ten grid covering the CBSA. A `foreach` loop is then used to loop in parallel over each of the one hundred grid elements.

For each grid element, the street network is cropped with a 20-m buffer beyond the boundaries of the grid element on each side. This buffer is used to make sure that the dead-ends produced by the crop will not be included in the grid element itself. Then, *if* the number of roads in the grid cell is at least two—the analysis will fail for an empty street network or one with only one road—the grid cell's road network is converted to an `sp` object and then, using `readshpnw` from the `shp2graph` library, into a graph object.

A list of nodes with their degrees is extracted from this graph object and two-way intersections—nodes within a road that are not actually intersections or dead-ends—are removed. The list of nodes is then converted to an `sf` points object and cropped to the actual boundaries of the grid cell, before being appended to the CBSA-wide point object created by the loop.

After the CBSA-wide point object of nodes is created, the Census-extracted hex grid for the CBSA and the buffered walkshed for the CBSA are loaded. The walkshed data from the buffered walkshed is joined to the hex grid and `st_contains` is used to count the numbers of dead-ends, three-way intersections, and four-or-more-way intersections in each hex. The nodes point object is then written to disk with `nodes-` as a prefix and the hex grid is written to disk with `final-hex-` as a prefix.

C.6 Initial Analysis of the Hex Cells

Finally, the script `FirstAnalysis-1-MakeCSV.R` reorganizes the variables, eliminating several that are no longer needed (for example, area in square meters), and outputs the entire national dataset into a single CSV file and a single ESRI Shapefile for easier processing. The variables included in the resulting national dataset are given in Table 2.1 on page 102.

The script `FirstAnalysis-2-AnalyzeCSV.R` then reorganizes the variables into a smaller set, combining related variables to produce more practical characterization variables, given in Table 2.2 on page 104.

The script then classifies hexes by activity density, percent ideal walkshed, land use type, and activity type, and removes 27 hexes that were determined to be invalid due to the Census data cropping error discussed in Section C.3. Finally, it generates summary tables of the numbers and fractions of hexes, residents, and jobs in each type nationally and by metro area.

Appendix D: Neighborhood Density and Connectivity Maps and Tables

This appendix contains tables showing breakdowns of the percentage of neighborhoods at different activity density and percent ideal walkshed levels—and the numbers and percentages of metro area population and jobs in those neighborhoods—in the twenty largest metropolitan statistical areas in the US, along with ten additional metropolitan statistical areas that were selected because they are particularly interesting: either that they are unusually dense for their size or have rapid transit or light rail.

Also included are maps of activity density and connectivity (measured as % ideal walksheds) of neighborhoods in the same metro areas. All the maps are at the same scale, and show a 40-mile by 40-mile square, which means that outlying parts of larger metro areas may be left out, while views of smaller metro areas may include areas outside the MSA limits. Neighborhoods with percent ideal walksheds greater than 55% are classified as "high connectivity," those with percent ideal walksheds between 55% and 35% are classified as "medium connectivity," and those with percent ideal walksheds of less than 35% are classified as "low connectivity."

Table D.1: Atlanta Population and Jobs by Activity Density

Density (/ sq. mi.)	Hexes	% of Hexes	Population	% of Population	Jobs	% of Jobs
> 80,000	9	0.03%	8,000	0.14%	152,000	6.3%
40,000 – 80,000	25	0.08%	31,000	0.5%	187,000	7.8%
20,000 – 40,000	52	0.2%	49,000	0.9%	175,000	7.3%
10,000 – 20,000	293	0.9%	251,000	4.4%	362,000	15.1%
5,000 – 10,000	1,358	4.3%	832,000	14.6%	616,000	25.7%
2,500 – 5,000	4,262	13.5%	1,808,000	31.8%	544,000	22.7%
< 2,500	25,590	81.0%	2,714,000	47.7%	359,000	15.0%

Table D.2: Atlanta Population and Jobs by % Ideal Walkshed

Percent Ideal Walkshed	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
> 65%	44	0.14%	43,000	0.8%	95,000	4.0%
55% – 65%	390	1.2%	216,000	3.8%	254,000	10.6%
45% – 55%	1,357	4.3%	552,000	9.7%	457,000	19.1%
35% – 45%	3,691	11.7%	1,037,000	18.2%	478,000	20.0%
25% – 35%	8,658	27.4%	1,527,000	26.8%	524,000	21.9%
15% – 25%	13,047	41.3%	1,708,000	30.0%	444,000	18.5%
< 15%	4,402	13.9%	609,000	10.7%	142,000	5.9%

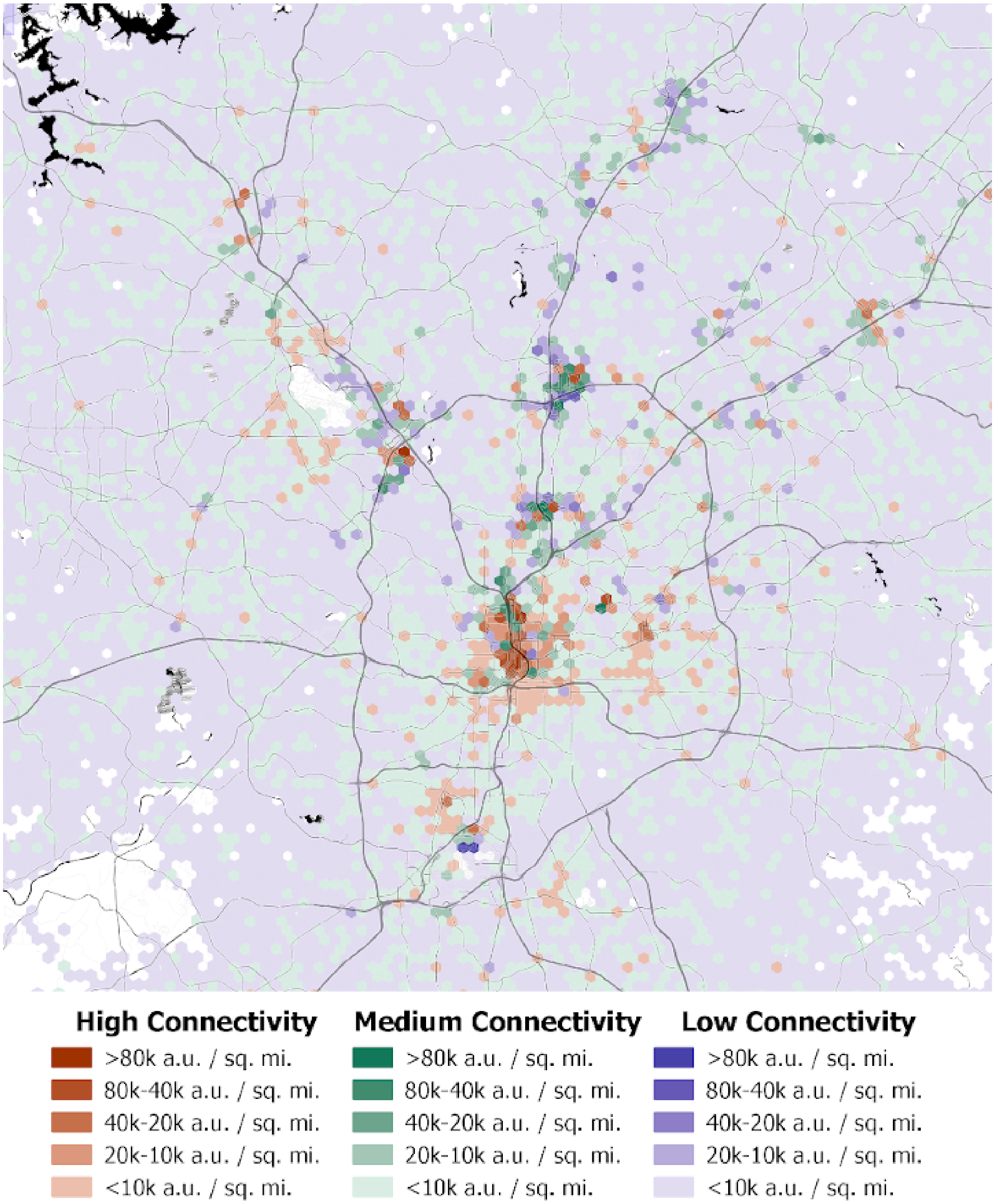

Figure D.1: Atlanta-Sandy Springs-Alpharetta, GA MSA activity-connectivity neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table D.3: Austin Population and Jobs by Activity Density

Density (/ sq. mi.)	Hexes	% of Hexes	Population	% of Population	Jobs	% of Jobs
> 80,000	2	0.02%	2,000	0.14%	40,000	4.8%
40,000 – 80,000	4	0.04%	9,000	0.4%	25,000	3.0%
20,000 – 40,000	25	0.3%	28,000	1.4%	76,000	9.1%
10,000 – 20,000	214	2.2%	22,5000	11.1%	219,000	26.2%
5,000 – 10,000	745	7.6%	57,0000	28.2%	230,000	27.5%
2,500 – 5,000	1,184	12.1%	54,0000	26.7%	138,000	16.5%
< 2,500	7,649	77.9%	64,8000	32.1%	107,000	12.9%

Table D.4: Austin Population and Jobs by % Ideal Walkshed

Percent Ideal Walkshed	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
> 65%	33	0.3%	28,000	1.4%	57,000	6.8%
55% – 65%	235	2.4%	187,000	9.2%	111,000	13.2%
45% – 55%	610	6.2%	370,000	18.3%	170,000	20.4%
35% – 45%	1,268	12.9%	453,000	22.4%	177,000	21.2%
25% – 35%	2,681	27.3%	479,000	23.7%	151,000	18.1%
15% – 25%	3,806	38.7%	401,000	19.8%	108,000	13.0%
< 15%	1,190	12.1%	103,000	5.1%	61,000	7.4%

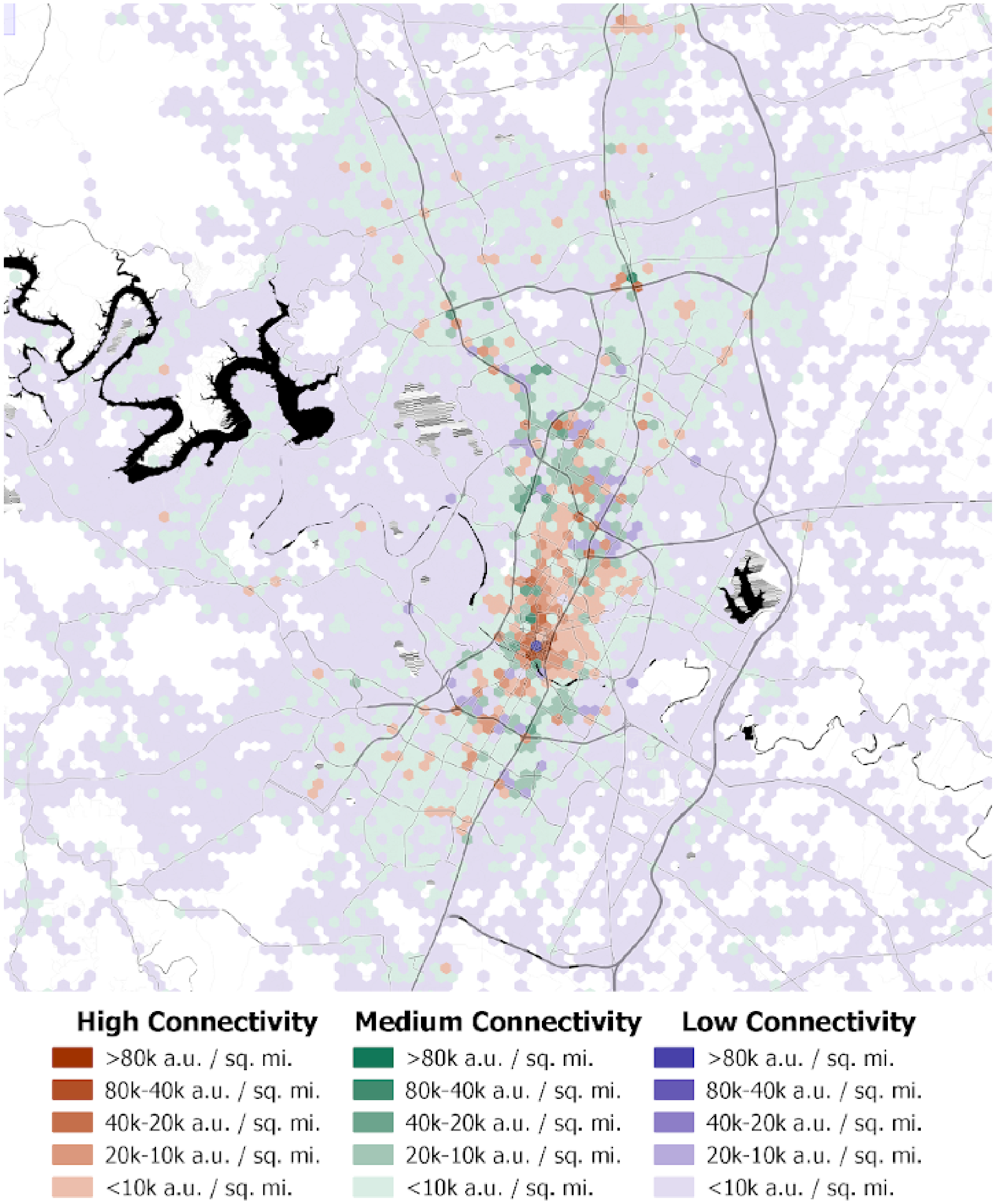

Figure D.2: Austin-Round Rock-Georgetown, TX MSA activity-connectivity neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table D.5: Baltimore Population and Jobs by Activity Density

Density (/ sq. mi.)	Hexes	% of Hexes	Population	% of Population	Jobs	% of Jobs
> 80,000	3	0.03%	4,000	0.2%	56,000	4.8%
40,000 – 80,000	13	0.1%	25,000	0.9%	62,000	5.3%
20,000 – 40,000	60	0.6%	124,000	4.5%	122,000	10.5%
10,000 – 20,000	375	3.6%	517,000	18.8%	253,000	21.9%
5,000 – 10,000	1,037	9.9%	788,000	28.7%	336,000	29.1%
2,500 – 5,000	1,440	13.8%	626,000	22.8%	189,000	16.4%
< 2,500	7,525	72.0%	663,000	24.1%	138,000	12.0%

Table D.6: Baltimore Population and Jobs by % Ideal Walkshed

Percent Ideal Walkshed	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
> 65%	84	0.8%	161,000	5.9%	83,000	7.2%
55% – 65%	307	2.9%	366,000	13.3%	188,000	16.3%
45% – 55%	649	6.2%	427,000	15.5%	192,000	16.6%
35% – 45%	1,498	14.3%	534,000	19.4%	239,000	20.7%
25% – 35%	3,004	28.7%	619,000	22.5%	216,000	18.7%
15% – 25%	3,712	35.5%	483,000	17.6%	174,000	15.1%
< 15%	1,199	11.5%	158,000	5.7%	62,000	5.4%

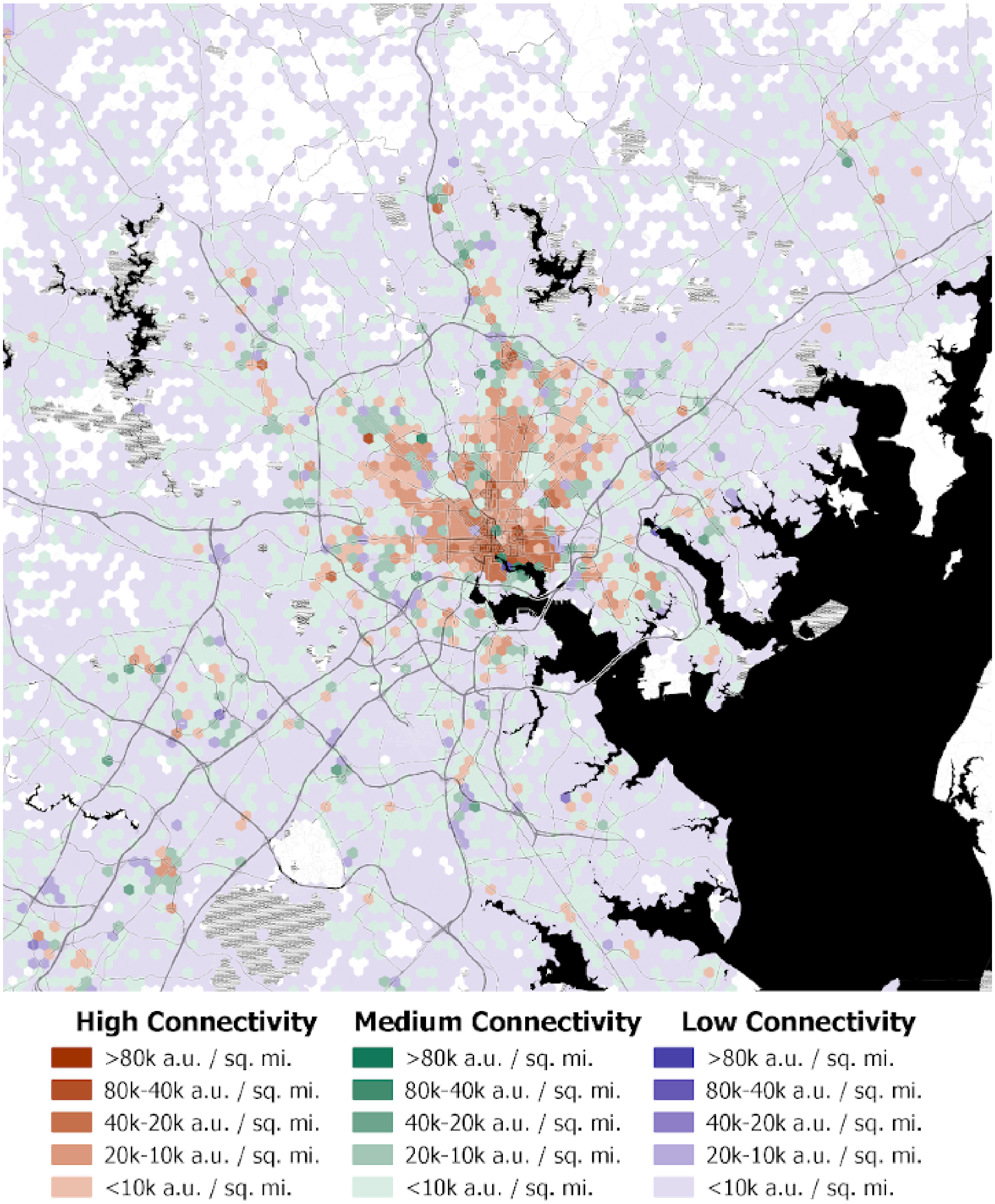

Figure D.3: Baltimore-Columbia-Towson, MD MSA activity-connectivity neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table D.7: Boston Population and Jobs by Activity Density

Density (/ sq. mi.)	Hexes	% of Hexes	Population	% of Population	Jobs	% of Jobs
> 80,000	22	0.12%	82,000	1.7%	409,000	16.9%
40,000 – 80,000	40	0.2%	161,000	3.4%	162,000	6.7%
20,000 – 40,000	260	1.4%	708,000	14.8%	342,000	14.1%
10,000 – 20,000	574	3.1%	780,000	16.3%	412,000	17.0%
5,000 – 10,000	1,152	6.2%	743,000	15.5%	461,000	19.1%
2,500 – 5,000	2,044	11.0%	773,000	16.1%	322,000	13.3%
< 2,500	14,445	77.9%	1,539,000	32.2%	310,000	12.8%

Table D.8: Boston Population and Jobs by % Ideal Walkshed

Percent Ideal Walkshed	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
> 65%	115	0.6%	304,000	6.4%	321,000	13.3%
55% – 65%	595	3.2%	907,000	18.9%	450,000	18.6%
45% – 55%	1,304	7.0%	842,000	17.6%	399,000	16.5%
35% – 45%	2,929	15.8%	859,000	17.9%	420,000	17.4%
25% – 35%	5,518	29.8%	937,000	19.6%	428,000	17.7%
15% – 25%	6,336	34.2%	739,000	15.4%	290,000	12.0%
< 15%	1,740	9.4%	198,000	4.1%	110,000	4.6%

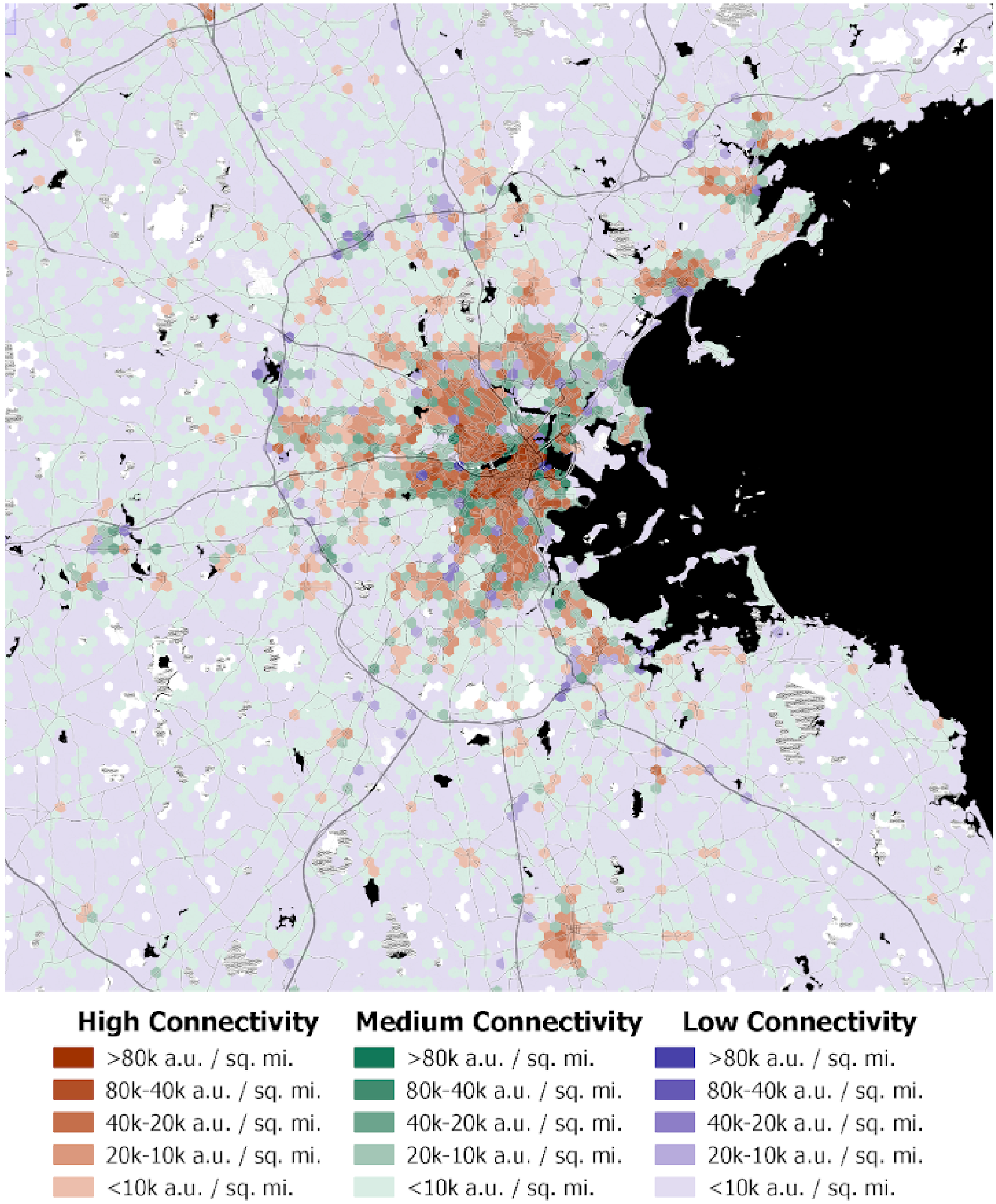

Figure D.4: Boston-Cambridge-Newton, MA-NH MSA activity-connectivity neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table D.9: Charlotte Population and Jobs by Activity Density

Density (/ sq. mi.)	**Hexes**	**% of Hexes**	**Population**	**% of Population**	**Jobs**	**% of Jobs**
> 80,000	2	0.01%	3,000	0.11%	53,000	5.0%
40,000 – 80,000	2	0.01%	1,000	0.04%	16,000	1.5%
20,000 – 40,000	16	0.09%	13,000	0.5%	52,000	4.9%
10,000 – 20,000	97	0.5%	61,000	2.5%	138,000	12.9%
5,000 – 10,000	547	3.0%	302,000	12.5%	275,000	25.8%
2,500 – 5,000	1,867	10.3%	734,000	30.2%	300,000	28.1%
< 2,500	15,607	86.0%	1,313,000	54.1%	233,000	21.8%

Table D.10: Charlotte Population and Jobs by % Ideal Walkshed

Percent Ideal Walkshed	**Hexes**	**% of Hexes**	**Population**	**% of Pop.**	**Jobs**	**% of Jobs**
> 65%	32	0.2%	17,000	0.7%	51,000	4.8%
55% – 65%	236	1.3%	106,000	4.4%	111,000	10.4%
45% – 55%	701	3.9%	251,000	10.3%	156,000	14.6%
35% – 45%	1,787	9.9%	432,000	17.8%	198,000	18.5%
25% – 35%	4,992	27.5%	679,000	28.0%	266,000	24.9%
15% – 25%	7,756	42.8%	707,000	29.1%	208,000	19.5%
< 15%	2,634	14.5%	235,000	9.7%	78,000	7.3%

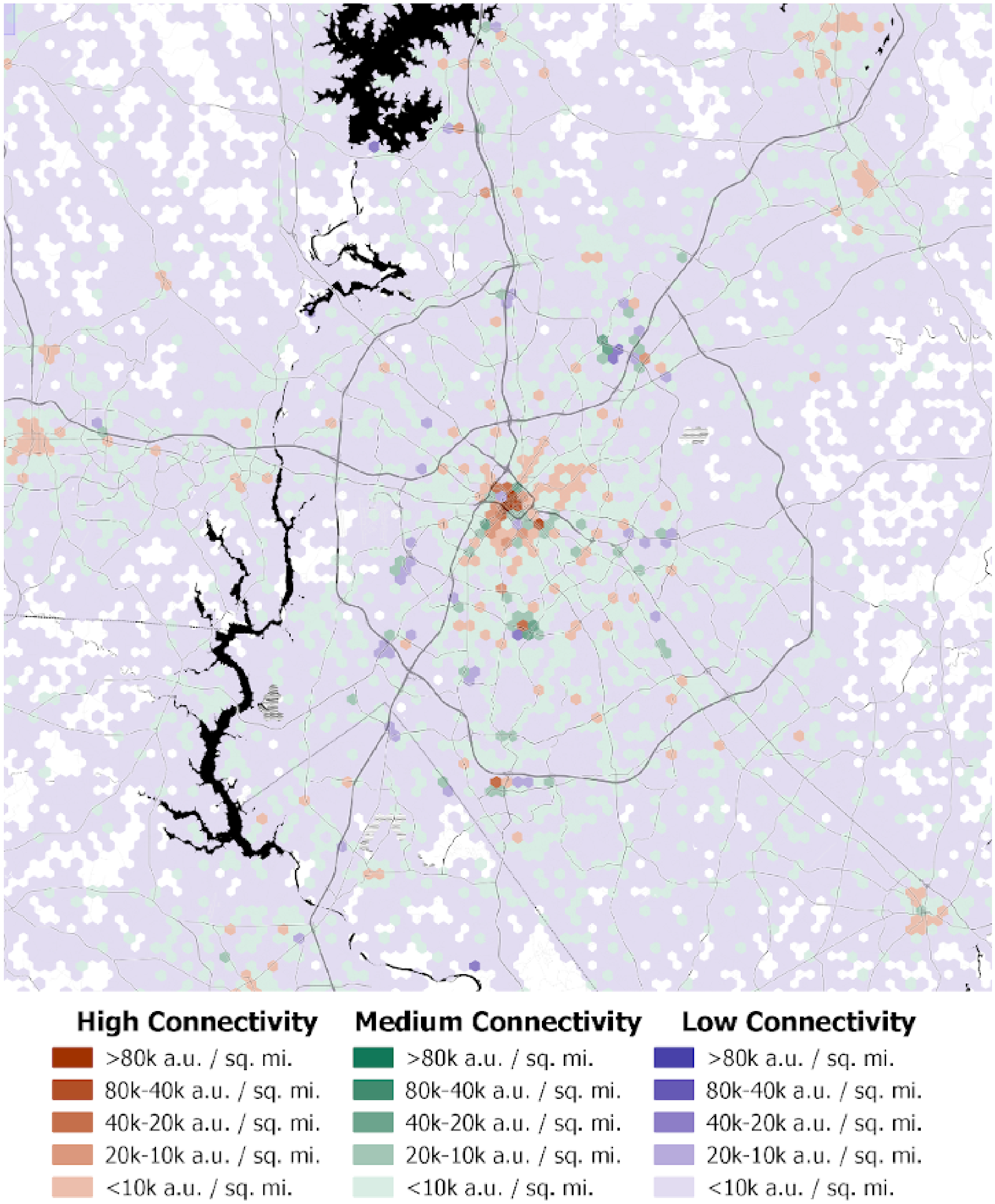

Figure D.5: Charlotte-Concord-Gastonia, NC-SC MSA activity-connectivity neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table D.11: Chicago Population and Jobs by Activity Density

Density (/ sq. mi.)	Hexes	% of Hexes	Population	% of Population	Jobs	% of Jobs
> 80,000	20	0.07%	97,000	1.0%	586,000	14.3%
40,000 – 80,000	47	0.2%	229,000	2.4%	167,000	4.1%
20,000 – 40,000	413	1.6%	1,205,000	12.8%	529,000	12.9%
10,000 – 20,000	1,171	4.5%	1,696,000	18.0%	838,000	20.4%
5,000 – 10,000	3,347	12.8%	2,590,000	27.4%	1,080,000	26.4%
2,500 – 5,000	4,340	16.7%	1,924,000	20.4%	568,000	13.9%
< 2,500	16,728	64.2%	1,704,000	18.0%	331,000	8.1%

Table D.12: Chicago Population and Jobs by % Ideal Walkshed

Percent Ideal Walkshed	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
> 65%	694	2.7%	1,481,000	15.7%	675,000	16.5%
55% – 65%	1,964	7.5%	2,266,000	24.0%	865,000	21.1%
45% – 55%	2,610	10.0%	1,658,000	17.6%	678,000	16.5%
35% – 45%	3,941	15.1%	1,525,000	16.1%	734,000	17.9%
25% – 35%	6,364	24.4%	1,318,000	14.0%	620,000	15.1%
15% – 25%	8,558	32.8%	953,000	10.1%	402,000	9.8%
< 15%	1,935	7.4%	244,000	2.6%	124,000	3.0%

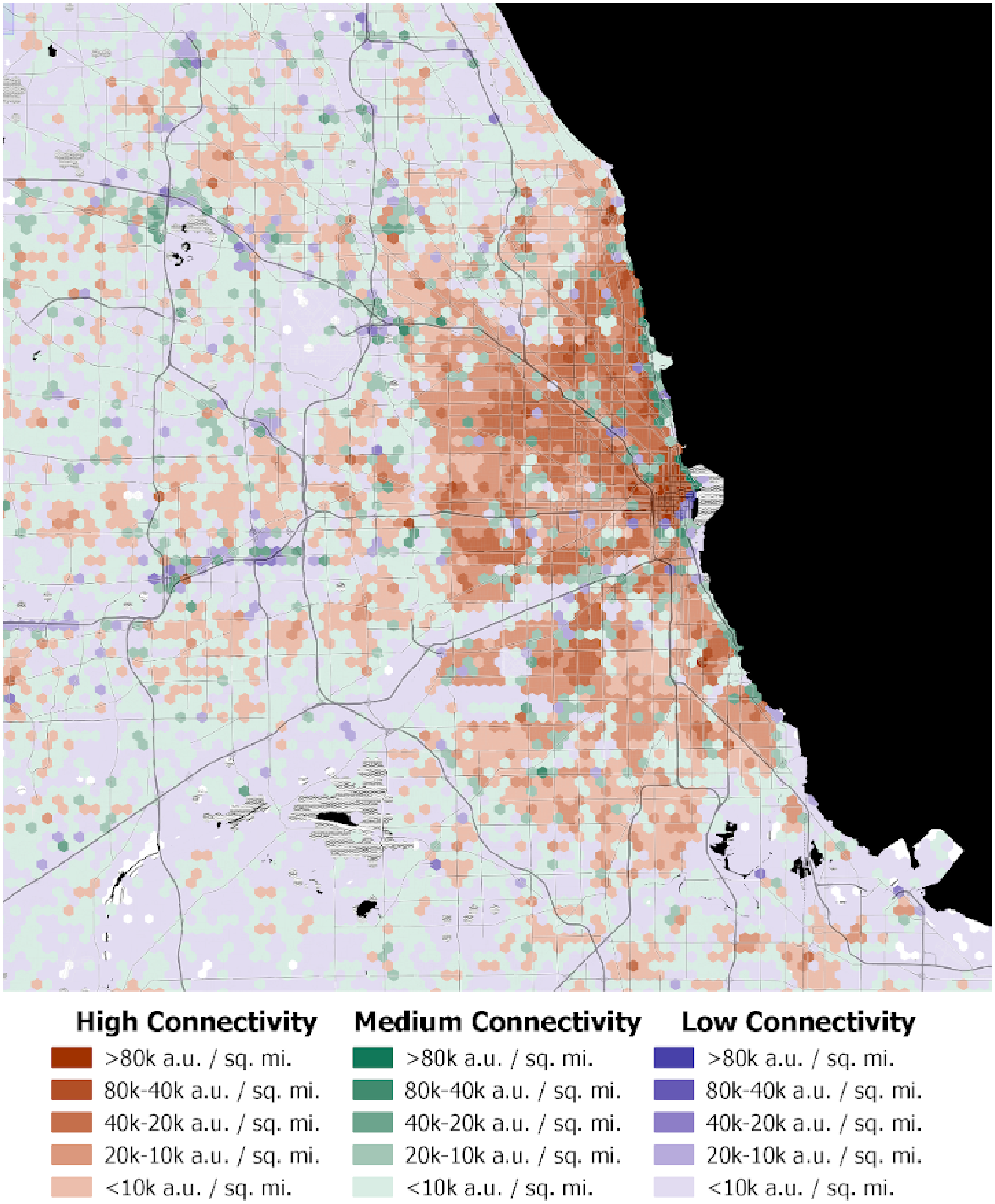

Figure D.6: Chicago-Naperville-Elgin, IL-IN-WI MSA activity-connectivity neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table D.13: Cleveland Population and Jobs by Activity Density

Density (/ sq. mi.)	Hexes	% of Hexes	Population	% of Population	Jobs	% of Jobs
> 80,000	5	0.05%	2,000	0.13%	92,000	10.0%
40,000 – 80,000	1	0.01%	1,000	0.04%	11,000	1.2%
20,000 – 40,000	15	0.2%	16,000	0.8%	35,000	3.8%
10,000 – 20,000	148	1.6%	174,000	8.5%	127,000	13.8%
5,000 – 10,000	869	9.3%	652,000	31.9%	289,000	31.6%
2,500 – 5,000	1,454	15.5%	584,000	28.6%	215,000	23.5%
< 2,500	6,885	73.4%	612,000	30.0%	147,000	16.1%

Table D.14: Cleveland Population and Jobs by % Ideal Walkshed

Percent Ideal Walkshed	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
> 65%	48	0.5%	49,000	2.4%	60,000	6.6%
55% – 65%	364	3.9%	327,000	16.0%	139,000	15.1%
45% – 55%	658	7.0%	393,000	19.3%	149,000	16.3%
35% – 45%	1,231	13.1%	412,000	20.2%	200,000	21.9%
25% – 35%	2,467	26.3%	411,000	20.1%	174,000	19.0%
15% – 25%	3,744	39.9%	360,000	17.6%	146,000	15.9%
< 15%	865	9.2%	88,000	4.3%	49,000	5.3%

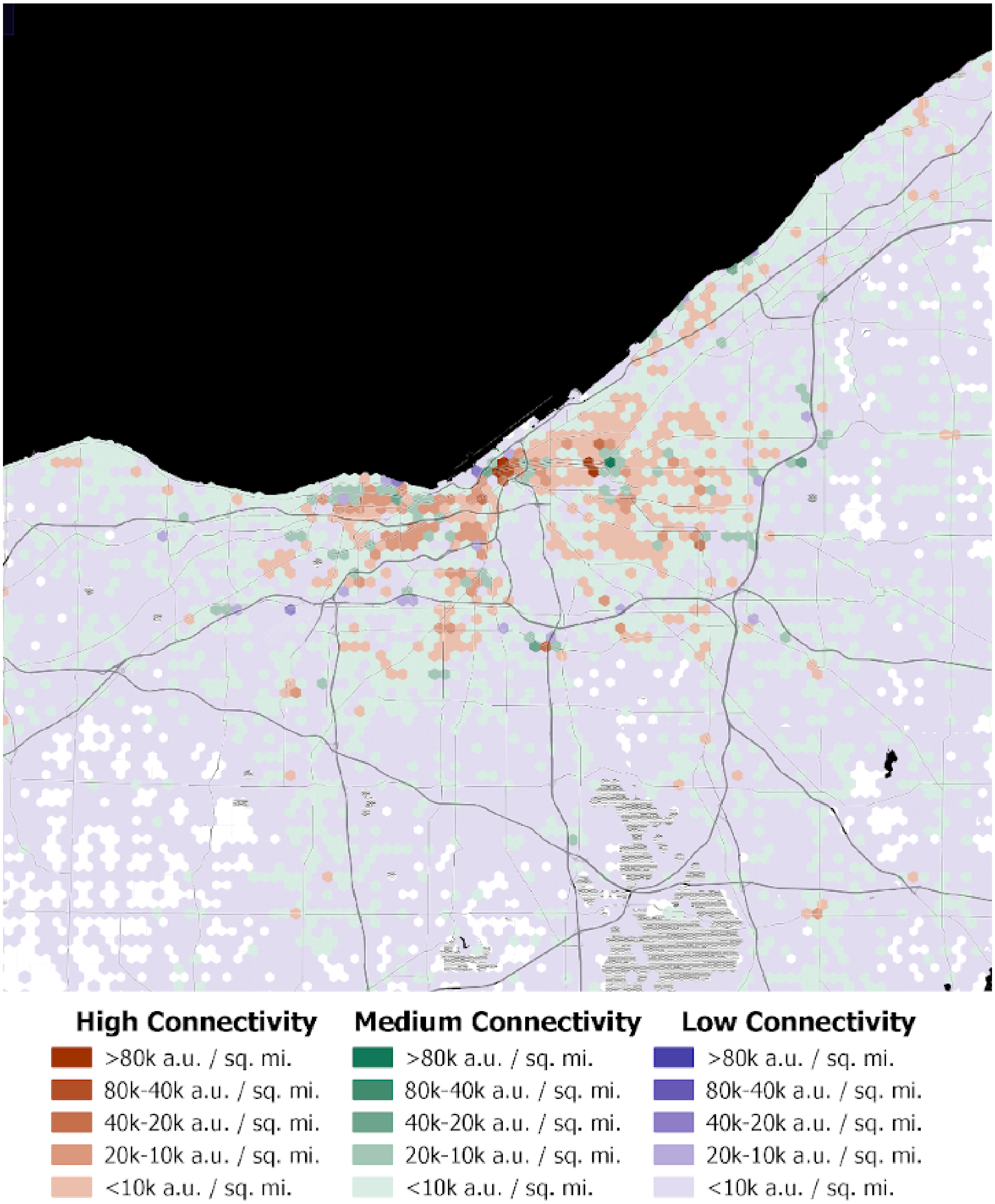

Figure D.7: Cleveland-Elyria, OH MSA activity-connectivity neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table D.15: Dallas Population and Jobs by Activity Density

Density (/ sq. mi.)	Hexes	% of Hexes	Population	% of Population	Jobs	% of Jobs
> 80,000	8	0.03%	7,000	0.1%	124,000	3.9%
40,000 – 80,000	27	0.1%	21,000	0.3%	206,000	6.5%
20,000 – 40,000	130	0.5%	171,000	2.4%	381,000	12.0%
10,000 – 20,000	694	2.6%	702,000	9.9%	738,000	23.3%
5,000 – 10,000	3,376	12.5%	2,715,000	38.4%	950,000	30.0%
2,500 – 5,000	4,092	15.1%	1,908,000	27.0%	463,000	14.6%
< 2,500	18,781	69.3%	1,537,000	21.8%	308,000	9.7%

Table D.16: Dallas Population and Jobs by % Ideal Walkshed

Percent Ideal Walkshed	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
> 65%	237	0.9%	236,000	3.3%	233,000	7.3%
55% – 65%	1,558	5.7%	1,141,000	16.2%	632,000	19.9%
45% – 55%	2,672	9.9%	1,648,000	23.3%	803,000	25.3%
35% – 45%	3,817	14.1%	1,518,000	21.5%	657,000	20.7%
25% – 35%	6,546	24.1%	1,316,000	18.6%	463,000	14.6%
15% – 25%	9,522	35.1%	959,000	13.6%	286,000	9.0%
< 15%	2,756	10.2%	243,000	3.4%	97,000	3.1%

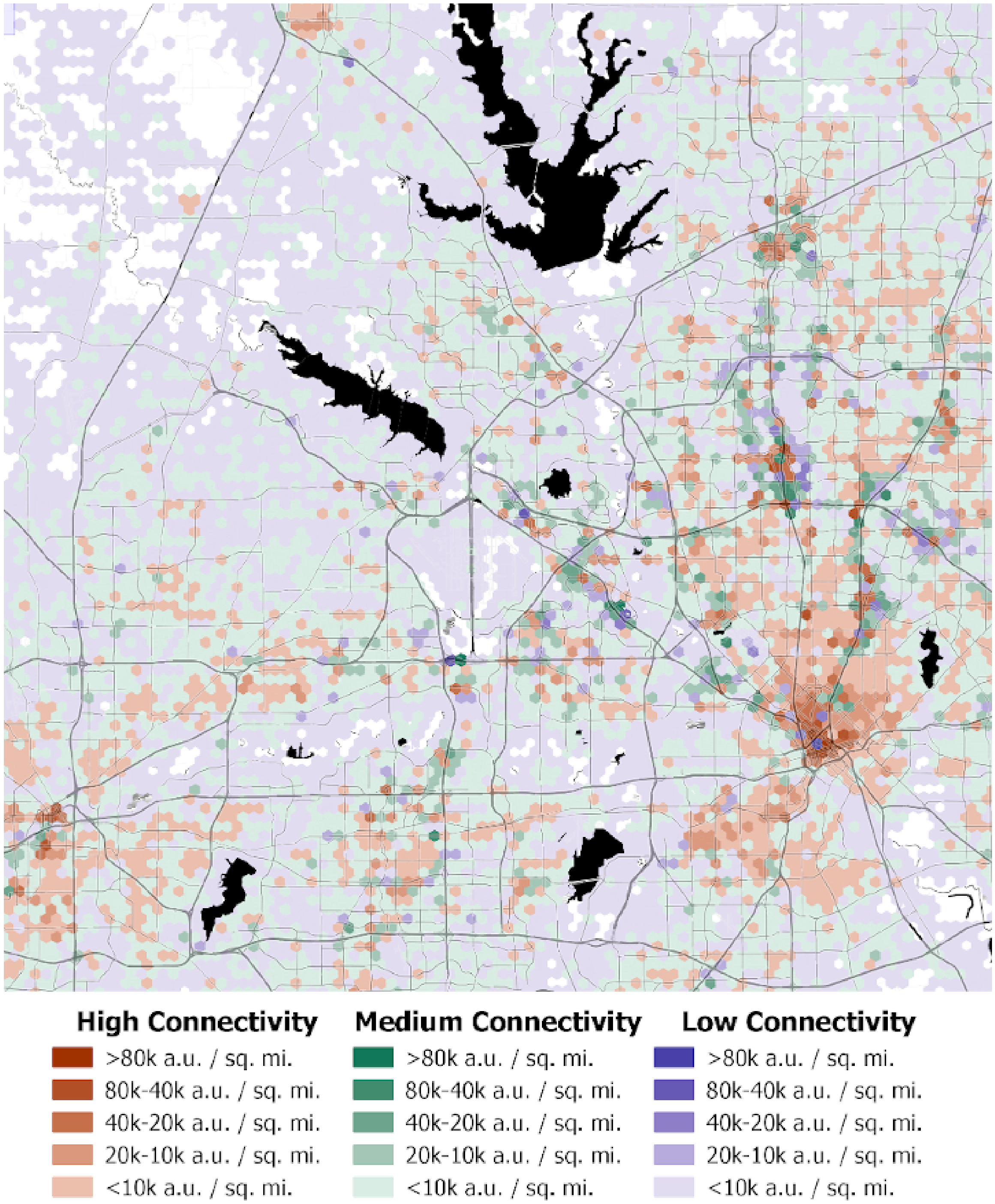

Figure D.8: Dallas-Fort Worth-Arlington, TX MSA activity-connectivity neighborhood map. Downtown Dallas is at the lower right and downtown Fort Worth is at the far lower left. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table D.17: Denver Population and Jobs by Activity Density

Density (/ sq. mi.)	Hexes	% of Hexes	Population	% of Population	Jobs	% of Jobs
> 80,000	3	0.04%	6,000	0.2%	67,000	5.2%
40,000 – 80,000	8	0.10%	18,000	0.6%	52,000	4.0%
20,000 – 40,000	68	0.9%	90,000	3.2%	206,000	15.8%
10,000 – 20,000	390	4.9%	466,000	16.5%	325,000	25.0%
5,000 – 10,000	1,523	19.3%	1,271,000	45.1%	414,000	31.9%
2,500 – 5,000	1,185	10.5%	552,000	19.6%	144,000	11.1%
< 2,500	4,719	59.8%	417,000	14.8%	91,000	7.0%

Table D.18: Denver Population and Jobs by % Ideal Walkshed

Percent Ideal Walkshed	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
> 65%	228	2.9%	294,000	10.4%	222,000	17.1%
55% – 65%	675	8.5%	586,000	20.8%	276,000	21.2%
45% – 55%	972	12.3%	651,000	23.1%	250,000	19.2%
35% – 45%	1,189	15.1%	559,000	19.8%	248,000	19.1%
25% – 35%	1,782	22.6%	416,000	14.7%	176,000	13.5%
15% – 25%	2,388	30.2%	247,000	8.8%	93,000	7.2%
< 15%	662	8.4%	67,000	2.4%	33,000	2.6%

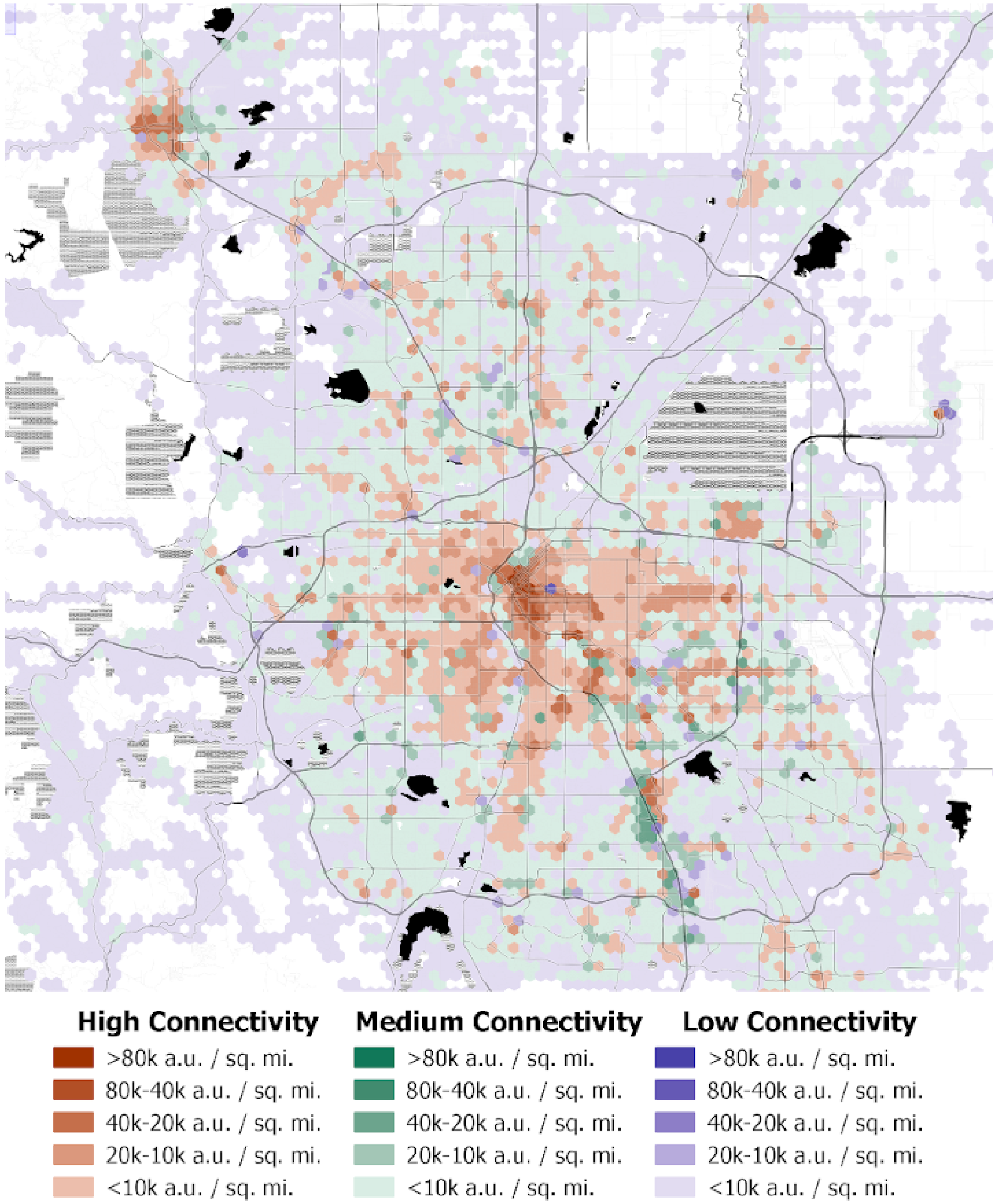

Figure D.9: Denver-Aurora-Lakewood, CO MSA activity-connectivity neighborhood map. Boulder (not in the Denver MSA) is at the upper left. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table D.19: Detroit Population and Jobs by Activity Density

Density (/ sq. mi.)	**Hexes**	**% of Hexes**	**Population**	**% of Population**	**Jobs**	**% of Jobs**
> 80,000	4	0.02%	4,000	0.06%	61,000	3.4%
40,000 – 80,000	6	0.03%	2,000	0.09%	48,000	2.7%
20,000 – 40,000	56	0.3%	40,000	0.9%	189,000	10.6%
10,000 – 20,000	274	1.6%	257,000	6.0%	294,000	16.4%
5,000 – 10,000	2,081	11.9%	1,598,000	37.4%	615,000	34.3%
2,500 – 5,000	3,017	17.2%	1,317,000	30.8%	396,000	22.1%
< 2,500	12,113	69.0%	1,056,000	24.7%	191,000	10.7%

Table D.20: Detroit Population and Jobs by % Ideal Walkshed

Percent Ideal Walkshed	**Hexes**	**% of Hexes**	**Population**	**% of Pop.**	**Jobs**	**% of Jobs**
> 65%	393	2.2%	374,000	8.7%	136,000	7.6%
55% – 65%	1,116	6.4%	867,000	20.3%	276,000	15.4%
45% – 55%	1,447	8.2%	744,000	17.4%	359,000	20.0%
35% – 45%	2,207	12.6%	730,000	17.1%	378,000	21.1%
25% – 35%	4,476	25.5%	802,000	18.8%	331,000	18.4%
15% – 25%	6,423	36.6%	598,000	14.0%	248,000	13.8%
< 15%	1,489	8.5%	161,000	3.8%	66,000	3.7%

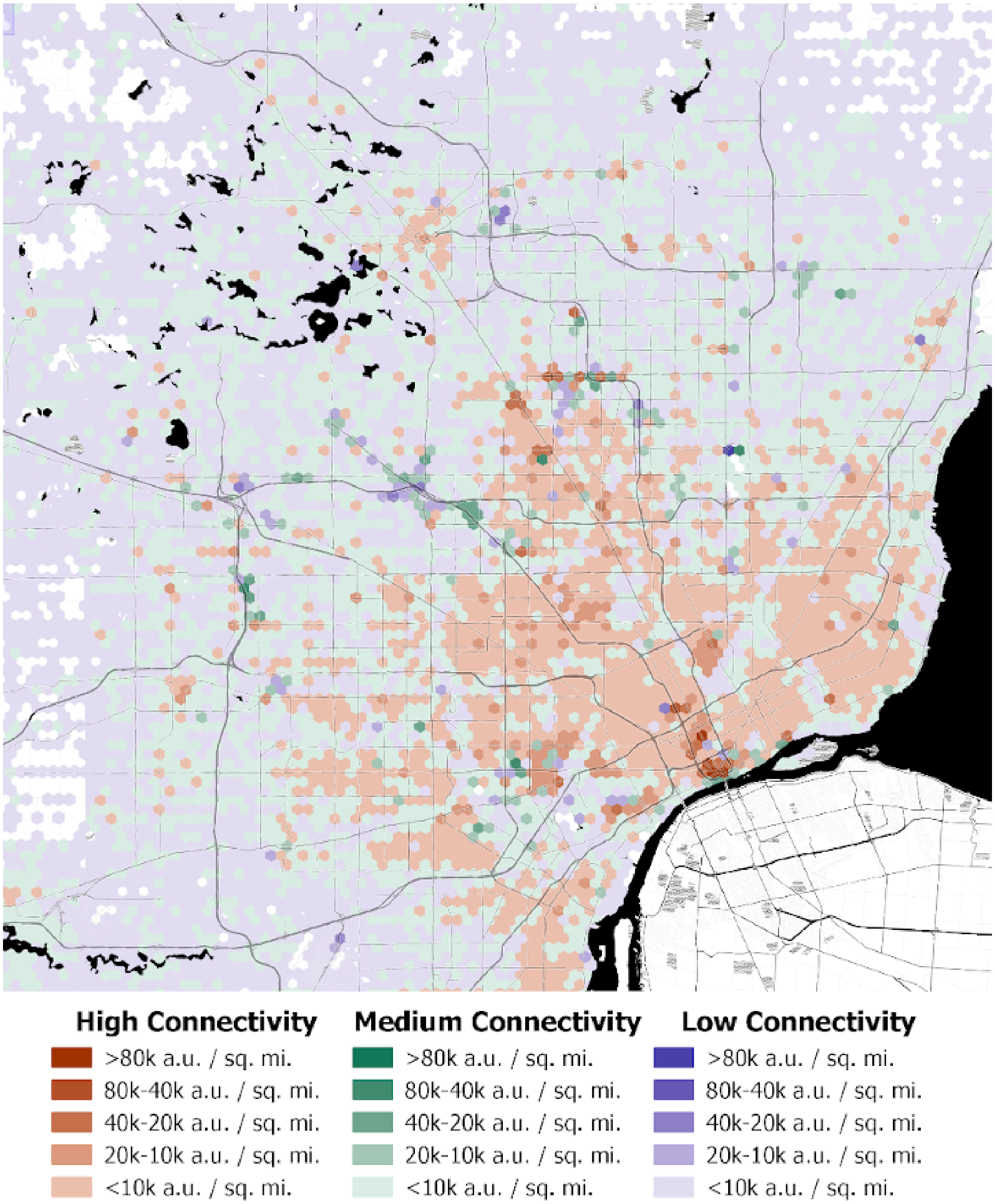

Figure D.10: Detroit-Warren-Dearborn, MI MSA activity-connectivity neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table D.21: Honolulu Population and Jobs by Activity Density

Density (/ sq. mi.)	Hexes	% of Hexes	Population	% of Population	Jobs	% of Jobs
> 80,000	4	0.3%	9,000	1.0%	62,000	17.1%
40,000 – 80,000	20	1.3%	79,000	8.9%	73,000	20.3%
20,000 – 40,000	46	2.9%	114,000	12.8%	71,000	19.5%
10,000 – 20,000	148	9.4%	242,000	27.2%	73,000	20.2%
5,000 – 10,000	269	17.1%	237,000	26.7%	45,000	12.5%
2,500 – 5,000	287	18.3%	124,000	14.0%	25,000	6.9%
< 2,500	796	50.7%	85,000	9.5%	13,000	3.6%

Table D.22: Honolulu Population and Jobs by % Ideal Walkshed

Percent Ideal Walkshed	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
> 65%	8	0.5%	26,000	3.0%	11,000	3.0%
55% – 65%	32	2.0%	77,000	8.6%	105,000	29.0%
45% – 55%	92	5.9%	141,000	15.9%	67,000	18.4%
35% – 45%	160	10.2%	191,000	21.4%	74,000	20.3%
25% – 35%	334	21.3%	200,000	22.4%	50,000	13.7%
15% – 25%	690	43.9%	198,000	22.2%	45,000	12.4%
< 15%	254	16.2%	58,000	6.5%	11,000	3.1%

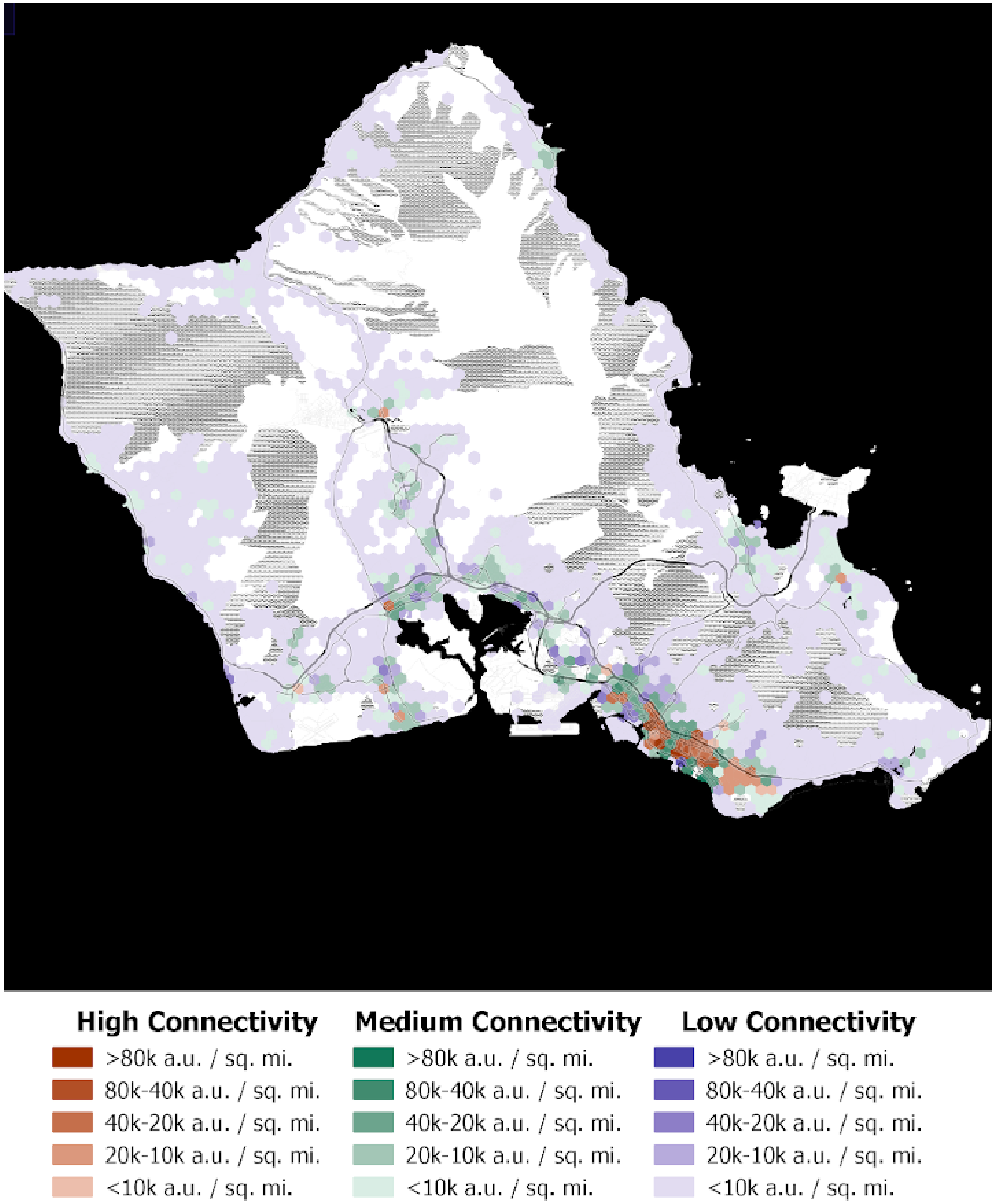

Figure D.11: Urban Honolulu, HI MSA activity-connectivity neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table D.23: Houston Population and Jobs by Activity Density

Density (/ sq. mi.)	Hexes	% of Hexes	Population	% of Population	Jobs	% of Jobs
> 80,000	7	0.03%	4,000	0.06%	156,000	6.0%
40,000 – 80,000	20	0.08%	32,000	0.5%	130,000	5.0%
20,000 – 40,000	138	0.6%	220,000	3.3%	335,000	12.9%
10,000 – 20,000	624	2.6%	751,000	11.2%	568,000	21.8%
5,000 – 10,000	2,760	11.7%	2,307,000	34.5%	712,000	27.4%
2,500 – 5,000	3,960	16.8%	1,851,000	27.7%	427,000	16.4%
< 2,500	16,064	68.1%	1,518,000	22.7%	277,000	10.6%

Table D.24: Houston Population and Jobs by % Ideal Walkshed

Percent Ideal Walkshed	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
> 65%	157	0.7%	156,000	2.3%	190,000	7.3%
55% – 65%	892	3.8%	745,000	11.2%	380,000	14.6%
45% – 55%	1,948	8.3%	1,252,000	18.7%	531,000	20.4%
35% – 45%	3,389	14.4%	1,500,000	22.4%	528,000	20.3%
25% – 35%	6,027	25.6%	1,484,000	22.2%	470,000	18.1%
15% – 25%	8,423	35.7%	1,190,000	17.8%	346,000	13.3%
< 15%	2,737	11.6%	356,000	5.3%	158,000	6.1%

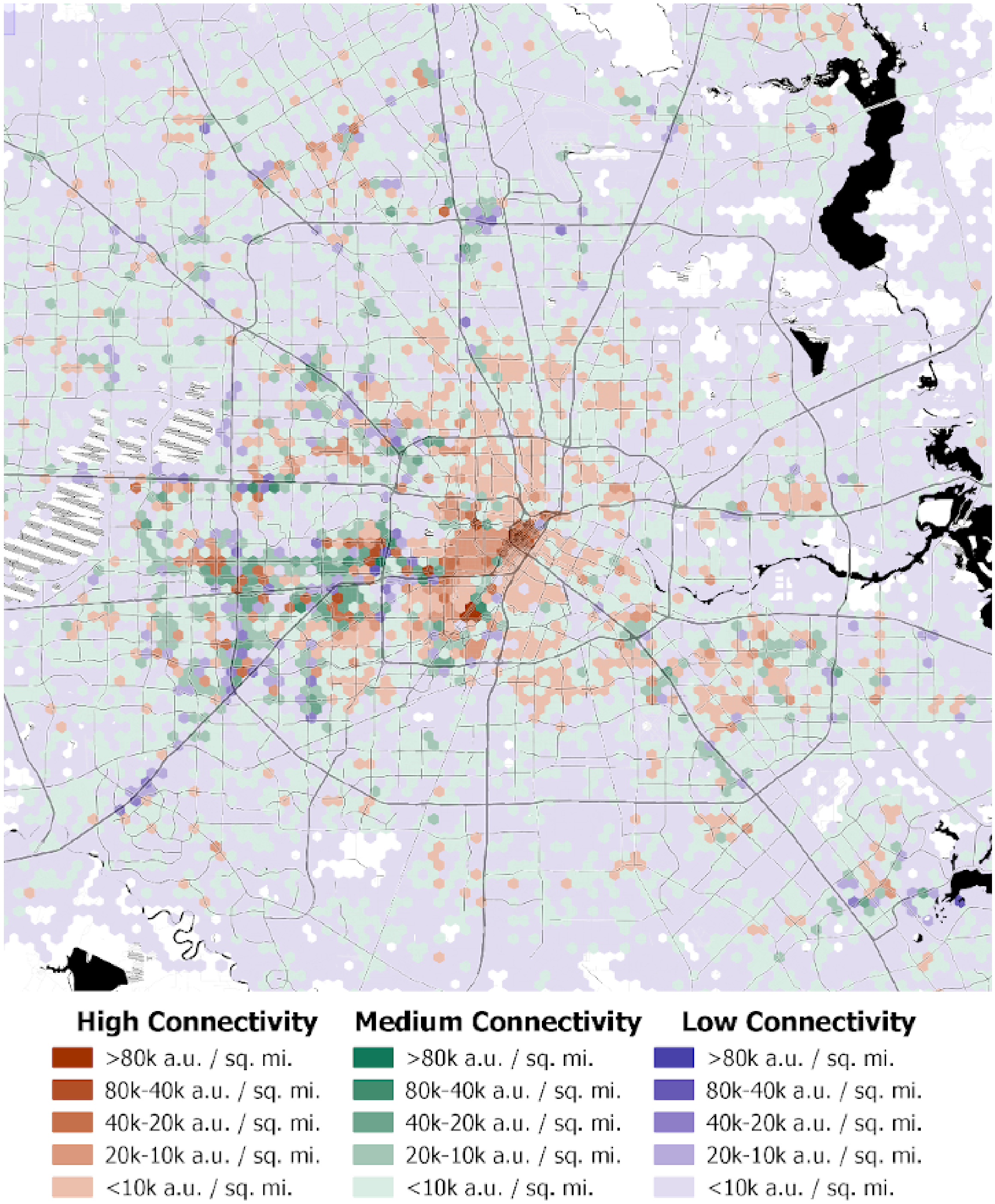

Figure D.12: Houston-The Woodlands-Sugar Land, TX MSA activity-connectivity neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table D.25: Los Angeles Population and Jobs by Activity Density

Density (/ sq. mi.)	Hexes	% of Hexes	Population	% of Population	Jobs	% of Jobs
> 80,000	24	0.2%	73,000	0.6%	411,000	7.3%
40,000 – 80,000	120	0.8%	393,000	3.0%	585,000	10.4%
20,000 – 40,000	1,017	7.2%	2,844,000	21.5%	1,328,000	23.7%
10,000 – 20,000	3,447	24.3%	5,444,000	41.1%	2,110,000	37.7%
5,000 – 10,000	3,273	23.1%	3,001,000	22.7%	883,000	15.8%
2,500 – 5,000	2,010	14.2%	964,000	7.3%	195,000	3.5%
< 2,500	4,277	30.2%	512,000	3.9%	87,000	1.6%

Table D.26: Los Angeles Population and Jobs by % Ideal Walkshed

Percent Ideal Walkshed	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
> 65%	552	3.9%	1,340,000	10.1%	674,000	12.0%
55% – 65%	2,165	15.3%	3,989,000	30.1%	1,378,000	24.6%
45% – 55%	2,354	16.6%	3,009,000	22.7%	1,319,000	23.6%
35% – 45%	2,316	16.3%	2,065,000	15.6%	1,003,000	17.9%
25% – 35%	2,734	19.3%	1,606,000	12.1%	785,000	14.0%
15% – 25%	3,094	21.8%	990,000	7.5%	346,000	6.2%
< 15%	953	6.7%	234,000	1.8%	92,000	1.6%

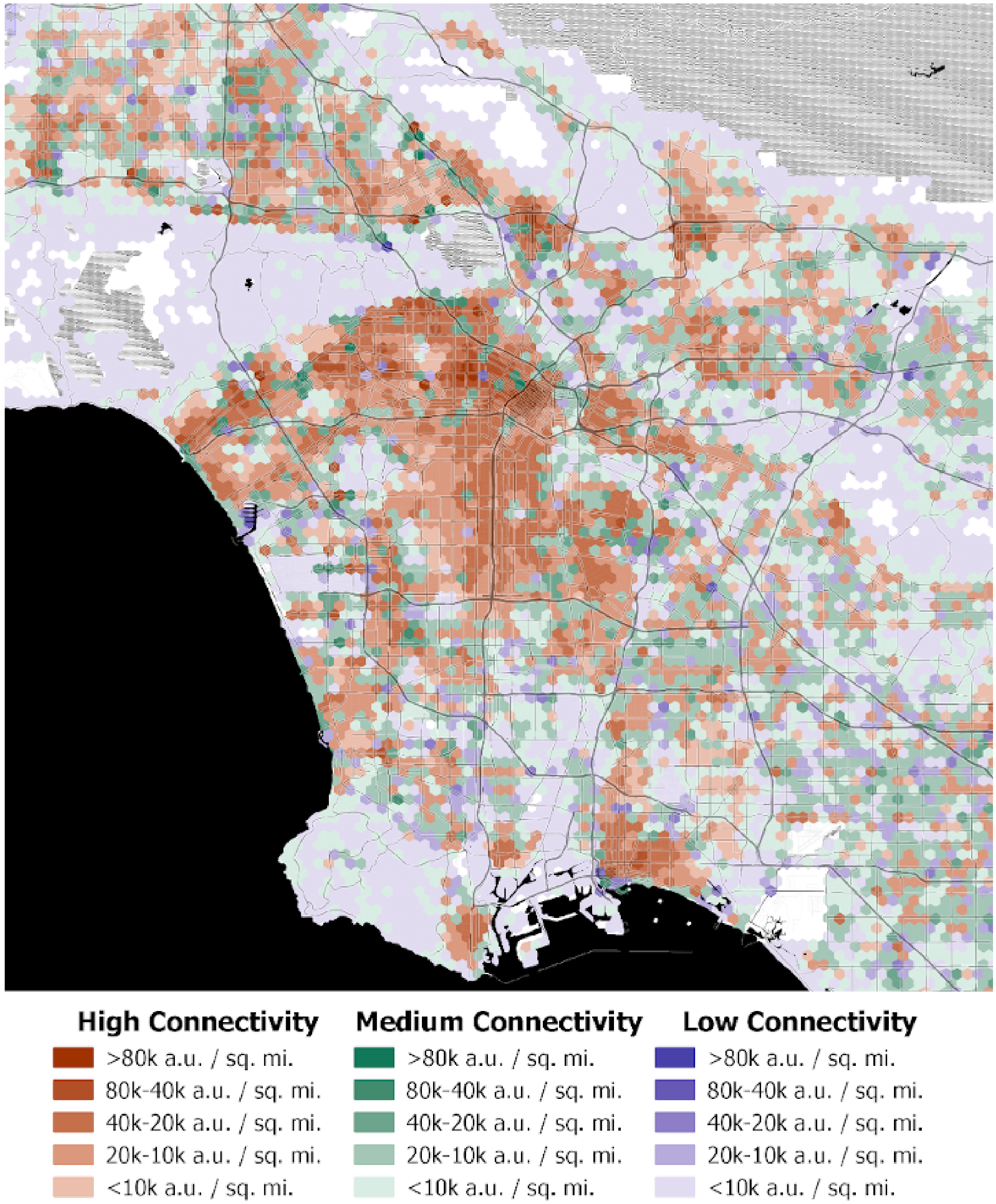

Figure D.13: Los Angeles-Long Beach-Anaheim, CA MSA activity-connectivity neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table D.27: Miami Population and Jobs by Activity Density

Density (/ sq. mi.)	Hexes	% of Hexes	Population	% of Population	Jobs	% of Jobs
> 80,000	4	0.04%	16,000	0.3%	37,000	1.6%
40,000 – 80,000	34	0.3%	63,000	1.0%	144,000	6.3%
20,000 – 40,000	217	2.2%	495,000	8.2%	312,000	13.6%
10,000 – 20,000	1,214	12.4%	1,655,000	27.3%	781,000	34.0%
5,000 – 10,000	2,904	29.7%	2,526,000	41.7%	719,000	31.3%
2,500 – 5,000	1,884	19.3%	871,000	14.4%	207,000	9.0%
< 2,500	3,522	36.0%	425,000	7.0%	95,000	4.1%

Table D.28: Miami Population and Jobs by % Ideal Walkshed

Percent Ideal Walkshed	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
> 65%	178	1.8%	294,000	4.9%	113,000	4.9%
55% – 65%	972	9.9%	1,136,000	18.8%	447,000	19.5%
45% – 55%	1,356	13.9%	1,156,000	19.1%	533,000	23.2%
35% – 45%	1,910	19.5%	1,241,000	20.5%	500,000	21.8%
25% – 35%	2,184	22.3%	1,101,000	18.2%	368,000	16.0%
15% – 25%	2,546	26.0%	892,000	14.7%	262,000	11.4%
< 15%	633	6.5%	231,000	3.8%	72,000	3.1%

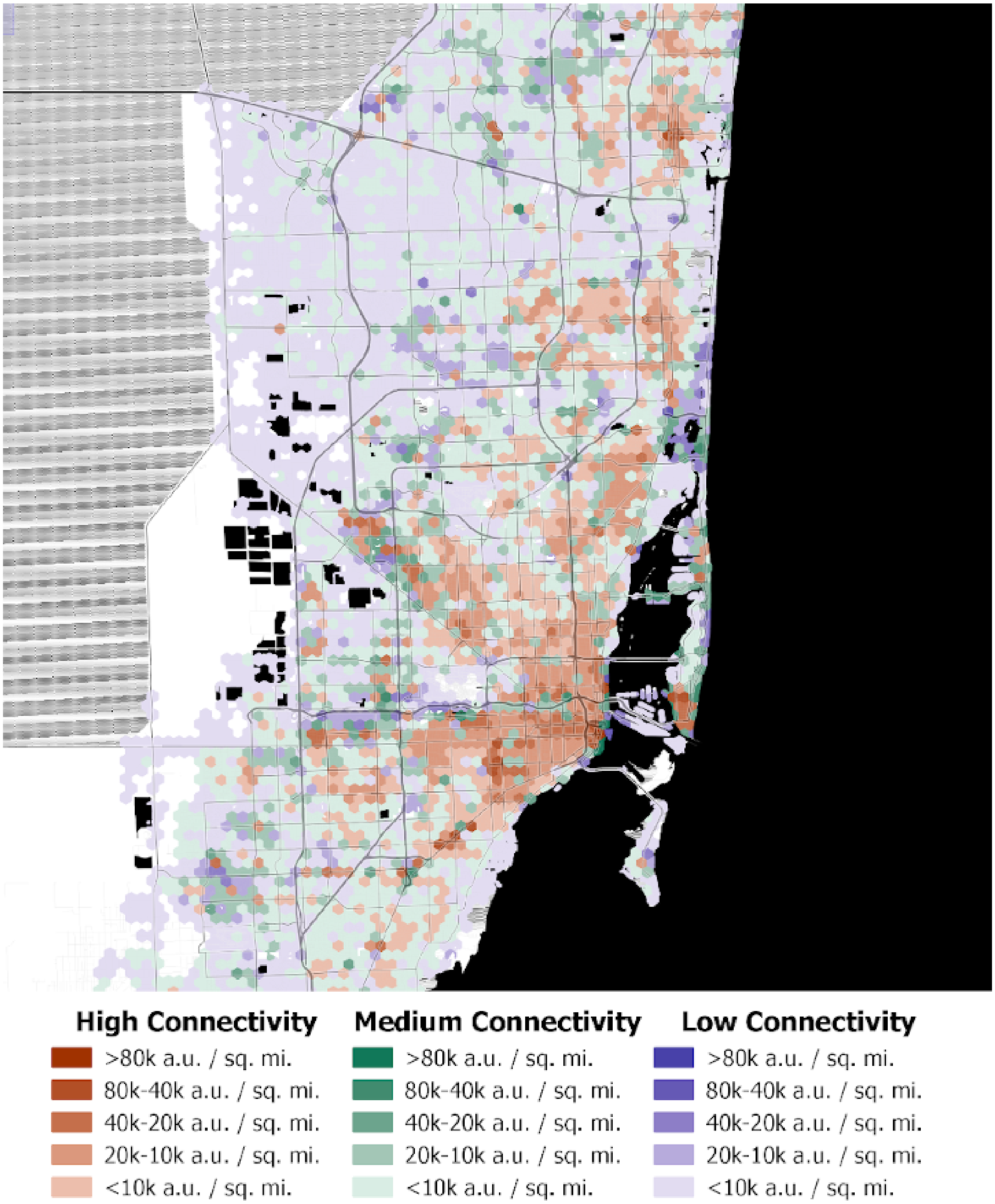

Figure D.14: Miami-Fort Lauderdale-Pompano Beach, FL MSA activity-connectivity neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table D.29: Minneapolis Population and Jobs by Activity Density

Density (/ sq. mi.)	**Hexes**	**% of Hexes**	**Population**	**% of Population**	**Jobs**	**% of Jobs**
> 80,000	7	0.03%	13,000	0.4%	136,000	8.0%
40,000 – 80,000	12	0.06%	24,000	0.7%	60,000	3.6%
20,000 – 40,000	69	0.4%	98,000	2.8%	185,000	11.0%
10,000 – 20,000	314	1.6%	330,000	9.6%	323,000	19.1%
5,000 – 10,000	1,175	6.1%	793,000	23.1%	480,000	28.4%
2,500 – 5,000	2,564	13.3%	1,075,000	31.3%	315,000	18.6%
< 2,500	15,160	78.5%	1,100,000	32.0%	189,000	11.2%

Table D.30: Minneapolis Population and Jobs by % Ideal Walkshed

Percent Ideal Walkshed	**Hexes**	**% of Hexes**	**Population**	**% of Pop.**	**Jobs**	**% of Jobs**
> 65%	208	1.1%	282,000	8.2%	202,000	12.0%
55% – 65%	669	3.5%	519,000	15.1%	256,000	15.2%
45% – 55%	1,357	7.0%	621,000	18.1%	320,000	19.0%
35% – 45%	2,362	12.2%	686,000	20.0%	319,000	18.9%
25% – 35%	5,489	28.4%	709,000	20.6%	346,000	20.5%
15% – 25%	7,530	39.0%	503,000	14.6%	178,000	10.5%
< 15%	1,686	8.7%	114,000	3.3%	68,000	4.1%

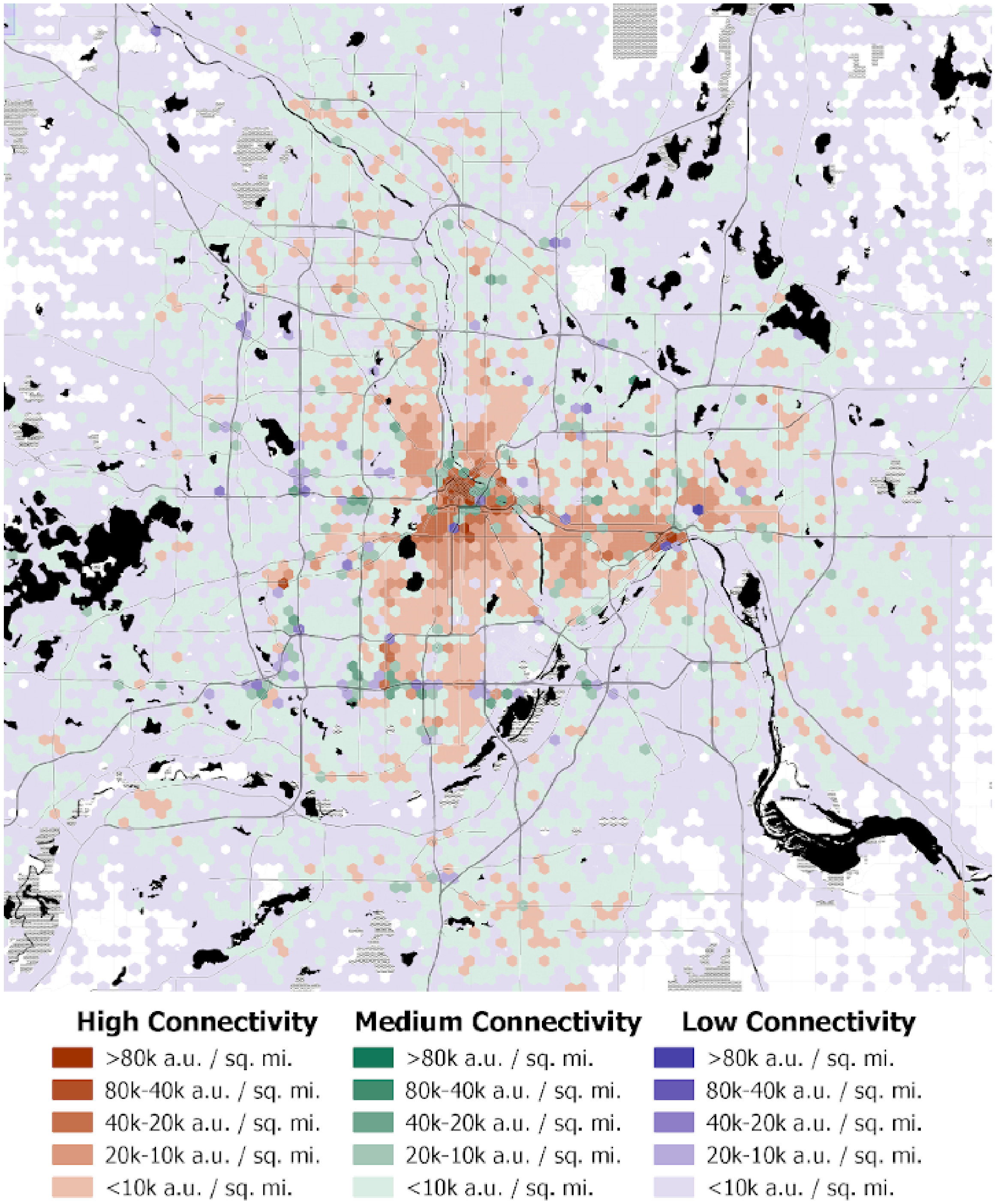

Figure D.15: Minneapolis-St. Paul-Bloomington, MN-WI MSA activity-connectivity neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table D.31: New York Population and Jobs by Activity Density

Density (/ sq. mi.)	Hexes	% of Hexes	Population	% of Population	Jobs	% of Jobs
> 80,000	228	0.7%	2,816,000	14.6%	2,782,000	34.6%
40,000 – 80,000	502	1.6%	3,560,000	18.5%	794,000	9.9%
20,000 – 40,000	850	2.7%	2,764,000	14.4%	804,000	10.0%
10,000 – 20,000	1,901	6.0%	2,782,000	14.4%	1,273,000	15.9%
5,000 – 10,000	3,922	12.4%	3,026,000	15.7%	1,254,000	15.6%
2,500 – 5,000	5,334	16.9%	2,264,000	11.8%	687,000	8.5%
< 2,500	18,780	59.6%	2,046,000	10.6%	438,000	5.4%

Table D.32: New York Population and Jobs by % Ideal Walkshed

Percent Ideal Walkshed	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
> 65%	794	2.5%	4,652,000	24.2%	2,533,000	31.5%
55% – 65%	2,026	6.4%	4,858,000	25.2%	1,639,000	20.4%
45% – 55%	3,132	9.9%	3,110,000	16.1%	1,012,000	12.6%
35% – 45%	5,030	16.0%	2,567,000	13.3%	1,040,000	13.0%
25% – 35%	7,988	25.3%	2,099,000	10.9%	907,000	11.3%
15% – 25%	9,535	30.3%	1,446,000	7.5%	662,000	8.2%
< 15%	3,012	9.6%	527,000	2.7%	240,000	3.0%

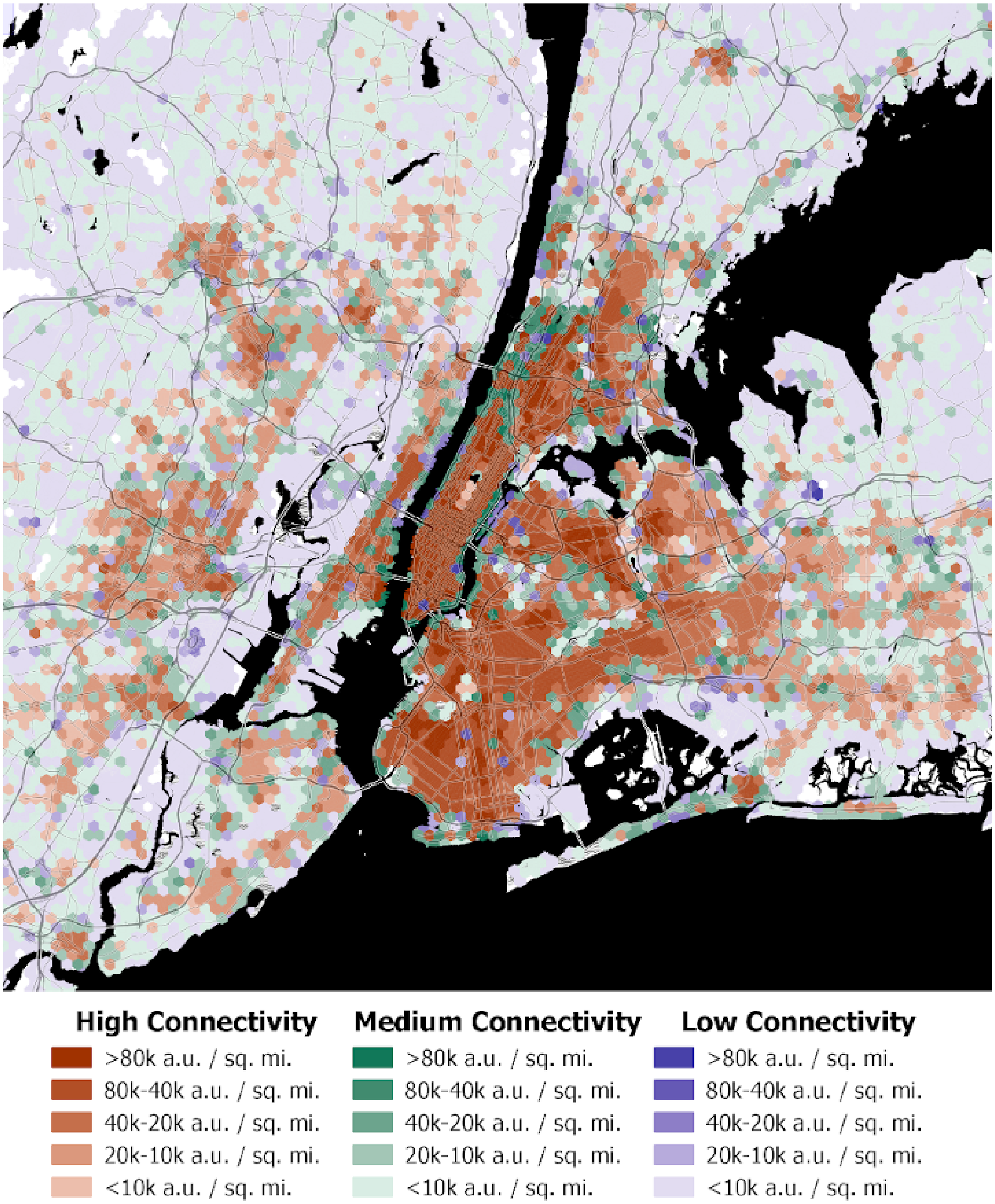

Figure D.16: New York-Newark-Jersey City, NY-NJ-PA MSA activity-connectivity neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table D.33: Philadelphia Population and Jobs by Activity Density

Density (/ sq. mi.)	Hexes	% of Hexes	Population	% of Population	Jobs	% of Jobs
> 80,000	11	0.05%	42,000	0.7%	253,000	9.8%
40,000 – 80,000	26	0.13%	118,000	2.0%	88,000	3.4%
20,000 – 40,000	263	1.3%	853,000	14.2%	260,000	10.1%
10,000 – 20,000	627	3.1%	894,000	14.9%	472,000	18.3%
5,000 – 10,000	1,837	9.2%	1,267,000	21.1%	712,000	27.6%
2,500 – 5,000	3,249	16.3%	1,331,000	22.1%	481,000	18.6%
< 2,500	13,957	69.9%	1,508,000	25.1%	317,000	12.3%

Table D.34: Philadelphia Population and Jobs by % Ideal Walkshed

Percent Ideal Walkshed	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
> 65%	281	1.4%	847,000	14.1%	384,000	14.9%
55% – 65%	700	3.5%	880,000	14.6%	266,000	10.3%
45% – 55%	1,585	7.9%	957,000	15.9%	429,000	16.6%
35% – 45%	3,193	16.0%	1,078,000	17.9%	511,000	19.8%
25% – 35%	5,738	28.7%	1,123,000	18.7%	478,000	18.5%
15% – 25%	6,535	32.7%	866,000	14.4%	370,000	14.3%
< 15%	1,938	9.7%	262,000	4.4%	144,000	5.6%

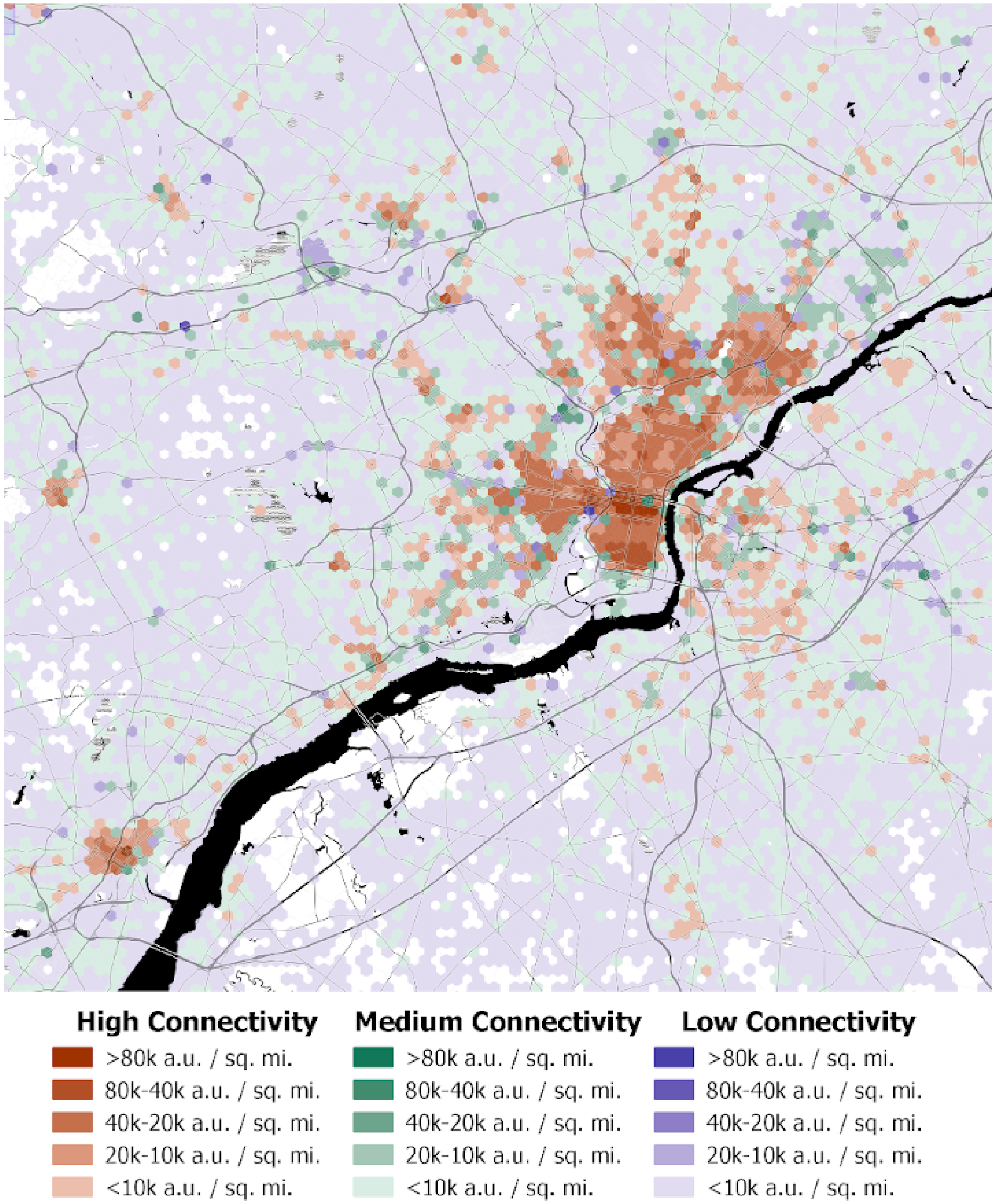

Figure D.17: Philadelphia-Camden-Wilmington, PA-NJ-DE-MD MSA activity-connectivity neighborhood map. Philadelphia is just right of center and Wilmington is at the lower left. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table D.35: Phoenix Population and Jobs by Activity Density

Density (/ sq. mi.)	**Hexes**	**% of Hexes**	**Population**	**% of Population**	**Jobs**	**% of Jobs**
> 80,000	2	0.02%	1,000	0.03%	32,000	1.8%
40,000 – 80,000	15	0.11%	10,000	0.2%	116,000	6.4%
20,000 – 40,000	69	0.5%	60,000	1.3%	223,000	12.3%
10,000 – 20,000	625	4.8%	764,000	16.6%	529,000	29.2%
5,000 – 10,000	2,184	16.7%	1,841,000	39.9%	552,000	30.5%
2,500 – 5,000	2,271	17.4%	1,118,000	24.2%	224,000	12.4%
< 2,500	7,895	60.4%	823,000	17.8%	134,000	7.4%

Table D.36: Phoenix Population and Jobs by % Ideal Walkshed

Percent Ideal Walkshed	**Hexes**	**% of Hexes**	**Population**	**% of Pop.**	**Jobs**	**% of Jobs**
> 65%	93	0.7%	79,000	1.7%	83,000	4.6%
55% – 65%	971	7.4%	851,000	18.4%	415,000	22.9%
45% – 55%	1,782	13.6%	1,135,000	24.6%	455,000	25.1%
35% – 45%	2,551	19.5%	1,105,000	23.9%	412,000	22.8%
25% – 35%	3,166	24.2%	823,000	17.8%	250,000	13.8%
15% – 25%	3,604	27.6%	513,000	11.1%	151,000	8.3%
< 15%	894	6.8%	111,000	2.4%	46,000	2.5%

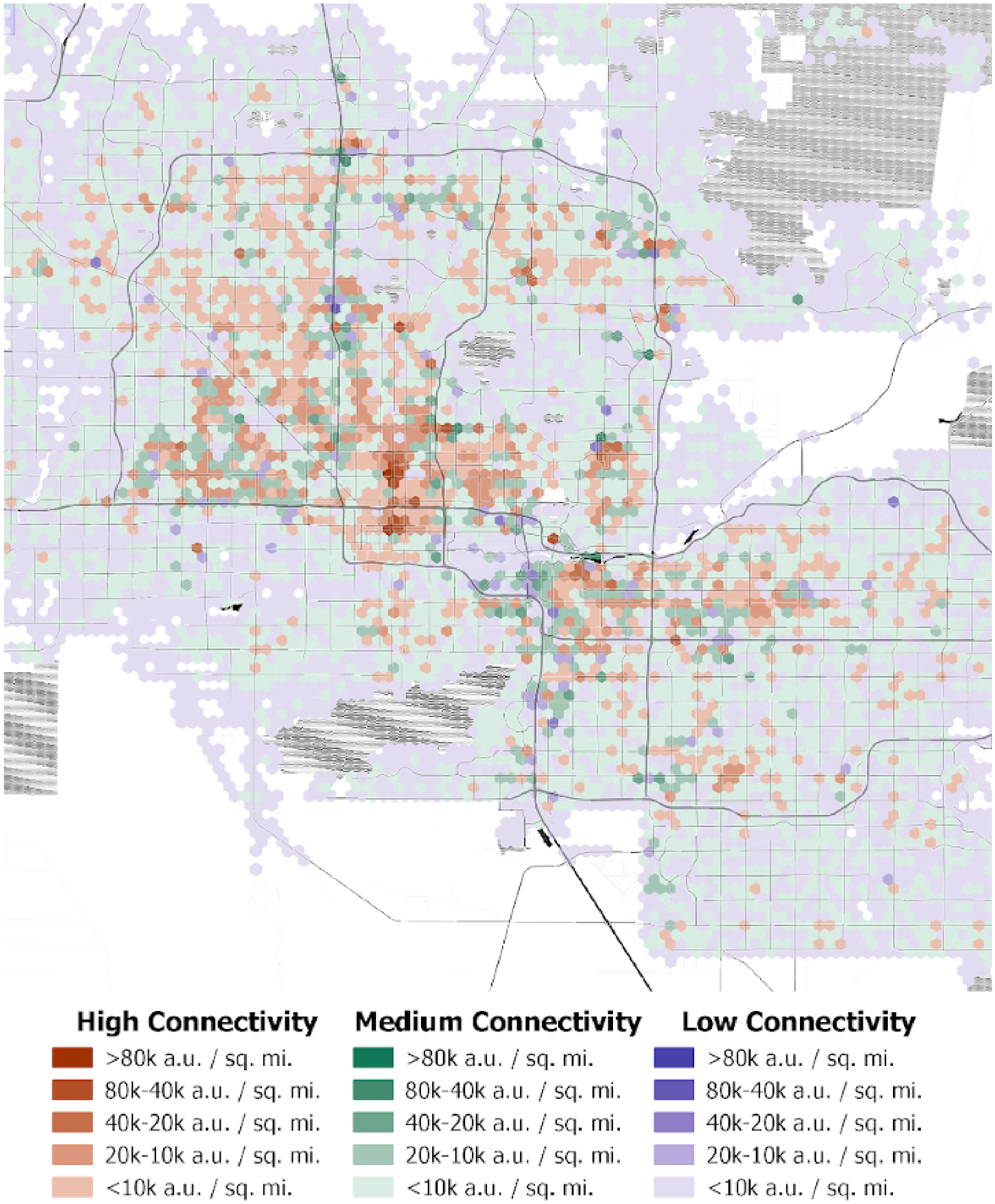

Figure D.18: Phoenix-Mesa-Chandler, AZ MSA activity-connectivity neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table D.37: Pittsburgh Population and Jobs by Activity Density

Density (/ sq. mi.)	Hexes	% of Hexes	Population	% of Population	Jobs	% of Jobs
> 80,000	5	0.03%	8,000	0.4%	105,000	10.0%
40,000 – 80,000	8	0.05%	17,000	0.8%	42,000	4.0%
20,000 – 40,000	19	0.1%	26,000	1.1%	46,000	4.4%
10,000 – 20,000	155	0.9%	160,000	7.1%	153,000	14.7%
5,000 – 10,000	656	3.8%	441,000	19.4%	250,000	23.9%
2,500 – 5,000	1,379	8.0%	536,000	23.6%	211,000	20.2%
< 2,500	15,092	87.2%	1,083,000	47.7%	239,000	22.8%

Table D.38: Pittsburgh Population and Jobs by % Ideal Walkshed

Percent Ideal Walkshed	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
> 65%	33	0.2%	47,000	2.1%	113,000	10.8%
55% – 65%	211	1.2%	205,000	9.0%	117,000	11.2%
45% – 55%	528	3.0%	283,000	12.5%	137,000	13.1%
35% – 45%	1,332	7.7%	387,000	17.0%	169,000	16.2%
25% – 35%	4,415	25.5%	535,000	23.5%	232,000	22.2%
15% – 25%	8,580	49.6%	631,000	27.8%	200,000	19.1%
< 15%	2,215	12.8%	183,000	8.1%	77,000	7.4%

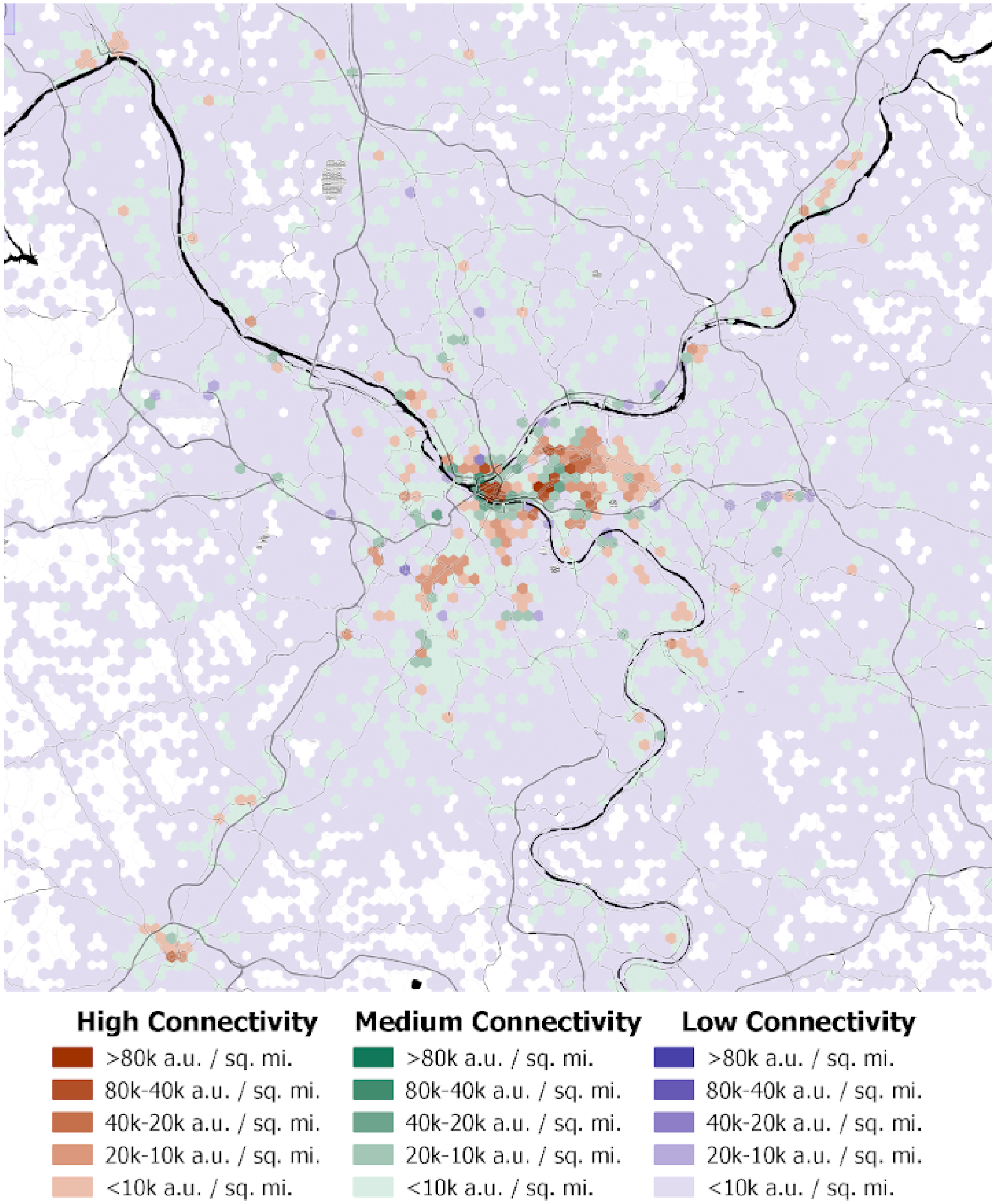

Figure D.19: Pittsburgh, PA MSA activity-connectivity neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table D.39: Portland Population and Jobs by Activity Density

Density (/ sq. mi.)	Hexes	% of Hexes	Population	% of Population	Jobs	% of Jobs
> 80,000	4	0.04%	7,000	0.3%	65,000	6.3%
40,000 – 80,000	9	0.09%	21,000	0.9%	50,000	4.8%
20,000 – 40,000	39	0.4%	46,000	1.9%	105,000	10.1%
10,000 – 20,000	336	3.4%	390,000	16.4%	292,000	28.3%
5,000 – 10,000	1,163	11.9%	978,000	41.2%	312,000	30.1%
2,500 – 5,000	1,035	10.6%	480,000	20.2%	125,000	12.1%
< 2,500	7,206	73.6%	452,000	19.0%	86,000	8.3%

Table D.40: Portland Population and Jobs by % Ideal Walkshed

Percent Ideal Walkshed	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
> 65%	141	1.4%	200,000	8.4%	175,000	16.9%
55% – 65%	431	4.4%	406,000	17.1%	200,000	19.4%
45% – 55%	738	7.5%	519,000	21.8%	185,000	17.9%
35% – 45%	1,288	13.2%	513,000	21.6%	214,000	20.7%
25% – 35%	2,497	25.5%	376,000	15.8%	141,000	13.7%
15% – 25%	3,694	37.7%	287,000	12.1%	96,000	9.3%
< 15%	1,003	10.2%	74,000	3.1%	21,000	2.1%

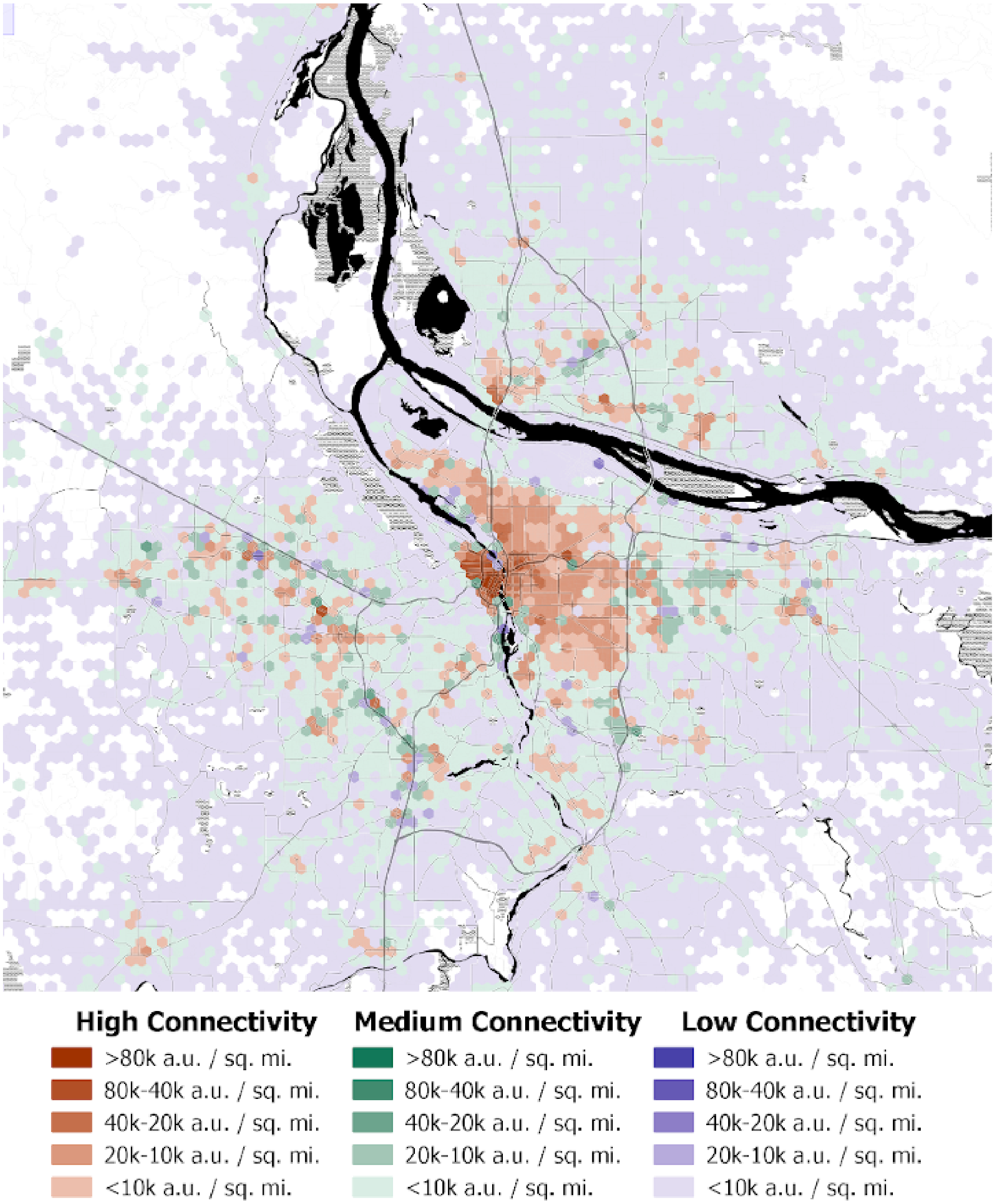

Figure D.20: Portland-Vancouver-Hillsboro, OR-WA MSA activity-connectivity neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table D.41: Riverside Population and Jobs by Activity Density

Density (/ sq. mi.)	Hexes	% of Hexes	Population	% of Population	Jobs	% of Jobs
> 80,000	0	0%	0	0%	0	0%
40,000 – 80,000	1	0.01%	1,000	0.02%	11,000	0.9%
20,000 – 40,000	20	0.14%	23,000	0.5%	54,000	4.5%
10,000 – 20,000	508	3.6%	699,000	15.8%	308,000	25.6%
5,000 – 10,000	1,867	13.2%	1,628,000	36.8%	447,000	37.1%
2,500 – 5,000	2,381	16.8%	1,111,000	25.1%	242,000	20.1%
< 2,500	9,355	66.2%	961,000	21.7%	142,000	11.8%

Table D.42: Riverside Population and Jobs by % Ideal Walkshed

Percent Ideal Walkshed	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
> 65%	49	0.3%	56,000	1.3%	18,000	1.5%
55% – 65%	704	5.0%	559,000	12.6%	152,000	12.6%
45% – 55%	1,760	12.5%	988,000	22.3%	283,000	23.5%
35% – 45%	2,700	19.1%	1,088,000	24.6%	294,000	24.4%
25% – 35%	3,629	25.7%	966,000	21.8%	264,000	21.9%
15% – 25%	4,185	29.6%	625,000	14.1%	160,000	13.3%
< 15%	1,105	7.8%	141,000	3.2%	34,000	2.8%

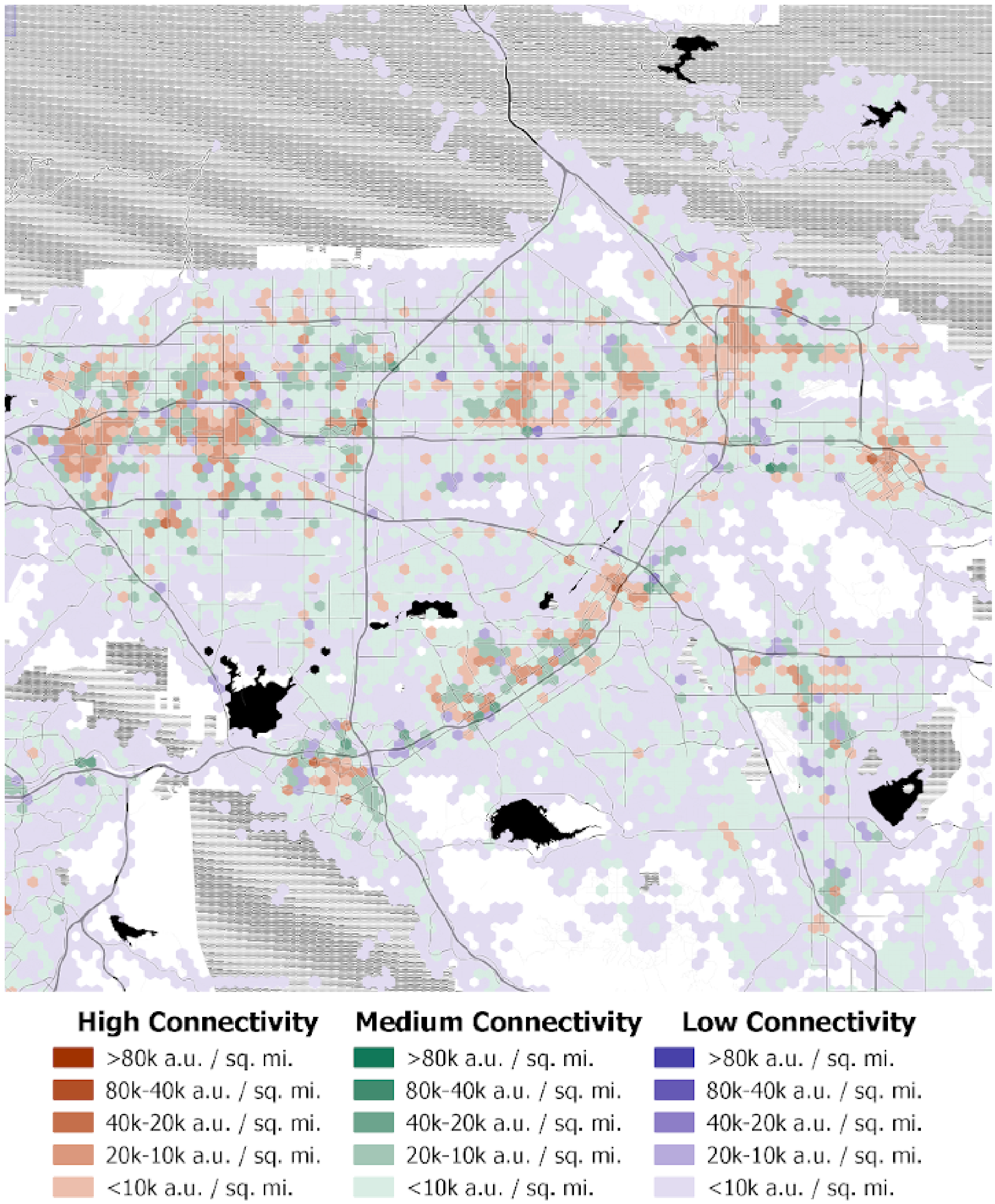

Figure D.21: Riverside-San Bernardino-Ontario, CA MSA activity-connectivity neighborhood map. Ontario is to the center left, San Bernardino is to the center right, and Riverside is to the lower center. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table D.43: Sacramento Population and Jobs by Activity Density

Density (/ sq. mi.)	Hexes	% of Hexes	Population	% of Population	Jobs	% of Jobs
> 80,000	0	0%	0	0%	0	0%
40,000 – 80,000	3	0.04%	3,000	0.11%	19,000	2.5%
20,000 – 40,000	25	0.4%	26,000	1.1%	79,000	10.6%
10,000 – 20,000	284	4.0%	369,000	16.3%	183,000	24.6%
5,000 – 10,000	1,163	16.3%	1,027,000	45.4%	279,000	37.5%
2,500 – 5,000	920	12.9%	417,000	18.4%	107,000	14.4%
< 2,500	4,746	66.5%	422,000	18.6%	78,000	10.4%

Table D.44: Sacramento Population and Jobs by % Ideal Walkshed

Percent Ideal Walkshed	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
> 65%	41	0.6%	45,000	2.0%	54,000	7.2%
55% – 65%	329	4.6%	317,000	14.0%	97,000	13%
45% – 55%	726	10.2%	539,000	23.8%	169,000	22.7%
35% – 45%	1,129	15.8%	546,000	24.1%	185,000	24.8%
25% – 35%	1,826	25.6%	463,000	20.5%	134,000	18.0%
15% – 25%	2,456	34.4%	291,000	12.8%	90,000	12.1%
< 15%	634	8.9%	64,000	2.8%	15,000	2.1%

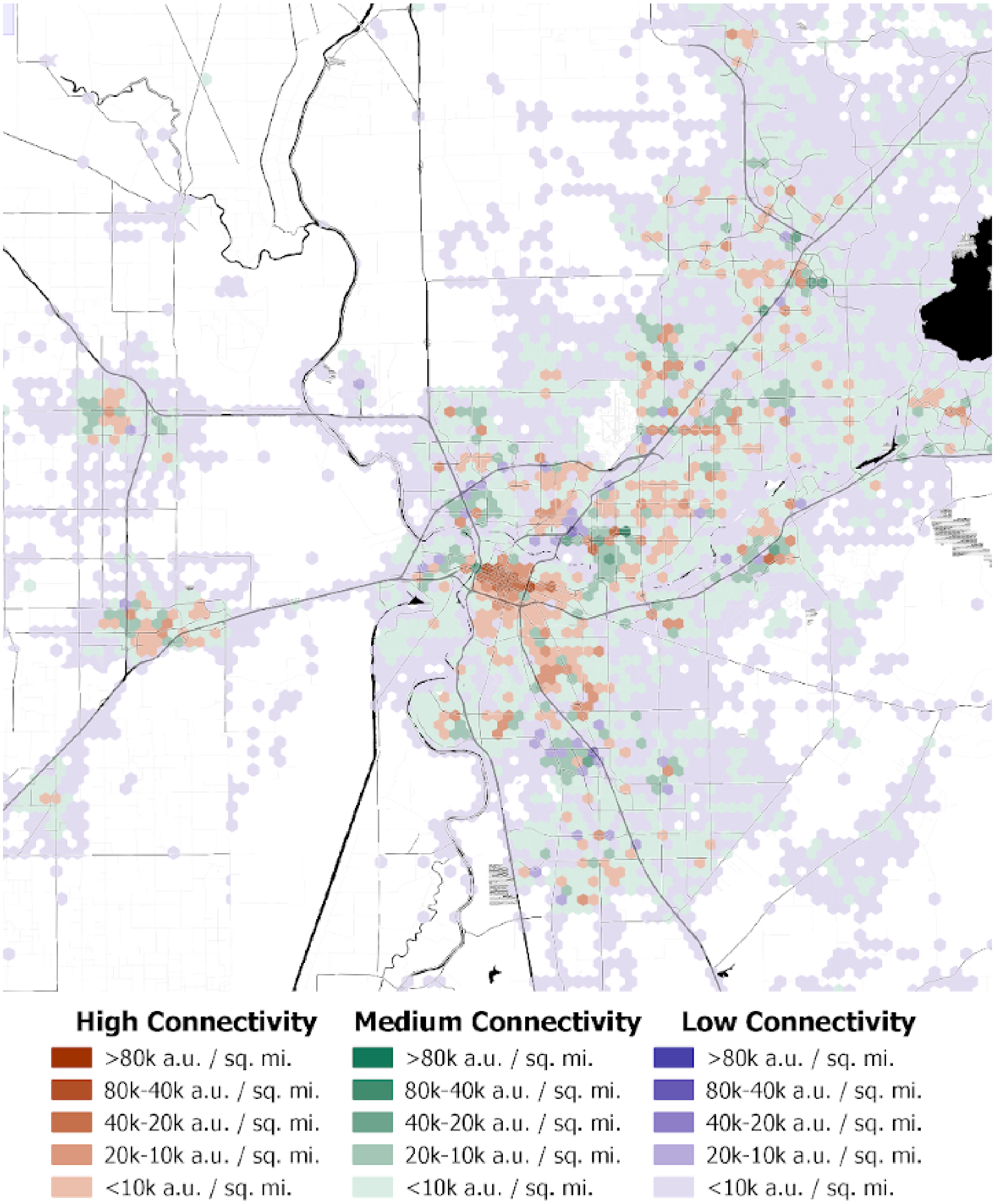

Figure D.22: Sacramento-Roseville-Folsom, CA MSA activity-connectivity neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table D.45: Salt Lake City Population and Jobs by Activity Density

Density (/ sq. mi.)	Hexes	% of Hexes	Population	% of Population	Jobs	% of Jobs
> 80,000	1	0.03%	0	0%	13,000	2.2%
40,000 – 80,000	3	0.1%	4,000	0.3%	23,000	3.8%
20,000 – 40,000	19	0.7%	19,000	1.6%	60,000	10.2%
10,000 – 20,000	156	5.9%	155,000	13.2%	155,000	26.1%
5,000 – 10,000	753	28.3%	612,000	52.1%	236,000	39.8%
2,500 – 5,000	558	21.0%	265,000	22.6%	74,000	12.5%
< 2,500	1,167	43.9%	119,000	10.2%	32,000	5.4%

Table D.46: Salt Lake City Population and Jobs by % Ideal Walkshed

Percent Ideal Walkshed	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
> 65%	49	1.8%	55,000	4.6%	63,000	10.6%
55% – 65%	233	8.8%	196,000	16.7%	91,000	15.3%
45% – 55%	418	15.7%	310,000	26.4%	138,000	23.2%
35% – 45%	499	18.8%	273,000	23.2%	129,000	21.7%
25% – 35%	558	21.0%	198,000	16.8%	93,000	15.7%
15% – 25%	713	26.8%	119,000	10.1%	71,000	11.9%
< 15%	187	7.0%	25,000	2.1%	10,000	1.7%

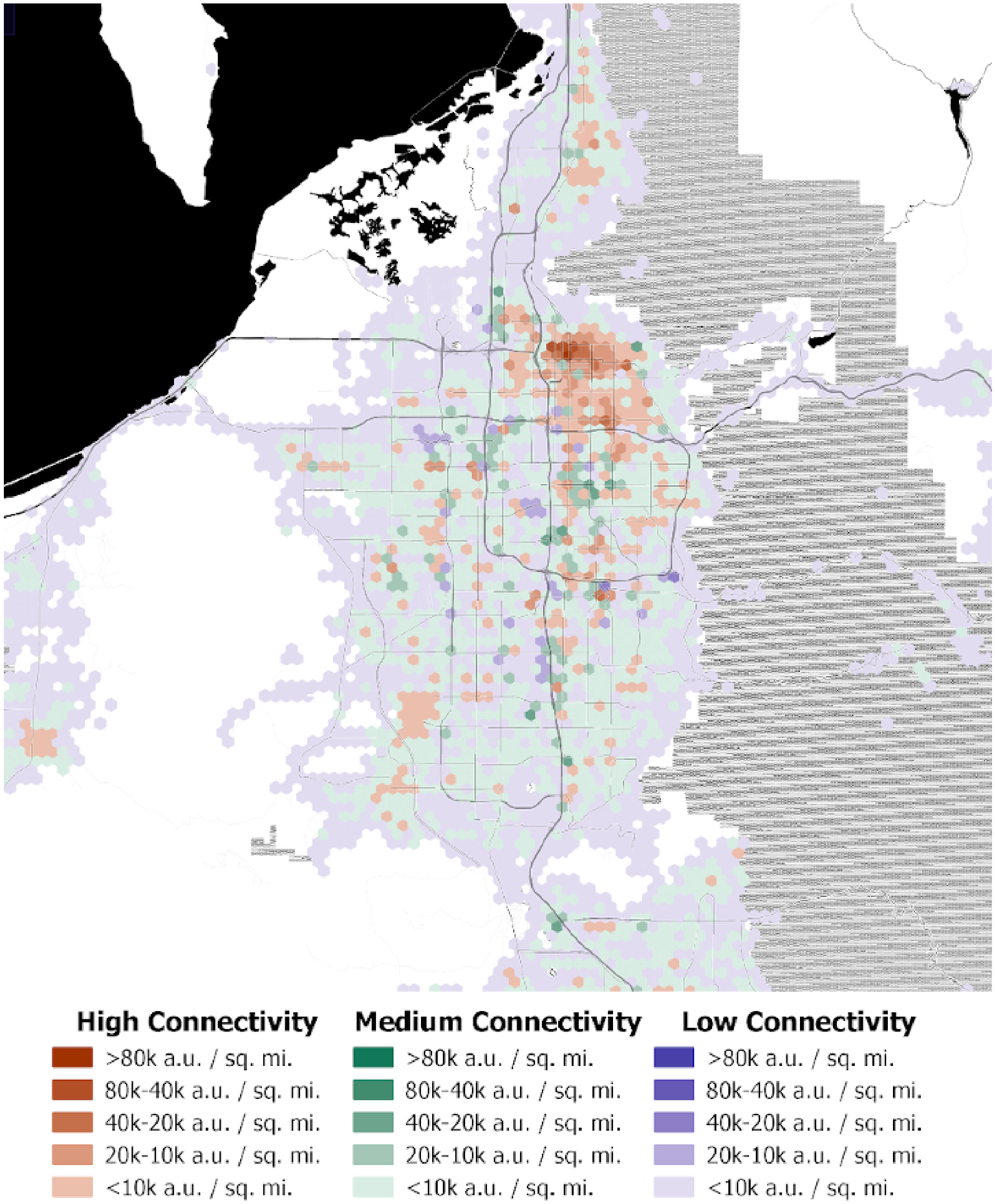

Figure D.23: Salt Lake City, UT MSA activity-connectivity neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table D.47: San Diego Population and Jobs by Activity Density

Density (/ sq. mi.)	Hexes	% of Hexes	Population	% of Population	Jobs	% of Jobs
> 80,000	1	0.01%	2,000	0.07%	12,000	1.0%
40,000 – 80,000	10	0.15%	21,000	0.7%	61,000	5.0%
20,000 – 40,000	102	1.5%	224,000	7.0%	180,000	14.9%
10,000 – 20,000	698	10.2%	1,006,000	31.4%	473,000	39.3%
5,000 – 10,000	1,250	18.3%	1,074,000	33.6%	322,000	26.7%
2,500 – 5,000	1,038	15.2%	502,000	15.7%	97,000	8.1%
< 2,500	3,733	54.6%	370,000	11.6%	59,000	4.9%

Table D.48: San Diego Population and Jobs by % Ideal Walkshed

Percent Ideal Walkshed	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
> 65%	56	0.8%	124,000	3.9%	54,000	4.5%
55% – 65%	319	4.7%	461,000	14.4%	193,000	16.0%
45% – 55%	696	10.2%	631,000	19.7%	231,000	19.2%
35% – 45%	1,077	15.8%	662,000	20.7%	257,000	21.4%
25% – 35%	1,709	25.0%	675,000	21.1%	253,000	21.0%
15% – 25%	2,300	33.7%	536,000	16.8%	182,000	15.1%
< 15%	675	9.9%	111,000	3.5%	34,000	2.9%

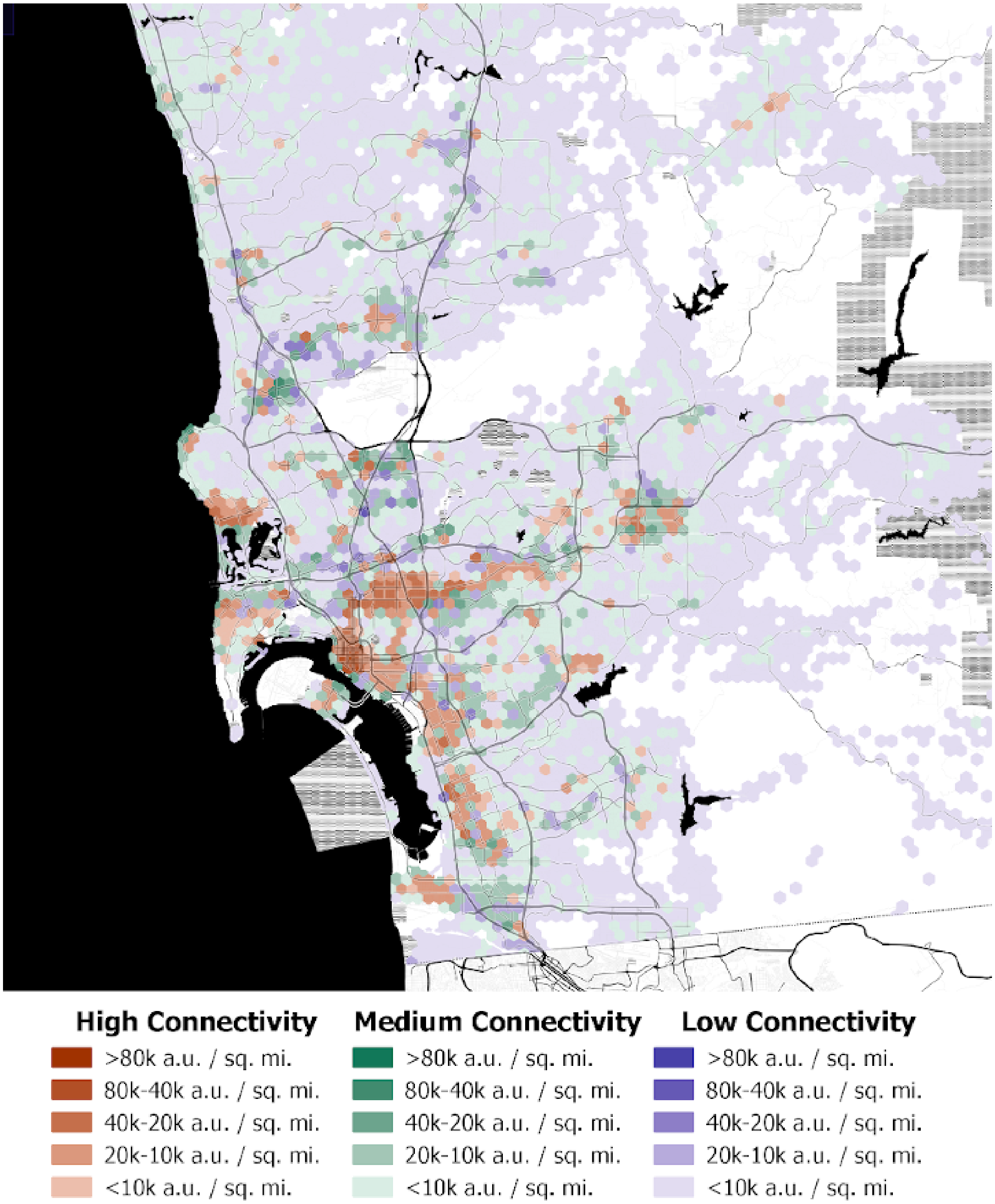

Figure D.24: San Diego-Chula Vista-Carlsbad, CA MSA activity-connectivity neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table D.49: San Francisco Population and Jobs by Activity Density

Density (/ sq. mi.)	Hexes	% of Hexes	Population	% of Population	Jobs	% of Jobs
> 80,000	22	0.3%	117,000	2.5%	425,000	19.9%
40,000 – 80,000	52	0.7%	241,000	5.2%	201,000	9.4%
20,000 – 40,000	306	4.4%	827,000	17.8%	436,000	20.4%
10,000 – 20,000	890	12.7%	1,359,000	29.2%	538,000	25.1%
5,000 – 10,000	1,347	19.2%	1,164,000	25.0%	351,000	16.4%
2,500 – 5,000	1,239	17.6%	577,000	12.4%	126,000	5.9%
< 2,500	3,172	45.1%	363,000	7.8%	64,000	3.0%

Table D.50: San Francisco Population and Jobs by % Ideal Walkshed

Percent Ideal Walkshed	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
> 65%	205	2.9%	645,000	13.9%	587,000	27.4%
55% – 65%	512	7.3%	971,000	20.9%	396,000	18.5%
45% – 55%	848	12.1%	927,000	19.9%	365,000	17.0%
35% – 45%	1,166	16.6%	846,000	18.2%	331,000	15.5%
25% – 35%	1,632	23.2%	707,000	15.2%	270,000	12.6%
15% – 25%	2,046	29.1%	429,000	9.2%	156,000	7.3%
< 15%	619	8.8%	122,000	2.6%	34,000	1.6%

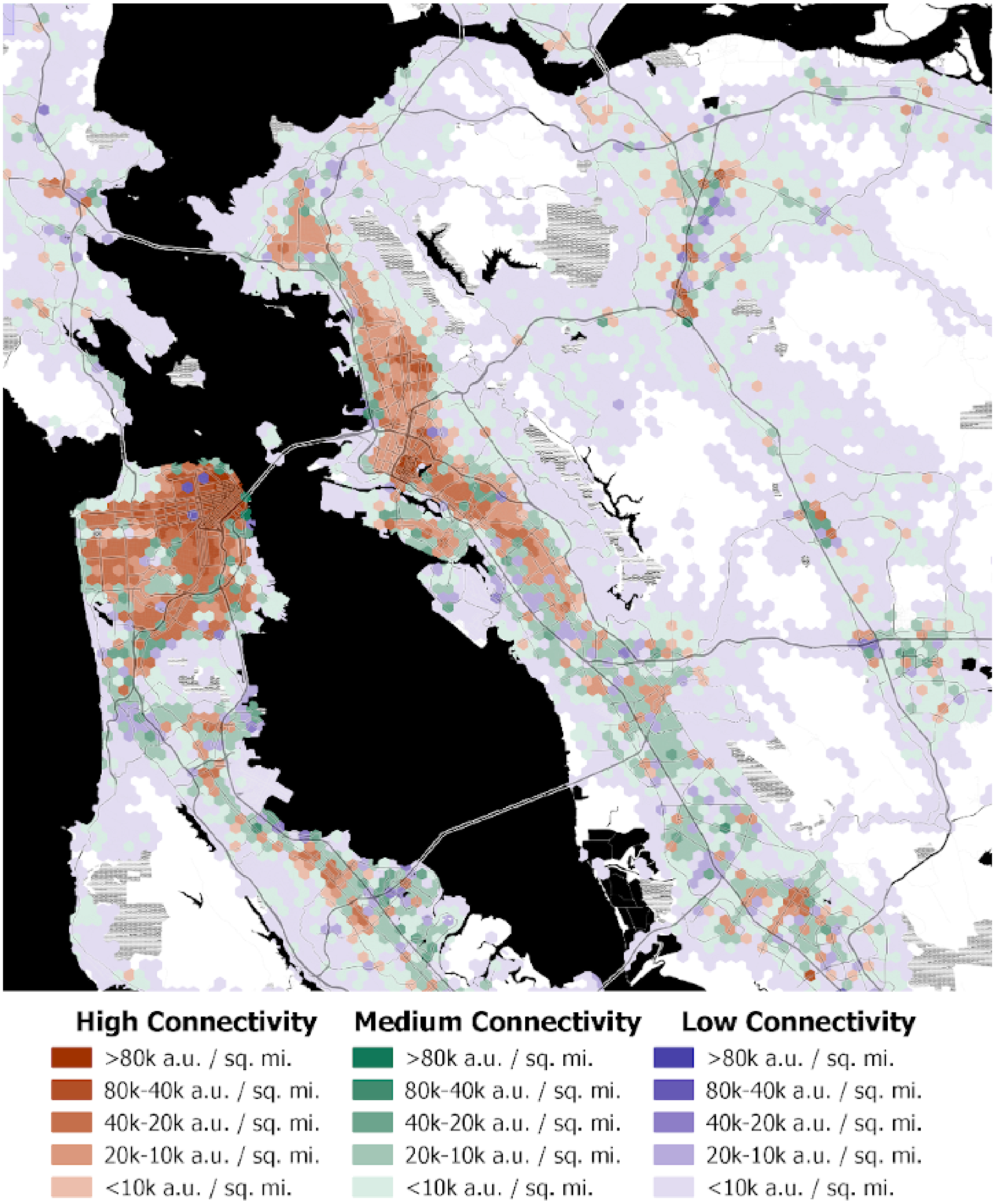

Figure D.25: San Francisco-Oakland-Berkeley, CA MSA activity-connectivity neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table D.51: San Jose Population and Jobs by Activity Density

Density (/ sq. mi.)	Hexes	% of Hexes	Population	% of Population	Jobs	% of Jobs
> 80,000	3	0.09%	2,000	0.12%	55,000	5.5%
40,000 – 80,000	13	0.4%	10,000	0.5%	93,000	9.3%
20,000 – 40,000	99	3.2%	179,000	9.1%	224,000	22.5%
10,000 – 20,000	611	19.8%	923,000	46.8%	399,000	40.0%
5,000 – 10,000	632	20.5%	607,000	30.8%	163,000	16.3%
2,500 – 5,000	274	8.9%	129,000	6.5%	33,000	3.4%
< 2,500	1,455	47.1%	124,000	6.3%	29,000	2.9%

Table D.52: San Jose Population and Jobs by % Ideal Walkshed

Percent Ideal Walkshed	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
> 65%	65	2.1%	103,000	5.2%	55,000	5.5%
55% – 65%	366	11.9%	502,000	25.4%	242,000	24.3%
45% – 55%	442	14.3%	504,000	25.5%	294,000	29.5%
35% – 45%	466	15.1%	375,000	19.0%	181,000	18.2%
25% – 35%	631	20.4%	279,000	14.1%	120,000	12.0%
15% – 25%	837	27.1%	135,000	6.9%	57,000	5.7%
< 15%	280	9.1%	76,000	3.8%	47,000	4.8%

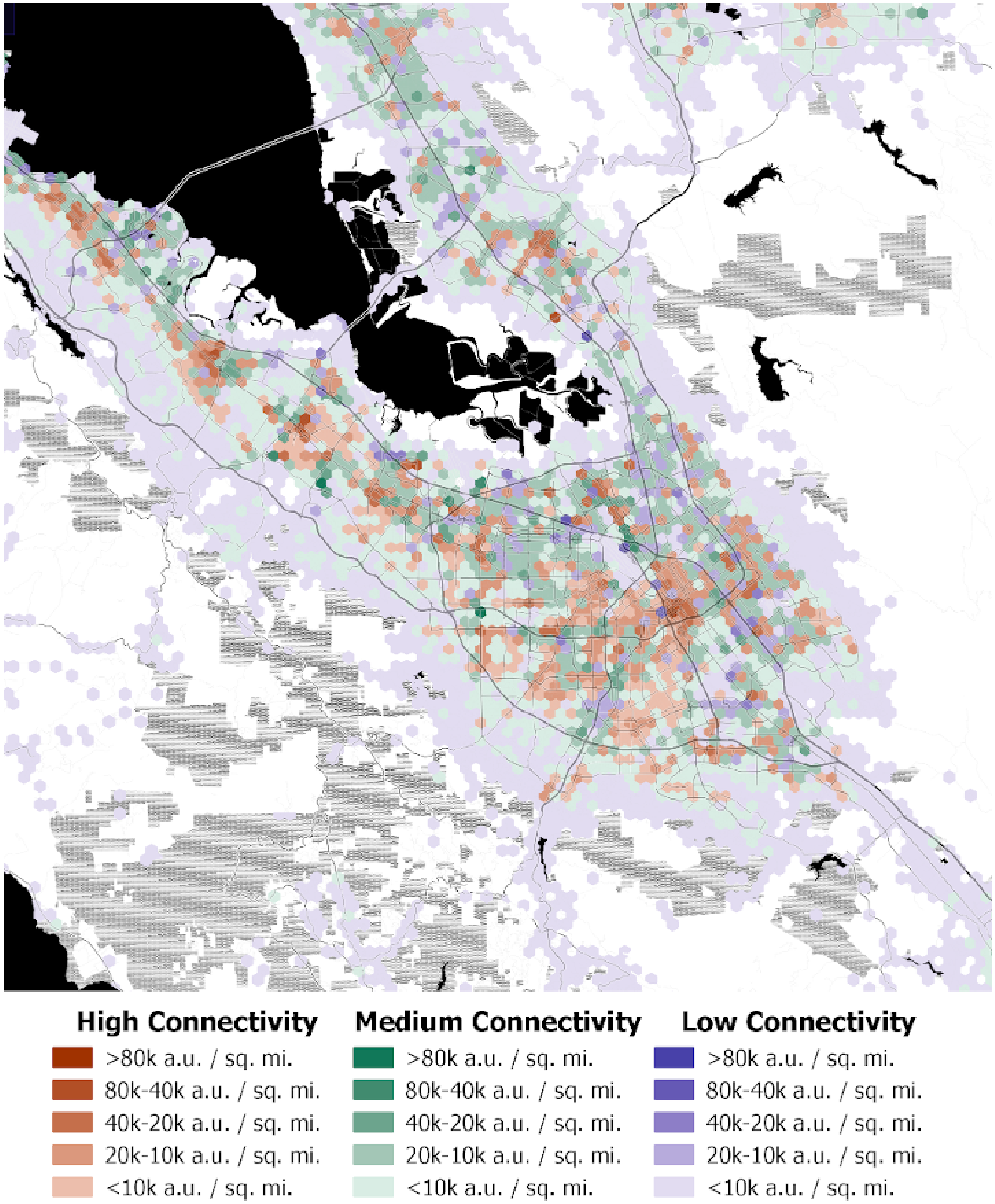

Figure D.26: San Jose-Sunnyvale-Santa Clara, CA MSA activity-connectivity neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table D.53: Seattle Population and Jobs by Activity Density

Density (/ sq. mi.)	Hexes	% of Hexes	Population	% of Population	Jobs	% of Jobs
> 80,000	20	0.2%	51,000	1.4%	332,000	19.5%
40,000 – 80,000	24	0.2%	63,000	1.7%	105,000	6.2%
20,000 – 40,000	78	0.7%	130,000	3.4%	181,000	10.7%
10,000 – 20,000	466	4.0%	563,000	14.9%	387,000	22.8%
5,000 – 10,000	1,610	13.7%	1,295,000	34.4%	422,000	24.9%
2,500 – 5,000	1,934	16.5%	933,000	24.8%	168,000	9.9%
< 2,500	7,580	64.7%	731,000	19.4%	100,000	5.9%

Table D.54: Seattle Population and Jobs by % Ideal Walkshed

Percent Ideal Walkshed	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
> 65%	191	1.6%	329,000	8.7%	308,000	18.1%
55% – 65%	559	4.8%	549,000	14.6%	286,000	16.9%
45% – 55%	1,075	9.2%	694,000	18.4%	388,000	22.9%
35% – 45%	1,843	15.7%	798,000	21.2%	287,000	16.9%
25% – 35%	3,084	26.3%	716,000	19.0%	239,000	14.1%
15% – 25%	3,843	32.8%	551,000	14.6%	143,000	8.4%
< 15%	1,117	9.5%	128,000	3.4%	46,000	2.7%

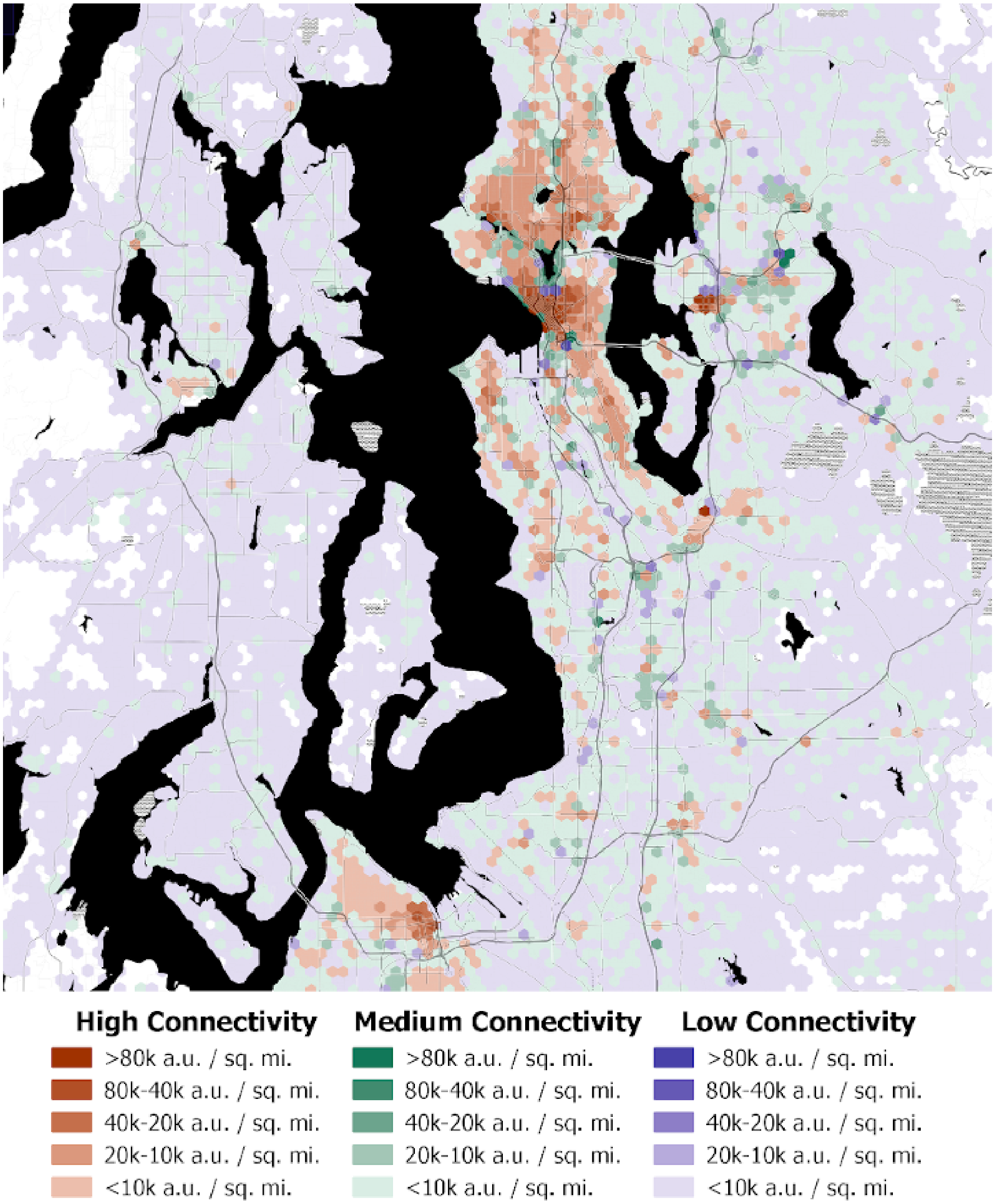

Figure D.27: Seattle-Tacoma-Bellevue, WA MSA activity-connectivity neighborhood map. Seattle is in the upper center and Tacoma is to the lower left. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table D.55: St. Louis Population and Jobs by Activity Density

Density (/ sq. mi.)	Hexes	% of Hexes	Population	% of Population	Jobs	% of Jobs
> 80,000	3	0.02%	3,000	0.12%	42,000	3.4%
40,000 – 80,000	7	0.0%	7,000	0.2%	57,000	4.7%
20,000 – 40,000	32	0.2%	23,000	0.8%	113,000	9.2%
10,000 – 20,000	153	0.9%	139,000	5.2%	175,000	14.3%
5,000 – 10,000	949	5.7%	640,000	23.8%	377,000	30.8%
2,500 – 5,000	2,052	12.4%	897,000	33.4%	269,000	22.0%
< 2,500	13,391	80.7%	978,000	36.4%	189,000	15.5%

Table D.56: St. Louis Population and Jobs by % Ideal Walkshed

Percent Ideal Walkshed	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
> 65%	122	0.7%	122,000	4.5%	72,000	5.9%
55% – 65%	517	3.1%	334,000	12.5%	214,000	17.5%
45% – 55%	837	5.0%	382,000	14.2%	213,000	17.5%
35% – 45%	1,727	10.4%	485,000	18.1%	244,000	20%
25% – 35%	4,386	26.4%	615,000	22.9%	222,000	18.2%
15% – 25%	7,025	42.4%	578,000	21.5%	205,000	16.8%
< 15%	1,973	11.9%	170,000	6.3%	52,000	4.2%

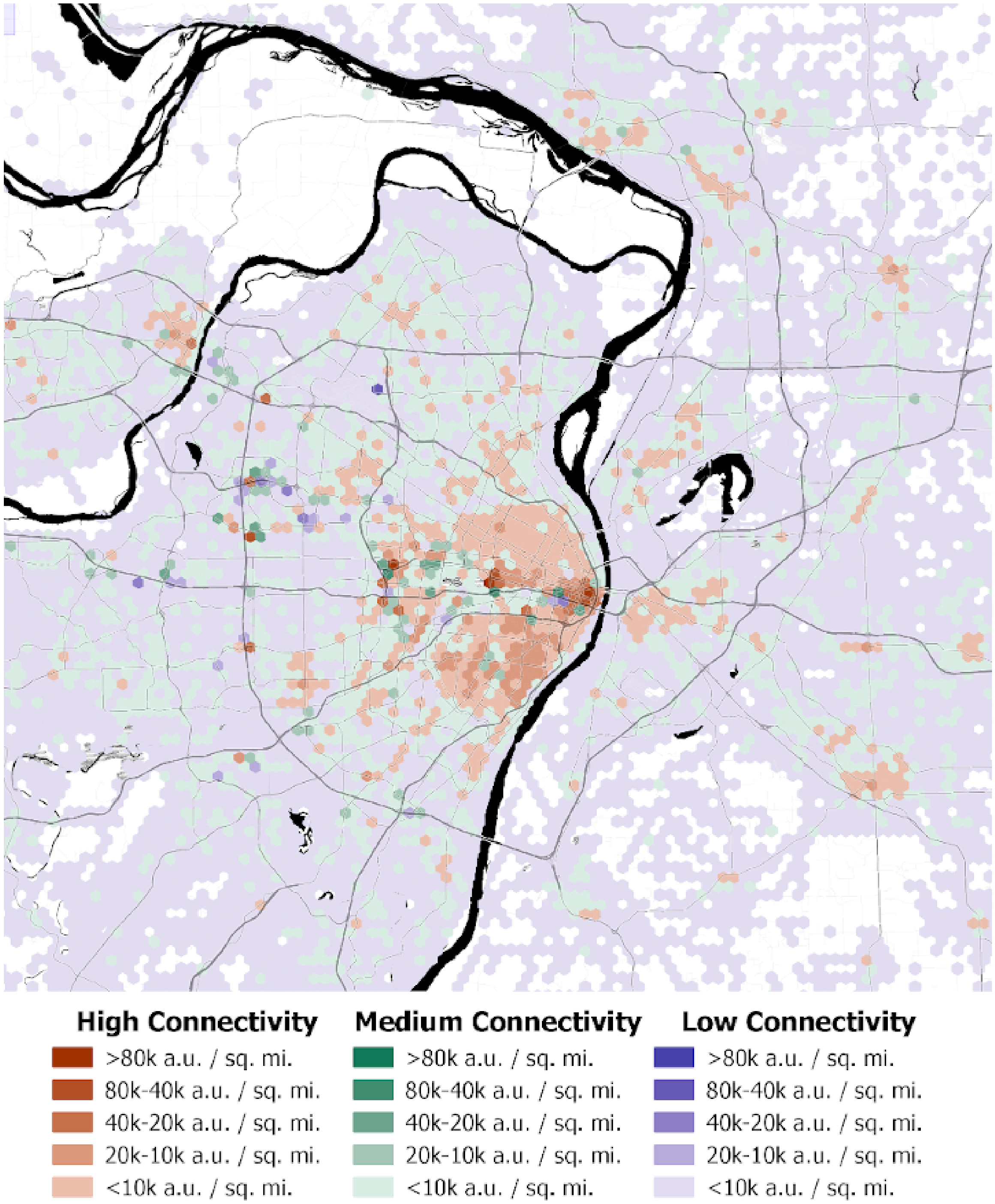

Figure D.28: St. Louis, MO-IL MSA activity-connectivity neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table D.57: Tampa Population and Jobs by Activity Density

Density (/ sq. mi.)	Hexes	% of Hexes	Population	% of Population	Jobs	% of Jobs
> 80,000	0	0%	0	0%	0	0%
40,000 – 80,000	11	0.10%	6,000	0.2%	58,000	4.8%
20,000 – 40,000	49	0.5%	59,000	1.9%	109,000	9.2%
10,000 – 20,000	246	2.3%	207,000	6.9%	267,000	22.3%
5,000 – 10,000	1,404	13.3%	1,014,000	33.7%	403,000	33.8%
2,500 – 5,000	2,171	20.6%	965,000	32.1%	222,000	18.6%
< 2,500	6,644	63.1%	760,000	25.3%	134,000	11.3%

Table D.58: Tampa Population and Jobs by % Ideal Walkshed

Percent Ideal Walkshed	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
> 65%	132	1.3%	106,000	3.5%	62,000	5.2%
55% – 65%	544	5.2%	384,000	12.8%	183,000	15.4%
45% – 55%	966	9.2%	505,000	16.8%	262,000	22%
35% – 45%	1,471	14.0%	546,000	18.1%	242,000	20.3%
25% – 35%	2,751	26.1%	689,000	22.9%	236,000	19.8%
15% – 25%	3,549	33.7%	610,000	20.2%	161,000	13.5%
< 15%	1,112	10.6%	171,000	5.7%	46,000	3.8%

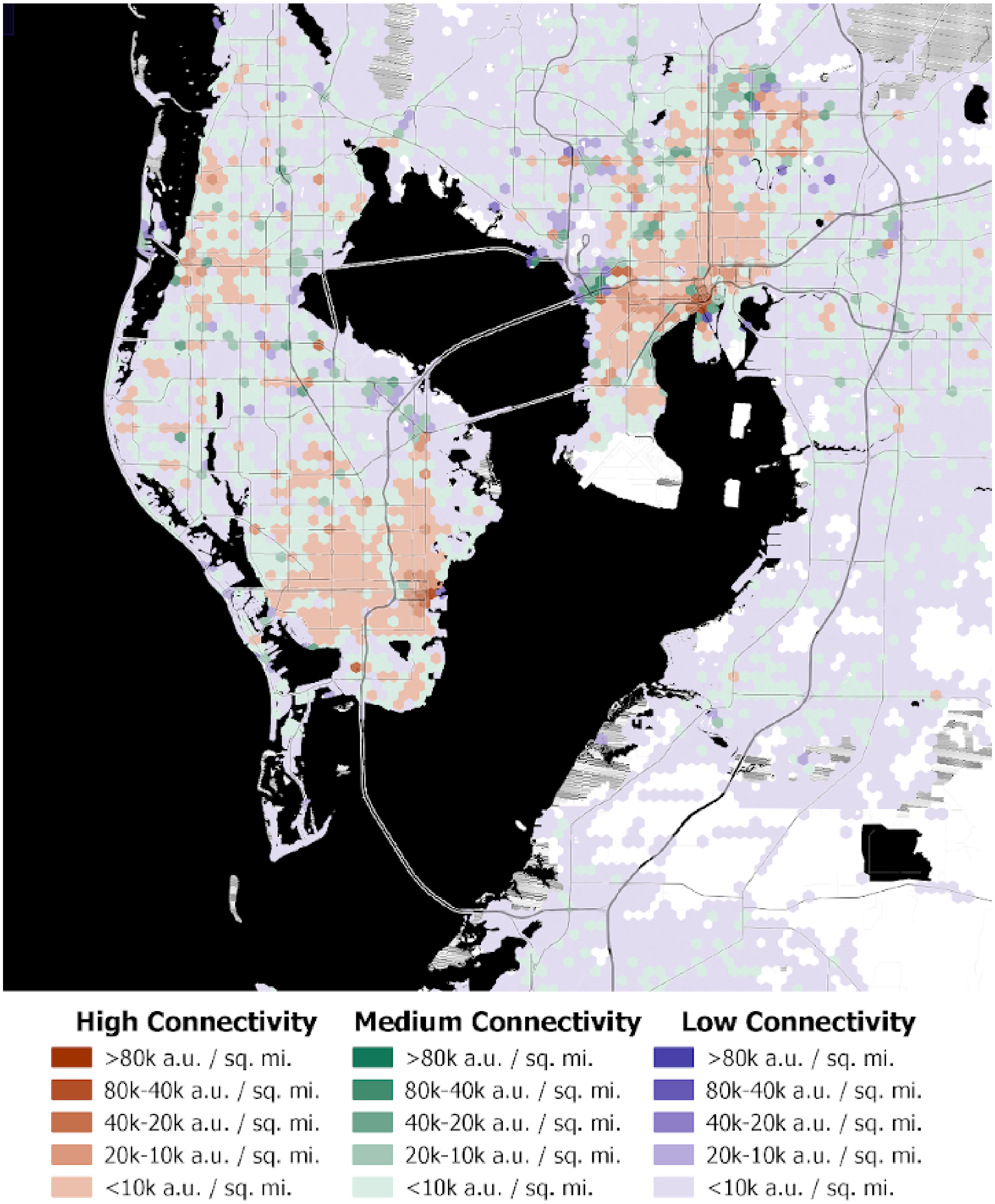

Figure D.29: Tampa-St. Petersburg-Clearwater, FL MSA activity-connectivity neighborhood map. Tampa is to the upper right and St. Petersburg is to the lower left. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table D.59: Washington Population and Jobs by Activity Density

Density (/ sq. mi.)	Hexes	% of Hexes	Population	% of Population	Jobs	% of Jobs
> 80,000	24	0.11%	58,000	1.0%	453,000	16.6%
40,000 – 80,000	53	0.3%	173,000	2.9%	286,000	10.5%
20,000 – 40,000	213	1.1%	475,000	7.8%	412,000	15.1%
10,000 – 20,000	780	3.9%	1,107,000	18.3%	588,000	21.6%
5,000 – 10,000	1,980	9.9%	1,664,000	27.5%	520,000	19.1%
2,500 – 5,000	2,739	13.6%	1,314,000	21.7%	276,000	10.1%
< 2,500	14,293	71.2%	1,267,000	20.9%	189,000	6.9%

Table D.60: Washington Population and Jobs by % Ideal Walkshed

Percent Ideal Walkshed	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
> 65%	173	0.9%	377,000	6.2%	571,000	21.0%
55% – 65%	597	3.0%	737,000	12.2%	378,000	13.9%
45% – 55%	1,284	6.4%	987,000	16.3%	500,000	18.3%
35% – 45%	2,691	13.4%	1,205,000	19.9%	464,000	17.0%
25% – 35%	5,676	28.3%	1,351,000	22.3%	445,000	16.3%
15% – 25%	7,140	35.6%	1,083,000	17.9%	285,000	10.4%
< 15%	2,521	12.6%	318,000	5.3%	81,000	3.0%

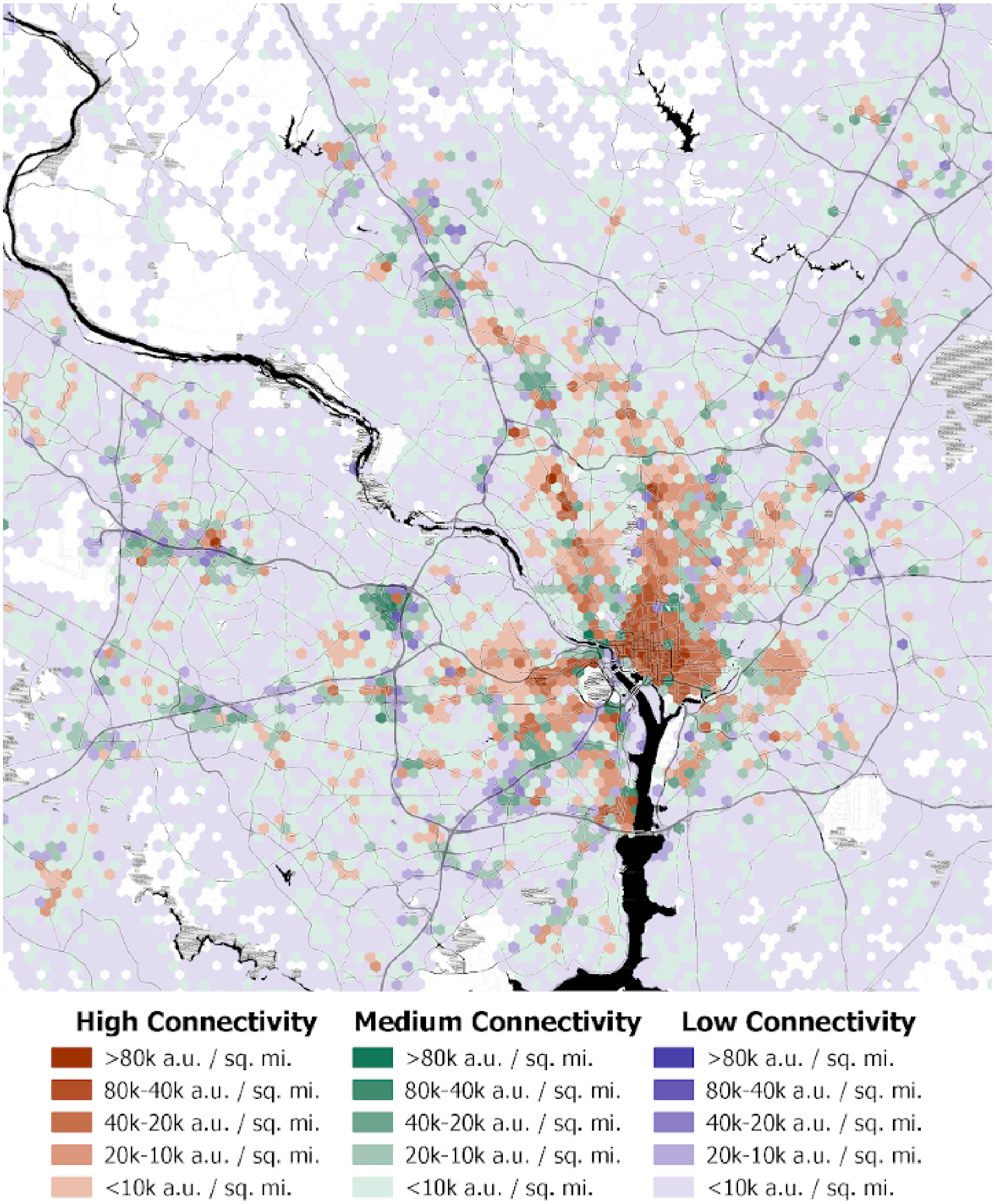

Figure D.30: Washington-Arlington-Alexandria, DC-VA-MD-WV MSA activity-connectivity neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Appendix E: Neighborhood Use Type Maps

This appendix contains tables showing breakdowns of the percentage of neighborhoods of different use types (as defined in Table 2.6 on page 113)—and the numbers and percentages of metro area population and jobs in those neighborhoods—in the twenty largest metropolitan statistical areas in the US, along with ten additional metropolitan statistical areas that were selected because they are particularly interesting: either that they are unusually dense for their size or have rapid transit or light rail.

Also included are maps of use types of neighborhoods in the same metro areas. All the maps are at the same scale, and show a 40-mile by 40-mile square, which means that outlying parts of larger metro areas may be left out, while views of smaller metro areas may include areas outside the MSA limits.

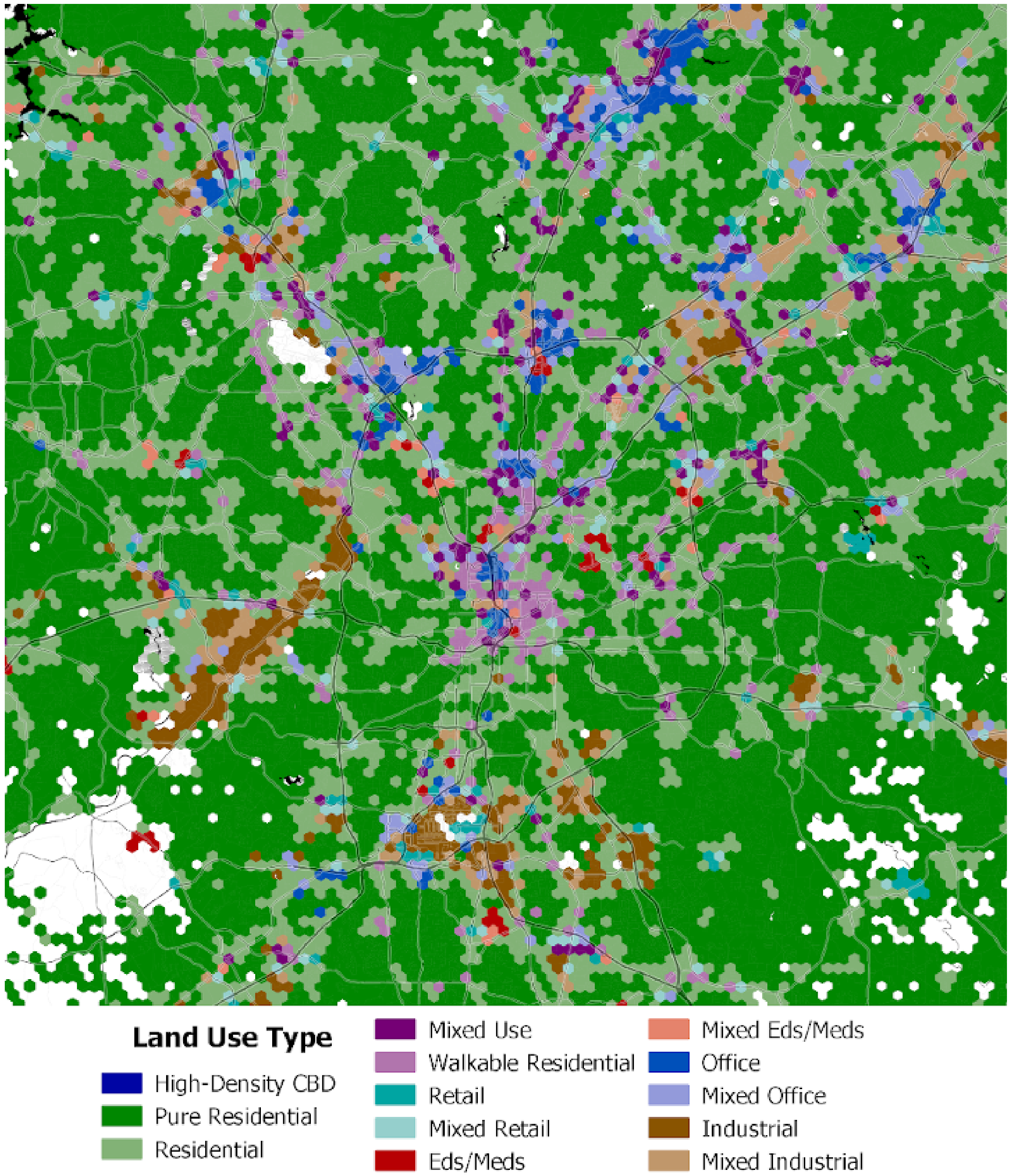

Figure E.1: Atlanta-Sandy Springs-Alpharetta, GA MSA use type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table E.1: Atlanta Distribution of Population and Jobs by Use Type

Use Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Residential	21,729	68.8%	3,372,000	59.2%	118,000	4.9%
Residential	7,209	22.8%	1,575,000	27.7%	517,000	21.6%
Walkable Residential	272	0.9%	201,000	3.5%	115,000	4.8%
Mixed Use	225	0.7%	99,000	1.7%	209,000	8.7%
Retail	261	0.8%	41,000	0.7%	129,000	5.4%
Retail Mix	286	0.9%	58,000	1.0%	103,000	4.3%
Education / Medical	97	0.3%	20,000	0.3%	121,000	5.0%
Education / Medical Mix	84	0.3%	21,000	0.4%	43,000	1.8%
Office	182	0.6%	69,000	1.2%	436,000	18.2%
Office Mix	267	0.8%	84,000	1.5%	201,000	8.4%
Industrial	508	1.6%	60,000	1.1%	225,000	9.4%
Industrial Mix	469	1.5%	92,000	1.6%	177,000	7.4%

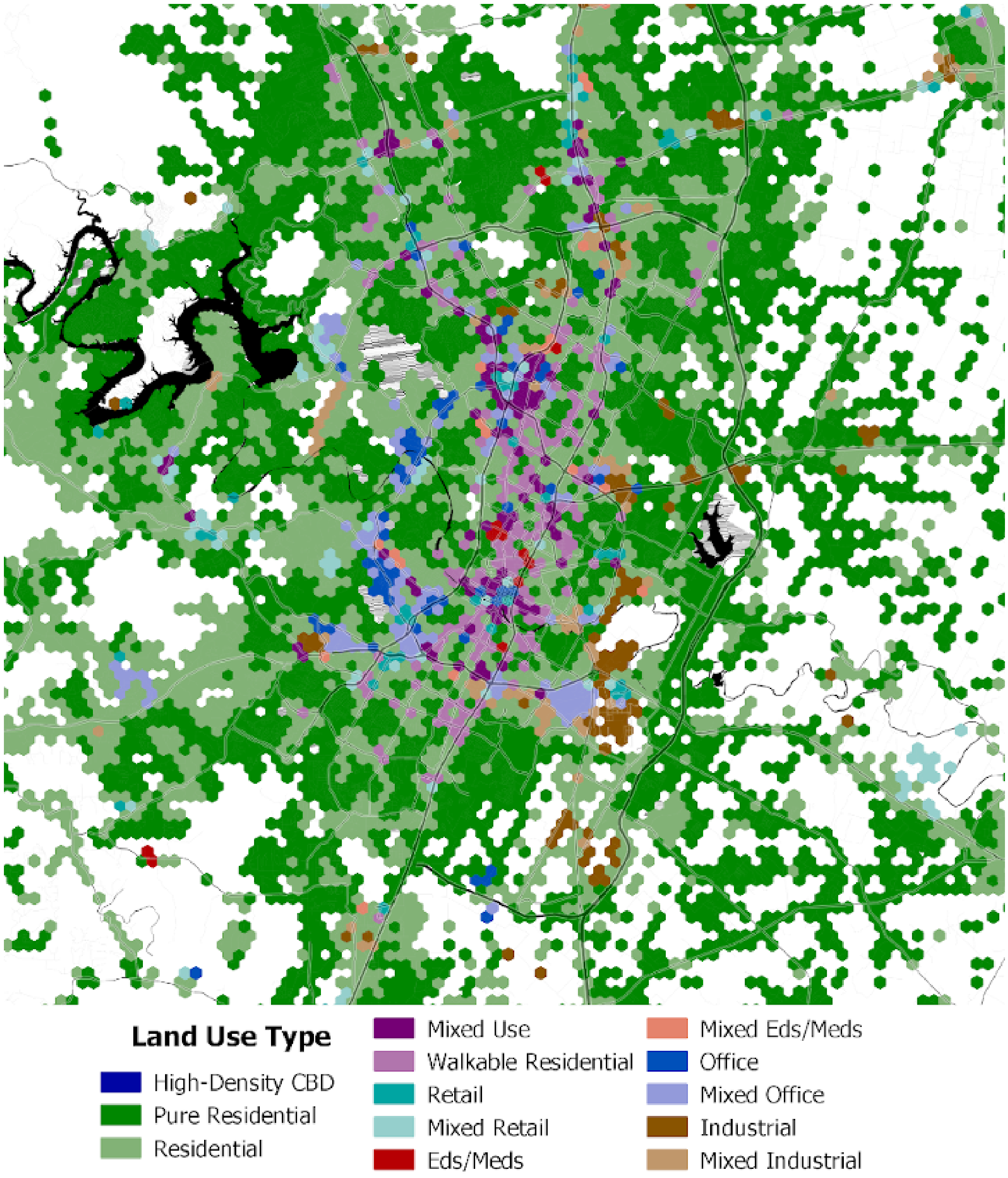

Figure E.2: Austin-Round Rock-Georgetown, TX MSA use type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table E.2: Austin Distribution of Population and Jobs by Use Type

Use Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Residential	5,719	58.2%	1,037,000	51.3%	41,000	5.0%
Residential	3,125	31.8%	616,000	30.5%	199,000	23.9%
Walkable Residential	184	1.9%	173,000	8.6%	84,000	10.1%
Mixed Use	100	1.0%	59,000	2.9%	118,000	14.1%
Retail	72	0.7%	16,000	0.8%	48,000	5.8%
Retail Mix	107	1.1%	18,000	0.9%	33,000	3.9%
Education / Medical	19	0.2%	7,000	0.3%	27,000	3.2%
Education / Medical Mix	26	0.3%	9,000	0.4%	15,000	1.8%
Office	63	0.6%	19,000	0.9%	104,000	12.4%
Office Mix	135	1.4%	38,000	1.9%	84,000	10.0%
Industrial	164	1.7%	11,000	0.6%	47,000	5.7%
Industrial Mix	109	1.1%	19,000	0.9%	34,000	4.1%

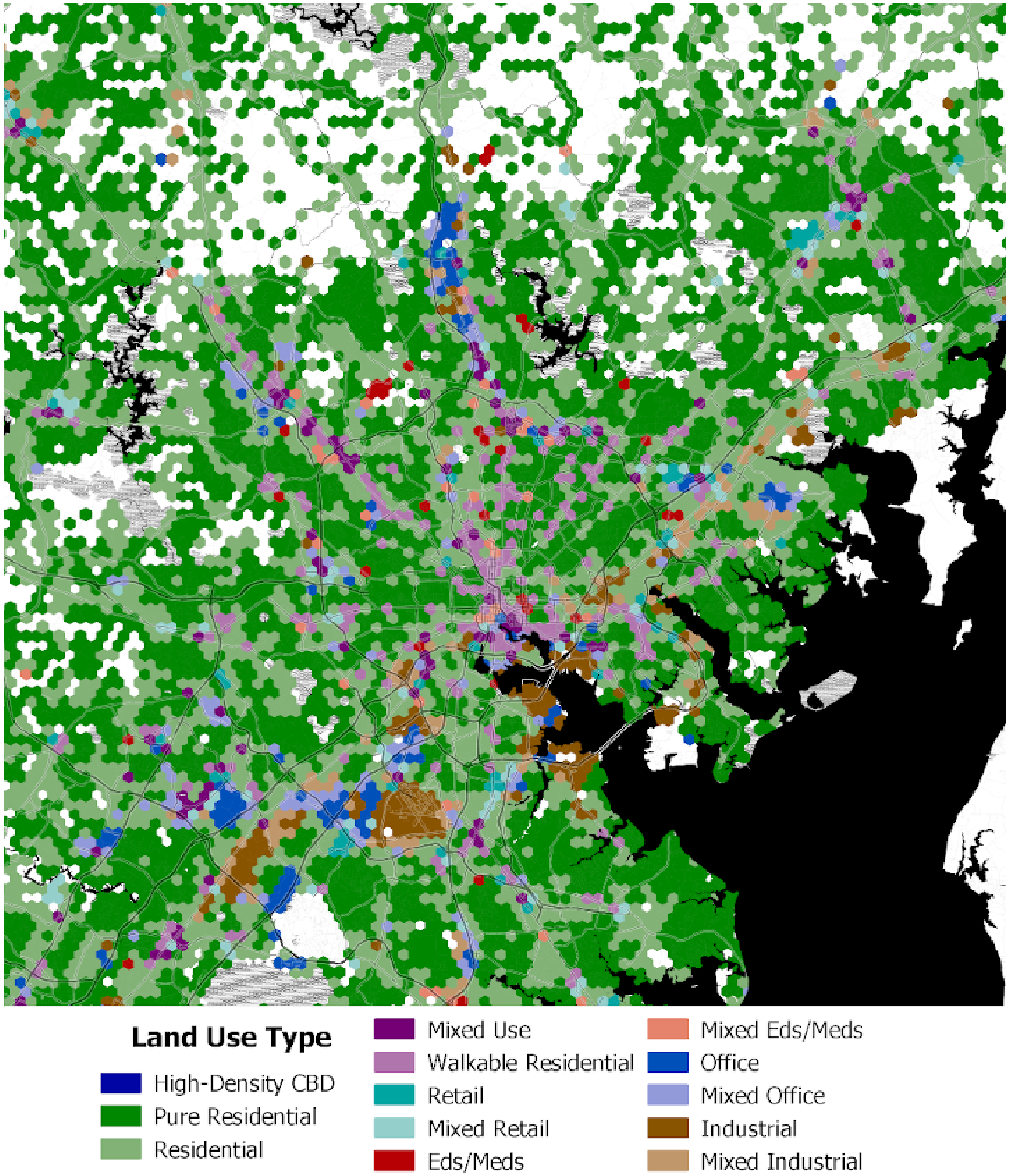

Figure E.3: Baltimore-Columbia-Towson, MD MSA use type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table E.3: Baltimore Distribution of Population and Jobs by Use Type

Use Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Residential	5,453	52.2%	1,431,000	52.1%	60,000	5.2%
Residential	3,748	35.9%	802,000	29.2%	245,000	21.2%
Walkable Residential	224	2.1%	269,000	9.8%	111,000	9.6%
Mixed Use	106	1.0%	61,000	2.2%	129,000	11.1%
Retail	79	0.8%	15,000	0.5%	59,000	5.1%
Retail Mix	112	1.1%	28,000	1.0%	54,000	4.7%
Education / Medical	46	0.4%	19,000	0.7%	71,000	6.1%
Education / Medical Mix	56	0.5%	29,000	1.0%	66,000	5.7%
Office	117	1.1%	16,000	0.6%	134,000	11.6%
Office Mix	143	1.4%	37,000	1.3%	81,000	7.1%
Industrial	219	2.1%	17,000	0.6%	86,000	7.4%
Industrial Mix	150	1.4%	24,000	0.9%	59,000	5.1%

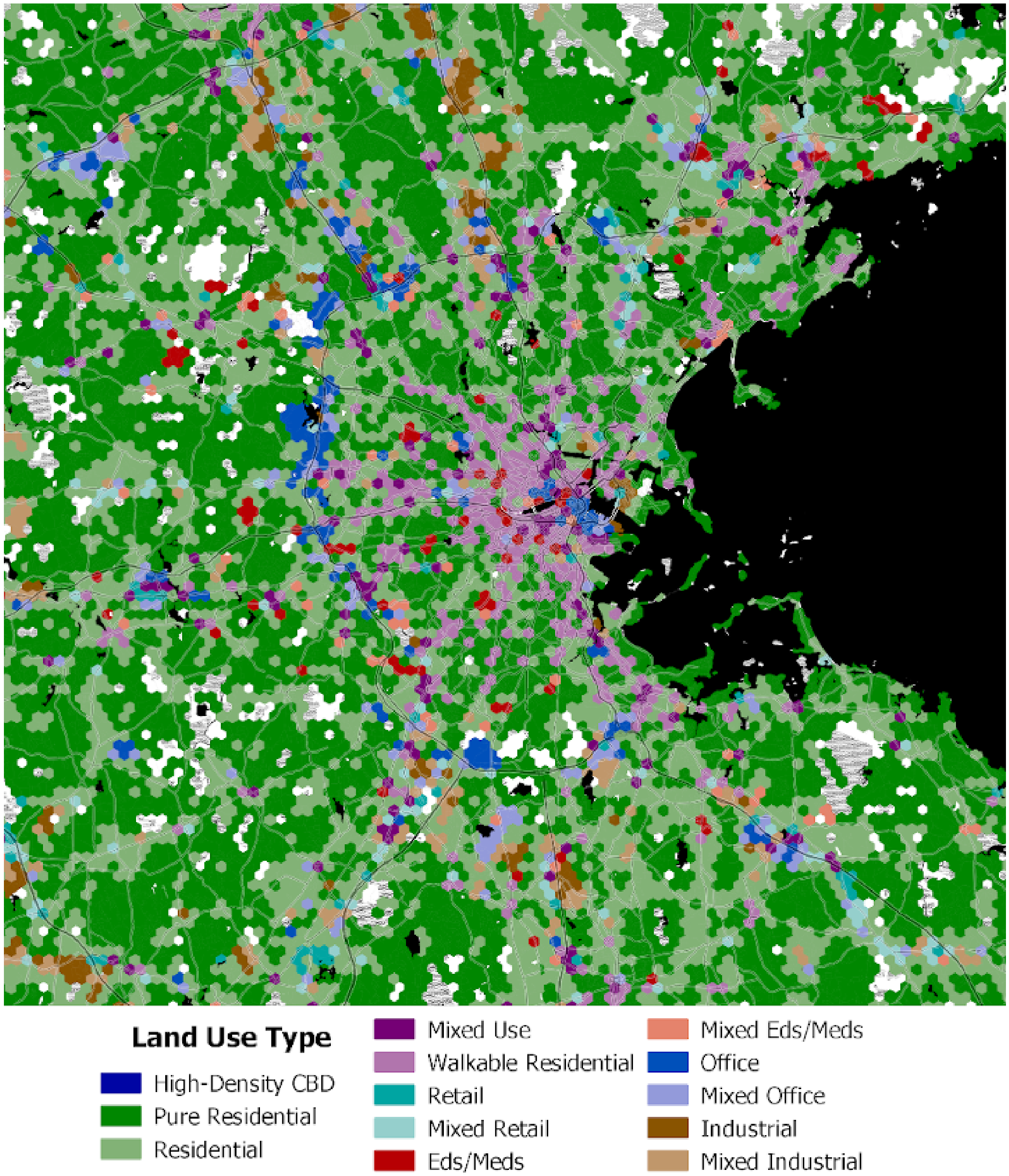

Figure E.4: Boston-Cambridge-Newton, MA-NH MSA use type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table E.4: Boston Distribution of Population and Jobs by Use Type

Use Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Residential	10,366	55.9%	2,114,000	44.2%	99,000	4.1%
Residential	5791	31.2%	1,319,000	27.6%	430,000	17.8%
Walkable Residential	444	2.4%	835,000	17.4%	313,000	13.0%
Mixed Use	172	0.9%	129,000	2.7%	255,000	10.6%
Retail	169	0.9%	28,000	0.6%	102,000	4.2%
Retail Mix	245	1.3%	41,000	0.9%	77,000	3.2%
Education / Medical	122	0.7%	73,000	1.5%	240,000	9.9%
Education / Medical Mix	107	0.6%	39,000	0.8%	81,000	3.4%
Office	193	1.0%	62,000	1.3%	434,000	18.0%
Office Mix	236	1.3%	51,000	1.1%	123,000	5.1%
Industrial	283	1.5%	30,000	0.6%	130,000	5.4%
Industrial Mix	409	2.2%	65,000	1.4%	133,000	5.5%

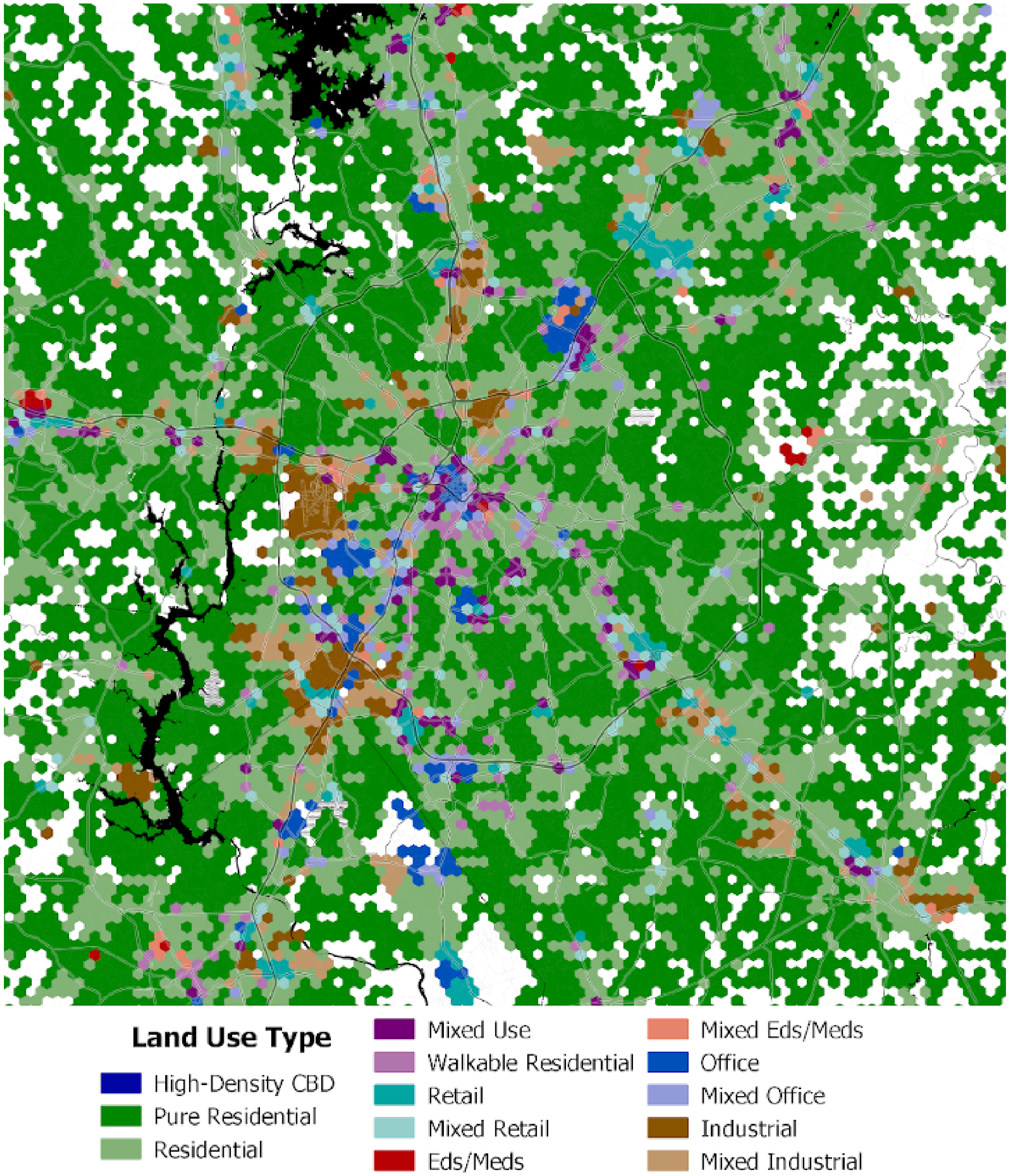

Figure E.5: Charlotte-Concord-Gastonia, NC-SC MSA use type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table E.5: Charlotte Distribution of Population and Jobs by Use Type

Use Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Residential	11,831	65.2%	1,344,000	55.4%	53,000	5.0%
Residential	4,724	26.0%	778,000	32.0%	263,000	24.7%
Walkable Residential	118	0.7%	63,000	2.6%	39,000	3.6%
Mixed Use	109	0.6%	43,000	1.8%	89,000	8.3%
Retail	145	0.8%	19,000	0.8%	65,000	6.1%
Retail Mix	162	0.9%	31,000	1.3%	60,000	5.6%
Education / Medical	28	0.2%	5,000	0.2%	27,000	2.5%
Education / Medical Mix	46	0.3%	9,000	0.4%	18,000	1.7%
Office	118	0.7%	27,000	1.1%	182,000	17.0%
Office Mix	124	0.7%	32,000	1.3%	75,000	7.0%
Industrial	453	2.5%	34,000	1.4%	125,000	11.7%
Industrial Mix	280	1.5%	43,000	1.8%	73,000	6.8%

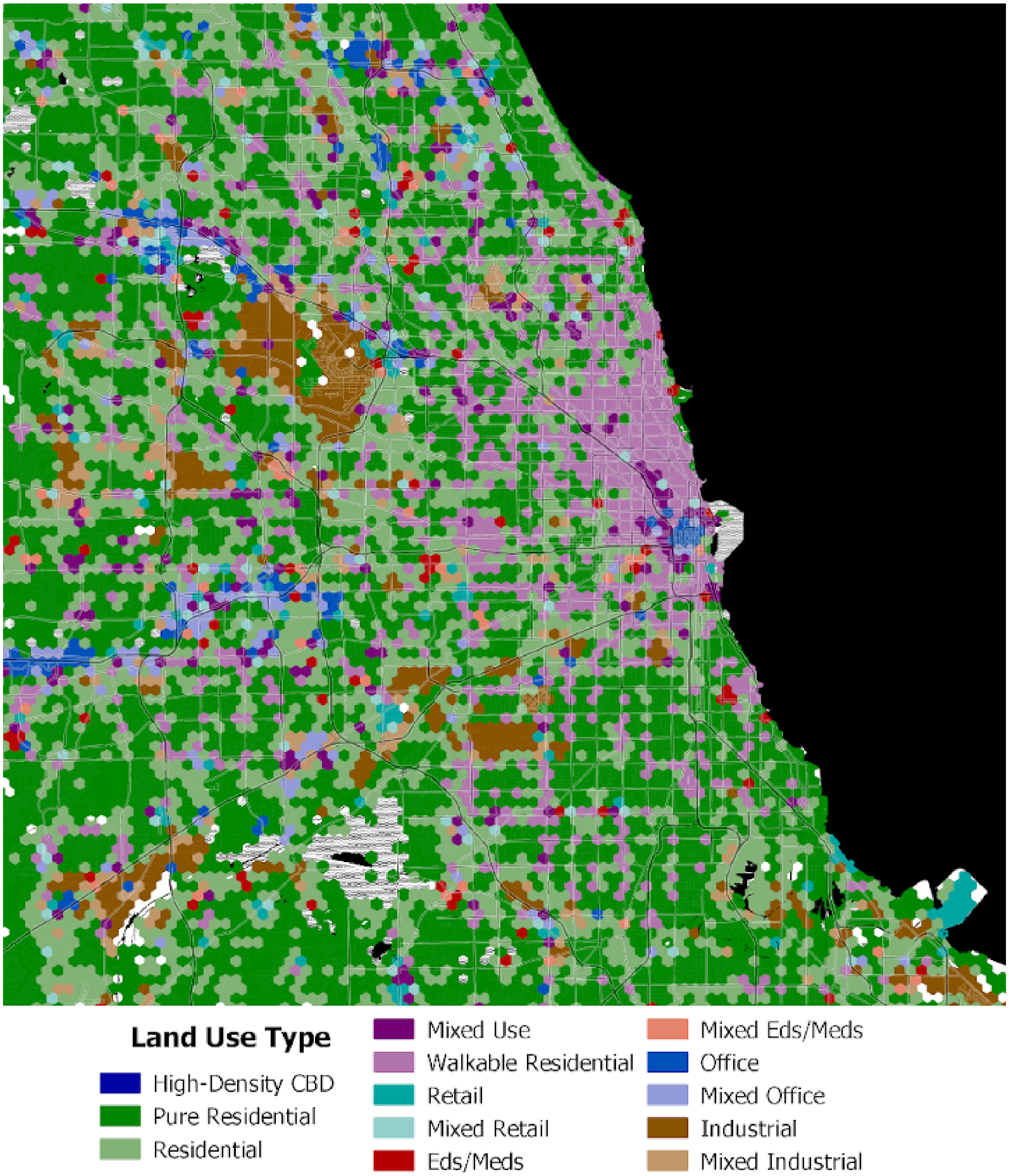

Figure E.6: Chicago-Naperville-Elgin, IL-IN-WI MSA use type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table E.6: Chicago Distribution of Population and Jobs by Use Type

Use Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Residential	14,902	57.2%	4,640,000	49.1%	180,000	4.4%
Residential	6,924	26.6%	2,226,000	23.6%	709,000	17.3%
Walkable Residential	1,054	4.0%	1,796,000	19.0%	572,000	13.9%
Mixed Use	303	1.2%	185,000	2.0%	381,000	9.3%
Retail	340	1.3%	55,000	0.6%	179,000	4.4%
Retail Mix	263	1.0%	75,000	0.8%	145,000	3.5%
Education / Medical	149	0.6%	63,000	0.7%	246,000	6.0%
Education / Medical Mix	145	0.6%	47,000	0.5%	84,000	2.0%
Office	228	0.9%	77,000	0.8%	682,000	16.6%
Office Mix	255	1.0%	84,000	0.9%	252,000	6.1%
Industrial	1,005	3.9%	95,000	1.0%	456,000	11.1%
Industrial Mix	498	1.9%	102,000	1.1%	214,000	5.2%

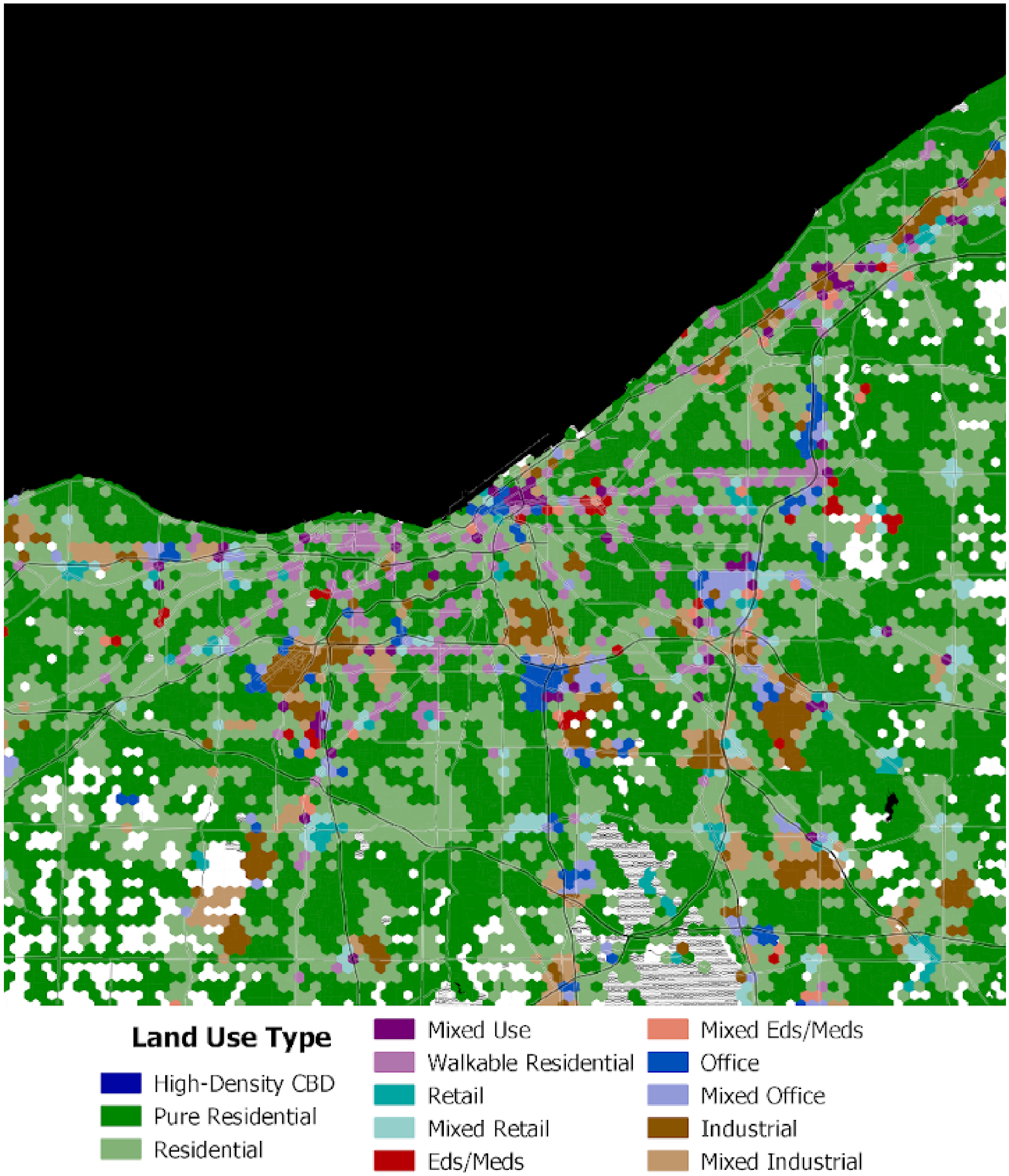

Figure E.7: Cleveland-Elyria, OH MSA use type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table E.7: Cleveland Distribution of Population and Jobs by Use Type

Use Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Residential	5,135	54.8%	1,054,000	51.6%	41,000	4.5%
Residential	2,995	31.9%	648,000	31.7%	211,000	23.1%
Walkable Residential	187	2.0%	166,000	8.1%	76,000	8.3%
Mixed Use	66	0.7%	25,000	1.2%	57,000	6.2%
Retail	76	0.8%	13,000	0.6%	38,000	4.2%
Retail Mix	132	1.4%	25,000	1.2%	42,000	4.6%
Education / Medical	46	0.5%	11,000	0.5%	79,000	8.6%
Education / Medical Mix	40	0.4%	7,000	0.4%	14,000	1.5%
Office	87	0.9%	16,000	0.8%	141,000	15.4%
Office Mix	99	1.1%	18,000	0.9%	48,000	5.3%
Industrial	288	3.1%	23,000	1.1%	102,000	11.1%
Industrial Mix	226	2.4%	36,000	1.8%	67,000	7.3%

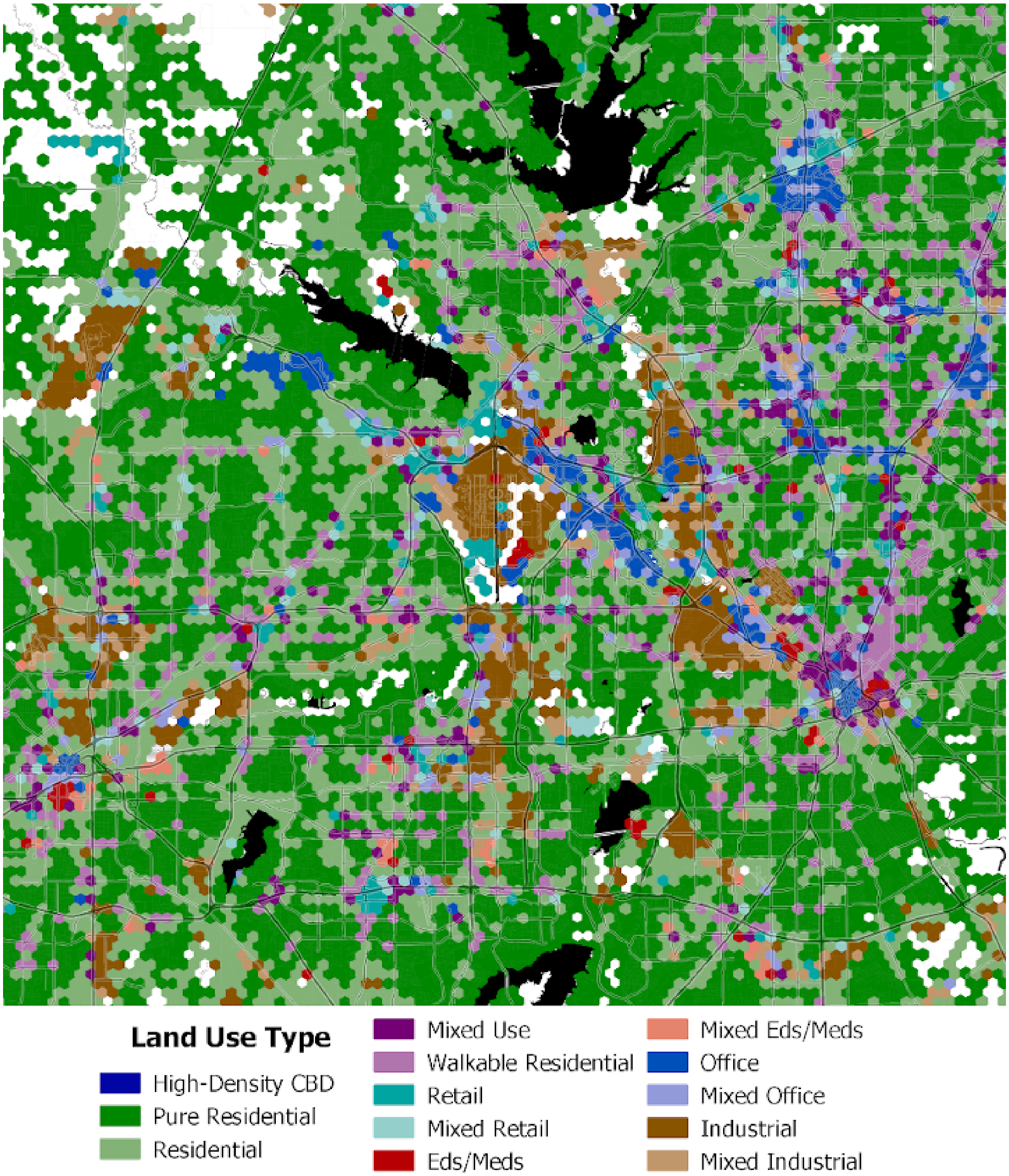

Figure E.8: Dallas-Fort Worth-Arlington, TX MSA use type neighborhood map. Downtown Dallas is at the lower right and downtown Fort Worth is at the far lower left. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table E.8: Dallas Distribution of Population and Jobs by Use Type

Use Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Residential	16,623	61.3%	4,049,000	57.3%	145,000	4.6%
Residential	6,981	25.8%	1,823,000	25.8%	567,000	17.9%
Walkable Residential	644	2.4%	571,000	8.1%	254,000	8.0%
Mixed Use	304	1.1%	157,000	2.2%	330,000	10.4%
Retail	283	1.0%	57,000	0.8%	194,000	6.1%
Retail Mix	248	0.9%	56,000	0.8%	117,000	3.7%
Education / Medical	86	0.3%	26,000	0.4%	120,000	3.8%
Education / Medical Mix	98	0.4%	29,000	0.4%	47,000	1.5%
Office	268	1.0%	77,000	1.1%	599,000	18.9%
Office Mix	204	0.8%	65,000	0.9%	199,000	6.3%
Industrial	906	3.3%	74,000	1.0%	416,000	13.1%
Industrial Mix	463	1.7%	76,000	1.1%	182,000	5.7%

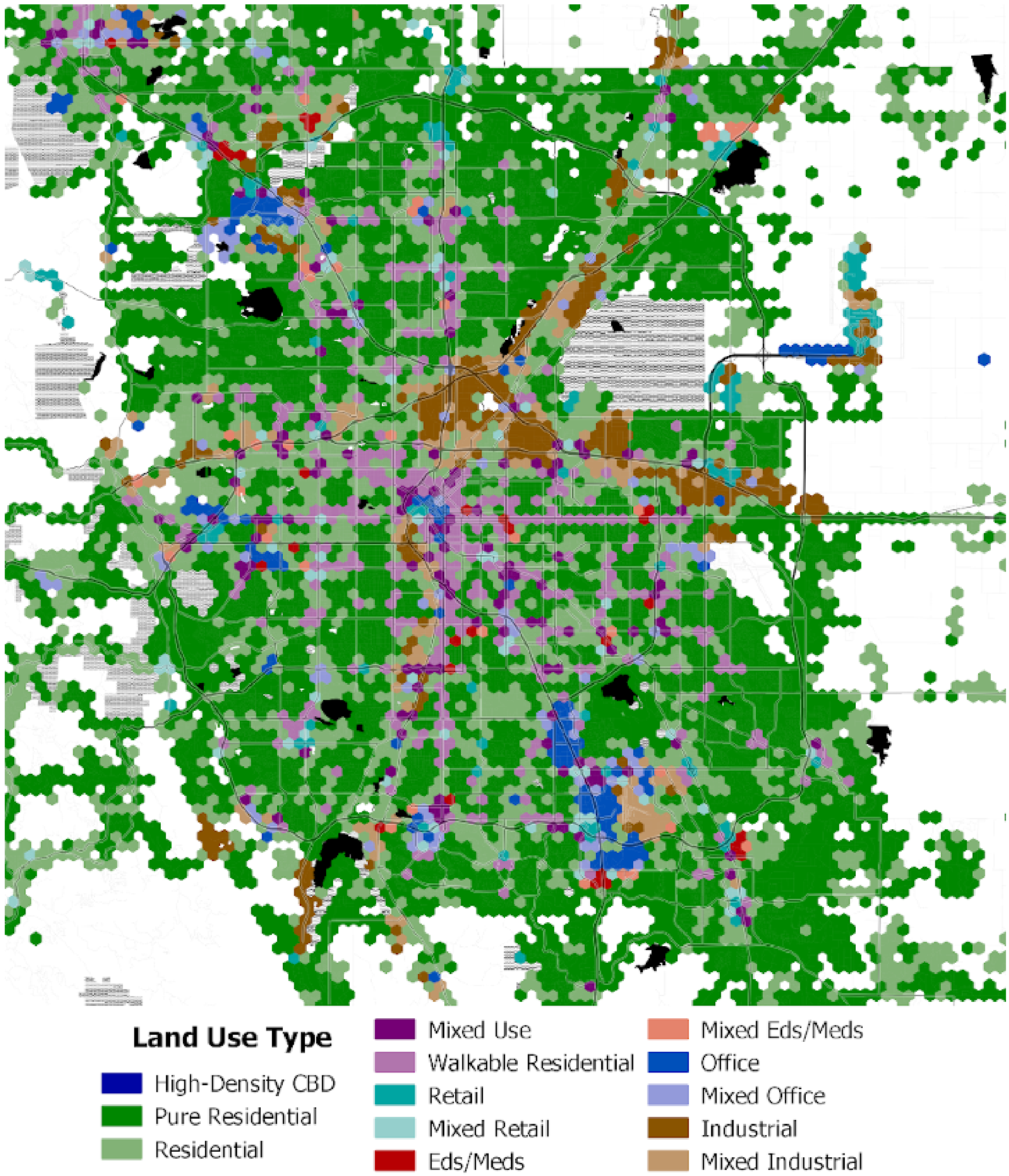

Figure E.9: Denver-Aurora-Lakewood, CO MSA use type neighborhood map. Boulder (not in the Denver MSA) is at the upper left. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table E.9: Denver Distribution of Population and Jobs by Use Type

Use Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Residential	4,543	57.5%	1,534,000	54.4%	67,000	5.2%
Residential	2,002	25.4%	630,000	22.3%	188,000	14.5%
Walkable Residential	347	4.4%	379,000	13.4%	169,000	13.1%
Mixed Use	127	1.6%	80,000	2.8%	145,000	11.2%
Retail	122	1.5%	19,000	0.7%	57,000	4.4%
Retail Mix	87	1.1%	28,000	1.0%	58,000	4.4%
Education / Medical	21	0.3%	12,000	0.4%	46,000	3.5%
Education / Medical Mix	35	0.4%	12,000	0.4%	20,000	1.5%
Office	122	1.5%	33,000	1.2%	252,000	19.4%
Office Mix	88	1.1%	32,000	1.1%	83,000	6.4%
Industrial	239	3.0%	25,000	0.9%	137,000	10.5%
Industrial Mix	163	2.1%	37,000	1.3%	77,000	5.9%

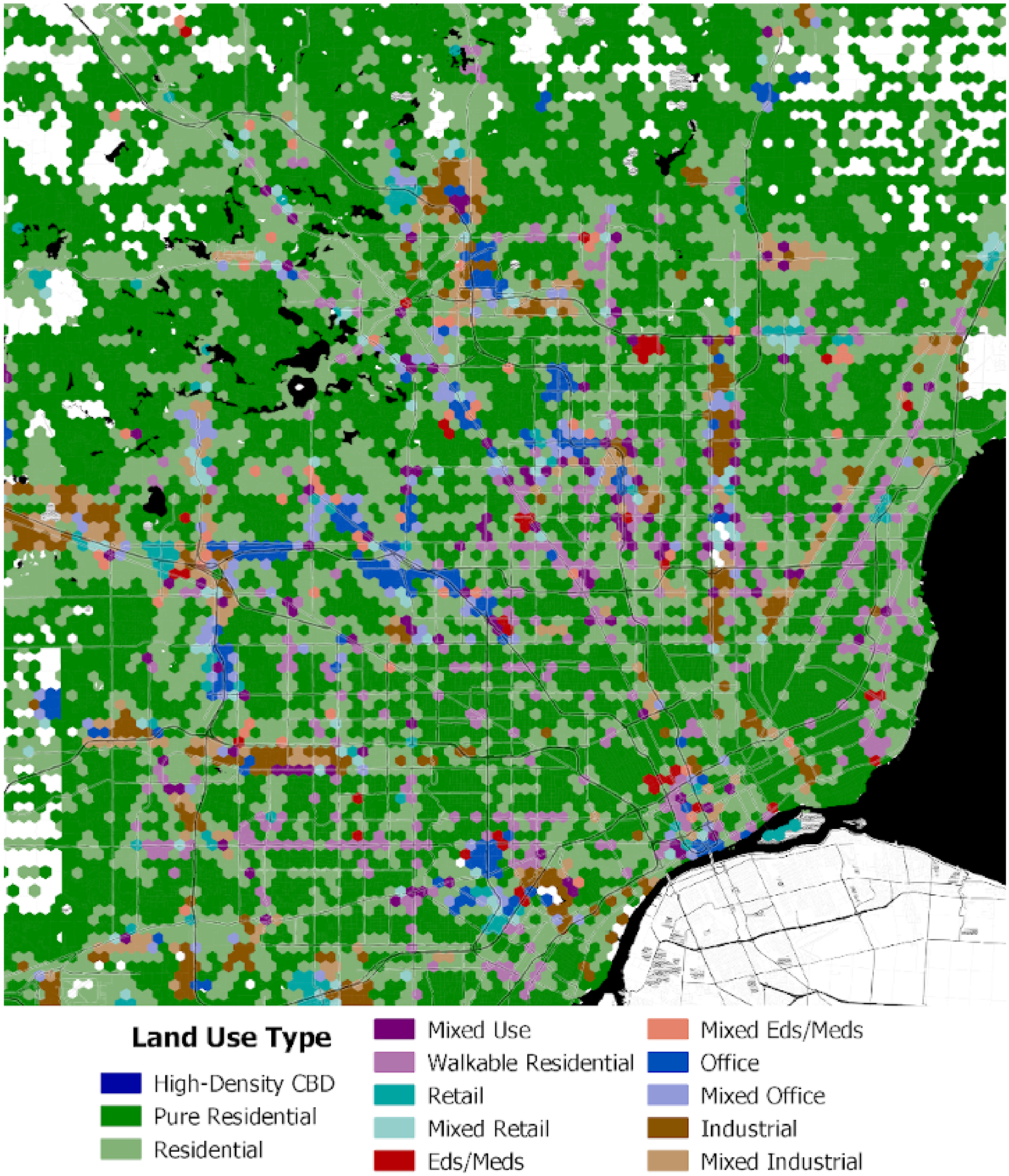

Figure E.10: Detroit-Warren-Dearborn, MI MSA use type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table E.10: Detroit Distribution of Population and Jobs by Use Type

Use Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Residential	10,770	61.4%	2,366,000	55.4%	94,000	5.2%
Residential	4,753	27.1%	1,269,000	29.7%	405,000	22.6%
Walkable Residential	387	2.2%	308,000	7.2%	130,000	7.3%
Mixed Use	138	0.8%	59,000	1.4%	119,000	6.7%
Retail	154	0.9%	25,000	0.6%	88,000	4.9%
Retail Mix	149	0.8%	30,000	0.7%	71,000	4.0%
Education / Medical	62	0.4%	21,000	0.5%	98,000	5.4%
Education / Medical Mix	74	0.4%	21,000	0.5%	37,000	2.1%
Office	203	1.2%	38,000	0.9%	315,000	17.6%
Office Mix	153	0.9%	37,000	0.9%	84,000	4.7%
Industrial	414	2.4%	45,000	1.1%	228,000	12.7%
Industrial Mix	294	1.7%	55,000	1.3%	124,000	6.9%

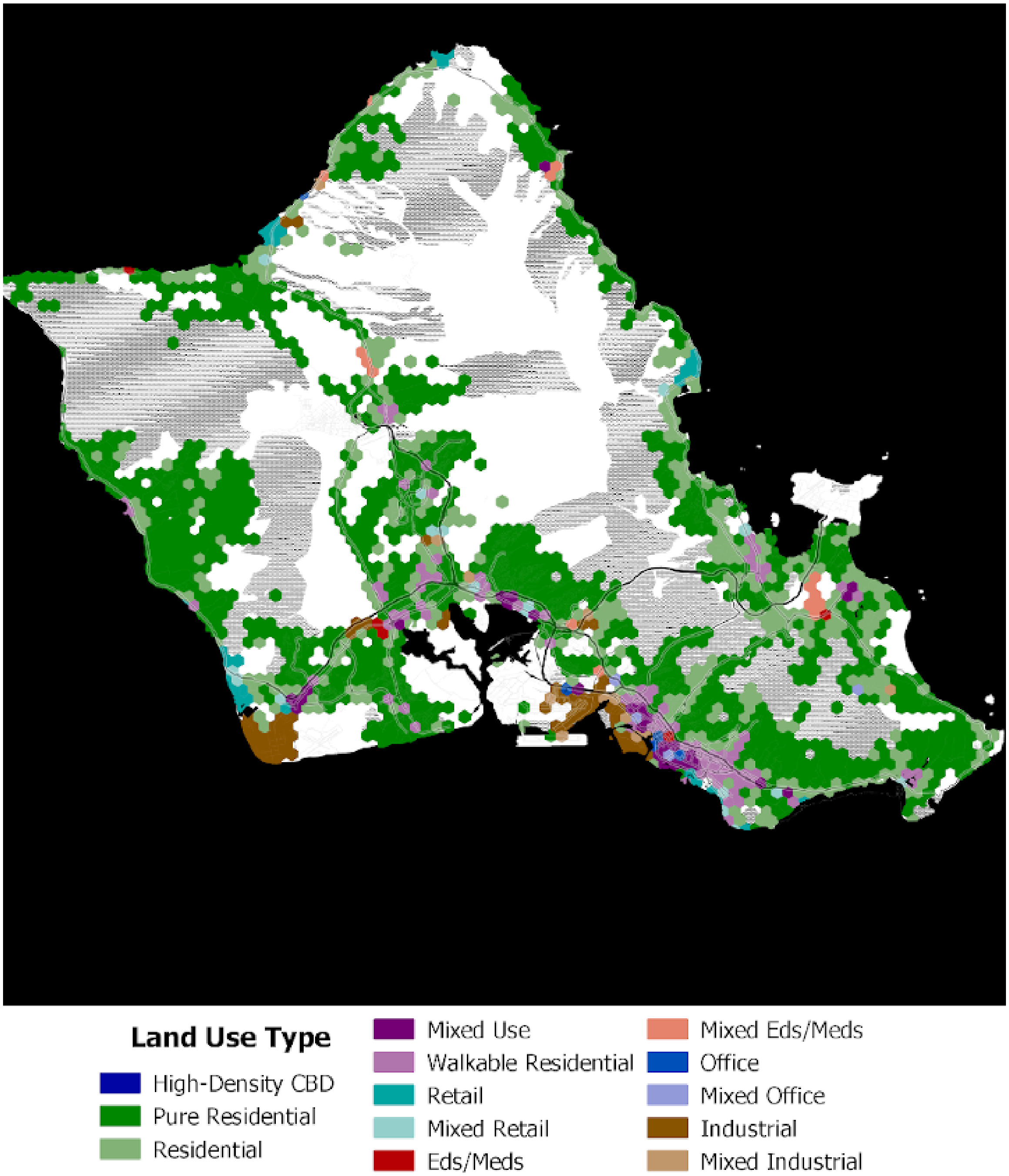

Figure E.11: Urban Honolulu, HI MSA use type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table E.11: Honolulu Distribution of Population and Jobs by Use Type

Use Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Residential	949	60.4%	488,000	54.8%	20,000	5.5%
Residential	366	23.3%	162,000	18.1%	42,000	11.7%
Walkable Residential	79	5.0%	167,000	18.7%	61,000	16.9%
Mixed Use	27	1.7%	37,000	4.2%	71,000	19.6%
Retail	32	2.0%	5,000	0.5%	29,000	7.9%
Retail Mix	17	1.1%	12,000	1.4%	18,000	4.9%
Education / Medical	5	0.3%	3,000	0.3%	11,000	3.1%
Education / Medical Mix	15	1.0%	3,000	0.3%	6,000	1.8%
Office	5	0.3%	5,000	0.5%	41,000	11.4%
Office Mix	4	0.3%	4,000	0.4%	15,000	4.2%
Industrial	59	3.8%	3,000	0.3%	38,000	10.5%
Industrial Mix	12	0.8%	4,000	0.4%	9,000	2.5%

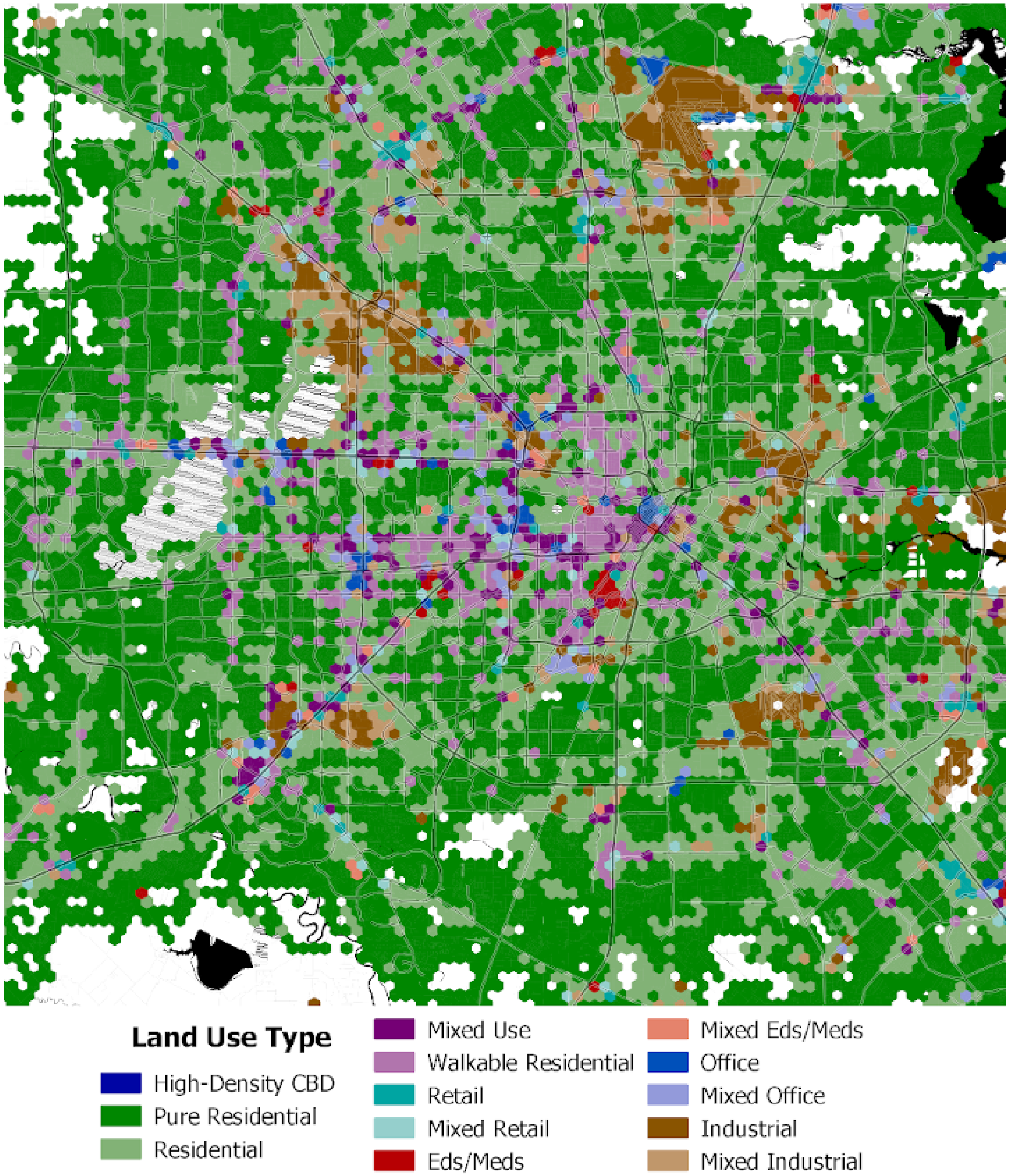

Figure E.12: Houston-The Woodlands-Sugar Land, TX MSA use type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table E.12: Houston Distribution of Population and Jobs by Use Type

Use Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Residential	14,089	59.8%	3,740,000	56%	144,000	5.5%
Residential	6,630	28.1%	1,856,000	27.8%	567,000	21.8%
Walkable Residential	515	2.2%	538,000	8.0%	258,000	9.9%
Mixed Use	230	1.0%	151,000	2.3%	289,000	11.1%
Retail	203	0.9%	39,000	0.6%	123,000	4.7%
Retail Mix	200	0.8%	52,000	0.8%	117,000	4.5%
Education / Medical	61	0.3%	23,000	0.3%	133,000	5.1%
Education / Medical Mix	63.0	0.3%	22,000	0.3%	39,000	1.5%
Office	96	0.4%	27,000	0.4%	230,000	8.8%
Office Mix	168	0.7%	67,000	1.0%	195,000	7.5%
Industrial	928	3.9%	84,000	1.3%	355,000	13.6%
Industrial Mix	390	1.7%	83,000	1.2%	155,000	6.0%

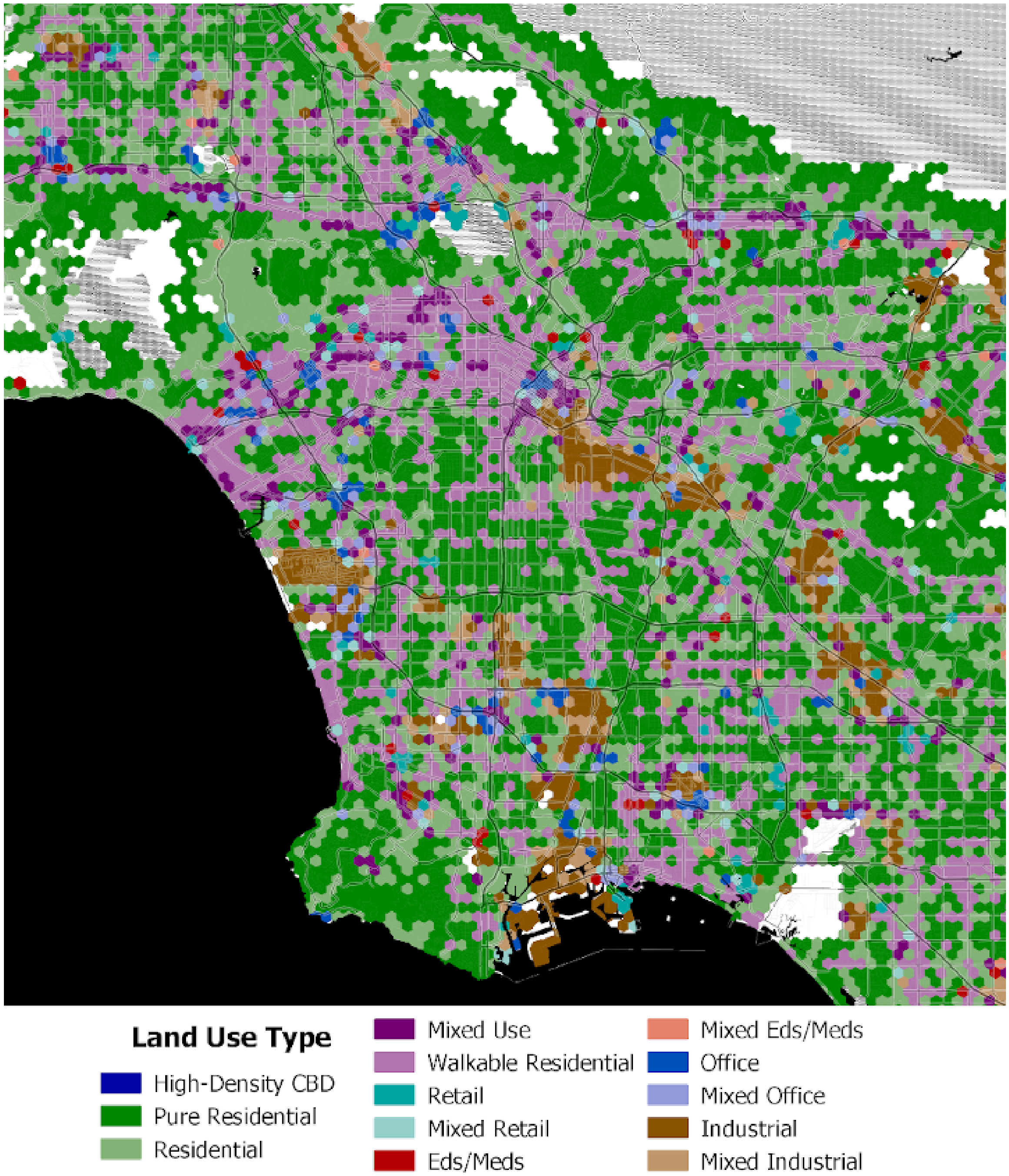

Figure E.13: Los Angeles-Long Beach-Anaheim, CA MSA use type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table E.13: Los Angeles Distribution of Population and Jobs by Use Type

Use Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Residential	6,918	48.8%	5,907,000	44.6%	307,000	5.5%
Residential	3,406	24.0%	2,737,000	20.7%	755,000	13.5%
Walkable Residential	1,764	12.5%	3,535,000	26.7%	1,204,000	21.5%
Mixed Use	401	2.8%	404,000	3.1%	718,000	12.8%
Retail	169	1.2%	55,000	0.4%	226,000	4.0%
Retail Mix	135	1.0%	70,000	0.5%	161,000	2.9%
Education / Medical	86	0.6%	46,000	0.3%	178,000	3.2%
Education / Medical Mix	49	0.3%	27,000	0.2%	48,000	0.9%
Office	195	1.4%	103,000	0.8%	769,000	13.7%
Office Mix	183	1.3%	127,000	1.0%	367,000	6.6%
Industrial	558	3.9%	100,000	0.8%	577,000	10.3%
Industrial Mix	304	2.1%	120,000	0.9%	286,000	5.1%

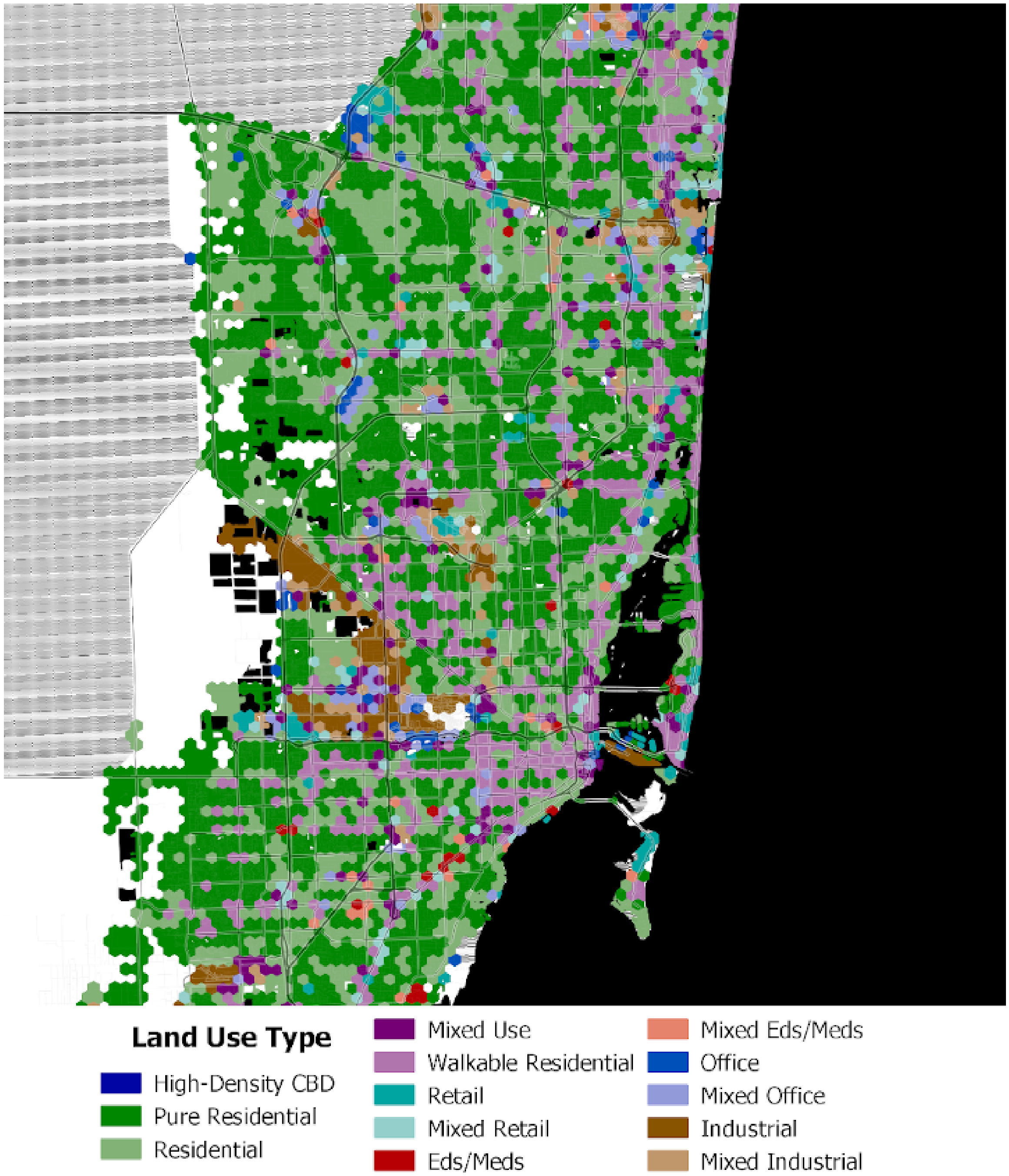

Figure E.14: Miami-Fort Lauderdale-Pompano Beach, FL MSA use type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table E.14: Miami Distribution of Population and Jobs by Use Type

Use Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Residential	4,413	45.1%	3,005,000	49.7%	135,000	5.9%
Residential	3,237	33.1%	1,590,000	26.3%	463,000	20.2%
Walkable Residential	713	7.3%	975,000	16.1%	383,000	16.7%
Mixed Use	240	2.5%	159,000	2.6%	296,000	12.9%
Retail	152	1.6%	32,000	0.5%	123,000	5.3%
Retail Mix	136	1.4%	57,000	0.9%	99,000	4.3%
Education / Medical	46	0.5%	23,000	0.4%	97,000	4.2%
Education / Medical Mix	48	0.5%	25,000	0.4%	40,000	1.7%
Office	108	1.1%	29,000	0.5%	176,000	7.7%
Office Mix	193	2%	72,000	1.2%	205,000	9%
Industrial	284	2.9%	26,000	0.4%	158,000	6.9%
Industrial Mix	209	2.1%	57,000	0.9%	121,000	5.3%

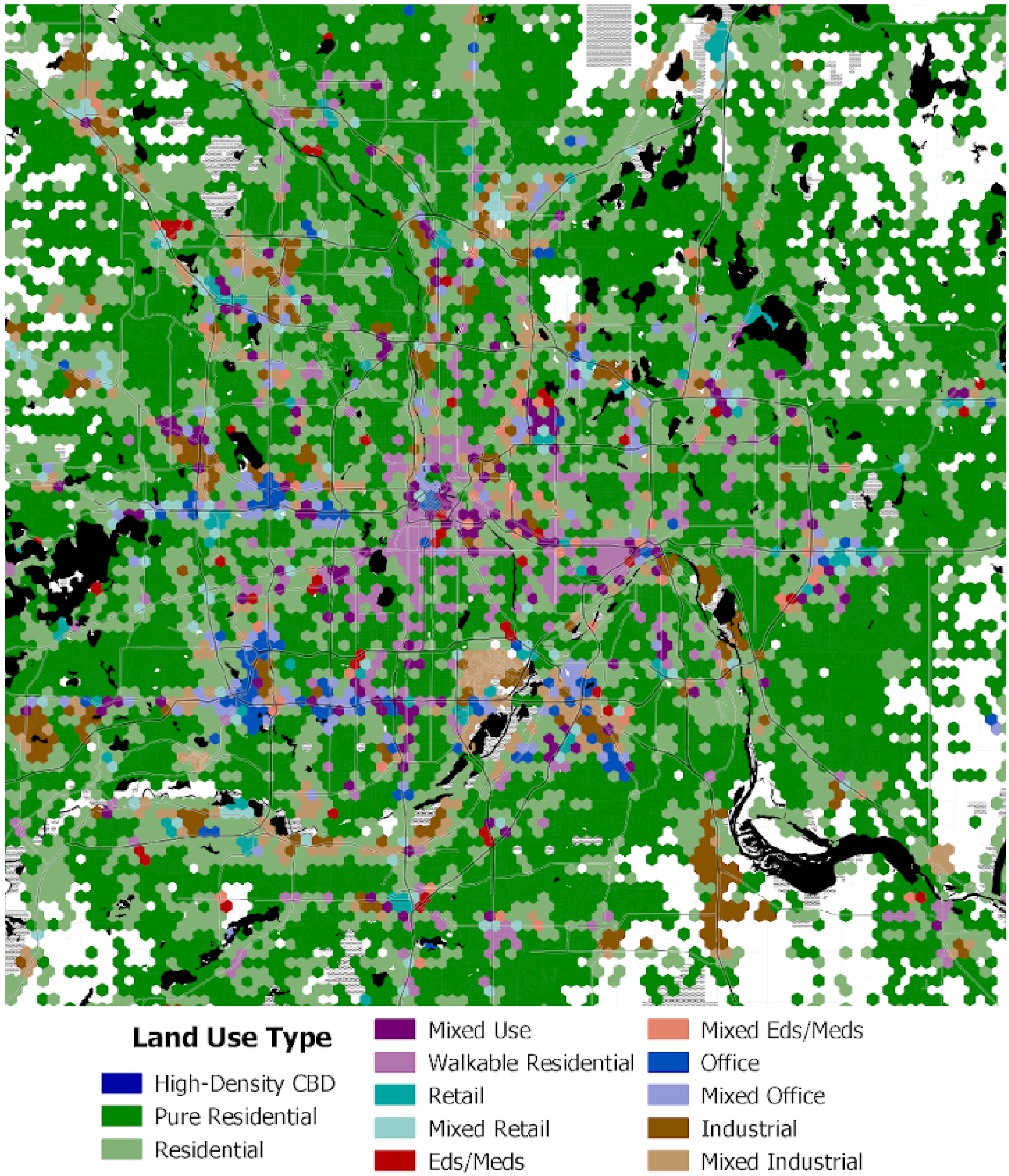

Figure E.15: Minneapolis-St. Paul-Bloomington, MN-WI MSA use type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table E.15: Minneapolis Distribution of Population and Jobs by Use Type

Use Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Residential	12,147	62.9%	1,797,000	52.4%	71,000	4.2%
Residential	5,113	26.5%	931,000	27.1%	311,000	18.4%
Walkable Residential	308	1.6%	310,000	9.0%	142,000	8.4%
Mixed Use	180	0.9%	92,000	2.7%	181,000	10.7%
Retail	153	0.8%	25,000	0.7%	75,000	4.5%
Retail Mix	171	0.9%	32,000	0.9%	63,000	3.7%
Education / Medical	101	0.5%	27,000	0.8%	101,000	6.0%
Education / Medical Mix	70	0.4%	25,000	0.7%	42,000	2.5%
Office	98	0.5%	33,000	1.0%	262,000	15.5%
Office Mix	145	0.8%	44,000	1.3%	115,000	6.8%
Industrial	423	2.2%	45,000	1.3%	169,000	10.0%
Industrial Mix	392	2.0%	71,000	2.1%	157,000	9.3%

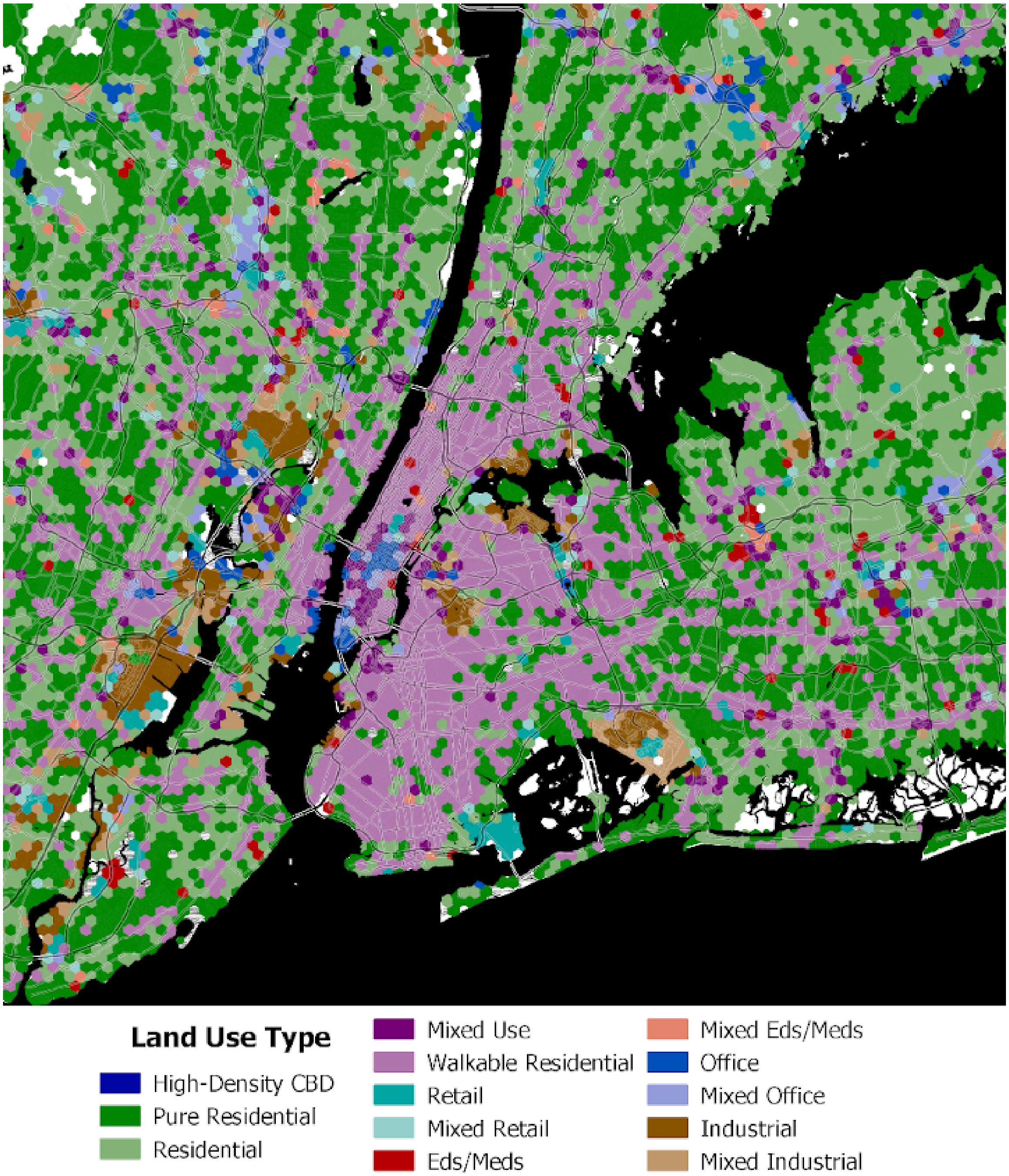

Figure E.16: New York-Newark-Jersey City, NY-NJ-PA MSA use type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table E.16: New York Distribution of Population and Jobs by Use Type

Use Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Residential	14,693	46.6%	6,022,000	31.3%	295,000	3.7%
Residential	11,184	35.5%	3,804,000	19.8%	1,140,000	14.2%
Walkable Residential	2,029	6.4%	7,937,000	41.2%	1,942,000	24.2%
Mixed Use	429	1.4%	550,000	2.9%	974,000	12.1%
Retail	349	1.1%	50,000	0.3%	175,000	2.2%
Retail Mix	414	1.3%	93,000	0.5%	165,000	2.1%
Education / Medical	214	0.7%	126,000	0.7%	378,000	4.7%
Education / Medical Mix	215	0.7%	111,000	0.6%	156,000	1.9%
Office	381	1.2%	184,000	1.0%	1539,000	19.2%
Office Mix	454	1.4%	172,000	0.9%	606,000	7.5%
Industrial	517	1.6%	63,000	0.3%	353,000	4.4%
Industrial Mix	638	2.0%	146,000	0.8%	309,000	3.8%

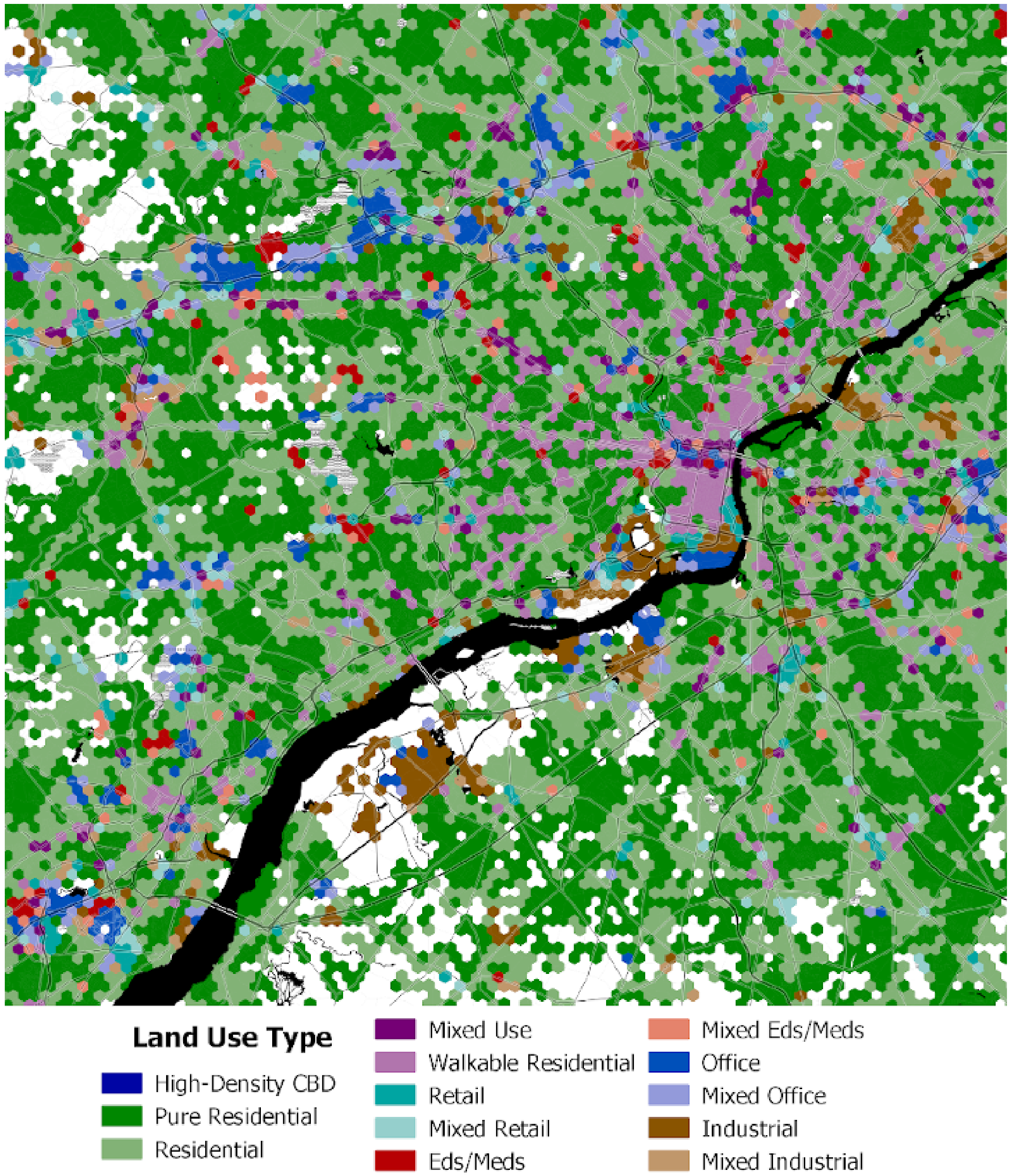

Figure E.17: Philadelphia-Camden-Wilmington, PA-NJ-DE-MD MSA use type neighborhood map. Philadelphia is just right of center and Wilmington is at the lower left. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table E.17: Philadelphia Distribution of Population and Jobs by Use Type

Use Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Residential	9,782	49%	2,723,000	45.3%	123,000	4.8%
Residential	7,280	36.5%	1,901,000	31.6%	608,000	23.5%
Walkable Residential	534	2.7%	867,000	14.4%	272,000	10.5%
Mixed Use	191	1.0%	119,000	2.0%	233,000	9.0%
Retail	237	1.2%	34,000	0.6%	125,000	4.8%
Retail Mix	235	1.2%	46,000	0.8%	83,000	3.2%
Education / Medical	188	0.9%	59,000	1.0%	221,000	8.6%
Education / Medical Mix	159	0.8%	45,000	0.7%	85,000	3.3%
Office	274	1.4%	60,000	1.0%	416,000	16.1%
Office Mix	274	1.4%	60,000	1.0%	142,000	5.5%
Industrial	476	2.4%	38,000	0.6%	162,000	6.3%
Industrial Mix	340	1.7%	61,000	1.0%	112,000	4.3%

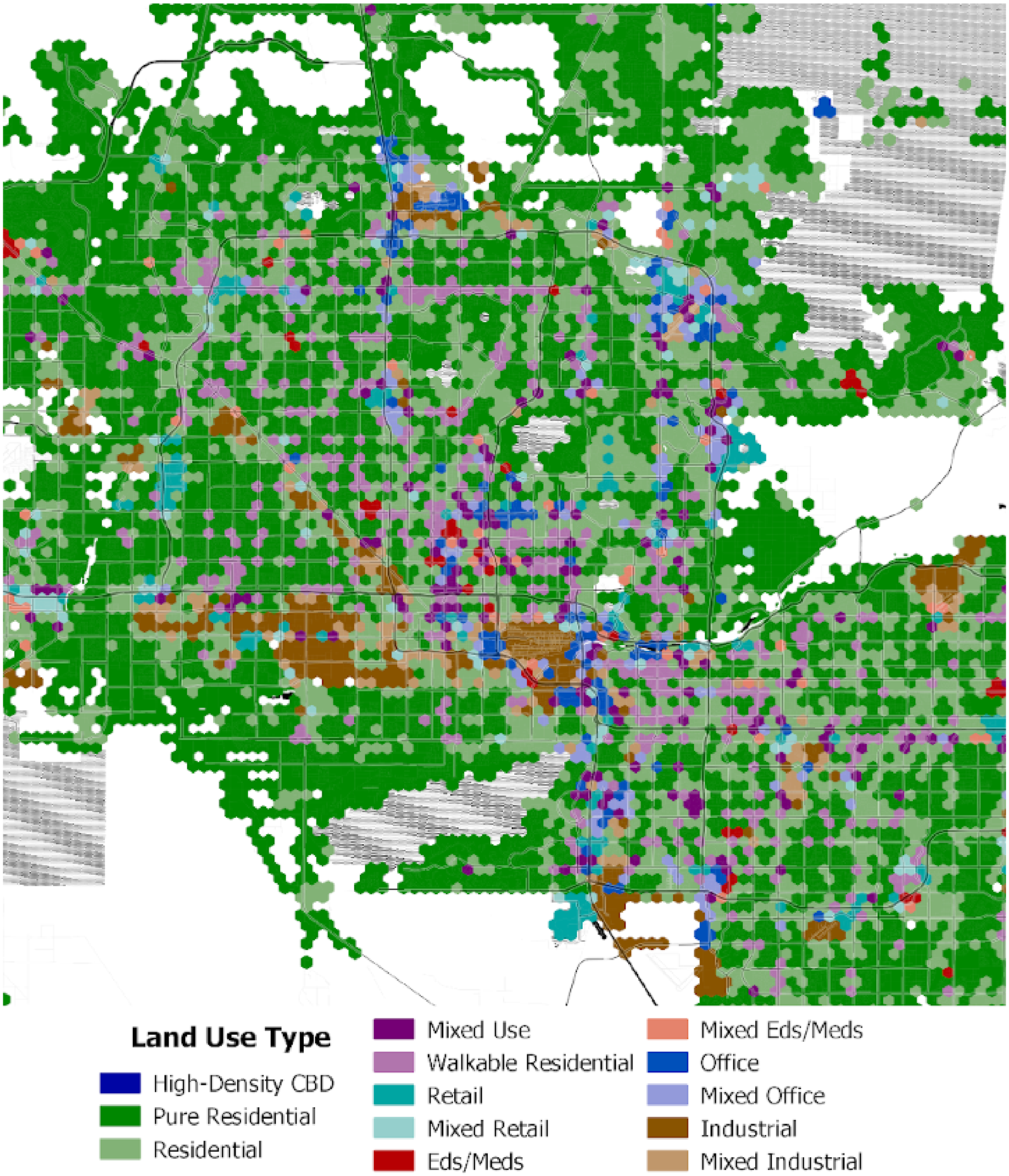

Figure E.18: Phoenix-Mesa-Chandler, AZ MSA use type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table E.18: Phoenix Distribution of Population and Jobs by Use Type

Use Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Residential	8,126	62.2%	2,732,000	59.2%	96,000	5.3%
Residential	3,035	23.2%	1,088,000	23.6%	327,000	18.1%
Walkable Residential	465	3.6%	443,000	9.6%	190,000	10.5%
Mixed Use	166	1.3%	90,000	1.9%	171,000	9.5%
Retail	188	1.4%	33,000	0.7%	133,000	7.3%
Retail Mix	119	0.9%	31,000	0.7%	68,000	3.7%
Education / Medical	56	0.4%	23,000	0.5%	103,000	5.7%
Education / Medical Mix	56	0.4%	22,000	0.5%	44,000	2.4%
Office	143	1.1%	41,000	0.9%	283,000	15.6%
Office Mix	139	1.1%	43,000	0.9%	126,000	6.9%
Industrial	418	3.2%	35,000	0.8%	184,000	10.2%
Industrial Mix	150	1.1%	36,000	0.8%	86,000	4.7%

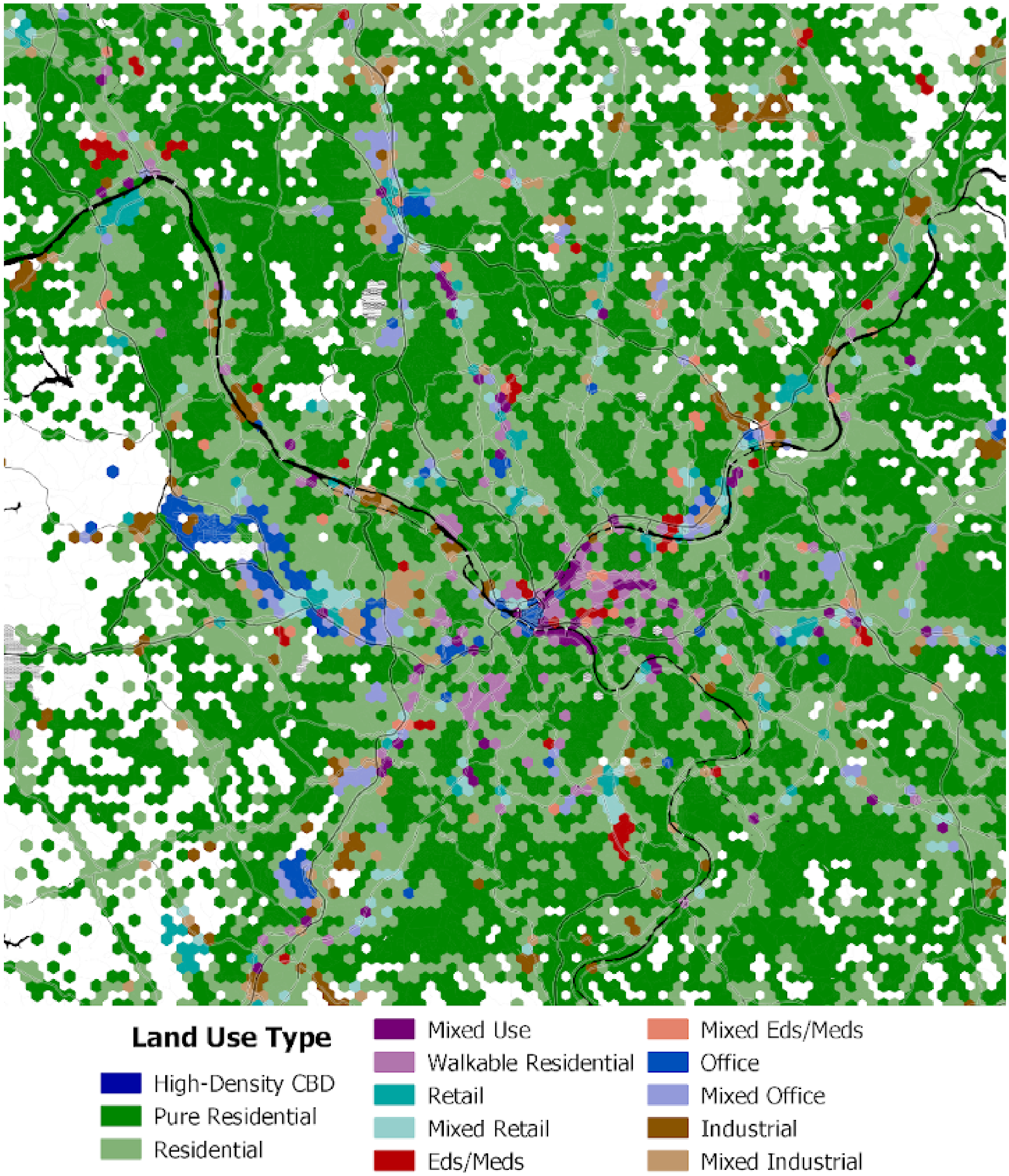

Figure E.19: Pittsburgh, PA MSA use type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table E.19: Pittsburgh Distribution of Population and Jobs by Use Type

Use Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Residential	10,008	57.8%	1,072,000	47.2%	47,000	4.5%
Residential	5,760	33.3%	842,000	37.1%	284,000	27.2%
Walkable Residential	123	0.7%	130,000	5.7%	63,000	6.1%
Mixed Use	81	0.5%	50,000	2.2%	89,000	8.5%
Retail	178	1.0%	19,000	0.8%	73,000	7.0%
Retail Mix	181	1.0%	28,000	1.3%	60,000	5.7%
Education / Medical	108	0.6%	27,000	1.2%	100,000	9.6%
Education / Medical Mix	75	0.4%	18,000	0.8%	28,000	2.7%
Office	118	0.7%	18,000	0.8%	146,000	14.0%
Office Mix	139	0.8%	21,000	0.9%	45,000	4.3%
Industrial	320	1.8%	20,000	0.9%	61,000	5.8%
Industrial Mix	223	1.3%	26,000	1.1%	50,000	4.8%

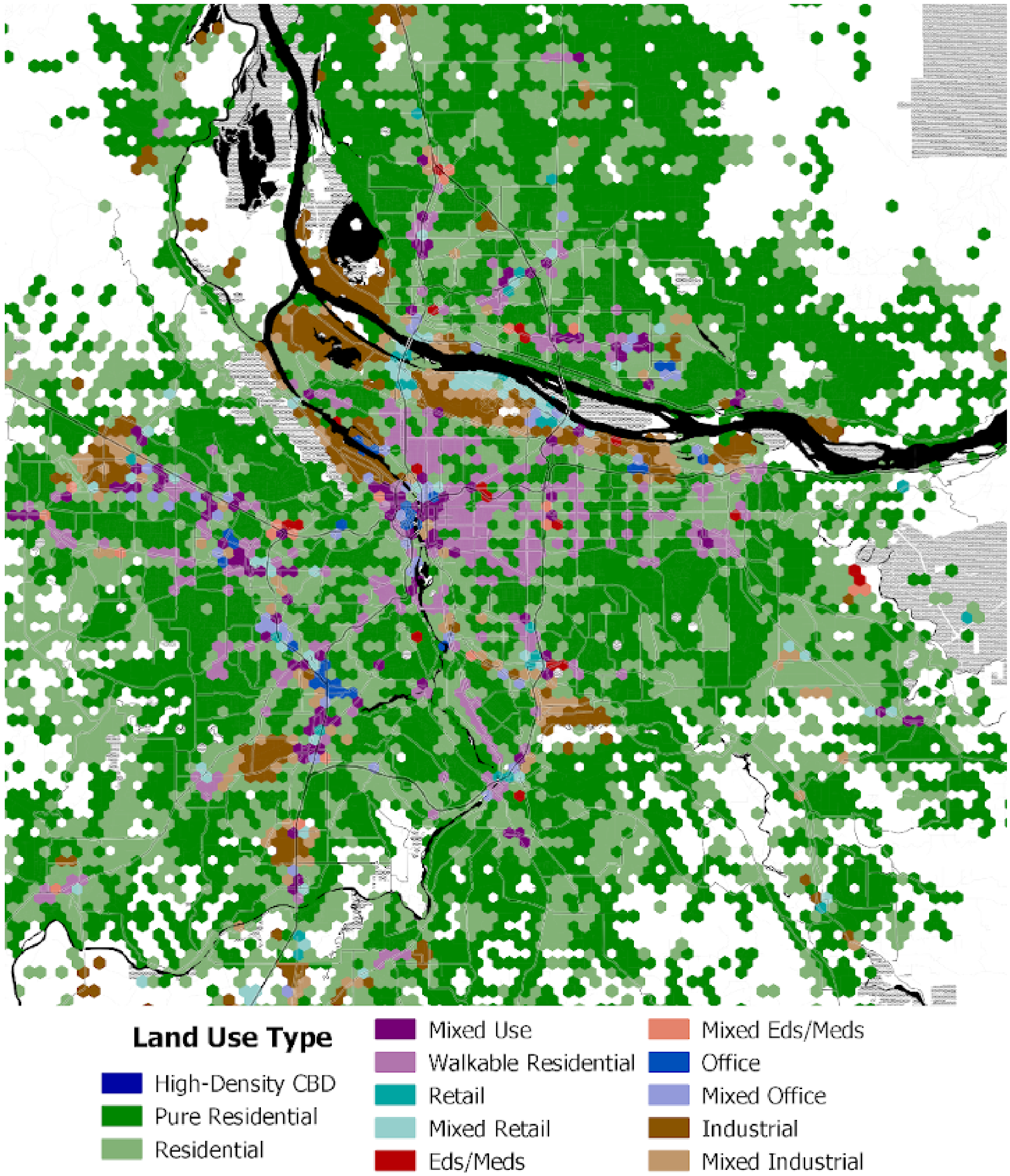

Figure E.20: Portland-Vancouver-Hillsboro, OR-WA MSA use type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table E.20: Portland Distribution of Population and Jobs by Use Type

Use Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Residential	5,464	55.8%	1,169,000	49.2%	58,000	5.6%
Residential	3,093	31.6%	638,000	26.9%	189,000	18.3%
Walkable Residential	306	3.1%	344,000	14.5%	149,000	14.4%
Mixed Use	113	1.2%	80,000	3.4%	150,000	14.5%
Retail	52	0.5%	6,000	0.3%	18,000	1.8%
Retail Mix	80	0.8%	17,000	0.7%	37,000	3.6%
Education / Medical	29	0.3%	12,000	0.5%	46,000	4.5%
Education / Medical Mix	29	0.3%	14,000	0.6%	21,000	2.0%
Office	28	0.3%	14,000	0.6%	97,000	9.4%
Office Mix	46	0.5%	20,000	0.8%	74,000	7.2%
Industrial	374	3.8%	29,000	1.2%	121,000	11.7%
Industrial Mix	178	1.8%	33,000	1.4%	74,000	7.2%

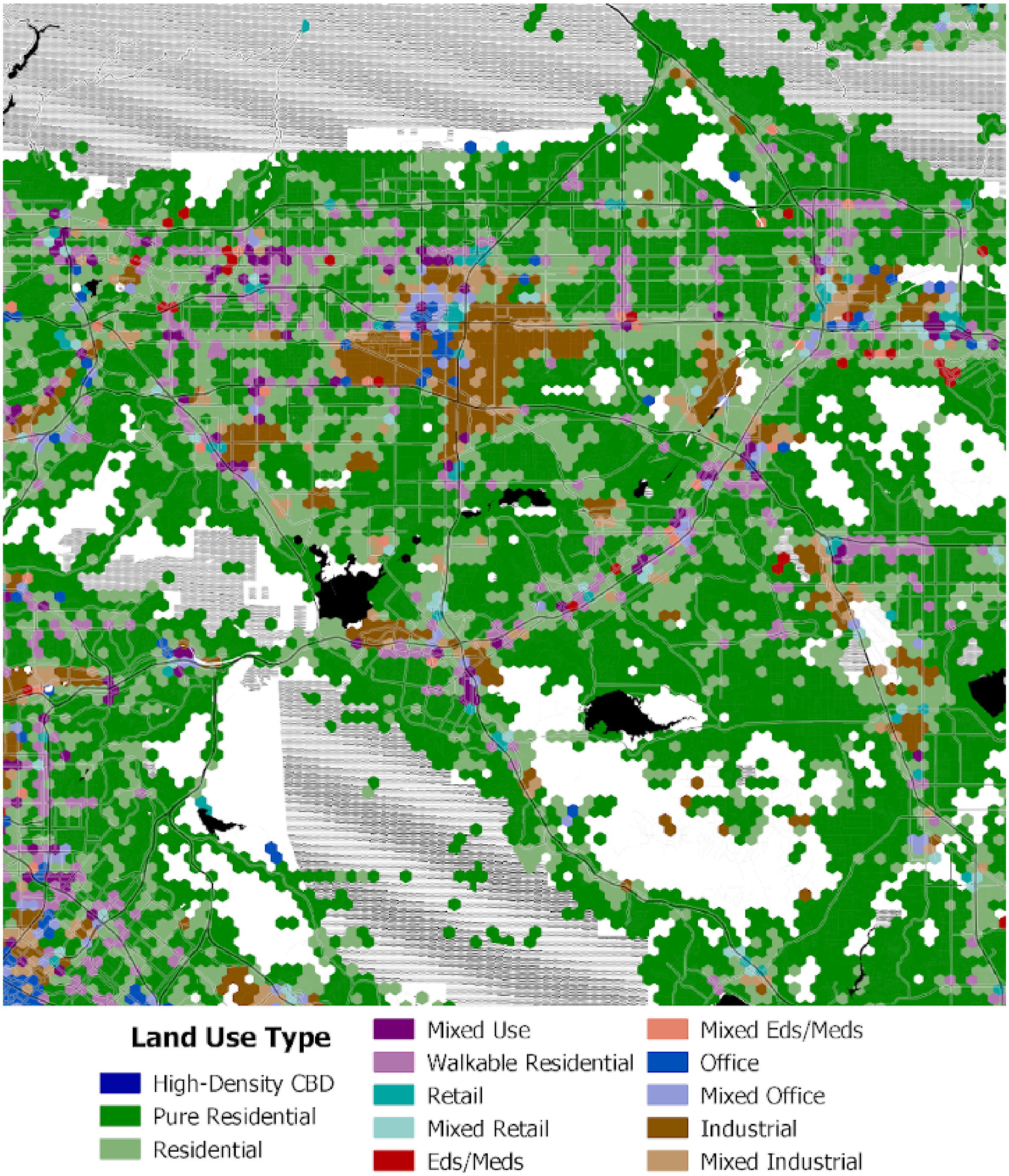

Figure E.21: Riverside-San Bernardino-Ontario, CA MSA use type neighborhood map. Ontario is to the center left, San Bernardino is to the center right, and Riverside is to the lower center. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table E.21: Riverside Distribution of Population and Jobs by Use Type

Use Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Residential	9,404	66.5%	2,911,000	65.8%	111,000	9.2%
Residential	3,171	22.4%	968,000	21.9%	292,000	24.2%
Walkable Residential	320	2.3%	323,000	7.3%	131,000	10.9%
Mixed Use	84	0.6%	40,000	0.9%	82,000	6.8%
Retail	203	1.4%	29,000	0.7%	91,000	7.5%
Retail Mix	128	0.9%	24,000	0.5%	48,000	4.0%
Education / Medical	42	0.3%	15,000	0.3%	50,000	4.2%
Education / Medical Mix	29	0.2%	13,000	0.3%	23,000	1.9%
Office	50	0.4%	7,000	0.2%	43,000	3.5%
Office Mix	76	0.5%	19,000	0.4%	54,000	4.5%
Industrial	460	3.3%	40,000	0.9%	211,000	17.5%
Industrial Mix	165	1.2%	35,000	0.8%	70,000	5.8%

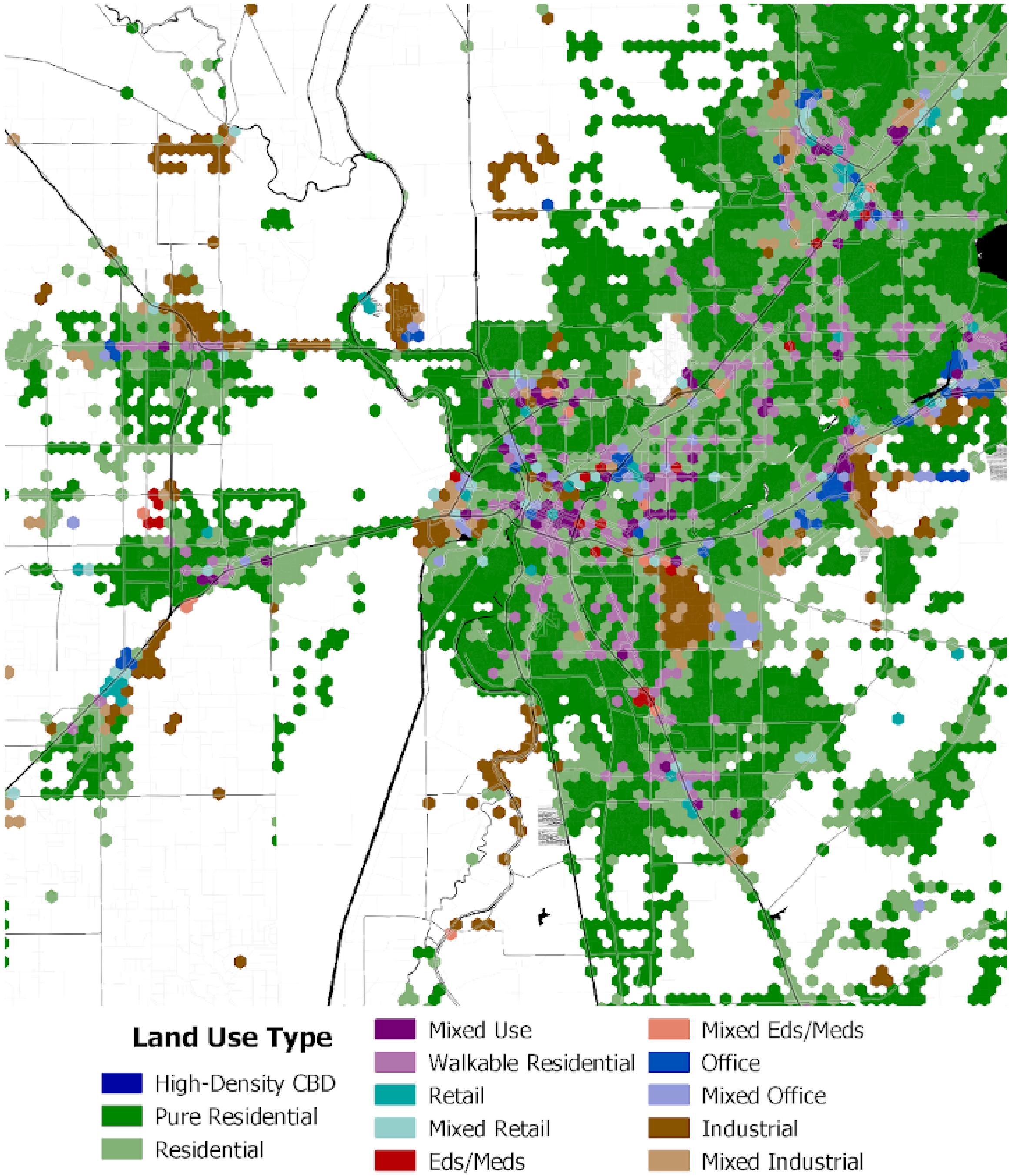

Figure E.22: Sacramento-Roseville-Folsom, CA MSA use type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table E.22: Sacramento Distribution of Population and Jobs by Use Type

Use Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Residential	4,197	58.8%	1,291,000	57.1%	57,000	7.7%
Residential	1,960	27.4%	619,000	27.4%	181,000	24.3%
Walkable Residential	219	3.1%	207,000	9.2%	96,000	12.9%
Mixed Use	78	1.1%	47,000	2.1%	85,000	11.4%
Retail	115	1.6%	11,000	0.5%	40,000	5.4%
Retail Mix	65	0.9%	12,000	0.5%	24,000	3.2%
Education / Medical	25	0.4%	10,000	0.4%	40,000	5.4%
Education / Medical Mix	18	0.3%	4,000	0.2%	8,000	1.1%
Office	54	0.8%	13,000	0.6%	65,000	8.7%
Office Mix	75	1.1%	22,000	1.0%	48,000	6.5%
Industrial	225	3.2%	8,000	0.4%	59,000	7.9%
Industrial Mix	110	1.5%	18,000	0.8%	41,000	5.5%

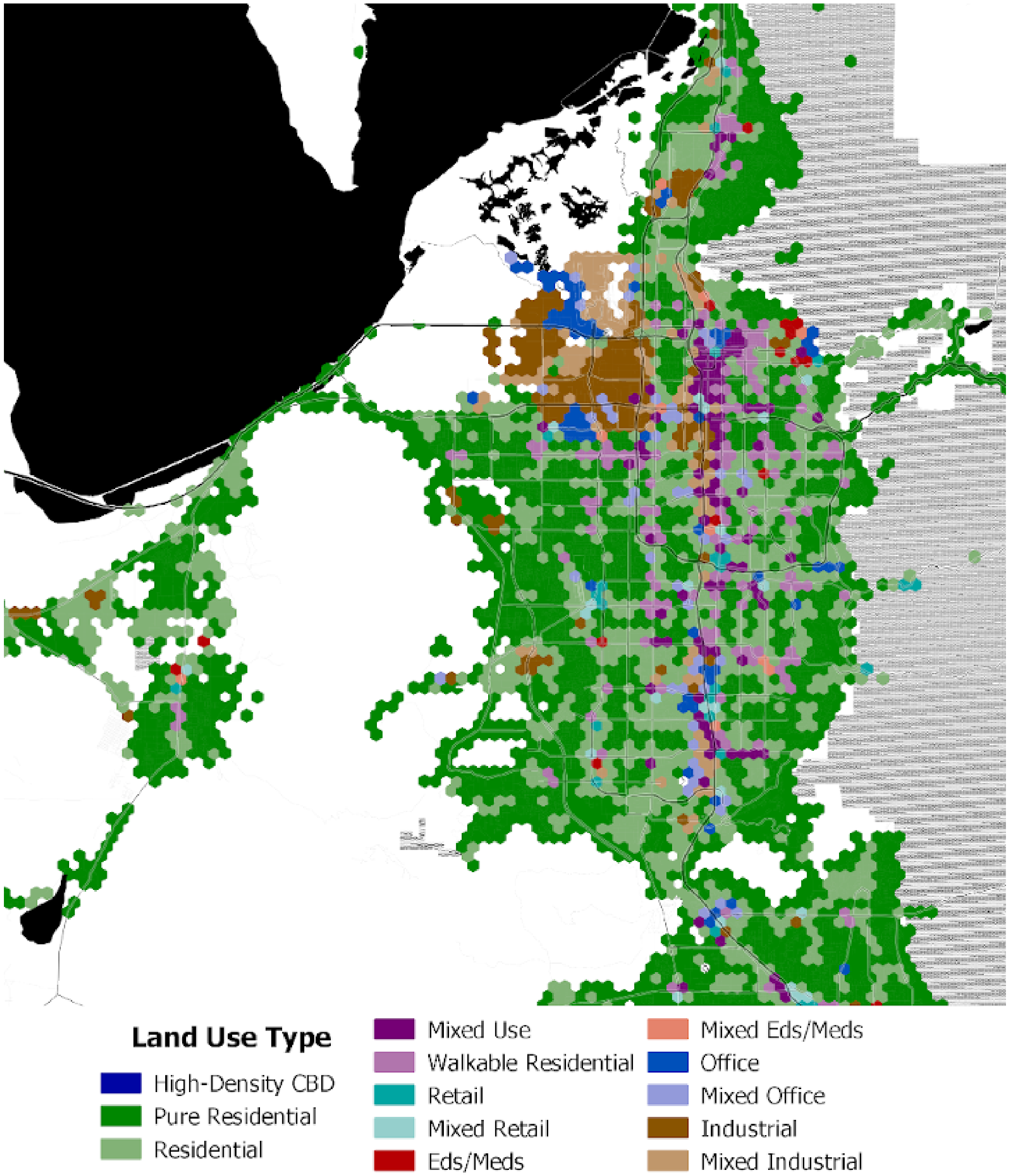

Figure E.23: Salt Lake City, UT MSA use type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table E.23: Salt Lake City Distribution of Population and Jobs by Use Type

Use Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Residential	1,276	48%	578,000	49.2%	27,000	4.6%
Residential	749	28.2%	340,000	29%	98,000	16.6%
Walkable Residential	126	4.7%	122,000	10.4%	56,000	9.4%
Mixed Use	81	3.0%	48,000	4.1%	95,000	16.1%
Retail	41	1.5%	7,000	0.6%	23,000	3.9%
Retail Mix	18	0.7%	7,000	0.6%	14,000	2.3%
Education / Medical	13	0.5%	5,000	0.4%	23,000	3.8%
Education / Medical Mix	9	0.3%	4,000	0.4%	6,000	1.0%
Office	57	2.1%	13,000	1.1%	88,000	14.8%
Office Mix	45	1.7%	19,000	1.6%	48,000	8.0%
Industrial	140	5.3%	14,000	1.2%	76,000	12.8%
Industrial Mix	102	3.8%	17,000	1.4%	40,000	6.7%

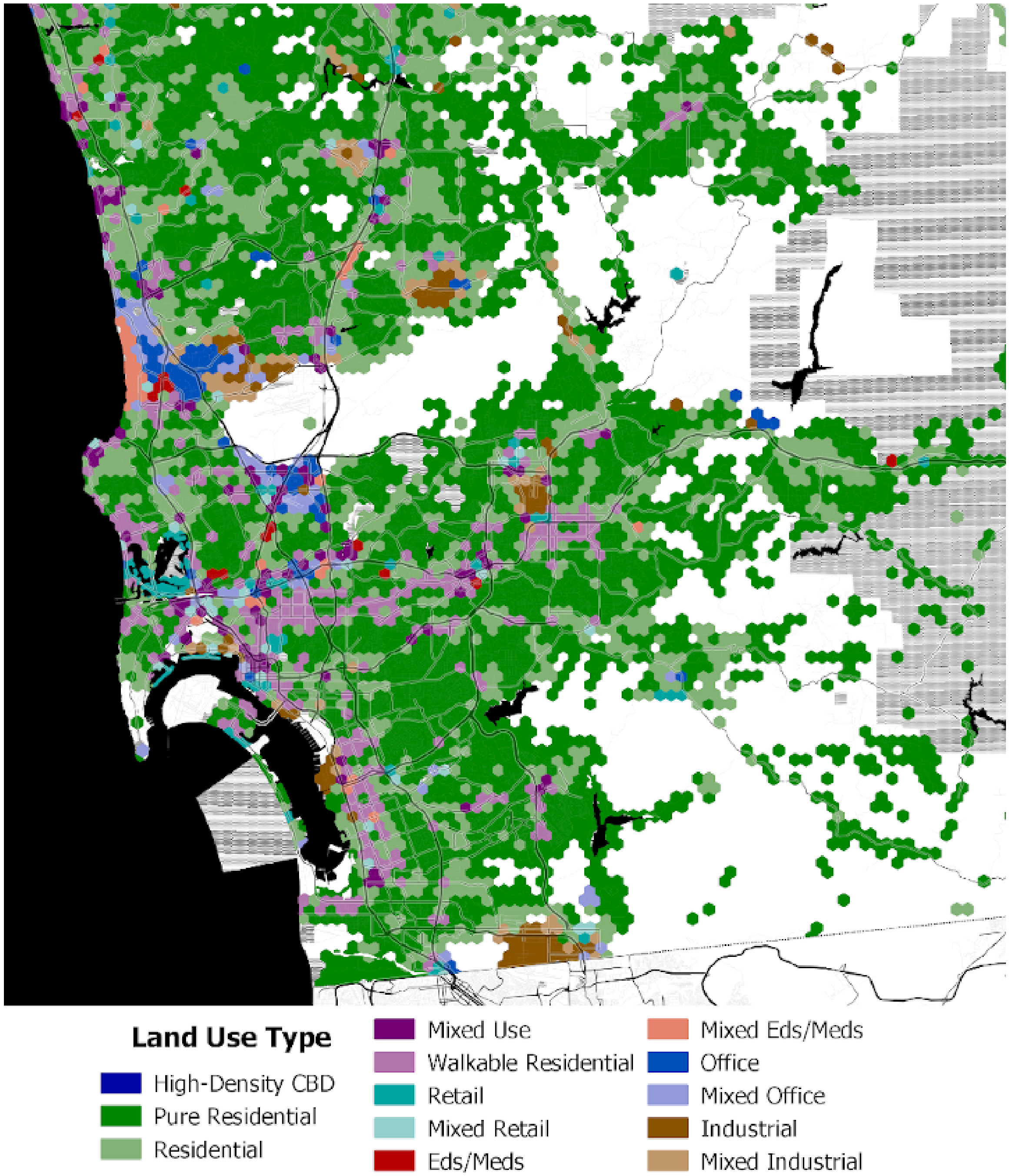

Figure E.24: San Diego-Chula Vista-Carlsbad, CA MSA use type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table E.24: San Diego Distribution of Population and Jobs by Use Type

Use Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Residential	3,977	58.2%	1,744,000	54.5%	78,000	6.5%
Residential	1,776	26.0%	703,000	22%	195,000	16.2%
Walkable Residential	348	5.1%	517,000	16.2%	179,000	14.9%
Mixed Use	120	1.8%	89,000	2.8%	174,000	14.4%
Retail	97	1.4%	23,000	0.7%	82,000	6.8%
Retail Mix	52	0.8%	19,000	0.6%	48,000	4.0%
Education / Medical	16	0.2%	10,000	0.3%	30,000	2.5%
Education / Medical Mix	37	0.5%	13,000	0.4%	26,000	2.2%
Office	71	1.0%	16,000	0.5%	134,000	11.1%
Office Mix	81	1.2%	21,000	0.7%	82,000	6.8%
Industrial	153	2.2%	18,000	0.6%	106,000	8.8%
Industrial Mix	104	1.5%	25,000	0.8%	71,000	5.9%

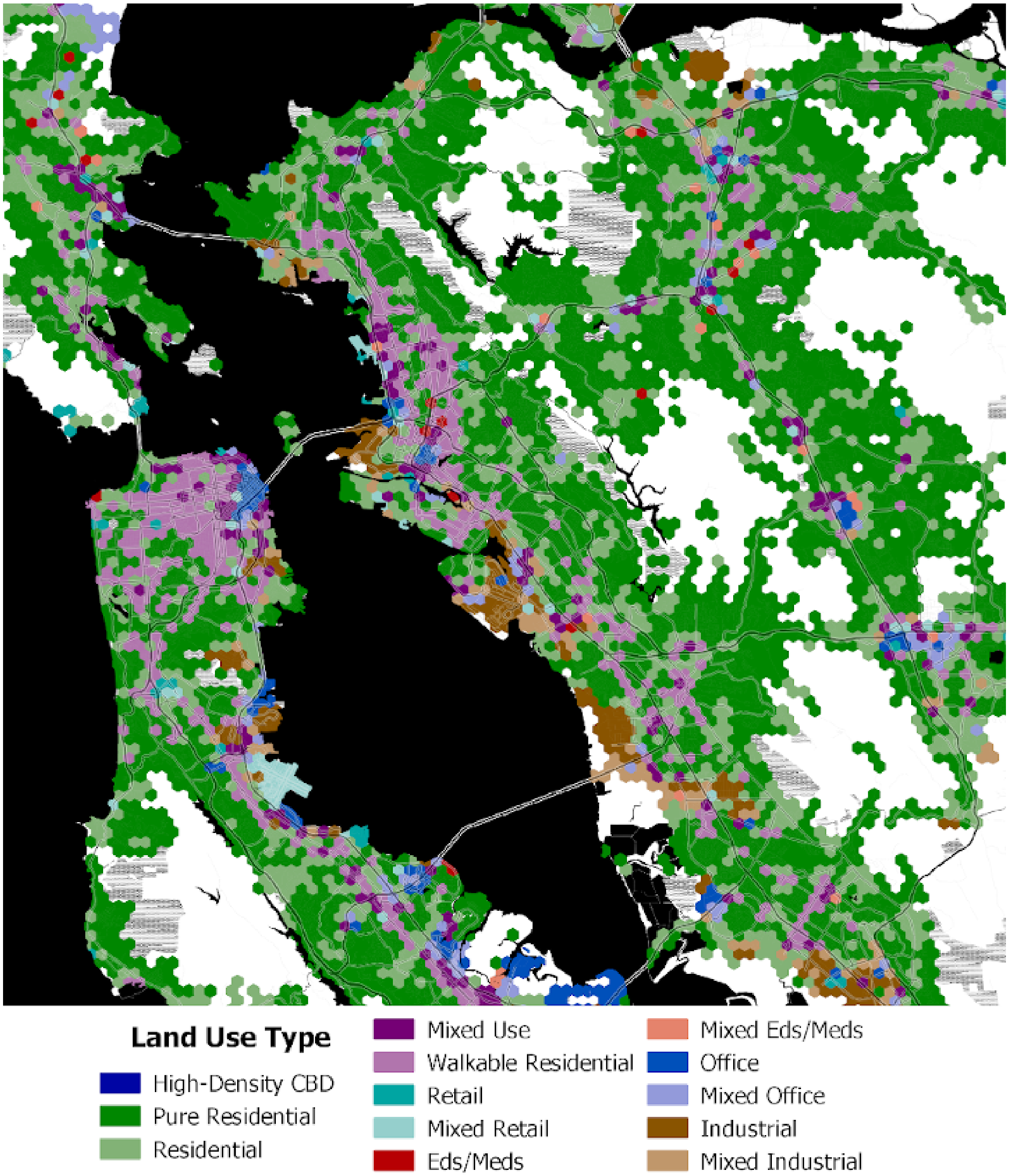

Figure E.25: San Francisco-Oakland-Berkeley, CA MSA use type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table E.25: San Francisco Distribution of Population and Jobs by Use Type

Use Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Residential	3,815	54.3%	2,211,000	47.6%	113,000	5.3%
Residential	1,701	24.2%	886,000	19.1%	249,000	11.6%
Walkable Residential	502	7.1%	1,131,000	24.3%	375,000	17.5%
Mixed Use	177	2.5%	193,000	4.1%	347,000	16.2%
Retail	89	1.3%	11,000	0.2%	35,000	1.7%
Retail Mix	87	1.2%	23,000	0.5%	71,000	3.3%
Education / Medical	18	0.3%	11,000	0.2%	42,000	1.9%
Education / Medical Mix	27	0.4%	12,000	0.2%	21,000	1.0%
Office	112	1.6%	64,000	1.4%	508,000	23.8%
Office Mix	124	1.8%	45,000	1.0%	133,000	6.2%
Industrial	233	3.3%	23,000	0.5%	164,000	7.7%
Industrial Mix	143	2.0%	37,000	0.8%	81,000	3.8%

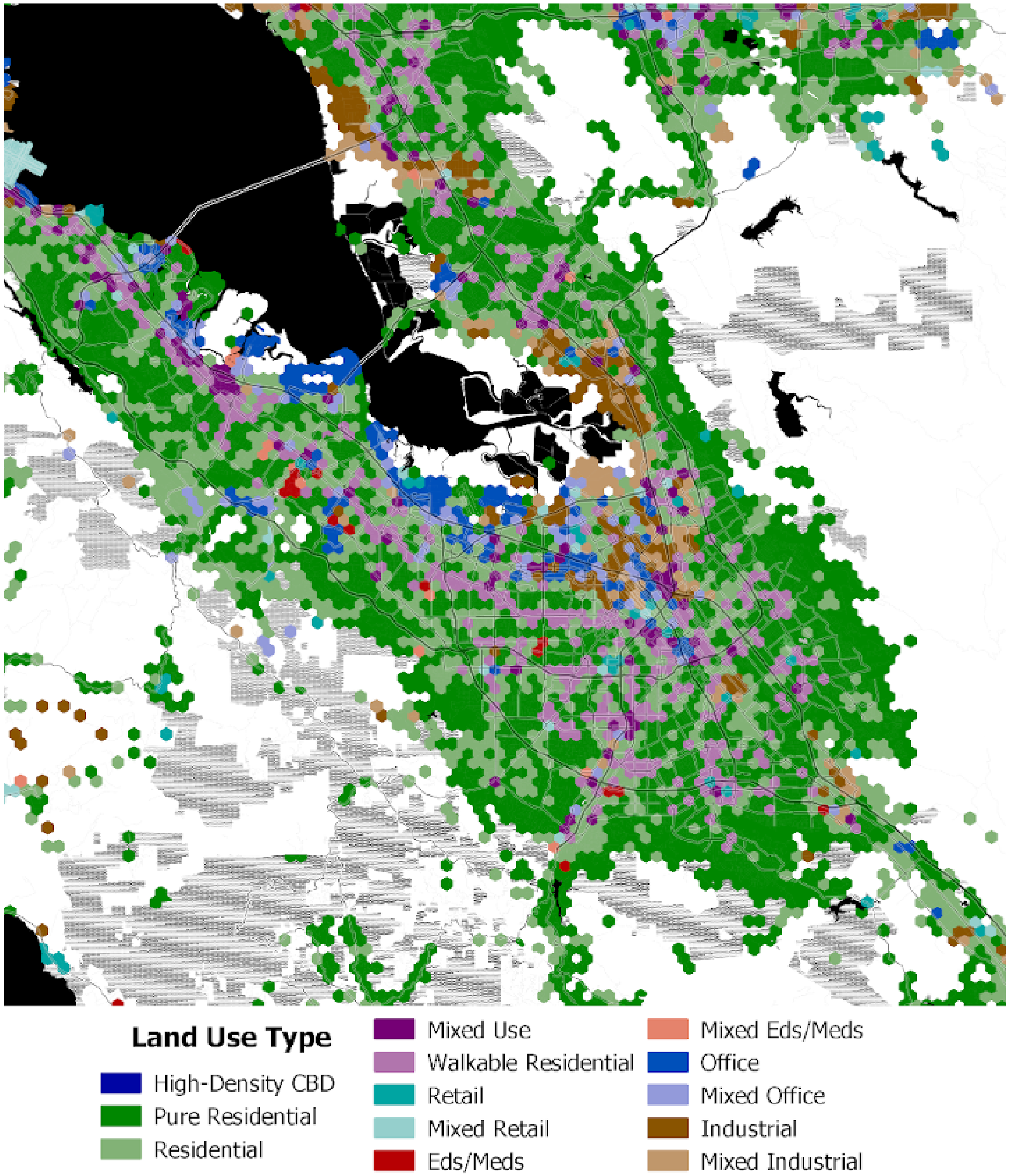

Figure E.26: San Jose-Sunnyvale-Santa Clara, CA MSA use type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table E.26: San Jose Distribution of Population and Jobs by Use Type

Use Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Residential	1,467	47.5%	955,000	48.4%	49,000	4.9%
Residential	901	29.2%	470,000	23.8%	133,000	13.3%
Walkable Residential	246	8.0%	387,000	19.6%	149,000	14.9%
Mixed Use	52	1.7%	45,000	2.3%	81,000	8.1%
Retail	43	1.4%	10,000	0.5%	30,000	3.1%
Retail Mix	23	0.7%	6,000	0.3%	11,000	1.1%
Education / Medical	16	0.5%	9,000	0.5%	48,000	4.8%
Education / Medical Mix	6	0.2%	3,000	0.1%	4,000	0.4%
Office	86	2.8%	21,000	1.1%	226,000	22.6%
Office Mix	47	1.5%	21,000	1.1%	60,000	6.0%
Industrial	125	4%	25,000	1.2%	143,000	14.4%
Industrial Mix	75	2.4%	21,000	1.1%	62,000	6.3%

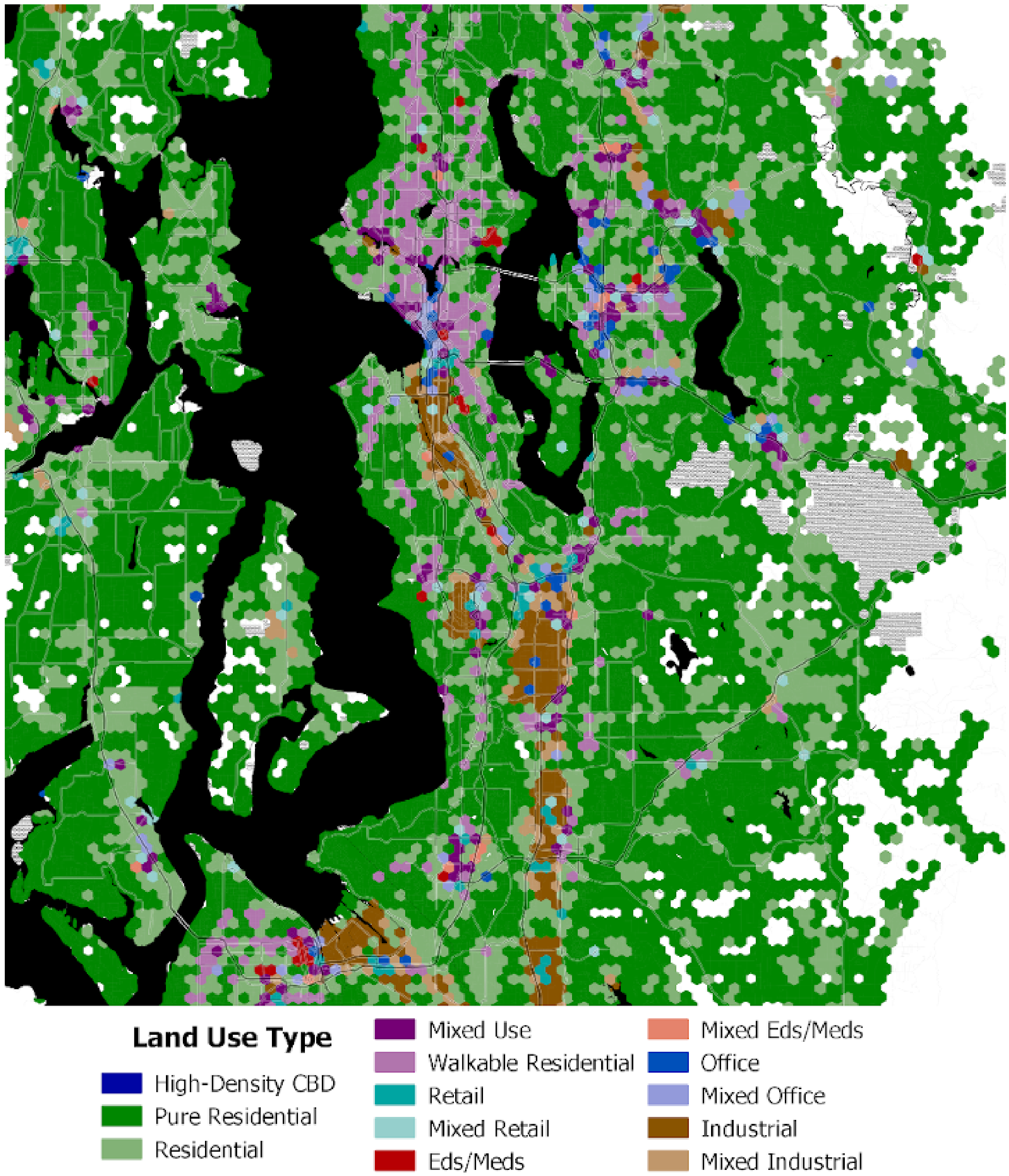

Figure E.27: Seattle-Tacoma-Bellevue, WA MSA use type neighborhood map. Seattle is in the upper center and Tacoma is to the lower left. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table E.27: Seattle Distribution of Population and Jobs by Use Type

Use Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Residential	7,608	65.0%	2,093,000	55.6%	90,000	5.3%
Residential	2,770	23.7%	847,000	22.5%	240,000	14.1%
Walkable Residential	395	3.4%	506,000	13.4%	216,000	12.7%
Mixed Use	153	1.3%	116,000	3.1%	223,000	13.2%
Retail	97	0.8%	14,000	0.4%	95,000	5.6%
Retail Mix	82	0.7%	28,000	0.7%	64,000	3.8%
Education / Medical	27	0.2%	19,000	0.5%	58,000	3.4%
Education / Medical Mix	22	0.2%	9,000	0.3%	22,000	1.3%
Office	59	0.5%	31,000	0.8%	247,000	14.6%
Office Mix	69	0.6%	38,000	1.0%	145,000	8.5%
Industrial	281	2.4%	31,000	0.8%	226,000	13.3%
Industrial Mix	149	1.3%	32,000	0.8%	71,000	4.2%

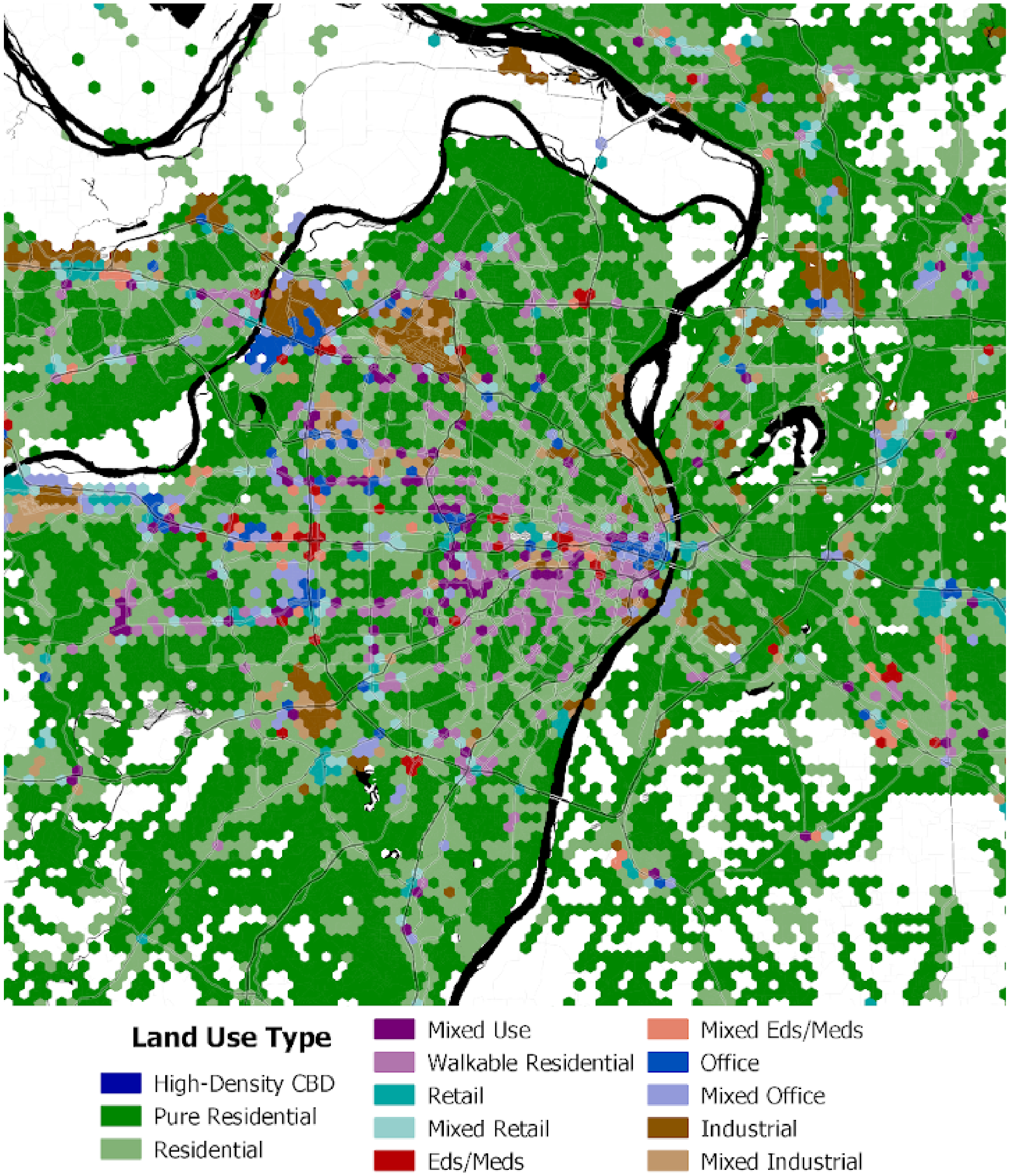

Figure E.28: St. Louis, MO-IL MSA use type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table E.28: St. Louis Distribution of Population and Jobs by Use Type

Use Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Residential	10,551	63.6%	1,405,000	52.3%	55,000	4.5%
Residential	4,402	26.5%	866,000	32.2%	281,000	23.0%
Walkable Residential	217	1.3%	161,000	6.0%	84,000	6.8%
Mixed Use	118	0.7%	49,000	1.8%	94,000	7.7%
Retail	159	1.0%	25,000	0.9%	74,000	6.0%
Retail Mix	168	1.0%	35,000	1.3%	61,000	5.0%
Education / Medical	81	0.5%	20,000	0.7%	107,000	8.8%
Education / Medical Mix	71	0.4%	15,000	0.6%	29,000	2.3%
Office	92	0.6%	22,000	0.8%	159,000	13.0%
Office Mix	140	0.8%	31,000	1.2%	77,000	6.3%
Industrial	392	2.4%	27,000	1.0%	135,000	11%
Industrial Mix	196	1.2%	30,000	1.1%	67,000	5.5%

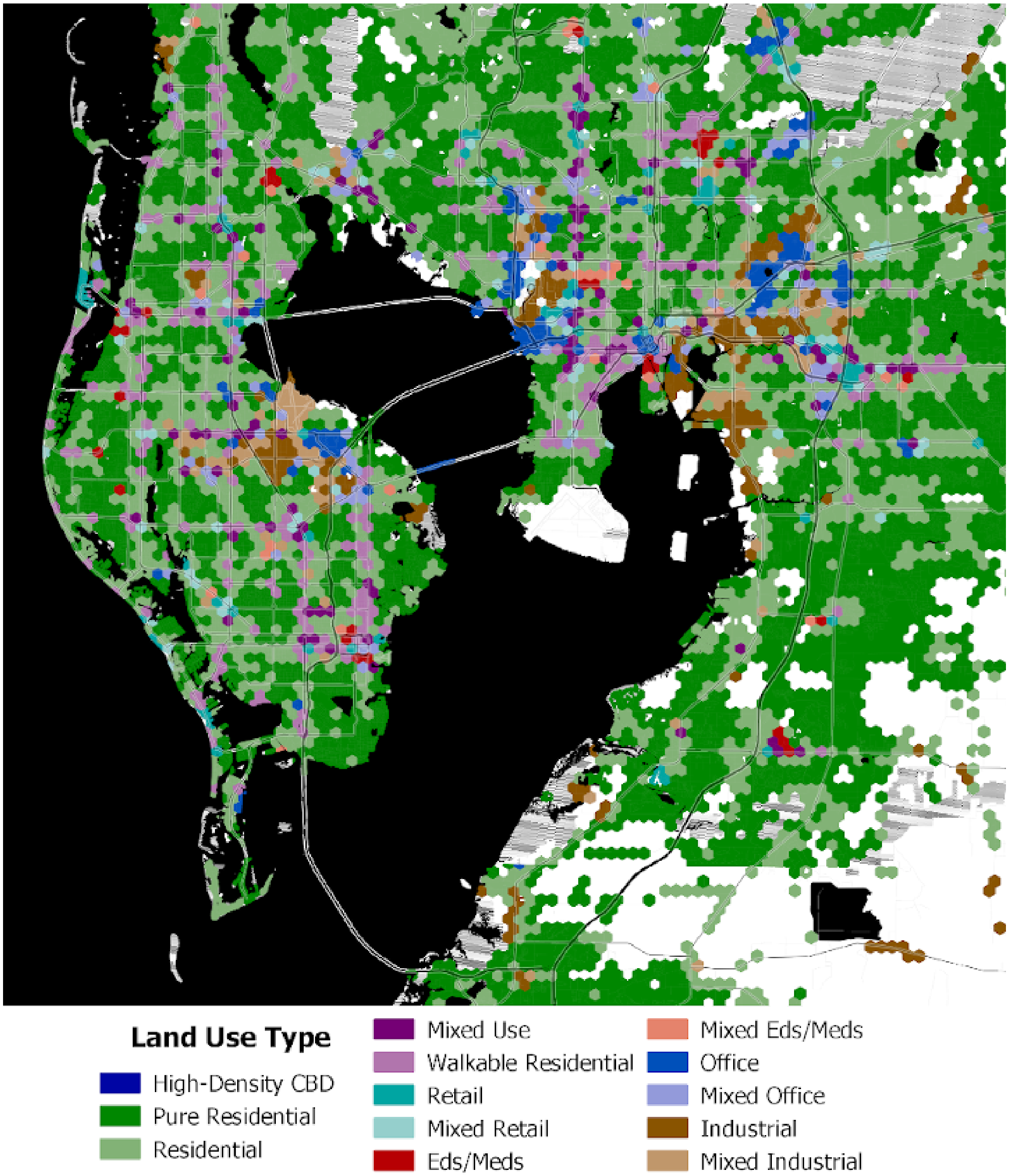

Figure E.29: Tampa-St. Petersburg-Clearwater, FL MSA use type neighborhood map. Tampa is to the upper right and St. Petersburg is to the lower left. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table E.29: Tampa Distribution of Population and Jobs by Use Type

Use Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Residential	5,751	54.6%	1,604,000	53.3%	69,000	5.7%
Residential	3,377	32.1%	930,000	30.9%	282,000	23.6%
Walkable Residential	302	2.9%	225,000	7.5%	114,000	9.6%
Mixed Use	113	1.1%	56,000	1.9%	92,000	7.7%
Retail	97	0.9%	23,000	0.8%	69,000	5.8%
Retail Mix	141	1.3%	30,000	1.0%	52,000	4.4%
Education / Medical	55	0.5%	21,000	0.7%	80,000	6.7%
Education / Medical Mix	50	0.5%	16,000	0.5%	24,000	2.0%
Office	121	1.1%	32,000	1.1%	189,000	15.9%
Office Mix	99	0.9%	33,000	1.1%	84,000	7.1%
Industrial	235	2.2%	14,000	0.5%	77,000	6.4%
Industrial Mix	184	1.7%	27,000	0.9%	61,000	5.1%

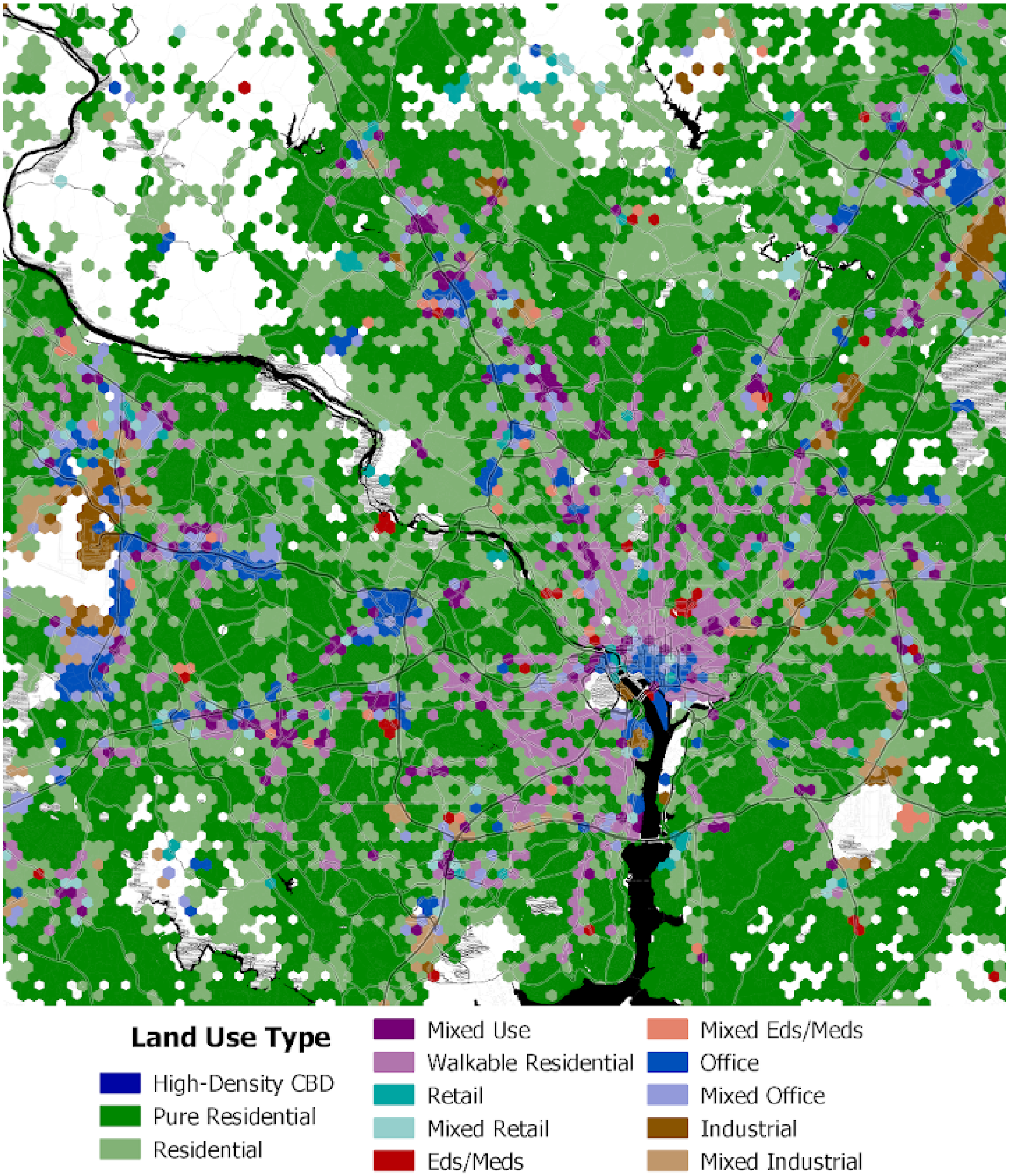

Figure E.30: Washington-Arlington-Alexandria, DC-VA-MD-WV MSA use type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table E.30: Washington Distribution of Population and Jobs by Use Type

Use Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Residential	12,451	62.0%	3,274,000	54.0%	131,000	4.8%
Residential	5,466	27.2%	1,394,000	23.0%	423,000	15.5%
Walkable Residential	503	2.5%	812,000	13.4%	333,000	12.2%
Mixed Use	220	1.1%	177,000	2.9%	308,000	11.3%
Retail	189	0.9%	30,000	0.5%	116,000	4.2%
Retail Mix	143	0.7%	42,000	0.7%	100,000	3.7%
Education / Medical	89	0.4%	27,000	0.4%	92,000	3.4%
Education / Medical Mix	67	0.3%	23,000	0.4%	41,000	1.5%
Office	265	1.3%	99,000	1.6%	653,000	24.0%
Office Mix	231	1.2%	118,000	1.9%	344,000	12.6%
Industrial	221	1.1%	17,000	0.3%	95,000	3.5%
Industrial Mix	237	1.2%	43,000	0.7%	90,000	3.3%

Appendix F: Neighborhood Housing Type Maps

This appendix contains tables showing breakdowns of the percentage of neighborhoods of different housing types (as defined in Table 2.8 on page 118)—and the numbers and percentages of metro area population and jobs in those neighborhoods—in the twenty largest metropolitan statistical areas in the US, along with ten additional metropolitan statistical areas that were selected because they are particularly interesting: either that they are unusually dense for their size or have rapid transit or light rail.

Also included are maps of housing types of neighborhoods in the same metro areas. All the maps are at the same scale, and show a 40-mile by 40-mile square, which means that outlying parts of larger metro areas may be left out, while views of smaller metro areas may include areas outside the MSA limits.

Table F.1: Atlanta Distribution of Population and Jobs by Housing Type

Housing Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Single-Family	13,864	43.9%	2,097,000	36.8%	283,000	11.8%
Single-Family	8,787	27.8%	1,149,000	20.2%	291,000	12.2%
Mixed Single-Family	5,787	18.3%	1,090,000	19.2%	463,000	19.3%
Multifamily: Small Building	313	1.0%	165,000	2.9%	114,000	4.8%
Multifamily: Large Building	583	1.8%	393,000	6.9%	680,000	28.4%
Multifamily: Mixed Types	1,588	5%	712,000	12.5%	471,000	19.6%
Mobile Homes	336	1.1%	28,000	0.5%	7,000	0.3%
Mixed Housing Types	262	0.8%	56,000	1.0%	35,000	1.5%
Few Housing Units	69	0.2%	0	0%	51,000	2.1%

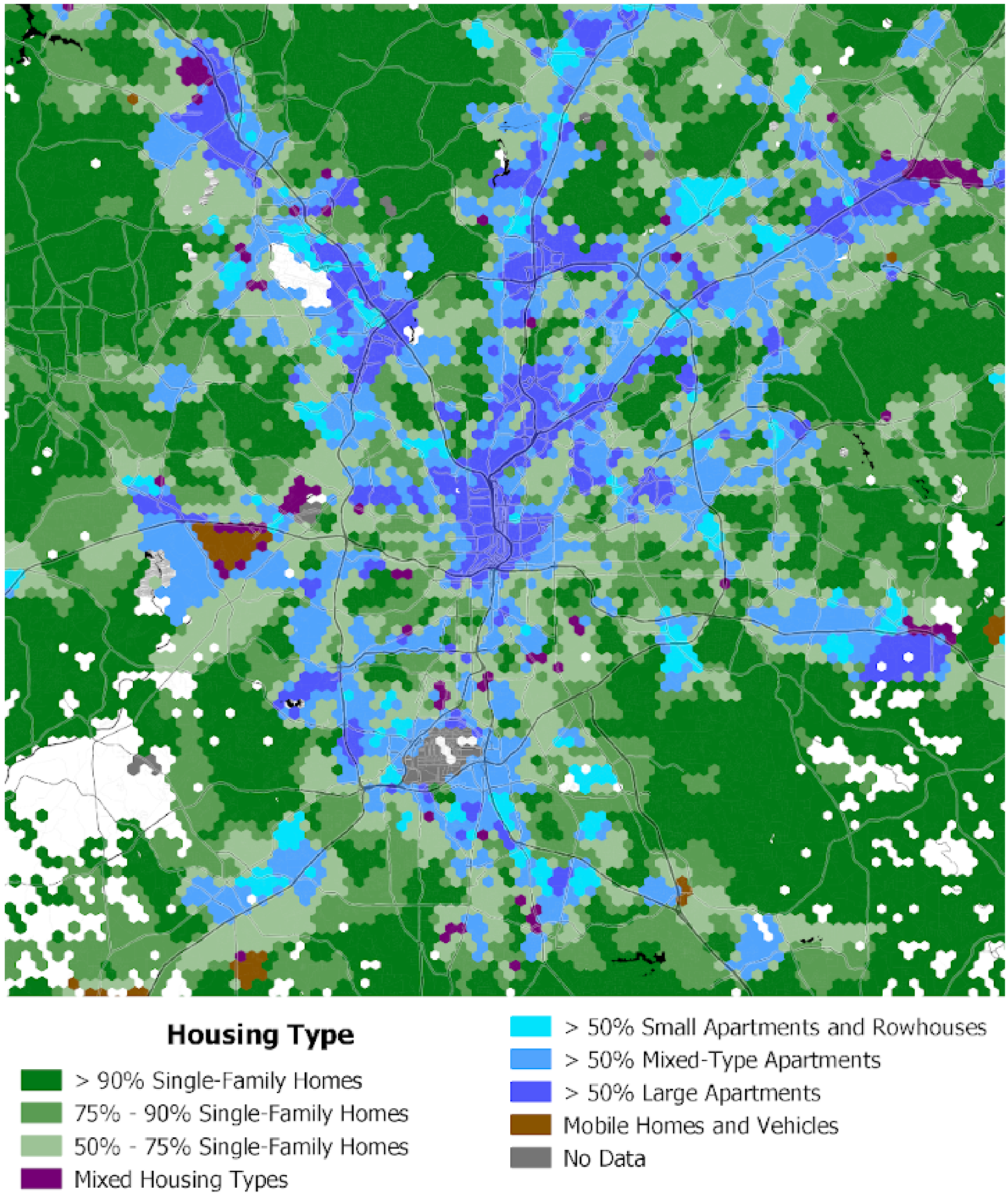

Figure F.1: Atlanta-Sandy Springs-Alpharetta, GA MSA housing type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table F.2: Austin Distribution of Population and Jobs by Housing Type

Housing Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Single-Family	2,460	25.0%	468,000	23.2%	66,000	7.9%
Single-Family	2,559	26.1%	387,000	19.1%	94,000	11.2%
Mixed Single-Family	2,532	25.8%	494,000	24.4%	196,000	23.4%
Multifamily: Small Building	26	0.3%	21,000	1.1%	13,000	1.5%
Multifamily: Large Building	330	3.4%	213,000	10.6%	252,000	30.1%
Multifamily: Mixed Types	555	5.7%	307,000	15.2%	183,000	21.9%
Mobile Homes	1,101	11.2%	82,000	4.1%	13,000	1.6%
Mixed Housing Types	204	2.1%	47,000	2.3%	16,000	2.0%
Few Housing Units	56	0.6%	2,000	0.1%	3,000	0.3%

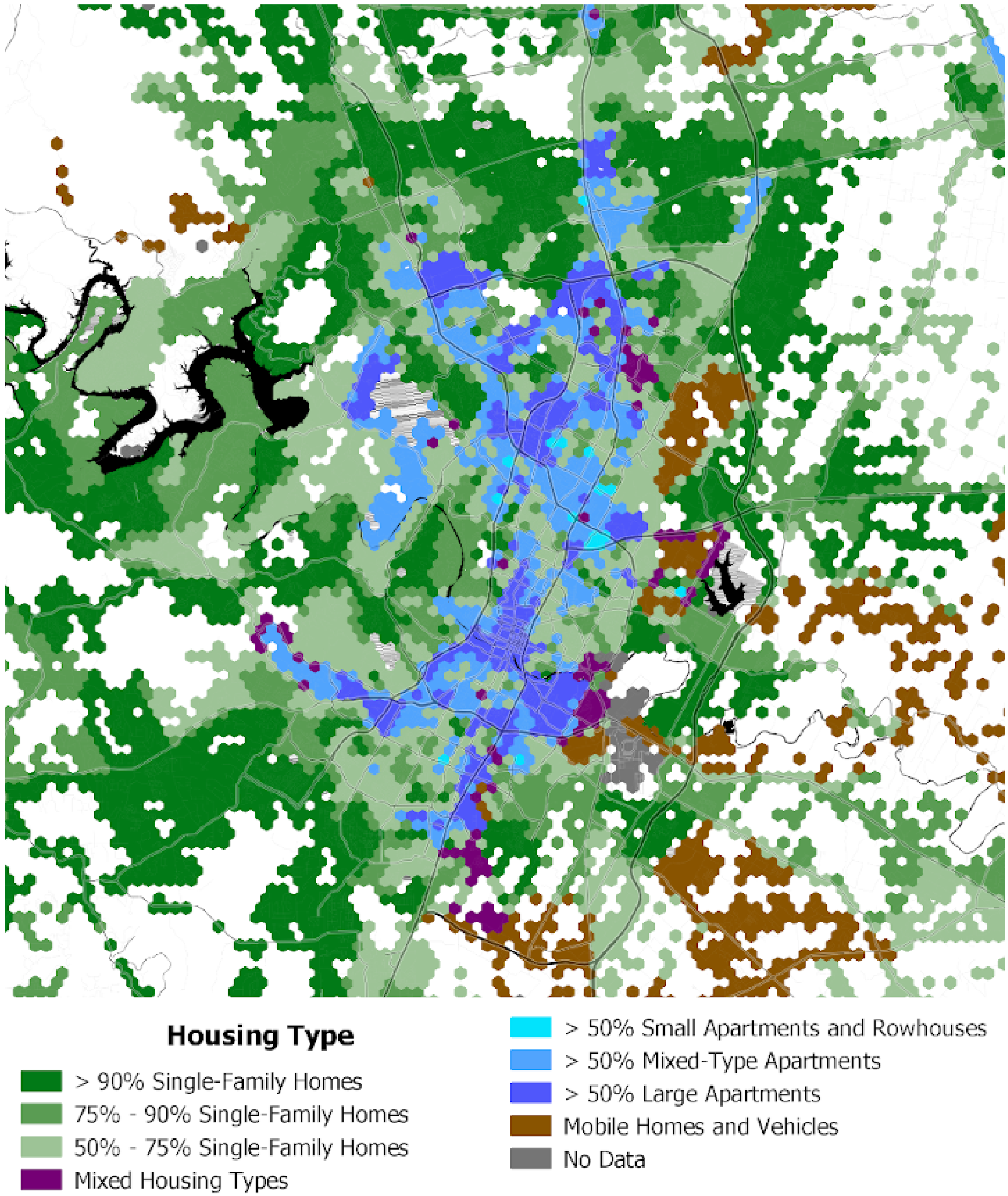

Figure F.2: Austin-Round Rock-Georgetown, TX MSA housing type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table F.3: Baltimore Distribution of Population and Jobs by Housing Type

Housing Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Single-Family	4,911	47.0%	506,000	18.4%	107,000	9.3%
Single-Family	1,742	16.7%	312,000	11.3%	99,000	8.6%
Mixed Single-Family	1,454	13.9%	471,000	17.2%	184,000	15.9%
Multifamily: Small Building	980	9.4%	863,000	31.4%	304,000	26.3%
Multifamily: Large Building	261	2.5%	157,000	5.7%	227,000	19.7%
Multifamily: Mixed Types	817	7.8%	406,000	14.8%	197,000	17.1%
Mobile Homes	131	1.3%	14,000	0.5%	15,000	1.3%
Mixed Housing Types	47	0.4%	14,000	0.5%	9,000	0.8%
Few Housing Units	110	1.1%	4,000	0.1%	13,000	1.1%

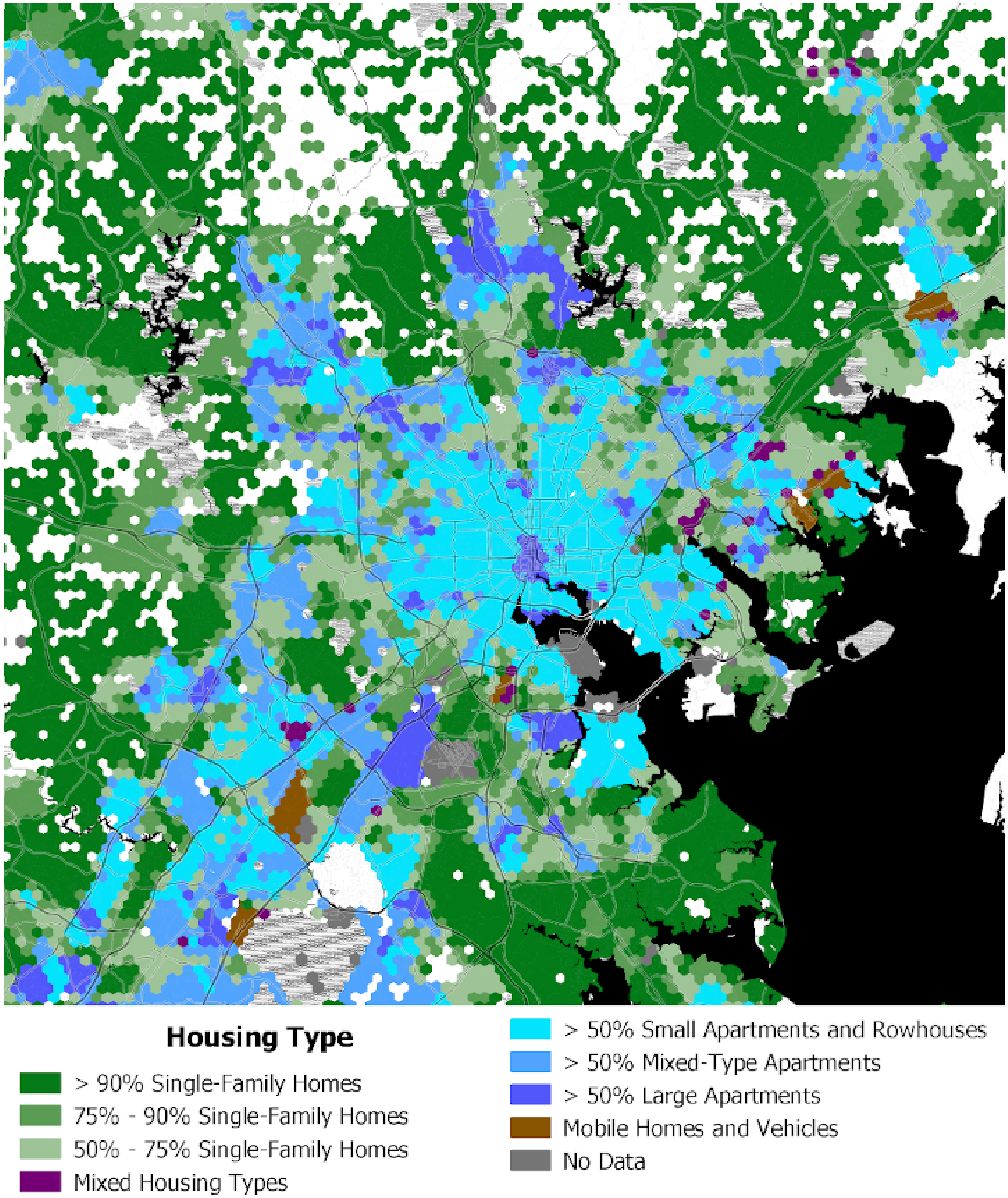

Figure F.3: Baltimore-Columbia-Towson, MD MSA housing type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table F.4: Boston Distribution of Population and Jobs by Housing Type

Housing Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Single-Family	4,959	26.8%	608,000	12.7%	145,000	6.0%
Single-Family	5,670	30.6%	803,000	16.8%	269,000	11.1%
Mixed Single-Family	5,026	27.1%	1,051,000	22.0%	539,000	22.3%
Multifamily: Small Building	826	4.5%	1,228,000	25.7%	408,000	16.9%
Multifamily: Large Building	321	1.7%	370,000	7.7%	652,000	27.0%
Multifamily: Mixed Types	1,323	7.1%	673,000	14.1%	370,000	15.3%
Mobile Homes	133	0.7%	13,000	0.3%	4,000	0.2%
Mixed Housing Types	205	1.1%	37,000	0.8%	24,000	1.0%
Few Housing Units	74	0.4%	2,000	0.04%	7,000	0.3%

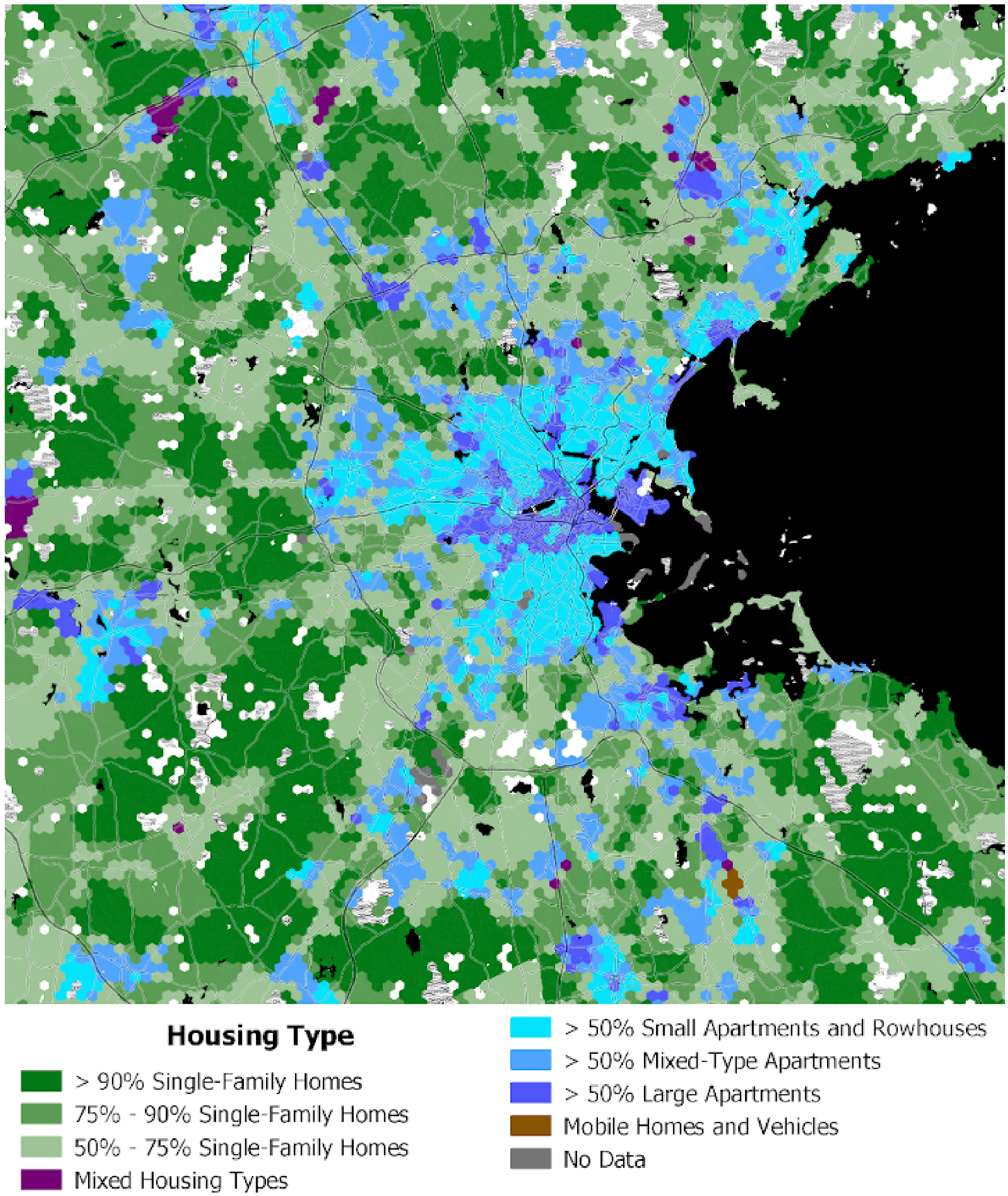

Figure F.4: Boston-Cambridge-Newton, MA-NH MSA housing type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table F.5: Charlotte Distribution of Population and Jobs by Housing Type

Housing Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Single-Family	3,661	20.2%	533,000	21.9%	113,000	10.5%
Single-Family	5,983	33%	682,000	28.1%	187,000	17.5%
Mixed Single-Family	6,141	33.9%	751,000	30.9%	301,000	28.2%
Multifamily: Small Building	49	0.3%	24,000	1.0%	17,000	1.6%
Multifamily: Large Building	248	1.4%	106,000	4.3%	218,000	20.5%
Multifamily: Mixed Types	561	3.1%	246,000	10.1%	170,000	15.9%
Mobile Homes	1,266	7%	60,000	2.5%	18,000	1.7%
Mixed Housing Types	145	0.8%	25,000	1.0%	21,000	2.0%
Few Housing Units	84	0.5%	1,000	0.03%	21,000	2.0%

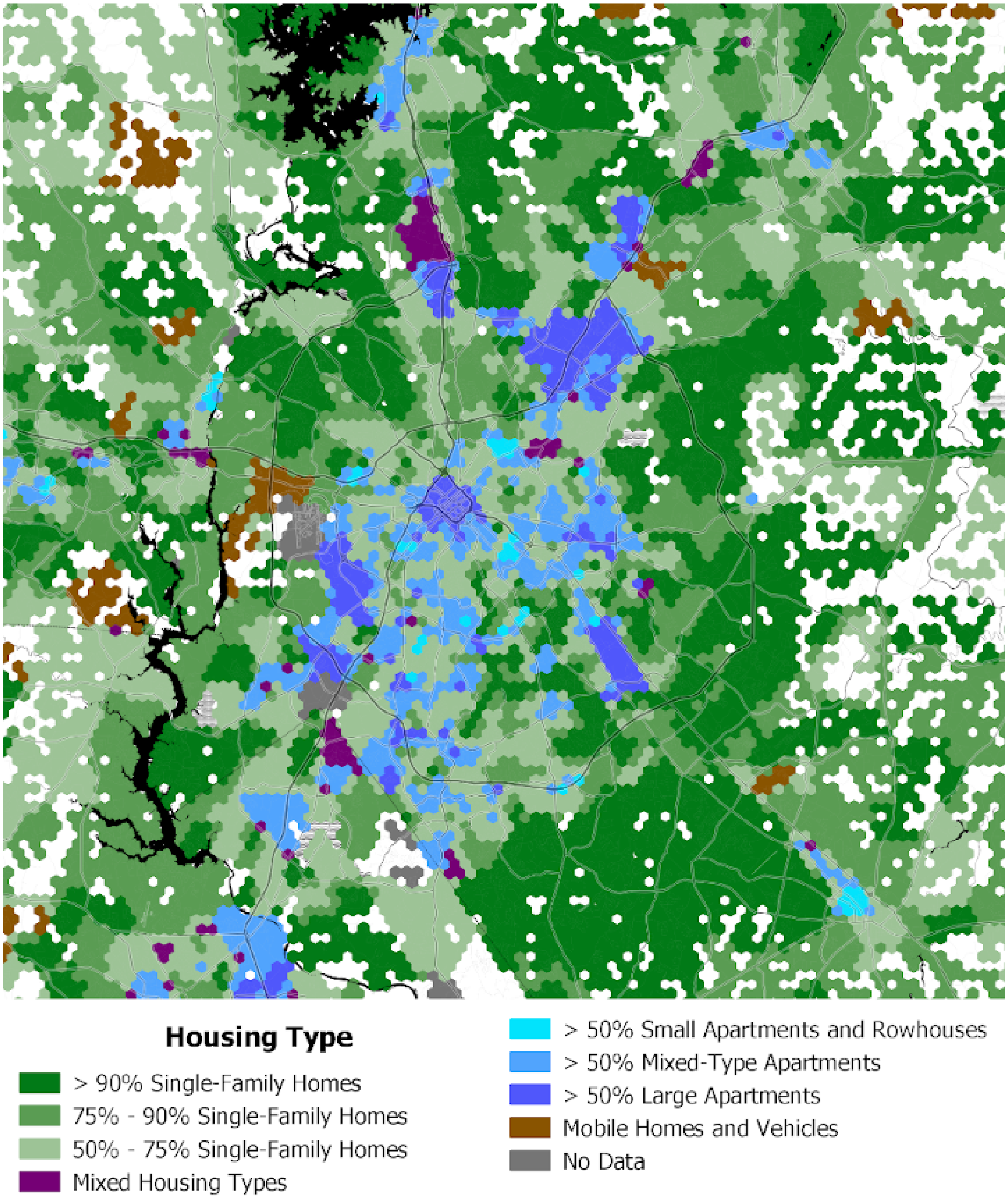

Figure F.5: Charlotte-Concord-Gastonia, NC-SC MSA housing type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table F.6: Chicago Distribution of Population and Jobs by Housing Type

Housing Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Single-Family	7,417	28.5%	1,470,000	15.6%	356,000	8.7%
Single-Family	7,835	30.1%	1,941,000	20.6%	521,000	12.7%
Mixed Single-Family	6,519	25%	2,337,000	24.7%	981,000	23.9%
Multifamily: Small Building	1478	5.7%	1,898,000	20.1%	560,000	13.7%
Multifamily: Large Building	551	2.1%	682,000	7.2%	962,000	23.5%
Multifamily: Mixed Types	1,671	6.4%	1,007,000	10.7%	609,000	14.9%
Mobile Homes	200	0.8%	39,000	0.4%	32,000	0.8%
Mixed Housing Types	213	0.8%	70,000	0.7%	33,000	0.8%
Few Housing Units	182	0.7%	1,000	0.01%	44,000	1.1%

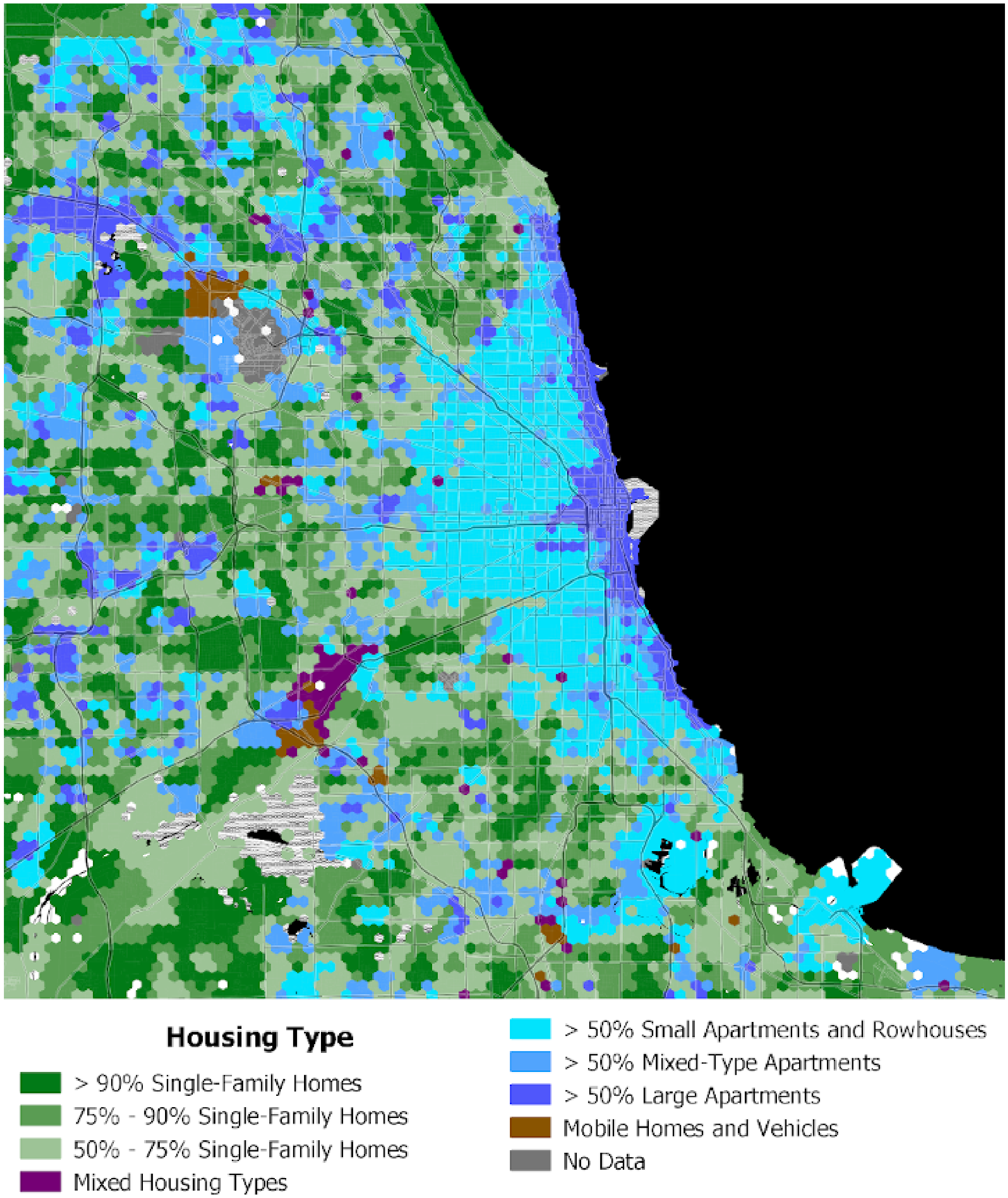

Figure F.6: Chicago-Naperville-Elgin, IL-IN-WI MSA housing type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table F.7: Cleveland Distribution of Population and Jobs by Housing Type

Housing Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Single-Family	4,455	47.5%	530,000	26.0%	137,000	14.9%
Single-Family	2,311	24.6%	508,000	24.9%	165,000	18.0%
Mixed Single-Family	1,636	17.4%	555,000	27.2%	224,000	24.5%
Multifamily: Small Building	117	1.2%	82,000	4.0%	33,000	3.6%
Multifamily: Large Building	183	2.0%	107,000	5.3%	166,000	18.1%
Multifamily: Mixed Types	514	5.5%	242,000	11.8%	166,000	18.2%
Mobile Homes	23	0.2%	5,000	0.2%	1,000	0.1%
Mixed Housing Types	71	0.8%	12,000	0.6%	8,000	0.9%
Few Housing Units	67	0.7%	0	0%	15,000	1.7%

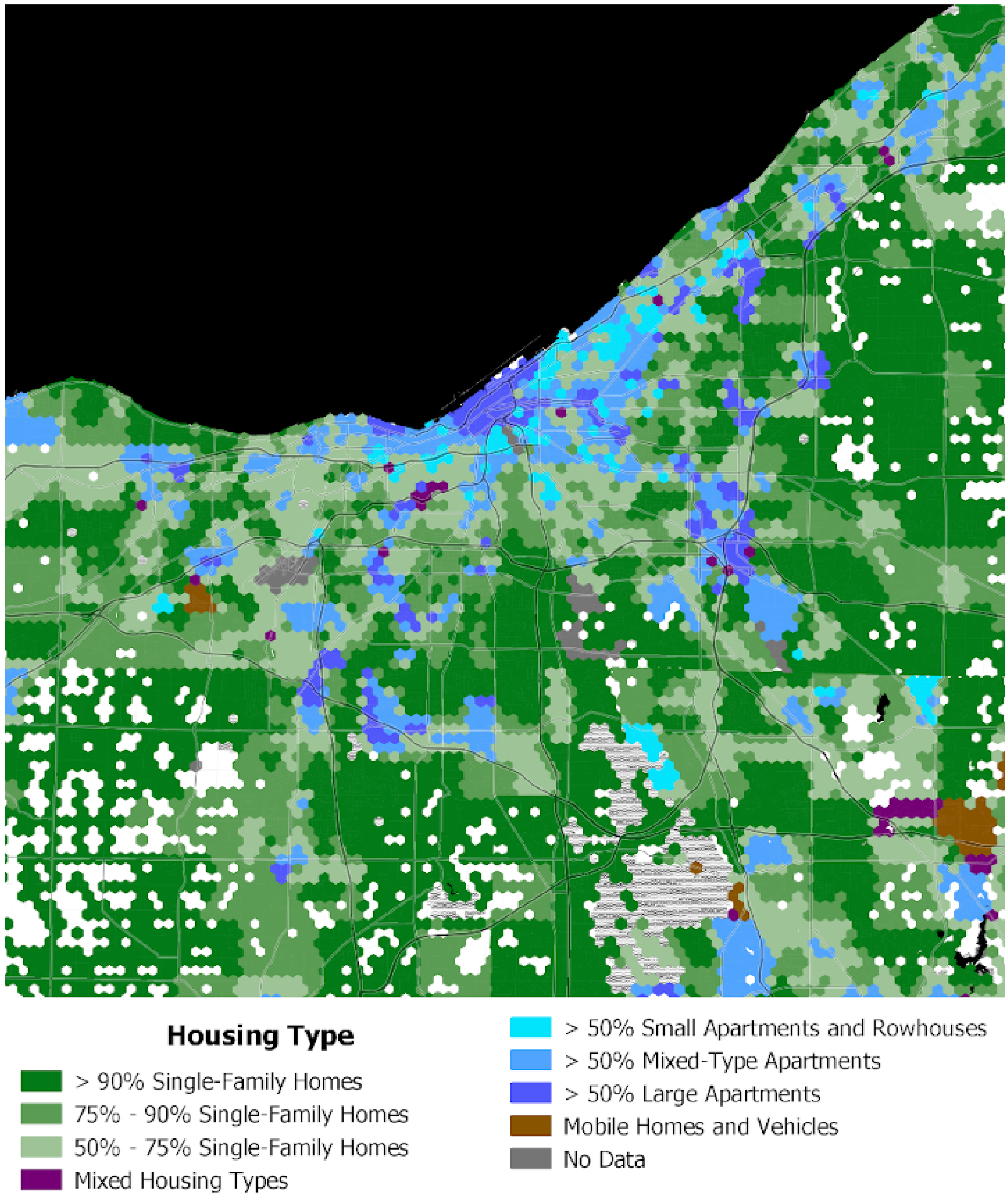

Figure F.7: Cleveland-Elyria, OH MSA housing type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table F.8: Dallas Distribution of Population and Jobs by Housing Type

Housing Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Single-Family	8,076	29.8%	2,362,000	33.4%	444,000	14%
Single-Family	6,986	25.8%	1,430,000	20.3%	388,000	12.2%
Mixed Single-Family	6,572	24.2%	1,458,000	20.6%	583,000	18.4%
Multifamily: Small Building	270	1.0%	171,000	2.4%	98,000	3.1%
Multifamily: Large Building	1,006	3.7%	668,000	9.5%	998,000	31.5%
Multifamily: Mixed Types	1,352	5.0%	771,000	10.9%	473,000	14.9%
Mobile Homes	2,218	8.2%	138,000	2.0%	52,000	1.6%
Mixed Housing Types	394	1.5%	62,000	0.9%	65,000	2.0%
Few Housing Units	234	0.9%	0	0%	71,000	2.2%

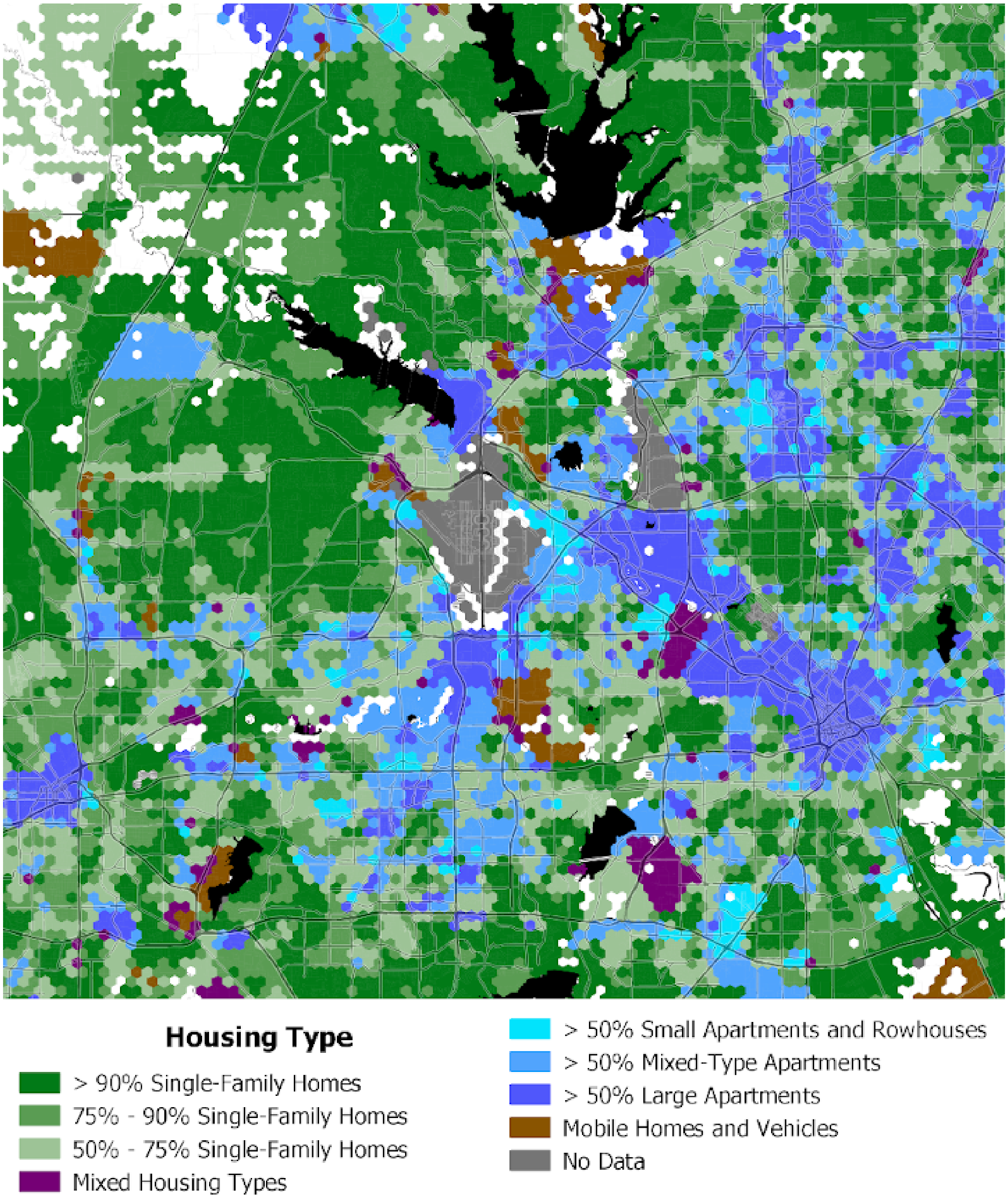

Figure F.8: Dallas-Fort Worth-Arlington, TX MSA housing type neighborhood map. Downtown Dallas is at the lower right and downtown Fort Worth is at the far lower left. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table F.9: Denver Distribution of Population and Jobs by Housing Type

Housing Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Single-Family	3,549	44.9%	782,000	27.7%	115,000	8.9%
Single-Family	1,511	19.1%	502,000	17.8%	110,000	8.5%
Mixed Single-Family	1,320	16.7%	635,000	22.5%	245,000	18.9%
Multifamily: Small Building	183	2.3%	87,000	3.1%	65,000	5.0%
Multifamily: Large Building	477	6.0%	355,000	12.6%	476,000	36.7%
Multifamily: Mixed Types	594	7.5%	389,000	13.8%	225,000	17.3%
Mobile Homes	126	1.6%	39,000	1.4%	15,000	1.1%
Mixed Housing Types	64	0.8%	32,000	1.1%	24,000	1.9%
Few Housing Units	72	0.9%	0	0%	23,000	1.7%

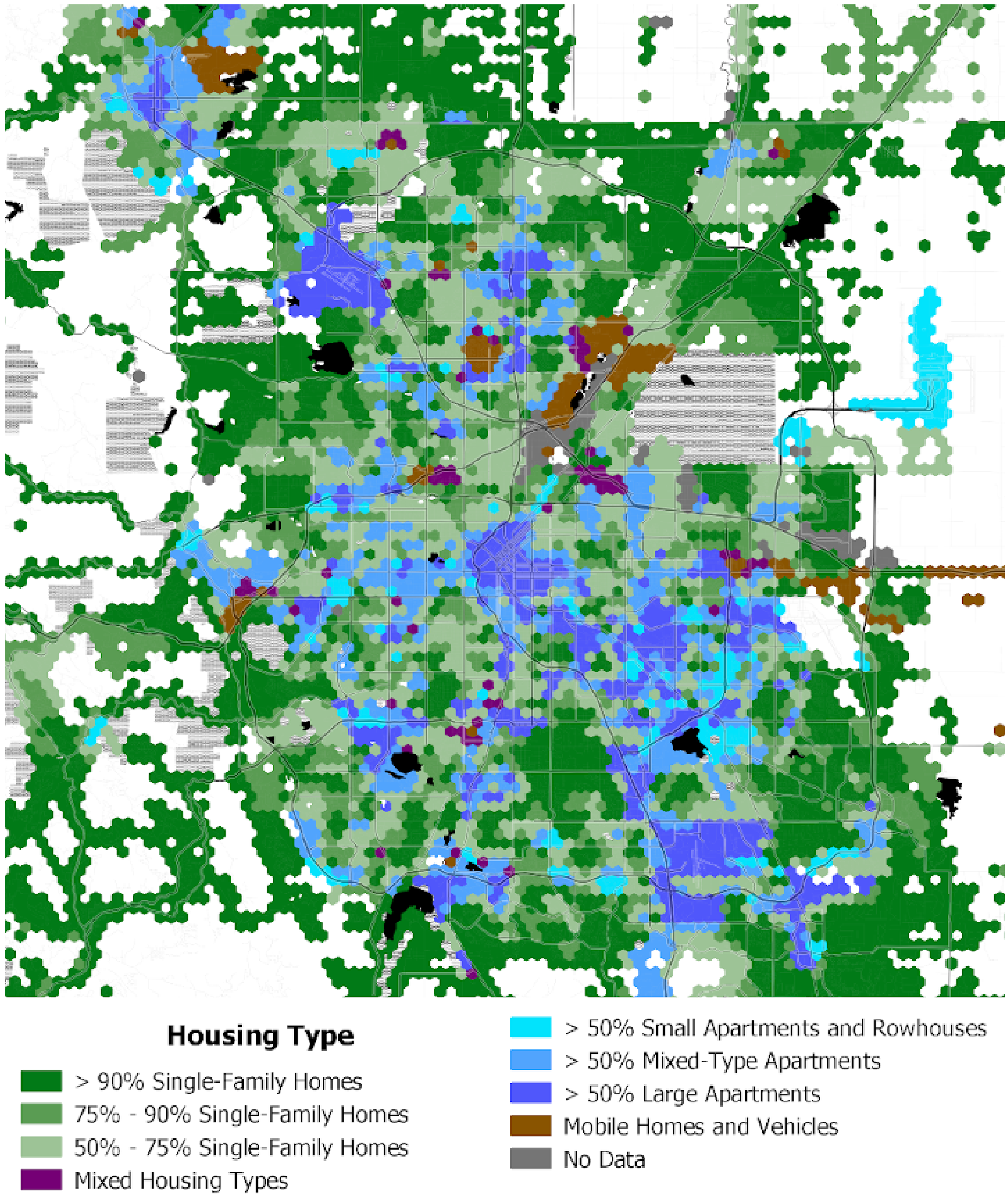

Figure F.9: Denver-Aurora-Lakewood, CO MSA housing type neighborhood map. Boulder (not in the Denver MSA) is at the upper left. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table F.10: Detroit Distribution of Population and Jobs by Housing Type

Housing Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Single-Family	8,769	50.0%	1,469,000	34.4%	337,000	18.8%
Single-Family	3,803	21.7%	1,055,000	24.7%	324,000	18.0%
Mixed Single-Family	2,788	15.9%	971,000	22.7%	435,000	24.2%
Multifamily: Small Building	340	1.9%	163,000	3.8%	117,000	6.5%
Multifamily: Large Building	205	1.2%	113,000	2.6%	185,000	10.3%
Multifamily: Mixed Types	786	4.5%	353,000	8.2%	262,000	14.6%
Mobile Homes	470	2.7%	93,000	2.2%	50,000	2.8%
Mixed Housing Types	286	1.6%	57,000	1.3%	36,000	2.0%
Few Housing Units	104	0.6%	0	0%	47,000	2.6%

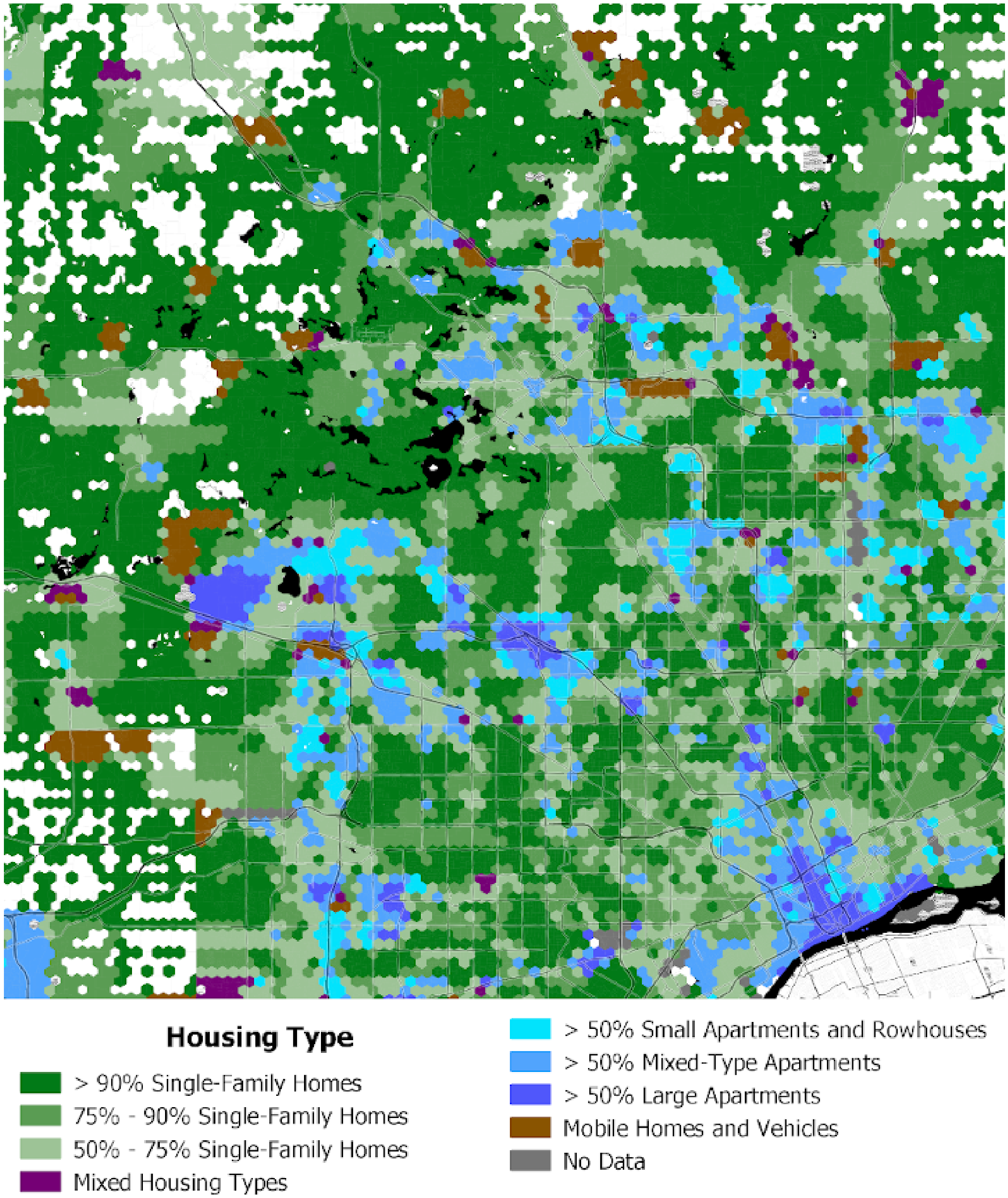

Figure F.10: Detroit-Warren-Dearborn, MI MSA housing type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table F.11: Honolulu Distribution of Population and Jobs by Housing Type

Housing Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Single-Family	293	18.7%	111,000	12.5%	9,000	2.5%
Single-Family	429	27.3%	187,000	21.0%	23,000	6.5%
Mixed Single-Family	398	25.4%	226,000	25.4%	42,000	11.6%
Multifamily: Small Building	118	7.5%	59,000	6.6%	35,000	9.6%
Multifamily: Large Building	100	6.4%	174,000	19.5%	190,000	52.5%
Multifamily: Mixed Types	168	10.7%	133,000	15.0%	43,000	11.8%
Mobile Homes	0	0%	0	0%	0	0%
Mixed Housing Types	0	0%	0	0%	0	0%
Few Housing Units	64	4.1%	1,000	0.1%	20,000	5.4%

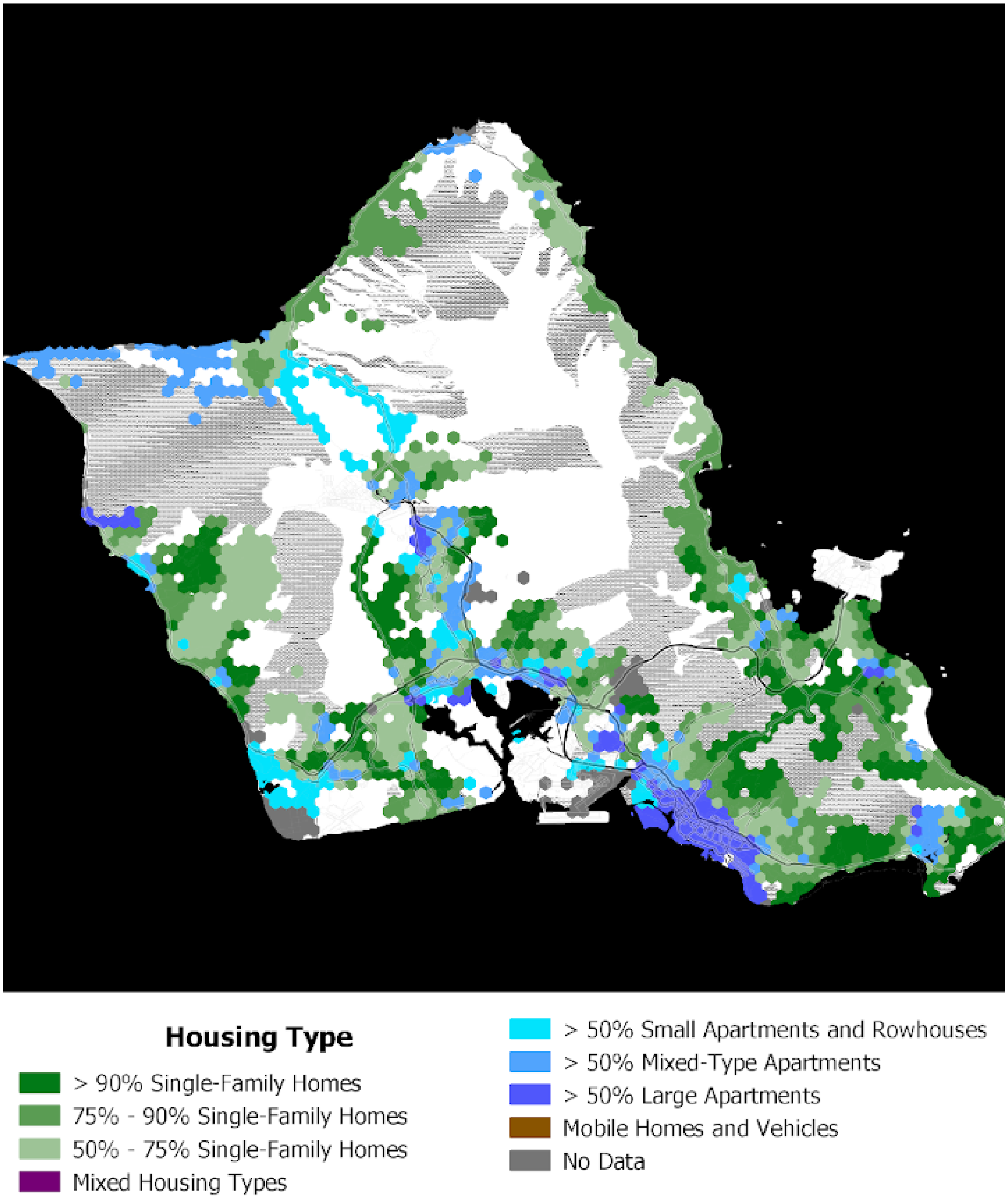

Figure F.11: Urban Honolulu, HI MSA housing type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table F.12: Houston Distribution of Population and Jobs by Housing Type

Housing Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Single-Family	5,538	23.5%	1,895,000	28.4%	315,000	12.1%
Single-Family	6,001	25.5%	1,470,000	22.0%	380,000	14.6%
Mixed Single-Family	7,032	29.8%	1,489,000	22.3%	517,000	19.8%
Multifamily: Small Building	53	0.2%	42,000	0.6%	29,000	1.1%
Multifamily: Large Building	996	4.2%	745,000	11.1%	847,000	32.5%
Multifamily: Mixed Types	1,077	4.6%	730,000	10.9%	398,000	15.3%
Mobile Homes	2,171	9.2%	186,000	2.8%	44,000	1.7%
Mixed Housing Types	525	2.2%	117,000	1.7%	69,000	2.6%
Few Housing Units	180	0.8%	8,000	0.1%	7,000	0.3%

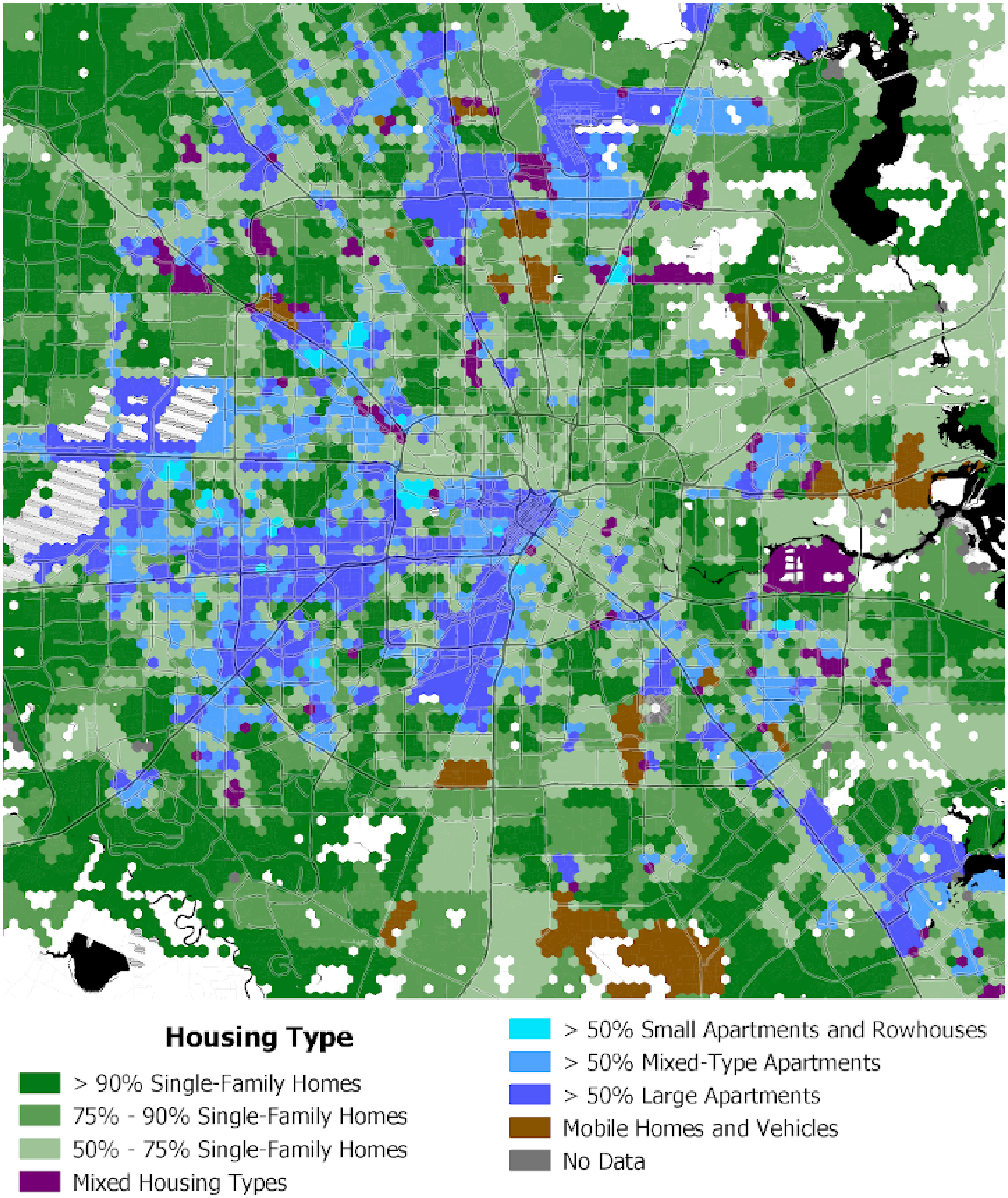

Figure F.12: Houston-The Woodlands-Sugar Land, TX MSA housing type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table F.13: Los Angeles Distribution of Population and Jobs by Housing Type

Housing Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Single-Family	3,730	26.3%	1,696,000	12.8%	364,000	6.5%
Single-Family	2,655	18.7%	1,861,000	14.1%	587,000	10.5%
Mixed Single-Family	3,533	24.9%	3,560,000	26.9%	1,199,000	21.4%
Multifamily: Small Building	673	4.8%	988,000	7.5%	415,000	7.4%
Multifamily: Large Building	880	6.2%	1,746,000	13.2%	1,472,000	26.3%
Multifamily: Mixed Types	1,959	13.8%	2,948,000	22.3%	1,231,000	22.0%
Mobile Homes	189	1.3%	81,000	0.6%	72,000	1.3%
Mixed Housing Types	280	2.0%	343,000	2.6%	118,000	2.1%
Few Housing Units	269	1.9%	8,000	0.1%	141,000	2.5%

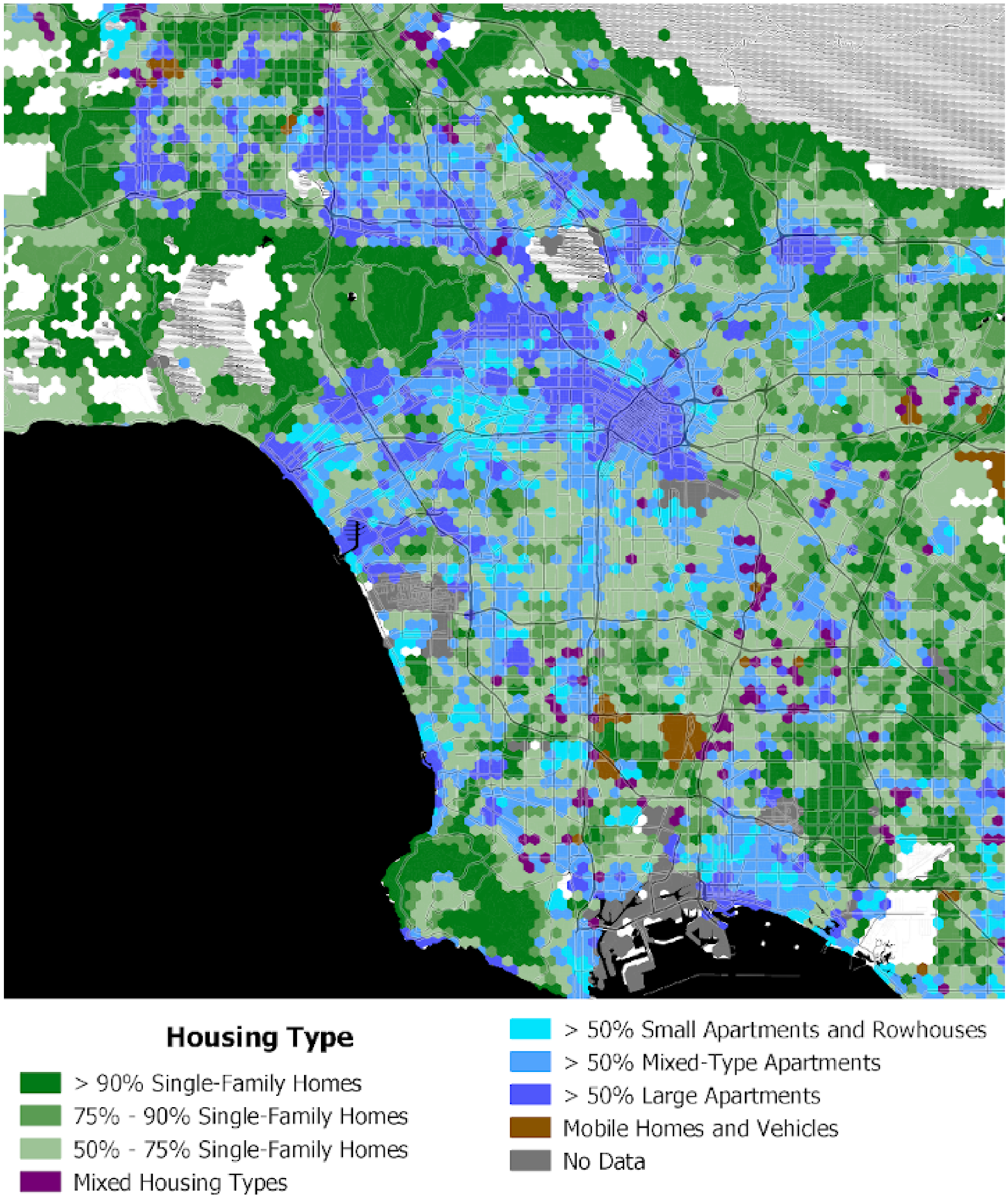

Figure F.13: Los Angeles-Long Beach-Anaheim, CA MSA housing type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table F.14: Miami Distribution of Population and Jobs by Housing Type

Housing Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Single-Family	2,562	26.2%	858,000	14.2%	167,000	7.3%
Single-Family	1,464	15.0%	830,000	13.7%	197,000	8.6%
Mixed Single-Family	1,911	19.5%	1,287,000	21.3%	439,000	19.1%
Multifamily: Small Building	783	8.0%	500,000	8.3%	172,000	7.5%
Multifamily: Large Building	1026	10.5%	1,091,000	18.0%	661,000	28.8%
Multifamily: Mixed Types	1526	15.6%	1,301,000	21.5%	552,000	24.1%
Mobile Homes	171	1.7%	58,000	1.0%	23,000	1.0%
Mixed Housing Types	155	1.6%	120,000	2.0%	43,000	1.9%
Few Housing Units	181	1.9%	6,000	0.1%	42,000	1.8%

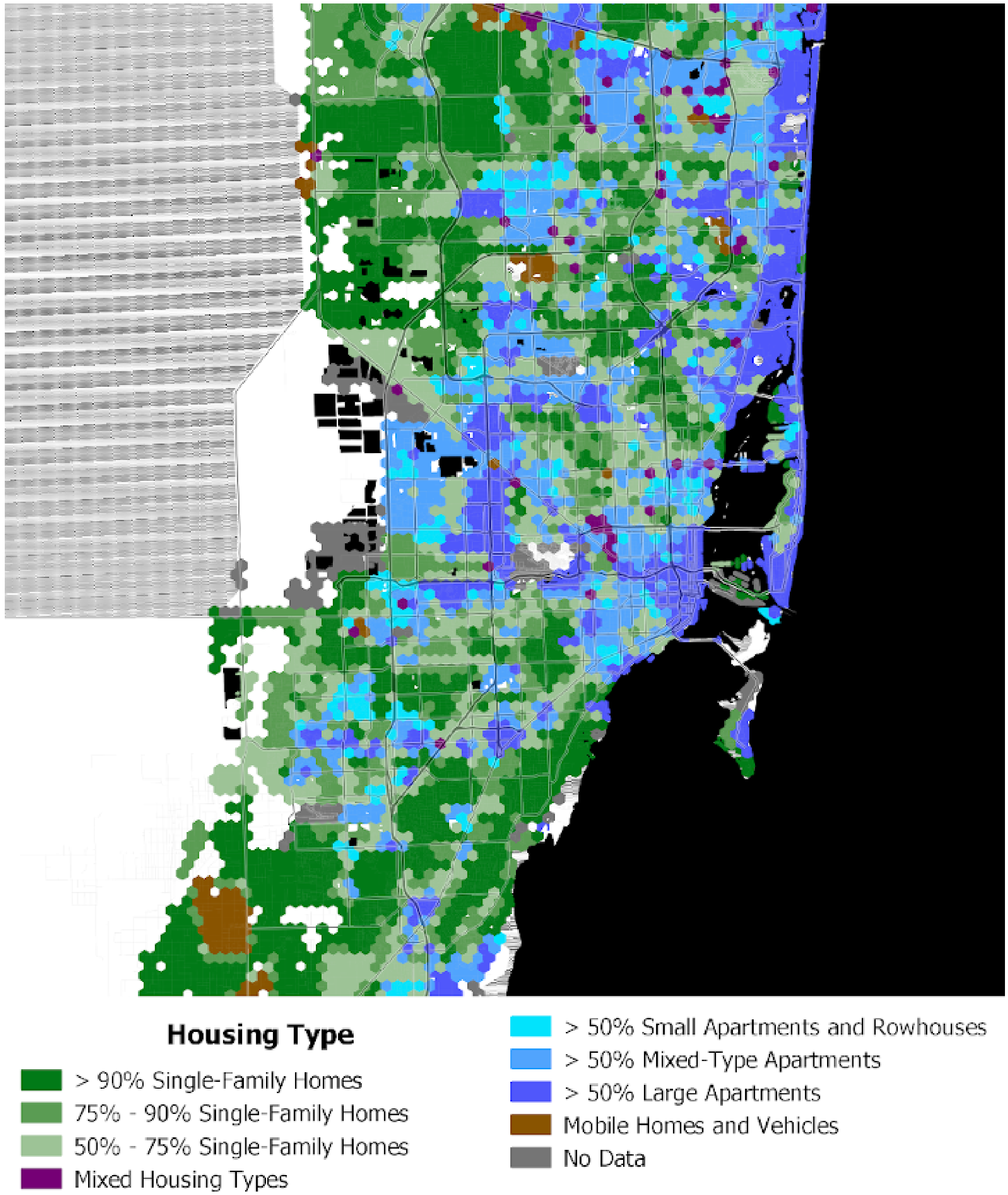

Figure F.14: Miami-Fort Lauderdale-Pompano Beach, FL MSA housing type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table F.15: Minneapolis Distribution of Population and Jobs by Housing Type

Housing Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Single-Family	7,833	40.6%	589,000	17.2%	87,000	5.1%
Single-Family	4,865	25.2%	762,000	22.2%	186,000	11.0%
Mixed Single-Family	4,512	23.4%	1096,000	31.9%	428,000	25.4%
Multifamily: Small Building	214	1.1%	87,000	2.5%	59,000	3.5%
Multifamily: Large Building	526	2.7%	346,000	10.1%	570,000	33.7%
Multifamily: Mixed Types	951	4.9%	473,000	13.8%	323,000	19.1%
Mobile Homes	76	0.4%	14,000	0.4%	5,000	0.3%
Mixed Housing Types	238	1.2%	64,000	1.9%	30,000	1.7%
Few Housing Units	86	0.4%	1,000	0%	3,000	0.2%

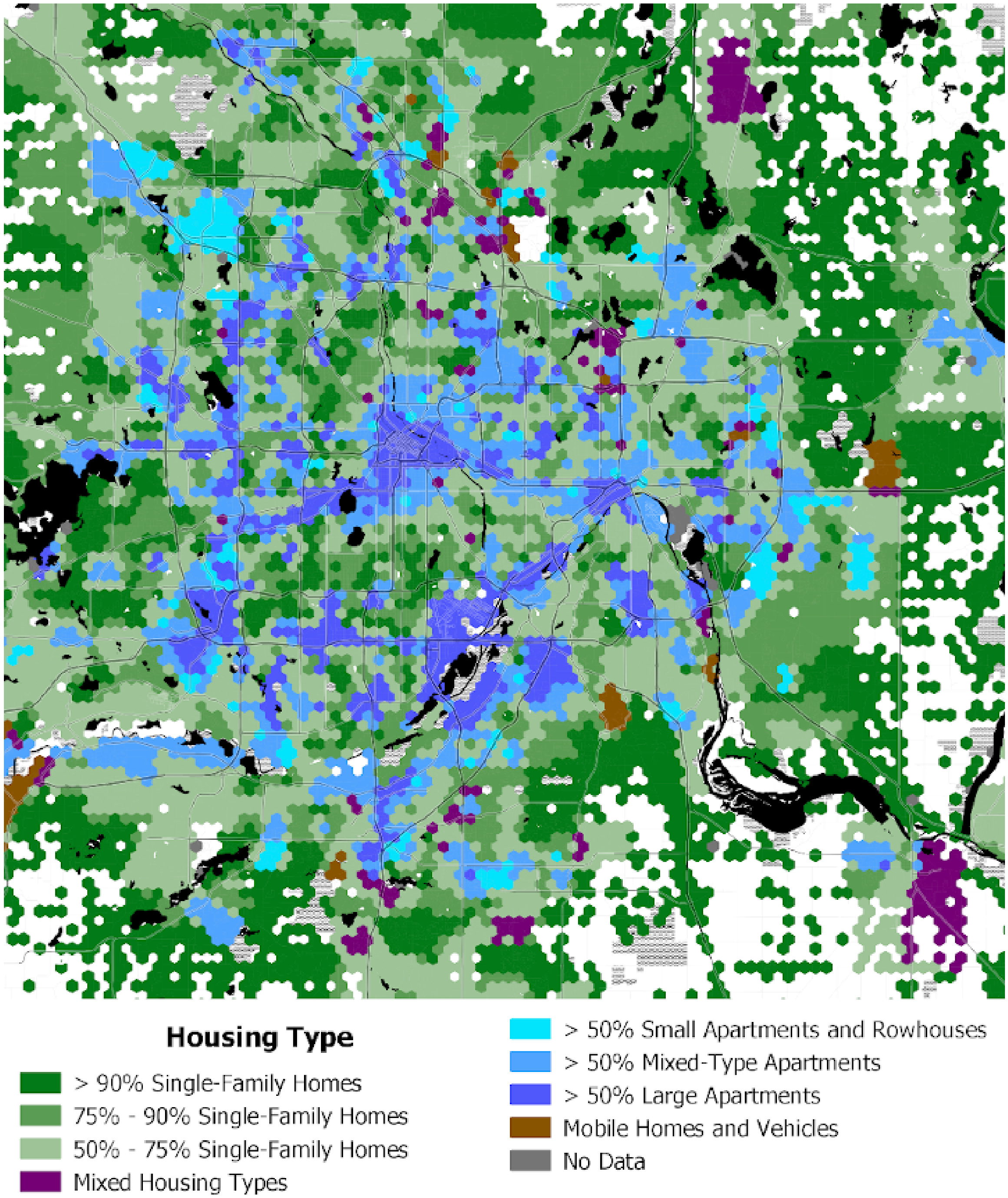

Figure F.15: Minneapolis-St. Paul-Bloomington, MN-WI MSA housing type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table F.16: New York Distribution of Population and Jobs by Housing Type

Housing Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Single-Family	13,265	42.1%	2,871,000	14.9%	735,000	9.1%
Single-Family	6,421	20.4%	1,998,000	10.4%	711,000	8.8%
Mixed Single-Family	5,311	16.9%	2,336,000	12.1%	1,037,000	12.9%
Multifamily: Small Building	2,496	7.9%	5,004,000	26.0%	1,158,000	14.4%
Multifamily: Large Building	1,184	3.8%	5,129,000	26.6%	3,396,000	42.3%
Multifamily: Mixed Types	2,240	7.1%	1,859,000	9.7%	866,000	10.8%
Mobile Homes	200	0.6%	17,000	0.1%	12,000	0.1%
Mixed Housing Types	88	0.3%	25,000	0.1%	16,000	0.2%
Few Housing Units	312	1.0%	19,000	0.1%	102,000	1.3%

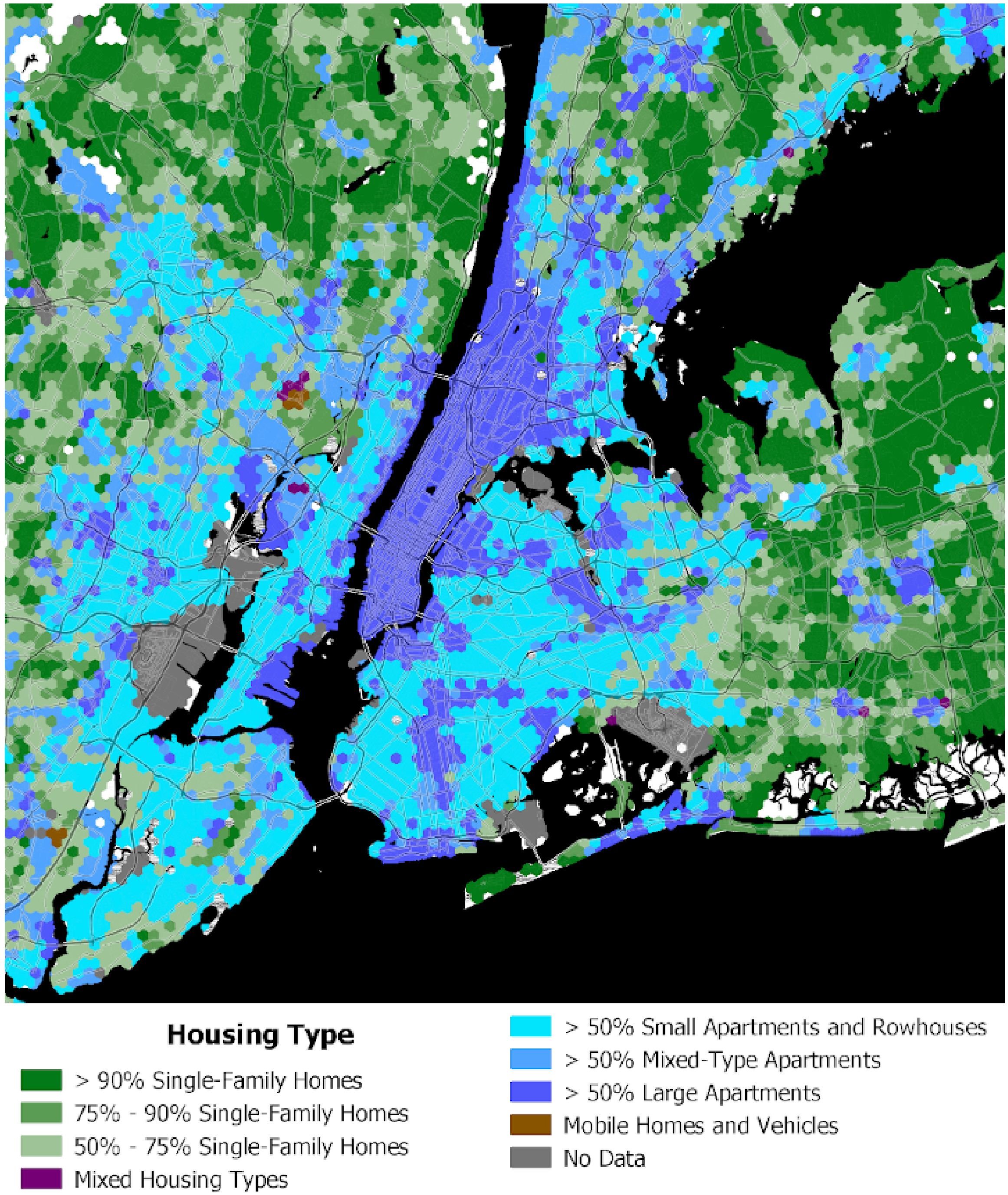

Figure F.16: New York-Newark-Jersey City, NY-NJ-PA MSA housing type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table F.17: Philadelphia Distribution of Population and Jobs by Housing Type

Housing Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Single-Family	6,058	30.3%	845,000	14.1%	217,000	8.4%
Single-Family	4,788	24.0%	876,000	14.6%	315,000	12.2%
Mixed Single-Family	4,867	24.4%	1,198,000	19.9%	595,000	23.1%
Multifamily: Small Building	1,899	9.5%	2,192,000	36.5%	617,000	23.9%
Multifamily: Large Building	268	1.3%	193,000	3.2%	396,000	15.3%
Multifamily: Mixed Types	1467	7.3%	630,000	10.5%	370,000	14.3%
Mobile Homes	187	0.9%	22,000	0.4%	7,000	0.3%
Mixed Housing Types	155	0.8%	51,000	0.8%	20,000	0.8%
Few Housing Units	281	1.4%	5,000	0.1%	47,000	1.8%

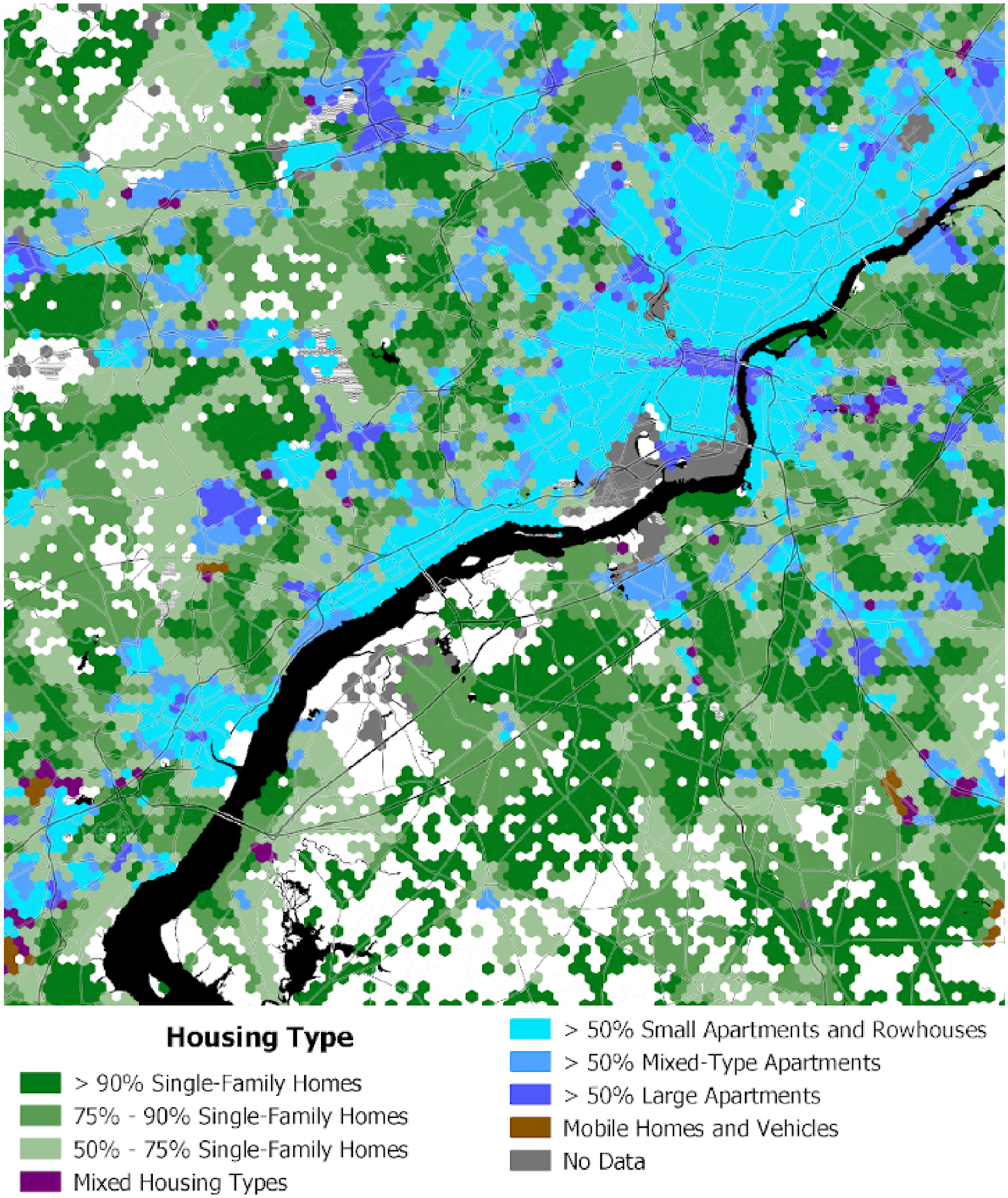

Figure F.17: Philadelphia-Camden-Wilmington, PA-NJ-DE-MD MSA housing type neighborhood map. Philadelphia is just right of center and Wilmington is at the lower left. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table F.18: Phoenix Distribution of Population and Jobs by Housing Type

Housing Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Single-Family	5,224	40.0%	1,704,000	36.9%	274,000	15.1%
Single-Family	2,672	20.5%	779,000	16.9%	224,000	12.4%
Mixed Single-Family	2,523	19.3%	951,000	20.6%	360,000	19.9%
Multifamily: Small Building	121	0.9%	87,000	1.9%	64,000	3.6%
Multifamily: Large Building	322	2.5%	182,000	3.9%	318,000	17.5%
Multifamily: Mixed Types	806	6.2%	618,000	13.4%	434,000	24.0%
Mobile Homes	900	6.9%	158,000	3.4%	47,000	2.6%
Mixed Housing Types	188	1.4%	117,000	2.5%	49,000	2.7%
Few Housing Units	305	2.3%	21,000	0.5%	40,000	2.2%

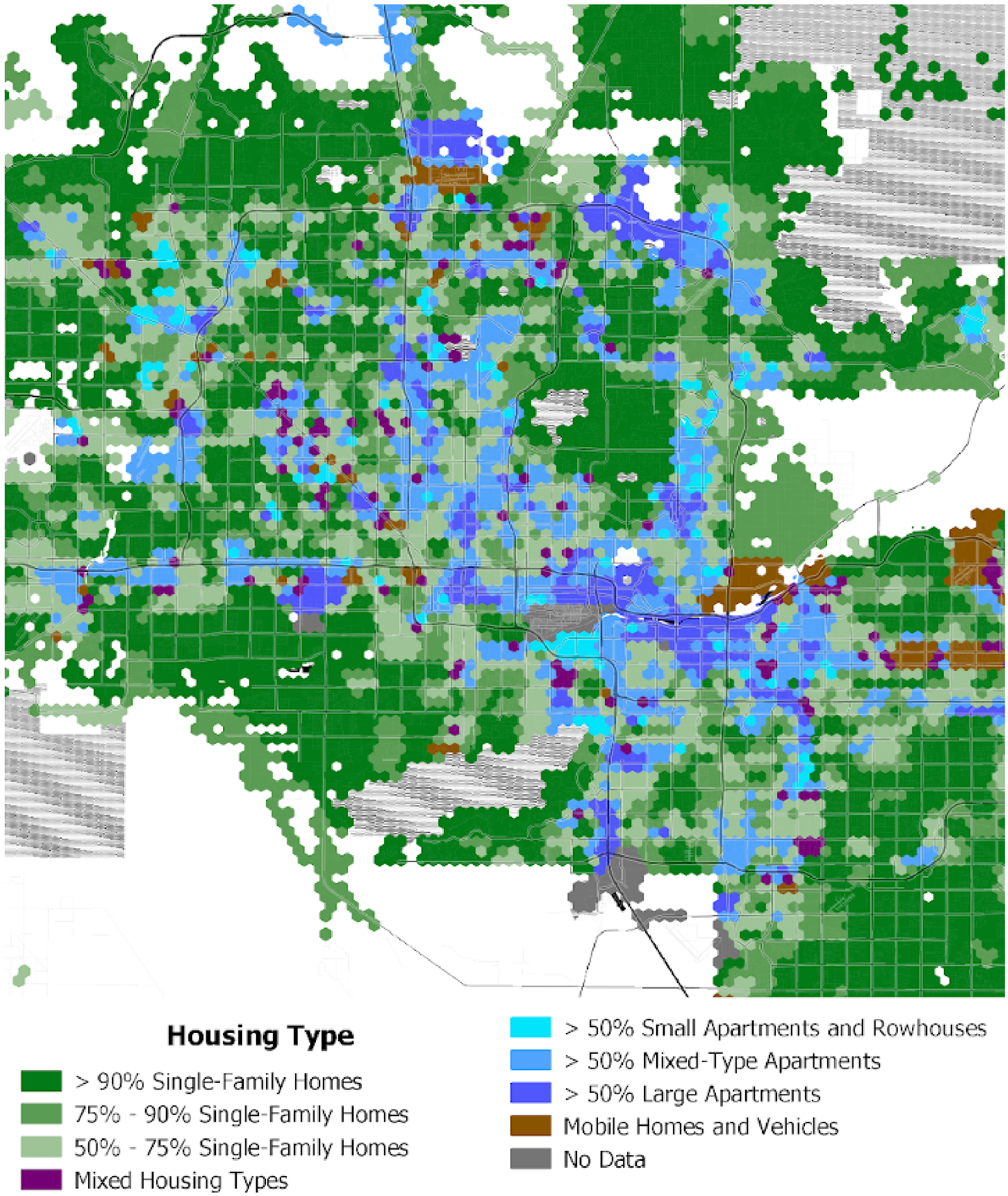

Figure F.18: Phoenix-Mesa-Chandler, AZ MSA housing type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table F.19: Pittsburgh Distribution of Population and Jobs by Housing Type

Housing Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Single-Family	3,673	21.2%	390,000	17.2%	94,000	9.0%
Single-Family	7,623	44.0%	710,000	31.3%	223,000	21.3%
Mixed Single-Family	4,948	28.6%	789,000	34.7%	346,000	33.1%
Multifamily: Small Building	159	0.9%	91,000	4.0%	79,000	7.5%
Multifamily: Large Building	50	0.3%	40,000	1.7%	136,000	13%
Multifamily: Mixed Types	484	2.8%	227,000	10.0%	152,000	14.5%
Mobile Homes	175	1.0%	8,000	0.4%	2,000	0.2%
Mixed Housing Types	161	0.9%	16,000	0.7%	11,000	1.1%
Few Housing Units	41	0.2%	1,000	0.03%	2,000	0.2%

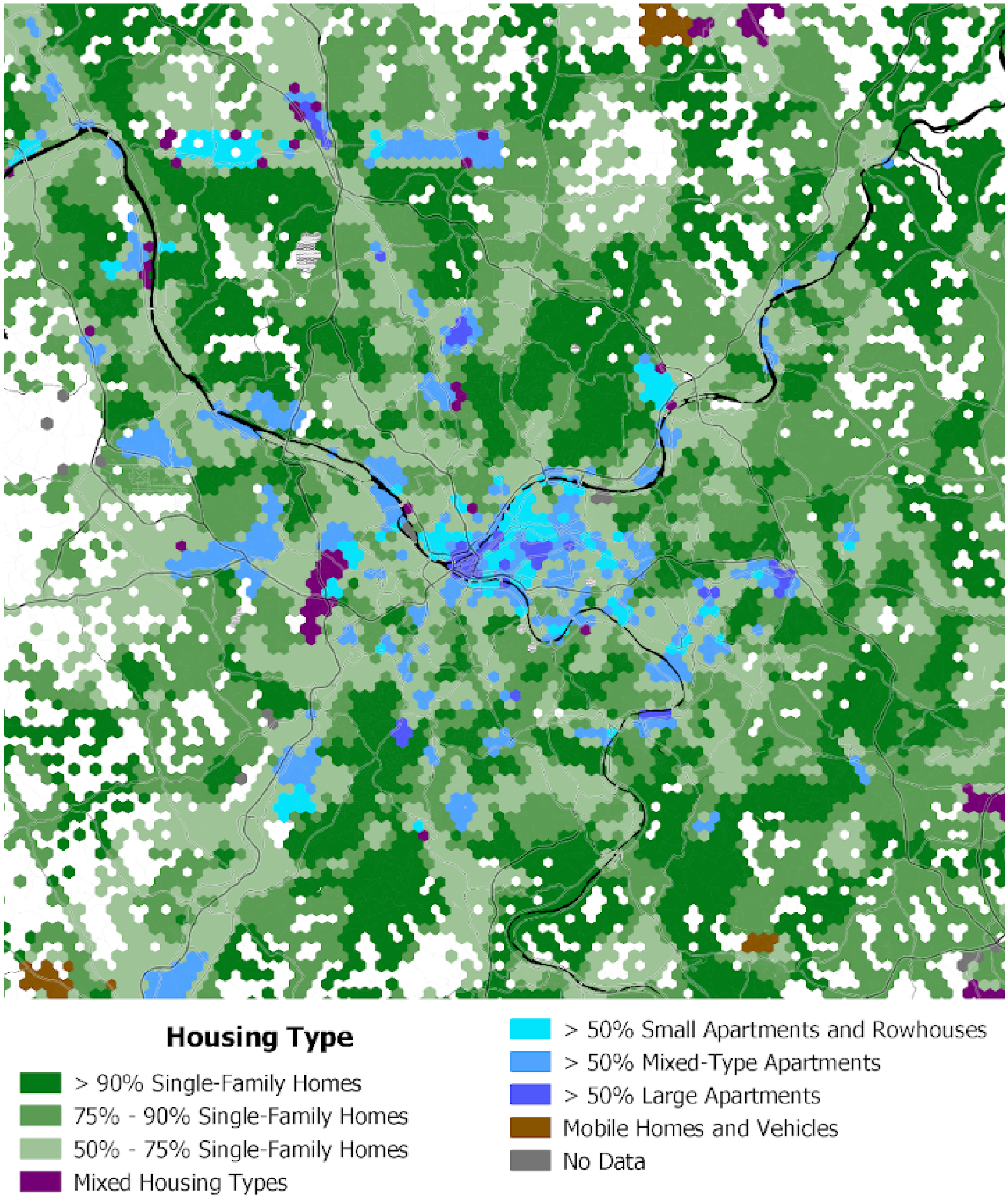

Figure F.19: Pittsburgh, PA MSA housing type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table F.20: Portland Distribution of Population and Jobs by Housing Type

Housing Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Single-Family	2,092	21.4%	379,000	16.0%	49,000	4.8%
Single-Family	4,269	43.6%	597,000	25.2%	154,000	14.9%
Mixed Single-Family	2,298	23.5%	748,000	31.5%	241,000	23.3%
Multifamily: Small Building	37	0.4%	38,000	1.6%	21,000	2.0%
Multifamily: Large Building	140	1.4%	103,000	4.3%	240,000	23.2%
Multifamily: Mixed Types	497	5.1%	404,000	17.0%	266,000	25.7%
Mobile Homes	198	2.0%	14,000	0.6%	8,000	0.8%
Mixed Housing Types	191	2.0%	90,000	3.8%	41,000	4.0%
Few Housing Units	70	0.7%	1,000	0.03%	13,000	1.2%

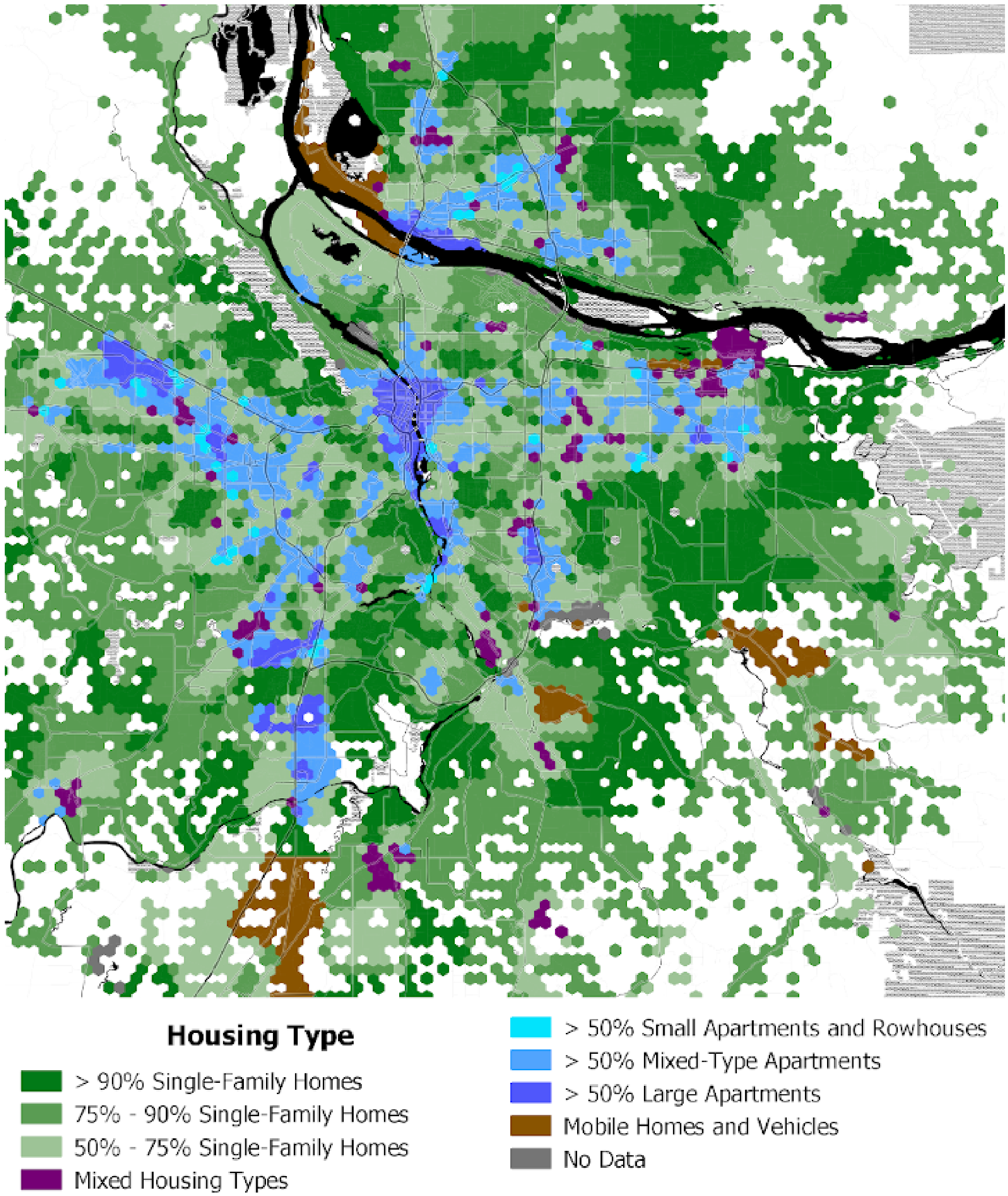

Figure F.20: Portland-Vancouver-Hillsboro, OR-WA MSA housing type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table F.21: Riverside Distribution of Population and Jobs by Housing Type

Housing Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Single-Family	4,788	33.9%	1,506,000	34.0%	211,000	17.5%
Single-Family	3,457	24.5%	918,000	20.8%	208,000	17.3%
Mixed Single-Family	3,041	21.5%	1086,000	24.6%	244,000	20.3%
Multifamily: Small Building	233	1.6%	98,000	2.2%	99,000	8.2%
Multifamily: Large Building	109	0.8%	50,000	1.1%	85,000	7.0%
Multifamily: Mixed Types	703	5.0%	433,000	9.8%	221,000	18.3%
Mobile Homes	1,332	9.4%	160,000	3.6%	42,000	3.5%
Mixed Housing Types	384	2.7%	164,000	3.7%	90,000	7.5%
Few Housing Units	85	0.6%	7,000	0.2%	5,000	0.4%

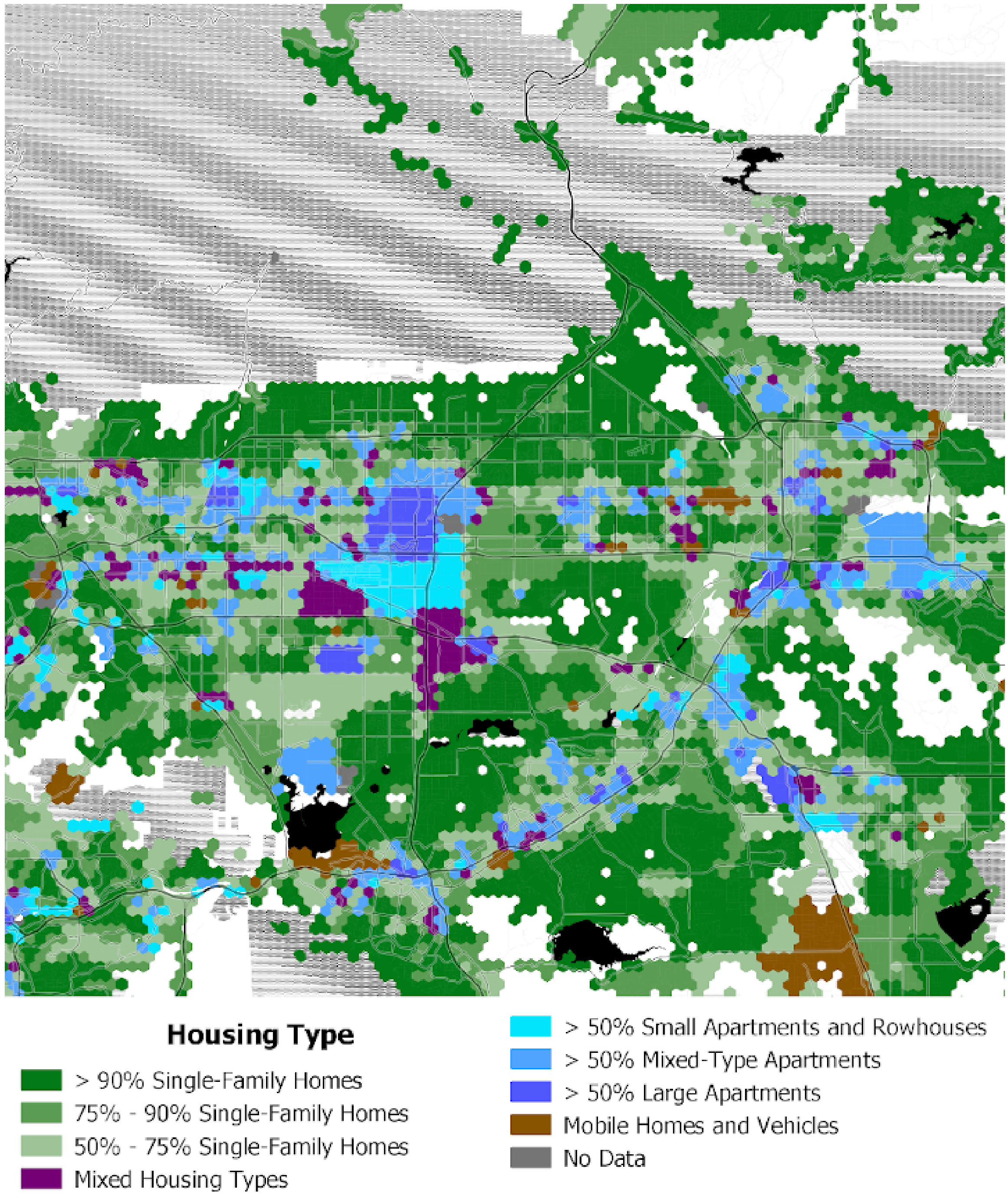

Figure F.21: Riverside-San Bernardino-Ontario, CA MSA housing type neighborhood map. Ontario is to the center left, San Bernardino is to the center right, and Riverside is to the lower center. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table F.22: Sacramento Distribution of Population and Jobs by Housing Type

Housing Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Single-Family	2,759	38.6%	608,000	26.9%	95,000	12.7%
Single-Family	2,106	29.5%	587,000	25.9%	121,000	16.3%
Mixed Single-Family	1,380	19.3%	589,000	26.0%	191,000	25.7%
Multifamily: Small Building	95	1.3%	64,000	2.8%	46,000	6.2%
Multifamily: Large Building	74	1.0%	34,000	1.5%	60,000	8.0%
Multifamily: Mixed Types	367	5.1%	304,000	13.4%	172,000	23.1%
Mobile Homes	87	1.2%	10,000	0.5%	28,000	3.8%
Mixed Housing Types	167	2.3%	66,000	2.9%	21,000	2.9%
Few Housing Units	106	1.5%	0	0%	10,000	1.4%

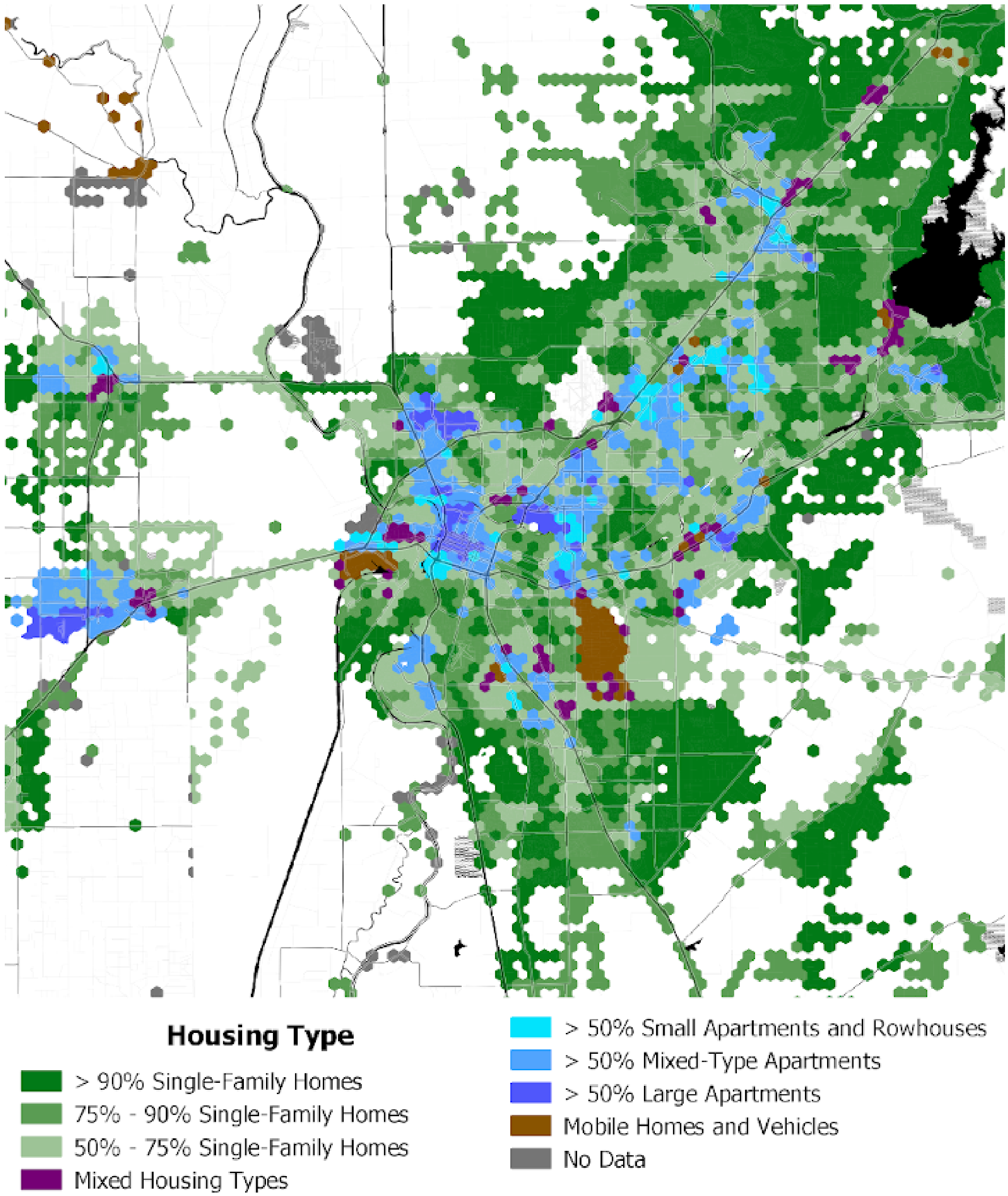

Figure F.22: Sacramento-Roseville-Folsom, CA MSA housing type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table F.23: Salt Lake City Distribution of Population and Jobs by Housing Type

Housing Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Single-Family	777	29.2%	332,000	28.2%	58,000	9.8%
Single-Family	703	26.5%	273,000	23.2%	68,000	11.4%
Mixed Single-Family	638	24.0%	286,000	24.4%	115,000	19.3%
Multifamily: Small Building	15	0.6%	11,000	1.0%	7,000	1.2%
Multifamily: Large Building	86	3.2%	50,000	4.2%	123,000	20.8%
Multifamily: Mixed Types	344	12.9%	196,000	16.7%	198,000	33.4%
Mobile Homes	8	0.3%	8,000	0.7%	1,000	0.2%
Mixed Housing Types	24	0.9%	17,000	1.5%	9,000	1.5%
Few Housing Units	62	2.3%	1,000	0.1%	14,000	2.4%

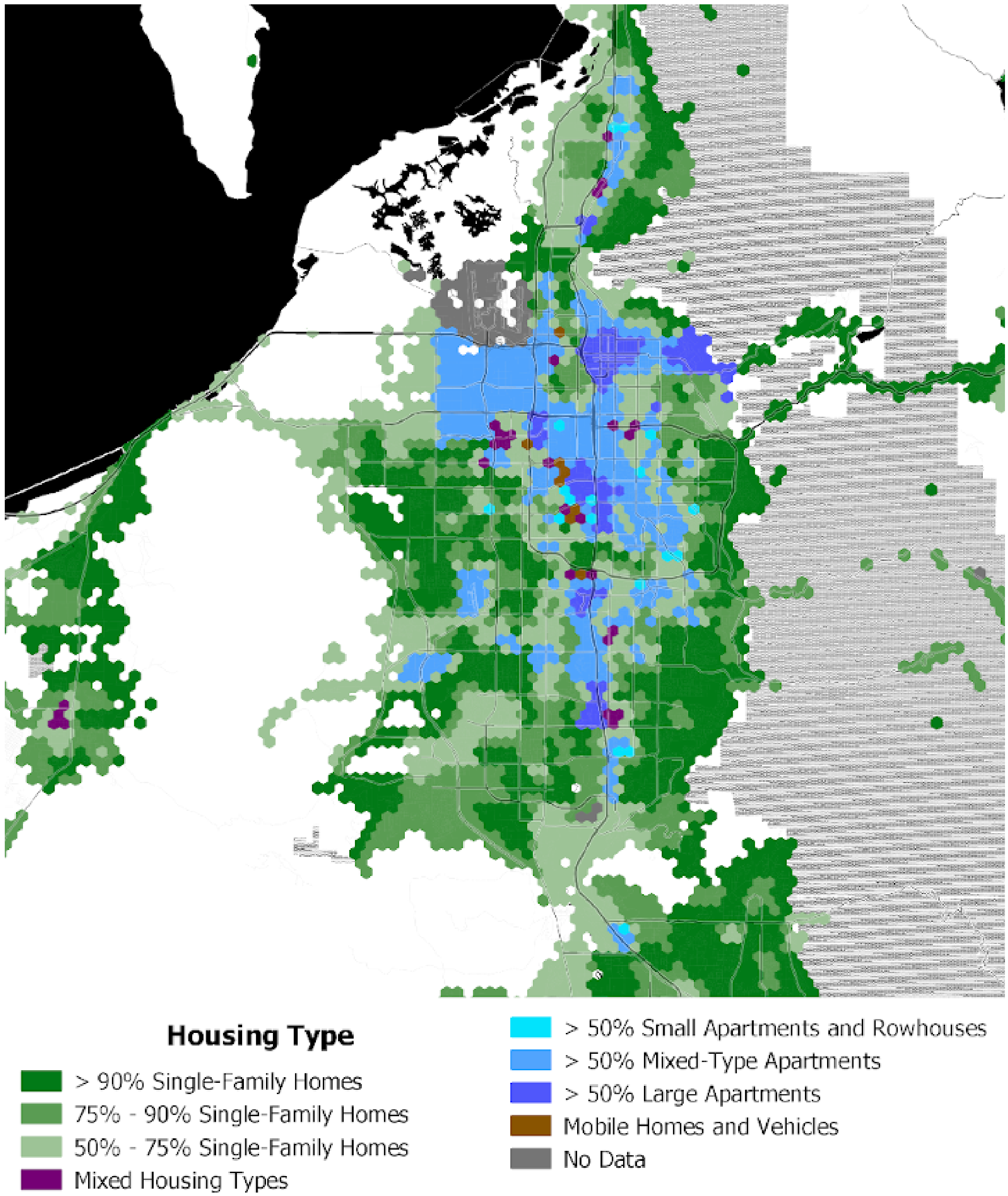

Figure F.23: Salt Lake City, UT MSA housing type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table F.24: San Diego Distribution of Population and Jobs by Housing Type

Housing Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Single-Family	1,795	26.3%	417,000	13.0%	55,000	4.6%
Single-Family	1,840	26.9%	464,000	14.5%	122,000	10.2%
Mixed Single-Family	1,618	23.7%	900,000	28.1%	288,000	23.9%
Multifamily: Small Building	221	3.2%	229,000	7.2%	97,000	8.1%
Multifamily: Large Building	204	3.0%	249,000	7.8%	221,000	18.3%
Multifamily: Mixed Types	732	10.7%	775,000	24.2%	349,000	29.0%
Mobile Homes	157	2.3%	38,000	1.2%	14,000	1.1%
Mixed Housing Types	157	2.3%	123,000	3.8%	40,000	3.4%
Few Housing Units	108	1.6%	4,000	0.1%	18,000	1.5%

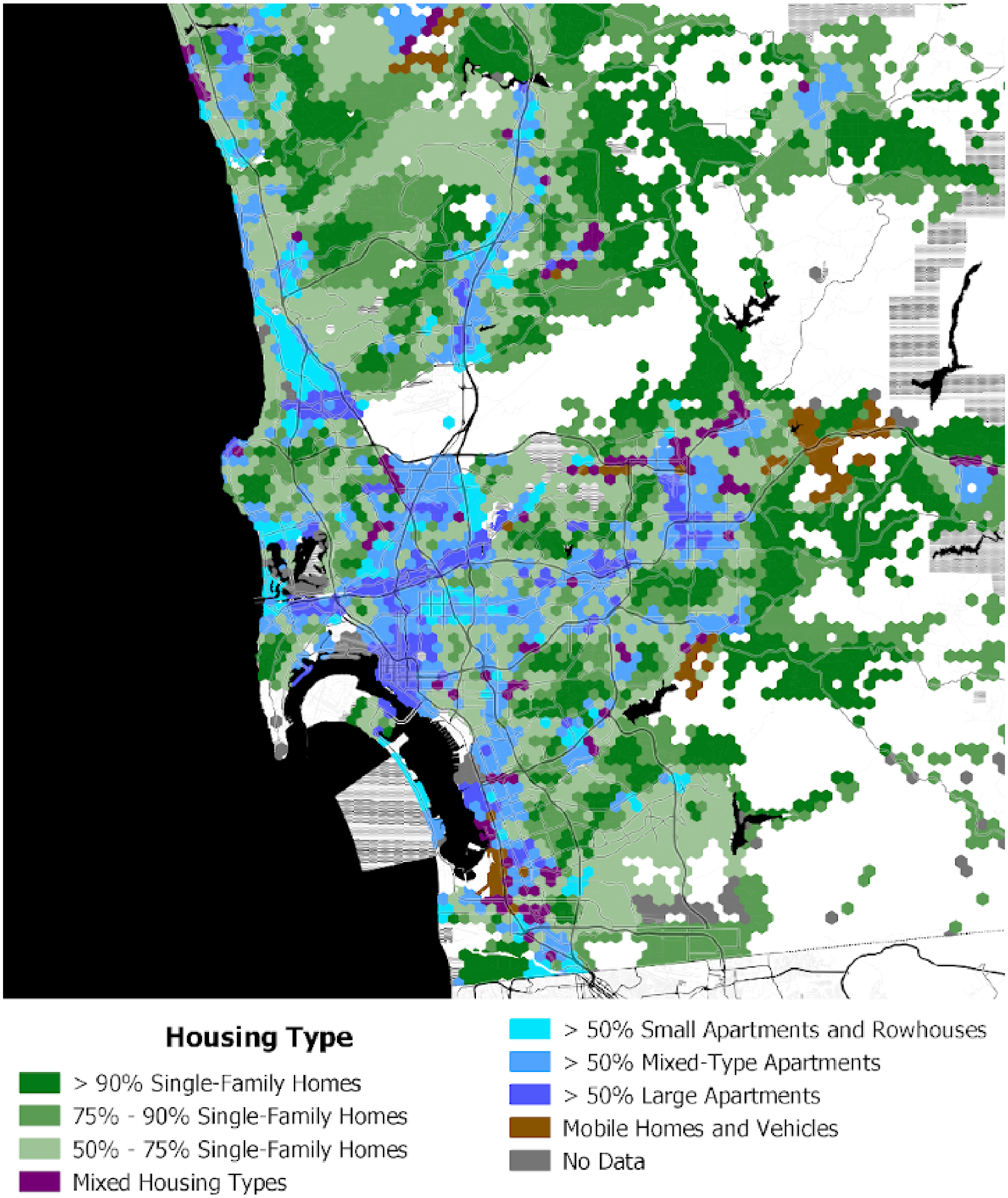

Figure F.24: San Diego-Chula Vista-Carlsbad, CA MSA housing type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table F.25: San Francisco Distribution of Population and Jobs by Housing Type

Housing Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Single-Family	2,134	30.4%	693,000	14.9%	139,000	6.5%
Single-Family	1,663	23.7%	756,000	16.3%	187,000	8.7%
Mixed Single-Family	1,479	21.0%	1,106,000	23.8%	358,000	16.7%
Multifamily: Small Building	380	5.4%	644,000	13.9%	228,000	10.7%
Multifamily: Large Building	264	3.8%	472,000	10.2%	714,000	33.4%
Multifamily: Mixed Types	827	11.8%	902,000	19.4%	431,000	20.1%
Mobile Homes	78	1.1%	20,000	0.4%	31,000	1.5%
Mixed Housing Types	58	0.8%	51,000	1.1%	19,000	0.9%
Few Housing Units	145	2.1%	3,000	0.1%	31,000	1.5%

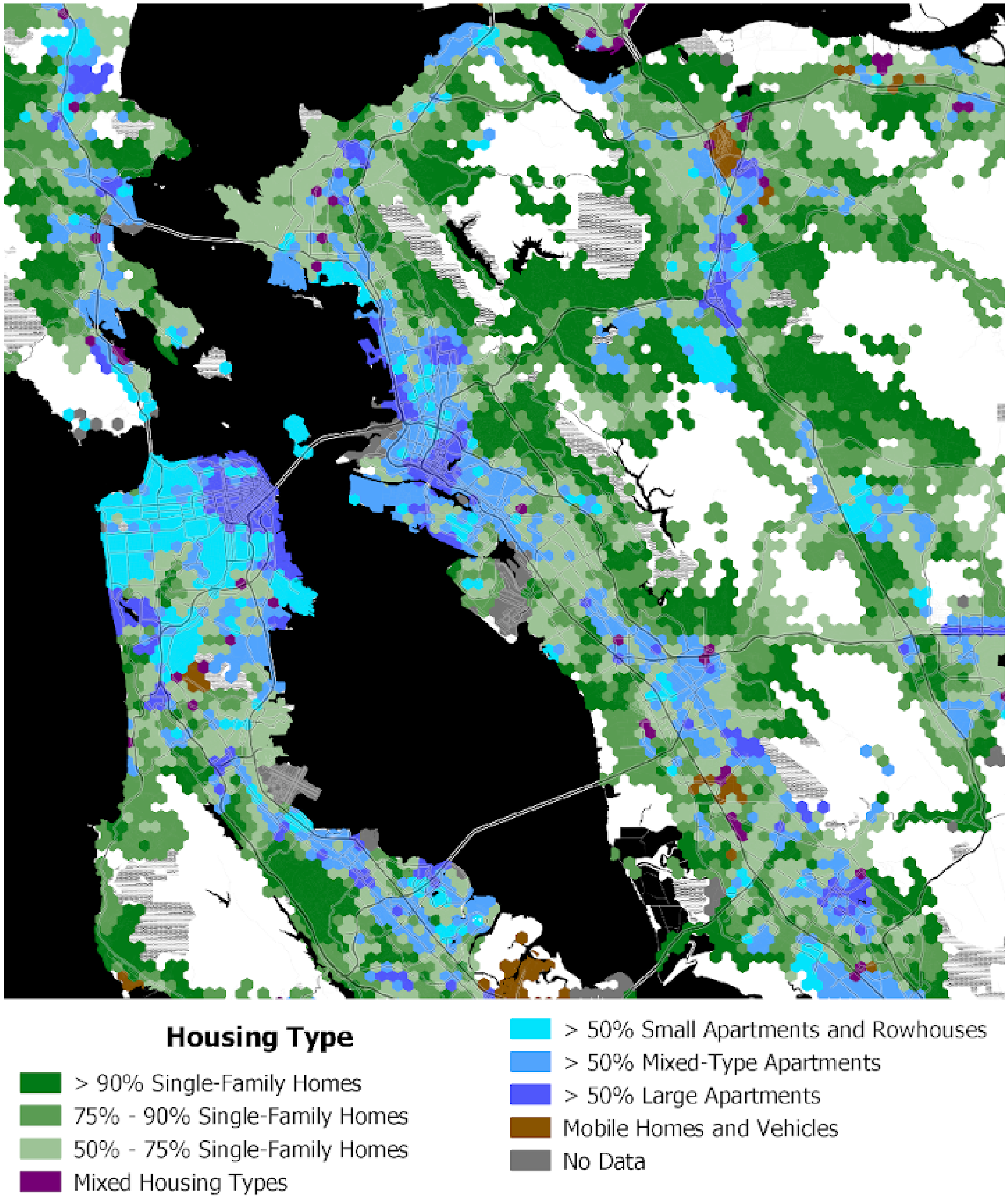

Figure F.25: San Francisco-Oakland-Berkeley, CA MSA housing type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table F.26: San Jose Distribution of Population and Jobs by Housing Type

Housing Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Single-Family	887	28.7%	362,000	18.3%	78,000	7.9%
Single-Family	804	26.0%	306,000	15.5%	71,000	7.1%
Mixed Single-Family	663	21.5%	453,000	23.0%	166,000	16.7%
Multifamily: Small Building	93	3.0%	93,000	4.7%	57,000	5.7%
Multifamily: Large Building	140	4.5%	167,000	8.5%	252,000	25.2%
Multifamily: Mixed Types	361	11.7%	499,000	25.3%	282,000	28.3%
Mobile Homes	52	1.7%	27,000	1.4%	53,000	5.3%
Mixed Housing Types	70	2.3%	68,000	3.4%	37,000	3.7%
Few Housing Units	17	0.6%	0	0%	1,000	0.07%

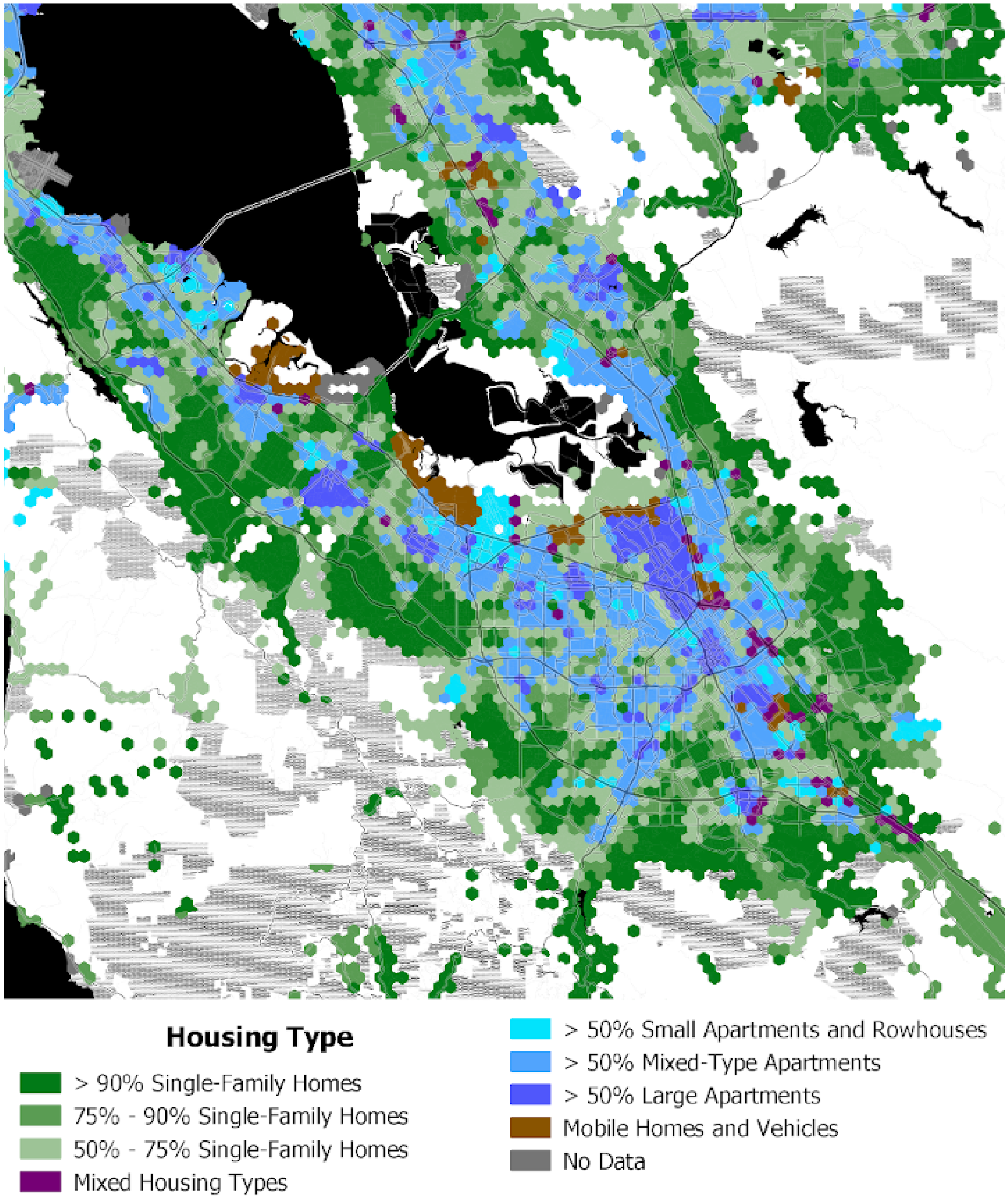

Figure F.26: San Jose-Sunnyvale-Santa Clara, CA MSA housing type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table F.27: Seattle Distribution of Population and Jobs by Housing Type

Housing Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Single-Family	3,321	28.4%	749,000	19.9%	120,000	7.1%
Single-Family	3,974	33.9%	863,000	22.9%	150,000	8.8%
Mixed Single-Family	2,707	23.1%	917,000	24.4%	300,000	17.7%
Multifamily: Small Building	114	1.0%	68,000	1.8%	31,000	1.8%
Multifamily: Large Building	317	2.7%	356,000	9.5%	598,000	35.3%
Multifamily: Mixed Types	922	7.9%	705,000	18.7%	411,000	24.2%
Mobile Homes	100	0.9%	17,000	0.5%	39,000	2.3%
Mixed Housing Types	196	1.7%	88,000	2.3%	43,000	2.5%
Few Housing Units	61	0.5%	1,000	0.02%	5,000	0.3%

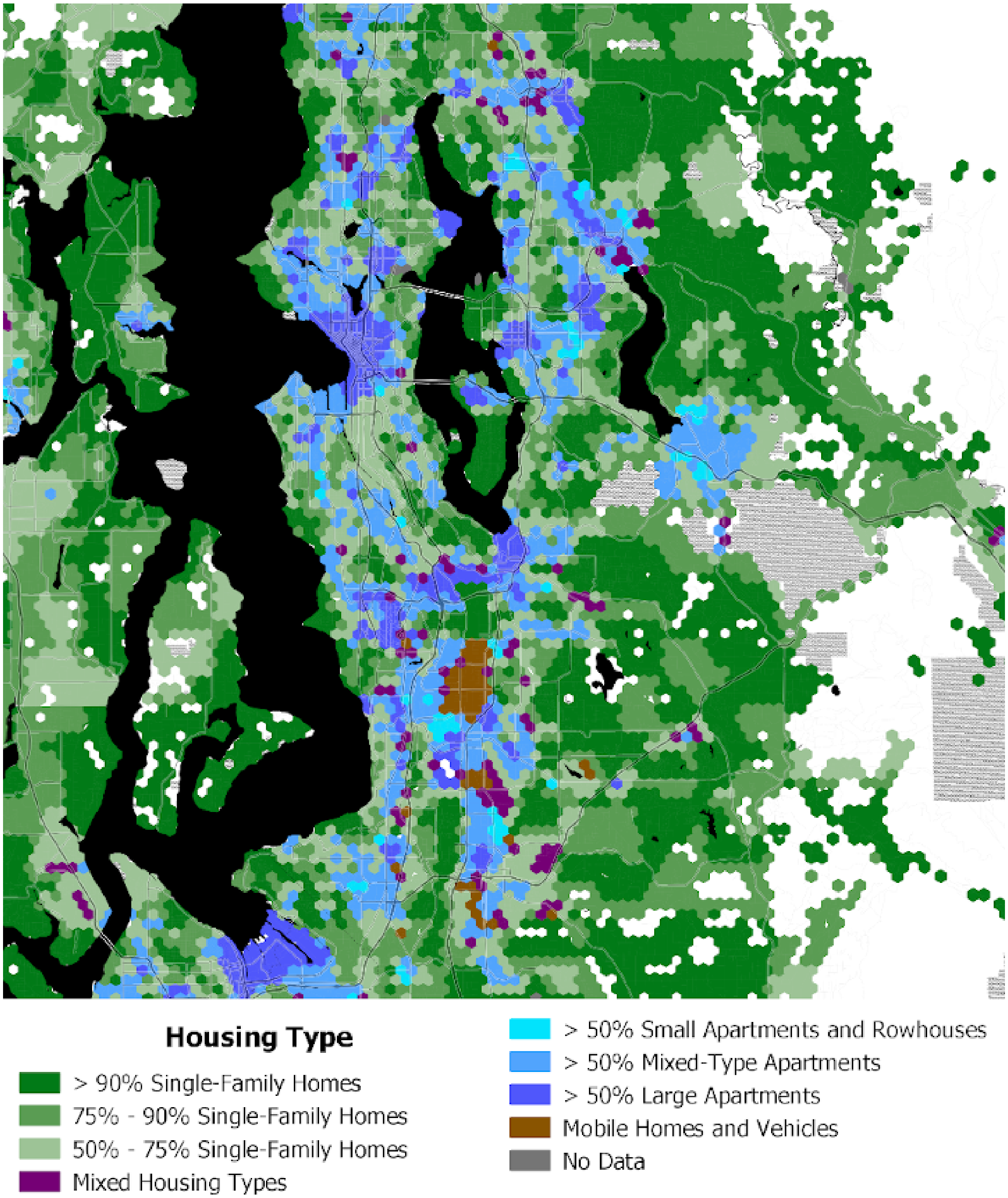

Figure F.27: Seattle-Tacoma-Bellevue, WA MSA housing type neighborhood map. Seattle is in the upper center and Tacoma is to the lower left. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table F.28: St. Louis Distribution of Population and Jobs by Housing Type

Housing Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Single-Family	5,544	33.4%	674,000	25.1%	184,000	15%
Single-Family	6,028	36.3%	839,000	31.2%	265,000	21.7%
Mixed Single-Family	3,820	23.0%	741,000	27.6%	362,000	29.6%
Multifamily: Small Building	263	1.6%	128,000	4.8%	62,000	5.1%
Multifamily: Large Building	59	0.4%	47,000	1.8%	123,000	10.0%
Multifamily: Mixed Types	482	2.9%	215,000	8.0%	203,000	16.6%
Mobile Homes	192	1.2%	17,000	0.6%	11,000	0.9%
Mixed Housing Types	156	0.9%	25,000	0.9%	13,000	1.0%
Few Housing Units	43	0.3%	0	0%	1,000	0.06%

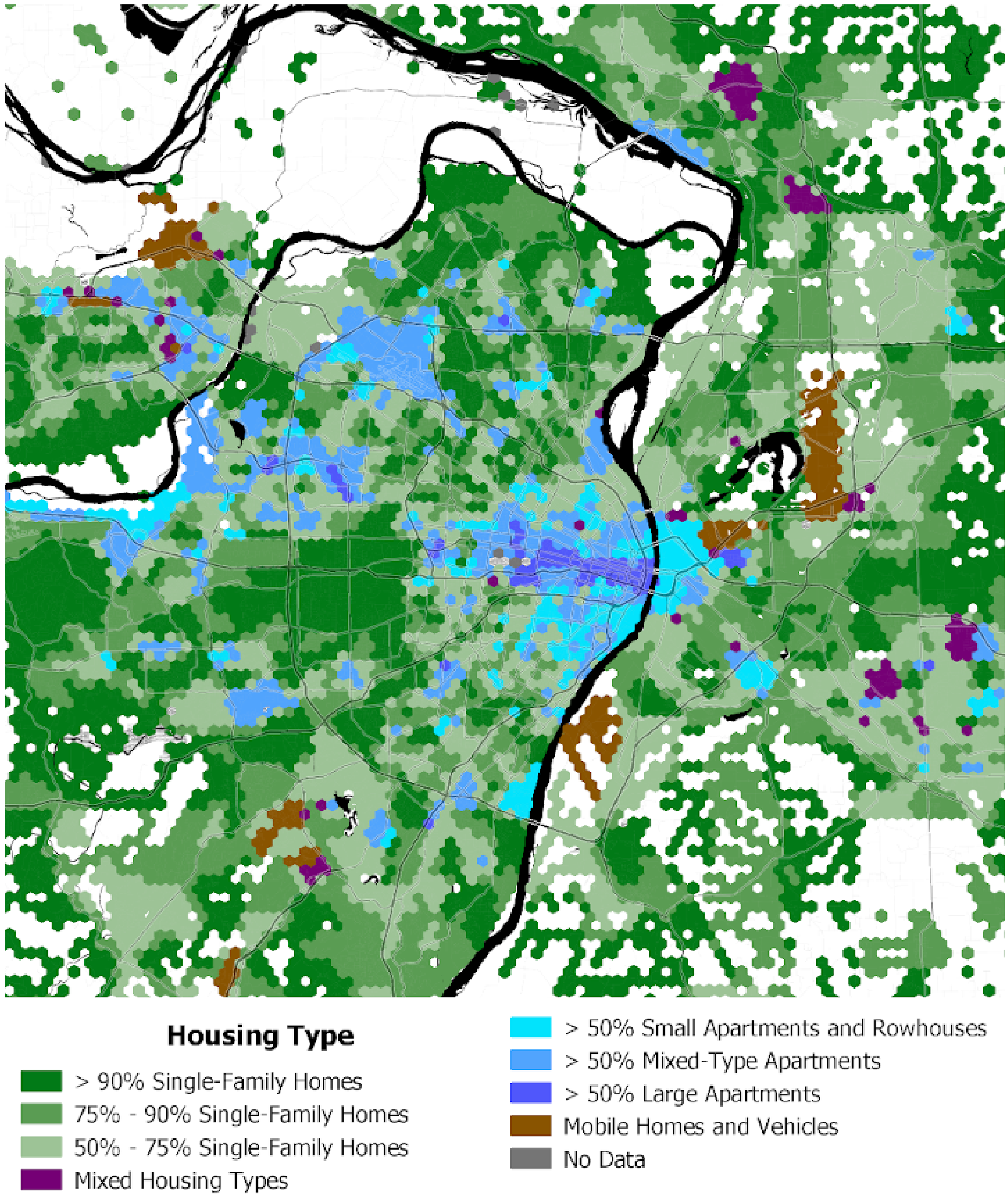

Figure F.28: St. Louis, MO-IL MSA housing type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table F.29: Tampa Distribution of Population and Jobs by Housing Type

Housing Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Single-Family	1,646	15.6%	513,000	17.0%	67,000	5.6%
Single-Family	2,370	22.5%	621,000	20.6%	162,000	13.6%
Mixed Single-Family	3,118	29.6%	865,000	28.7%	313,000	26.3%
Multifamily: Small Building	211	2%	122,000	4.1%	49,000	4.1%
Multifamily: Large Building	326	3.1%	180,000	6.0%	204,000	17.1%
Multifamily: Mixed Types	744	7.1%	374,000	12.4%	255,000	21.4%
Mobile Homes	1,650	15.7%	192,000	6.4%	64,000	5.4%
Mixed Housing Types	354	3.4%	139,000	4.6%	50,000	4.2%
Few Housing Units	106	1%	4,000	0.1%	27,000	2.3%

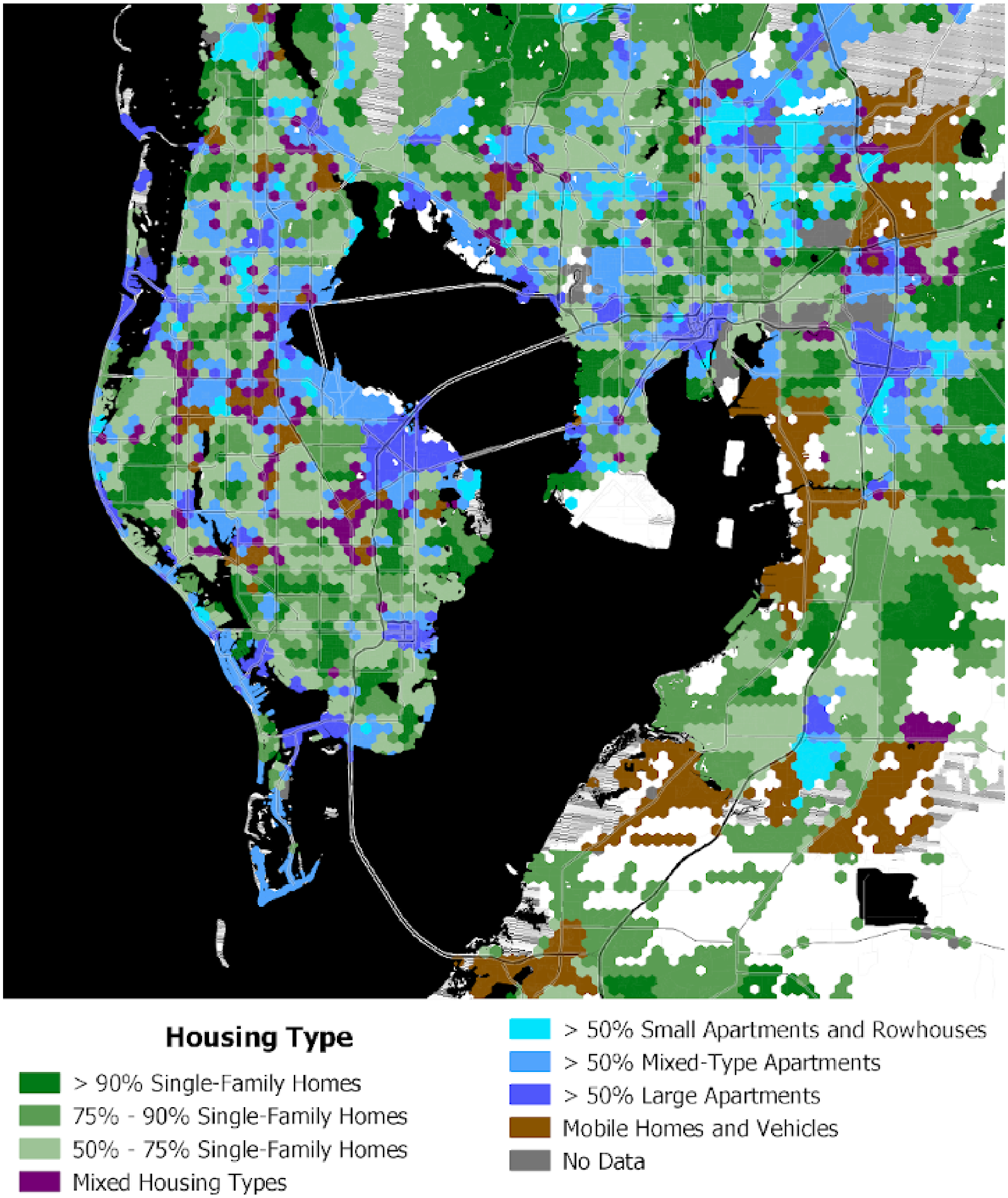

Figure F.29: Tampa-St. Petersburg-Clearwater, FL MSA housing type neighborhood map. Tampa is to the upper right and St. Petersburg is to the lower left. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table F.30: Washington Distribution of Population and Jobs by Housing Type

Housing Type	Hexes	% of Hexes	Population	% of Pop.	Jobs	% of Jobs
Pure Single-Family	9,566	47.6%	1,246,000	20.6%	203,000	7.5%
Single-Family	3,902	19.4%	756,000	12.5%	191,000	7.0%
Mixed Single-Family	2,970	14.8%	1007,000	16.6%	327,000	12%
Multifamily: Small Building	1,350	6.7%	1,169,000	19.3%	430,000	15.8%
Multifamily: Large Building	670	3.3%	935,000	15.4%	1,106,000	40.6%
Multifamily: Mixed Types	1,356	6.8%	901,000	14.9%	410,000	15.0%
Mobile Homes	47	0.2%	7,000	0.1%	12,000	0.5%
Mixed Housing Types	93	0.5%	33,000	0.5%	17,000	0.6%
Few Housing Units	128	0.6%	2,000	0.03%	27,000	1%

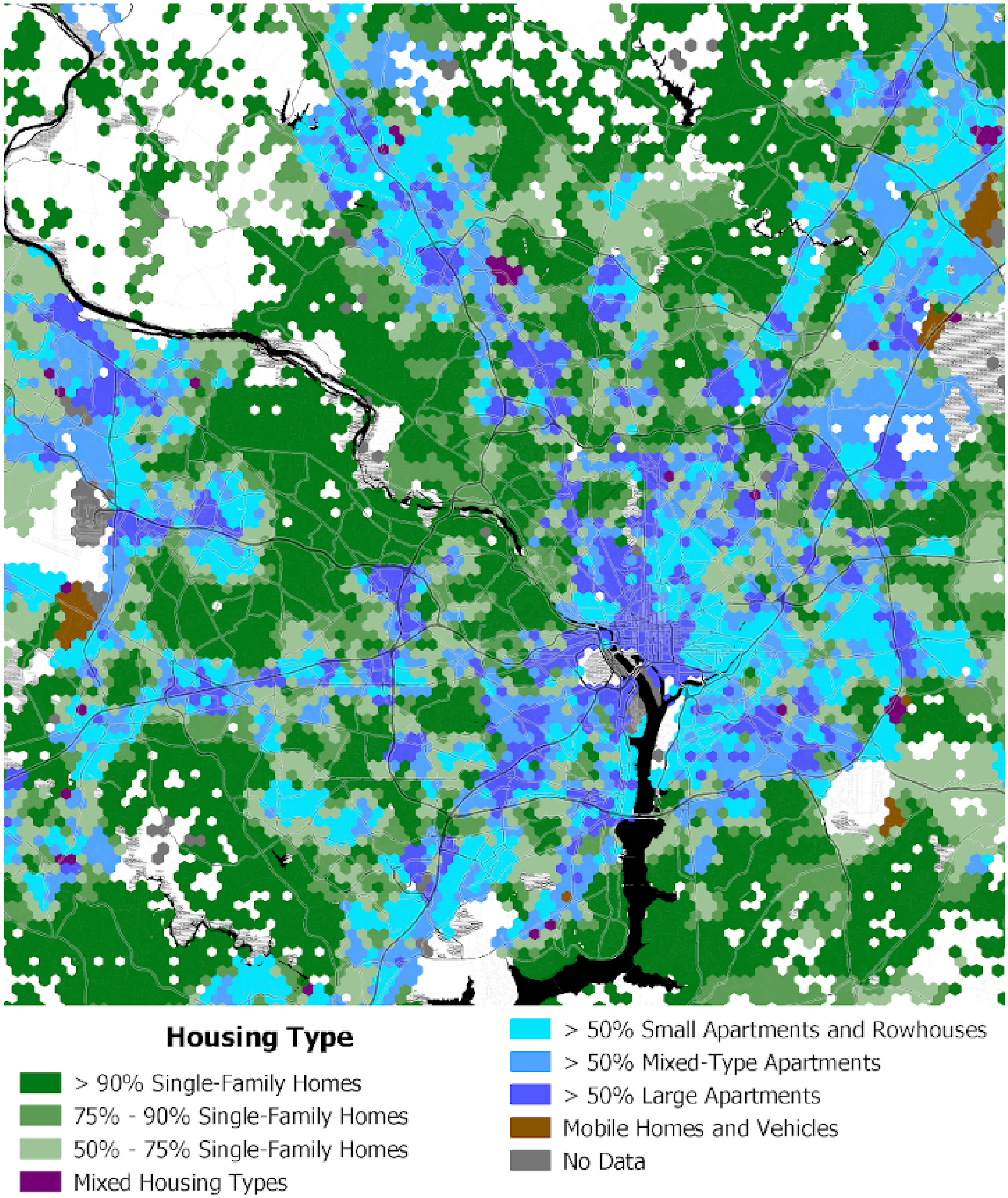

Figure F.30: Washington-Arlington-Alexandria, DC-VA-MD-WV MSA housing type neighborhood map. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Appendix G: Methodology and Scripts for Constructing Typologies

Once data was collected to characterize the hex cells, the hex cell neighborhoods were typologized using, a k-means non-hierarchical clustering analysis (Steinley (2006), Royall and Wortmann (2015)) as discussed in Chapter 3. This analysis was performed with R scripts using the `cluster` library and the `kmeans` function's MacQueen clustering algorithm. The source code for these scripts can be found in UMBC's ScholarWorks repository.

For the clustering analyses, all hex cells in all CBSAs were combined into a single data set, and cells located on military bases, cells containing no developed land, and cells with activity densities (the sum of population and job densities) below 100 activity units per square mile were removed[1].

Initially, it was planned to create clusters through a two-step process, with clusters based solely on density and connectivity data created first, and then a second clustering step based on land use data performed separately on each density-and-connectivity cluster. Section G.1 discusses the process of producing the first step density-and-connectivity clusters.

[1]The density cut-off was selected as one-fifth of the minimum density for a tract to be included in a Census Urban Area or Urban Cluster. It also corresponds to 16 activity units per hex cell.

However, it became clear that this approach added significant arbitrariness into the process, since the number of density-and-connectivity clusters, the number of land use clusters each density-and-connectivity was divided into, and the final grouping of clusters for use in the Chapter 3 metro area typology were all independently chosen.

As a result, a new approach—described in Section G.2—was used to generate the final clusters. Clusters were generated in a single step using activity-and-connectivity, land use, and housing type variables. It was necessary to increase the density cut-off to 500 activity units per square mile to make this computationally tractable: this resulted in a total of 765,058 hexes to cluster.

G.1 Density and Connectivity Clustering

Density-and-connectivity clusters were created using a pair of scripts. First, the `FirstAnalysis-3-MakeIntensityClusters.R` script loaded the hex cell characterization shapefile produced in Chapter 2 and created activity density, percent developed land, and percent ideal walkshed variables. Cells with activity densities less than 100 activity units per square mile were removed and z-scores were calculated for the three clustering variables.

Once the z-scores were prepared, the `kmeans` function was used to produce solutions with one to twenty-five clusters. For each value of k, 50 random seeds were used to increase the chance that the solution found was the global maximum. The script `FirstAnalysis-4-AnalyzeIntensityClusters.R` was then used to produce summaries of each cluster solution for use in selecting a number of clusters to use.

Summaries were produced for each set of clusters with minimum, first quartile, median, third quartile, and maximum values of the activity density, percent developed land, and percent ideal walkshed for each cluster. In all cases, the lowest-density hexes (which were by far the most numerous) were sorted primarily by percent ideal walkshed while the highest-density hexes (which were nearly all in high-connectivity areas) were primarily sorted by density.

The seventeen-cluster solution—in which 91% of variation is between clusters—was finally settled on as the best choice for number of clusters since it gave reasonable density breaks and broke most density levels into high-connectivity and low-connectivity clusters. The clusters of the seventeen-cluster solution can be found listed in Table 3.1 on page 133

The final component of the script imports a CSV file of new cluster numbers based on cluster size—recall that the numbering of k-means clusters is arbitrary and non-reproducible—and appends these new cluster numbers to the cells of the hex cell shapefile.

G.2 Density, Connectivity, Land Use, and Housing Clustering

The inadequacy of the multi-step clustering approach led to the decision to create a single set of clusters based on ten variables representing density, connectivity, land use, and housing. The use of three times as many variables significantly increased computational time so, to make the process tractable, it was necessary to reduce the number of neighborhoods included.

Only the 765,085 hex cell neighborhoods with activity densities of at least 500 activity units per square mile were included in this clustering process. While this density cut-off is higher than I would have preferred, it is the density cut-off the Census uses for the fringes of urban areas and urban clusters, and it is far lower than the densities generally considered necessary for walkability or effective public transit.

Besides the computational benefit of including fewer neighborhoods, using this density cut-off made it possible to make use of the recommendation of Royall and Wortmann (2015) that the number of clusters should be roughly $\sqrt{n/2}$ where n is the number of data points. Although $\sqrt{765085/2}$ is 618.49, this method only gives a rough estimate of the ideal number of clusters, and I decided to use $k = 600$ as a nearby round number that placed 89.8% of variation between clusters.

The script `FirstAnalysis-5-MakeUseClusters.R` establishes the ten variables used for clustering: activity density; percentages of activity units in each of retail, edmeds, office, and industrial jobs (percent of activity that is residents is constrained by these); percentages of housing units that are single-family detached homes, row houses or apartments of less than ten units, and apartments of more than ten units (percent of housing units that are mobile homes is constrained by these), percent developed land, and percent ideal walk-shed.

Neighborhoods with activity densities of less than 500 activity units per square mile are dropped and z-scores are created for each variable, as in the density-and-connectivity clustering and the `kmeans` function is used to find 600 clusters using the MacQueen algorithm and 50 randomly-selected sets of seed clusters.

In the next step, the script `FirstAnalysis-6-AnalyzeUseClusters.R` generates a summary of the values of the variables and their standard deviations for each cluster, allowing the clusters to be characterized. The summary file was then analyzed in Microsoft Excel to classify hex types as to their land use, housing type, density, and connectivity, based on the criteria described in Tables 3.2–3.6 on pages 136–140 In addition, hexes were assigned to the twenty-two neighborhood types listed in Table 3.7 on page 144.

Once clusters were assigned categories in Excel, the resulting spreadsheet was imported to R by the script `FirstAnalysis-7-ExportUseClusters.R` and the cluster assignments and categories were joined to the national hex shapefile, producing the shapefile used for the metro area typologies and to produce the neighborhood typology maps shown in Appendix H.

G.3 Initial Metro Area Clustering

Once neighborhood clusters were established, the next step was to develop clusters of metro areas based on the types of neighborhood they contained and the fractions of their residents living and working in each neighborhood type. However, to calculate the populations and numbers of jobs in each metro area, it was necessary to import all hexes in each metro area, rather than the hexes above a density cut-off that were used in the neighborhood typology.

The script `SecondAnalysis-1-MakeCSV.R` begins by loading the metro area neighborhood characterization shape files and combining them into a single large shapefile. The hexes with clusters attached produced by `FirstAnalysis-7-ExportUseClusters.R` are then loaded and joined to the complete hex shapefile, and the low-density hexes excluded from the cluster analysis are listed as falling into the two low-density neighborhood categories.

An additional step of correcting the assignments of some high-density hexes is necessary because the small number of neighborhoods at high densities lead the cluster analysis of high-density hexes to depend almost solely on density and not use type. All hexes with densities of at least 30,000 activity units per square mile were checked by hand and reassigned to a more appropriate neighborhood type if necessary.

In addition, the hexes with invalid population densities due to the Census block group cropping error discussed in Section C.3 are removed to keep them from skewing the high-density hex data. Once these corrections are made, the resulting shapefile is written to disk and the script goes on to process data for use in the metro area clustering analysis.

Because the twenty-two categories that neighborhood clusters were initially grouped into turned out to be too many for viable clustering analysis, they are grouped together into the six categories shown in Table 3.9 on page 149 before having jobs and population summed for each metro area.

Three files are then saved to disk: one containing eight population and jobs variables selected for use in metro area clustering and covering all 926 metro areas, one with twelve variables, showing population and jobs each for each neighborhood type in thirty-five metro areas, and one that sums the same twelve variables over all 926 metro areas.

The first of these files is then loaded by the `SecondAnalysis-2-MakeClusters.R` script, which uses the data in a pair of two-step clustering procedures to identify clusters of metro areas by their distributions of jobs and of population in different medium and high-density neighborhood types.

For job clusters, the first stage produces six clusters based on the fractions of jobs in CBD and high-density commercial hexes. Each of these clusters is then sub-divided into further clusters based on four variables: the fractions of jobs in CBD, high-density commercial, medium-density commercial, and high or medium-density residential hexes.

For population clusters, the first stage produces four clusters based on the fraction of populations in high-density commercial or residential and CBD hexes. Each of these clusters is then sub-divided further into clusters based on this variable and three others: the fractions of jobs in medium-density large-apartment hexes, in medium-density small-apartment and row house hexes, and in medium-density commercial hexes. Finally, the list of metro areas with both cluster and subcluster assignments is written to disk.

Appendix H: Neighborhood Typology Maps

This appendix contains maps of land use and intensity (measured as walkshed-adjusted density) types based on my neighborhood typology discussed in Chapter 3. Land use types are as described in Table 3.5 on page 3.5 and intensity levels from "Extremely-High Intensity" to "Very-Low Intensity" are as described in Table 3.4 on page 3.4.

All the maps are at the same scale, and show a 40-mile by 40-mile square, which means that outlying parts of larger metro areas may be left out, while views of smaller metro areas may include areas outside the MSA limits. Maps are shown for the twenty largest metropolitan statistical areas in the US, along with fifteen additional metropolitan statistical areas that were selected because they are particularly interesting: they are unusually dense for their size, have rapid transit or light rail, or are representatives of interesting types from my metro areas typology, discussed in Chapter 3.

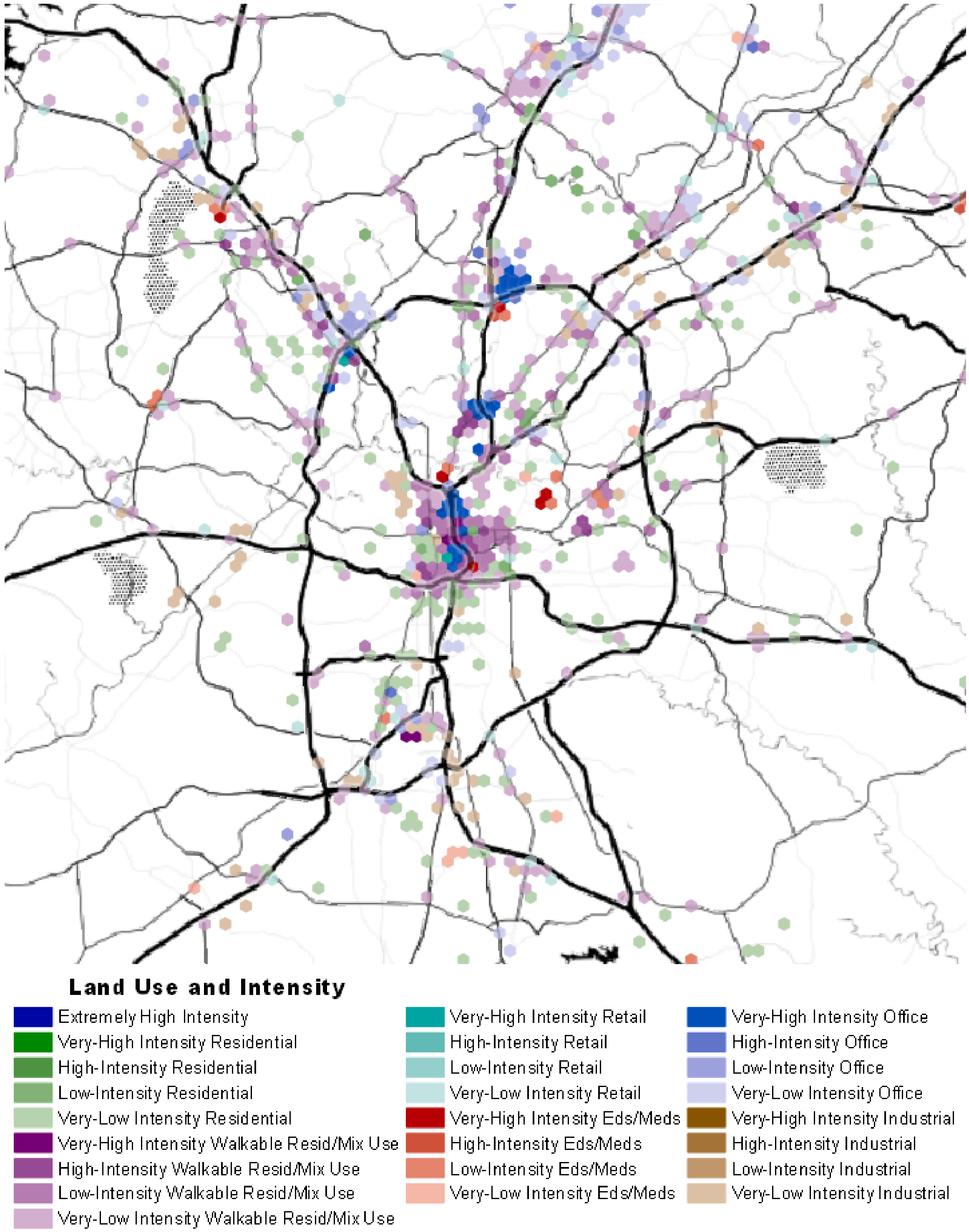

Figure H.1: Atlanta-Sandy Springs-Alpharetta, GA MSA map of land use and intensity, measured by walkshed-adjusted density. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

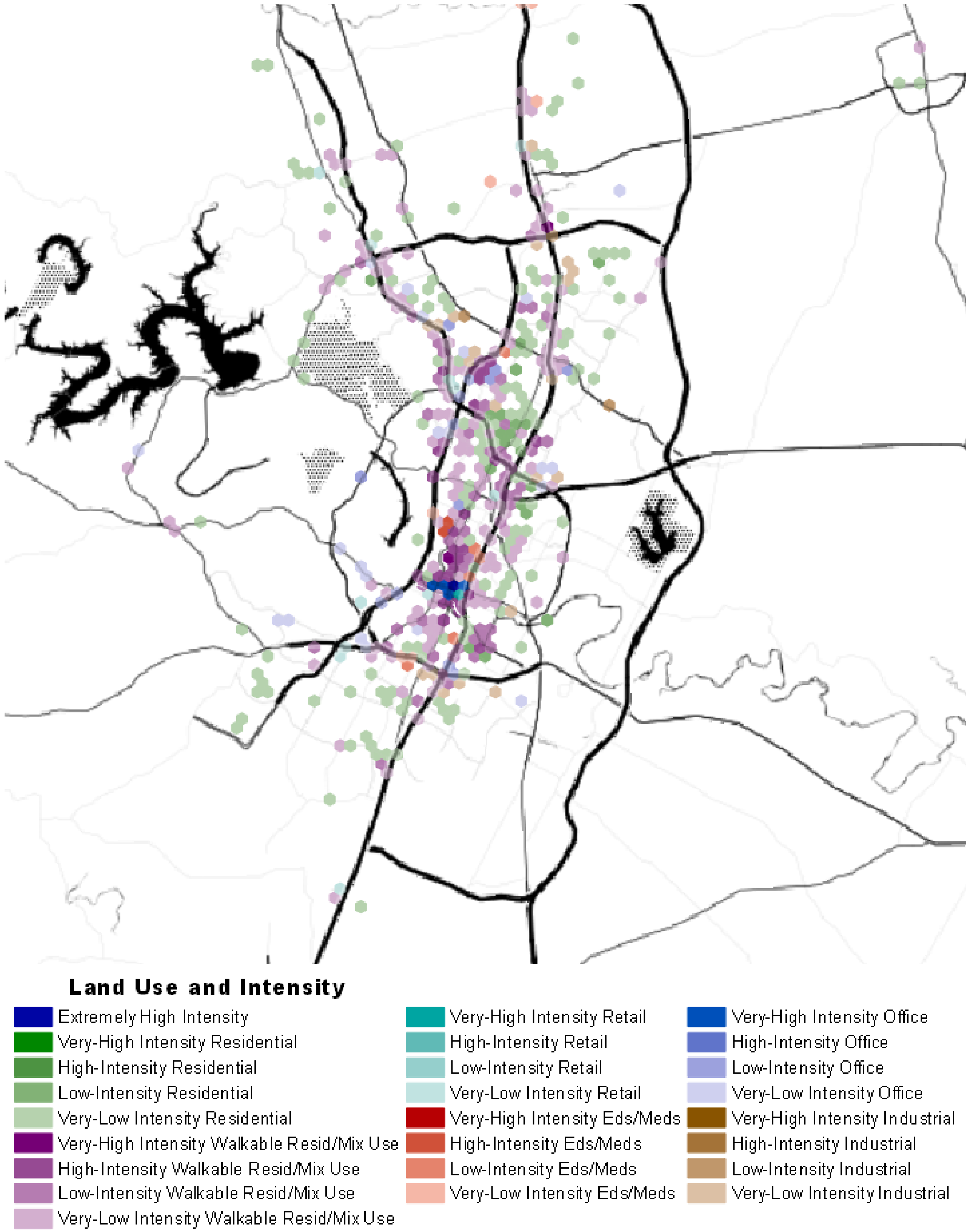

Figure H.2: Austin-Round Rock-Georgetown, TX MSA map of land use and intensity, measured by walkshed-adjusted density. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

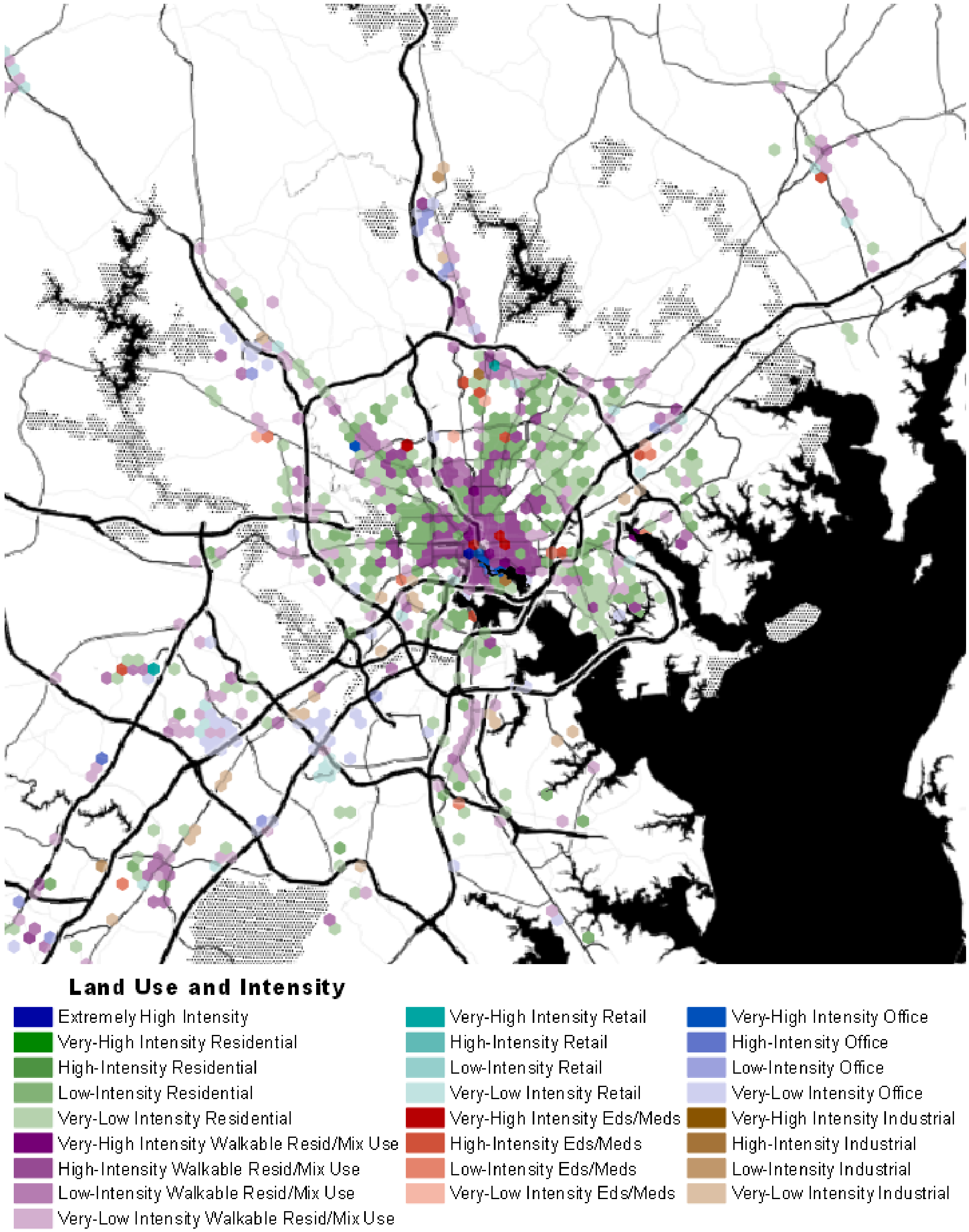

Figure H.3: Baltimore-Columbia-Towson, MD MSA map of land use and intensity, measured by walkshed-adjusted density. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

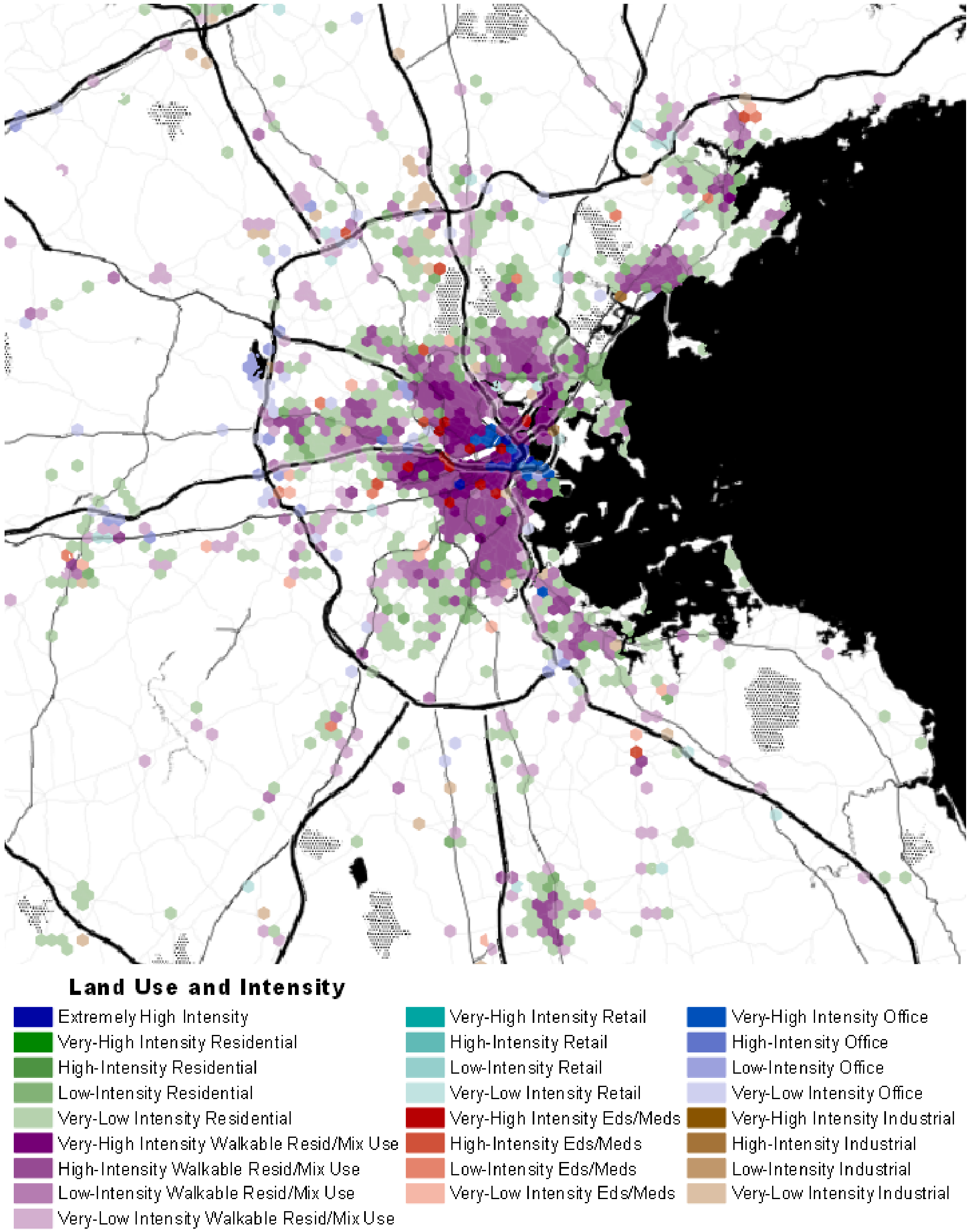

Figure H.4: Boston-Cambridge-Newton, MA-NH MSA map of land use and intensity, measured by walkshed-adjusted density. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

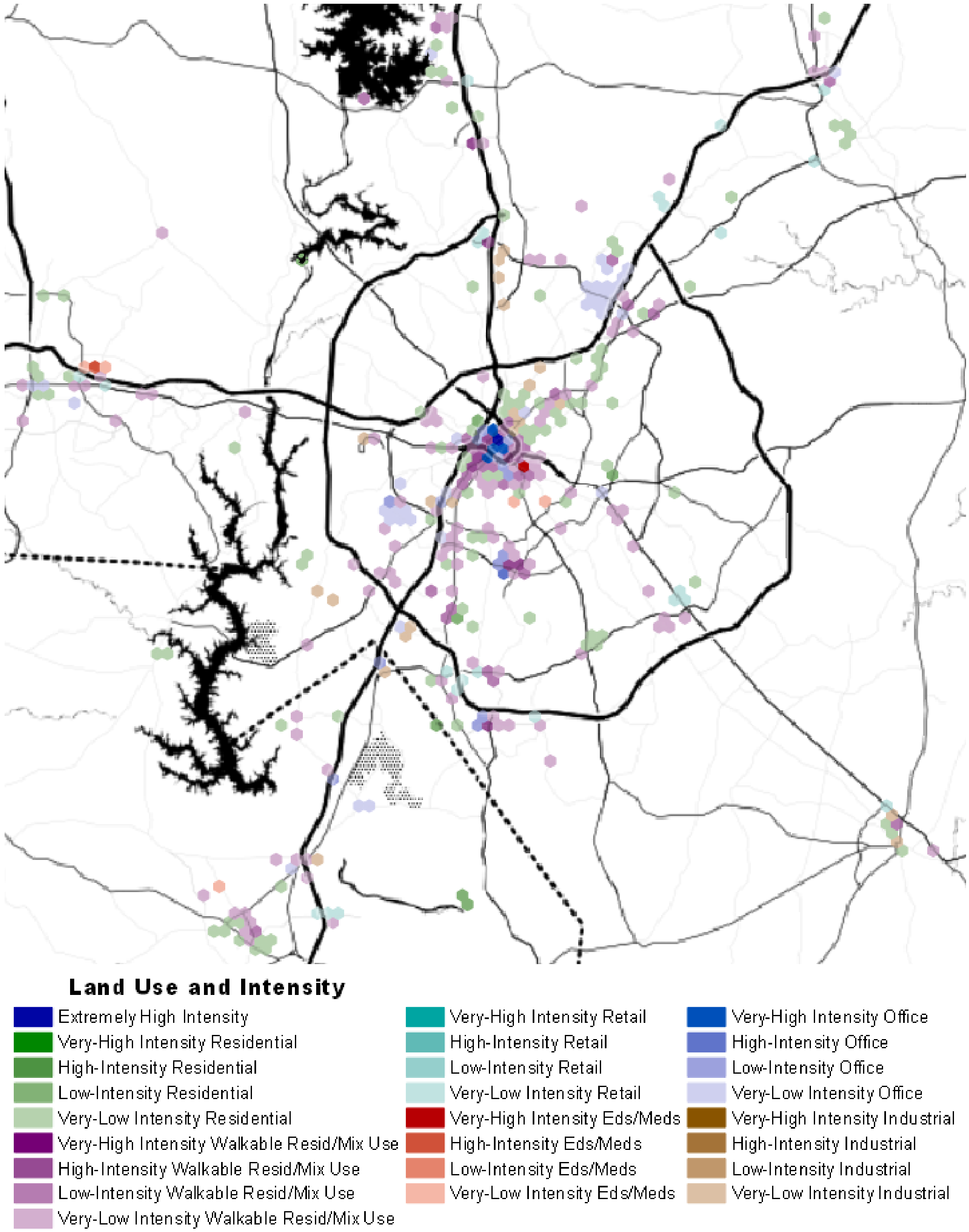

Figure H.5: Charlotte-Concord-Gastonia, NC-SC MSA map of land use and intensity, measured by walkshed-adjusted density. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

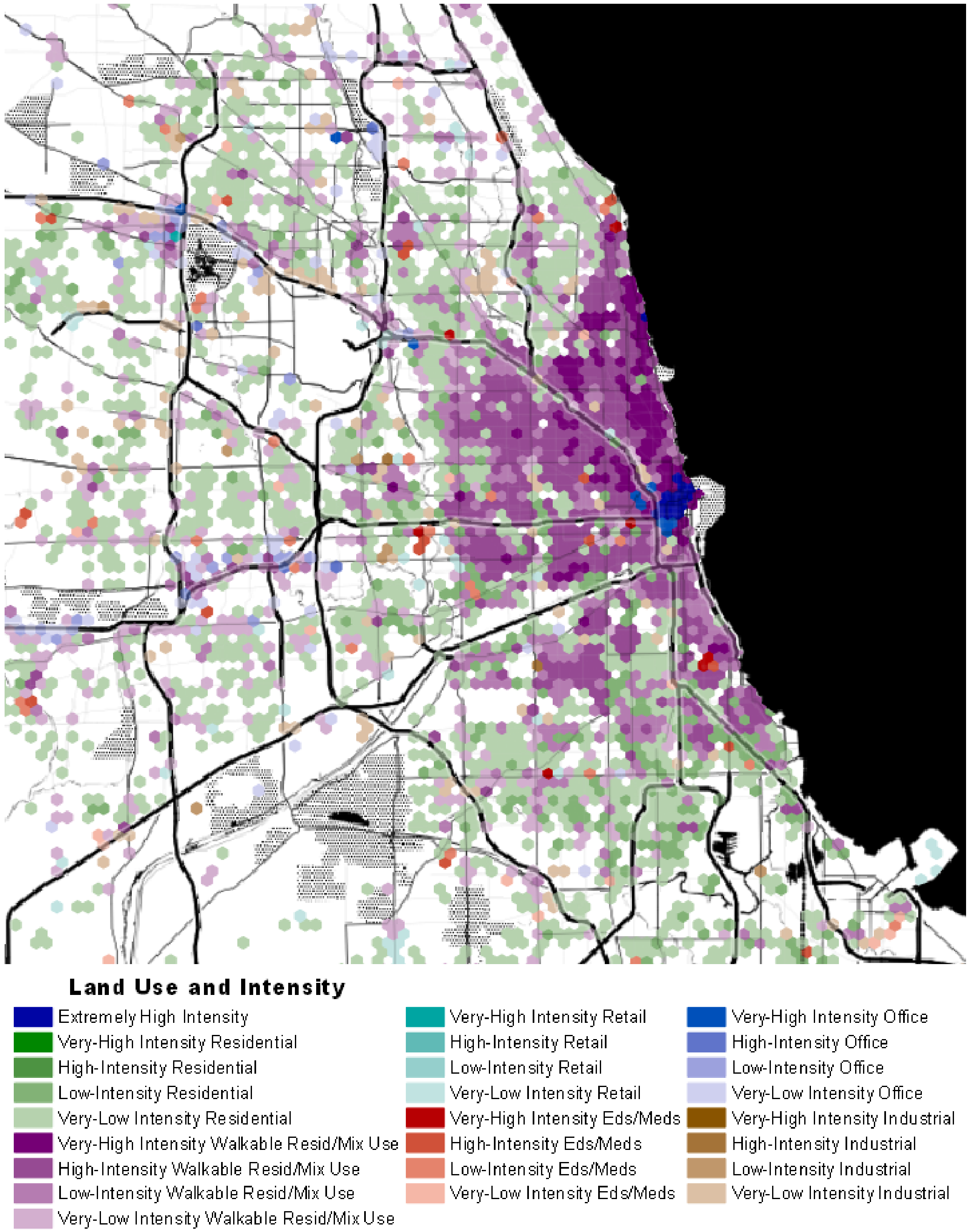

Figure H.6: Chicago-Naperville-Elgin, IL-IN-WI MSA map of land use and intensity, measured by walkshed-adjusted density. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

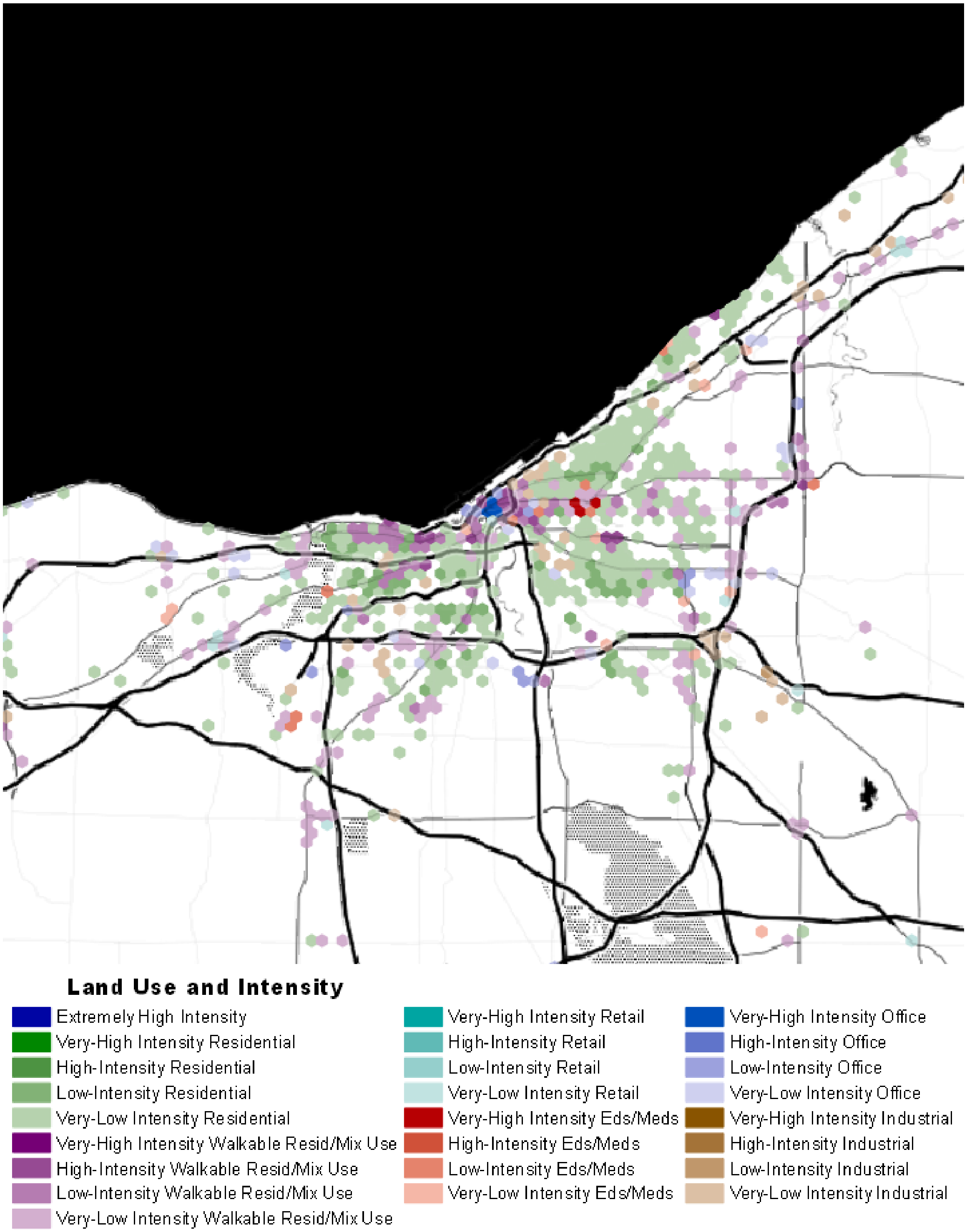

Figure H.7: Cleveland-Elyria, OH MSA map of land use and intensity, measured by walkshed-adjusted density. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

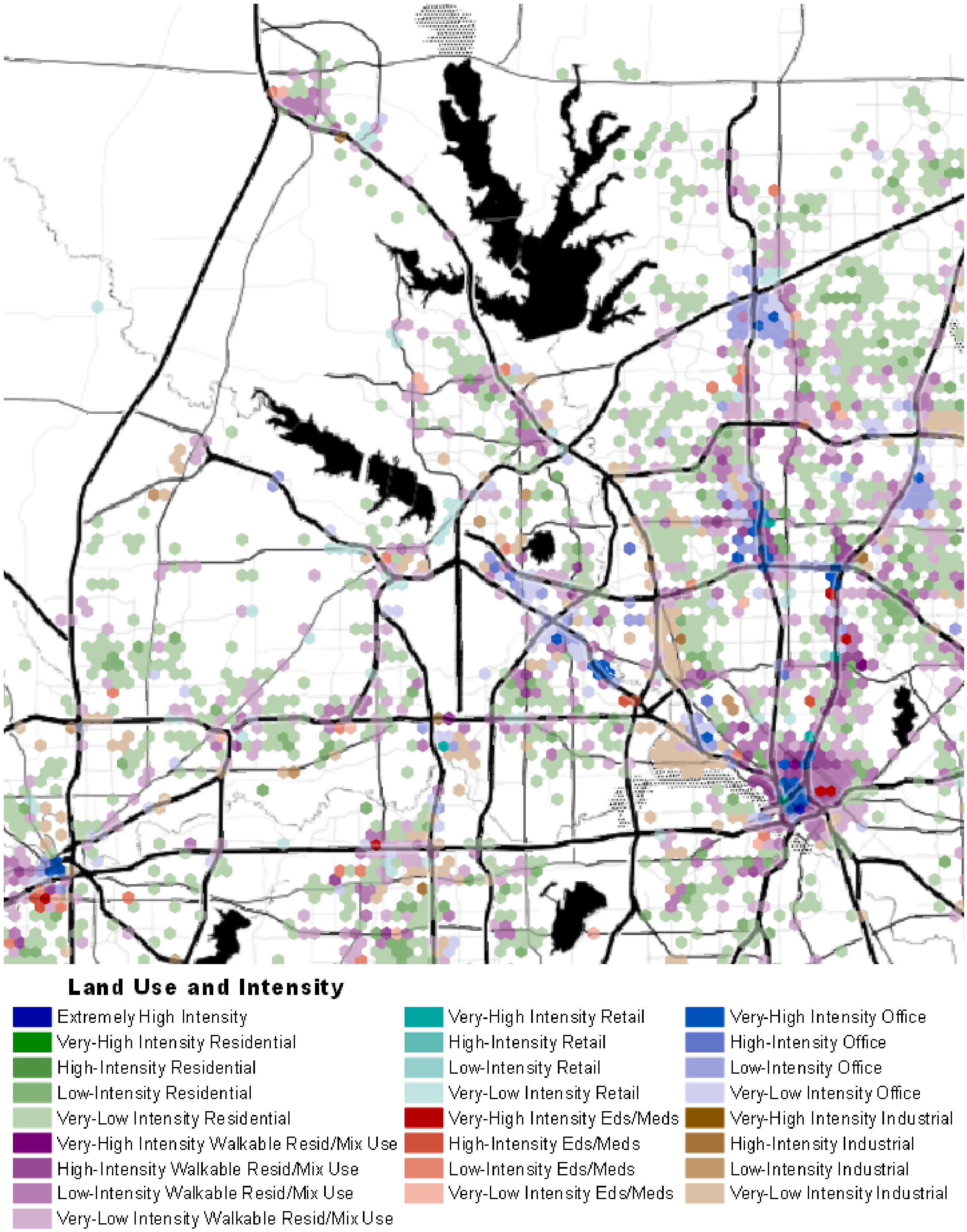

Figure H.8: Dallas-Fort Worth-Arlington, TX MSA map of land use and intensity, measured by walkshed-adjusted density. Downtown Dallas is at the lower right and downtown Fort Worth is at the far lower left. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

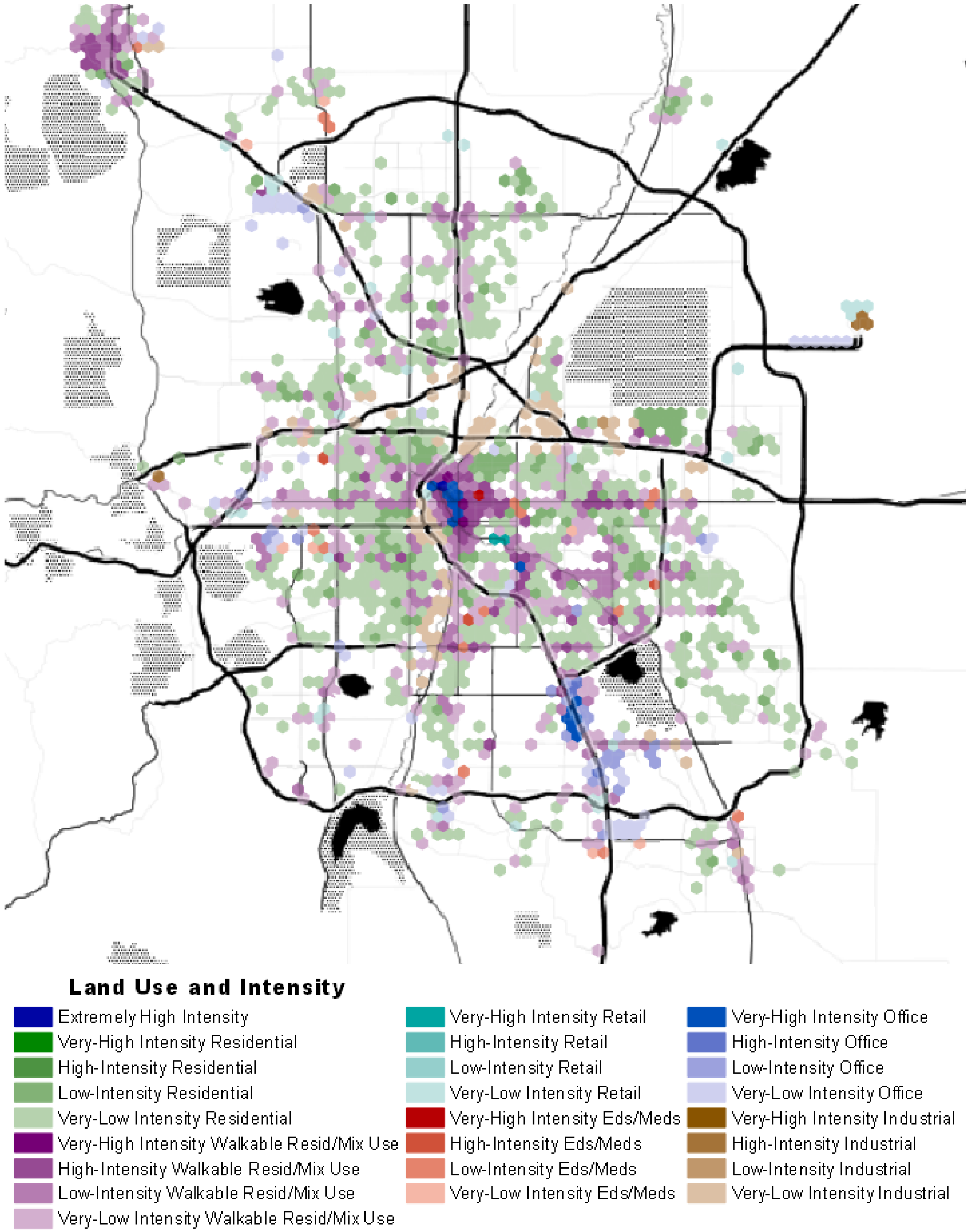

Figure H.9: Denver-Aurora-Lakewood, CO MSA map of land use and intensity, measured by walkshed-adjusted density. Boulder (not in the Denver MSA) is at the upper left. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

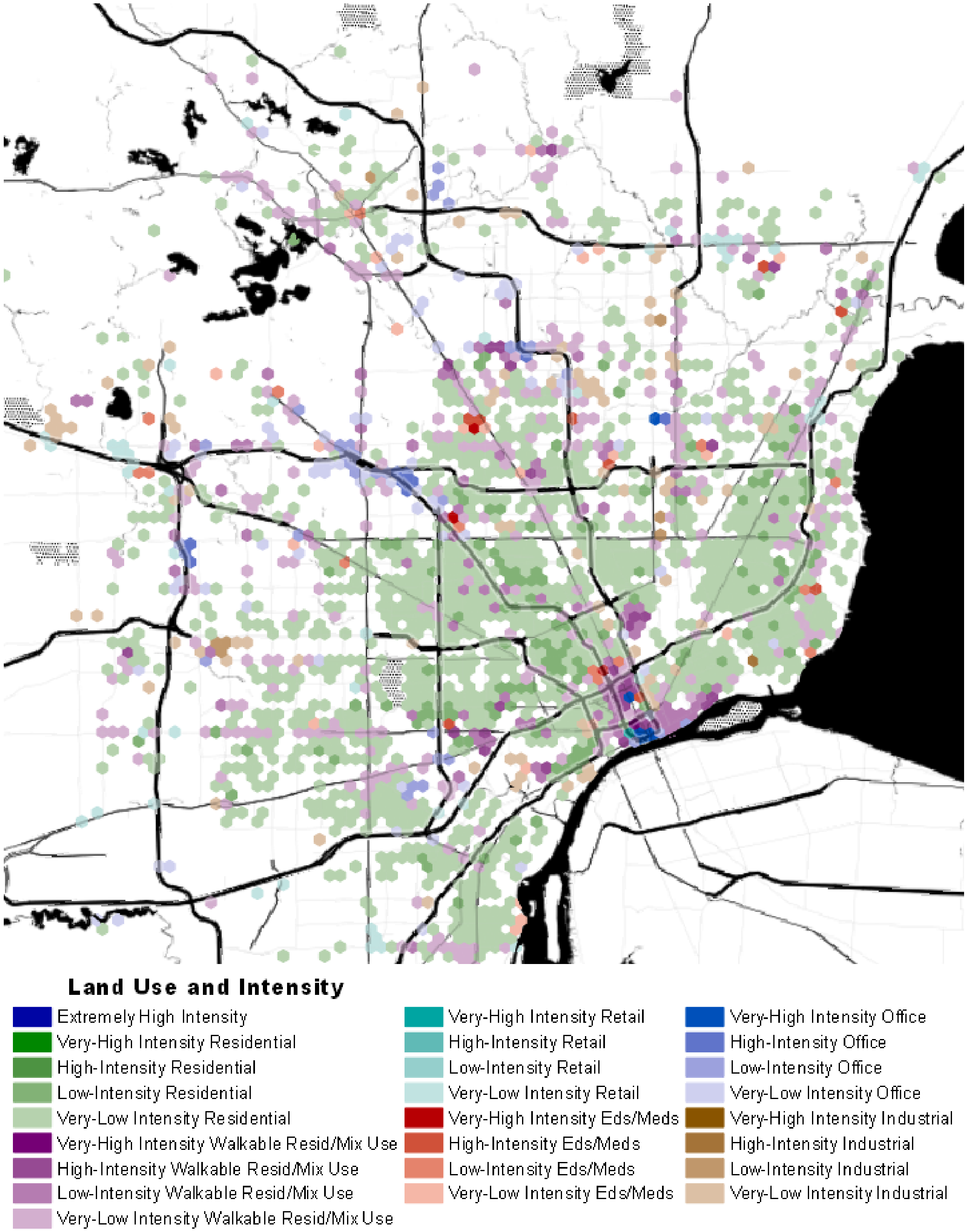

Figure H.10: Detroit-Warren-Dearborn, MI MSA map of land use and intensity, measured by walkshed-adjusted density. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

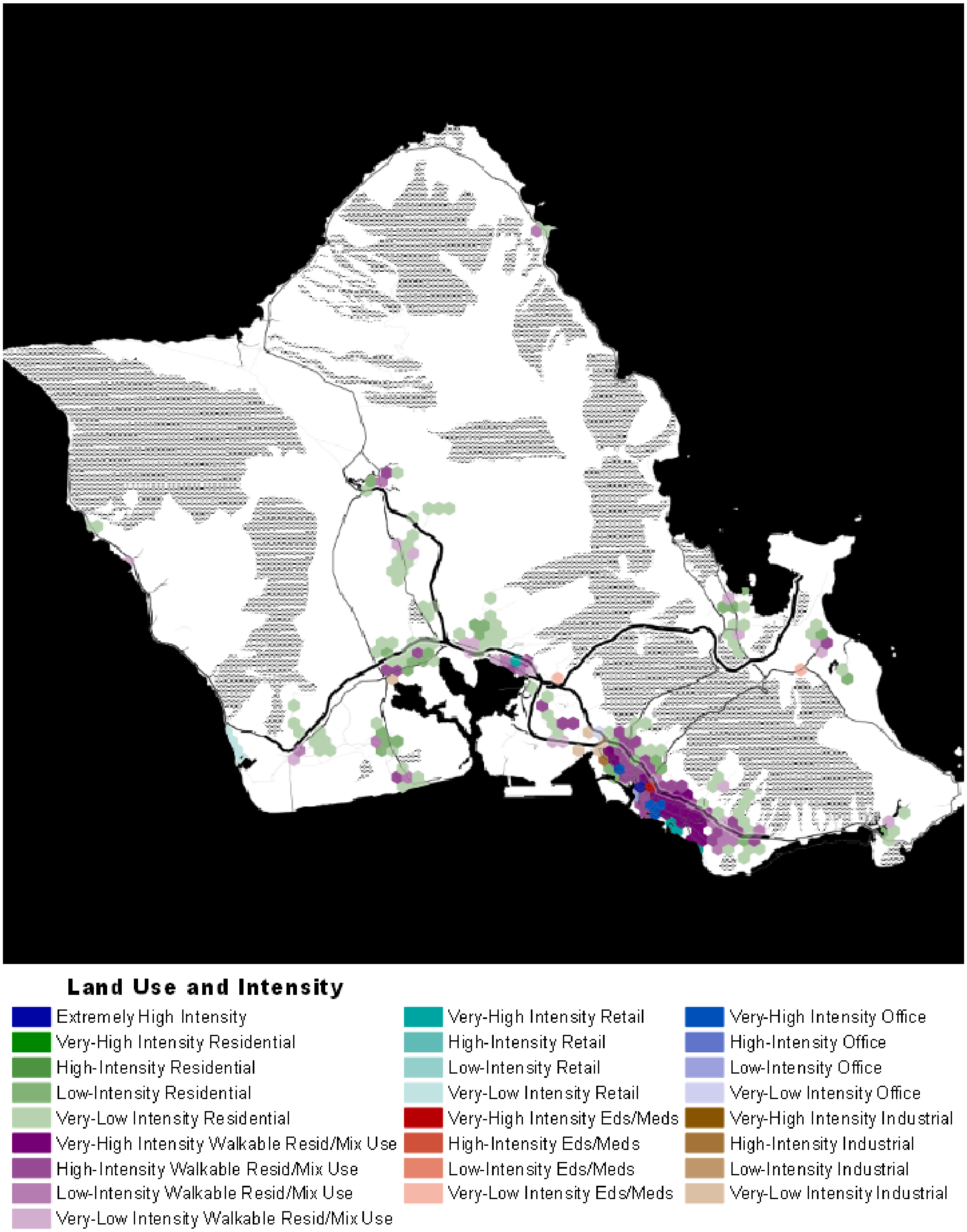

Figure H.11: Urban Honolulu, HI MSA map of land use and intensity, measured by walkshed-adjusted density. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

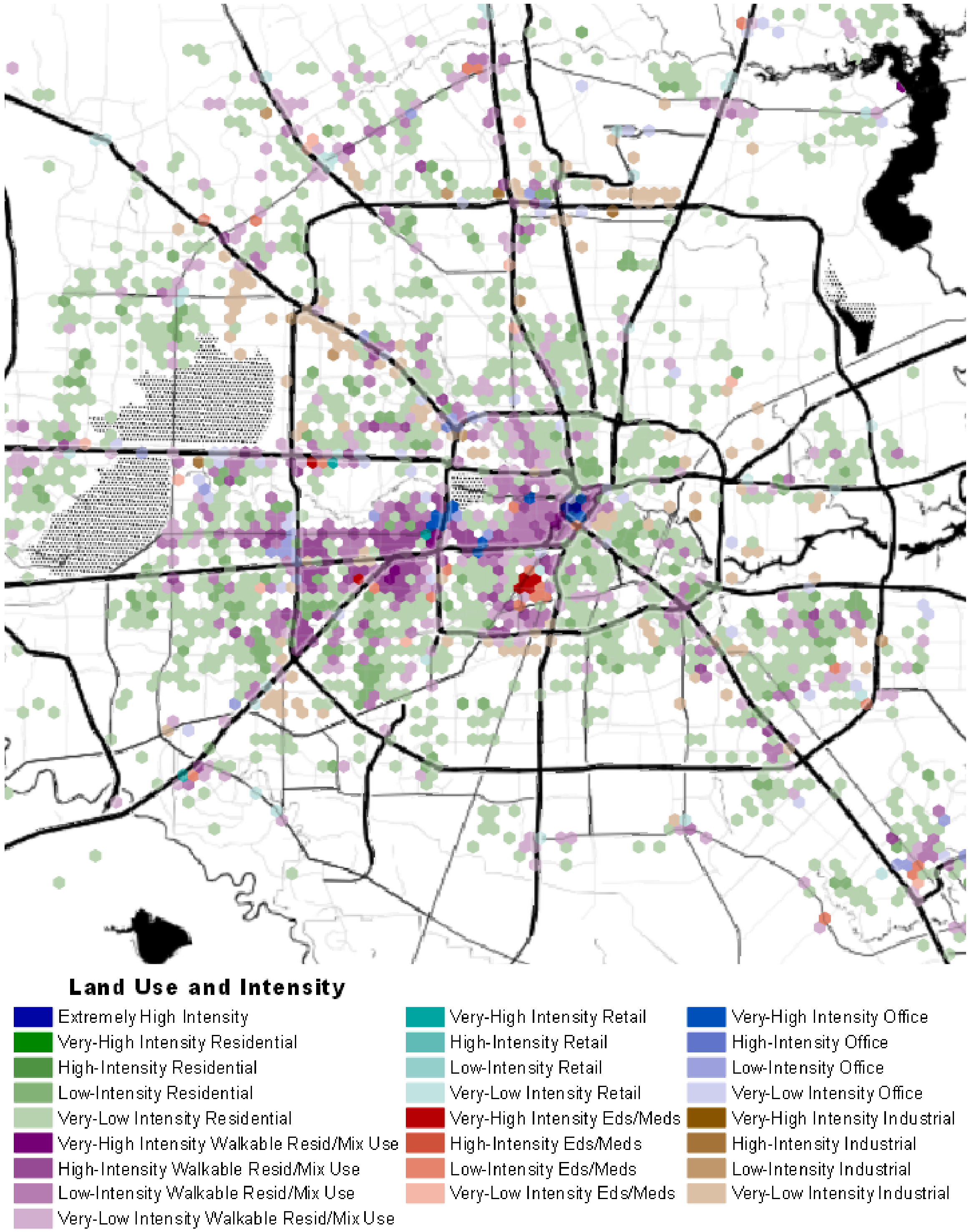

Figure H.12: Houston-The Woodlands-Sugar Land, TX MSA map of land use and intensity, measured by walkshed-adjusted density. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

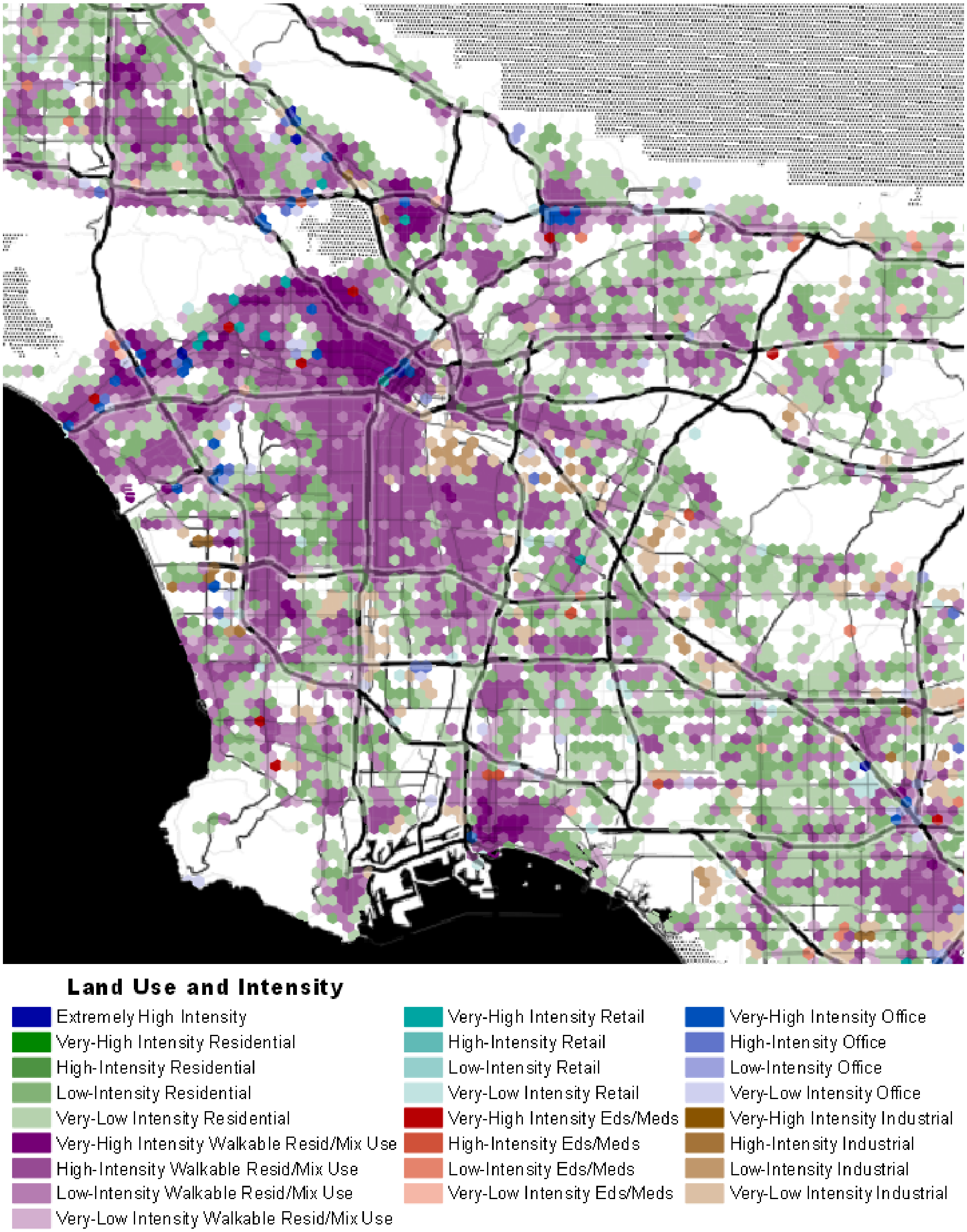

Figure H.13: Los Angeles-Long Beach-Anaheim, CA MSA map of land use and intensity, measured by walkshed-adjusted density. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

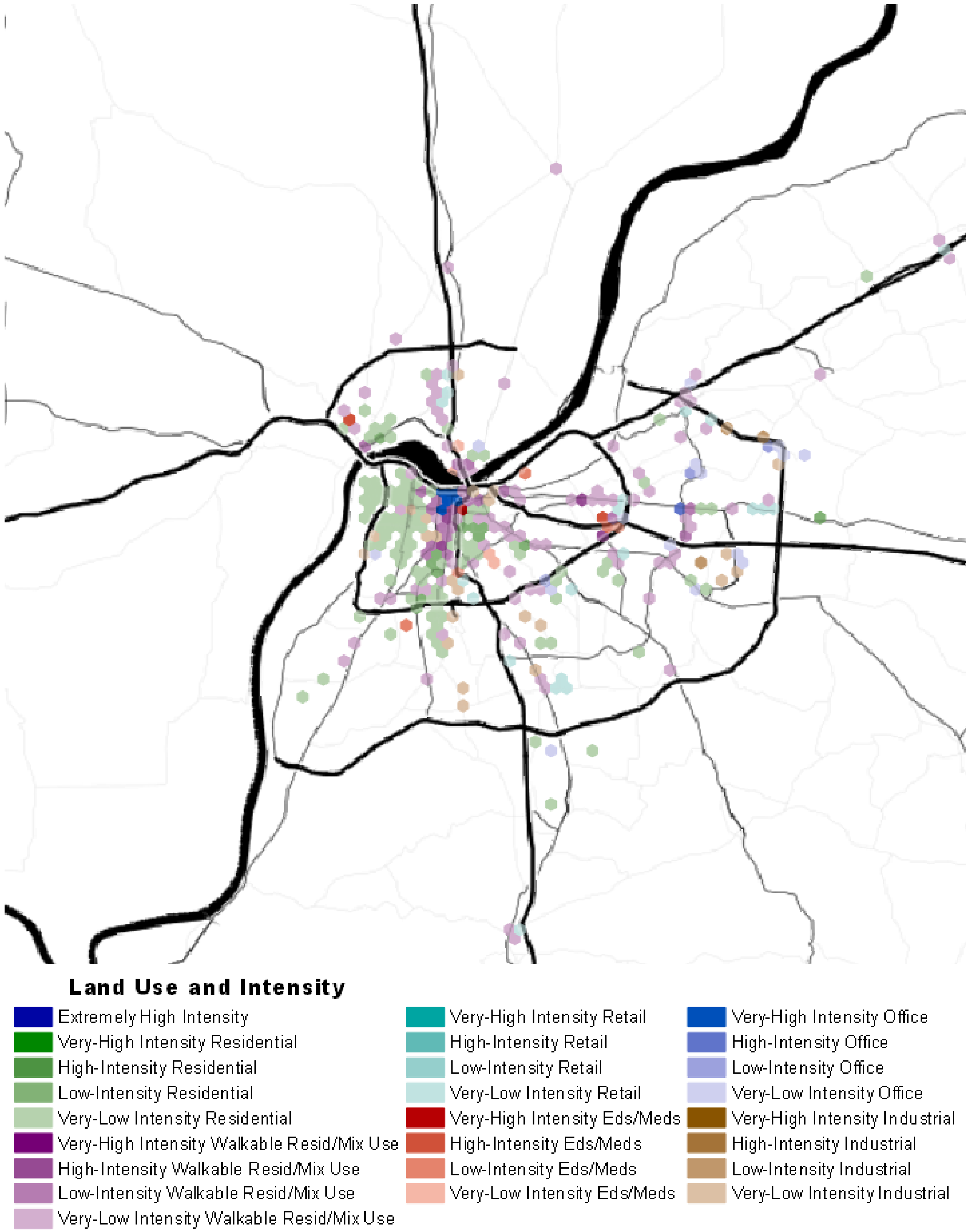

Figure H.14: Louisville-Jefferson County, KY-IN MSA map of land use and intensity, measured by walkshed-adjusted density. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

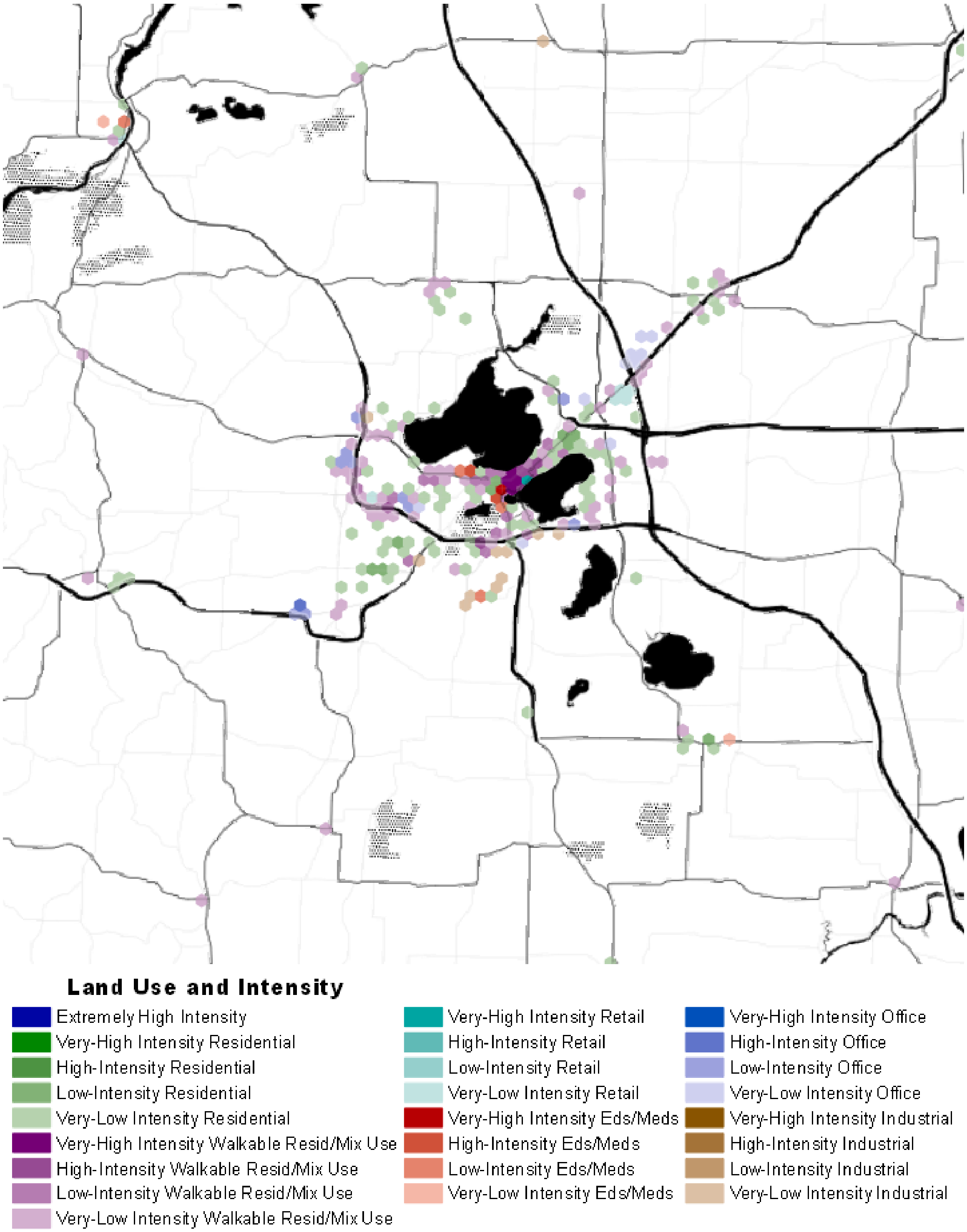

Figure H.15: Madison, WI MSA map of land use and intensity, measured by walkshed-adjusted density. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

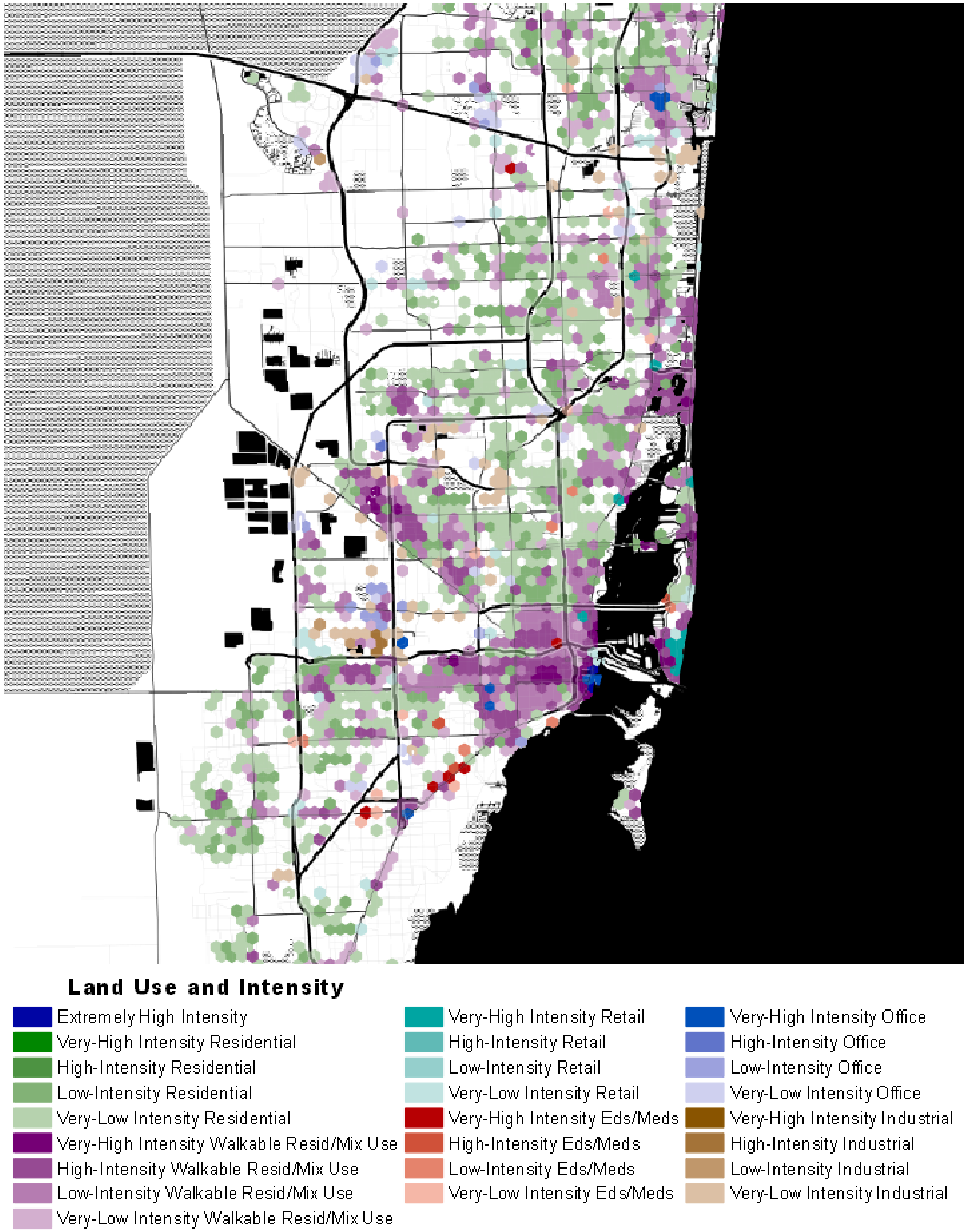

Figure H.16: Miami-Fort Lauderdale-Pompano Beach, FL MSA map of land use and intensity, measured by walkshed-adjusted density. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

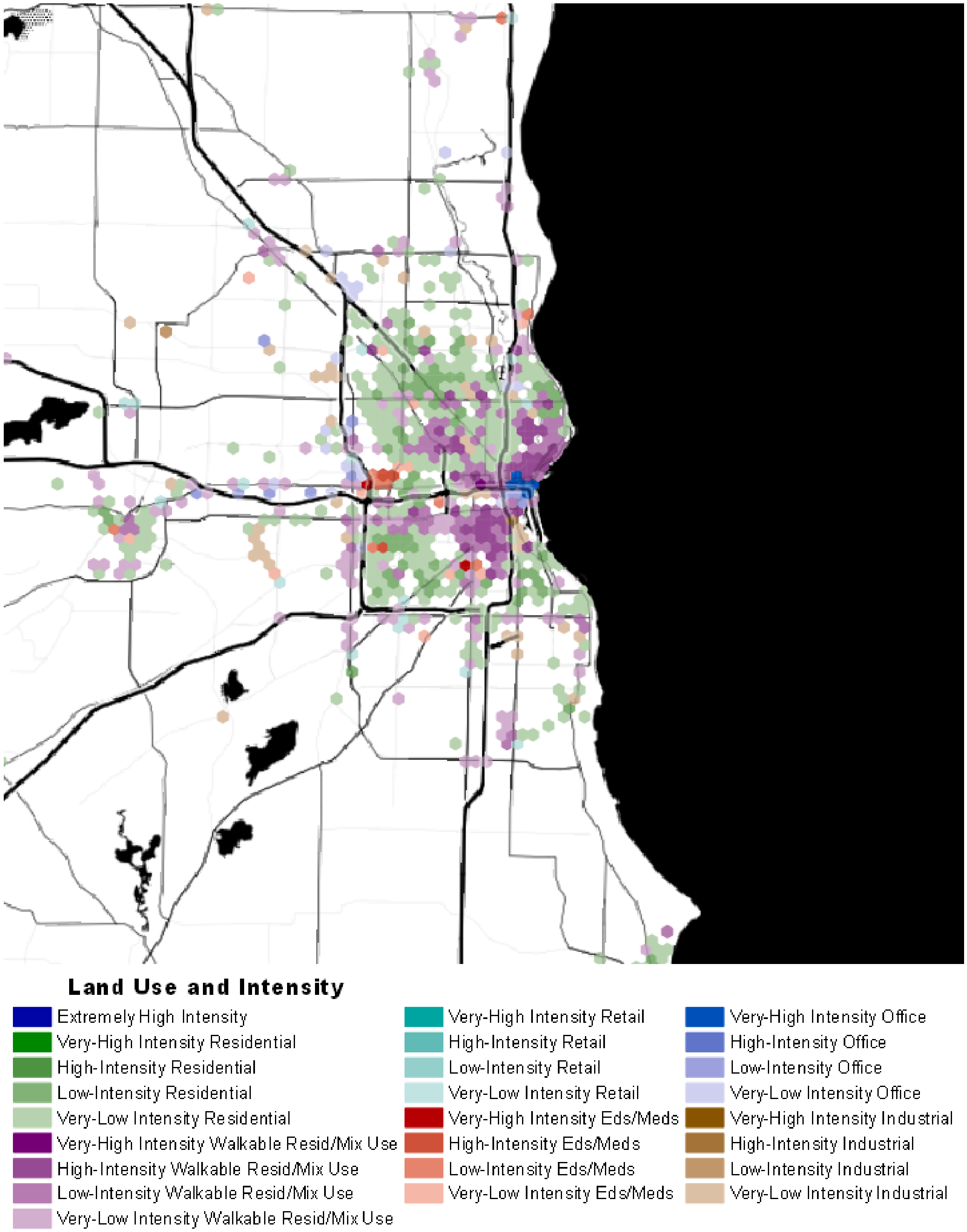

Figure H.17: Milwaukee-Waukesha, WI MSA map of land use and intensity, measured by walkshed-adjusted density. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

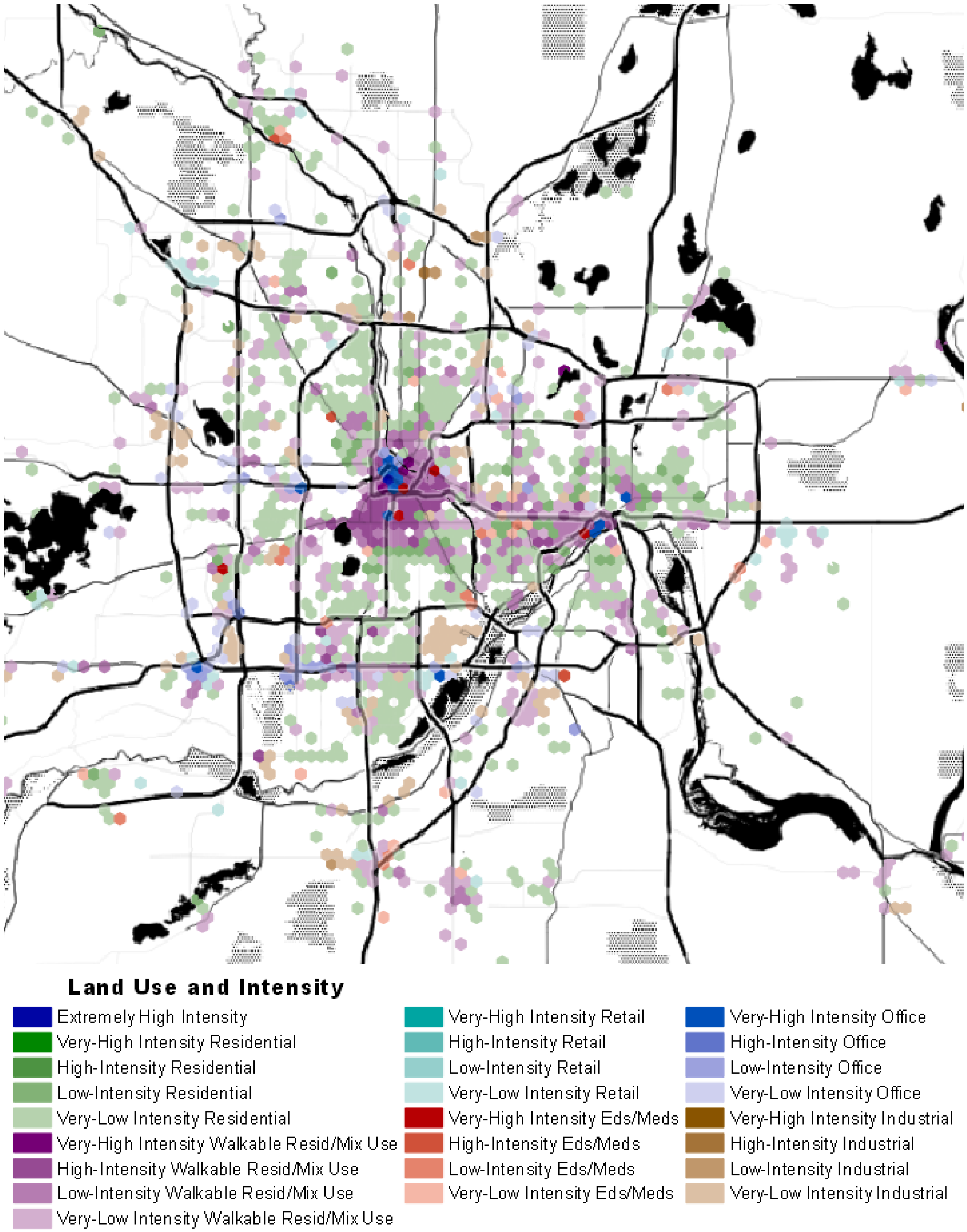

Figure H.18: Minneapolis-St. Paul-Bloomington, MN-WI MSA map of land use and intensity, measured by walkshed-adjusted density. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

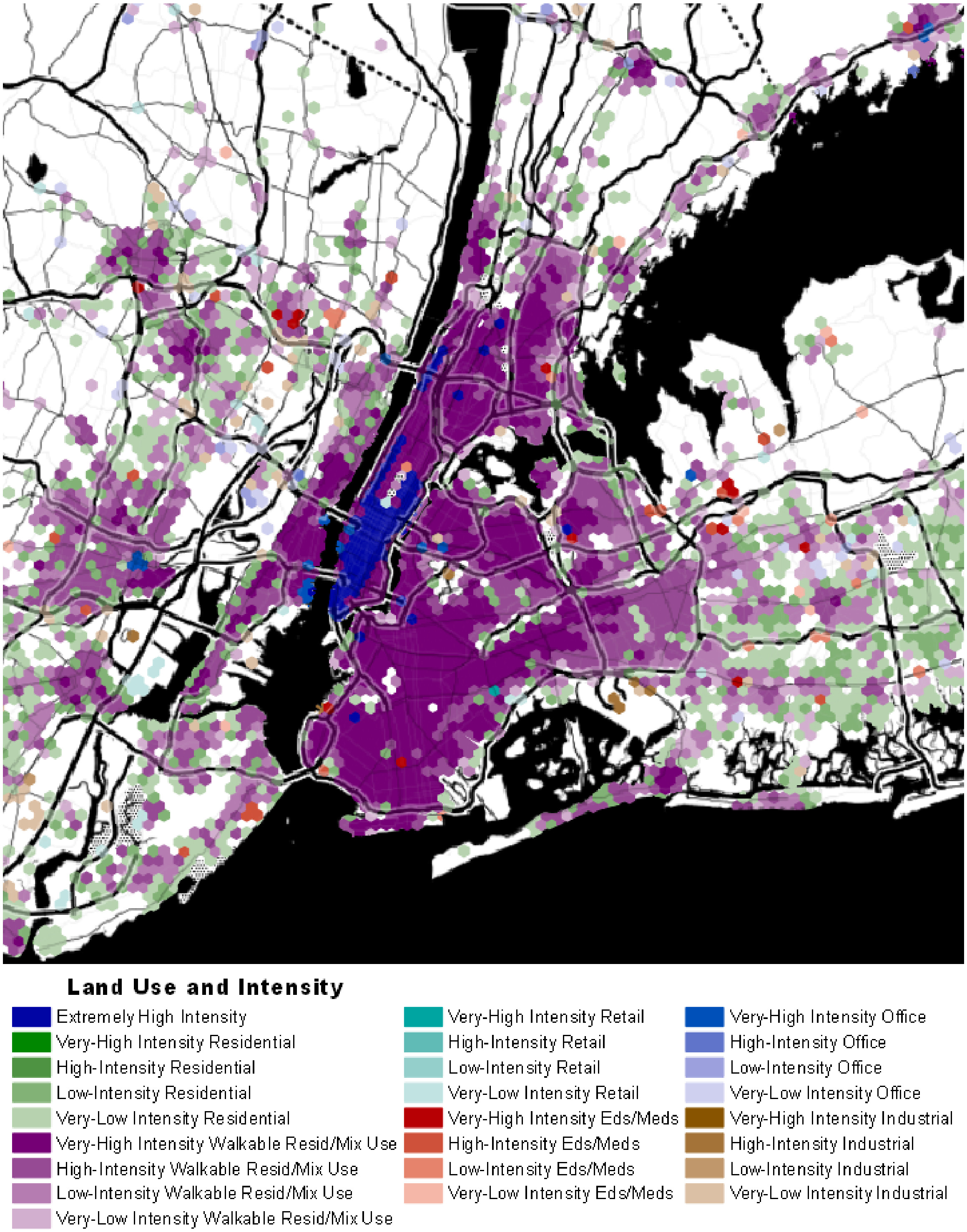

Figure H.19: New York-Newark-Jersey City, NY-NJ-PA MSA map of land use and intensity, measured by walkshed-adjusted density. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

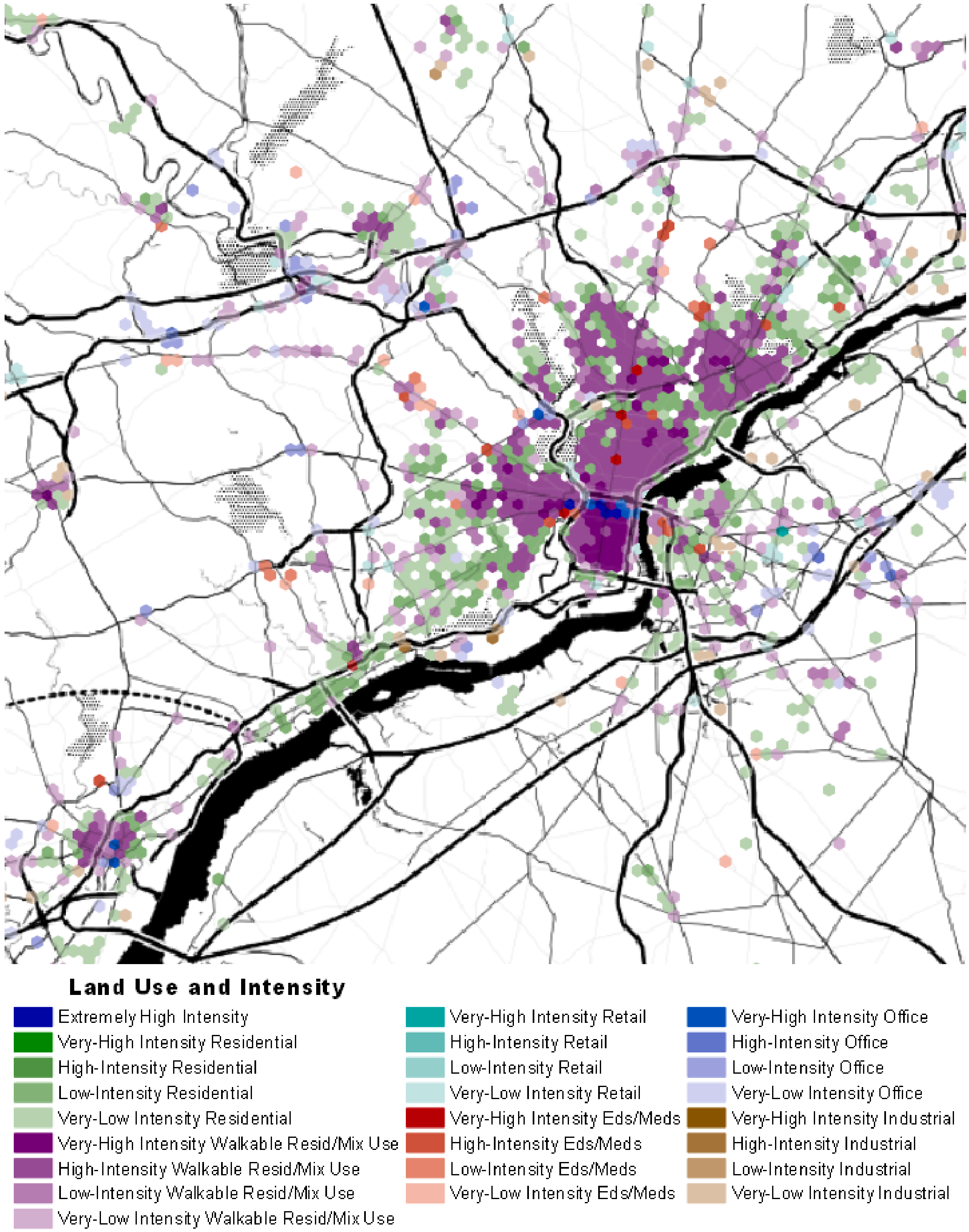

Figure H.20: Philadelphia-Camden-Wilmington, PA-NJ-DE-MD MSA map of land use and intensity, measured by walkshed-adjusted density. Philadelphia is just right of center and Wilmington is at the lower left. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

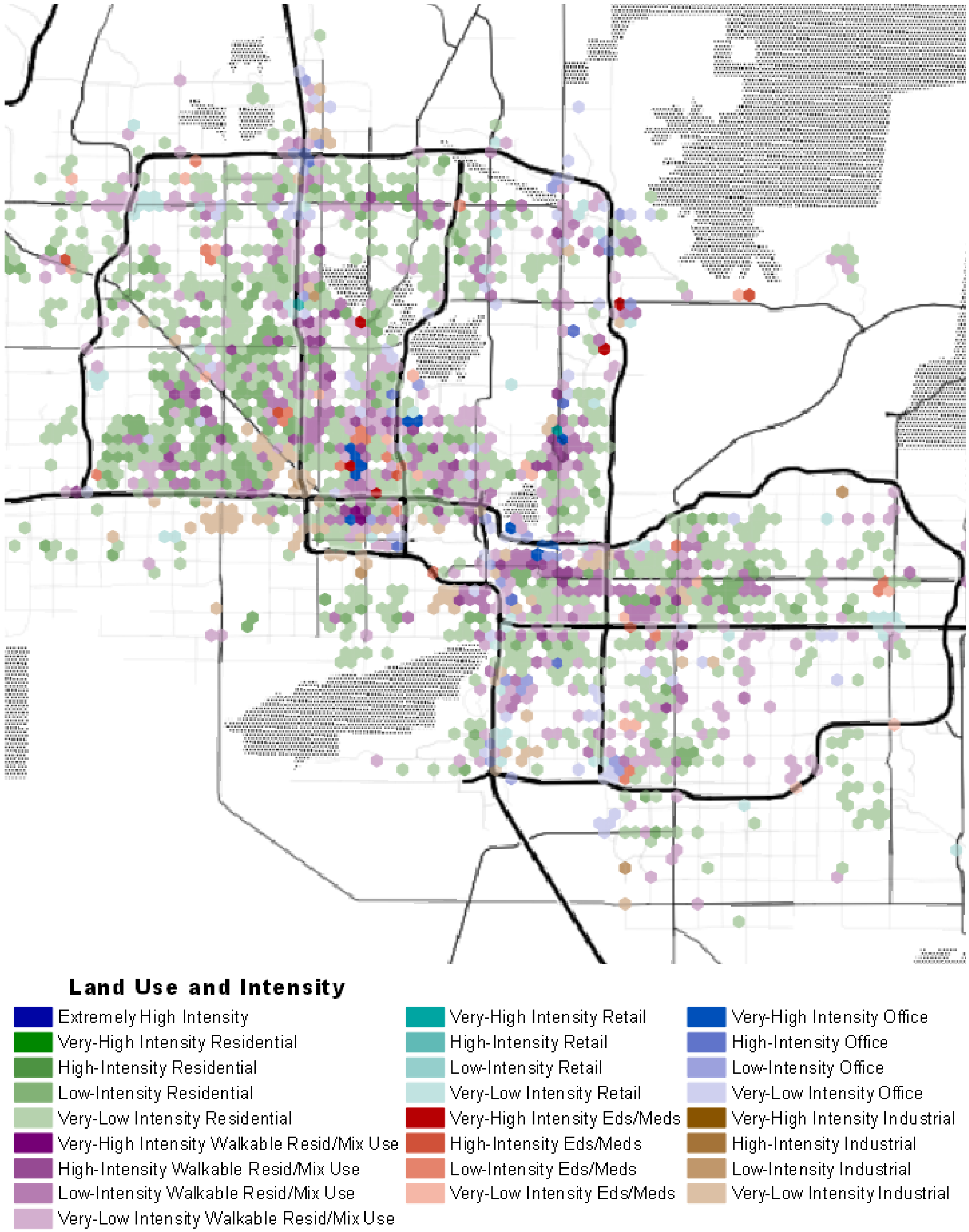

Figure H.21: Phoenix-Mesa-Chandler, AZ MSA map of land use and intensity, measured by walkshed-adjusted density. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

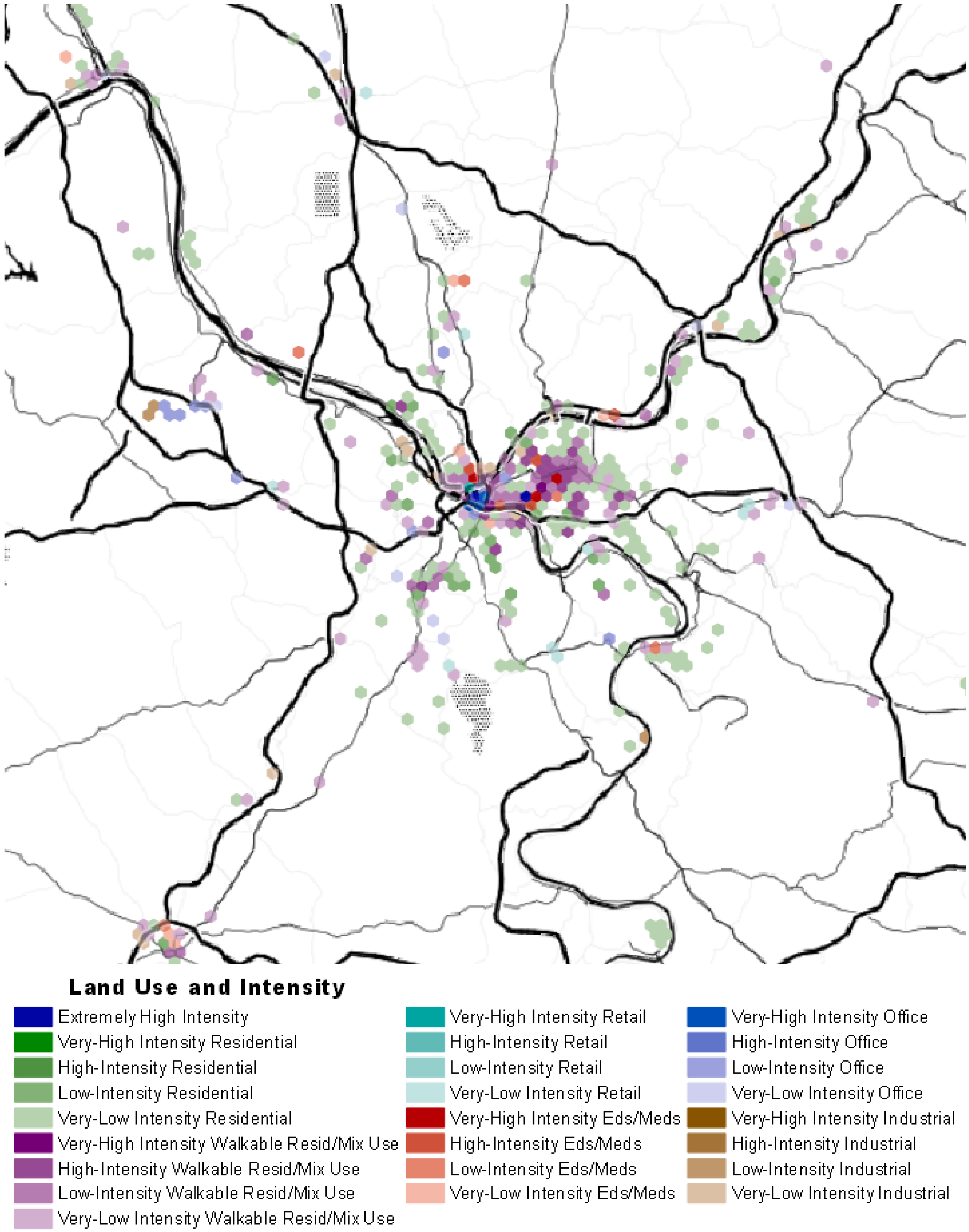

Figure H.22: Pittsburgh, PA MSA map of land use and intensity, measured by walkshed-adjusted density. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

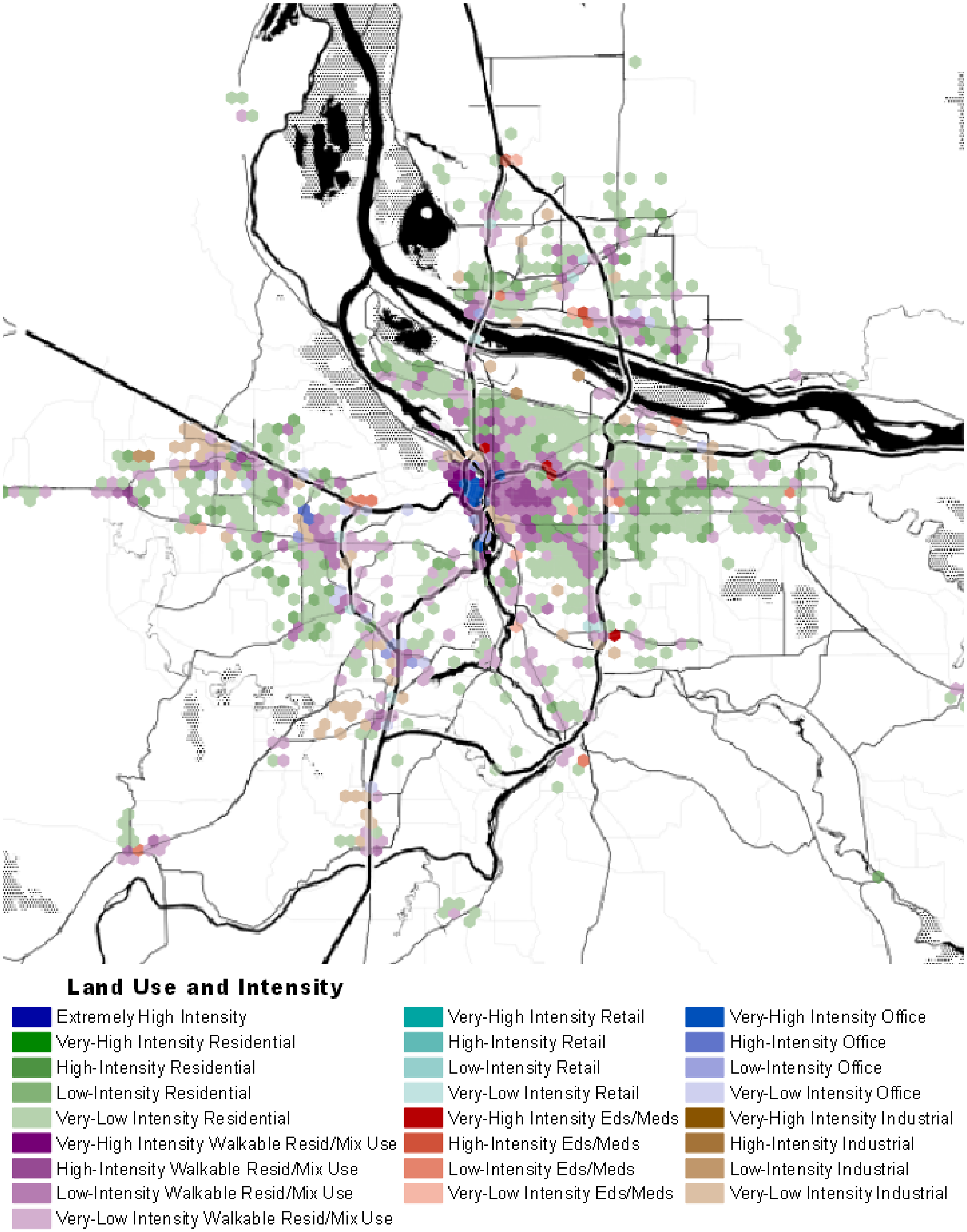

Figure H.23: Portland-Vancouver-Hillsboro, OR-WA MSA map of land use and intensity, measured by walkshed-adjusted density. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

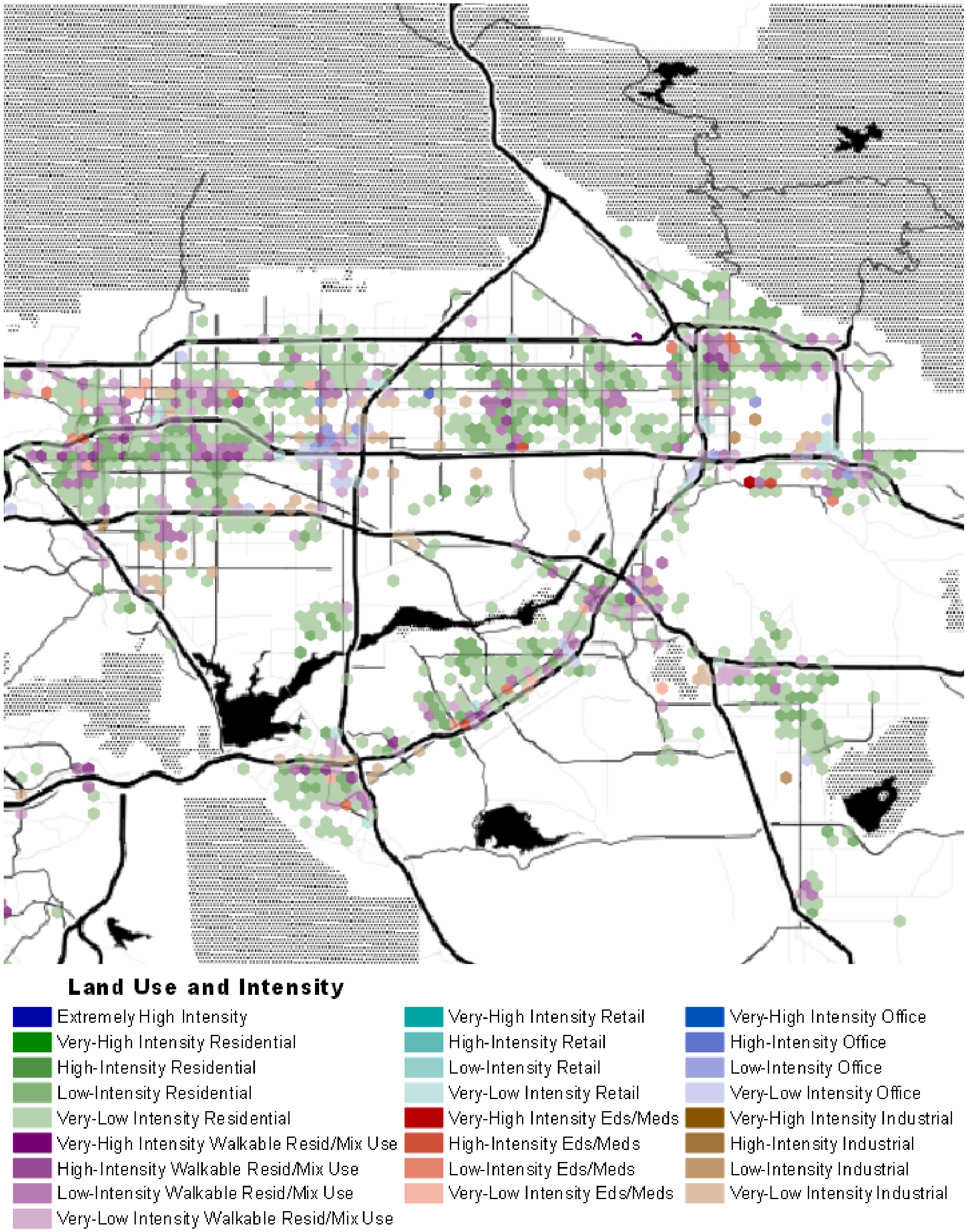

Figure H.24: Riverside-San Bernardino-Ontario, CA MSA map of land use and intensity, measured by walkshed-adjusted density. Ontario is to the center left, San Bernardino is to the center right, and Riverside is to the lower center. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

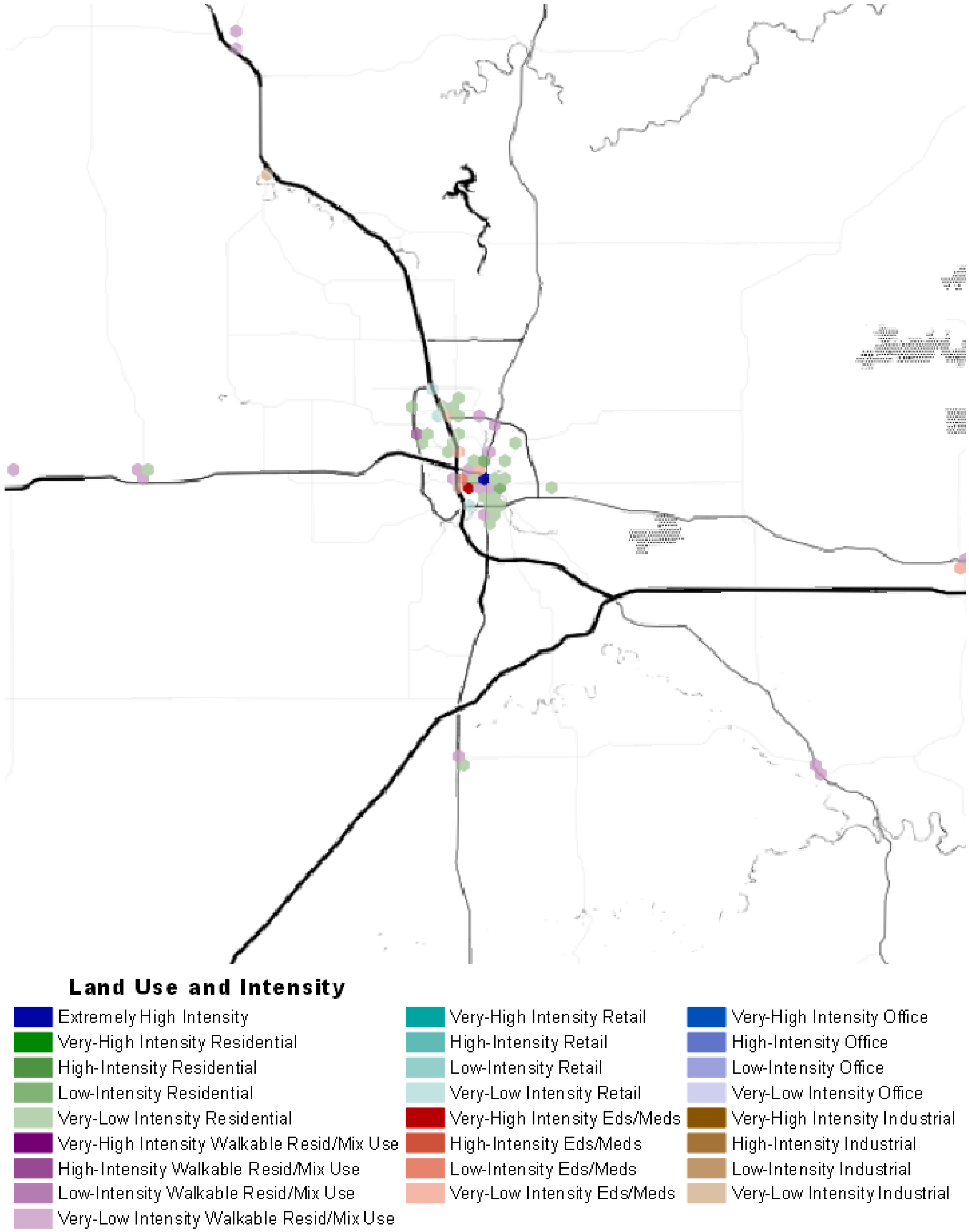

Figure H.25: Rochester, MN MSA map of land use and intensity, measured by walkshed-adjusted density. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

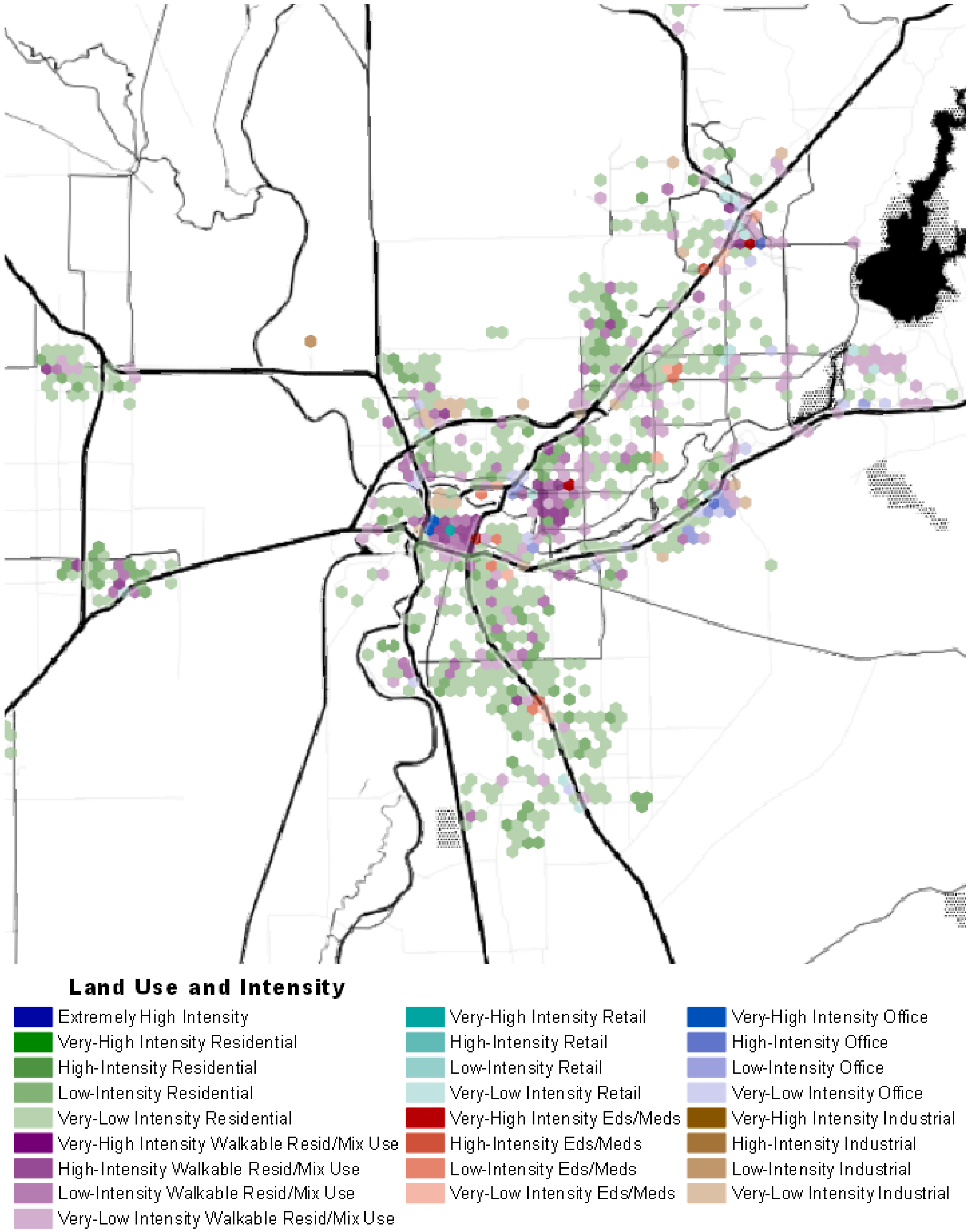

Figure H.26: Sacramento-Roseville-Folsom, CA MSA map of land use and intensity, measured by walkshed-adjusted density. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

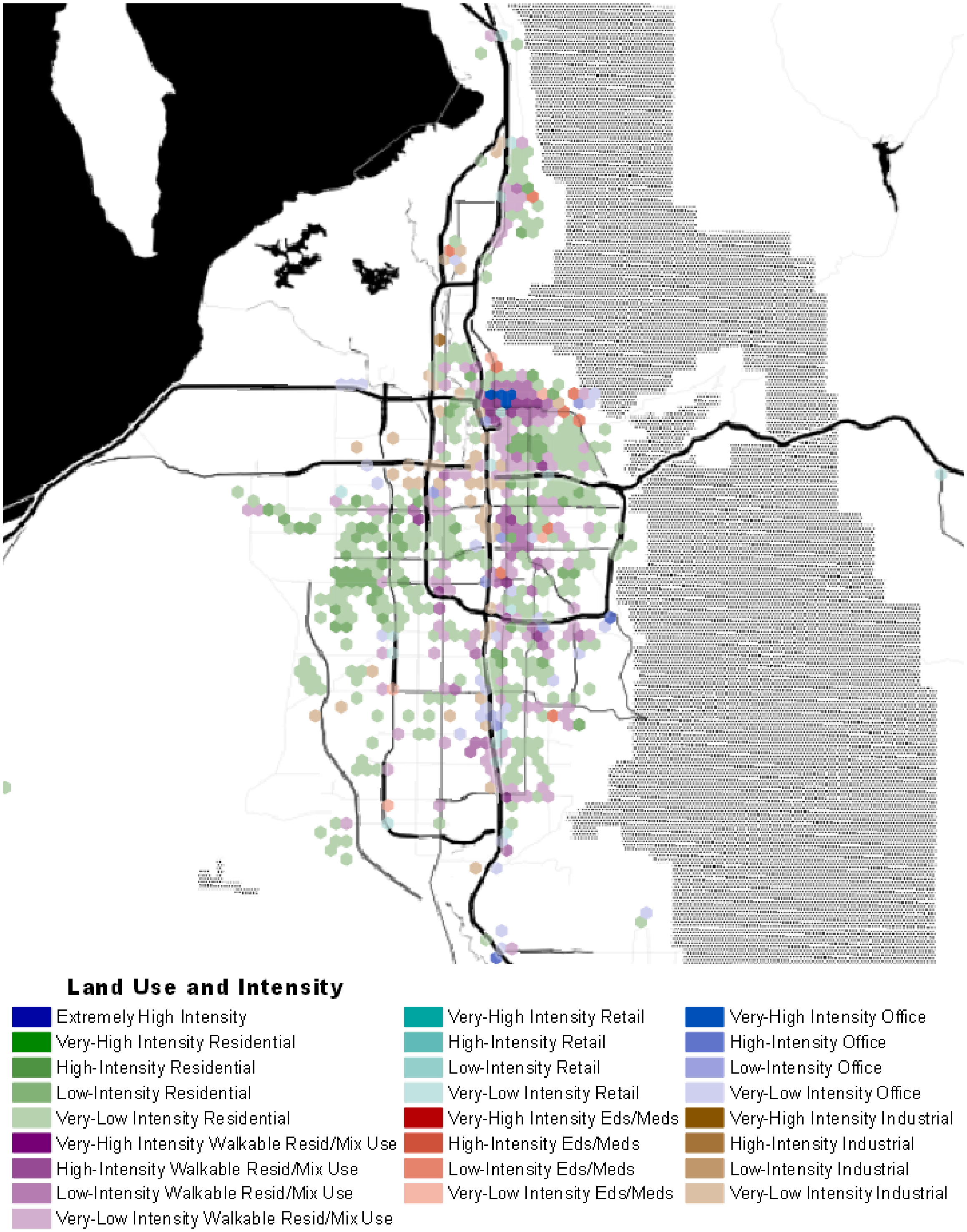

Figure H.27: Salt Lake City, UT MSA map of land use and intensity, measured by walkshed-adjusted density. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

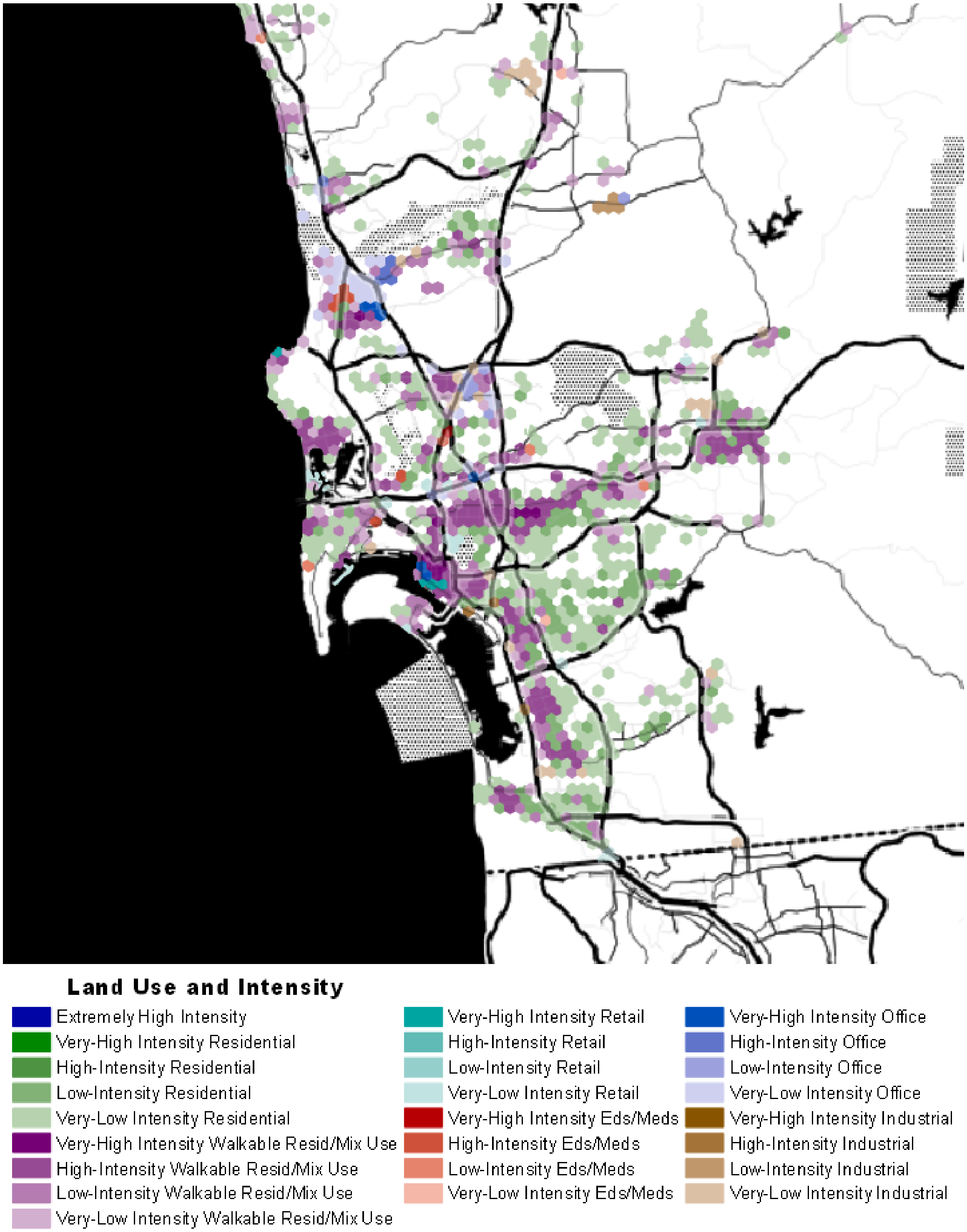

Figure H.28: San Diego-Chula Vista-Carlsbad, CA MSA map of land use and intensity, measured by walkshed-adjusted density. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

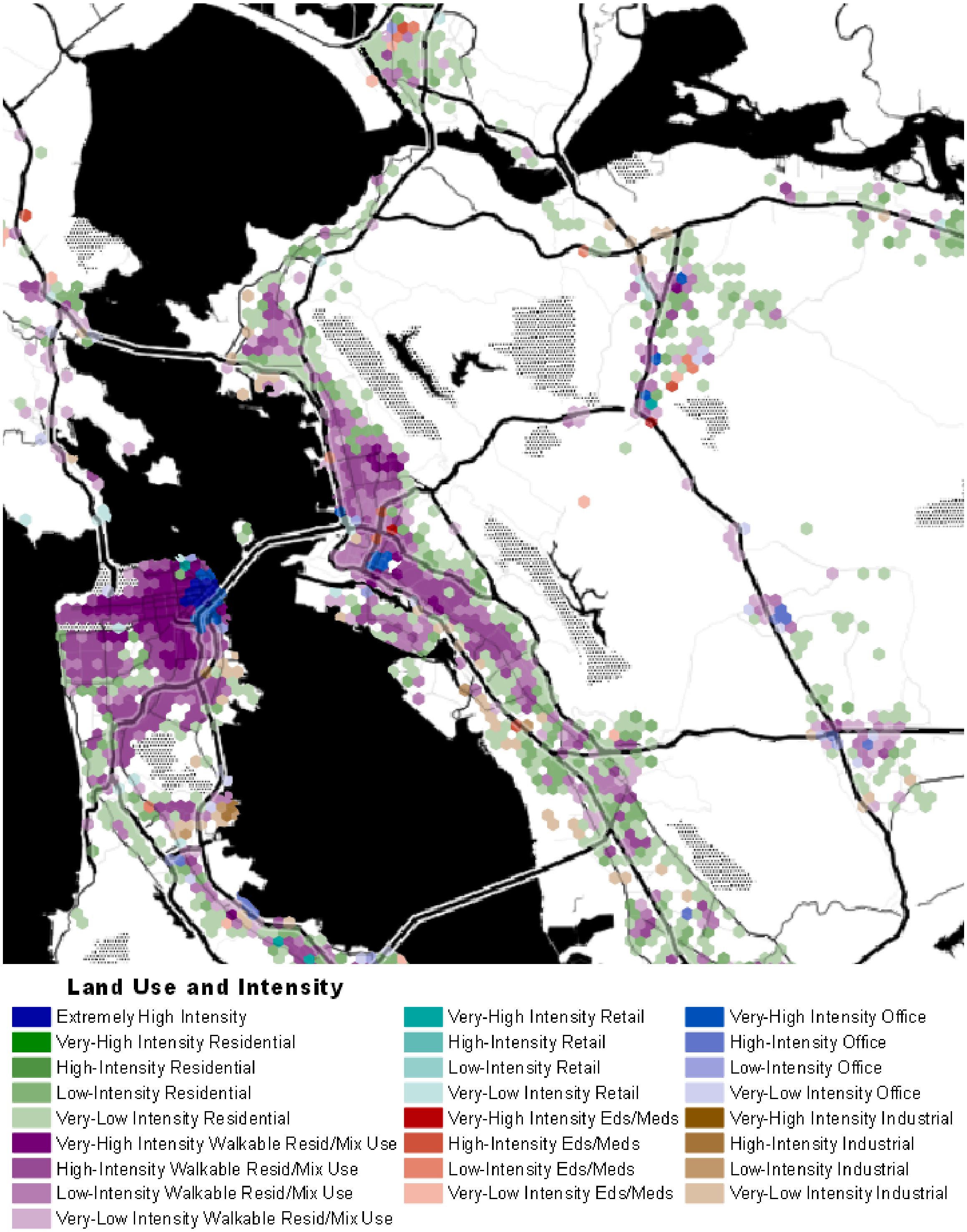

Figure H.29: San Francisco-Oakland-Berkeley, CA MSA map of land use and intensity, measured by walkshed-adjusted density. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

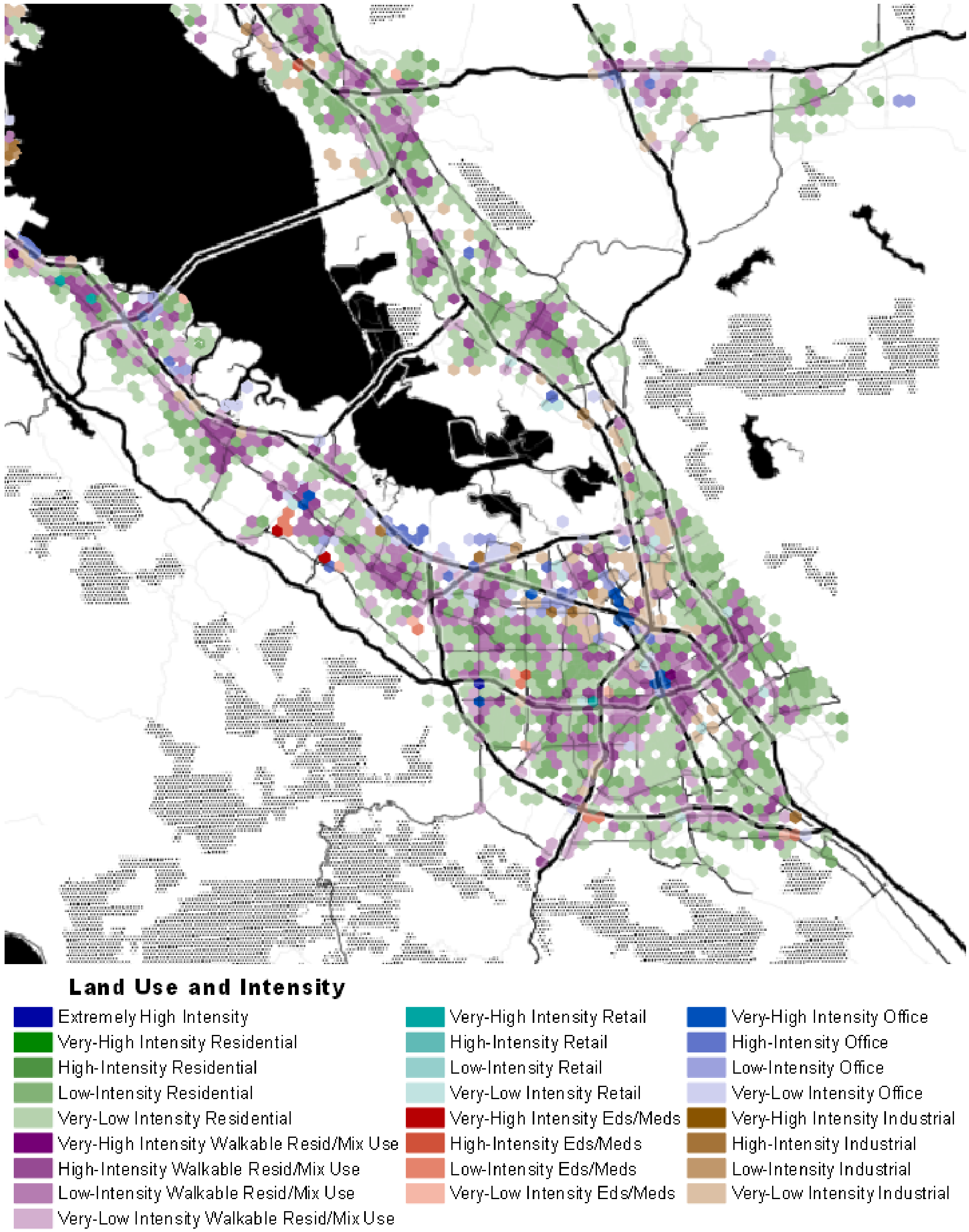

Figure H.30: San Jose-Sunnyvale-Santa Clara, CA MSA map of land use and intensity, measured by walkshed-adjusted density. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

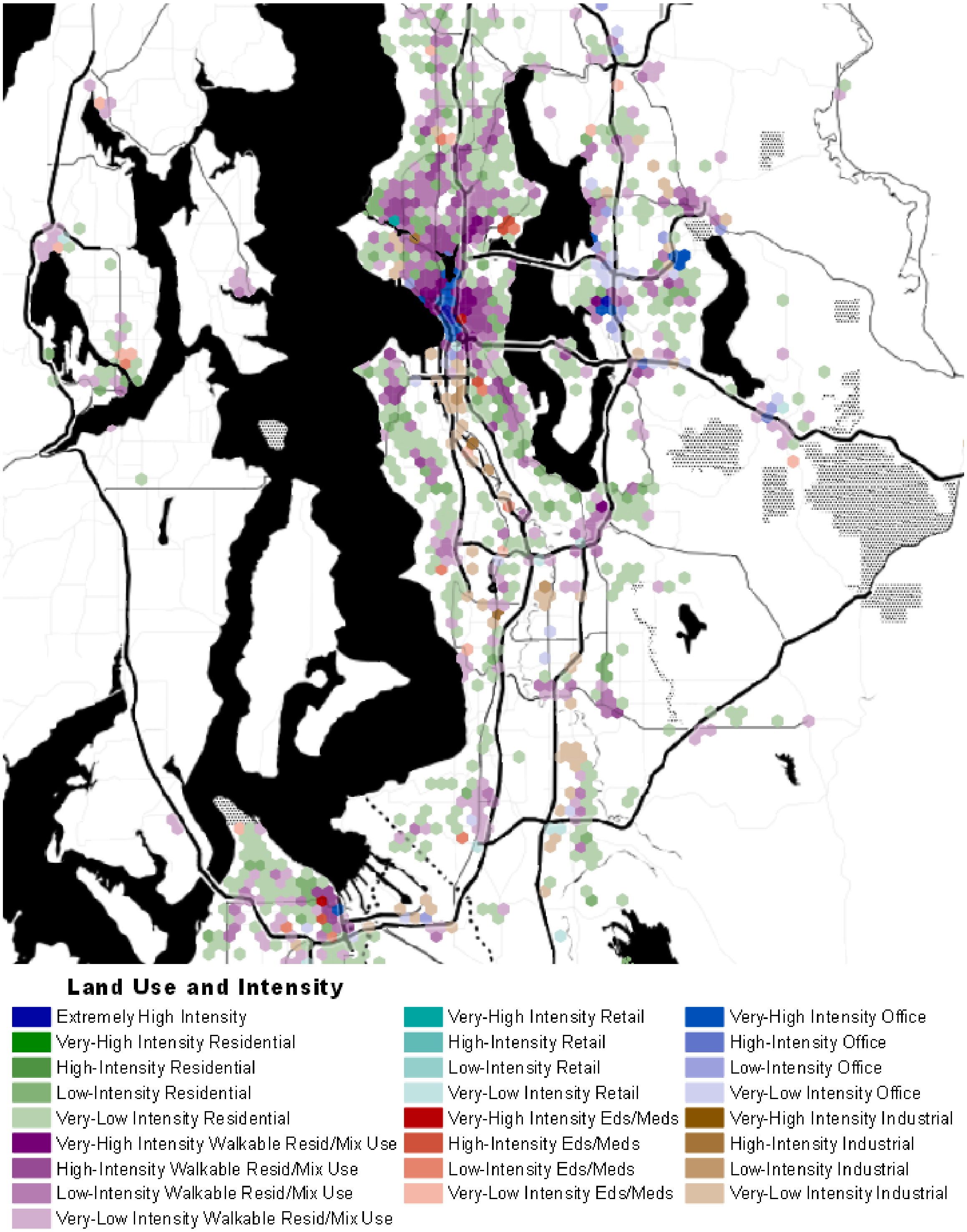

Figure H.31: Seattle-Tacoma-Bellevue, WA MSA map of land use and intensity, measured by walkshed-adjusted density. Seattle is in the upper center and Tacoma is to the lower left. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

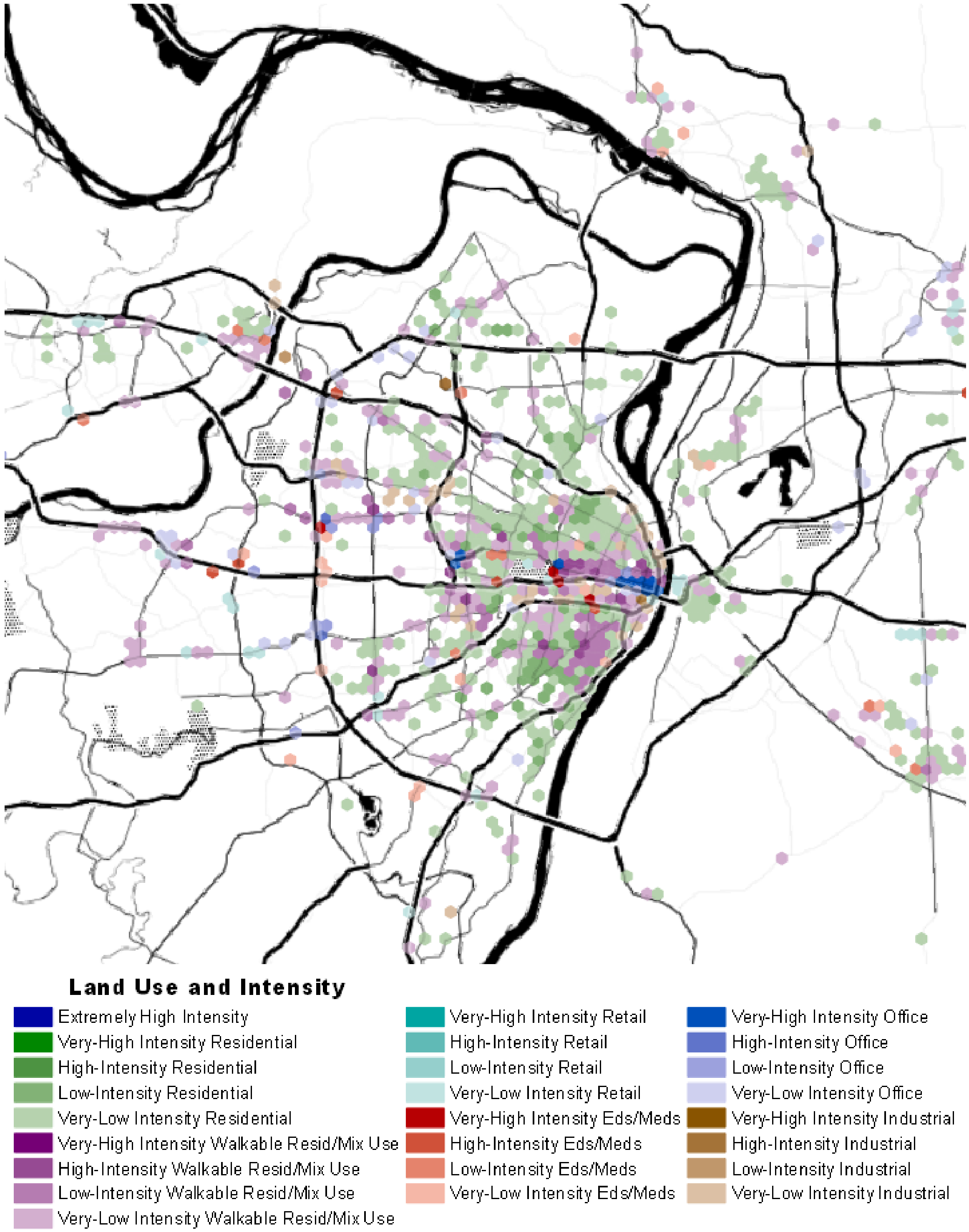

Figure H.32: St. Louis, MO-IL MSA map of land use and intensity, measured by walkshed-adjusted density. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

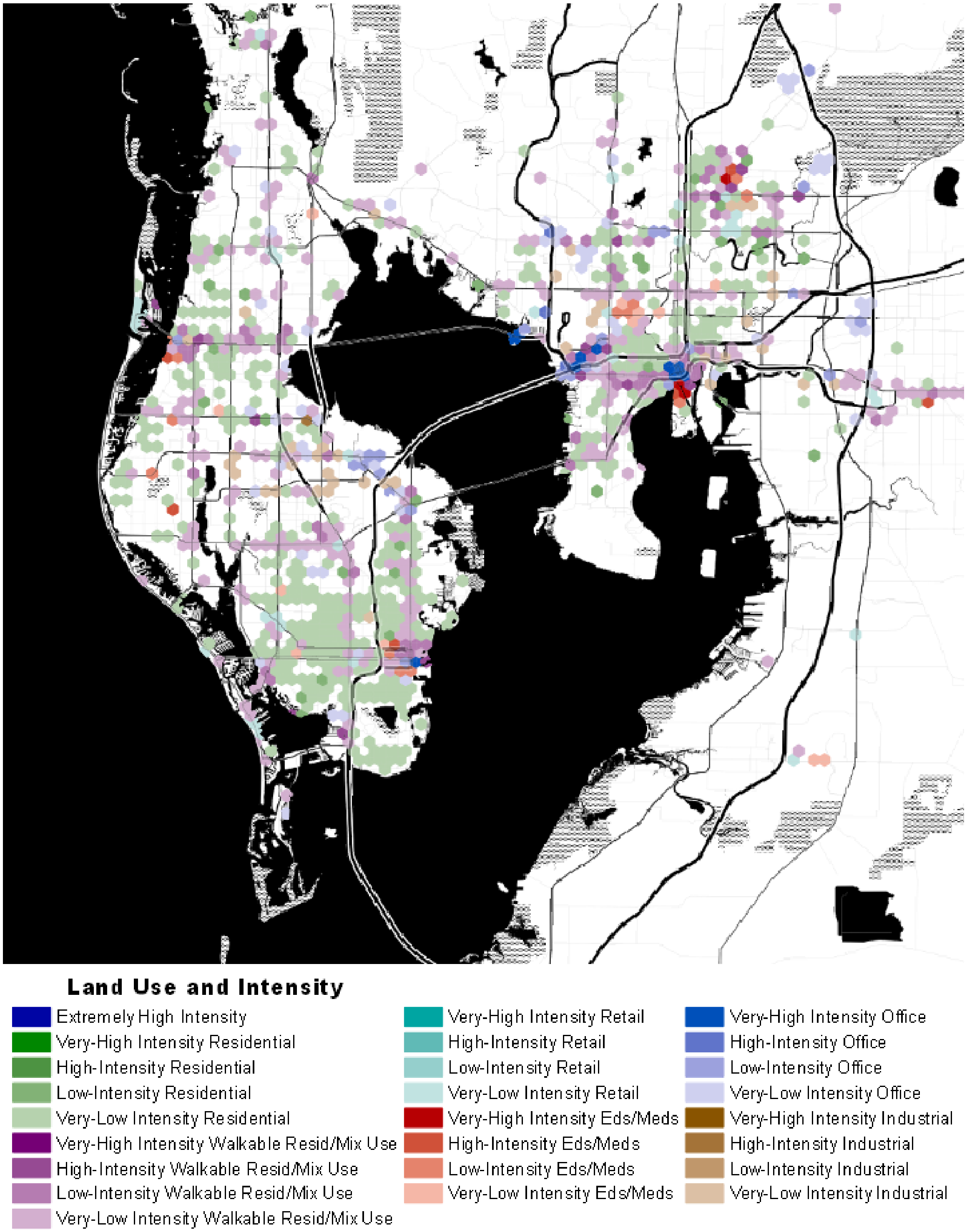

Figure H.33: Tampa-St. Petersburg-Clearwater, FL MSA map of land use and intensity, measured by walkshed-adjusted density. Tampa is to the upper right and St. Petersburg is to the lower left. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

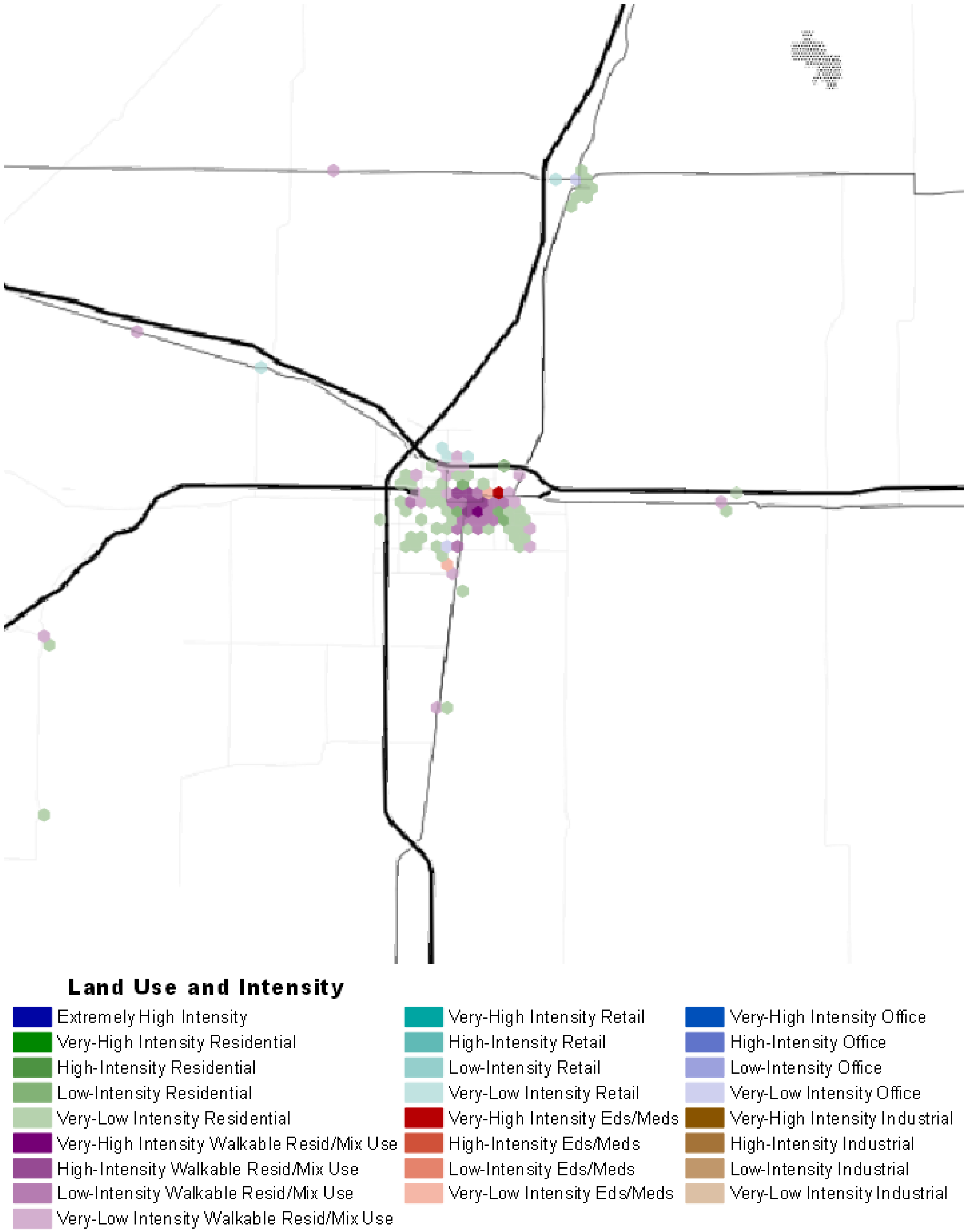

Figure H.34: Champaign-Urbana, IL MSA map of land use and intensity, measured by walkshed-adjusted density. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

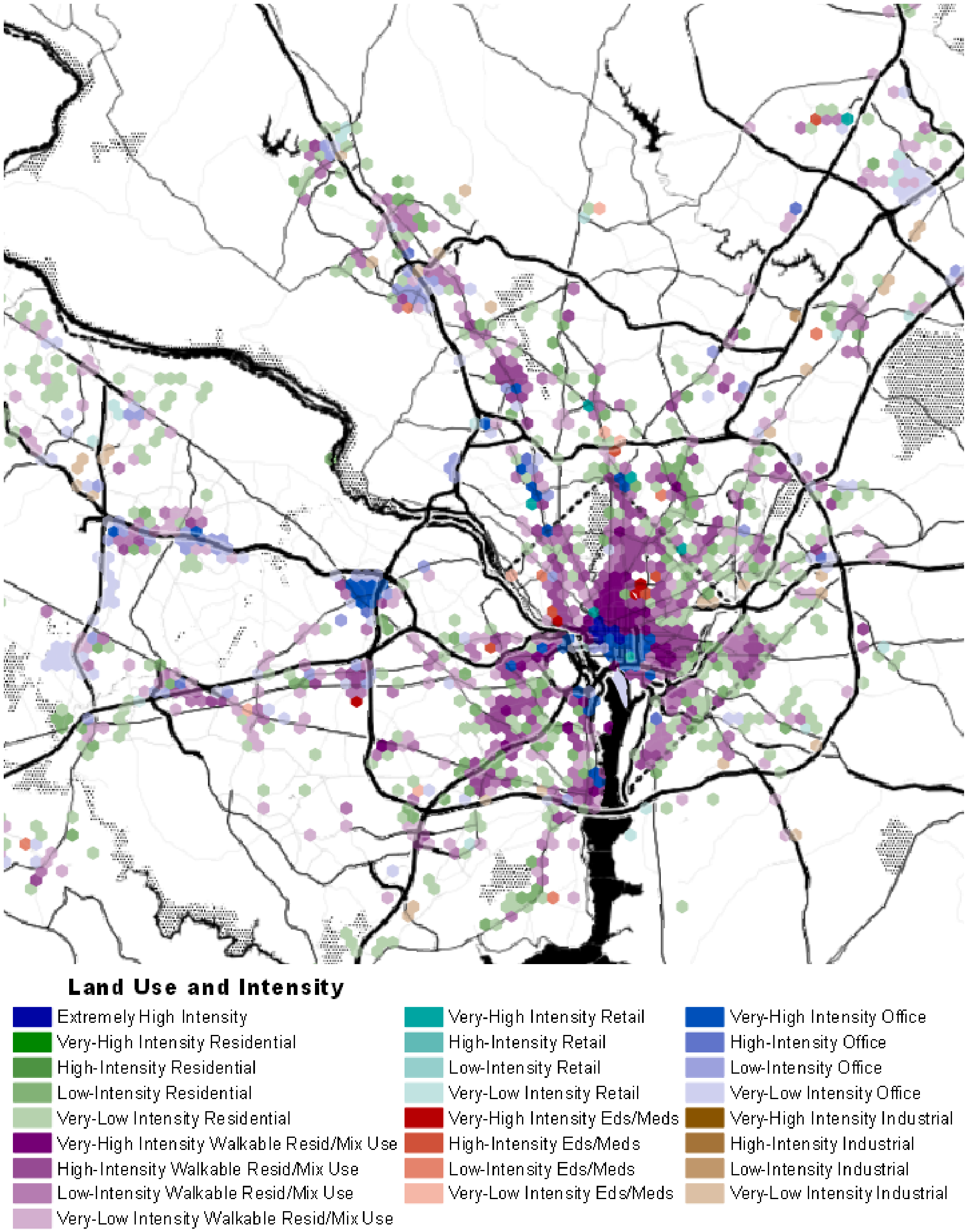

Figure H.35: Washington-Arlington-Alexandria, DC-VA-MD-WV MSA map of land use and intensity, measured by walkshed-adjusted density. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Appendix I: Metro Area Typology Tables

Tables I.1 on page 555 and I.2 on page 583 list all 926 CBSAs studied along with their job cluster and population cluster assignments and the fractions of jobs and residents in the neighborhood types used to typologize them. For the jobs clusters, the neighborhood types are:

- **CBD Jobs** — the fraction of the MSA's jobs in neighborhood type 00–Major Central Business District
- **HD Jobs** — the fraction of the MSA's jobs in neighborhood types 12–High-Density Retail, 14–High-Density Eds/Meds, and 16–High Density Office
- **MD Jobs** — the fraction of the MSA's jobs in neighborhood types 09–Medium-Density Mixed Use and 17–Medium-Density Office
- **Resid.** Jobs — the fraction of the MSA's jobs in neighborhood types 02–Very High Density Residential, 03–High Density Residential, 04–Medium Density Large Apartments, and 05-Medium-Density Small Apartments

For the population clusters, the neighborhood types are:

- **HD Pop.** — the fraction of the MSA's population in neighborhood types 02–Very High Density Residential or 03–High Density Residential

- **MD Large Apt. Pop.** — the fraction of the MSA's population in neighborhood type 04–Medium Density Large Apartments
- **MD Small Apt. Pop.** — the fraction of the MSA's population in neighborhood type 05-Medium-Density Small Apartments
- **MD Comm. Pop.** — the fraction of the MSA's population in any of the other neighborhood types included in the jobs data.

See Table 3.7 on page 144 for descriptions of the numbered neighborhood types.

Table I.1: List of CBSA Job Clusters and Distributions

CBSA Name	**Total Jobs**	**ID**	**CBD Jobs**	**HD Jobs**	**MD Jobs**	**Resid. Jobs**
New York-Newark-Jersey City, NY-NJ-PA	8,034,000	**1**	24.4%	5.0%	3.3%	21.8%
Urban Honolulu, HI	362,000	**2a**	8.2%	13.9%	6.2%	25.8%
Chicago-Naperville-Elgin, IL-IN-WI	4,104,000	**2b**	12.5%	5.3%	5.7%	8.6%
Boston-Cambridge-Newton, MA-NH	2,419,000	**2b**	7.8%	12.4%	5.5%	10.5%
San Francisco-Oakland-Berkeley, CA	2,140,000	**2b**	13.9%	10.3%	11.6%	12.8%
Washington-Arlington-Alexandria, DC-VA-MD-WV	2,723,000	**2c**	8.2%	17.6%	11.7%	5.2%
Seattle-Tacoma-Bellevue, WA	1,697,000	**2c**	7.2%	11.0%	10.3%	4.8%
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	2,587,000	**3a**	4.7%	8.6%	3.8%	7.3%
Pittsburgh, PA	1,048,000	**3a**	4.2%	9.8%	3.3%	2.1%
Los Angeles-Long Beach-Anaheim, CA	5,599,000	**3b**	3.0%	11.7%	11.7%	14.5%
San Jose-Sunnyvale-Santa Clara, CA	997,000	**3b**	2.5%	12.4%	15.0%	5.5%
Minneapolis-St. Paul-Bloomington, MN-WI	1,695,000	**3c**	3.3%	10.0%	7.8%	2.0%
Denver-Aurora-Lakewood, CO	1,300,000	**3c**	1.8%	12.1%	9.9%	1.7%
Baltimore-Columbia-Towson, MD	1,156,000	**3c**	2.0%	10.4%	5.4%	4.0%
Houston-The Woodlands-Sugar Land, TX	2,608,000	**3d**	2.9%	7.9%	10.0%	2.2%
Charlotte-Concord-Gastonia, NC-SC	1,071,000	**3d**	2.6%	4.8%	4.8%	0.0%
Austin-Round Rock-Georgetown, TX	837,000	**3d**	3.1%	6.1%	11.8%	0.5%
Dallas-Fort Worth-Arlington, TX	3,176,000	**4a**	0.8%	10.8%	9.5%	0.6%
Rochester, MN	104,000	**4b**	0.0%	32.4%	0.0%	0.0%
Bloomington, IL	74,000	**4b**	0.0%	25.2%	3.7%	0.1%
Bloomsburg-Berwick, PA	36,000	**4b**	0.0%	22.1%	0.0%	0.0%
Wisconsin Rapids-Marshfield, WI	35,000	**4b**	0.0%	18.4%	0.0%	0.0%
Sayre, PA	20,000	**4b**	0.0%	19.3%	0.0%	0.0%
Las Vegas-Henderson-Paradise, NV	867,000	**4c**	0.0%	15.9%	2.7%	3.9%
Milwaukee-Waukesha, WI	785,000	**4c**	0.0%	11.0%	5.6%	5.2%
Hartford-East Hartford-Middletown, CT	552,000	**4c**	0.0%	11.5%	2.5%	2.1%
New Orleans-Metairie, LA	488,000	**4c**	0.0%	16.7%	5.0%	2.8%
Rochester, NY	442,000	**4c**	0.0%	12.6%	1.9%	1.8%
New Haven-Milford, CT	333,000	**4c**	0.0%	14.7%	1.3%	2.4%
Syracuse, NY	249,000	**4c**	0.0%	12.6%	3.7%	1.9%
Duluth, MN-WI	100,000	**4c**	0.0%	16.3%	2.3%	2.1%
Champaign-Urbana, IL	68,000	**4c**	0.0%	9.8%	3.8%	5.6%
Ithaca, NY	42,000	**4c**	0.0%	12.7%	6.1%	2.8%
Atlanta-Sandy Springs-Alpharetta, GA	2,397,000	**4d**	0.0%	16.1%	6.4%	0.2%

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Table I.1 – *Continued from previous page*

CBSA Name	Total Jobs	ID	CBD	HD Jobs	MD Jobs	HD/ MD Resid
Phoenix-Mesa-Chandler, AZ	1,813,000	**4d**	0.0%	10.4%	9.2%	0.8%
St. Louis, MO-IL	1,228,000	**4d**	0.0%	10.3%	3.8%	0.7%
Orlando-Kissimmee-Sanford, FL	1,162,000	**4d**	0.0%	15.7%	3.8%	0.1%
Portland-Vancouver-Hillsboro, OR-WA	1,038,000	**4d**	0.0%	10.8%	7.4%	1.9%
Indianapolis-Carmel-Anderson, IN	942,000	**4d**	0.0%	11.9%	4.8%	0.5%
Nashville-Davidson–Murfreesboro–Franklin, TN	849,000	**4d**	0.0%	10.4%	9.2%	0.0%
Des Moines-West Des Moines, IA	331,000	**4d**	0.0%	13.0%	5.5%	0.0%
Durham-Chapel Hill, NC	264,000	**4d**	0.0%	14.4%	7.7%	0.0%
Spokane-Spokane Valley, WA	204,000	**4d**	0.0%	11.4%	8.3%	0.0%
South Bend-Mishawaka, IN-MI	120,000	**4d**	0.0%	10.2%	4.3%	0.0%
Charleston, WV	99,000	**4d**	0.0%	12.0%	4.2%	0.0%
Traverse City, MI	55,000	**4d**	0.0%	10.6%	5.4%	0.0%
Cleveland-Elyria, OH	917,000	**4e**	0.0%	11.8%	2.4%	0.6%
Louisville-Jefferson County, KY-IN	581,000	**4e**	0.0%	10.2%	3.3%	0.1%
Winston-Salem, NC	238,000	**4e**	0.0%	13.7%	0.6%	0.0%
Peoria, IL	153,000	**4e**	0.0%	14.3%	1.1%	0.0%
Roanoke, VA	143,000	**4e**	0.0%	12.9%	1.9%	0.0%
Gainesville, FL	106,000	**4e**	0.0%	11.5%	0.0%	0.0%
Atlantic City-Hammonton, NJ	103,000	**4e**	0.0%	13.0%	1.9%	1.4%
Killeen-Temple, TX	94,000	**4e**	0.0%	10.8%	1.5%	0.0%
Lebanon, NH-VT	87,000	**4e**	0.0%	14.7%	0.0%	0.0%
Saginaw, MI	74,000	**4e**	0.0%	10.4%	1.5%	0.0%
Concord, NH	67,000	**4e**	0.0%	9.9%	0.0%	0.0%
Alexandria, LA	49,000	**4e**	0.0%	10.6%	2.8%	0.0%
Albany, GA	46,000	**4e**	0.0%	10.2%	0.0%	0.0%
Grand Forks, ND-MN	42,000	**4e**	0.0%	10.7%	0.0%	0.0%
Cape Girardeau, MO-IL	38,000	**4e**	0.0%	12.7%	0.0%	0.0%
Quincy, IL-MO	32,000	**4e**	0.0%	11.4%	3.5%	0.0%
Plattsburgh, NY	23,000	**4e**	0.0%	12.0%	0.0%	0.0%
Mason City, IA	23,000	**4e**	0.0%	10.1%	0.0%	0.0%
Oneonta, NY	19,000	**4e**	0.0%	14.6%	0.0%	0.0%
Thomasville, GA	18,000	**4e**	0.0%	12.9%	0.0%	0.0%
Batesville, AR	17,000	**4e**	0.0%	14.6%	0.0%	0.0%
Easton, MD	17,000	**4e**	0.0%	13.6%	0.0%	0.0%

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Table I.1 – *Continued from previous page*

CBSA Name	Total Jobs	ID	CBD	HD Jobs	MD Jobs	HD/ MD Resid
Mountain Home, AR	13,000	**4e**	0.0%	12.7%	0.0%	0.0%
Miami-Fort Lauderdale-Pompano Beach, FL	2,296,000	**5a**	1.0%	7.5%	6.7%	5.3%
Jacksonville, FL	630,000	**5a**	0.9%	7.9%	5.2%	0.0%
Sacramento-Roseville-Folsom, CA	747,000	**5b**	0.0%	5.2%	8.1%	1.8%
Grand Rapids-Kentwood, MI	532,000	**5b**	0.0%	6.0%	8.2%	1.1%
Omaha-Council Bluffs, NE-IA	429,000	**5b**	0.0%	4.9%	10.2%	0.1%
Anchorage, AK	156,000	**5b**	0.0%	7.9%	15.4%	0.4%
Eugene-Springfield, OR	129,000	**5b**	0.0%	4.6%	9.4%	2.1%
Fargo, ND-MN	124,000	**5b**	0.0%	7.4%	12.9%	0.0%
Burlington-South Burlington, VT	100,000	**5b**	0.0%	3.8%	9.6%	1.8%
Topeka, KS	89,000	**5b**	0.0%	6.1%	7.5%	0.0%
Olympia-Lacey-Tumwater, WA	76,000	**5b**	0.0%	4.8%	9.5%	0.0%
La Crosse-Onalaska, WI-MN	68,000	**5b**	0.0%	8.1%	9.9%	1.7%
Bismarck, ND	58,000	**5b**	0.0%	4.7%	11.9%	0.0%
Missoula, MT	53,000	**5b**	0.0%	5.8%	10.3%	0.5%
Pittsfield, MA	50,000	**5b**	0.0%	5.8%	6.2%	0.0%
Santa Fe, NM	47,000	**5b**	0.0%	5.6%	10.8%	0.0%
Pueblo, CO	46,000	**5b**	0.0%	6.6%	8.0%	0.0%
San Diego-Chula Vista-Carlsbad, CA	1,205,000	**5c**	0.0%	7.1%	10.1%	5.9%
Providence-Warwick, RI-MA	619,000	**5c**	0.0%	6.6%	2.8%	9.5%
Buffalo-Cheektowaga, NY	463,000	**5c**	0.0%	3.9%	6.4%	3.4%
Bridgeport-Stamford-Norwalk, CT	387,000	**5c**	0.0%	6.1%	6.1%	5.9%
Albany-Schenectady-Troy, NY	351,000	**5c**	0.0%	8.6%	5.6%	3.5%
Worcester, MA-CT	329,000	**5c**	0.0%	9.1%	0.5%	5.2%
Allentown-Bethlehem-Easton, PA-NJ	320,000	**5c**	0.0%	8.3%	0.0%	4.2%
Springfield, MA	251,000	**5c**	0.0%	7.7%	6.2%	4.8%
Portland-South Portland, ME	235,000	**5c**	0.0%	6.6%	4.2%	3.2%
Manchester-Nashua, NH	189,000	**5c**	0.0%	6.7%	3.3%	5.2%
Trenton-Princeton, NJ	178,000	**5c**	0.0%	9.1%	5.4%	4.6%
Reading, PA	161,000	**5c**	0.0%	5.2%	1.7%	5.5%
Santa Maria-Santa Barbara, CA	153,000	**5c**	0.0%	4.1%	8.8%	5.7%
Erie, PA	109,000	**5c**	0.0%	7.5%	3.0%	3.5%
Iowa City, IA	65,000	**5c**	0.0%	4.1%	0.0%	5.6%
Lewiston-Auburn, ME	46,000	**5c**	0.0%	5.9%	6.4%	5.1%

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Table I.1 – *Continued from previous page*

CBSA Name	**Total Jobs**	**ID**	**CBD**	**HD Jobs**	**MD Jobs**	**HD/ MD Resid**
Longview, WA	31,000	**5c**	0.0%	7.8%	0.0%	7.9%
Detroit-Warren-Dearborn, MI	1,795,000	**5d**	0.0%	7.1%	6.8%	0.6%
Tampa-St. Petersburg-Clearwater, FL	1,194,000	**5d**	0.0%	8.1%	6.3%	0.3%
Cincinnati, OH-KY-IN	954,000	**5d**	0.0%	7.9%	3.6%	0.6%
Kansas City, MO-KS	943,000	**5d**	0.0%	7.0%	5.7%	0.2%
Columbus, OH	901,000	**5d**	0.0%	9.2%	5.5%	1.3%
San Antonio-New Braunfels, TX	842,000	**5d**	0.0%	7.8%	5.8%	0.2%
Salt Lake City, UT	594,000	**5d**	0.0%	8.4%	8.5%	0.2%
Richmond, VA	551,000	**5d**	0.0%	7.3%	3.4%	1.1%
Oklahoma City, OK	502,000	**5d**	0.0%	8.9%	3.8%	0.0%
Birmingham-Hoover, AL	432,000	**5d**	0.0%	7.5%	5.3%	0.6%
Columbia, SC	310,000	**5d**	0.0%	7.4%	5.8%	0.0%
Little Rock-North Little Rock-Conway, AR	288,000	**5d**	0.0%	9.4%	3.9%	0.5%
Boise City, ID	276,000	**5d**	0.0%	7.9%	3.9%	0.0%
Augusta-Richmond County, GA-SC	183,000	**5d**	0.0%	8.1%	5.3%	0.0%
Fort Wayne, IN	183,000	**5d**	0.0%	7.2%	7.3%	0.0%
Springfield, MO	181,000	**5d**	0.0%	9.2%	6.4%	0.0%
Lincoln, NE	148,000	**5d**	0.0%	8.8%	3.0%	1.2%
Sioux Falls, SD	139,000	**5d**	0.0%	9.3%	7.9%	0.3%
Evansville, IN-KY	138,000	**5d**	0.0%	7.2%	5.7%	0.8%
Cedar Rapids, IA	131,000	**5d**	0.0%	9.4%	4.1%	0.8%
Ann Arbor, MI	128,000	**5d**	0.0%	8.4%	5.1%	2.1%
Tallahassee, FL	120,000	**5d**	0.0%	6.7%	3.5%	0.0%
Amarillo, TX	100,000	**5d**	0.0%	7.2%	3.9%	0.0%
Macon-Bibb County, GA	86,000	**5d**	0.0%	9.0%	9.9%	0.0%
Springfield, IL	85,000	**5d**	0.0%	9.2%	9.5%	0.0%
Binghamton, NY	79,000	**5d**	0.0%	9.4%	3.9%	1.8%
Jackson, MI	51,000	**5d**	0.0%	6.6%	5.3%	0.0%
Flagstaff, AZ	46,000	**5d**	0.0%	8.0%	3.6%	0.0%
Memphis, TN-MS-AR	554,000	**5e**	0.0%	7.7%	1.2%	0.0%
Tulsa, OK	387,000	**5e**	0.0%	9.1%	1.1%	0.0%
Greenville-Anderson, SC	349,000	**5e**	0.0%	6.1%	3.0%	0.0%
Greensboro-High Point, NC	322,000	**5e**	0.0%	5.8%	0.7%	0.0%
Dayton-Kettering, OH	321,000	**5e**	0.0%	6.6%	1.1%	0.0%

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Table I.1 – *Continued from previous page*

CBSA Name	**Total Jobs**	**ID**	**CBD**	**HD Jobs**	**MD Jobs**	**HD/ MD Resid**
Akron, OH	289,000	**5e**	0.0%	7.2%	1.1%	0.0%
Chattanooga, TN-GA	214,000	**5e**	0.0%	7.3%	2.2%	0.0%
Ogden-Clearfield, UT	206,000	**5e**	0.0%	6.2%	0.0%	0.0%
Rockford, IL	126,000	**5e**	0.0%	6.6%	0.7%	0.0%
Kalamazoo-Portage, MI	109,000	**5e**	0.0%	6.7%	3.1%	0.5%
Tyler, TX	90,000	**5e**	0.0%	9.5%	0.0%	0.0%
Ocala, FL	87,000	**5e**	0.0%	7.1%	0.0%	0.0%
Gainesville, GA	80,000	**5e**	0.0%	8.2%	0.0%	0.0%
College Station-Bryan, TX	72,000	**5e**	0.0%	7.1%	0.0%	0.0%
Joplin, MO	68,000	**5e**	0.0%	5.8%	0.0%	0.0%
Morgantown, WV	54,000	**5e**	0.0%	6.8%	0.0%	0.4%
Muskegon, MI	52,000	**5e**	0.0%	7.1%	0.0%	0.0%
Abilene, TX	51,000	**5e**	0.0%	7.7%	0.0%	0.0%
Jonesboro, AR	48,000	**5e**	0.0%	6.7%	0.0%	0.0%
Owensboro, KY	45,000	**5e**	0.0%	9.0%	0.0%	0.0%
Johnstown, PA	45,000	**5e**	0.0%	7.8%	0.0%	0.0%
Wichita Falls, TX	42,000	**5e**	0.0%	5.9%	0.0%	0.0%
Muncie, IN	39,000	**5e**	0.0%	9.3%	0.0%	0.0%
San Angelo, TX	38,000	**5e**	0.0%	8.7%	0.0%	0.0%
Farmington, NM	37,000	**5e**	0.0%	5.9%	0.0%	0.0%
Kalispell, MT	37,000	**5e**	0.0%	7.9%	0.0%	0.0%
Brunswick, GA	34,000	**5e**	0.0%	6.5%	0.0%	0.0%
Rome, GA	33,000	**5e**	0.0%	8.8%	0.0%	0.0%
Great Falls, MT	31,000	**5e**	0.0%	6.3%	0.0%	0.0%
Roseburg, OR	31,000	**5e**	0.0%	5.7%	0.0%	0.0%
Keene, NH	27,000	**5e**	0.0%	5.9%	0.0%	0.0%
Salina, KS	27,000	**5e**	0.0%	9.6%	0.0%	0.0%
Fairbanks, AK	25,000	**5e**	0.0%	7.8%	0.0%	0.0%
Rutland, VT	24,000	**5e**	0.0%	8.7%	0.0%	0.0%
Pine Bluff, AR	23,000	**5e**	0.0%	7.1%	0.0%	0.0%
Hutchinson, KS	22,000	**5e**	0.0%	7.2%	0.0%	0.0%
Laconia, NH	21,000	**5e**	0.0%	6.7%	0.0%	0.0%
Galesburg, IL	15,000	**5e**	0.0%	8.9%	0.0%	0.0%
Pittsburg, KS	13,000	**5e**	0.0%	8.7%	0.0%	0.0%

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Table I.1 – *Continued from previous page*

CBSA Name	Total Jobs	ID	CBD	HD Jobs	MD Jobs	HD/ MD Resid
Centralia, IL	11,000	**5e**	0.0%	8.3%	0.0%	0.0%
Virginia Beach-Norfolk-Newport News, VA-NC	607,000	**5f**	0.0%	5.6%	5.0%	0.7%
Raleigh-Cary, NC	541,000	**5f**	0.0%	5.0%	3.4%	0.0%
Baton Rouge, LA	338,000	**5f**	0.0%	3.4%	2.5%	0.3%
Knoxville, TN	334,000	**5f**	0.0%	3.1%	1.9%	0.1%
Fresno, CA	315,000	**5f**	0.0%	3.4%	3.1%	1.9%
Albuquerque, NM	308,000	**5f**	0.0%	5.1%	5.8%	0.0%
Tucson, AZ	299,000	**5f**	0.0%	3.4%	2.1%	1.2%
Charleston-North Charleston, SC	285,000	**5f**	0.0%	5.6%	4.5%	0.0%
Harrisburg-Carlisle, PA	272,000	**5f**	0.0%	4.7%	1.1%	2.4%
Toledo, OH	264,000	**5f**	0.0%	5.5%	1.0%	0.0%
North Port-Sarasota-Bradenton, FL	259,000	**5f**	0.0%	3.8%	3.6%	0.0%
Wichita, KS	259,000	**5f**	0.0%	3.5%	3.0%	0.5%
Lancaster, PA	227,000	**5f**	0.0%	3.8%	2.4%	3.4%
Colorado Springs, CO	222,000	**5f**	0.0%	4.1%	0.8%	0.7%
Jackson, MS	222,000	**5f**	0.0%	4.6%	1.1%	0.0%
Provo-Orem, UT	203,000	**5f**	0.0%	4.3%	4.6%	2.8%
Lakeland-Winter Haven, FL	202,000	**5f**	0.0%	3.9%	3.5%	0.0%
McAllen-Edinburg-Mission, TX	200,000	**5f**	0.0%	4.7%	2.5%	0.0%
Reno, NV	200,000	**5f**	0.0%	5.6%	2.8%	1.2%
Lansing-East Lansing, MI	183,000	**5f**	0.0%	4.2%	2.2%	0.2%
Palm Bay-Melbourne-Titusville, FL	179,000	**5f**	0.0%	4.4%	2.0%	0.0%
Deltona-Daytona Beach-Ormond Beach, FL	172,000	**5f**	0.0%	3.7%	0.0%	0.0%
Asheville, NC	168,000	**5f**	0.0%	4.9%	5.1%	0.0%
Modesto, CA	157,000	**5f**	0.0%	4.2%	0.0%	0.3%
Green Bay, WI	154,000	**5f**	0.0%	3.4%	2.5%	0.9%
Canton-Massillon, OH	150,000	**5f**	0.0%	3.2%	2.8%	0.0%
Savannah, GA	146,000	**5f**	0.0%	3.2%	5.8%	1.8%
Shreveport-Bossier City, LA	140,000	**5f**	0.0%	3.6%	3.1%	0.0%
Salem, OR	129,000	**5f**	0.0%	3.5%	2.4%	1.2%
Naples-Marco Island, FL	128,000	**5f**	0.0%	3.3%	0.0%	0.1%
Lubbock, TX	117,000	**5f**	0.0%	3.3%	0.0%	0.3%
Huntington-Ashland, WV-KY-OH	113,000	**5f**	0.0%	4.7%	3.2%	0.7%
Brownsville-Harlingen, TX	107,000	**5f**	0.0%	5.1%	0.0%	0.0%

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Table I.1 – *Continued from previous page*

CBSA Name	**Total Jobs**	**ID**	**CBD**	**HD Jobs**	**MD Jobs**	**HD/ MD Resid**
Kennewick-Richland, WA	102,000	**5f**	0.0%	4.5%	0.0%	0.0%
Longview, TX	100,000	**5f**	0.0%	3.6%	3.3%	0.0%
Waco, TX	98,000	**5f**	0.0%	4.5%	3.9%	1.4%
St. Cloud, MN	98,000	**5f**	0.0%	3.8%	5.5%	0.0%
Columbus, GA-AL	91,000	**5f**	0.0%	3.6%	0.0%	0.0%
San Luis Obispo-Paso Robles, CA	89,000	**5f**	0.0%	3.5%	4.0%	0.6%
Greeley, CO	88,000	**5f**	0.0%	3.8%	0.0%	0.0%
Medford, OR	78,000	**5f**	0.0%	3.3%	3.0%	2.3%
Columbia, MO	77,000	**5f**	0.0%	3.3%	3.5%	0.0%
Tupelo, MS	76,000	**5f**	0.0%	4.1%	1.7%	0.0%
Barnstable Town, MA	74,000	**5f**	0.0%	3.8%	0.0%	0.0%
Monroe, LA	73,000	**5f**	0.0%	3.4%	3.2%	0.0%
Wausau-Weston, WI	73,000	**5f**	0.0%	4.5%	0.0%	1.1%
Bellingham, WA	69,000	**5f**	0.0%	4.1%	4.7%	0.0%
Johnson City, TN	65,000	**5f**	0.0%	4.8%	0.0%	0.0%
Kahului-Wailuku-Lahaina, HI	65,000	**5f**	0.0%	3.5%	0.0%	0.0%
Chico, CA	65,000	**5f**	0.0%	6.2%	2.1%	1.7%
Bowling Green, KY	63,000	**5f**	0.0%	3.4%	3.6%	1.6%
Terre Haute, IN	57,000	**5f**	0.0%	4.3%	0.0%	0.0%
Niles, MI	54,000	**5f**	0.0%	3.9%	0.0%	0.0%
Rapid City, SD	54,000	**5f**	0.0%	3.9%	4.7%	0.0%
Grand Junction, CO	53,000	**5f**	0.0%	5.4%	0.0%	0.0%
Yuma, AZ	48,000	**5f**	0.0%	4.1%	0.0%	1.0%
St. Joseph, MO-KS	48,000	**5f**	0.0%	5.3%	0.0%	0.0%
Mankato, MN	45,000	**5f**	0.0%	4.6%	0.0%	0.0%
Decatur, IL	44,000	**5f**	0.0%	5.2%	0.0%	0.0%
Punta Gorda, FL	43,000	**5f**	0.0%	5.4%	0.0%	0.0%
Kankakee, IL	37,000	**5f**	0.0%	4.7%	0.0%	0.0%
Victoria, TX	32,000	**5f**	0.0%	4.4%	0.0%	0.0%
Steamboat Springs, CO	12,000	**5f**	0.0%	4.9%	0.0%	0.0%
Riverside-San Bernardino-Ontario, CA	1,208,000	**6a**	0.0%	2.7%	2.8%	0.7%
Madison, WI	310,000	**6a**	0.0%	2.9%	11.5%	2.2%
Lexington-Fayette, KY	230,000	**6a**	0.0%	1.5%	3.4%	1.5%
Scranton–Wilkes-Barre, PA	227,000	**6a**	0.0%	2.2%	4.5%	2.7%

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Table I.1 – *Continued from previous page*

CBSA Name	Total Jobs	ID	CBD	HD Jobs	MD Jobs	HD/ MD Resid
Stockton, CA	207,000	**6a**	0.0%	2.2%	2.4%	3.0%
Poughkeepsie-Newburgh-Middletown, NY	206,000	**6a**	0.0%	2.5%	1.1%	4.2%
Youngstown-Warren-Boardman, OH-PA	186,000	**6a**	0.0%	1.4%	0.0%	0.0%
Lafayette, LA	175,000	**6a**	0.0%	2.2%	0.0%	0.0%
Huntsville, AL	175,000	**6a**	0.0%	2.5%	7.4%	0.0%
Santa Rosa-Petaluma, CA	173,000	**6a**	0.0%	1.6%	3.9%	0.2%
Pensacola-Ferry Pass-Brent, FL	171,000	**6a**	0.0%	1.7%	0.0%	0.0%
York-Hanover, PA	165,000	**6a**	0.0%	2.1%	1.8%	2.0%
Davenport-Moline-Rock Island, IA-IL	158,000	**6a**	0.0%	1.9%	1.9%	0.0%
Mobile, AL	155,000	**6a**	0.0%	2.3%	3.5%	0.0%
Corpus Christi, TX	146,000	**6a**	0.0%	2.6%	6.7%	2.3%
Beaumont-Port Arthur, TX	131,000	**6a**	0.0%	2.0%	0.0%	0.0%
Elkhart-Goshen, IN	126,000	**6a**	0.0%	1.7%	0.0%	0.0%
Port St. Lucie, FL	122,000	**6a**	0.0%	2.2%	1.1%	0.9%
Flint, MI	117,000	**6a**	0.0%	2.9%	2.1%	0.0%
Vallejo, CA	110,000	**6a**	0.0%	2.9%	2.9%	0.1%
Kingsport-Bristol, TN-VA	103,000	**6a**	0.0%	2.9%	0.0%	0.0%
Utica-Rome, NY	93,000	**6a**	0.0%	2.0%	4.3%	2.8%
Yakima, WA	88,000	**6a**	0.0%	3.1%	0.0%	1.8%
Oshkosh-Neenah, WI	86,000	**6a**	0.0%	1.1%	2.4%	0.6%
Waterloo-Cedar Falls, IA	78,000	**6a**	0.0%	2.9%	0.0%	0.0%
Lafayette-West Lafayette, IN	76,000	**6a**	0.0%	2.4%	0.0%	1.8%
Eau Claire, WI	74,000	**6a**	0.0%	2.8%	0.0%	0.0%
Bend, OR	69,000	**6a**	0.0%	2.5%	3.9%	0.0%
Dalton, GA	58,000	**6a**	0.0%	2.4%	0.0%	0.0%
Janesville-Beloit, WI	57,000	**6a**	0.0%	3.1%	0.0%	0.0%
Bangor, ME	57,000	**6a**	0.0%	2.7%	3.4%	0.0%
Burlington, NC	55,000	**6a**	0.0%	2.7%	3.7%	0.0%
Prescott Valley-Prescott, AZ	51,000	**6a**	0.0%	2.3%	0.0%	0.0%
Jefferson City, MO	50,000	**6a**	0.0%	2.4%	0.0%	0.0%
Battle Creek, MI	48,000	**6a**	0.0%	1.9%	0.0%	0.0%
Lebanon, PA	43,000	**6a**	0.0%	2.9%	0.0%	2.1%
Fremont, NE	14,000	**6a**	0.0%	2.6%	0.0%	0.0%
El Paso, TX	262,000	**6b**	0.0%	1.2%	6.8%	1.8%

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Table I.1 – *Continued from previous page*

CBSA Name	**Total Jobs**	**ID**	**CBD**	**HD Jobs**	**MD Jobs**	**HD/ MD Resid**
Fayetteville-Springdale-Rogers, AR	209,000	**6b**	0.0%	1.2%	9.2%	0.0%
Boulder, CO	147,000	**6b**	0.0%	0.0%	9.5%	1.4%
Billings, MT	81,000	**6b**	0.0%	0.0%	7.1%	0.0%
Charlottesville, VA	76,000	**6b**	0.0%	0.0%	12.3%	0.0%
Athens-Clarke County, GA	62,000	**6b**	0.0%	0.0%	5.0%	0.8%
Dubuque, IA	55,000	**6b**	0.0%	0.0%	6.6%	0.0%
Bloomington, IN	50,000	**6b**	0.0%	0.0%	5.7%	0.0%
Bozeman, MT	48,000	**6b**	0.0%	0.0%	6.3%	0.0%
Williamsport, PA	43,000	**6b**	0.0%	0.0%	6.5%	0.0%
Findlay, OH	42,000	**6b**	0.0%	0.0%	10.4%	0.0%
Glens Falls, NY	38,000	**6b**	0.0%	0.0%	9.3%	0.0%
Casper, WY	34,000	**6b**	0.0%	0.0%	5.4%	0.0%
Parkersburg-Vienna, WV	34,000	**6b**	0.0%	0.0%	11.3%	0.0%
Glenwood Springs, CO	33,000	**6b**	0.0%	0.0%	5.3%	0.0%
Key West, FL	32,000	**6b**	0.0%	0.0%	10.2%	1.6%
Gadsden, AL	32,000	**6b**	0.0%	0.0%	6.0%	0.0%
Corning, NY	30,000	**6b**	0.0%	0.0%	10.2%	0.0%
Winona, MN	23,000	**6b**	0.0%	0.0%	6.0%	0.0%
Stillwater, OK	21,000	**6b**	0.0%	0.0%	6.0%	0.0%
Durango, CO	19,000	**6b**	0.0%	0.0%	15.3%	0.0%
Jackson, WY-ID	18,000	**6b**	0.0%	0.0%	15.3%	0.0%
Paragould, AR	17,000	**6b**	0.0%	0.0%	22.0%	0.0%
Los Alamos, NM	13,000	**6b**	0.0%	0.0%	24.2%	0.0%
Ketchikan, AK	8,000	**6b**	0.0%	0.0%	9.9%	0.0%
State College, PA	44,000	**6c**	0.0%	0.0%	0.0%	10.5%
Rexburg, ID	15,000	**6c**	0.0%	0.0%	9.6%	9.2%
Butte-Silver Bow, MT	14,000	**6c**	0.0%	0.0%	0.0%	12.5%
Salinas, CA	141,000	**6d**	0.0%	0.0%	2.2%	2.0%
Hagerstown-Martinsburg, MD-WV	90,000	**6d**	0.0%	0.0%	0.0%	2.8%
Santa Cruz-Watsonville, CA	82,000	**6d**	0.0%	0.0%	6.0%	3.2%
Redding, CA	51,000	**6d**	0.0%	0.0%	0.0%	3.0%
Kingston, NY	45,000	**6d**	0.0%	0.0%	0.0%	2.9%
El Centro, CA	43,000	**6d**	0.0%	0.0%	0.0%	3.4%
Jamestown-Dunkirk-Fredonia, NY	38,000	**6d**	0.0%	0.0%	0.0%	2.4%

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Table I.1 – *Continued from previous page*

CBSA Name	**Total Jobs**	**ID**	**CBD**	**HD Jobs**	**MD Jobs**	**HD/ MD Resid**
Elmira, NY	29,000	**6d**	0.0%	0.0%	0.0%	4.2%
Corvallis, OR	28,000	**6d**	0.0%	0.0%	6.8%	5.0%
Meadville, PA	26,000	**6d**	0.0%	0.0%	0.0%	4.0%
Indiana, PA	26,000	**6d**	0.0%	0.0%	0.0%	3.6%
Sunbury, PA	23,000	**6d**	0.0%	0.0%	0.0%	6.4%
Auburn, NY	19,000	**6d**	0.0%	0.0%	0.0%	6.4%
Lewistown, PA	14,000	**6d**	0.0%	0.0%	0.0%	6.2%
Oxnard-Thousand Oaks-Ventura, CA	270,000	**6e**	0.0%	0.5%	0.0%	1.3%
Bakersfield, CA	227,000	**6e**	0.0%	0.6%	1.9%	0.5%
Cape Coral-Fort Myers, FL	212,000	**6e**	0.0%	0.6%	1.7%	0.0%
Myrtle Beach-Conway-North Myrtle Beach, SC-NC	137,000	**6e**	0.0%	0.0%	0.0%	0.0%
Hickory-Lenoir-Morganton, NC	132,000	**6e**	0.0%	0.0%	0.0%	0.0%
Visalia, CA	127,000	**6e**	0.0%	0.0%	0.0%	1.0%
Salisbury, MD-DE	125,000	**6e**	0.0%	0.0%	0.0%	0.0%
Montgomery, AL	125,000	**6e**	0.0%	0.0%	1.6%	0.0%
Gulfport-Biloxi, MS	123,000	**6e**	0.0%	0.8%	3.8%	0.0%
Spartanburg, SC	120,000	**6e**	0.0%	0.0%	1.8%	0.0%
Fort Collins, CO	120,000	**6e**	0.0%	0.0%	3.9%	0.3%
Appleton, WI	114,000	**6e**	0.0%	0.0%	4.8%	0.0%
Fayetteville, NC	109,000	**6e**	0.0%	0.0%	0.0%	0.0%
Wilmington, NC	101,000	**6e**	0.0%	1.0%	1.9%	0.0%
Crestview-Fort Walton Beach-Destin, FL	97,000	**6e**	0.0%	0.0%	0.0%	0.0%
Norwich-New London, CT	93,000	**6e**	0.0%	0.0%	0.0%	0.5%
Lake Charles, LA	88,000	**6e**	0.0%	0.0%	0.0%	0.0%
Fort Smith, AR-OK	88,000	**6e**	0.0%	0.0%	0.0%	0.0%
Midland, TX	84,000	**6e**	0.0%	0.0%	0.0%	0.0%
Lynchburg, VA	83,000	**6e**	0.0%	0.0%	3.2%	0.0%
Tuscaloosa, AL	78,000	**6e**	0.0%	0.0%	1.8%	0.0%
Laredo, TX	75,000	**6e**	0.0%	0.0%	2.6%	0.4%
Houma-Thibodaux, LA	69,000	**6e**	0.0%	0.0%	0.0%	0.0%
Florence, SC	68,000	**6e**	0.0%	0.0%	0.0%	0.0%
Clarksville, TN-KY	68,000	**6e**	0.0%	0.0%	0.0%	0.0%
Panama City, FL	67,000	**6e**	0.0%	0.0%	0.0%	0.0%
Sioux City, IA-NE-SD	67,000	**6e**	0.0%	0.0%	4.6%	0.0%

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Table I.1 – *Continued from previous page*

CBSA Name	Total Jobs	ID	CBD	HD Jobs	MD Jobs	HD/ MD Resid
Racine, WI	65,000	**6e**	0.0%	0.0%	4.2%	0.7%
Jackson, TN	64,000	**6e**	0.0%	0.0%	0.0%	0.0%
Napa, CA	64,000	**6e**	0.0%	0.0%	3.3%	0.0%
Daphne-Fairhope-Foley, AL	62,000	**6e**	0.0%	0.0%	0.0%	0.0%
Hilton Head Island-Bluffton, SC	61,000	**6e**	0.0%	0.0%	0.0%	0.0%
Merced, CA	58,000	**6e**	0.0%	0.0%	0.0%	0.0%
Idaho Falls, ID	58,000	**6e**	0.0%	0.0%	0.0%	0.0%
Odessa, TX	57,000	**6e**	0.0%	0.0%	0.0%	0.0%
Las Cruces, NM	55,000	**6e**	0.0%	0.0%	3.1%	0.0%
Sheboygan, WI	55,000	**6e**	0.0%	0.0%	0.0%	0.0%
Hilo, HI	55,000	**6e**	0.0%	0.0%	0.0%	0.0%
St. George, UT	55,000	**6e**	0.0%	0.0%	0.0%	0.0%
Harrisonburg, VA	54,000	**6e**	0.0%	0.0%	0.0%	0.0%
Wheeling, WV-OH	53,000	**6e**	0.0%	0.0%	3.9%	0.0%
Hattiesburg, MS	53,000	**6e**	0.0%	0.0%	0.0%	0.0%
Greenville, NC	53,000	**6e**	0.0%	0.0%	0.0%	0.0%
Altoona, PA	52,000	**6e**	0.0%	0.0%	0.0%	0.0%
Bremerton-Silverdale-Port Orchard, WA	52,000	**6e**	0.0%	0.0%	0.0%	0.0%
Torrington, CT	52,000	**6e**	0.0%	0.0%	0.0%	0.0%
Chambersburg-Waynesboro, PA	50,000	**6e**	0.0%	0.0%	0.0%	1.3%
Coeur d'Alene, ID	49,000	**6e**	0.0%	0.0%	3.5%	0.0%
Texarkana, TX-AR	49,000	**6e**	0.0%	0.0%	0.0%	0.0%
Blacksburg-Christiansburg, VA	49,000	**6e**	0.0%	0.0%	0.0%	0.0%
Dover, DE	48,000	**6e**	0.0%	0.0%	0.0%	0.0%
Ottawa, IL	48,000	**6e**	0.0%	0.0%	0.0%	0.0%
Vineland-Bridgeton, NJ	47,000	**6e**	0.0%	0.0%	0.0%	1.3%
Rocky Mount, NC	47,000	**6e**	0.0%	0.0%	0.0%	0.0%
Decatur, AL	46,000	**6e**	0.0%	0.0%	0.0%	0.0%
Dothan, AL	46,000	**6e**	0.0%	0.0%	0.0%	0.0%
Augusta-Waterville, ME	46,000	**6e**	0.0%	0.0%	0.0%	0.0%
Sebastian-Vero Beach, FL	45,000	**6e**	0.0%	0.0%	0.0%	0.0%
Mansfield, OH	45,000	**6e**	0.0%	0.0%	0.0%	0.0%
Logan, UT-ID	45,000	**6e**	0.0%	0.0%	2.5%	0.0%
Florence-Muscle Shoals, AL	44,000	**6e**	0.0%	0.0%	2.8%	0.0%

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Table I.1 – *Continued from previous page*

CBSA Name	Total Jobs	ID	CBD	HD Jobs	MD Jobs	HD/ MD Resid
Lima, OH	44,000	**6e**	0.0%	0.0%	0.0%	0.0%
Columbus, IN	44,000	**6e**	0.0%	0.0%	0.0%	0.0%
Carbondale-Marion, IL	44,000	**6e**	0.0%	0.0%	0.0%	1.7%
Auburn-Opelika, AL	43,000	**6e**	0.0%	0.0%	0.0%	0.0%
Pottsville, PA	43,000	**6e**	0.0%	0.0%	0.0%	1.3%
London, KY	43,000	**6e**	0.0%	0.0%	0.0%	0.0%
East Stroudsburg, PA	42,000	**6e**	0.0%	0.0%	0.0%	0.0%
Wenatchee, WA	42,000	**6e**	0.0%	0.0%	4.8%	0.0%
Twin Falls, ID	42,000	**6e**	0.0%	0.0%	0.0%	0.0%
Warner Robins, GA	42,000	**6e**	0.0%	0.0%	0.0%	0.0%
Valdosta, GA	42,000	**6e**	0.0%	0.0%	0.0%	0.0%
Wooster, OH	42,000	**6e**	0.0%	0.0%	0.0%	0.0%
Morristown, TN	42,000	**6e**	0.0%	0.0%	0.0%	0.0%
Springfield, OH	41,000	**6e**	0.0%	0.0%	0.0%	0.0%
LaGrange, GA-AL	41,000	**6e**	0.0%	0.0%	0.0%	0.0%
Lake Havasu City-Kingman, AZ	41,000	**6e**	0.0%	0.0%	0.0%	0.0%
Fond du Lac, WI	41,000	**6e**	0.0%	0.0%	0.0%	0.0%
Sevierville, TN	41,000	**6e**	0.0%	0.0%	0.0%	0.0%
Paducah, KY-IL	41,000	**6e**	0.0%	0.0%	0.0%	0.0%
Ames, IA	40,000	**6e**	0.0%	0.0%	0.0%	0.0%
Staunton, VA	40,000	**6e**	0.0%	0.0%	0.0%	0.0%
Cleveland, TN	39,000	**6e**	0.0%	0.0%	0.0%	0.0%
Monroe, MI	38,000	**6e**	0.0%	0.0%	0.0%	0.0%
Lawrence, KS	38,000	**6e**	0.0%	0.0%	4.1%	0.0%
Beckley, WV	38,000	**6e**	0.0%	0.0%	0.0%	0.0%
Sherman-Denison, TX	37,000	**6e**	0.0%	0.0%	0.0%	0.0%
Albany-Lebanon, OR	37,000	**6e**	0.0%	0.0%	3.3%	0.0%
Mount Vernon-Anacortes, WA	37,000	**6e**	0.0%	0.0%	0.0%	0.0%
Holland, MI	37,000	**6e**	0.0%	0.0%	0.0%	0.0%
Elizabethtown-Fort Knox, KY	37,000	**6e**	0.0%	0.0%	0.0%	0.0%
Madera, CA	36,000	**6e**	0.0%	0.0%	0.0%	0.0%
Eureka-Arcata, CA	36,000	**6e**	0.0%	0.0%	0.0%	0.0%
Kokomo, IN	36,000	**6e**	0.0%	0.0%	0.0%	0.0%
Warsaw, IN	36,000	**6e**	0.0%	0.0%	0.0%	0.0%

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Table I.1 – *Continued from previous page*

CBSA Name	**Total Jobs**	**ID**	**CBD**	**HD Jobs**	**MD Jobs**	**HD/ MD Resid**
Manhattan, KS	35,000	**6e**	0.0%	0.0%	0.0%	0.0%
Sumter, SC	35,000	**6e**	0.0%	0.0%	0.0%	0.0%
Whitewater, WI	34,000	**6e**	0.0%	0.0%	0.0%	0.0%
Michigan City-La Porte, IN	34,000	**6e**	0.0%	0.0%	0.0%	0.0%
Yuba City, CA	34,000	**6e**	0.0%	0.0%	0.0%	0.0%
Midland, MI	33,000	**6e**	0.0%	0.0%	0.0%	0.0%
Cheyenne, WY	33,000	**6e**	0.0%	0.0%	0.0%	0.0%
Clarksburg, WV	33,000	**6e**	0.0%	0.0%	0.0%	0.0%
Hot Springs, AR	33,000	**6e**	0.0%	0.0%	0.0%	0.0%
Grand Island, NE	33,000	**6e**	0.0%	0.0%	0.0%	0.0%
Goldsboro, NC	33,000	**6e**	0.0%	0.0%	0.0%	0.0%
Danville, VA	33,000	**6e**	0.0%	0.0%	0.0%	0.0%
Anniston-Oxford, AL	33,000	**6e**	0.0%	0.0%	0.0%	0.0%
Cookeville, TN	33,000	**6e**	0.0%	0.0%	0.0%	0.0%
Weirton-Steubenville, WV-OH	32,000	**6e**	0.0%	0.0%	0.0%	0.0%
Pinehurst-Southern Pines, NC	32,000	**6e**	0.0%	0.0%	0.0%	0.0%
Wilson, NC	32,000	**6e**	0.0%	0.0%	0.0%	0.0%
Hammond, LA	32,000	**6e**	0.0%	0.0%	0.0%	0.0%
Tullahoma-Manchester, TN	32,000	**6e**	0.0%	0.0%	0.0%	0.0%
Meridian, MS	32,000	**6e**	0.0%	0.0%	0.0%	0.0%
Albertville, AL	32,000	**6e**	0.0%	0.0%	0.0%	0.0%
New Philadelphia-Dover, OH	31,000	**6e**	0.0%	0.0%	0.0%	0.0%
Lumberton, NC	31,000	**6e**	0.0%	0.0%	0.0%	0.0%
Pocatello, ID	31,000	**6e**	0.0%	0.0%	0.0%	0.0%
Heber, UT	30,000	**6e**	0.0%	0.0%	0.0%	0.0%
Brainerd, MN	30,000	**6e**	0.0%	0.0%	0.0%	0.0%
Beaver Dam, WI	30,000	**6e**	0.0%	0.0%	0.0%	0.0%
Jacksonville, NC	30,000	**6e**	0.0%	0.0%	0.0%	0.0%
Manitowoc, WI	30,000	**6e**	0.0%	0.0%	0.0%	0.0%
Baraboo, WI	30,000	**6e**	0.0%	0.0%	0.0%	0.0%
Sandusky, OH	30,000	**6e**	0.0%	0.0%	0.0%	0.0%
Stevens Point, WI	29,000	**6e**	0.0%	0.0%	0.0%	0.0%
Lufkin, TX	29,000	**6e**	0.0%	0.0%	0.0%	0.0%
Gettysburg, PA	29,000	**6e**	0.0%	0.0%	0.0%	0.0%

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Table I.1 – *Continued from previous page*

CBSA Name	Total Jobs	ID	CBD	HD Jobs	MD Jobs	HD/ MD Resid
Hanford-Corcoran, CA	29,000	**6e**	0.0%	0.0%	0.0%	0.0%
Watertown-Fort Atkinson, WI	29,000	**6e**	0.0%	0.0%	0.0%	0.0%
Russellville, AR	29,000	**6e**	0.0%	0.0%	0.0%	0.0%
Bluefield, WV-VA	29,000	**6e**	0.0%	0.0%	0.0%	0.0%
Helena, MT	29,000	**6e**	0.0%	0.0%	0.0%	0.0%
Jasper, IN	28,000	**6e**	0.0%	0.0%	0.0%	0.0%
New Bern, NC	28,000	**6e**	0.0%	0.0%	0.0%	0.0%
Cumberland, MD-WV	28,000	**6e**	0.0%	0.0%	0.0%	0.0%
Lawton, OK	28,000	**6e**	0.0%	0.0%	0.0%	0.0%
Homosassa Springs, FL	28,000	**6e**	0.0%	0.0%	0.0%	0.0%
Minot, ND	28,000	**6e**	0.0%	0.0%	0.0%	0.0%
Bay City, MI	28,000	**6e**	0.0%	0.0%	0.0%	0.0%
Zanesville, OH	28,000	**6e**	0.0%	0.0%	0.0%	0.0%
Hermiston-Pendleton, OR	27,000	**6e**	0.0%	0.0%	0.0%	0.0%
Watertown-Fort Drum, NY	27,000	**6e**	0.0%	0.0%	0.0%	0.0%
Richmond-Berea, KY	27,000	**6e**	0.0%	0.0%	0.0%	0.0%
Moses Lake, WA	27,000	**6e**	0.0%	0.0%	0.0%	0.0%
Shelby, NC	27,000	**6e**	0.0%	0.0%	0.0%	0.0%
Edwards, CO	27,000	**6e**	0.0%	0.0%	0.0%	0.0%
DuBois, PA	26,000	**6e**	0.0%	0.0%	0.0%	0.0%
California-Lexington Park, MD	26,000	**6e**	0.0%	0.0%	0.0%	0.0%
Ocean City, NJ	26,000	**6e**	0.0%	0.0%	0.0%	0.0%
Barre, VT	25,000	**6e**	0.0%	0.0%	0.0%	0.0%
Kapaa, HI	25,000	**6e**	0.0%	0.0%	0.0%	0.0%
Hobbs, NM	25,000	**6e**	0.0%	0.0%	0.0%	0.0%
Richmond, IN	25,000	**6e**	0.0%	0.0%	0.0%	0.0%
Cullman, AL	25,000	**6e**	0.0%	0.0%	0.0%	0.0%
Talladega-Sylacauga, AL	25,000	**6e**	0.0%	0.0%	0.0%	0.0%
Salem, OH	25,000	**6e**	0.0%	0.0%	0.0%	0.0%
Laurel, MS	24,000	**6e**	0.0%	0.0%	0.0%	0.0%
Marion, IN	24,000	**6e**	0.0%	0.0%	0.0%	0.0%
Branson, MO	24,000	**6e**	0.0%	0.0%	0.0%	0.0%
Sidney, OH	24,000	**6e**	0.0%	0.0%	0.0%	0.0%
Kearney, NE	24,000	**6e**	0.0%	0.0%	0.0%	0.0%

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Table I.1 – *Continued from previous page*

CBSA Name	Total Jobs	ID	CBD	HD Jobs	MD Jobs	HD/ MD Resid
Ashtabula, OH	24,000	**6e**	0.0%	0.0%	0.0%	0.0%
Ukiah, CA	24,000	**6e**	0.0%	0.0%	0.0%	0.0%
Fremont, OH	24,000	**6e**	0.0%	0.0%	0.0%	0.0%
New Castle, PA	24,000	**6e**	0.0%	0.0%	0.0%	0.0%
Mount Airy, NC	24,000	**6e**	0.0%	0.0%	0.0%	0.0%
Lewiston, ID-WA	24,000	**6e**	0.0%	0.0%	0.0%	0.0%
Carlsbad-Artesia, NM	24,000	**6e**	0.0%	0.0%	0.0%	0.0%
Truckee-Grass Valley, CA	23,000	**6e**	0.0%	0.0%	0.0%	0.0%
Ogdensburg-Massena, NY	23,000	**6e**	0.0%	0.0%	0.0%	0.0%
Grants Pass, OR	23,000	**6e**	0.0%	0.0%	0.0%	0.0%
Sanford, NC	23,000	**6e**	0.0%	0.0%	0.0%	0.0%
Muskogee, OK	23,000	**6e**	0.0%	0.0%	0.0%	0.0%
The Villages, FL	23,000	**6e**	0.0%	0.0%	0.0%	0.0%
Orangeburg, SC	23,000	**6e**	0.0%	0.0%	0.0%	0.0%
Frankfort, KY	23,000	**6e**	0.0%	0.0%	0.0%	0.0%
Jefferson, GA	23,000	**6e**	0.0%	0.0%	0.0%	0.0%
Chillicothe, OH	23,000	**6e**	0.0%	0.0%	0.0%	0.0%
Charleston-Mattoon, IL	23,000	**6e**	0.0%	0.0%	0.0%	0.0%
Faribault-Northfield, MN	23,000	**6e**	0.0%	0.0%	0.0%	0.0%
Williston, ND	22,000	**6e**	0.0%	0.0%	0.0%	0.0%
Greeneville, TN	22,000	**6e**	0.0%	0.0%	0.0%	0.0%
Sebring-Avon Park, FL	22,000	**6e**	0.0%	0.0%	0.0%	0.0%
Ardmore, OK	22,000	**6e**	0.0%	0.0%	0.0%	0.0%
Danville, IL	22,000	**6e**	0.0%	0.0%	0.0%	0.0%
Marietta, OH	22,000	**6e**	0.0%	0.0%	0.0%	0.0%
Martinsville, VA	22,000	**6e**	0.0%	0.0%	0.0%	0.0%
Kinston, NC	22,000	**6e**	0.0%	0.0%	0.0%	0.0%
Walla Walla, WA	22,000	**6e**	0.0%	0.0%	0.0%	0.0%
Somerset, KY	21,000	**6e**	0.0%	0.0%	0.0%	0.0%
Marinette, WI-MI	21,000	**6e**	0.0%	0.0%	0.0%	0.0%
Marquette, MI	21,000	**6e**	0.0%	0.0%	0.0%	0.0%
Adrian, MI	21,000	**6e**	0.0%	0.0%	0.0%	0.0%
Willmar, MN	21,000	**6e**	0.0%	0.0%	0.0%	0.0%
Calhoun, GA	21,000	**6e**	0.0%	0.0%	0.0%	0.0%

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Table I.1 – *Continued from previous page*

CBSA Name	Total Jobs	ID	CBD	HD Jobs	MD Jobs	HD/ MD Resid
Marion, OH	21,000	**6e**	0.0%	0.0%	0.0%	0.0%
Greenwood, SC	21,000	**6e**	0.0%	0.0%	0.0%	0.0%
Muscatine, IA	21,000	**6e**	0.0%	0.0%	0.0%	0.0%
Searcy, AR	21,000	**6e**	0.0%	0.0%	0.0%	0.0%
Enid, OK	21,000	**6e**	0.0%	0.0%	0.0%	0.0%
Mount Pleasant, MI	20,000	**6e**	0.0%	0.0%	0.0%	0.1%
Fergus Falls, MN	20,000	**6e**	0.0%	0.0%	0.0%	0.0%
Norfolk, NE	20,000	**6e**	0.0%	0.0%	0.0%	0.0%
Elko, NV	20,000	**6e**	0.0%	0.0%	0.0%	0.0%
Gillette, WY	20,000	**6e**	0.0%	0.0%	0.0%	0.0%
Effingham, IL	20,000	**6e**	0.0%	0.0%	0.0%	0.0%
Seneca, SC	20,000	**6e**	0.0%	0.0%	0.0%	0.0%
Sierra Vista-Douglas, AZ	20,000	**6e**	0.0%	0.0%	0.0%	0.0%
Burlington, IA-IL	20,000	**6e**	0.0%	0.0%	0.0%	0.0%
Centralia, WA	19,000	**6e**	0.0%	0.0%	0.0%	0.0%
Carson City, NV	19,000	**6e**	0.0%	0.0%	0.0%	0.0%
Auburn, IN	19,000	**6e**	0.0%	0.0%	0.0%	0.0%
Aberdeen, SD	19,000	**6e**	0.0%	0.0%	0.0%	0.0%
Columbus, MS	19,000	**6e**	0.0%	0.0%	0.0%	0.0%
Owatonna, MN	19,000	**6e**	0.0%	0.0%	0.0%	0.0%
Statesboro, GA	19,000	**6e**	0.0%	0.0%	0.0%	0.0%
Opelousas, LA	19,000	**6e**	0.0%	0.0%	0.0%	0.0%
North Wilkesboro, NC	19,000	**6e**	0.0%	0.0%	0.0%	0.0%
Clinton, IA	19,000	**6e**	0.0%	0.0%	0.0%	0.0%
Lake City, FL	19,000	**6e**	0.0%	0.0%	0.0%	0.0%
Mount Vernon, IL	19,000	**6e**	0.0%	0.0%	0.0%	0.0%
Olean, NY	19,000	**6e**	0.0%	0.0%	0.0%	0.0%
Paris, TX	18,000	**6e**	0.0%	0.0%	0.0%	0.0%
Wapakoneta, OH	18,000	**6e**	0.0%	0.0%	0.0%	0.0%
Somerset, PA	18,000	**6e**	0.0%	0.0%	0.0%	0.0%
Norwalk, OH	18,000	**6e**	0.0%	0.0%	0.0%	0.0%
Klamath Falls, OR	18,000	**6e**	0.0%	0.0%	0.0%	0.0%
Portsmouth, OH	18,000	**6e**	0.0%	0.0%	0.0%	0.0%
Fort Payne, AL	18,000	**6e**	0.0%	0.0%	0.0%	0.0%

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Table I.1 – *Continued from previous page*

CBSA Name	Total Jobs	ID	CBD	HD Jobs	MD Jobs	HD/ MD Resid
Roswell, NM	18,000	**6e**	0.0%	0.0%	0.0%	0.0%
Seymour, IN	18,000	**6e**	0.0%	0.0%	0.0%	0.0%
Breckenridge, CO	18,000	**6e**	0.0%	0.0%	0.0%	0.0%
Sturgis, MI	18,000	**6e**	0.0%	0.0%	0.0%	0.0%
Farmington, MO	18,000	**6e**	0.0%	0.0%	0.0%	0.0%
Red Wing, MN	18,000	**6e**	0.0%	0.0%	0.0%	0.0%
Morehead City, NC	18,000	**6e**	0.0%	0.0%	0.0%	0.0%
Gaffney, SC	18,000	**6e**	0.0%	0.0%	0.0%	0.0%
Dublin, GA	17,000	**6e**	0.0%	0.0%	0.0%	0.0%
Rock Springs, WY	17,000	**6e**	0.0%	0.0%	0.0%	0.0%
Poplar Bluff, MO	17,000	**6e**	0.0%	0.0%	0.0%	0.0%
Show Low, AZ	17,000	**6e**	0.0%	0.0%	0.0%	0.0%
Georgetown, SC	17,000	**6e**	0.0%	0.0%	0.0%	0.0%
Oxford, MS	17,000	**6e**	0.0%	0.0%	0.0%	0.0%
Bellefontaine, OH	17,000	**6e**	0.0%	0.0%	0.0%	0.0%
Shawnee, OK	17,000	**6e**	0.0%	0.0%	0.0%	0.0%
Bartlesville, OK	17,000	**6e**	0.0%	0.0%	0.0%	0.0%
Mount Vernon, OH	17,000	**6e**	0.0%	0.0%	0.0%	0.0%
Fort Madison-Keokuk, IA-IL-MO	17,000	**6e**	0.0%	0.0%	0.0%	0.0%
Celina, OH	17,000	**6e**	0.0%	0.0%	0.0%	0.0%
Kendallville, IN	17,000	**6e**	0.0%	0.0%	0.0%	0.0%
Boone, NC	17,000	**6e**	0.0%	0.0%	0.0%	0.0%
Lewisburg, PA	17,000	**6e**	0.0%	0.0%	0.0%	0.0%
Mount Pleasant, TX	17,000	**6e**	0.0%	0.0%	0.0%	0.0%
Hudson, NY	17,000	**6e**	0.0%	0.0%	0.0%	0.0%
Tiffin, OH	17,000	**6e**	0.0%	0.0%	0.0%	0.0%
Morgan City, LA	17,000	**6e**	0.0%	0.0%	0.0%	0.0%
Coos Bay, OR	16,000	**6e**	0.0%	0.0%	0.0%	0.0%
Plymouth, IN	16,000	**6e**	0.0%	0.0%	0.0%	0.0%
Batavia, NY	16,000	**6e**	0.0%	0.0%	0.0%	0.0%
Columbus, NE	16,000	**6e**	0.0%	0.0%	0.0%	0.0%
Athens, TN	16,000	**6e**	0.0%	0.0%	0.0%	0.0%
Nacogdoches, TX	16,000	**6e**	0.0%	0.0%	0.0%	0.0%
Ontario, OR-ID	16,000	**6e**	0.0%	0.0%	0.0%	0.0%

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Table I.1 – *Continued from previous page*

CBSA Name	Total Jobs	ID	CBD	HD Jobs	MD Jobs	HD/ MD Resid
Glasgow, KY	16,000	**6e**	0.0%	0.0%	0.0%	0.0%
Dickinson, ND	16,000	**6e**	0.0%	0.0%	0.0%	0.0%
Garden City, KS	16,000	**6e**	0.0%	0.0%	0.0%	0.0%
Sedalia, MO	16,000	**6e**	0.0%	0.0%	0.0%	0.0%
Douglas, GA	16,000	**6e**	0.0%	0.0%	0.0%	0.0%
Greenville, OH	16,000	**6e**	0.0%	0.0%	0.0%	0.0%
Crossville, TN	16,000	**6e**	0.0%	0.0%	0.0%	0.0%
Waycross, GA	16,000	**6e**	0.0%	0.0%	0.0%	0.0%
Gallup, NM	16,000	**6e**	0.0%	0.0%	0.0%	0.0%
Ashland, OH	16,000	**6e**	0.0%	0.0%	0.0%	0.0%
Pella, IA	16,000	**6e**	0.0%	0.0%	0.0%	0.0%
Sterling, IL	16,000	**6e**	0.0%	0.0%	0.0%	0.0%
Danville, KY	16,000	**6e**	0.0%	0.0%	0.0%	0.0%
Albemarle, NC	16,000	**6e**	0.0%	0.0%	0.0%	0.0%
Gardnerville Ranchos, NV	16,000	**6e**	0.0%	0.0%	0.0%	0.0%
Amsterdam, NY	16,000	**6e**	0.0%	0.0%	0.0%	0.0%
Roanoke Rapids, NC	16,000	**6e**	0.0%	0.0%	0.0%	0.0%
Burley, ID	15,000	**6e**	0.0%	0.0%	0.0%	0.0%
Vicksburg, MS	15,000	**6e**	0.0%	0.0%	0.0%	0.0%
Wilmington, OH	15,000	**6e**	0.0%	0.0%	0.0%	0.0%
Port Angeles, WA	15,000	**6e**	0.0%	0.0%	0.0%	0.0%
Forest City, NC	15,000	**6e**	0.0%	0.0%	0.0%	0.0%
Alice, TX	15,000	**6e**	0.0%	0.0%	0.0%	0.0%
El Dorado, AR	15,000	**6e**	0.0%	0.0%	0.0%	0.0%
Fort Dodge, IA	15,000	**6e**	0.0%	0.0%	0.0%	0.0%
Watertown, SD	15,000	**6e**	0.0%	0.0%	0.0%	0.0%
Ruston, LA	15,000	**6e**	0.0%	0.0%	0.0%	0.0%
Selinsgrove, PA	15,000	**6e**	0.0%	0.0%	0.0%	0.0%
Blytheville, AR	15,000	**6e**	0.0%	0.0%	0.0%	0.0%
Bennington, VT	15,000	**6e**	0.0%	0.0%	0.0%	0.0%
Cadillac, MI	15,000	**6e**	0.0%	0.0%	0.0%	0.0%
Alexandria, MN	15,000	**6e**	0.0%	0.0%	0.0%	0.0%
Fairmont, WV	15,000	**6e**	0.0%	0.0%	0.0%	0.0%
Bemidji, MN	15,000	**6e**	0.0%	0.0%	0.0%	0.0%

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Table I.1 – *Continued from previous page*

CBSA Name	Total Jobs	ID	CBD	HD Jobs	MD Jobs	HD/ MD Resid
Freeport, IL	15,000	**6e**	0.0%	0.0%	0.0%	0.0%
Oil City, PA	15,000	**6e**	0.0%	0.0%	0.0%	0.0%
Hannibal, MO	14,000	**6e**	0.0%	0.0%	0.0%	0.0%
Marshalltown, IA	14,000	**6e**	0.0%	0.0%	0.0%	0.0%
Aberdeen, WA	14,000	**6e**	0.0%	0.0%	0.0%	0.0%
Hutchinson, MN	14,000	**6e**	0.0%	0.0%	0.0%	0.0%
Menomonie, WI	14,000	**6e**	0.0%	0.0%	0.0%	0.0%
Shelbyville, TN	14,000	**6e**	0.0%	0.0%	0.0%	0.0%
Scottsbluff, NE	14,000	**6e**	0.0%	0.0%	0.0%	0.0%
Marion, NC	14,000	**6e**	0.0%	0.0%	0.0%	0.0%
Tifton, GA	14,000	**6e**	0.0%	0.0%	0.0%	0.0%
Kerrville, TX	14,000	**6e**	0.0%	0.0%	0.0%	0.0%
Bardstown, KY	14,000	**6e**	0.0%	0.0%	0.0%	0.0%
Dodge City, KS	14,000	**6e**	0.0%	0.0%	0.0%	0.0%
Gloversville, NY	14,000	**6e**	0.0%	0.0%	0.0%	0.0%
Kill Devil Hills, NC	14,000	**6e**	0.0%	0.0%	0.0%	0.0%
Greenville, MS	14,000	**6e**	0.0%	0.0%	0.0%	0.0%
Ottumwa, IA	14,000	**6e**	0.0%	0.0%	0.0%	0.0%
Cortland, NY	14,000	**6e**	0.0%	0.0%	0.0%	0.0%
Astoria, OR	14,000	**6e**	0.0%	0.0%	0.0%	0.0%
Madisonville, KY	14,000	**6e**	0.0%	0.0%	0.0%	0.0%
Starkville, MS	14,000	**6e**	0.0%	0.0%	0.0%	0.0%
Jasper, AL	14,000	**6e**	0.0%	0.0%	0.0%	0.0%
Elizabeth City, NC	14,000	**6e**	0.0%	0.0%	0.0%	0.0%
St. Marys, PA	14,000	**6e**	0.0%	0.0%	0.0%	0.0%
Brookings, SD	14,000	**6e**	0.0%	0.0%	0.0%	0.0%
Clovis, NM	14,000	**6e**	0.0%	0.0%	0.0%	0.0%
Platteville, WI	14,000	**6e**	0.0%	0.0%	0.0%	0.0%
Enterprise, AL	13,000	**6e**	0.0%	0.0%	0.0%	0.0%
Hastings, NE	13,000	**6e**	0.0%	0.0%	0.0%	0.0%
Angola, IN	13,000	**6e**	0.0%	0.0%	0.0%	0.0%
Point Pleasant, WV-OH	13,000	**6e**	0.0%	0.0%	0.0%	0.0%
Vincennes, IN	13,000	**6e**	0.0%	0.0%	0.0%	0.0%
Ponca City, OK	13,000	**6e**	0.0%	0.0%	0.0%	0.0%

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Table I.1 – *Continued from previous page*

CBSA Name	Total Jobs	ID	CBD	HD Jobs	MD Jobs	HD/ MD Resid
Austin, MN	13,000	**6e**	0.0%	0.0%	0.0%	0.0%
Newport, OR	13,000	**6e**	0.0%	0.0%	0.0%	0.0%
Defiance, OH	13,000	**6e**	0.0%	0.0%	0.0%	0.0%
Athens, TX	13,000	**6e**	0.0%	0.0%	0.0%	0.0%
Grand Rapids, MN	13,000	**6e**	0.0%	0.0%	0.0%	0.0%
Crawfordsville, IN	13,000	**6e**	0.0%	0.0%	0.0%	0.0%
Red Bluff, CA	13,000	**6e**	0.0%	0.0%	0.0%	0.0%
Sikeston, MO	13,000	**6e**	0.0%	0.0%	0.0%	0.0%
Cullowhee, NC	13,000	**6e**	0.0%	0.0%	0.0%	0.0%
Washington, NC	13,000	**6e**	0.0%	0.0%	0.0%	0.0%
Henderson, NC	13,000	**6e**	0.0%	0.0%	0.0%	0.0%
Corsicana, TX	13,000	**6e**	0.0%	0.0%	0.0%	0.0%
Warren, PA	13,000	**6e**	0.0%	0.0%	0.0%	0.0%
Montrose, CO	13,000	**6e**	0.0%	0.0%	0.0%	0.0%
Palatka, FL	13,000	**6e**	0.0%	0.0%	0.0%	0.0%
Scottsboro, AL	13,000	**6e**	0.0%	0.0%	0.0%	0.0%
Athens, OH	13,000	**6e**	0.0%	0.0%	0.0%	0.0%
Alexander City, AL	13,000	**6e**	0.0%	0.0%	0.0%	0.0%
Palestine, TX	13,000	**6e**	0.0%	0.0%	0.0%	0.0%
Duncan, OK	13,000	**6e**	0.0%	0.0%	0.0%	0.0%
Cambridge, OH	13,000	**6e**	0.0%	0.0%	0.0%	0.0%
Dyersburg, TN	13,000	**6e**	0.0%	0.0%	0.0%	0.0%
Jacksonville, IL	13,000	**6e**	0.0%	0.0%	0.0%	0.0%
El Campo, TX	13,000	**6e**	0.0%	0.0%	0.0%	0.0%
Bradford, PA	13,000	**6e**	0.0%	0.0%	0.0%	0.0%
Natchez, MS-LA	13,000	**6e**	0.0%	0.0%	0.0%	0.0%
Rolla, MO	12,000	**6e**	0.0%	0.0%	0.0%	0.0%
Cedar City, UT	12,000	**6e**	0.0%	0.0%	0.0%	0.0%
Rochelle, IL	12,000	**6e**	0.0%	0.0%	0.0%	0.0%
Iron Mountain, MI-WI	12,000	**6e**	0.0%	0.0%	0.0%	0.0%
Lebanon, MO	12,000	**6e**	0.0%	0.0%	0.0%	0.0%
Big Stone Gap, VA	12,000	**6e**	0.0%	0.0%	0.0%	0.0%
McPherson, KS	12,000	**6e**	0.0%	0.0%	0.0%	0.0%
Brownwood, TX	12,000	**6e**	0.0%	0.0%	0.0%	0.0%

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Table I.1 – *Continued from previous page*

CBSA Name	Total Jobs	ID	CBD	HD Jobs	MD Jobs	HD/ MD Resid
New Ulm, MN	12,000	**6e**	0.0%	0.0%	0.0%	0.0%
Granbury, TX	12,000	**6e**	0.0%	0.0%	0.0%	0.0%
Corinth, MS	12,000	**6e**	0.0%	0.0%	0.0%	0.0%
West Plains, MO	12,000	**6e**	0.0%	0.0%	0.0%	0.0%
Emporia, KS	12,000	**6e**	0.0%	0.0%	0.0%	0.0%
Hays, KS	12,000	**6e**	0.0%	0.0%	0.0%	0.0%
Huntington, IN	12,000	**6e**	0.0%	0.0%	0.0%	0.0%
Ada, OK	12,000	**6e**	0.0%	0.0%	0.0%	0.0%
Newberry, SC	12,000	**6e**	0.0%	0.0%	0.0%	0.0%
Greensburg, IN	12,000	**6e**	0.0%	0.0%	0.0%	0.0%
Escanaba, MI	12,000	**6e**	0.0%	0.0%	0.0%	0.0%
Brenham, TX	12,000	**6e**	0.0%	0.0%	0.0%	0.0%
Stephenville, TX	12,000	**6e**	0.0%	0.0%	0.0%	0.0%
North Platte, NE	12,000	**6e**	0.0%	0.0%	0.0%	0.0%
Juneau, AK	12,000	**6e**	0.0%	0.0%	0.0%	0.0%
McComb, MS	12,000	**6e**	0.0%	0.0%	0.0%	0.0%
Greenwood, MS	12,000	**6e**	0.0%	0.0%	0.0%	0.0%
Cornelia, GA	12,000	**6e**	0.0%	0.0%	0.0%	0.0%
Decatur, IN	12,000	**6e**	0.0%	0.0%	0.0%	0.0%
Marshall, MN	12,000	**6e**	0.0%	0.0%	0.0%	0.0%
Del Rio, TX	12,000	**6e**	0.0%	0.0%	0.0%	0.0%
Clearlake, CA	11,000	**6e**	0.0%	0.0%	0.0%	0.0%
Huntsville, TX	11,000	**6e**	0.0%	0.0%	0.0%	0.0%
Vidalia, GA	11,000	**6e**	0.0%	0.0%	0.0%	0.0%
Hood River, OR	11,000	**6e**	0.0%	0.0%	0.0%	0.0%
Logansport, IN	11,000	**6e**	0.0%	0.0%	0.0%	0.0%
Mitchell, SD	11,000	**6e**	0.0%	0.0%	0.0%	0.0%
Mount Sterling, KY	11,000	**6e**	0.0%	0.0%	0.0%	0.0%
Pontiac, IL	11,000	**6e**	0.0%	0.0%	0.0%	0.0%
Moultrie, GA	11,000	**6e**	0.0%	0.0%	0.0%	0.0%
Jacksonville, TX	11,000	**6e**	0.0%	0.0%	0.0%	0.0%
Harrison, AR	11,000	**6e**	0.0%	0.0%	0.0%	0.0%
Milledgeville, GA	11,000	**6e**	0.0%	0.0%	0.0%	0.0%
Murray, KY	11,000	**6e**	0.0%	0.0%	0.0%	0.0%

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Table I.1 – *Continued from previous page*

CBSA Name	Total Jobs	ID	CBD	HD Jobs	MD Jobs	HD/ MD Resid
Eagle Pass, TX	11,000	**6e**	0.0%	0.0%	0.0%	0.0%
Winfield, KS	11,000	**6e**	0.0%	0.0%	0.0%	0.0%
Sonora, CA	11,000	**6e**	0.0%	0.0%	0.0%	0.0%
Gainesville, TX	11,000	**6e**	0.0%	0.0%	0.0%	0.0%
Wabash, IN	11,000	**6e**	0.0%	0.0%	0.0%	0.0%
Coffeyville, KS	11,000	**6e**	0.0%	0.0%	0.0%	0.0%
Brookhaven, MS	11,000	**6e**	0.0%	0.0%	0.0%	0.0%
Hillsdale, MI	11,000	**6e**	0.0%	0.0%	0.0%	0.0%
Bedford, IN	11,000	**6e**	0.0%	0.0%	0.0%	0.0%
Bucyrus-Galion, OH	11,000	**6e**	0.0%	0.0%	0.0%	0.0%
Blackfoot, ID	11,000	**6e**	0.0%	0.0%	0.0%	0.0%
Troy, AL	11,000	**6e**	0.0%	0.0%	0.0%	0.0%
Sulphur Springs, TX	11,000	**6e**	0.0%	0.0%	0.0%	0.0%
Pullman, WA	11,000	**6e**	0.0%	0.0%	0.0%	0.0%
Yankton, SD	11,000	**6e**	0.0%	0.0%	0.0%	0.0%
Ellensburg, WA	11,000	**6e**	0.0%	0.0%	0.0%	0.0%
New Castle, IN	11,000	**6e**	0.0%	0.0%	0.0%	0.0%
Oak Harbor, WA	10,000	**6e**	0.0%	0.0%	0.0%	0.0%
Campbellsville, KY	10,000	**6e**	0.0%	0.0%	0.0%	0.0%
Alma, MI	10,000	**6e**	0.0%	0.0%	0.0%	0.0%
Dixon, IL	10,000	**6e**	0.0%	0.0%	0.0%	0.0%
Frankfort, IN	10,000	**6e**	0.0%	0.0%	0.0%	0.0%
Madison, IN	10,000	**6e**	0.0%	0.0%	0.0%	0.0%
Sandpoint, ID	10,000	**6e**	0.0%	0.0%	0.0%	0.0%
Coldwater, MI	10,000	**6e**	0.0%	0.0%	0.0%	0.0%
Carroll, IA	10,000	**6e**	0.0%	0.0%	0.0%	0.0%
Fort Morgan, CO	10,000	**6e**	0.0%	0.0%	0.0%	0.0%
Hailey, ID	10,000	**6e**	0.0%	0.0%	0.0%	0.0%
Durant, OK	10,000	**6e**	0.0%	0.0%	0.0%	0.0%
Selma, AL	10,000	**6e**	0.0%	0.0%	0.0%	0.0%
Alamogordo, NM	10,000	**6e**	0.0%	0.0%	0.0%	0.0%
Sheridan, WY	10,000	**6e**	0.0%	0.0%	0.0%	0.0%
Riverton, WY	10,000	**6e**	0.0%	0.0%	0.0%	0.0%
Rockingham, NC	10,000	**6e**	0.0%	0.0%	0.0%	0.0%

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Table I.1 – *Continued from previous page*

CBSA Name	**Total Jobs**	**ID**	**CBD**	**HD Jobs**	**MD Jobs**	**HD/ MD Resid**
Shawano, WI	10,000	**6e**	0.0%	0.0%	0.0%	0.0%
Washington, IN	10,000	**6e**	0.0%	0.0%	0.0%	0.0%
Okeechobee, FL	10,000	**6e**	0.0%	0.0%	0.0%	0.0%
Lock Haven, PA	10,000	**6e**	0.0%	0.0%	0.0%	0.0%
McMinnville, TN	10,000	**6e**	0.0%	0.0%	0.0%	0.0%
Albert Lea, MN	10,000	**6e**	0.0%	0.0%	0.0%	0.0%
Plainview, TX	10,000	**6e**	0.0%	0.0%	0.0%	0.0%
Laurinburg, NC	10,000	**6e**	0.0%	0.0%	0.0%	0.0%
Laramie, WY	10,000	**6e**	0.0%	0.0%	0.0%	0.0%
Lexington, NE	10,000	**6e**	0.0%	0.0%	0.0%	0.0%
Weatherford, OK	10,000	**6e**	0.0%	0.0%	0.0%	0.0%
Huntingdon, PA	10,000	**6e**	0.0%	0.0%	0.0%	0.0%
Great Bend, KS	10,000	**6e**	0.0%	0.0%	0.0%	0.0%
Natchitoches, LA	10,000	**6e**	0.0%	0.0%	0.0%	0.0%
Clewiston, FL	10,000	**6e**	0.0%	0.0%	0.0%	0.0%
Spearfish, SD	10,000	**6e**	0.0%	0.0%	0.0%	0.0%
Washington Court House, OH	10,000	**6e**	0.0%	0.0%	0.0%	0.0%
Hinesville, GA	10,000	**6e**	0.0%	0.0%	0.0%	0.0%
Cleveland, MS	9,000	**6e**	0.0%	0.0%	0.0%	0.0%
Nogales, AZ	9,000	**6e**	0.0%	0.0%	0.0%	0.0%
Dumas, TX	9,000	**6e**	0.0%	0.0%	0.0%	0.0%
Van Wert, OH	9,000	**6e**	0.0%	0.0%	0.0%	0.0%
Worthington, MN	9,000	**6e**	0.0%	0.0%	0.0%	0.0%
Malone, NY	9,000	**6e**	0.0%	0.0%	0.0%	0.0%
Grenada, MS	9,000	**6e**	0.0%	0.0%	0.0%	0.0%
Vernal, UT	9,000	**6e**	0.0%	0.0%	0.0%	0.0%
Minden, LA	9,000	**6e**	0.0%	0.0%	0.0%	0.0%
Alpena, MI	9,000	**6e**	0.0%	0.0%	0.0%	0.0%
Cedartown, GA	9,000	**6e**	0.0%	0.0%	0.0%	0.0%
Warrensburg, MO	9,000	**6e**	0.0%	0.0%	0.0%	0.0%
Mayfield, KY	9,000	**6e**	0.0%	0.0%	0.0%	0.0%
Elkins, WV	9,000	**6e**	0.0%	0.0%	0.0%	0.0%
Big Spring, TX	9,000	**6e**	0.0%	0.0%	0.0%	0.0%
McAlester, OK	9,000	**6e**	0.0%	0.0%	0.0%	0.0%

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Table I.1 – *Continued from previous page*

CBSA Name	Total Jobs	ID	CBD	HD Jobs	MD Jobs	HD/ MD Resid
Jamestown, ND	9,000	**6e**	0.0%	0.0%	0.0%	0.0%
Fredericksburg, TX	9,000	**6e**	0.0%	0.0%	0.0%	0.0%
Americus, GA	9,000	**6e**	0.0%	0.0%	0.0%	0.0%
Seneca Falls, NY	9,000	**6e**	0.0%	0.0%	0.0%	0.0%
Atmore, AL	9,000	**6e**	0.0%	0.0%	0.0%	0.0%
Fernley, NV	9,000	**6e**	0.0%	0.0%	0.0%	0.0%
Urbana, OH	9,000	**6e**	0.0%	0.0%	0.0%	0.0%
Moscow, ID	9,000	**6e**	0.0%	0.0%	0.0%	0.0%
Elk City, OK	9,000	**6e**	0.0%	0.0%	0.0%	0.0%
The Dalles, OR	9,000	**6e**	0.0%	0.0%	0.0%	0.0%
Houghton, MI	9,000	**6e**	0.0%	0.0%	0.0%	0.0%
Cambridge, MD	9,000	**6e**	0.0%	0.0%	0.0%	0.0%
Taylorville, IL	9,000	**6e**	0.0%	0.0%	0.0%	0.0%
Union City, TN	9,000	**6e**	0.0%	0.0%	0.0%	0.0%
Huron, SD	9,000	**6e**	0.0%	0.0%	0.0%	0.0%
Coshocton, OH	9,000	**6e**	0.0%	0.0%	0.0%	0.0%
La Grande, OR	9,000	**6e**	0.0%	0.0%	0.0%	0.0%
Storm Lake, IA	9,000	**6e**	0.0%	0.0%	0.0%	0.0%
Berlin, NH	9,000	**6e**	0.0%	0.0%	0.0%	0.0%
Payson, AZ	9,000	**6e**	0.0%	0.0%	0.0%	0.0%
Paris, TN	8,000	**6e**	0.0%	0.0%	0.0%	0.0%
Ludington, MI	8,000	**6e**	0.0%	0.0%	0.0%	0.0%
Jackson, OH	8,000	**6e**	0.0%	0.0%	0.0%	0.0%
Lawrenceburg, TN	8,000	**6e**	0.0%	0.0%	0.0%	0.0%
Big Rapids, MI	8,000	**6e**	0.0%	0.0%	0.0%	0.0%
Martin, TN	8,000	**6e**	0.0%	0.0%	0.0%	0.0%
Canon City, CO	8,000	**6e**	0.0%	0.0%	0.0%	0.0%
Taos, NM	8,000	**6e**	0.0%	0.0%	0.0%	0.0%
Rio Grande City-Roma, TX	8,000	**6e**	0.0%	0.0%	0.0%	0.0%
Pahrump, NV	8,000	**6e**	0.0%	0.0%	0.0%	0.0%
Spirit Lake, IA	8,000	**6e**	0.0%	0.0%	0.0%	0.0%
Camden, AR	8,000	**6e**	0.0%	0.0%	0.0%	0.0%
Liberal, KS	8,000	**6e**	0.0%	0.0%	0.0%	0.0%
Bogalusa, LA	8,000	**6e**	0.0%	0.0%	0.0%	0.0%

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Table I.1 – *Continued from previous page*

CBSA Name	Total Jobs	ID	CBD	HD Jobs	MD Jobs	HD/ MD Resid
Kirksville, MO	8,000	**6e**	0.0%	0.0%	0.0%	0.0%
Port Lavaca, TX	8,000	**6e**	0.0%	0.0%	0.0%	0.0%
Pierre, SD	8,000	**6e**	0.0%	0.0%	0.0%	0.0%
Bay City, TX	8,000	**6e**	0.0%	0.0%	0.0%	0.0%
Shelton, WA	8,000	**6e**	0.0%	0.0%	0.0%	0.0%
Hope, AR	8,000	**6e**	0.0%	0.0%	0.0%	0.0%
Guymon, OK	8,000	**6e**	0.0%	0.0%	0.0%	0.0%
Woodward, OK	8,000	**6e**	0.0%	0.0%	0.0%	0.0%
Dayton, TN	8,000	**6e**	0.0%	0.0%	0.0%	0.0%
Mount Gay-Shamrock, WV	8,000	**6e**	0.0%	0.0%	0.0%	0.0%
Kennett, MO	8,000	**6e**	0.0%	0.0%	0.0%	0.0%
St. Marys, GA	8,000	**6e**	0.0%	0.0%	0.0%	0.0%
Ottawa, KS	8,000	**6e**	0.0%	0.0%	0.0%	0.0%
Lewisburg, TN	8,000	**6e**	0.0%	0.0%	0.0%	0.0%
Fairmont, MN	8,000	**6e**	0.0%	0.0%	0.0%	0.0%
Parsons, KS	8,000	**6e**	0.0%	0.0%	0.0%	0.0%
Levelland, TX	7,000	**6e**	0.0%	0.0%	0.0%	0.0%
Wahpeton, ND-MN	7,000	**6e**	0.0%	0.0%	0.0%	0.0%
Lincoln, IL	7,000	**6e**	0.0%	0.0%	0.0%	0.0%
Tahlequah, OK	7,000	**6e**	0.0%	0.0%	0.0%	0.0%
Moberly, MO	7,000	**6e**	0.0%	0.0%	0.0%	0.0%
Brevard, NC	7,000	**6e**	0.0%	0.0%	0.0%	0.0%
Oskaloosa, IA	7,000	**6e**	0.0%	0.0%	0.0%	0.0%
Marshall, MO	7,000	**6e**	0.0%	0.0%	0.0%	0.0%
Macomb, IL	7,000	**6e**	0.0%	0.0%	0.0%	0.0%
Borger, TX	7,000	**6e**	0.0%	0.0%	0.0%	0.0%
Picayune, MS	7,000	**6e**	0.0%	0.0%	0.0%	0.0%
Beatrice, NE	7,000	**6e**	0.0%	0.0%	0.0%	0.0%
Malvern, AR	7,000	**6e**	0.0%	0.0%	0.0%	0.0%
Mexico, MO	7,000	**6e**	0.0%	0.0%	0.0%	0.0%
Scottsburg, IN	7,000	**6e**	0.0%	0.0%	0.0%	0.0%
Spencer, IA	7,000	**6e**	0.0%	0.0%	0.0%	0.0%
Maysville, KY	7,000	**6e**	0.0%	0.0%	0.0%	0.0%
Peru, IN	7,000	**6e**	0.0%	0.0%	0.0%	0.0%

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Table I.1 – *Continued from previous page*

CBSA Name	Total Jobs	ID	CBD	HD Jobs	MD Jobs	HD/ MD Resid
Toccoa, GA	7,000	**6e**	0.0%	0.0%	0.0%	0.0%
Jennings, LA	7,000	**6e**	0.0%	0.0%	0.0%	0.0%
Arcadia, FL	7,000	**6e**	0.0%	0.0%	0.0%	0.0%
Arkadelphia, AR	7,000	**6e**	0.0%	0.0%	0.0%	0.0%
Ozark, AL	7,000	**6e**	0.0%	0.0%	0.0%	0.0%
Eufaula, AL-GA	7,000	**6e**	0.0%	0.0%	0.0%	0.0%
Central City, KY	6,000	**6e**	0.0%	0.0%	0.0%	0.0%
Fairfield, IA	6,000	**6e**	0.0%	0.0%	0.0%	0.0%
Cordele, GA	6,000	**6e**	0.0%	0.0%	0.0%	0.0%
Miami, OK	6,000	**6e**	0.0%	0.0%	0.0%	0.0%
DeRidder, LA	6,000	**6e**	0.0%	0.0%	0.0%	0.0%
Middlesborough, KY	6,000	**6e**	0.0%	0.0%	0.0%	0.0%
Kingsville, TX	6,000	**6e**	0.0%	0.0%	0.0%	0.0%
Uvalde, TX	6,000	**6e**	0.0%	0.0%	0.0%	0.0%
Clarksdale, MS	6,000	**6e**	0.0%	0.0%	0.0%	0.0%
Magnolia, AR	6,000	**6e**	0.0%	0.0%	0.0%	0.0%
Safford, AZ	6,000	**6e**	0.0%	0.0%	0.0%	0.0%
Sault Ste. Marie, MI	6,000	**6e**	0.0%	0.0%	0.0%	0.0%
Silver City, NM	6,000	**6e**	0.0%	0.0%	0.0%	0.0%
Evanston, WY	6,000	**6e**	0.0%	0.0%	0.0%	0.0%
North Vernon, IN	6,000	**6e**	0.0%	0.0%	0.0%	0.0%
Union, SC	6,000	**6e**	0.0%	0.0%	0.0%	0.0%
Pampa, TX	6,000	**6e**	0.0%	0.0%	0.0%	0.0%
Vineyard Haven, MA	6,000	**6e**	0.0%	0.0%	0.0%	0.0%
Forrest City, AR	6,000	**6e**	0.0%	0.0%	0.0%	0.0%
Winnemucca, NV	6,000	**6e**	0.0%	0.0%	0.0%	0.0%
Price, UT	6,000	**6e**	0.0%	0.0%	0.0%	0.0%
Fort Polk South, LA	6,000	**6e**	0.0%	0.0%	0.0%	0.0%
Jesup, GA	6,000	**6e**	0.0%	0.0%	0.0%	0.0%
Othello, WA	6,000	**6e**	0.0%	0.0%	0.0%	0.0%
Fallon, NV	6,000	**6e**	0.0%	0.0%	0.0%	0.0%
Newport, TN	6,000	**6e**	0.0%	0.0%	0.0%	0.0%
Maryville, MO	6,000	**6e**	0.0%	0.0%	0.0%	0.0%
Mineral Wells, TX	6,000	**6e**	0.0%	0.0%	0.0%	0.0%

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Table I.1 – *Continued from previous page*

CBSA Name	**Total Jobs**	**ID**	**CBD**	**HD Jobs**	**MD Jobs**	**HD/ MD Resid**
Fort Leonard Wood, MO	6,000	**6e**	0.0%	0.0%	0.0%	0.0%
Bainbridge, GA	6,000	**6e**	0.0%	0.0%	0.0%	0.0%
Altus, OK	6,000	**6e**	0.0%	0.0%	0.0%	0.0%
Bonham, TX	5,000	**6e**	0.0%	0.0%	0.0%	0.0%
Indianola, MS	5,000	**6e**	0.0%	0.0%	0.0%	0.0%
Andrews, TX	5,000	**6e**	0.0%	0.0%	0.0%	0.0%
Las Vegas, NM	5,000	**6e**	0.0%	0.0%	0.0%	0.0%
Sterling, CO	5,000	**6e**	0.0%	0.0%	0.0%	0.0%
Connersville, IN	5,000	**6e**	0.0%	0.0%	0.0%	0.0%
Hereford, TX	5,000	**6e**	0.0%	0.0%	0.0%	0.0%
Wauchula, FL	5,000	**6e**	0.0%	0.0%	0.0%	0.0%
Espanola, NM	5,000	**6e**	0.0%	0.0%	0.0%	0.0%
Beeville, TX	5,000	**6e**	0.0%	0.0%	0.0%	0.0%
Pearsall, TX	5,000	**6e**	0.0%	0.0%	0.0%	0.0%
Summerville, GA	5,000	**6e**	0.0%	0.0%	0.0%	0.0%
Deming, NM	5,000	**6e**	0.0%	0.0%	0.0%	0.0%
Brookings, OR	5,000	**6e**	0.0%	0.0%	0.0%	0.0%
Atchison, KS	5,000	**6e**	0.0%	0.0%	0.0%	0.0%
Prineville, OR	5,000	**6e**	0.0%	0.0%	0.0%	0.0%
Rockport, TX	5,000	**6e**	0.0%	0.0%	0.0%	0.0%
Thomaston, GA	5,000	**6e**	0.0%	0.0%	0.0%	0.0%
West Point, MS	5,000	**6e**	0.0%	0.0%	0.0%	0.0%
Grants, NM	5,000	**6e**	0.0%	0.0%	0.0%	0.0%
Fitzgerald, GA	5,000	**6e**	0.0%	0.0%	0.0%	0.0%
Snyder, TX	5,000	**6e**	0.0%	0.0%	0.0%	0.0%
Sweetwater, TX	5,000	**6e**	0.0%	0.0%	0.0%	0.0%
Crescent City, CA	5,000	**6e**	0.0%	0.0%	0.0%	0.0%
Ruidoso, NM	4,000	**6e**	0.0%	0.0%	0.0%	0.0%
Mountain Home, ID	4,000	**6e**	0.0%	0.0%	0.0%	0.0%
Helena-West Helena, AR	4,000	**6e**	0.0%	0.0%	0.0%	0.0%
Portales, NM	4,000	**6e**	0.0%	0.0%	0.0%	0.0%
Bennettsville, SC	4,000	**6e**	0.0%	0.0%	0.0%	0.0%
Brownsville, TN	4,000	**6e**	0.0%	0.0%	0.0%	0.0%
Susanville, CA	4,000	**6e**	0.0%	0.0%	0.0%	0.0%

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Table I.1 – *Continued from previous page*

CBSA Name	Total Jobs	ID	CBD	HD Jobs	MD Jobs	HD/ MD Resid
Craig, CO	3,000	**6e**	0.0%	0.0%	0.0%	0.0%
Pecos, TX	3,000	**6e**	0.0%	0.0%	0.0%	0.0%
Vernon, TX	3,000	**6e**	0.0%	0.0%	0.0%	0.0%
Winchester, VA-WV	3,000	**6e**	0.0%	0.0%	0.0%	0.0%
Vermillion, SD	3,000	**6e**	0.0%	0.0%	0.0%	0.0%
Lamesa, TX	3,000	**6e**	0.0%	0.0%	0.0%	0.0%
Raymondville, TX	2,000	**6e**	0.0%	0.0%	0.0%	0.0%
Zapata, TX	1,000	**6e**	0.0%	0.0%	0.0%	0.0%

Table I.2: List of CBSA Population Clusters and Distributions

CBSA Name	Population	ID	HD Pop.	MD Large Apt. Pop.	MD Small Apt. Pop.	MD Comm. Pop.
New York-Newark-Jersey City, NY-NJ-PA	19,274,000	**1**	35.9%	2.7%	10.9%	0.7%
Los Angeles-Long Beach-Anaheim, CA	13,242,000	**2a**	5.6%	7.6%	16.3%	1.8%
San Francisco-Oakland-Berkeley, CA	4,654,000	**2a**	9.8%	3.6%	14.8%	2.0%
Urban Honolulu, HI	893,000	**2b**	11.5%	5.0%	4.7%	0.9%
Chicago-Naperville-Elgin, IL-IN-WI	9,511,000	**2c**	6.0%	1.3%	13.8%	0.8%
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	6,030,000	**2c**	5.1%	0.2%	15.2%	0.4%
Boston-Cambridge-Newton, MA-NH	4,795,000	**2c**	7.8%	1.0%	13.9%	1.4%
Washington-Arlington-Alexandria, DC-VA-MD-WV	6,081,000	**2d**	4.6%	2.8%	3.1%	2.2%
San Diego-Chula Vista-Carlsbad, CA	3,211,000	**3a**	1.4%	5.1%	4.7%	1.0%
San Jose-Sunnyvale-Santa Clara, CA	1,980,000	**3a**	0.8%	6.3%	4.9%	1.4%
Ann Arbor, MI	364,000	**3a**	0.8%	4.5%	0.4%	0.8%
Iowa City, IA	167,000	**3a**	1.2%	3.5%	1.2%	0.0%
Seattle-Tacoma-Bellevue, WA	3,784,000	**3b**	2.7%	2.7%	1.0%	1.5%
Madison, WI	641,000	**3b**	3.5%	0.1%	0.2%	2.2%
Santa Maria-Santa Barbara, CA	434,000	**3b**	3.1%	3.0%	7.5%	1.1%
Miami-Fort Lauderdale-Pompano Beach, FL	6,057,000	**3c**	2.5%	5.0%	2.5%	1.0%
Champaign-Urbana, IL	223,000	**3c**	3.4%	4.8%	0.0%	0.2%
State College, PA	158,000	**3c**	3.1%	5.7%	0.0%	0.0%
Baltimore-Columbia-Towson, MD	2,758,000	**3d**	1.6%	0.1%	6.7%	0.7%
Milwaukee-Waukesha, WI	1,572,000	**3d**	0.8%	1.5%	9.4%	1.0%
Hartford-East Hartford-Middletown, CT	1,204,000	**3d**	0.9%	0.2%	4.0%	0.5%
Worcester, MA-CT	931,000	**3d**	0.7%	0.2%	5.1%	0.0%
Bridgeport-Stamford-Norwalk, CT	931,000	**3d**	1.4%	1.5%	8.4%	1.2%
Albany-Schenectady-Troy, NY	864,000	**3d**	1.1%	0.2%	4.4%	0.5%
New Haven-Milford, CT	855,000	**3d**	1.6%	0.4%	3.8%	0.4%
Allentown-Bethlehem-Easton, PA-NJ	821,000	**3d**	2.0%	0.0%	5.5%	0.0%
Springfield, MA	692,000	**3d**	0.7%	0.0%	5.3%	0.7%
Lancaster, PA	533,000	**3d**	0.8%	0.0%	6.3%	1.0%
Reading, PA	414,000	**3d**	1.7%	0.0%	10.8%	0.6%
Manchester-Nashua, NH	409,000	**3d**	0.9%	0.0%	7.5%	0.6%
Trenton-Princeton, NJ	362,000	**3d**	1.0%	0.0%	12.9%	0.6%
Lebanon, PA	137,000	**3d**	0.8%	0.0%	5.4%	0.0%
Lewiston-Auburn, ME	106,000	**3d**	1.5%	0.0%	4.5%	0.6%

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Table I.2 – *Continued from previous page*

CBSA Name	Total Jobs	ID	HD Pop.	MD Large Apt. Pop.	MD Small Apt. Pop.	MD Comm. Pop.
Minneapolis-St. Paul-Bloomington, MN-WI	3,524,000	**3e**	1.1%	1.8%	0.8%	1.5%
Denver-Aurora-Lakewood, CO	2,840,000	**3e**	1.1%	2.2%	0.1%	1.6%
Portland-Vancouver-Hillsboro, OR-WA	2,409,000	**3e**	1.1%	0.7%	0.8%	1.3%
Austin-Round Rock-Georgetown, TX	2,043,000	**3e**	0.7%	0.7%	0.2%	1.4%
Eugene-Springfield, OR	366,000	**3e**	1.5%	0.9%	0.0%	1.5%
Sioux Falls, SD	250,000	**3e**	1.3%	0.7%	0.0%	1.1%
Fargo, ND-MN	234,000	**3e**	0.7%	0.0%	0.0%	2.3%
Burlington-South Burlington, VT	213,000	**3e**	0.9%	0.0%	3.2%	2.3%
La Crosse-Onalaska, WI-MN	135,000	**3e**	0.7%	0.0%	1.6%	1.5%
Dallas-Fort Worth-Arlington, TX	7,139,000	**3f**	0.7%	0.9%	0.3%	0.8%
Atlanta-Sandy Springs-Alpharetta, GA	5,751,000	**3f**	0.7%	0.1%	0.0%	0.8%
Orlando-Kissimmee-Sanford, FL	2,435,000	**3f**	0.7%	0.0%	0.0%	0.5%
Pittsburgh, PA	2,322,000	**3f**	1.1%	0.2%	1.6%	0.6%
Indianapolis-Carmel-Anderson, IN	1,991,000	**3f**	0.7%	0.0%	0.1%	0.4%
Syracuse, NY	644,000	**3f**	1.1%	0.2%	1.7%	0.7%
Portland-South Portland, ME	521,000	**3f**	1.2%	0.0%	0.5%	0.8%
Reno, NV	452,000	**3f**	0.7%	0.4%	0.3%	0.5%
Rockford, IL	338,000	**3f**	0.7%	0.0%	0.0%	0.2%
South Bend-Mishawaka, IN-MI	318,000	**3f**	1.0%	0.0%	0.0%	0.2%
Utica-Rome, NY	287,000	**3f**	0.7%	0.0%	3.5%	0.3%
Atlantic City-Hammonton, NJ	263,000	**3f**	2.2%	0.8%	2.0%	0.4%
Duluth, MN-WI	241,000	**3f**	1.2%	0.0%	1.3%	0.2%
Binghamton, NY	239,000	**3f**	0.8%	0.0%	1.3%	0.2%
Rochester, MN	214,000	**3f**	0.8%	0.0%	0.0%	0.0%
Pittsfield, MA	126,000	**3f**	1.1%	0.0%	0.0%	0.6%
Muncie, IN	114,000	**3f**	0.9%	0.0%	0.0%	0.0%
Owensboro, KY	113,000	**3f**	0.7%	0.0%	0.0%	0.0%
Longview, WA	102,000	**3f**	0.7%	0.0%	1.5%	0.0%
Grand Forks, ND-MN	97,000	**3f**	0.9%	0.0%	0.0%	0.0%
Cape Girardeau, MO-IL	95,000	**3f**	0.8%	0.0%	0.0%	0.0%
Victoria, TX	95,000	**3f**	0.9%	0.0%	0.0%	0.0%
Great Falls, MT	77,000	**3f**	0.7%	0.0%	0.0%	0.0%
Plattsburgh, NY	74,000	**3f**	1.0%	0.0%	0.0%	0.0%
Wisconsin Rapids-Marshfield, WI	72,000	**3f**	0.9%	0.0%	0.0%	0.0%

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Table I.2 – *Continued from previous page*

CBSA Name	Total Jobs	ID	HD Pop.	MD Large Apt. Pop.	MD Small Apt. Pop.	MD Comm. Pop.
Laconia, NH	60,000	**3f**	1.4%	0.0%	0.0%	0.0%
Salina, KS	59,000	**3f**	1.1%	0.0%	0.0%	0.0%
Sayre, PA	58,000	**3f**	1.0%	0.0%	0.0%	0.0%
Galesburg, IL	50,000	**3f**	1.8%	0.0%	0.0%	0.0%
Mason City, IA	49,000	**3f**	1.0%	0.0%	0.0%	0.0%
Thomasville, GA	44,000	**3f**	1.0%	0.0%	0.0%	0.0%
Centralia, IL	37,000	**3f**	0.7%	0.0%	0.0%	0.0%
Easton, MD	35,000	**3f**	1.8%	0.0%	0.0%	0.0%
Corvallis, OR	85,000	**4a**	0.0%	6.5%	0.0%	0.0%
Mount Pleasant, MI	69,000	**4a**	0.0%	3.7%	0.0%	0.0%
Butte-Silver Bow, MT	34,000	**4a**	0.0%	3.6%	0.0%	0.0%
Providence-Warwick, RI-MA	1,607,000	**4b**	0.6%	0.0%	13.3%	0.4%
New Orleans-Metairie, LA	1,248,000	**4b**	0.6%	0.4%	4.6%	0.9%
Buffalo-Cheektowaga, NY	1,123,000	**4b**	0.3%	0.0%	6.7%	0.6%
Oxnard-Thousand Oaks-Ventura, CA	838,000	**4b**	0.1%	0.3%	4.4%	0.0%
Poughkeepsie-Newburgh-Middletown, NY	660,000	**4b**	0.2%	0.0%	3.3%	0.4%
Provo-Orem, UT	598,000	**4b**	0.2%	0.0%	3.4%	0.5%
Harrisburg-Carlisle, PA	553,000	**4b**	0.1%	0.0%	3.1%	0.1%
Scranton–Wilkes-Barre, PA	549,000	**4b**	0.4%	0.0%	5.0%	0.7%
York-Hanover, PA	440,000	**4b**	0.1%	0.0%	5.1%	0.2%
Salinas, CA	423,000	**4b**	0.0%	0.6%	6.9%	0.2%
Erie, PA	272,000	**4b**	0.5%	0.0%	3.8%	0.3%
Santa Cruz-Watsonville, CA	272,000	**4b**	0.0%	0.8%	3.0%	0.6%
El Centro, CA	176,000	**4b**	0.0%	0.0%	3.9%	0.0%
Bowling Green, KY	164,000	**4b**	0.2%	0.0%	2.9%	0.3%
Blacksburg-Christiansburg, VA	163,000	**4b**	0.0%	0.0%	3.2%	0.0%
Ithaca, NY	101,000	**4b**	0.3%	0.0%	5.3%	1.5%
Sunbury, PA	85,000	**4b**	0.0%	0.0%	4.4%	0.0%
Houston-The Woodlands-Sugar Land, TX	6,730,000	**4c**	0.6%	1.9%	0.1%	1.5%
Las Vegas-Henderson-Paradise, NV	2,123,000	**4c**	0.3%	1.3%	2.2%	0.2%
Lansing-East Lansing, MI	540,000	**4c**	0.1%	1.6%	0.0%	0.2%
Fort Collins, CO	336,000	**4c**	0.0%	1.5%	0.0%	0.1%
Boulder, CO	320,000	**4c**	0.0%	2.5%	2.4%	1.1%
Lafayette-West Lafayette, IN	221,000	**4c**	0.3%	2.8%	0.0%	0.0%

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Table I.2 – *Continued from previous page*

CBSA Name	**Total Jobs**	**ID**	**HD Pop.**	**MD Large Apt. Pop.**	**MD Small Apt. Pop.**	**MD Comm. Pop.**
Greenville, NC	175,000	**4c**	0.0%	1.3%	0.0%	0.0%
Bloomington, IL	172,000	**4c**	0.2%	1.2%	0.0%	0.3%
Wausau-Weston, WI	159,000	**4c**	0.1%	1.5%	0.0%	0.0%
Morgantown, WV	136,000	**4c**	0.1%	1.4%	0.0%	0.0%
Missoula, MT	114,000	**4c**	0.6%	2.2%	0.0%	1.1%
Indiana, PA	80,000	**4c**	0.0%	2.8%	3.8%	0.0%
Salt Lake City, UT	1,178,000	**4d**	0.5%	0.3%	0.0%	1.4%
Omaha-Council Bluffs, NE-IA	913,000	**4d**	0.2%	0.2%	0.0%	1.5%
Durham-Chapel Hill, NC	608,000	**4d**	0.4%	0.0%	0.0%	1.2%
Spokane-Spokane Valley, WA	535,000	**4d**	0.5%	0.0%	0.0%	1.0%
Anchorage, AK	381,000	**4d**	0.4%	0.0%	0.8%	1.2%
Chico, CA	225,000	**4d**	0.2%	0.0%	0.3%	0.7%
Charlottesville, VA	209,000	**4d**	0.0%	0.0%	0.0%	0.7%
St. Cloud, MN	193,000	**4d**	0.1%	0.0%	0.0%	0.7%
Bloomington, IN	162,000	**4d**	0.0%	0.0%	0.0%	1.0%
Glens Falls, NY	115,000	**4d**	0.0%	0.0%	0.0%	0.8%
Bozeman, MT	103,000	**4d**	0.0%	0.0%	0.0%	0.8%
Dubuque, IA	95,000	**4d**	0.0%	0.0%	0.0%	0.7%
Stillwater, OK	79,000	**4d**	0.0%	0.0%	0.0%	2.3%
Glenwood Springs, CO	75,000	**4d**	0.0%	0.0%	0.0%	1.1%
Findlay, OH	74,000	**4d**	0.0%	0.0%	0.0%	0.7%
Key West, FL	72,000	**4d**	0.0%	0.0%	2.4%	2.4%
Rexburg, ID	51,000	**4d**	0.0%	0.0%	2.0%	1.2%
Winona, MN	48,000	**4d**	0.0%	0.0%	0.0%	0.8%
Paragould, AR	43,000	**4d**	0.0%	0.0%	0.0%	1.2%
Jackson, WY-ID	33,000	**4d**	0.0%	0.0%	0.0%	1.8%
Los Alamos, NM	18,000	**4d**	0.0%	0.0%	0.0%	1.2%
Ketchikan, AK	13,000	**4d**	0.0%	0.0%	0.0%	1.1%
Phoenix-Mesa-Chandler, AZ	4,648,000	**4e**	0.4%	0.9%	0.5%	0.7%
Riverside-San Bernardino-Ontario, CA	4,461,000	**4e**	0.1%	0.2%	0.8%	0.2%
Detroit-Warren-Dearborn, MI	4,305,000	**4e**	0.3%	0.2%	0.5%	0.5%
Tampa-St. Petersburg-Clearwater, FL	3,018,000	**4e**	0.4%	0.4%	0.0%	0.6%
St. Louis, MO-IL	2,789,000	**4e**	0.6%	0.1%	1.6%	0.4%
Charlotte-Concord-Gastonia, NC-SC	2,471,000	**4e**	0.3%	0.0%	0.0%	0.5%

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Table I.2 – *Continued from previous page*

CBSA Name	Total Jobs	ID	HD Pop.	MD Large Apt. Pop.	MD Small Apt. Pop.	MD Comm. Pop.
San Antonio-New Braunfels, TX	2,386,000	**4e**	0.4%	0.0%	0.1%	0.4%
Sacramento-Roseville-Folsom, CA	2,278,000	**4e**	0.3%	0.7%	0.5%	0.6%
Cincinnati, OH-KY-IN	2,170,000	**4e**	0.2%	0.0%	0.8%	0.5%
Kansas City, MO-KS	2,087,000	**4e**	0.4%	0.0%	0.2%	0.5%
Cleveland-Elyria, OH	2,052,000	**4e**	0.2%	0.5%	0.8%	0.4%
Columbus, OH	2,037,000	**4e**	0.6%	0.1%	1.9%	0.4%
Nashville-Davidson–Murfreesboro–Franklin, TN	1,813,000	**4e**	0.5%	0.0%	0.1%	0.8%
Virginia Beach-Norfolk-Newport News, VA-NC	1,697,000	**4e**	0.4%	0.3%	0.3%	0.4%
Jacksonville, FL	1,450,000	**4e**	0.3%	0.0%	0.0%	0.4%
Oklahoma City, OK	1,351,000	**4e**	0.3%	0.0%	0.3%	0.3%
Memphis, TN-MS-AR	1,324,000	**4e**	0.4%	0.0%	0.0%	0.2%
Raleigh-Cary, NC	1,295,000	**4e**	0.2%	0.2%	0.0%	0.4%
Richmond, VA	1,239,000	**4e**	0.3%	0.2%	1.2%	0.4%
Louisville-Jefferson County, KY-IN	1,238,000	**4e**	0.4%	0.0%	0.2%	0.4%
Rochester, NY	1,061,000	**4e**	0.6%	0.0%	2.4%	0.2%
Birmingham-Hoover, AL	1,057,000	**4e**	0.3%	0.3%	0.1%	0.5%
Grand Rapids-Kentwood, MI	1,049,000	**4e**	0.3%	0.0%	1.1%	0.4%
Tucson, AZ	1,009,000	**4e**	0.2%	0.4%	0.2%	0.2%
Fresno, CA	972,000	**4e**	0.2%	0.0%	1.4%	0.2%
Tulsa, OK	972,000	**4e**	0.3%	0.0%	0.0%	0.1%
Albuquerque, NM	891,000	**4e**	0.2%	0.0%	0.0%	0.3%
Knoxville, TN	838,000	**4e**	0.3%	0.4%	0.0%	0.4%
El Paso, TX	813,000	**4e**	0.1%	0.0%	0.4%	0.4%
Dayton-Kettering, OH	795,000	**4e**	0.3%	0.0%	0.0%	0.2%
Columbia, SC	790,000	**4e**	0.1%	0.0%	0.0%	0.4%
North Port-Sarasota-Bradenton, FL	782,000	**4e**	0.2%	0.0%	0.0%	0.4%
Greensboro-High Point, NC	748,000	**4e**	0.3%	0.0%	0.0%	0.1%
Charleston-North Charleston, SC	741,000	**4e**	0.4%	0.0%	0.0%	0.3%
Little Rock-North Little Rock-Conway, AR	720,000	**4e**	0.2%	0.0%	0.1%	0.3%
Akron, OH	701,000	**4e**	0.3%	0.0%	0.3%	0.1%
Boise City, ID	686,000	**4e**	0.2%	0.0%	0.0%	0.1%
Stockton, CA	676,000	**4e**	0.2%	0.2%	1.2%	0.2%
Lakeland-Winter Haven, FL	656,000	**4e**	0.2%	0.0%	0.0%	0.1%
Winston-Salem, NC	656,000	**4e**	0.2%	0.0%	0.0%	0.1%

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Table I.2 – *Continued from previous page*

CBSA Name	Total Jobs	ID	HD Pop.	MD Large Apt. Pop.	MD Small Apt. Pop.	MD Comm. Pop.
Des Moines-West Des Moines, IA	654,000	**4e**	0.4%	0.0%	0.0%	0.6%
Toledo, OH	640,000	**4e**	0.3%	0.0%	0.0%	0.1%
Augusta-Richmond County, GA-SC	577,000	**4e**	0.2%	0.0%	0.0%	0.2%
Chattanooga, TN-GA	544,000	**4e**	0.5%	0.0%	0.0%	0.1%
Modesto, CA	536,000	**4e**	0.4%	0.0%	0.7%	0.0%
Lexington-Fayette, KY	499,000	**4e**	0.1%	0.0%	0.4%	0.4%
Springfield, MO	450,000	**4e**	0.5%	0.0%	0.0%	0.7%
Asheville, NC	445,000	**4e**	0.2%	0.0%	0.0%	0.4%
Huntsville, AL	440,000	**4e**	0.1%	0.0%	0.0%	0.3%
Vallejo, CA	430,000	**4e**	0.3%	0.0%	0.4%	0.4%
Corpus Christi, TX	421,000	**4e**	0.4%	0.0%	0.3%	0.3%
Peoria, IL	402,000	**4e**	0.4%	0.0%	0.0%	0.1%
Fort Wayne, IN	400,000	**4e**	0.2%	0.0%	0.0%	0.5%
Canton-Massillon, OH	398,000	**4e**	0.2%	0.0%	0.0%	0.1%
Tallahassee, FL	373,000	**4e**	0.4%	0.0%	0.0%	0.3%
Huntington-Ashland, WV-KY-OH	357,000	**4e**	0.3%	0.0%	0.2%	0.3%
Lincoln, NE	325,000	**4e**	0.4%	0.9%	1.0%	0.4%
Gainesville, FL	315,000	**4e**	0.5%	0.0%	0.0%	0.0%
Green Bay, WI	315,000	**4e**	0.3%	0.0%	0.3%	0.2%
Roanoke, VA	310,000	**4e**	0.4%	0.0%	0.0%	0.1%
Evansville, IN-KY	308,000	**4e**	0.3%	0.0%	0.2%	0.1%
Wilmington, NC	278,000	**4e**	0.2%	0.0%	0.0%	0.1%
San Luis Obispo-Paso Robles, CA	275,000	**4e**	0.5%	0.0%	0.5%	0.2%
Olympia-Lacey-Tumwater, WA	273,000	**4e**	0.1%	0.0%	0.0%	0.4%
Cedar Rapids, IA	265,000	**4e**	0.5%	0.0%	0.4%	0.3%
Waco, TX	260,000	**4e**	0.5%	0.0%	0.3%	0.2%
Kalamazoo-Portage, MI	260,000	**4e**	0.3%	0.0%	0.6%	0.2%
Amarillo, TX	260,000	**4e**	0.5%	0.0%	0.0%	0.0%
Charleston, WV	258,000	**4e**	0.4%	0.0%	0.0%	0.2%
College Station-Bryan, TX	247,000	**4e**	0.4%	0.0%	0.0%	0.0%
Yakima, WA	246,000	**4e**	0.3%	0.6%	1.3%	0.0%
Topeka, KS	229,000	**4e**	0.3%	0.0%	0.0%	0.5%
Macon-Bibb County, GA	220,000	**4e**	0.5%	0.0%	0.0%	0.2%
Tyler, TX	219,000	**4e**	0.4%	0.0%	0.0%	0.0%

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Table I.2 – *Continued from previous page*

CBSA Name	**Total Jobs**	**ID**	**HD Pop.**	**MD Large Apt. Pop.**	**MD Small Apt. Pop.**	**MD Comm. Pop.**
Prescott Valley-Prescott, AZ	217,000	**4e**	0.2%	0.0%	0.0%	0.0%
Bellingham, WA	212,000	**4e**	0.2%	0.0%	0.0%	0.4%
Medford, OR	211,000	**4e**	0.4%	0.0%	0.7%	0.4%
Lebanon, NH-VT	211,000	**4e**	0.2%	0.0%	0.0%	0.0%
Springfield, IL	207,000	**4e**	0.4%	0.0%	0.0%	0.8%
Columbia, MO	199,000	**4e**	0.6%	0.0%	0.0%	0.4%
Gainesville, GA	193,000	**4e**	0.6%	0.0%	0.0%	0.0%
Saginaw, MI	191,000	**4e**	0.3%	0.0%	0.0%	0.1%
Terre Haute, IN	181,000	**4e**	0.2%	0.0%	0.0%	0.0%
Bend, OR	178,000	**4e**	0.4%	0.0%	0.0%	0.3%
Punta Gorda, FL	176,000	**4e**	0.3%	0.0%	0.0%	0.0%
Oshkosh-Neenah, WI	166,000	**4e**	0.3%	0.0%	1.9%	0.2%
Abilene, TX	164,000	**4e**	0.2%	0.0%	0.0%	0.0%
Eau Claire, WI	163,000	**4e**	0.4%	0.0%	0.0%	0.0%
Pueblo, CO	163,000	**4e**	0.2%	0.0%	0.0%	0.2%
Janesville-Beloit, WI	160,000	**4e**	0.3%	0.0%	0.0%	0.0%
Jackson, MI	157,000	**4e**	0.5%	0.0%	0.0%	0.3%
Niles, MI	153,000	**4e**	0.2%	0.0%	0.0%	0.0%
Kahului-Wailuku-Lahaina, HI	152,000	**4e**	0.3%	0.0%	0.0%	0.0%
Grand Junction, CO	148,000	**4e**	0.4%	0.0%	0.0%	0.0%
Alexandria, LA	148,000	**4e**	0.4%	0.0%	0.0%	0.4%
Concord, NH	147,000	**4e**	0.3%	0.0%	0.0%	0.0%
Bangor, ME	147,000	**4e**	0.5%	0.0%	0.0%	0.5%
Traverse City, MI	146,000	**4e**	0.4%	0.0%	0.0%	0.3%
Santa Fe, NM	145,000	**4e**	0.2%	0.0%	0.0%	0.3%
Jefferson City, MO	145,000	**4e**	0.5%	0.0%	0.0%	0.0%
Dalton, GA	140,000	**4e**	0.3%	0.0%	0.0%	0.0%
Flagstaff, AZ	136,000	**4e**	0.2%	0.0%	0.0%	0.3%
Johnstown, PA	131,000	**4e**	0.4%	0.0%	0.0%	0.0%
Rapid City, SD	131,000	**4e**	0.5%	0.0%	0.0%	0.4%
Jonesboro, AR	127,000	**4e**	0.4%	0.0%	0.0%	0.0%
St. Joseph, MO-KS	124,000	**4e**	0.2%	0.0%	0.0%	0.0%
Bismarck, ND	124,000	**4e**	0.6%	0.0%	0.0%	0.8%
Farmington, NM	124,000	**4e**	0.2%	0.0%	0.0%	0.0%

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Table I.2 – *Continued from previous page*

CBSA Name	Total Jobs	ID	HD Pop.	MD Large Apt. Pop.	MD Small Apt. Pop.	MD Comm. Pop.
San Angelo, TX	116,000	**4e**	0.2%	0.0%	0.0%	0.0%
Kankakee, IL	109,000	**4e**	0.3%	0.0%	0.0%	0.0%
Decatur, IL	104,000	**4e**	0.4%	0.0%	0.0%	0.0%
Mankato, MN	98,000	**4e**	0.3%	0.0%	0.0%	0.0%
Kalispell, MT	97,000	**4e**	0.5%	0.0%	0.0%	0.0%
Rome, GA	93,000	**4e**	0.4%	0.0%	0.0%	0.0%
Fairbanks, AK	84,000	**4e**	0.4%	0.0%	0.0%	0.0%
Bloomsburg-Berwick, PA	83,000	**4e**	0.6%	0.0%	0.0%	0.0%
Quincy, IL-MO	75,000	**4e**	0.6%	0.0%	0.0%	0.5%
Keene, NH	75,000	**4e**	0.2%	0.0%	0.0%	0.0%
Hutchinson, KS	61,000	**4e**	0.4%	0.0%	0.0%	0.0%
Oneonta, NY	58,000	**4e**	0.4%	0.0%	0.0%	0.0%
Rutland, VT	58,000	**4e**	0.6%	0.0%	0.0%	0.0%
Batesville, AR	52,000	**4e**	0.3%	0.0%	0.0%	0.0%
Mountain Home, AR	40,000	**4e**	0.3%	0.0%	0.0%	0.0%
Pittsburg, KS	38,000	**4e**	0.6%	0.0%	0.0%	0.0%
Fremont, NE	35,000	**4e**	0.4%	0.0%	0.0%	0.0%
Steamboat Springs, CO	24,000	**4e**	0.6%	0.0%	0.0%	0.0%
Greenville-Anderson, SC	875,000	**4f**	0.2%	0.0%	0.0%	0.2%
Bakersfield, CA	869,000	**4f**	0.2%	0.0%	1.4%	0.0%
McAllen-Edinburg-Mission, TX	841,000	**4f**	0.1%	0.0%	0.0%	0.2%
Baton Rouge, LA	831,000	**4f**	0.1%	0.0%	0.1%	0.2%
Cape Coral-Fort Myers, FL	715,000	**4f**	0.1%	0.0%	0.0%	0.1%
Colorado Springs, CO	681,000	**4f**	0.1%	0.0%	0.1%	0.1%
Ogden-Clearfield, UT	646,000	**4f**	0.1%	0.0%	0.0%	0.0%
Wichita, KS	629,000	**4f**	0.1%	0.0%	0.1%	0.2%
Deltona-Daytona Beach-Ormond Beach, FL	624,000	**4f**	0.2%	0.0%	0.0%	0.0%
Jackson, MS	585,000	**4f**	0.2%	0.0%	0.0%	0.0%
Palm Bay-Melbourne-Titusville, FL	567,000	**4f**	0.1%	0.0%	0.0%	0.0%
Youngstown-Warren-Boardman, OH-PA	538,000	**4f**	0.1%	0.0%	0.0%	0.0%
Santa Rosa-Petaluma, CA	498,000	**4f**	0.1%	0.0%	0.7%	0.5%
Fayetteville-Springdale-Rogers, AR	497,000	**4f**	0.1%	0.0%	0.0%	0.1%
Lafayette, LA	479,000	**4f**	0.1%	0.0%	0.0%	0.0%
Fayetteville, NC	475,000	**4f**	0.0%	0.0%	0.0%	0.0%

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Table I.2 – *Continued from previous page*

CBSA Name	**Total Jobs**	**ID**	**HD Pop.**	**MD Large Apt. Pop.**	**MD Small Apt. Pop.**	**MD Comm. Pop.**
Pensacola-Ferry Pass-Brent, FL	458,000	**4f**	0.1%	0.0%	0.0%	0.0%
Port St. Lucie, FL	457,000	**4f**	0.0%	0.0%	0.1%	0.2%
Visalia, CA	456,000	**4f**	0.0%	0.0%	0.8%	0.0%
Myrtle Beach-Conway-North Myrtle Beach, SC-NC	435,000	**4f**	0.0%	0.0%	0.0%	0.0%
Mobile, AL	423,000	**4f**	0.1%	0.0%	0.0%	0.1%
Salem, OR	413,000	**4f**	0.1%	0.0%	0.7%	0.1%
Brownsville-Harlingen, TX	412,000	**4f**	0.2%	0.0%	0.0%	0.0%
Flint, MI	406,000	**4f**	0.2%	0.0%	0.0%	0.1%
Killeen-Temple, TX	403,000	**4f**	0.1%	0.0%	0.0%	0.1%
Gulfport-Biloxi, MS	394,000	**4f**	0.0%	0.0%	0.0%	0.0%
Salisbury, MD-DE	394,000	**4f**	0.0%	0.0%	0.0%	0.0%
Beaumont-Port Arthur, TX	388,000	**4f**	0.1%	0.0%	0.0%	0.0%
Shreveport-Bossier City, LA	382,000	**4f**	0.2%	0.0%	0.0%	0.1%
Davenport-Moline-Rock Island, IA-IL	376,000	**4f**	0.1%	0.0%	0.0%	0.2%
Savannah, GA	370,000	**4f**	0.1%	0.0%	0.7%	0.1%
Hickory-Lenoir-Morganton, NC	361,000	**4f**	0.0%	0.0%	0.0%	0.0%
Montgomery, AL	360,000	**4f**	0.0%	0.0%	0.0%	0.0%
Naples-Marco Island, FL	359,000	**4f**	0.1%	0.0%	1.1%	0.0%
Ocala, FL	343,000	**4f**	0.1%	0.0%	0.0%	0.0%
Lubbock, TX	310,000	**4f**	0.1%	0.4%	0.0%	0.0%
Kingsport-Bristol, TN-VA	299,000	**4f**	0.2%	0.0%	0.0%	0.0%
Spartanburg, SC	298,000	**4f**	0.0%	0.0%	0.0%	0.1%
Columbus, GA-AL	295,000	**4f**	0.1%	0.0%	0.0%	0.0%
Greeley, CO	291,000	**4f**	0.2%	0.0%	0.0%	0.0%
Kennewick-Richland, WA	282,000	**4f**	0.2%	0.0%	0.0%	0.0%
Hagerstown-Martinsburg, MD-WV	277,000	**4f**	0.0%	0.0%	2.3%	0.0%
Longview, TX	275,000	**4f**	0.1%	0.0%	0.0%	0.1%
Clarksville, TN-KY	270,000	**4f**	0.0%	0.0%	0.0%	0.0%
Laredo, TX	268,000	**4f**	0.0%	0.0%	0.7%	0.2%
Merced, CA	267,000	**4f**	0.0%	0.0%	0.0%	0.0%
Norwich-New London, CT	262,000	**4f**	0.0%	0.0%	0.5%	0.0%
Lynchburg, VA	257,000	**4f**	0.0%	0.0%	0.0%	0.2%
Bremerton-Silverdale-Port Orchard, WA	253,000	**4f**	0.0%	0.0%	0.0%	0.0%
Crestview-Fort Walton Beach-Destin, FL	247,000	**4f**	0.0%	0.0%	0.0%	0.0%

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Table I.2 – *Continued from previous page*

CBSA Name	Total Jobs	ID	HD Pop.	MD Large Apt. Pop.	MD Small Apt. Pop.	MD Comm. Pop.
Tuscaloosa, AL	243,000	**4f**	0.0%	0.0%	0.0%	0.1%
Fort Smith, AR-OK	240,000	**4f**	0.0%	0.0%	0.0%	0.0%
Appleton, WI	232,000	**4f**	0.0%	0.0%	0.0%	0.3%
Barnstable Town, MA	212,000	**4f**	0.2%	0.0%	0.0%	0.0%
Las Cruces, NM	211,000	**4f**	0.0%	0.0%	0.0%	0.4%
Houma-Thibodaux, LA	205,000	**4f**	0.0%	0.0%	0.0%	0.0%
Elkhart-Goshen, IN	202,000	**4f**	0.1%	0.0%	0.0%	0.0%
Lake Charles, LA	202,000	**4f**	0.0%	0.0%	0.0%	0.0%
Athens-Clarke County, GA	202,000	**4f**	0.0%	0.0%	1.5%	0.4%
Daphne-Fairhope-Foley, AL	200,000	**4f**	0.0%	0.0%	0.0%	0.0%
Lake Havasu City-Kingman, AZ	200,000	**4f**	0.0%	0.0%	0.0%	0.0%
Yuma, AZ	200,000	**4f**	0.1%	0.6%	0.0%	0.0%
Johnson City, TN	199,000	**4f**	0.2%	0.0%	0.0%	0.0%
Florence, SC	198,000	**4f**	0.0%	0.0%	0.0%	0.0%
Hilton Head Island-Bluffton, SC	198,000	**4f**	0.0%	0.0%	0.0%	0.0%
Monroe, LA	198,000	**4f**	0.1%	0.0%	0.0%	0.1%
Racine, WI	195,000	**4f**	0.0%	0.0%	0.9%	0.5%
Hilo, HI	186,000	**4f**	0.0%	0.0%	0.0%	0.0%
Torrington, CT	181,000	**4f**	0.0%	0.0%	0.0%	0.0%
Redding, CA	177,000	**4f**	0.0%	0.0%	0.3%	0.0%
Panama City, FL	177,000	**4f**	0.0%	0.0%	0.0%	0.0%
Billings, MT	175,000	**4f**	0.0%	0.0%	0.0%	0.3%
Kingston, NY	174,000	**4f**	0.0%	0.0%	1.6%	0.0%
Joplin, MO	174,000	**4f**	0.1%	0.0%	0.0%	0.0%
Warner Robins, GA	173,000	**4f**	0.0%	0.0%	0.0%	0.0%
Jackson, TN	173,000	**4f**	0.0%	0.0%	0.0%	0.0%
Muskegon, MI	172,000	**4f**	0.1%	0.0%	0.0%	0.0%
Dover, DE	171,000	**4f**	0.0%	0.0%	0.0%	0.0%
Waterloo-Cedar Falls, IA	168,000	**4f**	0.1%	0.0%	0.0%	0.0%
Yuba City, CA	166,000	**4f**	0.0%	0.0%	0.0%	0.0%
East Stroudsburg, PA	165,000	**4f**	0.0%	0.0%	0.0%	0.0%
Midland, TX	164,000	**4f**	0.0%	0.0%	0.0%	0.0%
Hattiesburg, MS	161,000	**4f**	0.0%	0.0%	0.0%	0.0%
Tupelo, MS	160,000	**4f**	0.1%	0.0%	0.0%	0.2%

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Table I.2 – *Continued from previous page*

CBSA Name	Total Jobs	ID	HD Pop.	MD Large Apt. Pop.	MD Small Apt. Pop.	MD Comm. Pop.
Burlington, NC	159,000	**4f**	0.1%	0.0%	0.0%	0.2%
St. George, UT	159,000	**4f**	0.0%	0.0%	0.0%	0.0%
Jacksonville, NC	158,000	**4f**	0.0%	0.0%	0.0%	0.0%
Auburn-Opelika, AL	157,000	**4f**	0.0%	0.0%	0.0%	0.0%
Odessa, TX	155,000	**4f**	0.0%	0.0%	0.0%	0.0%
Madera, CA	153,000	**4f**	0.0%	0.0%	0.0%	0.0%
Coeur d'Alene, ID	151,000	**4f**	0.0%	0.0%	0.0%	0.2%
Vineland-Bridgeton, NJ	151,000	**4f**	0.0%	0.0%	1.0%	0.0%
Chambersburg-Waynesboro, PA	149,000	**4f**	0.0%	0.0%	0.9%	0.0%
Sebastian-Vero Beach, FL	148,000	**4f**	0.0%	0.0%	0.0%	0.0%
Monroe, MI	148,000	**4f**	0.0%	0.0%	0.0%	0.0%
Ottawa, IL	146,000	**4f**	0.0%	0.0%	0.0%	0.0%
Albany, GA	146,000	**4f**	0.1%	0.0%	0.0%	0.0%
Dothan, AL	145,000	**4f**	0.0%	0.0%	0.0%	0.0%
London, KY	145,000	**4f**	0.0%	0.0%	0.0%	0.0%
Decatur, AL	144,000	**4f**	0.0%	0.0%	0.0%	0.0%
Texarkana, TX-AR	144,000	**4f**	0.0%	0.0%	0.0%	0.0%
Rocky Mount, NC	144,000	**4f**	0.0%	0.0%	0.0%	0.0%
Florence-Muscle Shoals, AL	142,000	**4f**	0.0%	0.0%	0.0%	0.6%
Wichita Falls, TX	142,000	**4f**	0.2%	0.0%	0.0%	0.0%
Idaho Falls, ID	141,000	**4f**	0.0%	0.0%	0.0%	0.0%
Sioux City, IA-NE-SD	141,000	**4f**	0.0%	0.0%	0.0%	0.1%
Hanford-Corcoran, CA	141,000	**4f**	0.0%	0.0%	0.0%	0.0%
Homosassa Springs, FL	140,000	**4f**	0.0%	0.0%	0.0%	0.0%
Pottsville, PA	140,000	**4f**	0.0%	0.0%	1.2%	0.0%
Valdosta, GA	140,000	**4f**	0.0%	0.0%	0.0%	0.0%
Napa, CA	140,000	**4f**	0.0%	0.0%	0.0%	0.5%
Morristown, TN	138,000	**4f**	0.0%	0.0%	0.0%	0.0%
Wheeling, WV-OH	138,000	**4f**	0.0%	0.0%	0.0%	0.2%
Carbondale-Marion, IL	135,000	**4f**	0.0%	0.0%	0.8%	0.0%
Logan, UT-ID	134,000	**4f**	0.0%	0.0%	0.0%	0.3%
Elizabethtown-Fort Knox, KY	134,000	**4f**	0.0%	0.0%	0.0%	0.0%
Eureka-Arcata, CA	133,000	**4f**	0.0%	0.0%	0.0%	0.0%
Springfield, OH	133,000	**4f**	0.0%	0.0%	0.0%	0.0%

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Table I.2 – *Continued from previous page*

CBSA Name	Total Jobs	ID	HD Pop.	MD Large Apt. Pop.	MD Small Apt. Pop.	MD Comm. Pop.
Sumter, SC	133,000	**4f**	0.0%	0.0%	0.0%	0.0%
Battle Creek, MI	132,000	**4f**	0.0%	0.0%	0.0%	0.0%
Harrisonburg, VA	132,000	**4f**	0.0%	0.0%	0.0%	0.0%
Lumberton, NC	130,000	**4f**	0.0%	0.0%	0.0%	0.0%
Hammond, LA	128,000	**4f**	0.0%	0.0%	0.0%	0.0%
Jamestown-Dunkirk-Fredonia, NY	126,000	**4f**	0.0%	0.0%	0.6%	0.0%
Sherman-Denison, TX	124,000	**4f**	0.0%	0.0%	0.0%	0.0%
Mount Vernon-Anacortes, WA	123,000	**4f**	0.0%	0.0%	0.0%	0.0%
Altoona, PA	122,000	**4f**	0.0%	0.0%	0.0%	0.0%
Ames, IA	121,000	**4f**	0.0%	0.0%	0.0%	0.0%
Staunton, VA	120,000	**4f**	0.0%	0.0%	0.0%	0.0%
Mansfield, OH	120,000	**4f**	0.0%	0.0%	0.0%	0.0%
The Villages, FL	119,000	**4f**	0.0%	0.0%	0.0%	0.0%
Augusta-Waterville, ME	119,000	**4f**	0.0%	0.0%	0.0%	0.0%
Goldsboro, NC	118,000	**4f**	0.0%	0.0%	0.0%	0.0%
Albany-Lebanon, OR	118,000	**4f**	0.0%	0.0%	0.0%	0.5%
Cleveland, TN	118,000	**4f**	0.0%	0.0%	0.0%	0.0%
Beckley, WV	117,000	**4f**	0.0%	0.0%	0.0%	0.0%
Lawrence, KS	117,000	**4f**	0.0%	0.0%	0.0%	0.3%
Weirton-Steubenville, WV-OH	116,000	**4f**	0.0%	0.0%	0.0%	0.0%
Manhattan, KS	116,000	**4f**	0.0%	0.0%	0.0%	0.0%
Wenatchee, WA	115,000	**4f**	0.0%	0.0%	0.0%	0.6%
New Bern, NC	115,000	**4f**	0.0%	0.0%	0.0%	0.0%
Wooster, OH	114,000	**4f**	0.0%	0.0%	0.0%	0.0%
Sierra Vista-Douglas, AZ	114,000	**4f**	0.0%	0.0%	0.0%	0.0%
Holland, MI	113,000	**4f**	0.0%	0.0%	0.0%	0.0%
Brunswick, GA	113,000	**4f**	0.2%	0.0%	0.0%	0.0%
Lawton, OK	113,000	**4f**	0.0%	0.0%	0.0%	0.0%
Sheboygan, WI	113,000	**4f**	0.0%	0.0%	0.0%	0.0%
Williamsport, PA	112,000	**4f**	0.0%	0.0%	0.0%	0.3%
Anniston-Oxford, AL	112,000	**4f**	0.0%	0.0%	0.0%	0.0%
Michigan City-La Porte, IN	109,000	**4f**	0.0%	0.0%	0.0%	0.0%
California-Lexington Park, MD	108,000	**4f**	0.0%	0.0%	0.0%	0.0%
Cookeville, TN	107,000	**4f**	0.0%	0.0%	0.0%	0.0%

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Table I.2 – *Continued from previous page*

CBSA Name	Total Jobs	ID	HD Pop.	MD Large Apt. Pop.	MD Small Apt. Pop.	MD Comm. Pop.
Bluefield, WV-VA	107,000	**4f**	0.0%	0.0%	0.0%	0.0%
Roseburg, OR	105,000	**4f**	0.1%	0.0%	0.0%	0.0%
Twin Falls, ID	105,000	**4f**	0.0%	0.0%	0.0%	0.0%
Ogdensburg-Massena, NY	104,000	**4f**	0.0%	0.0%	0.0%	0.0%
Bay City, MI	104,000	**4f**	0.0%	0.0%	0.0%	0.0%
Lima, OH	102,000	**4f**	0.0%	0.0%	0.0%	0.0%
Show Low, AZ	102,000	**4f**	0.0%	0.0%	0.0%	0.0%
Whitewater, WI	101,000	**4f**	0.0%	0.0%	0.0%	0.0%
Danville, VA	101,000	**4f**	0.0%	0.0%	0.0%	0.0%
Sebring-Avon Park, FL	101,000	**4f**	0.0%	0.0%	0.0%	0.0%
Gadsden, AL	101,000	**4f**	0.0%	0.0%	0.0%	0.4%
LaGrange, GA-AL	101,000	**4f**	0.0%	0.0%	0.0%	0.0%
Fond du Lac, WI	101,000	**4f**	0.0%	0.0%	0.0%	0.0%
Gettysburg, PA	100,000	**4f**	0.0%	0.0%	0.0%	0.0%
Salem, OH	100,000	**4f**	0.0%	0.0%	0.0%	0.0%
Richmond-Berea, KY	100,000	**4f**	0.0%	0.0%	0.0%	0.0%
Watertown-Fort Drum, NY	98,000	**4f**	0.0%	0.0%	0.0%	0.0%
Tullahoma-Manchester, TN	98,000	**4f**	0.0%	0.0%	0.0%	0.0%
Meridian, MS	98,000	**4f**	0.0%	0.0%	0.0%	0.0%
Cumberland, MD-WV	97,000	**4f**	0.0%	0.0%	0.0%	0.0%
Truckee-Grass Valley, CA	97,000	**4f**	0.0%	0.0%	0.0%	0.0%
Adrian, MI	96,000	**4f**	0.0%	0.0%	0.0%	0.0%
Shelby, NC	96,000	**4f**	0.0%	0.0%	0.0%	0.0%
Hot Springs, AR	96,000	**4f**	0.0%	0.0%	0.0%	0.0%
Ashtabula, OH	95,000	**4f**	0.0%	0.0%	0.0%	0.0%
Sevierville, TN	95,000	**4f**	0.0%	0.0%	0.0%	0.0%
Pinehurst-Southern Pines, NC	94,000	**4f**	0.0%	0.0%	0.0%	0.0%
Corning, NY	94,000	**4f**	0.0%	0.0%	0.0%	0.4%
Paducah, KY-IL	94,000	**4f**	0.0%	0.0%	0.0%	0.0%
Cheyenne, WY	93,000	**4f**	0.0%	0.0%	0.0%	0.0%
Moses Lake, WA	93,000	**4f**	0.0%	0.0%	0.0%	0.0%
Albertville, AL	92,000	**4f**	0.0%	0.0%	0.0%	0.0%
Pocatello, ID	92,000	**4f**	0.0%	0.0%	0.0%	0.0%
New Philadelphia-Dover, OH	91,000	**4f**	0.0%	0.0%	0.0%	0.0%

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Table I.2 – *Continued from previous page*

CBSA Name	Total Jobs	ID	HD Pop.	MD Large Apt. Pop.	MD Small Apt. Pop.	MD Comm. Pop.
Clarksburg, WV	91,000	**4f**	0.0%	0.0%	0.0%	0.0%
Brainerd, MN	90,000	**4f**	0.0%	0.0%	0.0%	0.0%
Ocean City, NJ	89,000	**4f**	0.0%	0.0%	0.0%	0.0%
Pine Bluff, AR	88,000	**4f**	0.2%	0.0%	0.0%	0.0%
Beaver Dam, WI	86,000	**4f**	0.0%	0.0%	0.0%	0.0%
New Castle, PA	86,000	**4f**	0.0%	0.0%	0.0%	0.0%
Parkersburg-Vienna, WV	86,000	**4f**	0.0%	0.0%	0.0%	0.2%
Orangeburg, SC	86,000	**4f**	0.0%	0.0%	0.0%	0.0%
Lufkin, TX	85,000	**4f**	0.0%	0.0%	0.0%	0.0%
Hermiston-Pendleton, OR	85,000	**4f**	0.0%	0.0%	0.0%	0.0%
Elmira, NY	84,000	**4f**	0.0%	0.0%	1.5%	0.0%
Zanesville, OH	84,000	**4f**	0.0%	0.0%	0.0%	0.0%
Grants Pass, OR	84,000	**4f**	0.0%	0.0%	0.0%	0.0%
Watertown-Fort Atkinson, WI	83,000	**4f**	0.0%	0.0%	0.0%	0.0%
Meadville, PA	83,000	**4f**	0.0%	0.0%	1.2%	0.0%
Ukiah, CA	83,000	**4f**	0.0%	0.0%	0.0%	0.0%
Russellville, AR	82,000	**4f**	0.0%	0.0%	0.0%	0.0%
Laurel, MS	82,000	**4f**	0.0%	0.0%	0.0%	0.0%
Midland, MI	82,000	**4f**	0.0%	0.0%	0.0%	0.0%
Kokomo, IN	82,000	**4f**	0.0%	0.0%	0.0%	0.0%
Opelousas, LA	81,000	**4f**	0.0%	0.0%	0.0%	0.0%
Wilson, NC	80,000	**4f**	0.0%	0.0%	0.0%	0.0%
Columbus, IN	79,000	**4f**	0.0%	0.0%	0.0%	0.0%
Manitowoc, WI	79,000	**4f**	0.0%	0.0%	0.0%	0.0%
Cullman, AL	79,000	**4f**	0.0%	0.0%	0.0%	0.0%
Casper, WY	78,000	**4f**	0.0%	0.0%	0.0%	0.3%
DuBois, PA	77,000	**4f**	0.0%	0.0%	0.0%	0.0%
Helena, MT	77,000	**4f**	0.0%	0.0%	0.0%	0.0%
Talladega-Sylacauga, AL	77,000	**4f**	0.0%	0.0%	0.0%	0.0%
Danville, IL	77,000	**4f**	0.0%	0.0%	0.0%	0.0%
Athens, TX	76,000	**4f**	0.0%	0.0%	0.0%	0.0%
Auburn, NY	75,000	**4f**	0.0%	0.0%	1.5%	0.0%
Searcy, AR	75,000	**4f**	0.0%	0.0%	0.0%	0.0%
Chillicothe, OH	75,000	**4f**	0.0%	0.0%	0.0%	0.0%

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Table I.2 – *Continued from previous page*

CBSA Name	**Total Jobs**	**ID**	**HD Pop.**	**MD Large Apt. Pop.**	**MD Small Apt. Pop.**	**MD Comm. Pop.**
Centralia, WA	74,000	**4f**	0.0%	0.0%	0.0%	0.0%
Portsmouth, OH	74,000	**4f**	0.0%	0.0%	0.0%	0.0%
Olean, NY	74,000	**4f**	0.0%	0.0%	0.0%	0.0%
Oak Harbor, WA	74,000	**4f**	0.0%	0.0%	0.0%	0.0%
Sandusky, OH	74,000	**4f**	0.0%	0.0%	0.0%	0.0%
Statesboro, GA	74,000	**4f**	0.0%	0.0%	0.0%	0.0%
Port Angeles, WA	73,000	**4f**	0.0%	0.0%	0.0%	0.0%
Seneca, SC	73,000	**4f**	0.0%	0.0%	0.0%	0.0%
Grand Island, NE	72,000	**4f**	0.0%	0.0%	0.0%	0.0%
Somerset, PA	72,000	**4f**	0.0%	0.0%	0.0%	0.0%
Warsaw, IN	71,000	**4f**	0.0%	0.0%	0.0%	0.0%
Minot, ND	71,000	**4f**	0.0%	0.0%	0.0%	0.0%
Mount Airy, NC	71,000	**4f**	0.0%	0.0%	0.0%	0.0%
Palatka, FL	71,000	**4f**	0.0%	0.0%	0.0%	0.0%
Huntsville, TX	70,000	**4f**	0.0%	0.0%	0.0%	0.0%
Aberdeen, WA	70,000	**4f**	0.0%	0.0%	0.0%	0.0%
Heber, UT	70,000	**4f**	0.0%	0.0%	0.0%	0.0%
Roanoke Rapids, NC	70,000	**4f**	0.0%	0.0%	0.0%	0.0%
Kapaa, HI	70,000	**4f**	0.0%	0.0%	0.0%	0.0%
Fort Payne, AL	69,000	**4f**	0.0%	0.0%	0.0%	0.0%
Stevens Point, WI	69,000	**4f**	0.0%	0.0%	0.0%	0.0%
Gallup, NM	69,000	**4f**	0.0%	0.0%	0.0%	0.0%
Greenwood, SC	69,000	**4f**	0.0%	0.0%	0.0%	0.0%
Shawnee, OK	69,000	**4f**	0.0%	0.0%	0.0%	0.0%
Hobbs, NM	68,000	**4f**	0.0%	0.0%	0.0%	0.0%
Frankfort, KY	68,000	**4f**	0.0%	0.0%	0.0%	0.0%
Hinesville, GA	67,000	**4f**	0.0%	0.0%	0.0%	0.0%
Lake City, FL	67,000	**4f**	0.0%	0.0%	0.0%	0.0%
North Wilkesboro, NC	66,000	**4f**	0.0%	0.0%	0.0%	0.0%
Greeneville, TN	66,000	**4f**	0.0%	0.0%	0.0%	0.0%
Marquette, MI	66,000	**4f**	0.0%	0.0%	0.0%	0.0%
Farmington, MO	65,000	**4f**	0.0%	0.0%	0.0%	0.0%
Forest City, NC	65,000	**4f**	0.0%	0.0%	0.0%	0.0%
Richmond, IN	65,000	**4f**	0.0%	0.0%	0.0%	0.0%

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Table I.2 – *Continued from previous page*

CBSA Name	**Total Jobs**	**ID**	**HD Pop.**	**MD Large Apt. Pop.**	**MD Small Apt. Pop.**	**MD Comm. Pop.**
Klamath Falls, OR	65,000	**4f**	0.0%	0.0%	0.0%	0.0%
Faribault-Northfield, MN	65,000	**4f**	0.0%	0.0%	0.0%	0.0%
Jefferson, GA	65,000	**4f**	0.0%	0.0%	0.0%	0.0%
Marion, IN	65,000	**4f**	0.0%	0.0%	0.0%	0.0%
Athens, OH	64,000	**4f**	0.0%	0.0%	0.0%	0.0%
Morehead City, NC	64,000	**4f**	0.0%	0.0%	0.0%	0.0%
Marion, OH	64,000	**4f**	0.0%	0.0%	0.0%	0.0%
Roswell, NM	63,000	**4f**	0.0%	0.0%	0.0%	0.0%
Clearlake, CA	63,000	**4f**	0.0%	0.0%	0.0%	0.0%
Martinsville, VA	62,000	**4f**	0.0%	0.0%	0.0%	0.0%
Coos Bay, OR	62,000	**4f**	0.0%	0.0%	0.0%	0.0%
Somerset, KY	62,000	**4f**	0.0%	0.0%	0.0%	0.0%
Lewiston, ID-WA	62,000	**4f**	0.0%	0.0%	0.0%	0.0%
Charleston-Mattoon, IL	61,000	**4f**	0.0%	0.0%	0.0%	0.0%
Red Bluff, CA	61,000	**4f**	0.0%	0.0%	0.0%	0.0%
Dublin, GA	61,000	**4f**	0.0%	0.0%	0.0%	0.0%
Baraboo, WI	61,000	**4f**	0.0%	0.0%	0.0%	0.0%
Muskogee, OK	61,000	**4f**	0.0%	0.0%	0.0%	0.0%
Nacogdoches, TX	61,000	**4f**	0.0%	0.0%	0.0%	0.0%
Jasper, AL	60,000	**4f**	0.0%	0.0%	0.0%	0.0%
Marinette, WI-MI	60,000	**4f**	0.0%	0.0%	0.0%	0.0%
Enid, OK	60,000	**4f**	0.0%	0.0%	0.0%	0.0%
Sturgis, MI	60,000	**4f**	0.0%	0.0%	0.0%	0.0%
Shelton, WA	60,000	**4f**	0.0%	0.0%	0.0%	0.0%
Gillette, WY	60,000	**4f**	0.0%	0.0%	0.0%	0.0%
Hudson, NY	59,000	**4f**	0.0%	0.0%	0.0%	0.0%
Mount Vernon, OH	59,000	**4f**	0.0%	0.0%	0.0%	0.0%
Rio Grande City-Roma, TX	59,000	**4f**	0.0%	0.0%	0.0%	0.0%
Walla Walla, WA	59,000	**4f**	0.0%	0.0%	0.0%	0.0%
Albemarle, NC	58,000	**4f**	0.0%	0.0%	0.0%	0.0%
Georgetown, SC	58,000	**4f**	0.0%	0.0%	0.0%	0.0%
Marietta, OH	58,000	**4f**	0.0%	0.0%	0.0%	0.0%
Fremont, OH	58,000	**4f**	0.0%	0.0%	0.0%	0.0%
Fort Madison-Keokuk, IA-IL-MO	58,000	**4f**	0.0%	0.0%	0.0%	0.0%

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Table I.2 – *Continued from previous page*

CBSA Name	**Total Jobs**	**ID**	**HD Pop.**	**MD Large Apt. Pop.**	**MD Small Apt. Pop.**	**MD Comm. Pop.**
Crossville, TN	58,000	**4f**	0.0%	0.0%	0.0%	0.0%
Sanford, NC	57,000	**4f**	0.0%	0.0%	0.0%	0.0%
Norwalk, OH	57,000	**4f**	0.0%	0.0%	0.0%	0.0%
Starkville, MS	57,000	**4f**	0.0%	0.0%	0.0%	0.0%
Batavia, NY	57,000	**4f**	0.0%	0.0%	0.0%	0.0%
Barre, VT	56,000	**4f**	0.0%	0.0%	0.0%	0.0%
Columbus, MS	56,000	**4f**	0.0%	0.0%	0.0%	0.0%
Kinston, NC	56,000	**4f**	0.0%	0.0%	0.0%	0.0%
Alamogordo, NM	56,000	**4f**	0.0%	0.0%	0.0%	0.0%
Carlsbad-Artesia, NM	56,000	**4f**	0.0%	0.0%	0.0%	0.0%
Granbury, TX	56,000	**4f**	0.0%	0.0%	0.0%	0.0%
Gaffney, SC	56,000	**4f**	0.0%	0.0%	0.0%	0.0%
Ardmore, OK	55,000	**4f**	0.0%	0.0%	0.0%	0.0%
Fergus Falls, MN	55,000	**4f**	0.0%	0.0%	0.0%	0.0%
Fairmont, WV	55,000	**4f**	0.0%	0.0%	0.0%	0.0%
Cullowhee, NC	55,000	**4f**	0.0%	0.0%	0.0%	0.0%
Calhoun, GA	55,000	**4f**	0.0%	0.0%	0.0%	0.0%
Sterling, IL	55,000	**4f**	0.0%	0.0%	0.0%	0.0%
Eagle Pass, TX	55,000	**4f**	0.0%	0.0%	0.0%	0.0%
Palestine, TX	55,000	**4f**	0.0%	0.0%	0.0%	0.0%
Kearney, NE	55,000	**4f**	0.0%	0.0%	0.0%	0.0%
Poplar Bluff, MO	55,000	**4f**	0.0%	0.0%	0.0%	0.0%
Carson City, NV	54,000	**4f**	0.0%	0.0%	0.0%	0.0%
Tiffin, OH	54,000	**4f**	0.0%	0.0%	0.0%	0.0%
Waycross, GA	54,000	**4f**	0.0%	0.0%	0.0%	0.0%
Branson, MO	54,000	**4f**	0.0%	0.0%	0.0%	0.0%
Sonora, CA	53,000	**4f**	0.0%	0.0%	0.0%	0.0%
Point Pleasant, WV-OH	53,000	**4f**	0.0%	0.0%	0.0%	0.0%
Gloversville, NY	53,000	**4f**	0.0%	0.0%	0.0%	0.0%
Jasper, IN	53,000	**4f**	0.0%	0.0%	0.0%	0.0%
Boone, NC	53,000	**4f**	0.0%	0.0%	0.0%	0.0%
Edwards, CO	53,000	**4f**	0.0%	0.0%	0.0%	0.0%
Durango, CO	53,000	**4f**	0.0%	0.0%	0.0%	0.4%
Oxford, MS	52,000	**4f**	0.0%	0.0%	0.0%	0.0%

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Table I.2 – *Continued from previous page*

CBSA Name	Total Jobs	ID	HD Pop.	MD Large Apt. Pop.	MD Small Apt. Pop.	MD Comm. Pop.
Ashland, OH	52,000	**4f**	0.0%	0.0%	0.0%	0.0%
Ontario, OR-ID	52,000	**4f**	0.0%	0.0%	0.0%	0.0%
Danville, KY	52,000	**4f**	0.0%	0.0%	0.0%	0.0%
Milledgeville, GA	52,000	**4f**	0.0%	0.0%	0.0%	0.0%
Fernley, NV	52,000	**4f**	0.0%	0.0%	0.0%	0.0%
Elko, NV	52,000	**4f**	0.0%	0.0%	0.0%	0.0%
Picayune, MS	51,000	**4f**	0.0%	0.0%	0.0%	0.0%
Bartlesville, OK	51,000	**4f**	0.0%	0.0%	0.0%	0.0%
Athens, TN	51,000	**4f**	0.0%	0.0%	0.0%	0.0%
Elizabeth City, NC	51,000	**4f**	0.0%	0.0%	0.0%	0.0%
Oil City, PA	51,000	**4f**	0.0%	0.0%	0.0%	0.0%
Jacksonville, TX	50,000	**4f**	0.0%	0.0%	0.0%	0.0%
Alice, TX	50,000	**4f**	0.0%	0.0%	0.0%	0.0%
Greenville, OH	50,000	**4f**	0.0%	0.0%	0.0%	0.0%
Kerrville, TX	50,000	**4f**	0.0%	0.0%	0.0%	0.0%
Glasgow, KY	50,000	**4f**	0.0%	0.0%	0.0%	0.0%
Rochelle, IL	50,000	**4f**	0.0%	0.0%	0.0%	0.0%
Platteville, WI	50,000	**4f**	0.0%	0.0%	0.0%	0.0%
Natchez, MS-LA	50,000	**4f**	0.0%	0.0%	0.0%	0.0%
Scottsboro, AL	50,000	**4f**	0.0%	0.0%	0.0%	0.0%
Douglas, GA	49,000	**4f**	0.0%	0.0%	0.0%	0.0%
Warrensburg, MO	49,000	**4f**	0.0%	0.0%	0.0%	0.0%
St. Marys, GA	49,000	**4f**	0.0%	0.0%	0.0%	0.0%
Amsterdam, NY	49,000	**4f**	0.0%	0.0%	0.0%	0.0%
Enterprise, AL	48,000	**4f**	0.0%	0.0%	0.0%	0.0%
Morgan City, LA	48,000	**4f**	0.0%	0.0%	0.0%	0.0%
Payson, AZ	48,000	**4f**	0.0%	0.0%	0.0%	0.0%
Pullman, WA	48,000	**4f**	0.0%	0.0%	0.0%	0.0%
Malone, NY	48,000	**4f**	0.0%	0.0%	0.0%	0.0%
Cedar City, UT	48,000	**4f**	0.0%	0.0%	0.0%	0.0%
Corsicana, TX	47,000	**4f**	0.0%	0.0%	0.0%	0.0%
Norfolk, NE	47,000	**4f**	0.0%	0.0%	0.0%	0.0%
Gardnerville Ranchos, NV	47,000	**4f**	0.0%	0.0%	0.0%	0.0%
Cortland, NY	47,000	**4f**	0.0%	0.0%	0.0%	0.0%

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Table I.2 – *Continued from previous page*

CBSA Name	Total Jobs	ID	HD Pop.	MD Large Apt. Pop.	MD Small Apt. Pop.	MD Comm. Pop.
New Castle, IN	47,000	**4f**	0.0%	0.0%	0.0%	0.0%
Cadillac, MI	47,000	**4f**	0.0%	0.0%	0.0%	0.0%
Newport, OR	47,000	**4f**	0.0%	0.0%	0.0%	0.0%
Paris, TX	47,000	**4f**	0.0%	0.0%	0.0%	0.0%
Clovis, NM	47,000	**4f**	0.0%	0.0%	0.0%	0.0%
Del Rio, TX	47,000	**4f**	0.0%	0.0%	0.0%	0.0%
Tahlequah, OK	46,000	**4f**	0.0%	0.0%	0.0%	0.0%
Clinton, IA	46,000	**4f**	0.0%	0.0%	0.0%	0.0%
Ruston, LA	46,000	**4f**	0.0%	0.0%	0.0%	0.0%
Kendallville, IN	46,000	**4f**	0.0%	0.0%	0.0%	0.0%
Sidney, OH	46,000	**4f**	0.0%	0.0%	0.0%	0.0%
Washington, NC	46,000	**4f**	0.0%	0.0%	0.0%	0.0%
Shelbyville, TN	46,000	**4f**	0.0%	0.0%	0.0%	0.0%
Plymouth, IN	45,000	**4f**	0.0%	0.0%	0.0%	0.0%
Lewistown, PA	45,000	**4f**	0.0%	0.0%	1.8%	0.0%
Nogales, AZ	45,000	**4f**	0.0%	0.0%	0.0%	0.0%
Montrose, CO	45,000	**4f**	0.0%	0.0%	0.0%	0.0%
Canon City, CO	45,000	**4f**	0.0%	0.0%	0.0%	0.0%
Burlington, IA-IL	45,000	**4f**	0.0%	0.0%	0.0%	0.0%
Wapakoneta, OH	45,000	**4f**	0.0%	0.0%	0.0%	0.0%
Freeport, IL	45,000	**4f**	0.0%	0.0%	0.0%	0.0%
Hillsdale, MI	45,000	**4f**	0.0%	0.0%	0.0%	0.0%
Alexander City, AL	45,000	**4f**	0.0%	0.0%	0.0%	0.0%
Bemidji, MN	45,000	**4f**	0.0%	0.0%	0.0%	0.0%
Greenville, MS	45,000	**4f**	0.0%	0.0%	0.0%	0.0%
Mount Sterling, KY	44,000	**4f**	0.0%	0.0%	0.0%	0.0%
Moultrie, GA	44,000	**4f**	0.0%	0.0%	0.0%	0.0%
Red Wing, MN	44,000	**4f**	0.0%	0.0%	0.0%	0.0%
Shawano, WI	44,000	**4f**	0.0%	0.0%	0.0%	0.0%
Bellefontaine, OH	44,000	**4f**	0.0%	0.0%	0.0%	0.0%
Lewisburg, PA	44,000	**4f**	0.0%	0.0%	0.0%	0.0%
Huntingdon, PA	44,000	**4f**	0.0%	0.0%	0.0%	0.0%
Mount Pleasant, TX	44,000	**4f**	0.0%	0.0%	0.0%	0.0%
Blackfoot, ID	44,000	**4f**	0.0%	0.0%	0.0%	0.0%

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Table I.2 – *Continued from previous page*

CBSA Name	Total Jobs	ID	HD Pop.	MD Large Apt. Pop.	MD Small Apt. Pop.	MD Comm. Pop.
Rolla, MO	44,000	**4f**	0.0%	0.0%	0.0%	0.0%
Bedford, IN	44,000	**4f**	0.0%	0.0%	0.0%	0.0%
Cornelia, GA	44,000	**4f**	0.0%	0.0%	0.0%	0.0%
Grand Rapids, MN	44,000	**4f**	0.0%	0.0%	0.0%	0.0%
Marion, NC	44,000	**4f**	0.0%	0.0%	0.0%	0.0%
Henderson, NC	43,000	**4f**	0.0%	0.0%	0.0%	0.0%
Rock Springs, WY	43,000	**4f**	0.0%	0.0%	0.0%	0.0%
Harrison, AR	43,000	**4f**	0.0%	0.0%	0.0%	0.0%
Ponca City, OK	43,000	**4f**	0.0%	0.0%	0.0%	0.0%
Ellensburg, WA	43,000	**4f**	0.0%	0.0%	0.0%	0.0%
Menomonie, WI	43,000	**4f**	0.0%	0.0%	0.0%	0.0%
Burley, ID	43,000	**4f**	0.0%	0.0%	0.0%	0.0%
Bogalusa, LA	43,000	**4f**	0.0%	0.0%	0.0%	0.0%
Rockingham, NC	43,000	**4f**	0.0%	0.0%	0.0%	0.0%
Coldwater, MI	43,000	**4f**	0.0%	0.0%	0.0%	0.0%
Madisonville, KY	42,000	**4f**	0.0%	0.0%	0.0%	0.0%
Big Rapids, MI	42,000	**4f**	0.0%	0.0%	0.0%	0.0%
Big Stone Gap, VA	42,000	**4f**	0.0%	0.0%	0.0%	0.0%
Durant, OK	42,000	**4f**	0.0%	0.0%	0.0%	0.0%
Pahrump, NV	42,000	**4f**	0.0%	0.0%	0.0%	0.0%
Vicksburg, MS	42,000	**4f**	0.0%	0.0%	0.0%	0.0%
Sandpoint, ID	42,000	**4f**	0.0%	0.0%	0.0%	0.0%
Willmar, MN	42,000	**4f**	0.0%	0.0%	0.0%	0.0%
Ozark, AL	42,000	**4f**	0.0%	0.0%	0.0%	0.0%
Duncan, OK	42,000	**4f**	0.0%	0.0%	0.0%	0.0%
Seymour, IN	42,000	**4f**	0.0%	0.0%	0.0%	0.0%
Auburn, IN	41,000	**4f**	0.0%	0.0%	0.0%	0.0%
McAlester, OK	41,000	**4f**	0.0%	0.0%	0.0%	0.0%
Lawrenceburg, TN	41,000	**4f**	0.0%	0.0%	0.0%	0.0%
Bucyrus-Galion, OH	41,000	**4f**	0.0%	0.0%	0.0%	0.0%
Aberdeen, SD	41,000	**4f**	0.0%	0.0%	0.0%	0.0%
Bardstown, KY	41,000	**4f**	0.0%	0.0%	0.0%	0.0%
Muscatine, IA	41,000	**4f**	0.0%	0.0%	0.0%	0.0%
Cedartown, GA	41,000	**4f**	0.0%	0.0%	0.0%	0.0%

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Table I.2 – *Continued from previous page*

CBSA Name	Total Jobs	ID	HD Pop.	MD Large Apt. Pop.	MD Small Apt. Pop.	MD Comm. Pop.
Alma, MI	40,000	**4f**	0.0%	0.0%	0.0%	0.0%
El Campo, TX	40,000	**4f**	0.0%	0.0%	0.0%	0.0%
Blytheville, AR	40,000	**4f**	0.0%	0.0%	0.0%	0.0%
Stephenville, TX	40,000	**4f**	0.0%	0.0%	0.0%	0.0%
Garden City, KS	40,000	**4f**	0.0%	0.0%	0.0%	0.0%
Okeechobee, FL	40,000	**4f**	0.0%	0.0%	0.0%	0.0%
Sedalia, MO	40,000	**4f**	0.0%	0.0%	0.0%	0.0%
Bradford, PA	40,000	**4f**	0.0%	0.0%	0.0%	0.0%
Tifton, GA	40,000	**4f**	0.0%	0.0%	0.0%	0.0%
Celina, OH	40,000	**4f**	0.0%	0.0%	0.0%	0.0%
Marshalltown, IA	39,000	**4f**	0.0%	0.0%	0.0%	0.0%
Wilmington, OH	39,000	**4f**	0.0%	0.0%	0.0%	0.0%
Selinsgrove, PA	39,000	**4f**	0.0%	0.0%	0.0%	0.0%
Riverton, WY	39,000	**4f**	0.0%	0.0%	0.0%	0.0%
Clewiston, FL	39,000	**4f**	0.0%	0.0%	0.0%	0.0%
Austin, MN	39,000	**4f**	0.0%	0.0%	0.0%	0.0%
Jacksonville, IL	39,000	**4f**	0.0%	0.0%	0.0%	0.0%
El Dorado, AR	39,000	**4f**	0.0%	0.0%	0.0%	0.0%
McComb, MS	39,000	**4f**	0.0%	0.0%	0.0%	0.0%
Warren, PA	39,000	**4f**	0.0%	0.0%	0.0%	0.0%
West Plains, MO	39,000	**4f**	0.0%	0.0%	0.0%	0.0%
Moscow, ID	38,000	**4f**	0.0%	0.0%	0.0%	0.0%
Selma, AL	38,000	**4f**	0.0%	0.0%	0.0%	0.0%
Greenwood, MS	38,000	**4f**	0.0%	0.0%	0.0%	0.0%
Hannibal, MO	38,000	**4f**	0.0%	0.0%	0.0%	0.0%
Lock Haven, PA	38,000	**4f**	0.0%	0.0%	0.0%	0.0%
Gainesville, TX	38,000	**4f**	0.0%	0.0%	0.0%	0.0%
Cambridge, OH	38,000	**4f**	0.0%	0.0%	0.0%	0.0%
Houghton, MI	38,000	**4f**	0.0%	0.0%	0.0%	0.0%
Sikeston, MO	38,000	**4f**	0.0%	0.0%	0.0%	0.0%
Scottsbluff, NE	38,000	**4f**	0.0%	0.0%	0.0%	0.0%
Urbana, OH	37,000	**4f**	0.0%	0.0%	0.0%	0.0%
Astoria, OR	37,000	**4f**	0.0%	0.0%	0.0%	0.0%
Defiance, OH	37,000	**4f**	0.0%	0.0%	0.0%	0.0%

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Table I.2 – *Continued from previous page*

CBSA Name	Total Jobs	ID	HD Pop.	MD Large Apt. Pop.	MD Small Apt. Pop.	MD Comm. Pop.
Logansport, IN	37,000	**4f**	0.0%	0.0%	0.0%	0.0%
Minden, LA	37,000	**4f**	0.0%	0.0%	0.0%	0.0%
Murray, KY	37,000	**4f**	0.0%	0.0%	0.0%	0.0%
Laramie, WY	37,000	**4f**	0.0%	0.0%	0.0%	0.0%
McMinnville, TN	37,000	**4f**	0.0%	0.0%	0.0%	0.0%
Crawfordsville, IN	37,000	**4f**	0.0%	0.0%	0.0%	0.0%
Newberry, SC	37,000	**4f**	0.0%	0.0%	0.0%	0.0%
Sault Ste. Marie, MI	37,000	**4f**	0.0%	0.0%	0.0%	0.0%
Espanola, NM	37,000	**4f**	0.0%	0.0%	0.0%	0.0%
Fort Polk South, LA	37,000	**4f**	0.0%	0.0%	0.0%	0.0%
Vincennes, IN	37,000	**4f**	0.0%	0.0%	0.0%	0.0%
Ada, OK	37,000	**4f**	0.0%	0.0%	0.0%	0.0%
Bay City, TX	36,000	**4f**	0.0%	0.0%	0.0%	0.0%
Alexandria, MN	36,000	**4f**	0.0%	0.0%	0.0%	0.0%
DeRidder, LA	36,000	**4f**	0.0%	0.0%	0.0%	0.0%
Mount Vernon, IL	36,000	**4f**	0.0%	0.0%	0.0%	0.0%
Corinth, MS	36,000	**4f**	0.0%	0.0%	0.0%	0.0%
North Platte, NE	36,000	**4f**	0.0%	0.0%	0.0%	0.0%
Dyersburg, TN	36,000	**4f**	0.0%	0.0%	0.0%	0.0%
Fort Dodge, IA	36,000	**4f**	0.0%	0.0%	0.0%	0.0%
Owatonna, MN	36,000	**4f**	0.0%	0.0%	0.0%	0.0%
Fort Leonard Wood, MO	36,000	**4f**	0.0%	0.0%	0.0%	0.0%
Escanaba, MI	36,000	**4f**	0.0%	0.0%	0.0%	0.0%
Pontiac, IL	35,000	**4f**	0.0%	0.0%	0.0%	0.0%
Huntington, IN	35,000	**4f**	0.0%	0.0%	0.0%	0.0%
Vernal, UT	35,000	**4f**	0.0%	0.0%	0.0%	0.0%
Atmore, AL	35,000	**4f**	0.0%	0.0%	0.0%	0.0%
Emporia, KS	35,000	**4f**	0.0%	0.0%	0.0%	0.0%
Sulphur Springs, TX	35,000	**4f**	0.0%	0.0%	0.0%	0.0%
Coshocton, OH	35,000	**4f**	0.0%	0.0%	0.0%	0.0%
Kill Devil Hills, NC	35,000	**4f**	0.0%	0.0%	0.0%	0.0%
Bennington, VT	35,000	**4f**	0.0%	0.0%	0.0%	0.0%
Vidalia, GA	35,000	**4f**	0.0%	0.0%	0.0%	0.0%
Hutchinson, MN	35,000	**4f**	0.0%	0.0%	0.0%	0.0%

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Table I.2 – *Continued from previous page*

CBSA Name	Total Jobs	ID	HD Pop.	MD Large Apt. Pop.	MD Small Apt. Pop.	MD Comm. Pop.
Campbellsville, KY	35,000	**4f**	0.0%	0.0%	0.0%	0.0%
Brownwood, TX	35,000	**4f**	0.0%	0.0%	0.0%	0.0%
Ottumwa, IA	35,000	**4f**	0.0%	0.0%	0.0%	0.0%
Winfield, KS	35,000	**4f**	0.0%	0.0%	0.0%	0.0%
Safford, AZ	35,000	**4f**	0.0%	0.0%	0.0%	0.0%
Arcadia, FL	35,000	**4f**	0.0%	0.0%	0.0%	0.0%
Lebanon, MO	35,000	**4f**	0.0%	0.0%	0.0%	0.0%
Americus, GA	34,000	**4f**	0.0%	0.0%	0.0%	0.0%
Decatur, IN	34,000	**4f**	0.0%	0.0%	0.0%	0.0%
Big Spring, TX	34,000	**4f**	0.0%	0.0%	0.0%	0.0%
Mayfield, KY	34,000	**4f**	0.0%	0.0%	0.0%	0.0%
Natchitoches, LA	34,000	**4f**	0.0%	0.0%	0.0%	0.0%
Dixon, IL	34,000	**4f**	0.0%	0.0%	0.0%	0.0%
Peru, IN	34,000	**4f**	0.0%	0.0%	0.0%	0.0%
Angola, IN	34,000	**4f**	0.0%	0.0%	0.0%	0.0%
Laurinburg, NC	34,000	**4f**	0.0%	0.0%	0.0%	0.0%
Plainview, TX	33,000	**4f**	0.0%	0.0%	0.0%	0.0%
Williston, ND	33,000	**4f**	0.0%	0.0%	0.0%	0.0%
Brookhaven, MS	33,000	**4f**	0.0%	0.0%	0.0%	0.0%
Effingham, IL	33,000	**4f**	0.0%	0.0%	0.0%	0.0%
Dodge City, KS	33,000	**4f**	0.0%	0.0%	0.0%	0.0%
Brenham, TX	33,000	**4f**	0.0%	0.0%	0.0%	0.0%
Newport, TN	33,000	**4f**	0.0%	0.0%	0.0%	0.0%
Brevard, NC	33,000	**4f**	0.0%	0.0%	0.0%	0.0%
Taylorville, IL	33,000	**4f**	0.0%	0.0%	0.0%	0.0%
Columbus, NE	32,000	**4f**	0.0%	0.0%	0.0%	0.0%
Coffeyville, KS	32,000	**4f**	0.0%	0.0%	0.0%	0.0%
Watertown, SD	32,000	**4f**	0.0%	0.0%	0.0%	0.0%
Brookings, SD	32,000	**4f**	0.0%	0.0%	0.0%	0.0%
Pella, IA	32,000	**4f**	0.0%	0.0%	0.0%	0.0%
Malvern, AR	32,000	**4f**	0.0%	0.0%	0.0%	0.0%
Bonham, TX	32,000	**4f**	0.0%	0.0%	0.0%	0.0%
Mount Gay-Shamrock, WV	32,000	**4f**	0.0%	0.0%	0.0%	0.0%
Troy, AL	32,000	**4f**	0.0%	0.0%	0.0%	0.0%

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Table I.2 – *Continued from previous page*

CBSA Name	Total Jobs	ID	HD Pop.	MD Large Apt. Pop.	MD Small Apt. Pop.	MD Comm. Pop.
Washington, IN	32,000	**4f**	0.0%	0.0%	0.0%	0.0%
Dayton, TN	32,000	**4f**	0.0%	0.0%	0.0%	0.0%
Martin, TN	32,000	**4f**	0.0%	0.0%	0.0%	0.0%
Beeville, TX	32,000	**4f**	0.0%	0.0%	0.0%	0.0%
Taos, NM	32,000	**4f**	0.0%	0.0%	0.0%	0.0%
Cleveland, MS	31,000	**4f**	0.0%	0.0%	0.0%	0.0%
Berlin, NH	31,000	**4f**	0.0%	0.0%	0.0%	0.0%
Frankfort, IN	31,000	**4f**	0.0%	0.0%	0.0%	0.0%
Jackson, OH	31,000	**4f**	0.0%	0.0%	0.0%	0.0%
Dickinson, ND	31,000	**4f**	0.0%	0.0%	0.0%	0.0%
Lewisburg, TN	31,000	**4f**	0.0%	0.0%	0.0%	0.0%
Seneca Falls, NY	31,000	**4f**	0.0%	0.0%	0.0%	0.0%
Las Vegas, NM	31,000	**4f**	0.0%	0.0%	0.0%	0.0%
Wabash, IN	31,000	**4f**	0.0%	0.0%	0.0%	0.0%
Cambridge, MD	31,000	**4f**	0.0%	0.0%	0.0%	0.0%
Kingsville, TX	31,000	**4f**	0.0%	0.0%	0.0%	0.0%
Paris, TN	31,000	**4f**	0.0%	0.0%	0.0%	0.0%
Hastings, NE	31,000	**4f**	0.0%	0.0%	0.0%	0.0%
Macomb, IL	31,000	**4f**	0.0%	0.0%	0.0%	0.0%
Miami, OK	30,000	**4f**	0.0%	0.0%	0.0%	0.0%
Madison, IN	30,000	**4f**	0.0%	0.0%	0.0%	0.0%
Breckenridge, CO	30,000	**4f**	0.0%	0.0%	0.0%	0.0%
Juneau, AK	30,000	**4f**	0.0%	0.0%	0.0%	0.0%
Albert Lea, MN	30,000	**4f**	0.0%	0.0%	0.0%	0.0%
St. Marys, PA	29,000	**4f**	0.0%	0.0%	0.0%	0.0%
Kennett, MO	29,000	**4f**	0.0%	0.0%	0.0%	0.0%
Jennings, LA	29,000	**4f**	0.0%	0.0%	0.0%	0.0%
Kirksville, MO	29,000	**4f**	0.0%	0.0%	0.0%	0.0%
Hope, AR	29,000	**4f**	0.0%	0.0%	0.0%	0.0%
Susanville, CA	29,000	**4f**	0.0%	0.0%	0.0%	0.0%
Iron Mountain, MI-WI	29,000	**4f**	0.0%	0.0%	0.0%	0.0%
Sheridan, WY	29,000	**4f**	0.0%	0.0%	0.0%	0.0%
Jesup, GA	29,000	**4f**	0.0%	0.0%	0.0%	0.0%
Lincoln, IL	29,000	**4f**	0.0%	0.0%	0.0%	0.0%

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Table I.2 – *Continued from previous page*

CBSA Name	Total Jobs	ID	HD Pop.	MD Large Apt. Pop.	MD Small Apt. Pop.	MD Comm. Pop.
Union City, TN	29,000	**4f**	0.0%	0.0%	0.0%	0.0%
Weatherford, OK	29,000	**4f**	0.0%	0.0%	0.0%	0.0%
Hays, KS	28,000	**4f**	0.0%	0.0%	0.0%	0.0%
Ludington, MI	28,000	**4f**	0.0%	0.0%	0.0%	0.0%
Camden, AR	28,000	**4f**	0.0%	0.0%	0.0%	0.0%
Alpena, MI	28,000	**4f**	0.0%	0.0%	0.0%	0.0%
Elkins, WV	28,000	**4f**	0.0%	0.0%	0.0%	0.0%
Central City, KY	28,000	**4f**	0.0%	0.0%	0.0%	0.0%
McPherson, KS	28,000	**4f**	0.0%	0.0%	0.0%	0.0%
Washington Court House, OH	28,000	**4f**	0.0%	0.0%	0.0%	0.0%
Fort Morgan, CO	28,000	**4f**	0.0%	0.0%	0.0%	0.0%
Van Wert, OH	27,000	**4f**	0.0%	0.0%	0.0%	0.0%
Mineral Wells, TX	27,000	**4f**	0.0%	0.0%	0.0%	0.0%
Winchester, VA-WV	27,000	**4f**	0.0%	0.0%	0.0%	0.0%
Silver City, NM	27,000	**4f**	0.0%	0.0%	0.0%	0.0%
Crescent City, CA	27,000	**4f**	0.0%	0.0%	0.0%	0.0%
North Vernon, IN	27,000	**4f**	0.0%	0.0%	0.0%	0.0%
Eufaula, AL-GA	27,000	**4f**	0.0%	0.0%	0.0%	0.0%
Middlesborough, KY	26,000	**4f**	0.0%	0.0%	0.0%	0.0%
Great Bend, KS	26,000	**4f**	0.0%	0.0%	0.0%	0.0%
Union, SC	26,000	**4f**	0.0%	0.0%	0.0%	0.0%
Bainbridge, GA	26,000	**4f**	0.0%	0.0%	0.0%	0.0%
Greensburg, IN	26,000	**4f**	0.0%	0.0%	0.0%	0.0%
Uvalde, TX	26,000	**4f**	0.0%	0.0%	0.0%	0.0%
Indianola, MS	26,000	**4f**	0.0%	0.0%	0.0%	0.0%
Wauchula, FL	25,000	**4f**	0.0%	0.0%	0.0%	0.0%
La Grande, OR	25,000	**4f**	0.0%	0.0%	0.0%	0.0%
Thomaston, GA	25,000	**4f**	0.0%	0.0%	0.0%	0.0%
Marshall, MN	25,000	**4f**	0.0%	0.0%	0.0%	0.0%
Forrest City, AR	25,000	**4f**	0.0%	0.0%	0.0%	0.0%
Grants, NM	25,000	**4f**	0.0%	0.0%	0.0%	0.0%
Lexington, NE	25,000	**4f**	0.0%	0.0%	0.0%	0.0%
Ottawa, KS	25,000	**4f**	0.0%	0.0%	0.0%	0.0%
Bennettsville, SC	25,000	**4f**	0.0%	0.0%	0.0%	0.0%

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Table I.2 – *Continued from previous page*

CBSA Name	**Total Jobs**	**ID**	**HD Pop.**	**MD Large Apt. Pop.**	**MD Small Apt. Pop.**	**MD Comm. Pop.**
Mexico, MO	25,000	**4f**	0.0%	0.0%	0.0%	0.0%
Fredericksburg, TX	25,000	**4f**	0.0%	0.0%	0.0%	0.0%
New Ulm, MN	25,000	**4f**	0.0%	0.0%	0.0%	0.0%
The Dalles, OR	24,000	**4f**	0.0%	0.0%	0.0%	0.0%
Spearfish, SD	24,000	**4f**	0.0%	0.0%	0.0%	0.0%
Moberly, MO	24,000	**4f**	0.0%	0.0%	0.0%	0.0%
Summerville, GA	24,000	**4f**	0.0%	0.0%	0.0%	0.0%
Woodward, OK	23,000	**4f**	0.0%	0.0%	0.0%	0.0%
Altus, OK	23,000	**4f**	0.0%	0.0%	0.0%	0.0%
Magnolia, AR	23,000	**4f**	0.0%	0.0%	0.0%	0.0%
Toccoa, GA	23,000	**4f**	0.0%	0.0%	0.0%	0.0%
Deming, NM	23,000	**4f**	0.0%	0.0%	0.0%	0.0%
Pampa, TX	23,000	**4f**	0.0%	0.0%	0.0%	0.0%
Scottsburg, IN	23,000	**4f**	0.0%	0.0%	0.0%	0.0%
Hood River, OR	23,000	**4f**	0.0%	0.0%	0.0%	0.0%
Mountain Home, ID	23,000	**4f**	0.0%	0.0%	0.0%	0.0%
Connersville, IN	23,000	**4f**	0.0%	0.0%	0.0%	0.0%
Hailey, ID	22,000	**4f**	0.0%	0.0%	0.0%	0.0%
Levelland, TX	22,000	**4f**	0.0%	0.0%	0.0%	0.0%
Fallon, NV	22,000	**4f**	0.0%	0.0%	0.0%	0.0%
Cordele, GA	22,000	**4f**	0.0%	0.0%	0.0%	0.0%
Clarksdale, MS	22,000	**4f**	0.0%	0.0%	0.0%	0.0%
Maryville, MO	22,000	**4f**	0.0%	0.0%	0.0%	0.0%
Marshall, MO	22,000	**4f**	0.0%	0.0%	0.0%	0.0%
Liberal, KS	22,000	**4f**	0.0%	0.0%	0.0%	0.0%
Mitchell, SD	22,000	**4f**	0.0%	0.0%	0.0%	0.0%
Wahpeton, ND-MN	22,000	**4f**	0.0%	0.0%	0.0%	0.0%
Prineville, OR	22,000	**4f**	0.0%	0.0%	0.0%	0.0%
Elk City, OK	22,000	**4f**	0.0%	0.0%	0.0%	0.0%
Borger, TX	21,000	**4f**	0.0%	0.0%	0.0%	0.0%
Oskaloosa, IA	21,000	**4f**	0.0%	0.0%	0.0%	0.0%
Dumas, TX	21,000	**4f**	0.0%	0.0%	0.0%	0.0%
Arkadelphia, AR	21,000	**4f**	0.0%	0.0%	0.0%	0.0%
Raymondville, TX	21,000	**4f**	0.0%	0.0%	0.0%	0.0%

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Table I.2 – *Continued from previous page*

CBSA Name	Total Jobs	ID	HD Pop.	MD Large Apt. Pop.	MD Small Apt. Pop.	MD Comm. Pop.
Worthington, MN	21,000	**4f**	0.0%	0.0%	0.0%	0.0%
Port Lavaca, TX	21,000	**4f**	0.0%	0.0%	0.0%	0.0%
Beatrice, NE	21,000	**4f**	0.0%	0.0%	0.0%	0.0%
Sterling, CO	21,000	**4f**	0.0%	0.0%	0.0%	0.0%
Guymon, OK	20,000	**4f**	0.0%	0.0%	0.0%	0.0%
Jamestown, ND	20,000	**4f**	0.0%	0.0%	0.0%	0.0%
Grenada, MS	20,000	**4f**	0.0%	0.0%	0.0%	0.0%
Pierre, SD	20,000	**4f**	0.0%	0.0%	0.0%	0.0%
Evanston, WY	20,000	**4f**	0.0%	0.0%	0.0%	0.0%
Parsons, KS	20,000	**4f**	0.0%	0.0%	0.0%	0.0%
Carroll, IA	20,000	**4f**	0.0%	0.0%	0.0%	0.0%
Huron, SD	20,000	**4f**	0.0%	0.0%	0.0%	0.0%
Rockport, TX	20,000	**4f**	0.0%	0.0%	0.0%	0.0%
Storm Lake, IA	20,000	**4f**	0.0%	0.0%	0.0%	0.0%
Brookings, OR	19,000	**4f**	0.0%	0.0%	0.0%	0.0%
Yankton, SD	19,000	**4f**	0.0%	0.0%	0.0%	0.0%
Fairmont, MN	19,000	**4f**	0.0%	0.0%	0.0%	0.0%
Price, UT	19,000	**4f**	0.0%	0.0%	0.0%	0.0%
Othello, WA	19,000	**4f**	0.0%	0.0%	0.0%	0.0%
Hereford, TX	19,000	**4f**	0.0%	0.0%	0.0%	0.0%
Ruidoso, NM	18,000	**4f**	0.0%	0.0%	0.0%	0.0%
Pearsall, TX	18,000	**4f**	0.0%	0.0%	0.0%	0.0%
Portales, NM	18,000	**4f**	0.0%	0.0%	0.0%	0.0%
West Point, MS	18,000	**4f**	0.0%	0.0%	0.0%	0.0%
Fairfield, IA	18,000	**4f**	0.0%	0.0%	0.0%	0.0%
Vineyard Haven, MA	17,000	**4f**	0.0%	0.0%	0.0%	0.0%
Brownsville, TN	17,000	**4f**	0.0%	0.0%	0.0%	0.0%
Helena-West Helena, AR	17,000	**4f**	0.0%	0.0%	0.0%	0.0%
Fitzgerald, GA	17,000	**4f**	0.0%	0.0%	0.0%	0.0%
Snyder, TX	17,000	**4f**	0.0%	0.0%	0.0%	0.0%
Spirit Lake, IA	17,000	**4f**	0.0%	0.0%	0.0%	0.0%
Andrews, TX	16,000	**4f**	0.0%	0.0%	0.0%	0.0%
Maysville, KY	16,000	**4f**	0.0%	0.0%	0.0%	0.0%
Spencer, IA	16,000	**4f**	0.0%	0.0%	0.0%	0.0%

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Table I.2 – *Continued from previous page*

CBSA Name	**Total Jobs**	**ID**	**HD Pop.**	**MD Large Apt. Pop.**	**MD Small Apt. Pop.**	**MD Comm. Pop.**
Winnemucca, NV	15,000	**4f**	0.0%	0.0%	0.0%	0.0%
Atchison, KS	15,000	**4f**	0.0%	0.0%	0.0%	0.0%
Sweetwater, TX	15,000	**4f**	0.0%	0.0%	0.0%	0.0%
Pecos, TX	14,000	**4f**	0.0%	0.0%	0.0%	0.0%
Zapata, TX	13,000	**4f**	0.0%	0.0%	0.0%	0.0%
Vermillion, SD	13,000	**4f**	0.0%	0.0%	0.0%	0.0%
Craig, CO	13,000	**4f**	0.0%	0.0%	0.0%	0.0%
Lamesa, TX	13,000	**4f**	0.0%	0.0%	0.0%	0.0%
Vernon, TX	13,000	**4f**	0.0%	0.0%	0.0%	0.0%

Appendix J: Metro Area Typology Neighborhood Maps

This appendix contains maps of the six neighborhood types used to perform the metro area typology in Chapter 3, along with tables showing the fractions of population and jobs for each metro area found in those neighborhood types. Neighborhood types are as described in Table 3.9 on page 3.9

All the maps are at the same scale, and show a 40-mile by 40-mile square, which means that outlying parts of larger metro areas may be left out, while views of smaller metro areas may include areas outside the MSA limits. Maps are shown for the twenty largest metropolitan statistical areas in the US, along with fifteen additional metropolitan statistical areas that were selected because they are particularly interesting: they are unusually dense for their size, have rapid transit or light rail, or are representatives of interesting types from my metro areas typology, discussed in Chapter 3.

Table J.1: Prevalence of Dense Neighborhood Types in Atlanta

Neighborhood Type	# Hexes	Pop.	% Pop.	Jobs	% Jobs
Central Business District	0	0	0%	0	0%
High-Density Commercial	50	41,000	0.7%	386,000	16.1%
Medium-Density Commercial	55	45,000	0.8%	154,000	6.4%
High-Density Residential	0	0	0%	0	0%
Medium-Density Residential (Large Apartments)	4	7,000	0.1%	5,000	0.2%
Medium-Density Residential (Small Apartments)	0	0	0%	0	0%

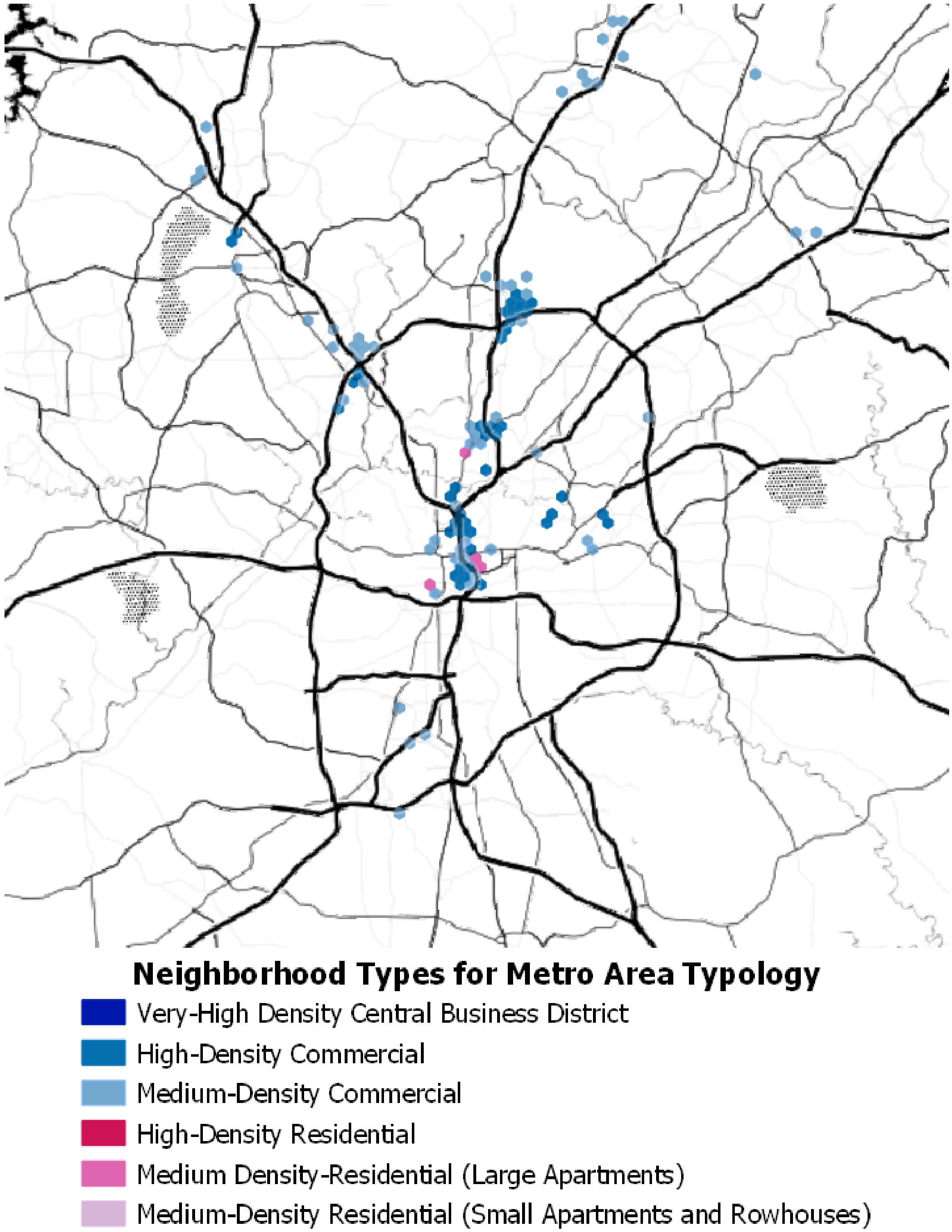

Figure J.1: Atlanta-Sandy Springs-Alpharetta, GA MSA map of dense neighborhoods used in my metro area typology. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table J.2: Prevalence of Dense Neighborhood Types in Austin

Neighborhood Type	# Hexes	Pop.	% Pop.	Jobs	% Jobs
Central Business District	1	1,000	0.0%	26,000	3.1%
High-Density Commercial	9	7,000	0.3%	51,000	6.1%
Medium-Density Commercial	40	28,000	1.4%	99,000	11.8%
High-Density Residential	1	6,000	0.3%	1,000	0.2%
Medium-Density Residential (Large Apartments)	4	14,000	0.7%	2,000	0.2%
Medium-Density Residential (Small Apartments)	2	5,000	0.2%	0	0.0%

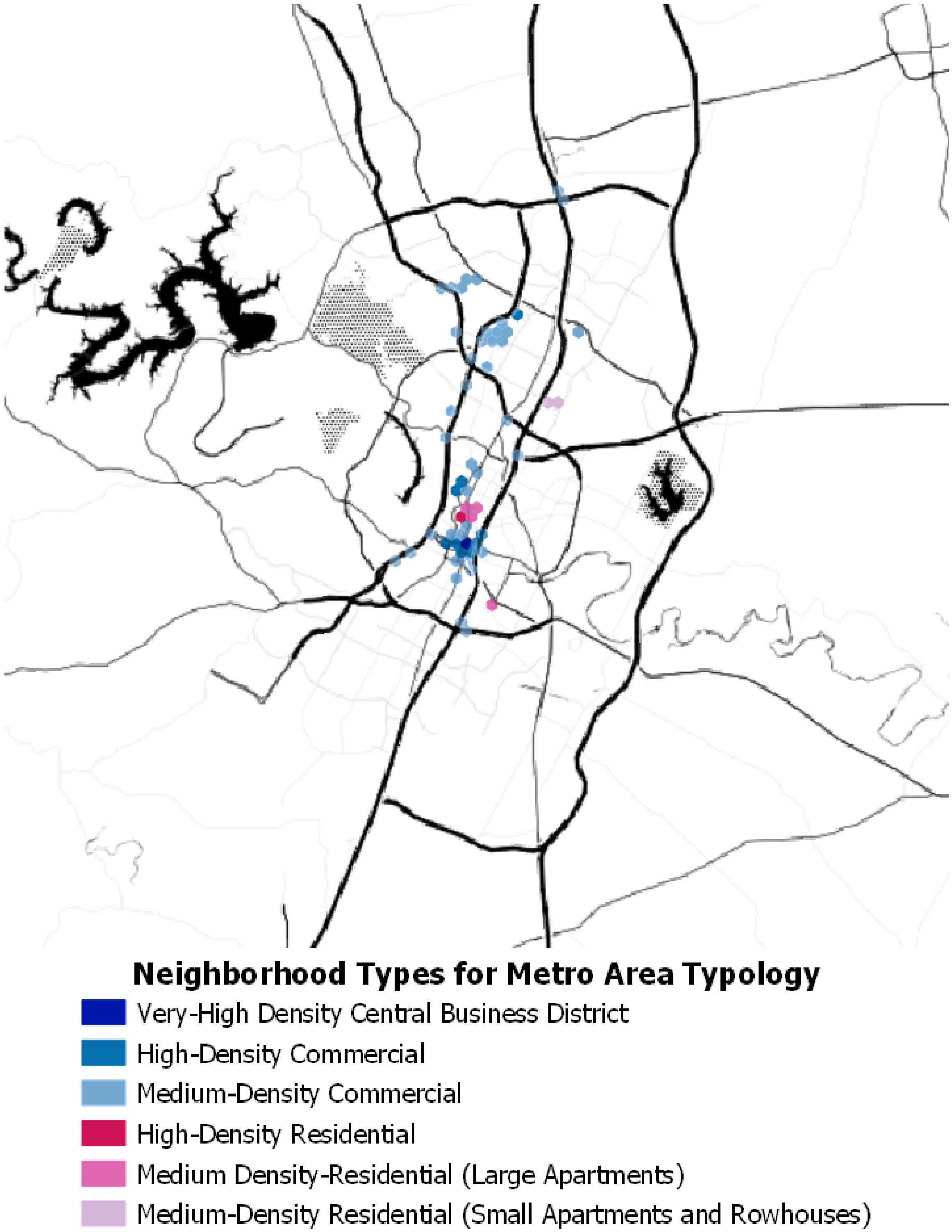

Figure J.2: Austin-Round Rock-Georgetown, TX MSA map of dense neighborhoods used in my metro area typology. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table J.3: Prevalence of Dense Neighborhood Types in Baltimore

Neighborhood Type	# Hexes	Pop.	% Pop.	Jobs	% Jobs
Central Business District	1	2,000	0.1%	23,000	2.0%
High-Density Commercial	24	27,000	1.0%	120,000	10.4%
Medium-Density Commercial	22	20,000	0.7%	62,000	5.4%
High-Density Residential	5	16,000	0.6%	7,000	0.6%
Medium-Density Residential (Large Apartments)	2	4,000	0.1%	3,000	0.3%
Medium-Density Residential (Small Apartments)	76	186,000	6.7%	37,000	3.2%

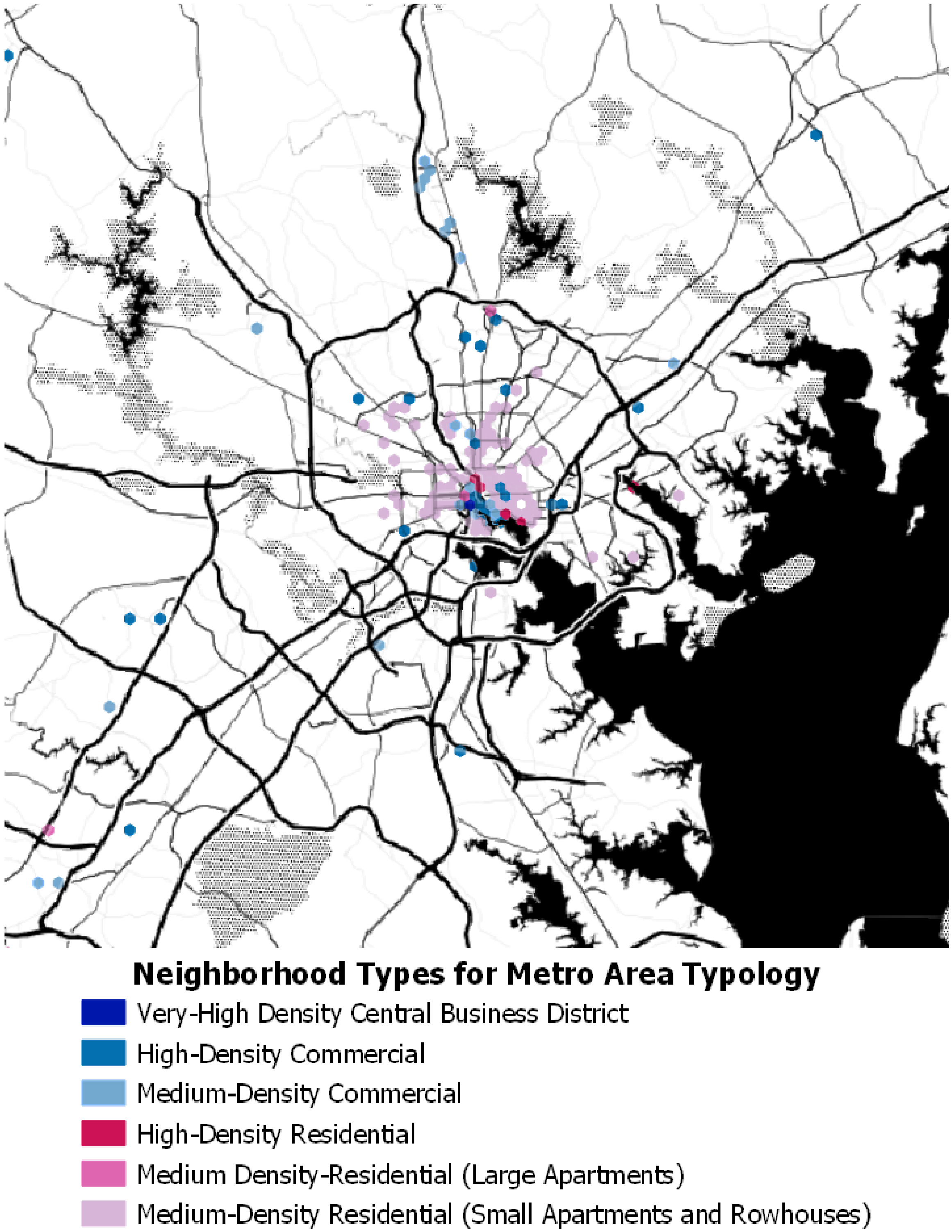

Figure J.3: Baltimore-Columbia-Towson, MD MSA map of dense neighborhoods used in my metro area typology. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table J.4: Prevalence of Dense Neighborhood Types in Boston

Neighborhood Type	**# Hexes**	**Pop.**	**% Pop.**	**Jobs**	**% Jobs**
Central Business District	6	20,000	0.4%	190,000	7.8%
High-Density Commercial	37	75,000	1.6%	299,000	12.4%
Medium-Density Commercial	41	66,000	1.4%	132,000	5.5%
High-Density Residential	57	280,000	5.8%	103,000	4.3%
Medium-Density Residential (Large Apartments)	23	50,000	1.0%	21,000	0.9%
Medium-Density Residential (Small Apartments)	247	667,000	13.9%	131,000	5.4%

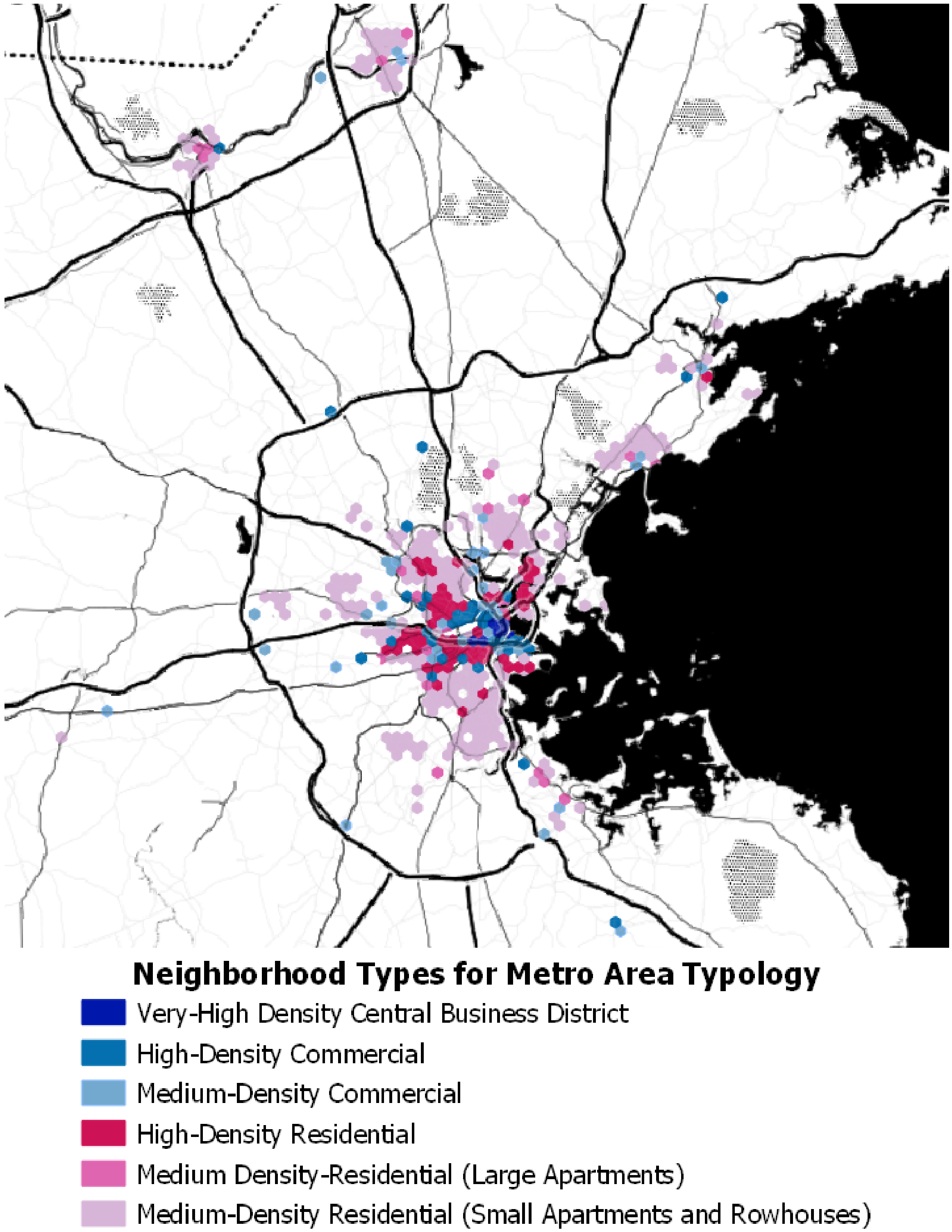

Figure J.4: Boston-Cambridge-Newton, MA-NH MSA map of dense neighborhoods used in my metro area typology. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table J.5: Prevalence of Dense Neighborhood Types in Charlotte

Neighborhood Type	# Hexes	Pop.	% Pop.	Jobs	% Jobs
Central Business District	1	2,000	0.1%	28,000	2.6%
High-Density Commercial	6	5,000	0.2%	52,000	4.8%
Medium-Density Commercial	22	12,000	0.5%	51,000	4.8%
High-Density Residential	0	0	0%	0	0%
Medium-Density Residential (Large Apartments)	0	0	0%	0	0%
Medium-Density Residential (Small Apartments)	0	0	0%	0	0%

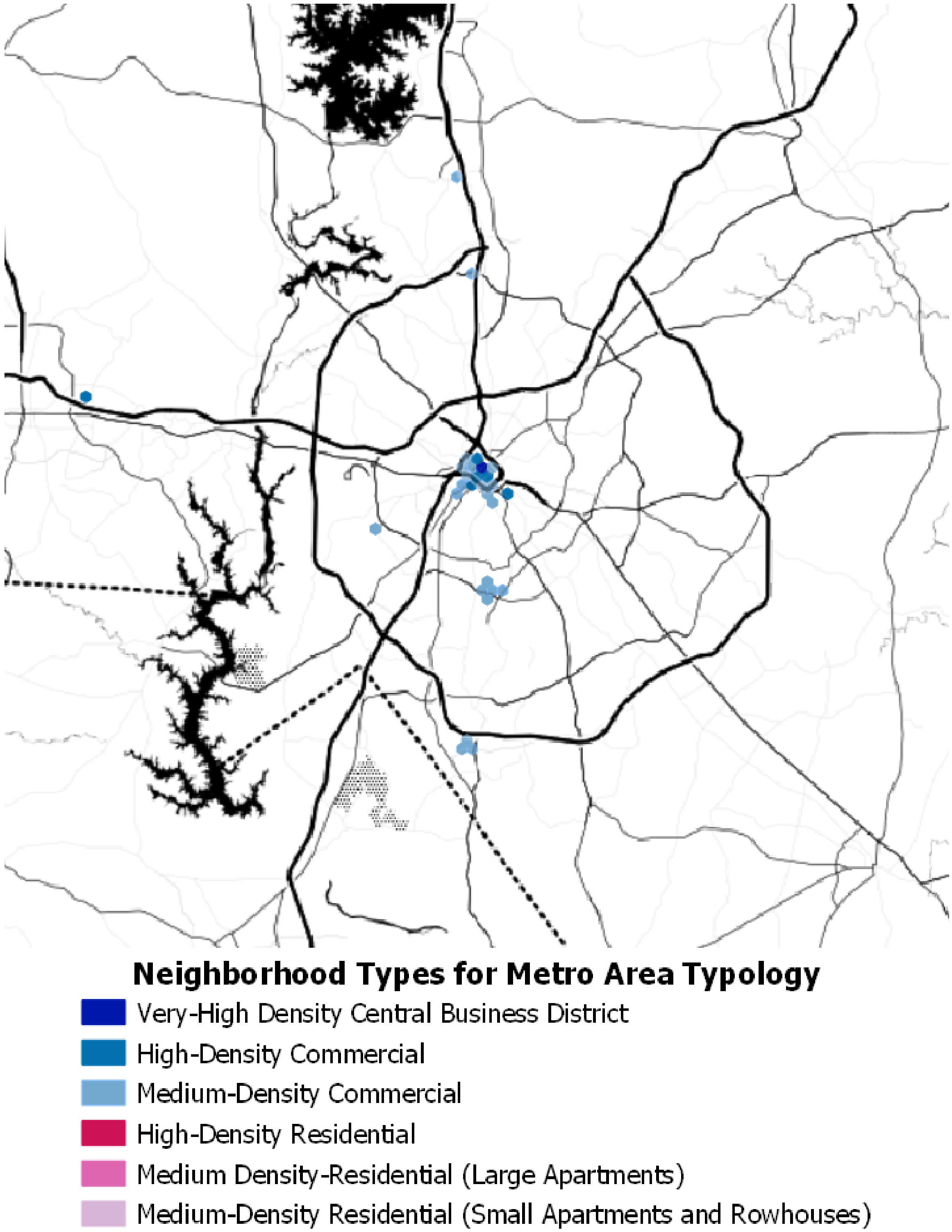

Figure J.5: Charlotte-Concord-Gastonia, NC-SC MSA map of dense neighborhoods used in my metro area typology. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table J.6: Prevalence of Dense Neighborhood Types in Chicago

Neighborhood Type	# Hexes	Pop.	% Pop.	Jobs	% Jobs
Central Business District	13	65,000	0.7%	513,000	12.5%
High-Density Commercial	44	46,000	0.5%	218,000	5.3%
Medium-Density Commercial	73	76,000	0.8%	233,000	5.7%
High-Density Residential	89	463,000	4.9%	119,000	2.9%
Medium-Density Residential (Large Apartments)	45	125,000	1.3%	30,000	0.7%
Medium-Density Residential (Small Apartments)	474	1,316,000	13.8%	204,000	5.0%

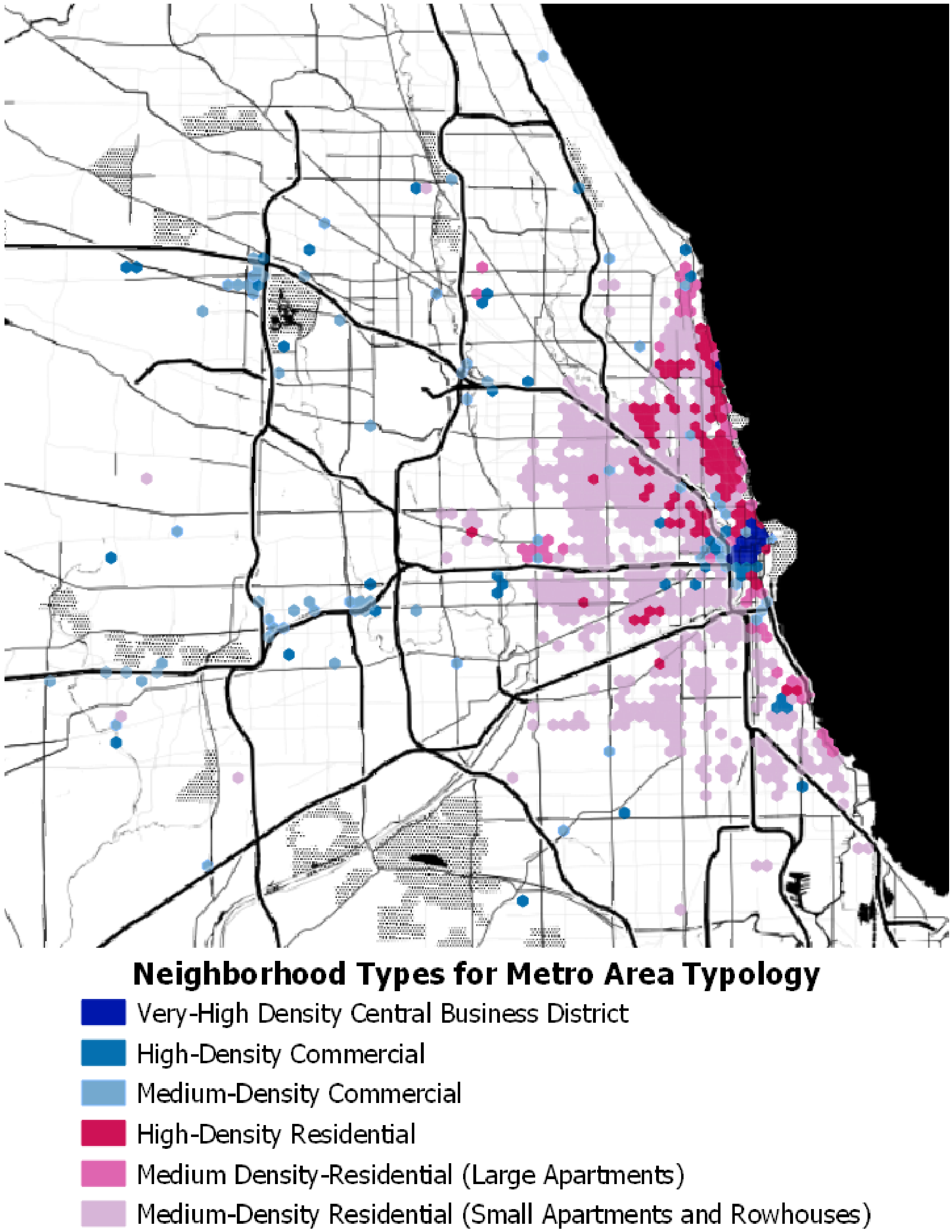

Figure J.6: Chicago-Naperville-Elgin, IL-IN-WI MSA map of dense neighborhoods used in my metro area typology. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table J.7: Prevalence of Dense Neighborhood Types in Cleveland

Neighborhood Type	# Hexes	Pop.	% Pop.	Jobs	% Jobs
Central Business District	0	0	0%	0	0%
High-Density Commercial	9	4,000	0.2%	108,000	11.8%
Medium-Density Commercial	11	9,000	0.4%	22,000	2.4%
High-Density Residential	0	0	0%	0	0%
Medium-Density Residential (Large Apartments)	5	10,000	0.5%	2,000	0.2%
Medium-Density Residential (Small Apartments)	9	16,000	0.8%	4,000	0.4%

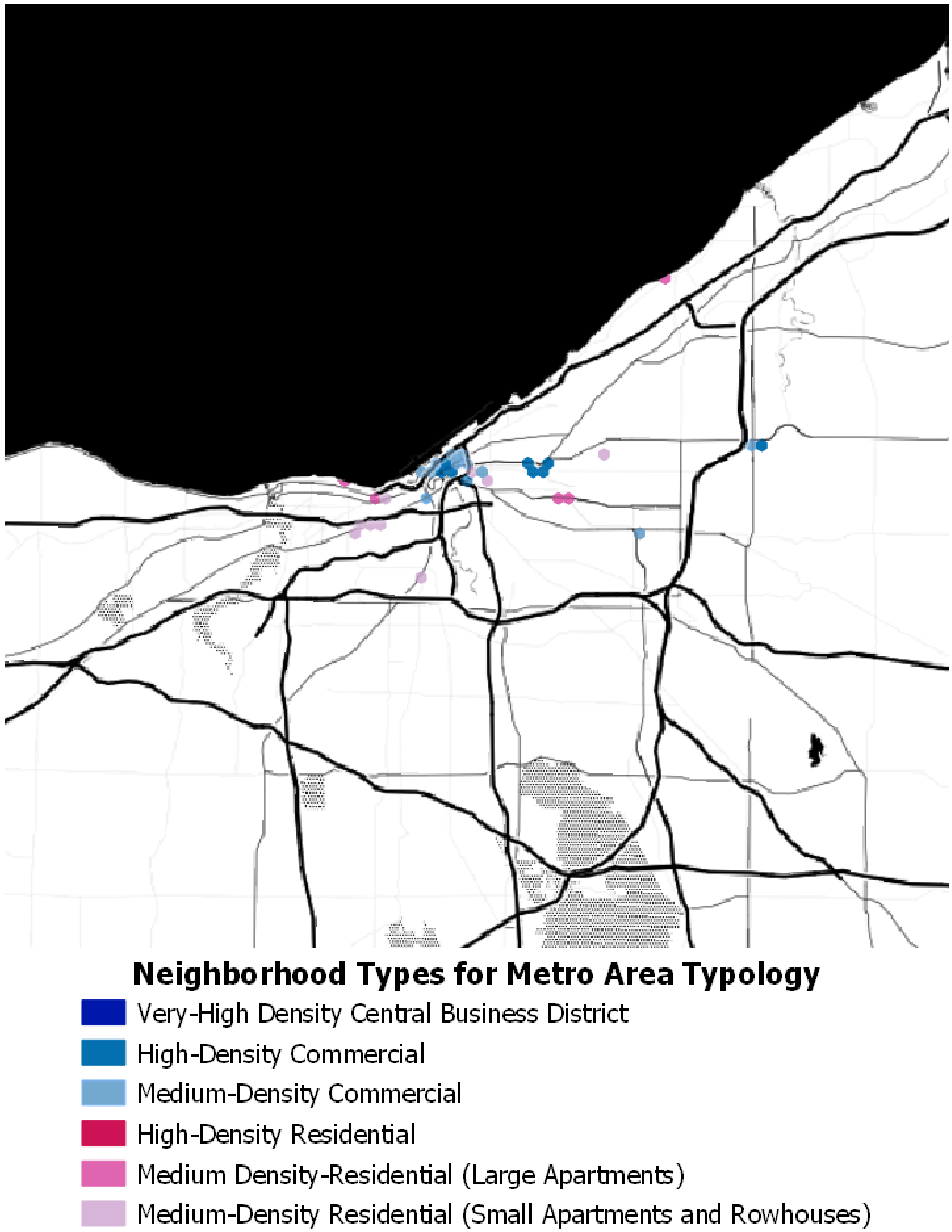

Figure J.7: Cleveland-Elyria, OH MSA map of dense neighborhoods used in my metro area typology. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table J.8: Prevalence of Dense Neighborhood Types in Dallas

Neighborhood Type	**# Hexes**	**Pop.**	**% Pop.**	**Jobs**	**% Jobs**
Central Business District	1	2,000	0.0%	26,000	0.8%
High-Density Commercial	54	44,000	0.6%	342,000	10.8%
Medium-Density Commercial	112	59,000	0.8%	301,000	9.5%
High-Density Residential	1	6,000	0.1%	0	0.0%
Medium-Density Residential (Large Apartments)	21	62,000	0.9%	14,000	0.4%
Medium-Density Residential (Small Apartments)	7	19,000	0.3%	4,000	0.1%

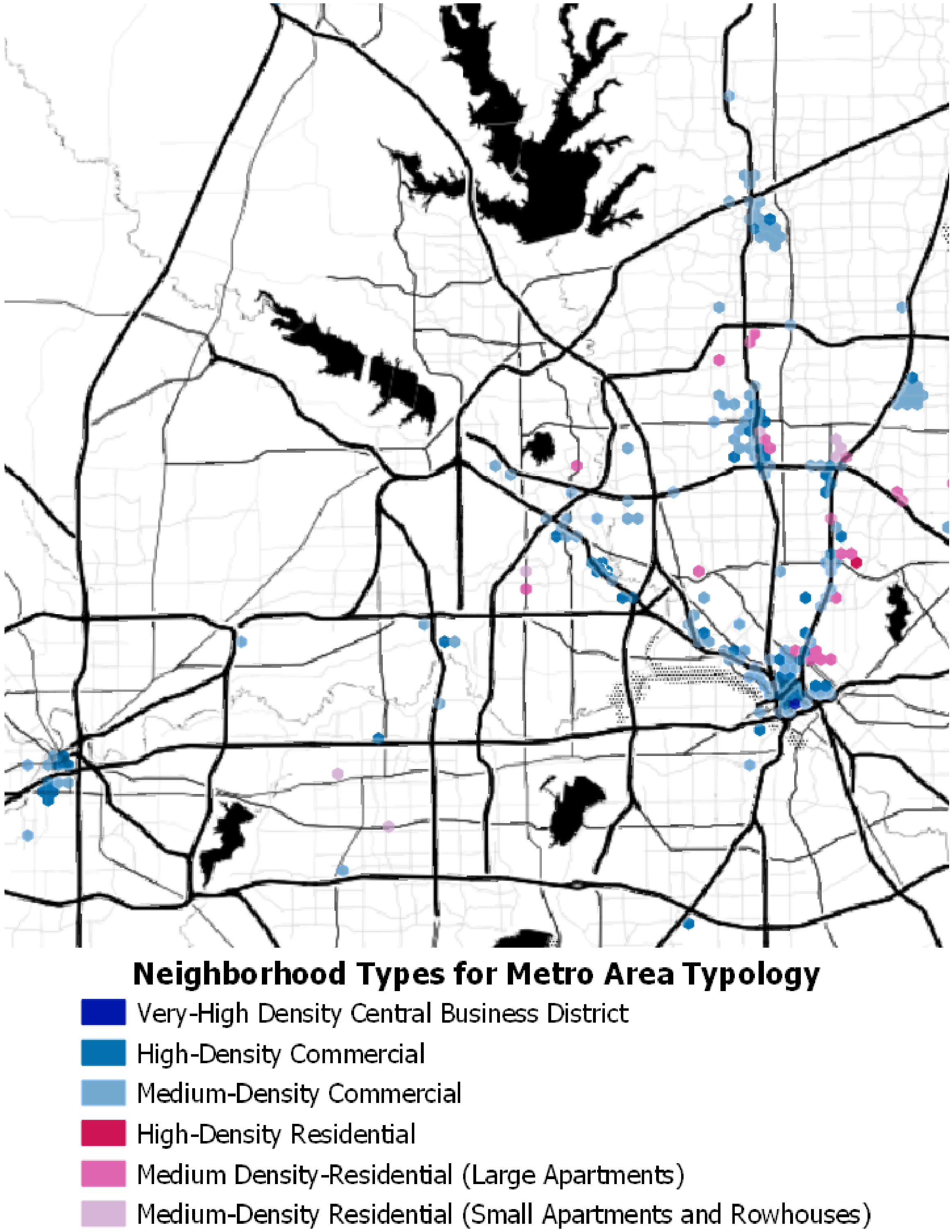

Figure J.8: Dallas-Fort Worth-Arlington, TX MSA map of dense neighborhoods used in my metro area typology. Downtown Dallas is at the lower right and downtown Fort Worth is at the far lower left. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table J.9: Prevalence of Dense Neighborhood Types in Denver

Neighborhood Type	# Hexes	Pop.	% Pop.	Jobs	% Jobs
Central Business District	1	2,000	0.1%	23,000	1.8%
High-Density Commercial	25	24,000	0.8%	157,000	12.1%
Medium-Density Commercial	53	46,000	1.6%	129,000	9.9%
High-Density Residential	1	4,000	0.1%	3,000	0.2%
Medium-Density Residential (Large Apartments)	24	61,000	2.2%	18,000	1.4%
Medium-Density Residential (Small Apartments)	2	4,000	0.1%	1,000	0.1%

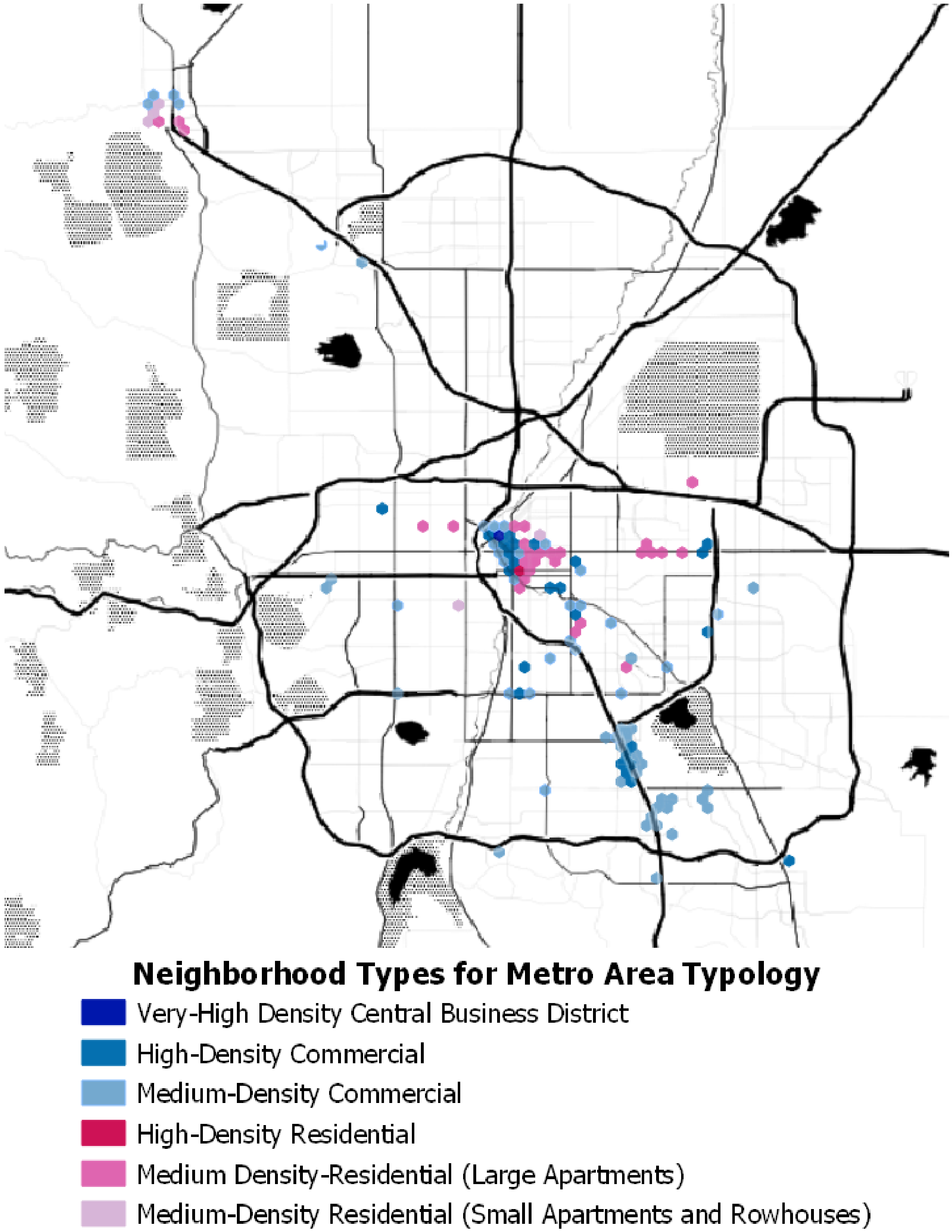

Figure J.9: Denver-Aurora-Lakewood, CO MSA map of dense neighborhoods used in my metro area typology. Boulder (not in the Denver MSA) is at the upper left. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table J.10: Prevalence of Dense Neighborhood Types in Detroit

Neighborhood Type	# Hexes	Pop.	% Pop.	Jobs	% Jobs
Central Business District	0	0	0%	0	0%
High-Density Commercial	21	15,000	0.3%	128,000	7.1%
Medium-Density Commercial	38	21,000	0.5%	122,000	6.8%
High-Density Residential	0	0	0%	0	0%
Medium-Density Residential (Large Apartments)	5	9,000	0.2%	4,000	0.2%
Medium-Density Residential (Small Apartments)	13	23,000	0.5%	7,000	0.4%

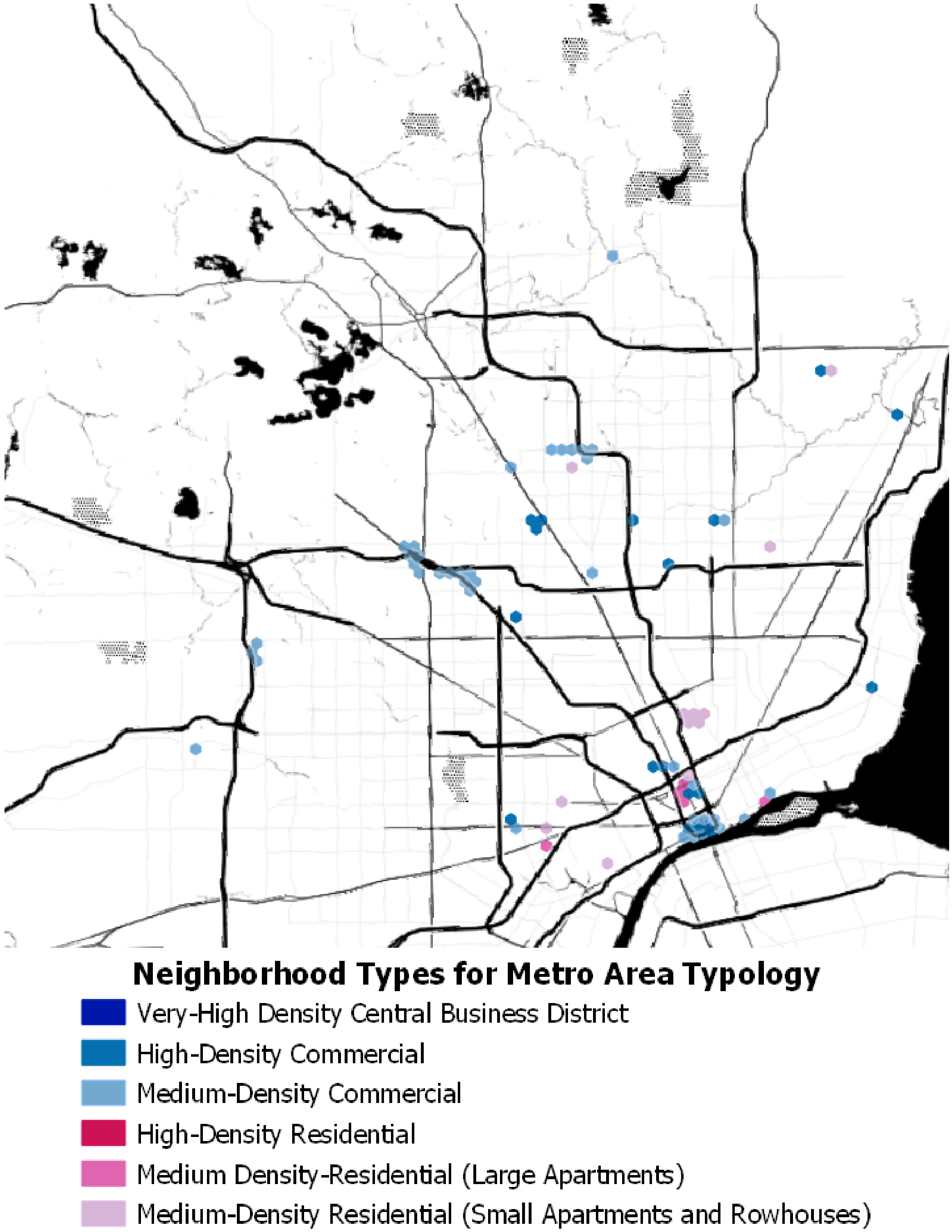

Figure J.10: Detroit-Warren-Dearborn, MI MSA map of dense neighborhoods used in my metro area typology. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table J.11: Prevalence of Dense Neighborhood Types in Honolulu

Neighborhood Type	# Hexes	Pop.	% Pop.	Jobs	% Jobs
Central Business District	1	3,000	0.3%	30,000	8.2%
High-Density Commercial	9	14,000	1.6%	50,000	13.9%
Medium-Density Commercial	9	8,000	0.9%	22,000	6.2%
High-Density Residential	19	86,000	9.6%	70,000	19.3%
Medium-Density Residential (Large Apartments)	15	45,000	5.0%	14,000	3.9%
Medium-Density Residential (Small Apartments)	15	42,000	4.7%	9,000	2.6%

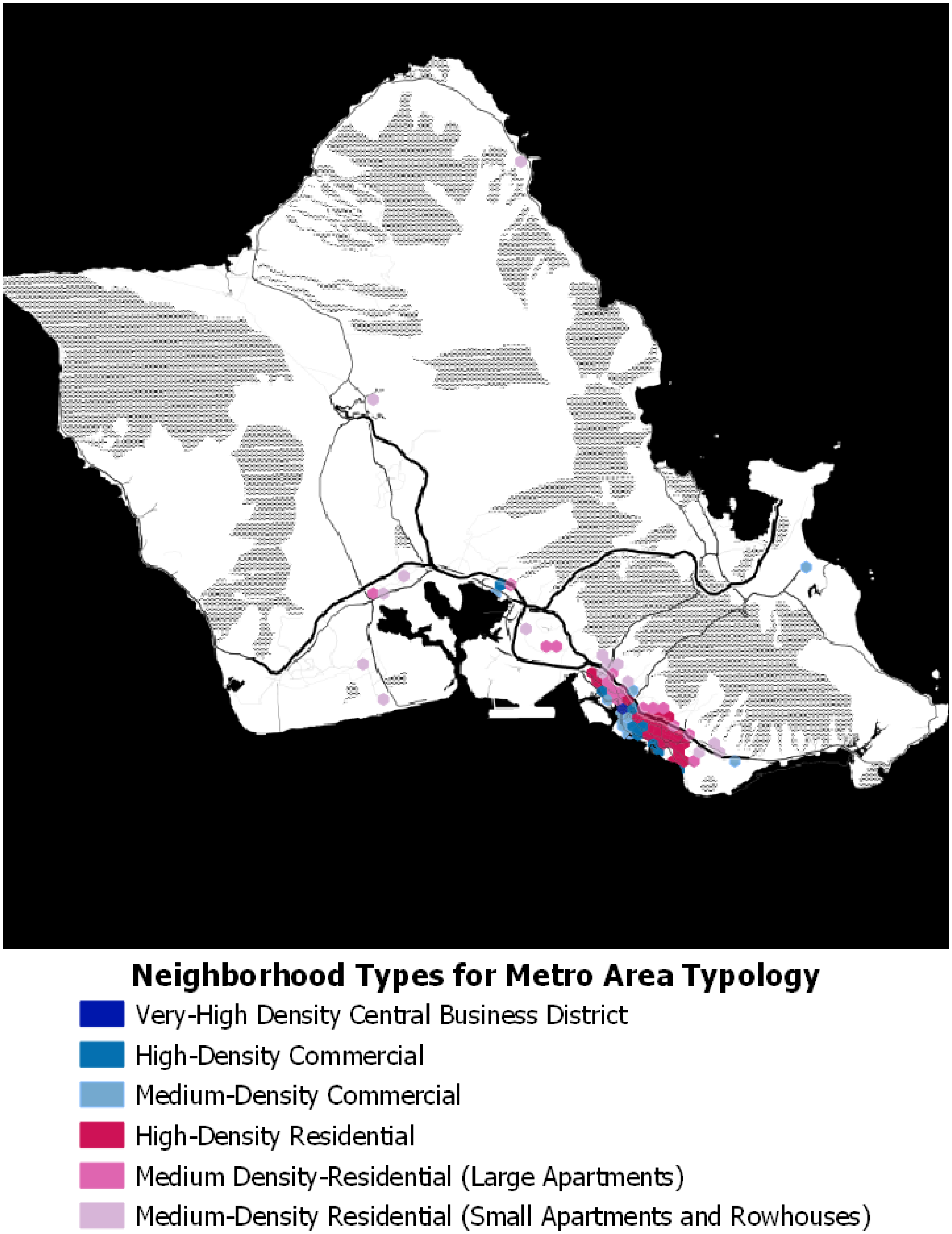

Figure J.11: Urban Honolulu, HI MSA map of dense neighborhoods used in my metro area typology. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table J.12: Prevalence of Dense Neighborhood Types in Houston

Neighborhood Type	# Hexes	Pop.	% Pop.	Jobs	% Jobs
Central Business District	2	1,000	0.0%	77,000	2.9%
High-Density Commercial	31	23,000	0.3%	206,000	7.9%
Medium-Density Commercial	91	98,000	1.5%	261,000	10.0%
High-Density Residential	3	15,000	0.2%	1,000	0.0%
Medium-Density Residential (Large Apartments)	50	127,000	1.9%	50,000	1.9%
Medium-Density Residential (Small Apartments)	5	9,000	0.1%	6,000	0.2%

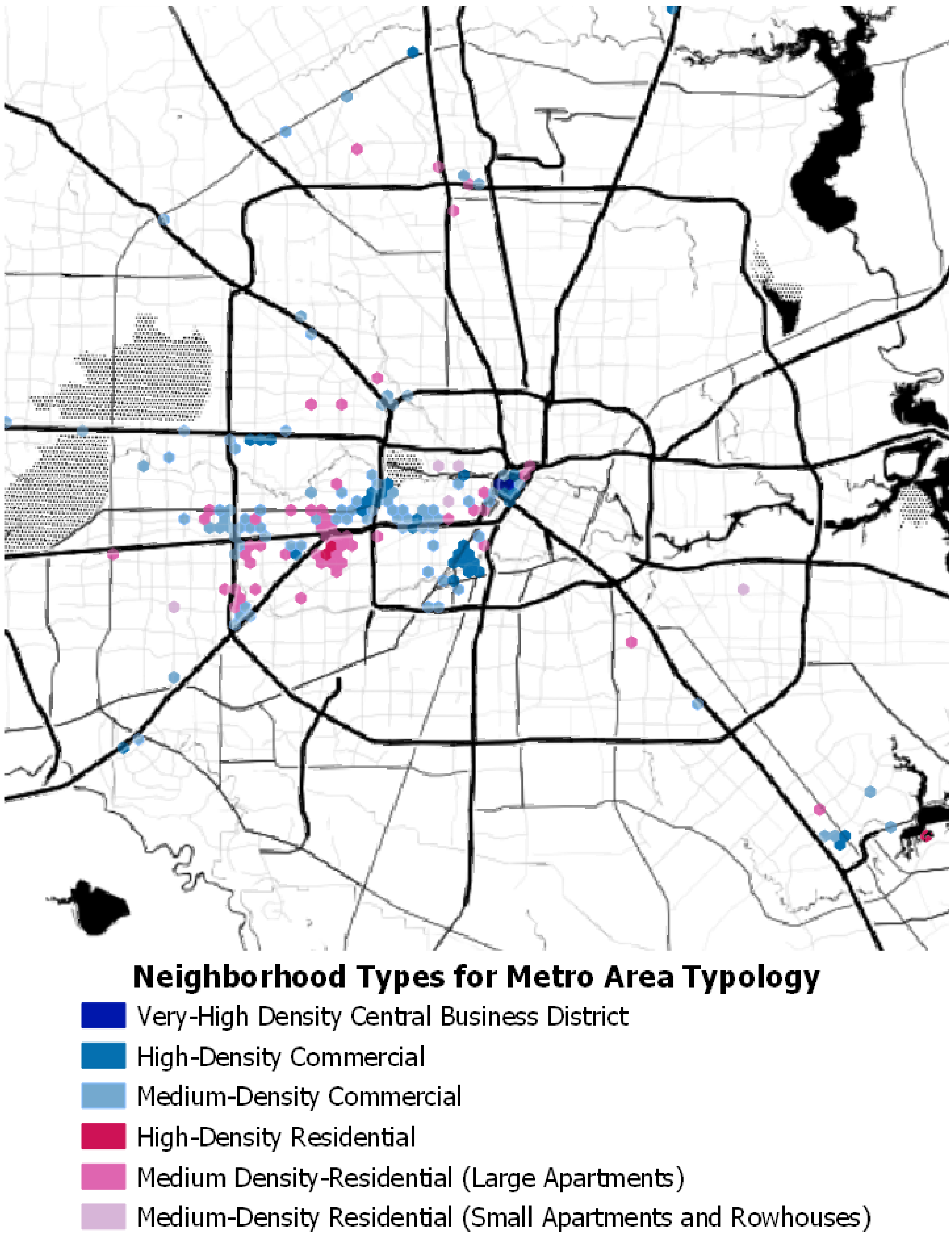

Figure J.12: Houston-The Woodlands-Sugar Land, TX MSA map of dense neighborhoods used in my metro area typology. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table J.13: Prevalence of Dense Neighborhood Types in Los Angeles

Neighborhood Type	# Hexes	Pop.	% Pop.	Jobs	% Jobs
Central Business District	5	5,000	0.0%	166,000	3.0%
High-Density Commercial	95	126,000	0.9%	657,000	11.7%
Medium-Density Commercial	193	243,000	1.8%	655,000	11.7%
High-Density Residential	115	615,000	4.6%	170,000	3.0%
Medium-Density Residential (Large Apartments)	376	1,013,000	7.6%	274,000	4.9%
Medium-Density Residential (Small Apartments)	756	2,161,000	16.3%	370,000	6.6%

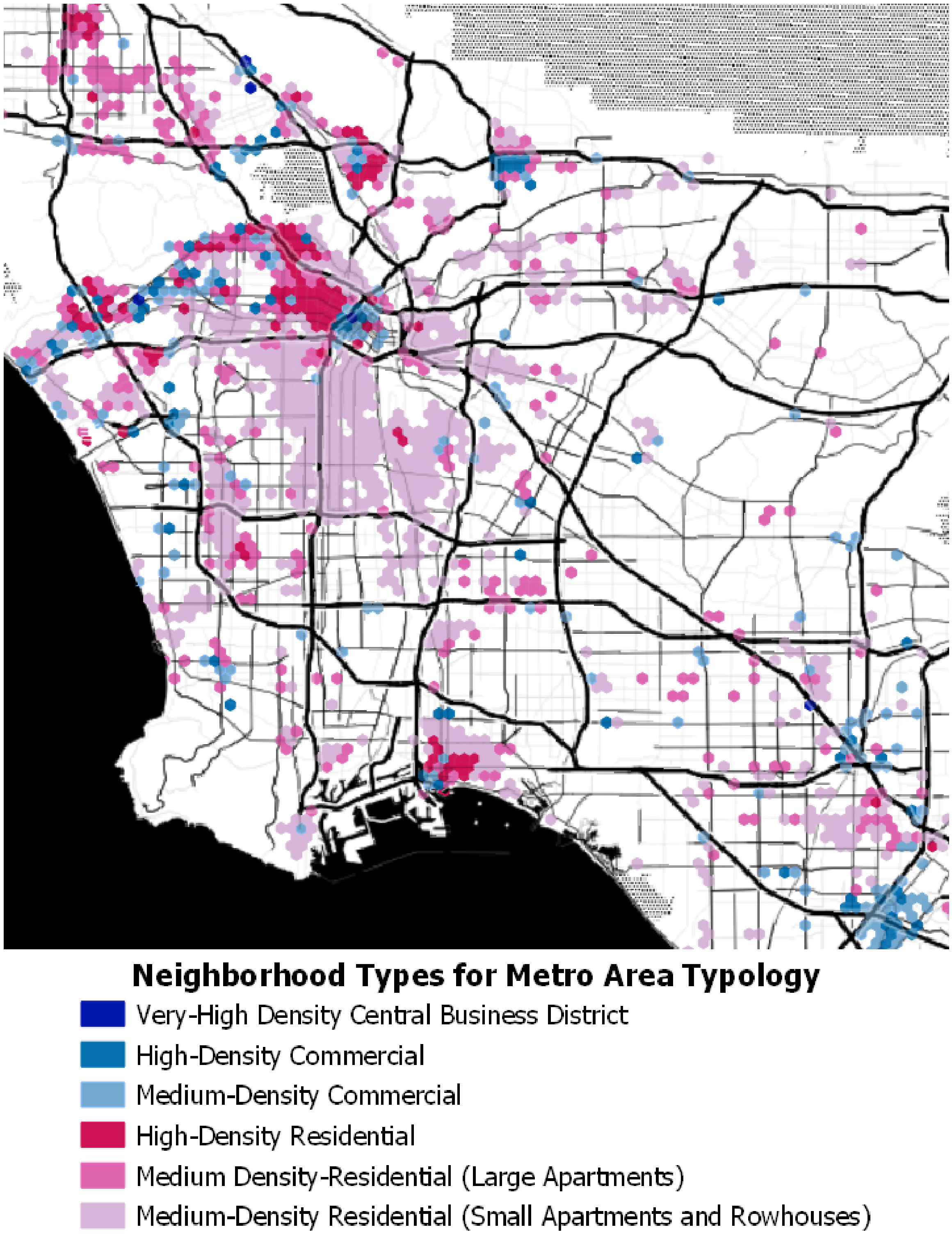

Figure J.13: Los Angeles-Long Beach-Anaheim, CA MSA map of dense neighborhoods used in my metro area typology. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table J.14: Prevalence of Dense Neighborhood Types in Louisville

Neighborhood Type	# Hexes	Pop.	% Pop.	Jobs	% Jobs
Central Business District	0	0	0%	0	0%
High-Density Commercial	9	5,000	0.4%	60,000	10.2%
Medium-Density Commercial	6	5,000	0.4%	19,000	3.3%
High-Density Residential	0	0	0%	0	0%
Medium-Density Residential (Large Apartments)	0	0	0%	0	0%
Medium-Density Residential (Small Apartments)	1	3,000	0.2%	0	0.1%

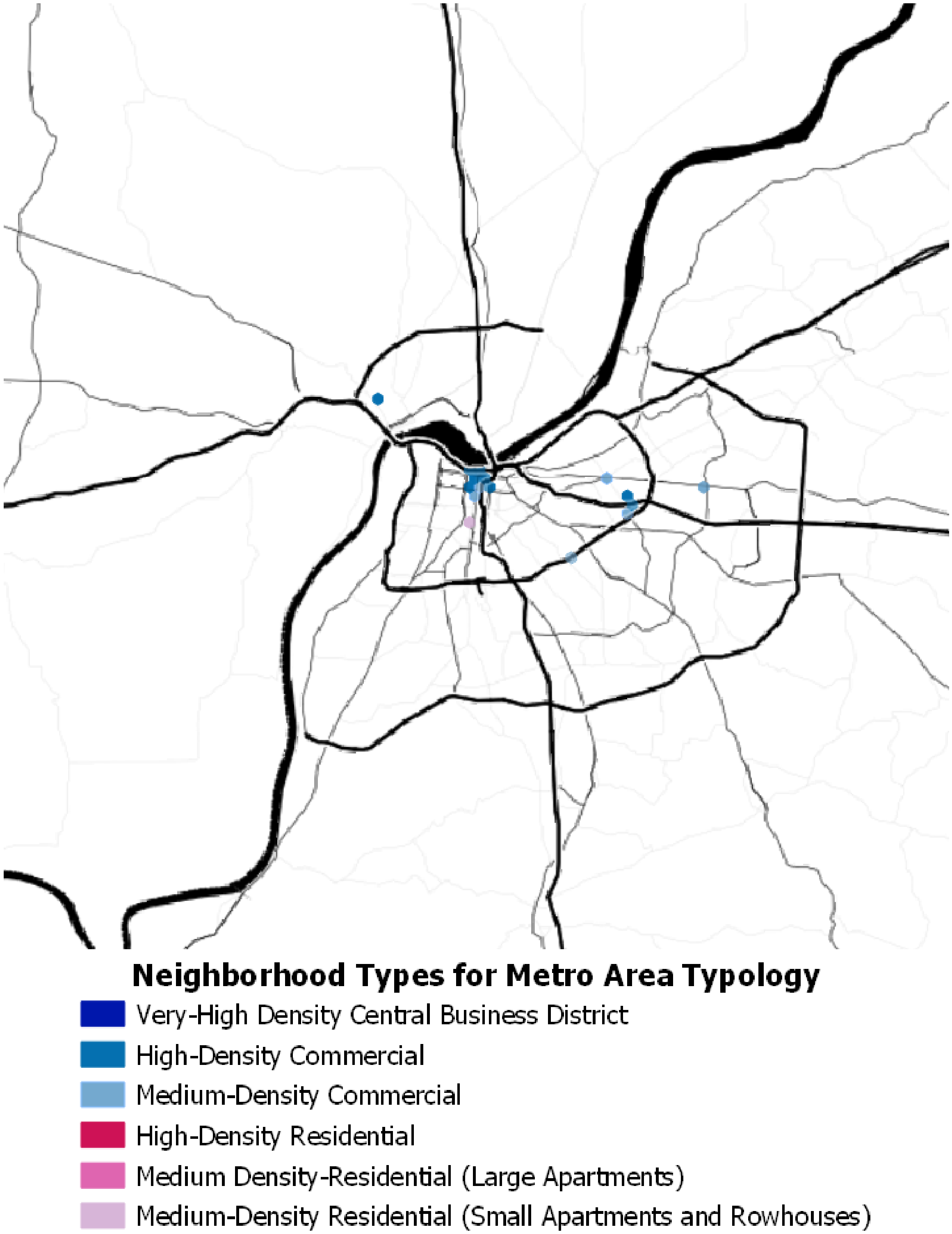

Figure J.14: Louisville-Jefferson County, KY-IN MSA map of dense neighborhoods used in my metro area typology. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table J.15: Prevalence of Dense Neighborhood Types in Madison, WI

Neighborhood Type	# Hexes	Pop.	% Pop.	Jobs	% Jobs
Central Business District	0	0	0%	0	0%
High-Density Commercial	3	5,000	0.7%	9,000	2.9%
Medium-Density Commercial	13	14,000	2.2%	36,000	11.5%
High-Density Residential	3	18,000	2.8%	6,000	1.9%
Medium-Density Residential (Large Apartments)	1	1,000	0.1%	0	0.1%
Medium-Density Residential (Small Apartments)	1	1,000	0.2%	1,000	0.2%

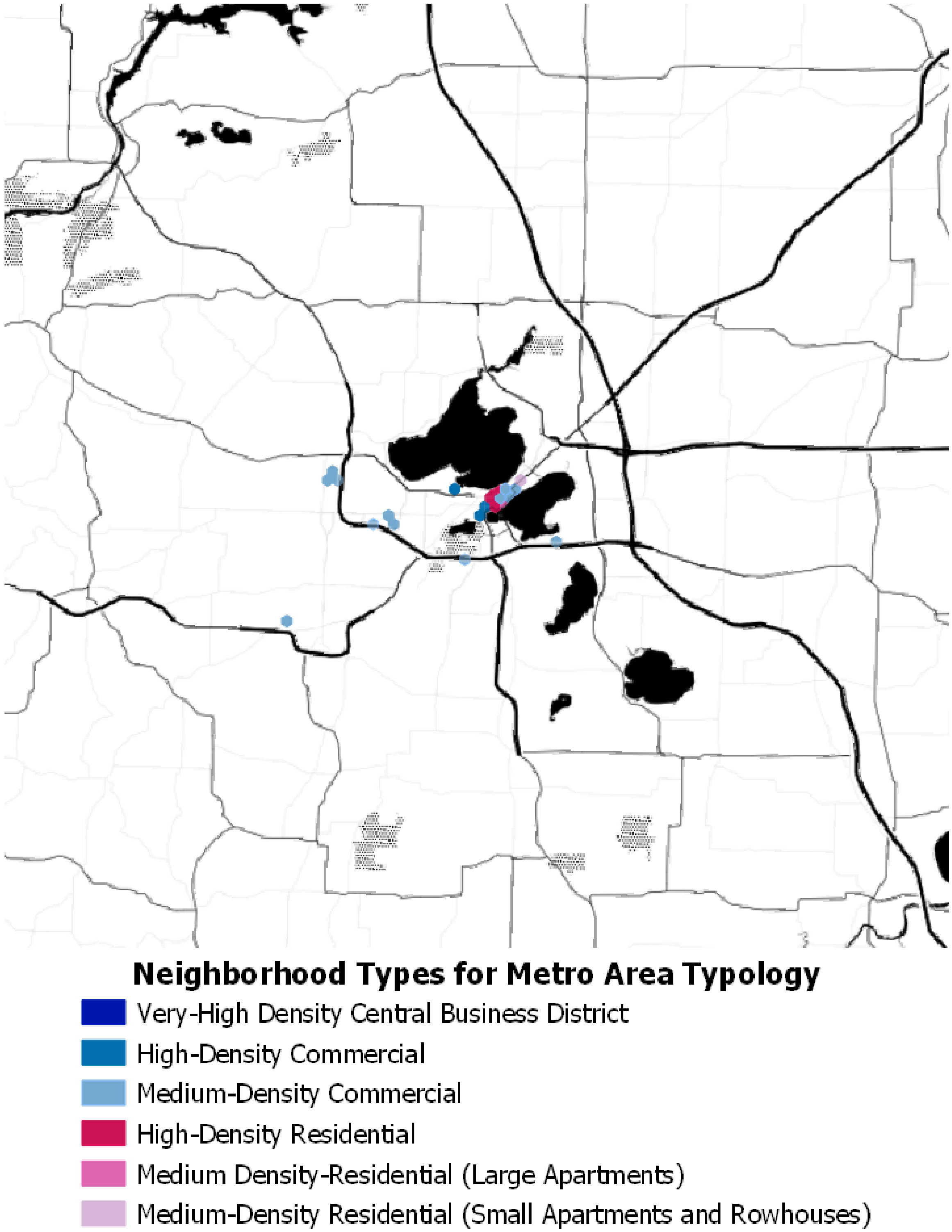

Figure J.15: Madison, WI MSA map of dense neighborhoods used in my metro area typology. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table J.16: Prevalence of Dense Neighborhood Types in Miami

Neighborhood Type	# Hexes	Pop.	% Pop.	Jobs	% Jobs
Central Business District	2	7,000	0.1%	23,000	1.0%
High-Density Commercial	38	47,000	0.8%	172,000	7.5%
Medium-Density Commercial	63	63,000	1.0%	153,000	6.7%
High-Density Residential	23	96,000	1.6%	28,000	1.2%
Medium-Density Residential (Large Apartments)	116	301,000	5.0%	66,000	2.9%
Medium-Density Residential (Small Apartments)	62	153,000	2.5%	27,000	1.2%

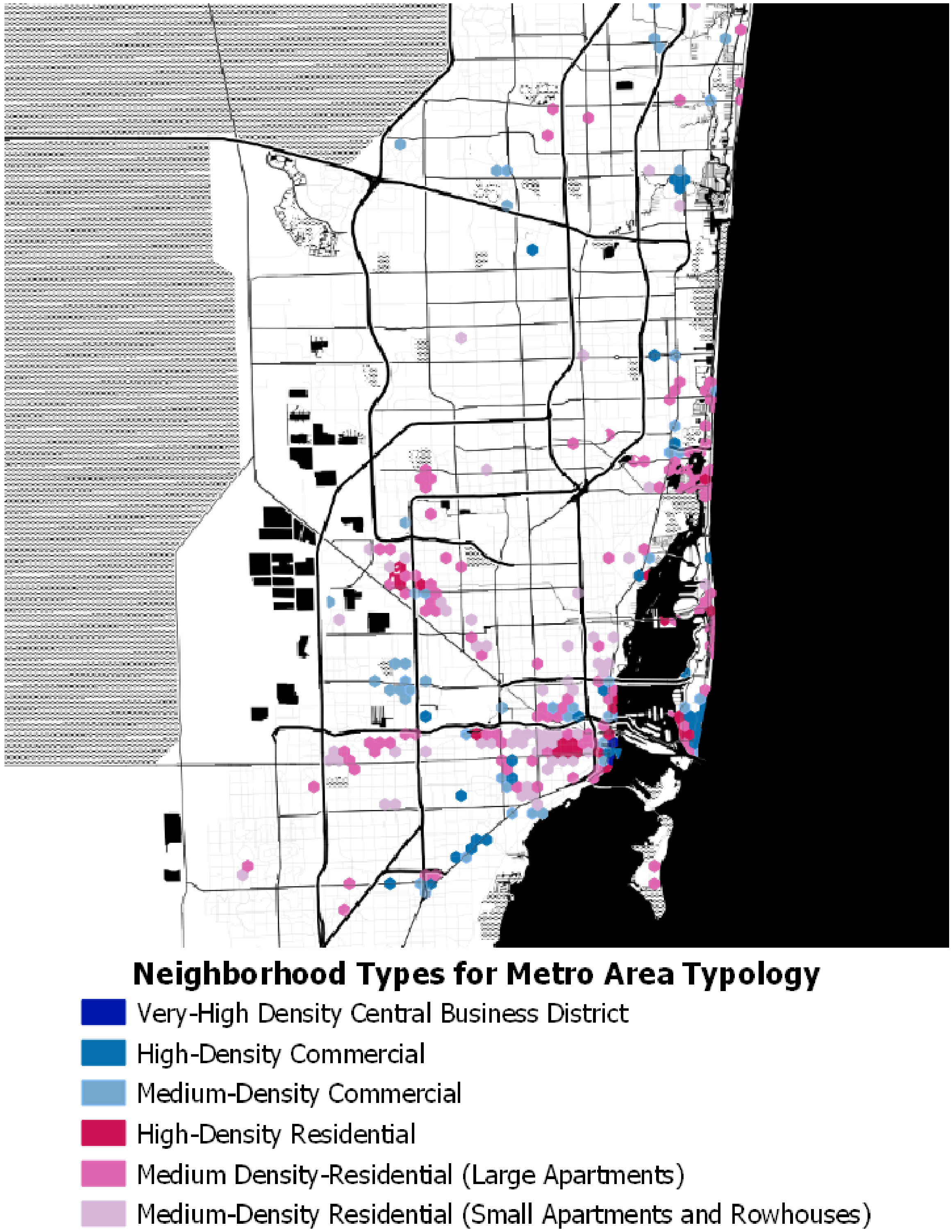

Figure J.16: Miami-Fort Lauderdale-Pompano Beach, FL MSA map of dense neighborhoods used in my metro area typology. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table J.17: Prevalence of Dense Neighborhood Types in Milwaukee

Neighborhood Type	# Hexes	Pop.	% Pop.	Jobs	% Jobs
Central Business District	0	0	0%	0	0%
High-Density Commercial	13	10,000	0.6%	86,000	11.0%
Medium-Density Commercial	14	16,000	1.0%	44,000	5.6%
High-Density Residential	1	3,000	0.2%	8,000	1.0%
Medium-Density Residential (Large Apartments)	9	24,000	1.5%	8,000	1.0%
Medium-Density Residential (Small Apartments)	70	149,000	9.4%	25,000	3.2%

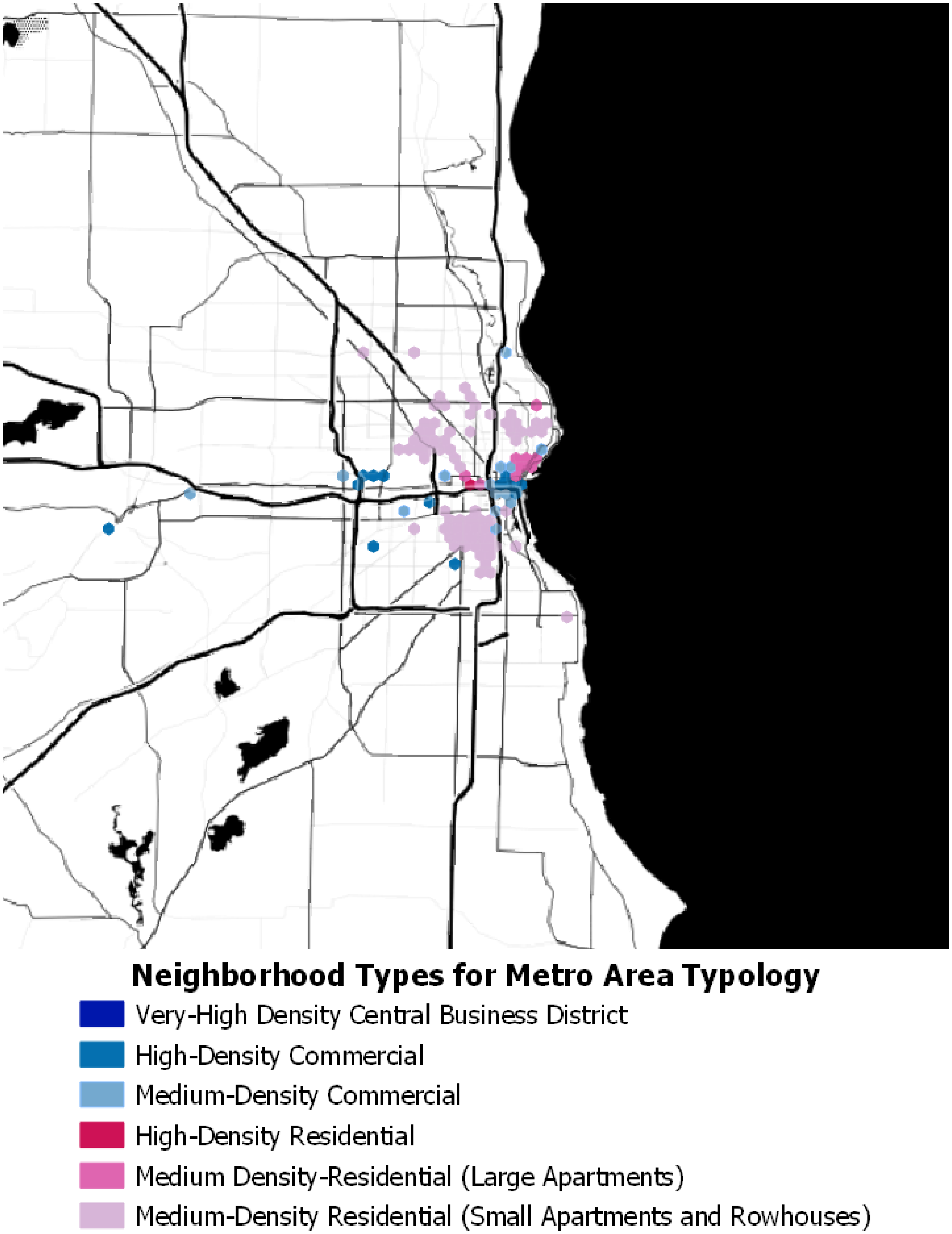

Figure J.17: Milwaukee-Waukesha, WI MSA map of dense neighborhoods used in my metro area typology. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table J.18: Prevalence of Dense Neighborhood Types in Minneapolis

Neighborhood Type	# Hexes	Pop.	% Pop.	Jobs	% Jobs
Central Business District	1	1,000	0.0%	56,000	3.3%
High-Density Commercial	25	31,000	0.9%	170,000	10.0%
Medium-Density Commercial	50	51,000	1.5%	133,000	7.8%
High-Density Residential	2	7,000	0.2%	2,000	0.1%
Medium-Density Residential (Large Apartments)	24	63,000	1.8%	21,000	1.2%
Medium-Density Residential (Small Apartments)	15	27,000	0.8%	11,000	0.6%

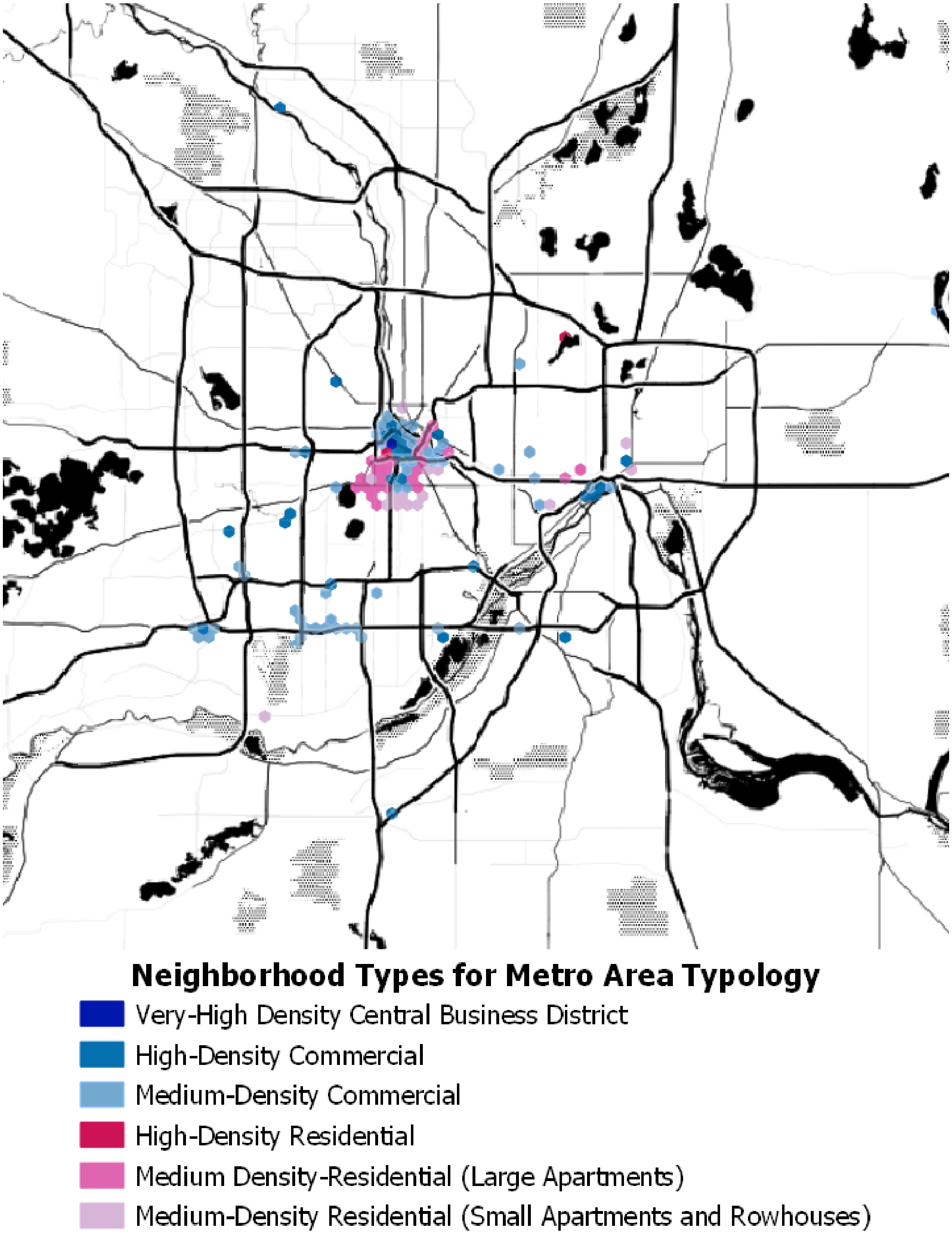

Figure J.18: Minneapolis-St. Paul-Bloomington, MN-WI MSA map of dense neighborhoods used in my metro area typology. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table J.19: Prevalence of Dense Neighborhood Types in New York

Neighborhood Type	# Hexes	Pop.	% Pop.	Jobs	% Jobs
Central Business District	48	483,000	2.5%	1,959,000	24.4%
High-Density Commercial	75	141,000	0.7%	403,000	5.0%
Medium-Density Commercial	67	137,000	0.7%	268,000	3.3%
High-Density Residential	753	6,289,000	32.6%	1,279,000	15.9%
Medium-Density Residential (Large Apartments)	182	516,000	2.7%	115,000	1.4%
Medium-Density Residential (Small Apartments)	705	2,096,000	10.9%	355,000	4.4%

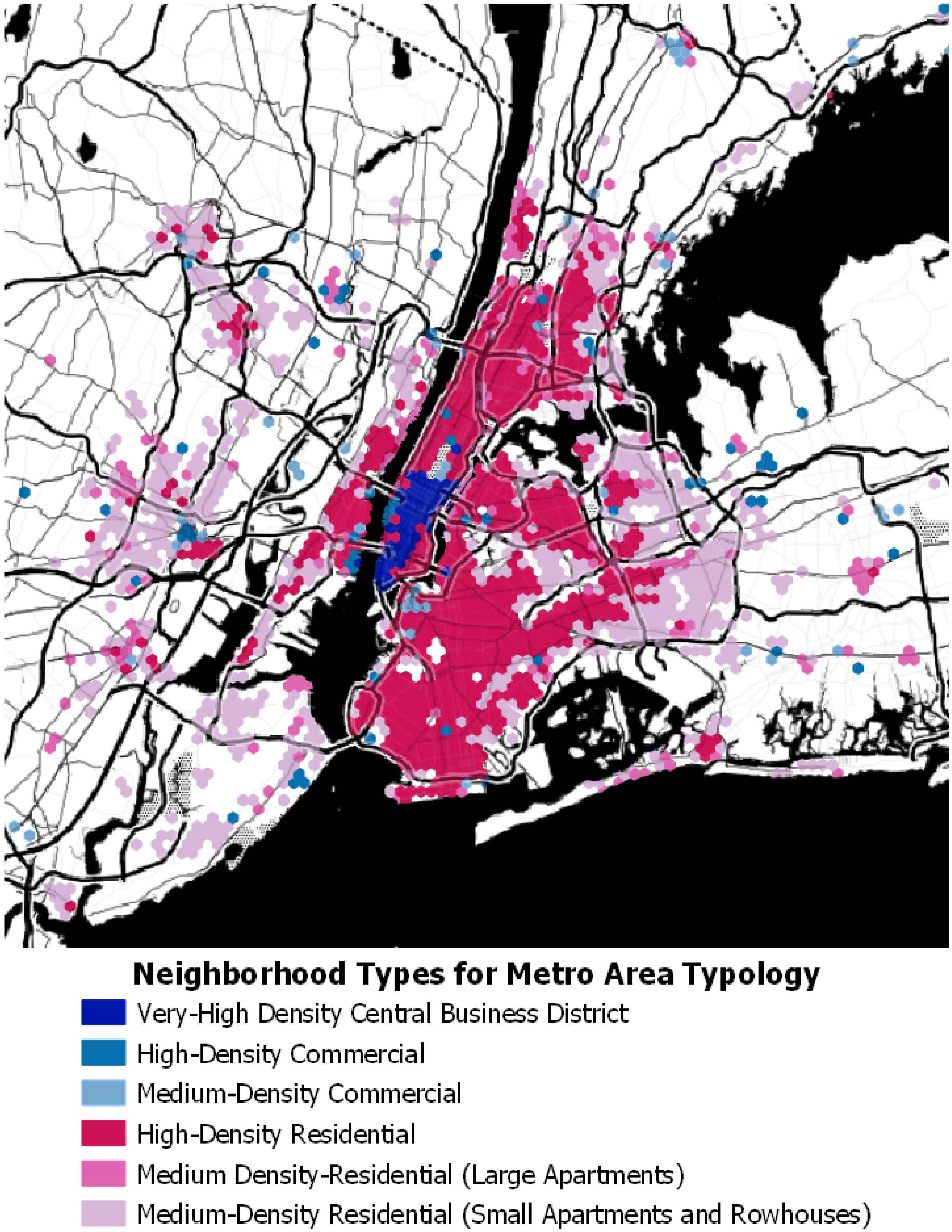

Figure J.19: New York-Newark-Jersey City, NY-NJ-PA MSA map of dense neighborhoods used in my metro area typology. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table J.20: Prevalence of Dense Neighborhood Types in Philadelphia

Neighborhood Type	# Hexes	Pop.	% Pop.	Jobs	% Jobs
Central Business District	3	17,000	0.3%	121,000	4.7%
High-Density Commercial	39	50,000	0.8%	223,000	8.6%
Medium-Density Commercial	29	26,000	0.4%	99,000	3.8%
High-Density Residential	43	242,000	4.0%	47,000	1.8%
Medium-Density Residential (Large Apartments)	4	10,000	0.2%	4,000	0.2%
Medium-Density Residential (Small Apartments)	304	919,000	15.2%	138,000	5.4%

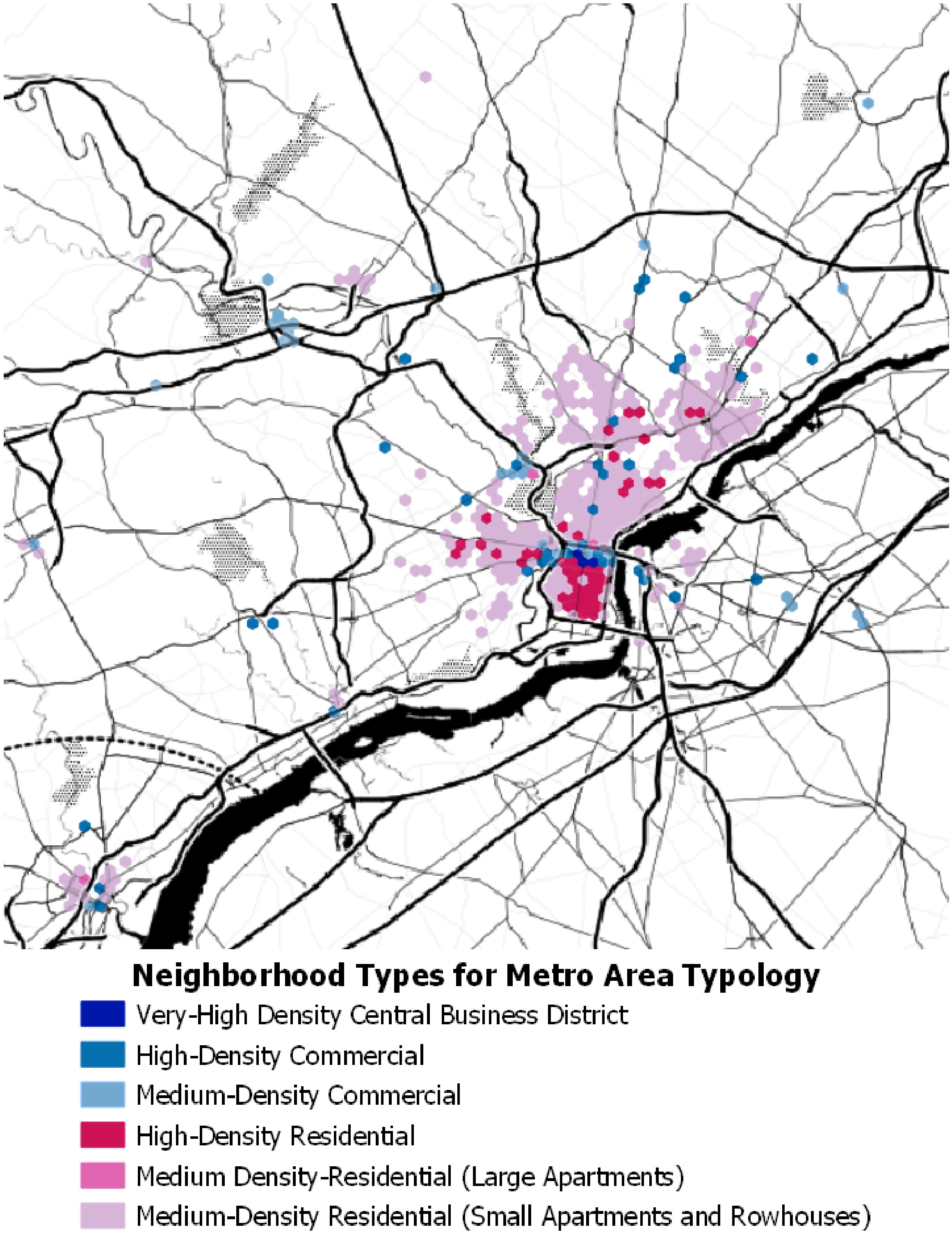

Figure J.20: Philadelphia-Camden-Wilmington, PA-NJ-DE-MD MSA map of dense neighborhoods used in my metro area typology. Philadelphia is just right of center and Wilmington is at the lower left. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table J.21: Prevalence of Dense Neighborhood Types in Phoenix

Neighborhood Type	# Hexes	Pop.	% Pop.	Jobs	% Jobs
Central Business District	0	0	0%	0	0%
High-Density Commercial	30	18,000	0.4%	188,000	10.4%
Medium-Density Commercial	57	34,000	0.7%	168,000	9.2%
High-Density Residential	0	0	0%	0	0%
Medium-Density Residential (Large Apartments)	19	41,000	0.9%	10,000	0.5%
Medium-Density Residential (Small Apartments)	12	25,000	0.5%	4,000	0.2%

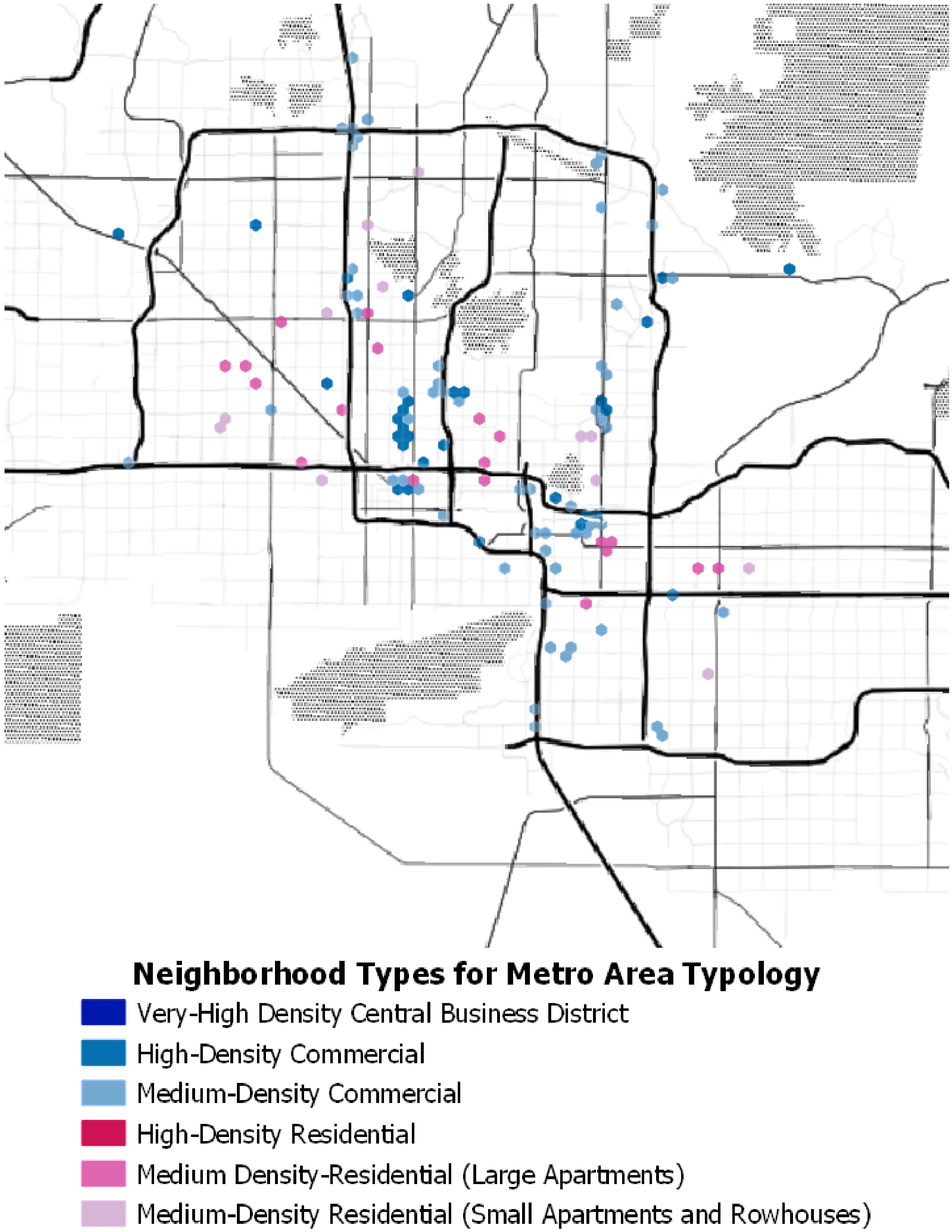

Figure J.21: Phoenix-Mesa-Chandler, AZ MSA map of dense neighborhoods used in my metro area typology. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table J.22: Prevalence of Dense Neighborhood Types in Pittsburgh

Neighborhood Type	# Hexes	Pop.	% Pop.	Jobs	% Jobs
Central Business District	2	4,000	0.2%	44,000	4.2%
High-Density Commercial	13	18,000	0.8%	103,000	9.8%
Medium-Density Commercial	13	15,000	0.6%	35,000	3.3%
High-Density Residential	1	4,000	0.2%	3,000	0.3%
Medium-Density Residential (Large Apartments)	2	4,000	0.2%	1,000	0.1%
Medium-Density Residential (Small Apartments)	20	38,000	1.6%	17,000	1.6%

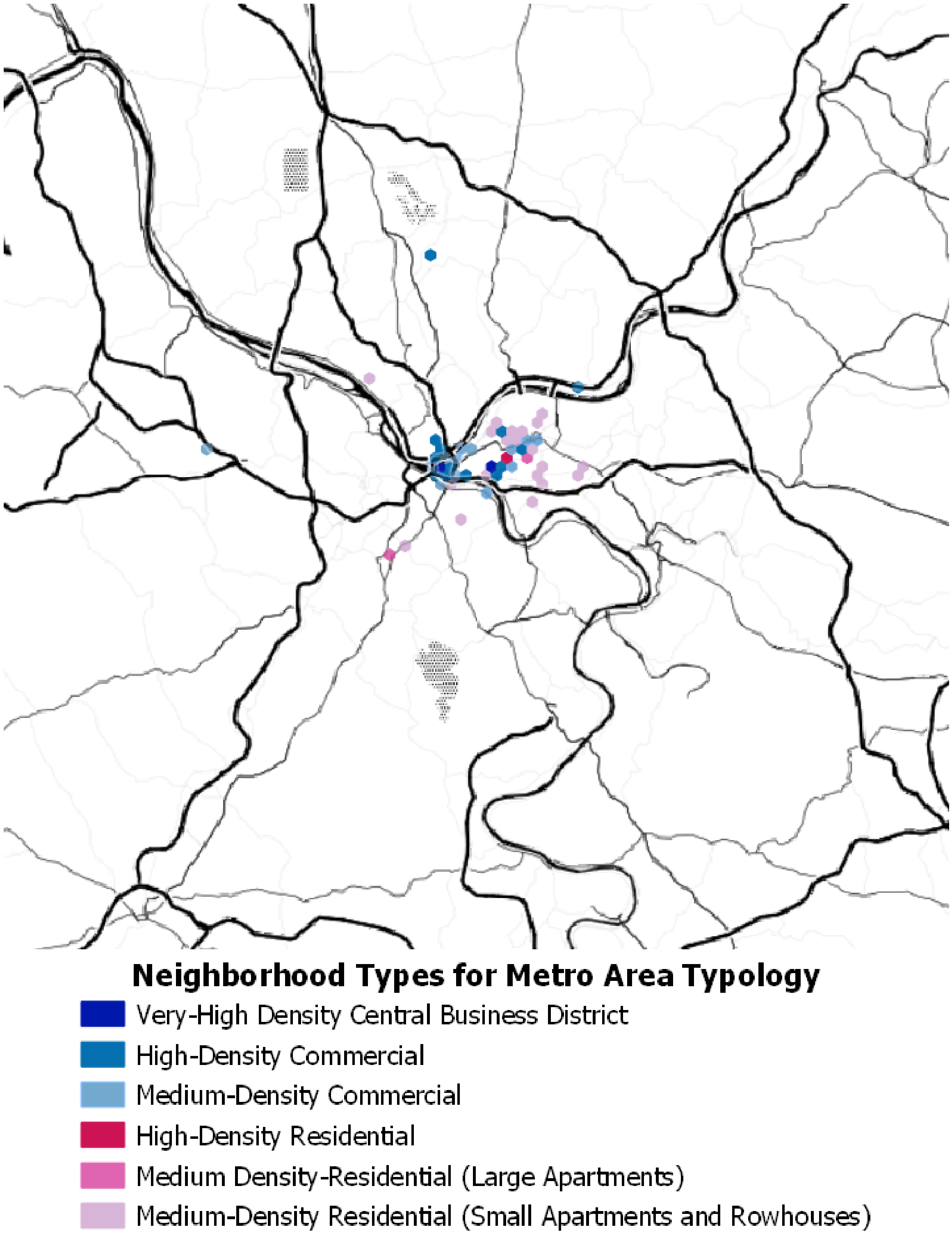

Figure J.22: Pittsburgh, PA MSA map of dense neighborhoods used in my metro area typology. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table J.23: Prevalence of Dense Neighborhood Types in Portland

Neighborhood Type	# Hexes	Pop.	% Pop.	Jobs	% Jobs
Central Business District	0	0	0.0%	0	0.0%
High-Density Commercial	13	18,000	0.7%	112,000	10.8%
Medium-Density Commercial	27	31,000	1.3%	77,000	7.4%
High-Density Residential	2	10,000	0.4%	4,000	0.4%
Medium-Density Residential (Large Apartments)	8	16,000	0.7%	7,000	0.7%
Medium-Density Residential (Small Apartments)	11	19,000	0.8%	9,000	0.8%

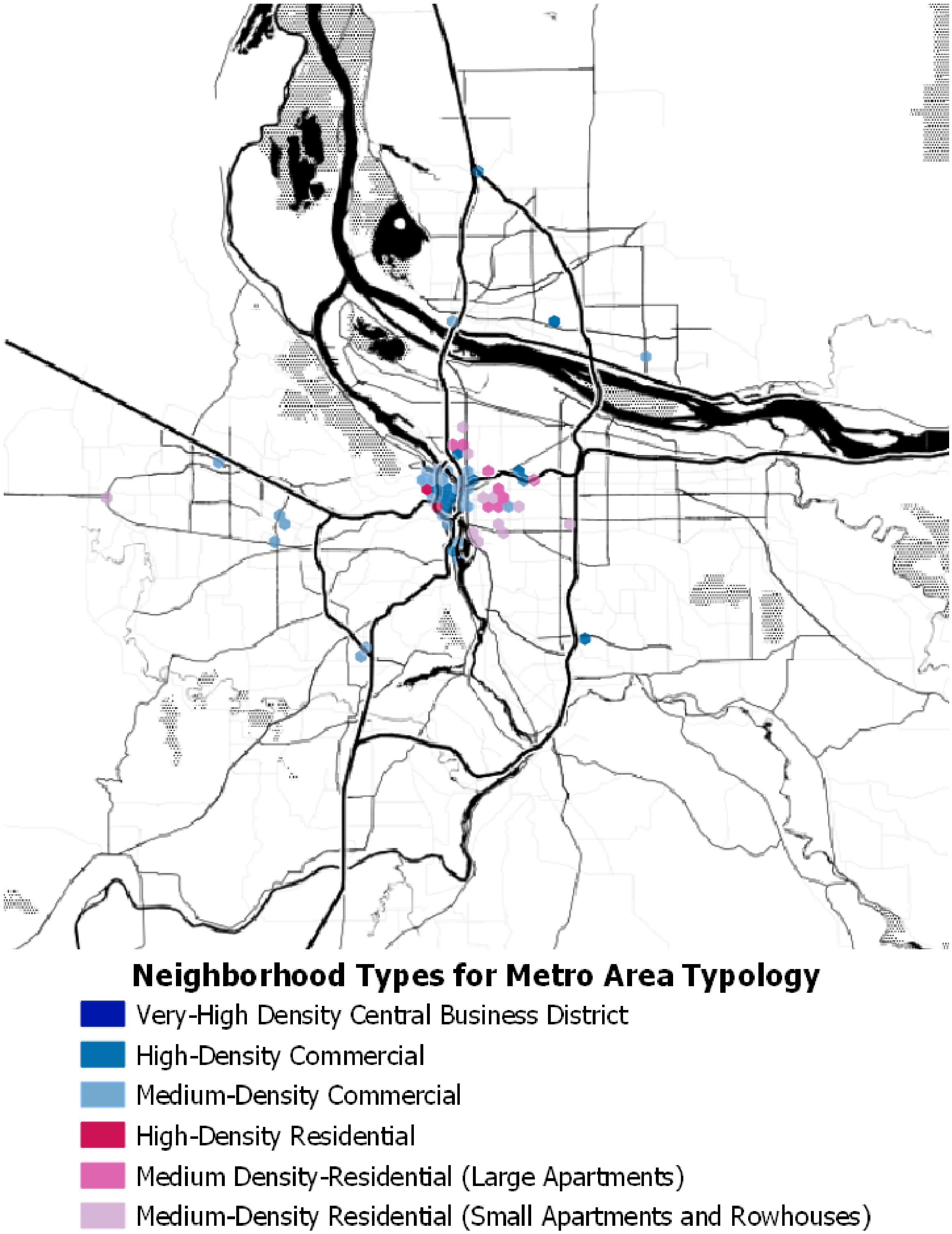

Figure J.23: Portland-Vancouver-Hillsboro, OR-WA MSA map of dense neighborhoods used in my metro area typology. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table J.24: Prevalence of Dense Neighborhood Types in Riverside

Neighborhood Type	# Hexes	Pop.	% Pop.	Jobs	% Jobs
Central Business District	0	0	0%	0	0%
High-Density Commercial	9	7,000	0.1%	33,000	2.7%
Medium-Density Commercial	14	9,000	0.2%	34,000	2.8%
High-Density Residential	0	0	0%	0	0%
Medium-Density Residential (Large Apartments)	5	11,000	0.2%	3,000	0.2%
Medium-Density Residential (Small Apartments)	17	37,000	0.8%	6,000	0.5%

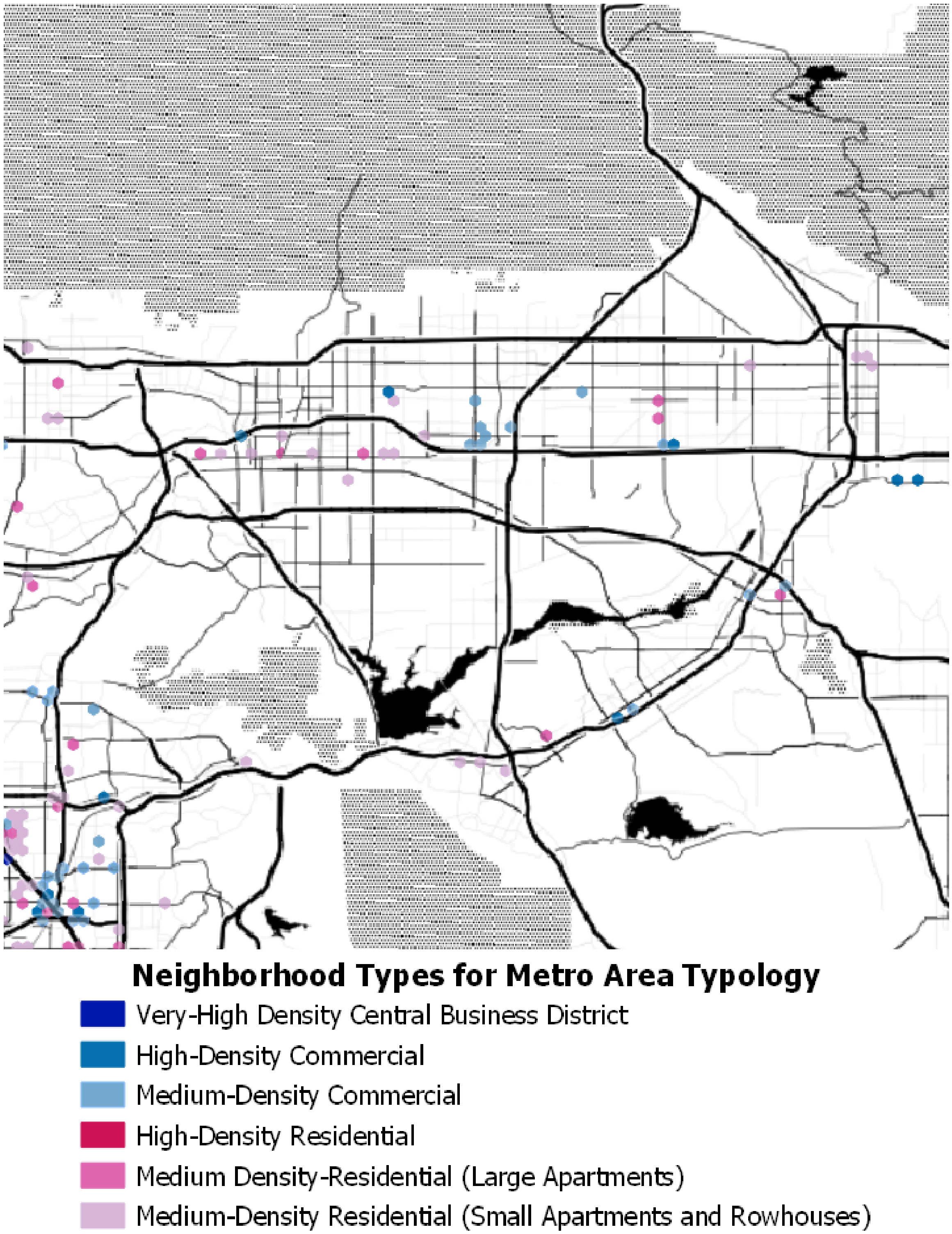

Figure J.24: Riverside-San Bernardino-Ontario, CA MSA map of dense neighborhoods used in my metro area typology. Ontario is to the center left, San Bernardino is to the center right, and Riverside is to the lower center. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table J.25: Prevalence of Dense Neighborhood Types in Rochester, MN

Neighborhood Type	# Hexes	Pop.	% Pop.	Jobs	% Jobs
Central Business District	0	0	0%	0	0%
High-Density Commercial	2	2,000	0.8%	34,000	32.4%
Medium-Density Commercial	0	0	0%	0	0%
High-Density Residential	0	0	0%	0	0%
Medium-Density Residential (Large Apartments)	0	0	0%	0	0%
Medium-Density Residential (Small Apartments)	0	0	0%	0	0%

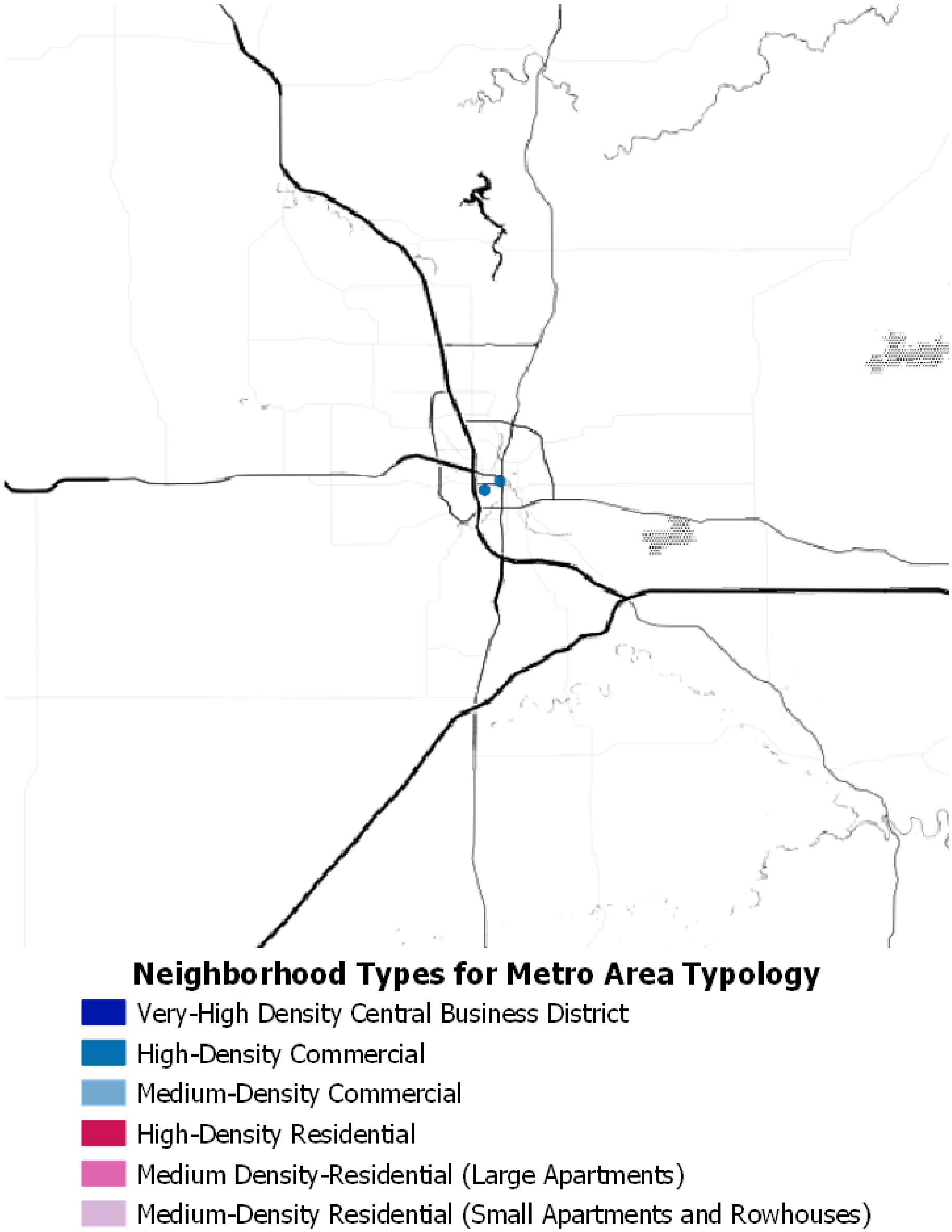

Figure J.25: Rochester, MN MSA map of dense neighborhoods used in my metro area typology. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table J.26: Prevalence of Dense Neighborhood Types in Sacramento

Neighborhood Type	# Hexes	Pop.	% Pop.	Jobs	% Jobs
Central Business District	0	0	0%	0	0%
High-Density Commercial	8	7,000	0.3%	39,000	5.2%
Medium-Density Commercial	21	13,000	0.6%	60,000	8.1%
High-Density Residential	0	0	0%	0	0%
Medium-Density Residential (Large Apartments)	8	15,000	0.7%	5,000	0.7%
Medium-Density Residential (Small Apartments)	7	12,000	0.5%	8,000	1.1%

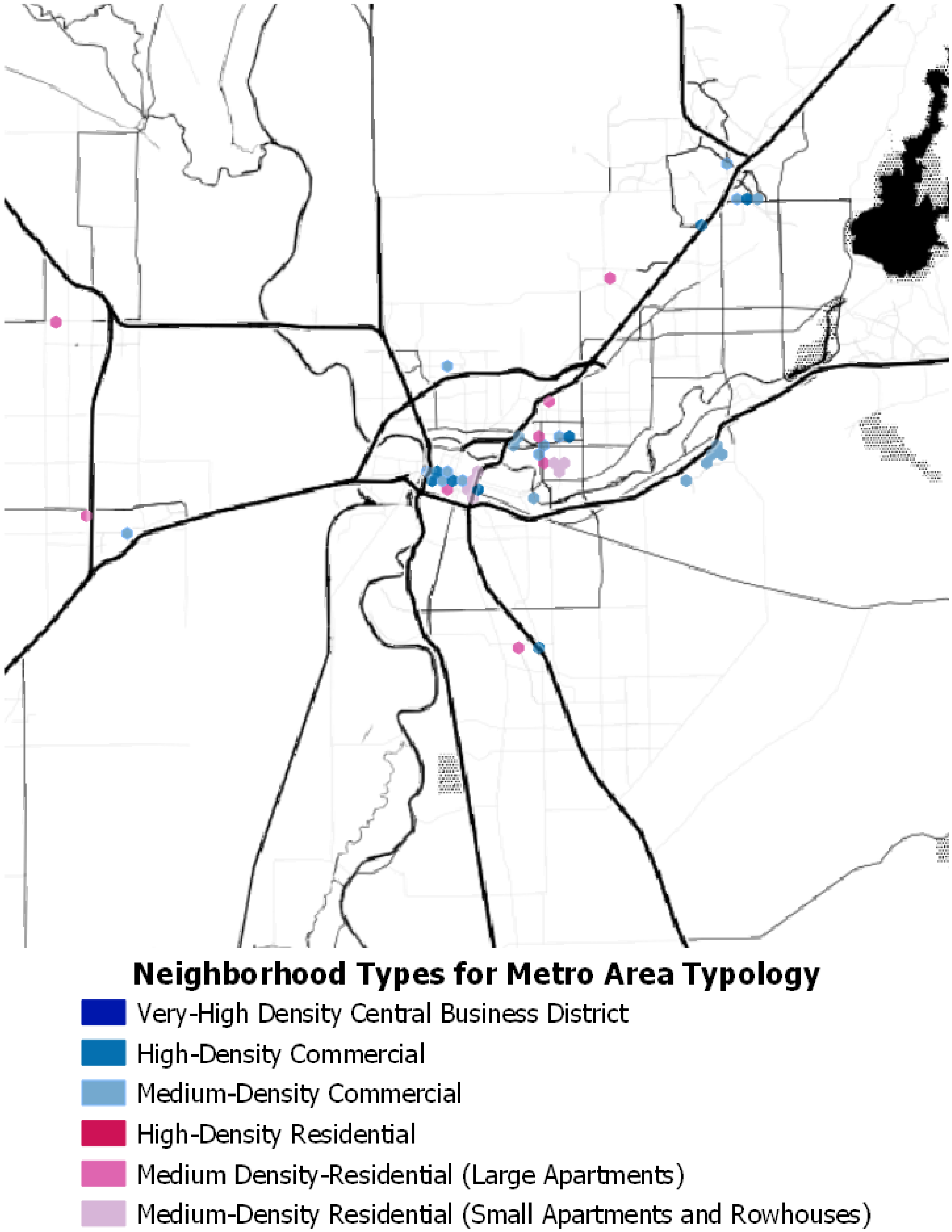

Figure J.26: Sacramento-Roseville-Folsom, CA MSA map of dense neighborhoods used in my metro area typology. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table J.27: Prevalence of Dense Neighborhood Types in Salt Lake City

Neighborhood Type	# Hexes	Pop.	% Pop.	Jobs	% Jobs
Central Business District	0	0	0%	0	0%
High-Density Commercial	8	6,000	0.5%	50,000	8.4%
Medium-Density Commercial	23	17,000	1.4%	50,000	8.5%
High-Density Residential	0	0	0%	0	0%
Medium-Density Residential (Large Apartments)	2	4,000	0.3%	1,000	0.2%
Medium-Density Residential (Small Apartments)	0	0	0%	0	0%

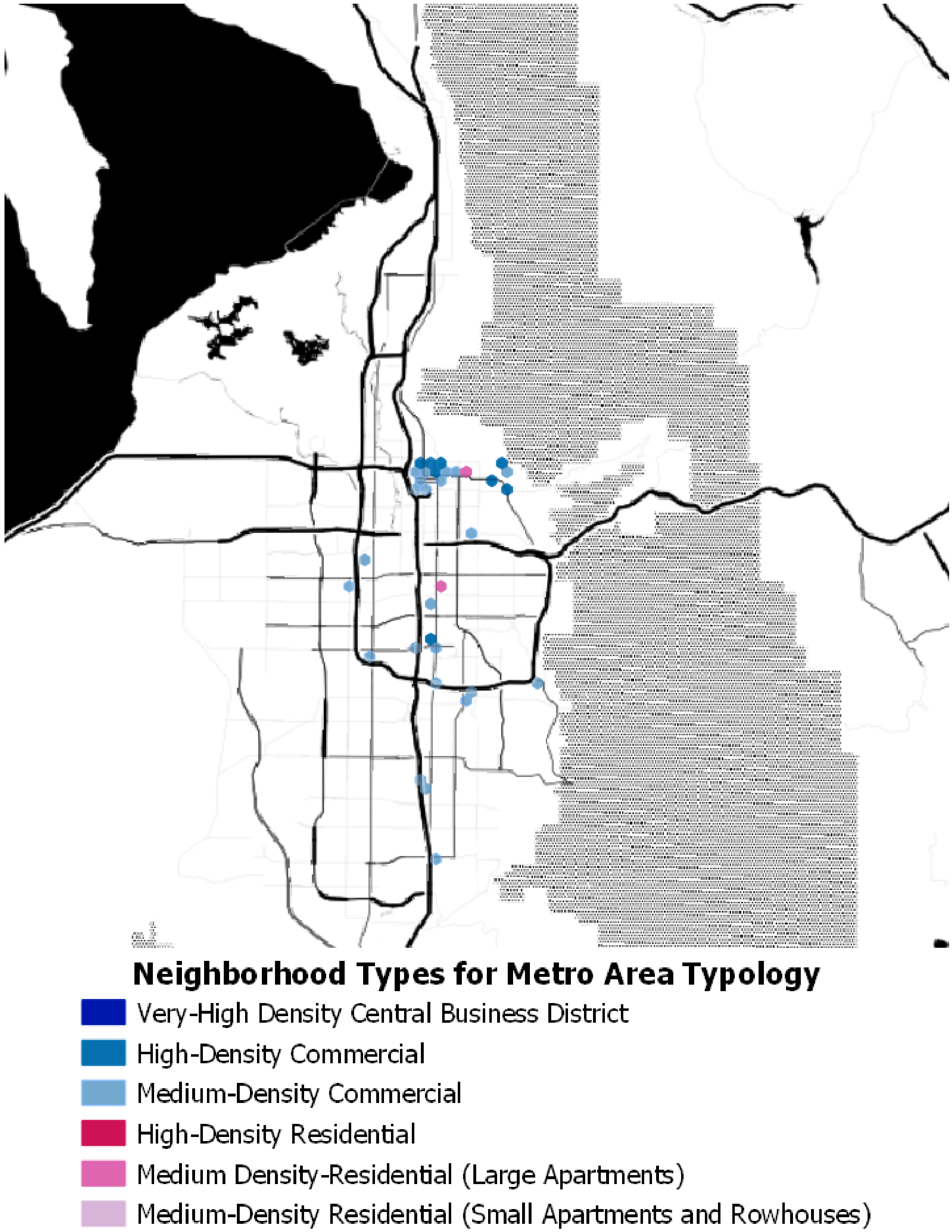

Figure J.27: Salt Lake City, UT MSA map of dense neighborhoods used in my metro area typology. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table J.28: Prevalence of Dense Neighborhood Types in San Diego

Neighborhood Type	# Hexes	Pop.	% Pop.	Jobs	% Jobs
Central Business District	0	0	0%	0	0%
High-Density Commercial	20	26,000	0.8%	86,000	7.1%
Medium-Density Commercial	39	31,000	1.0%	122,000	10.1%
High-Density Residential	4	19,000	0.6%	5,000	0.4%
Medium-Density Residential (Large Apartments)	67	162,000	5.1%	40,000	3.3%
Medium-Density Residential (Small Apartments)	58	151,000	4.7%	26,000	2.2%

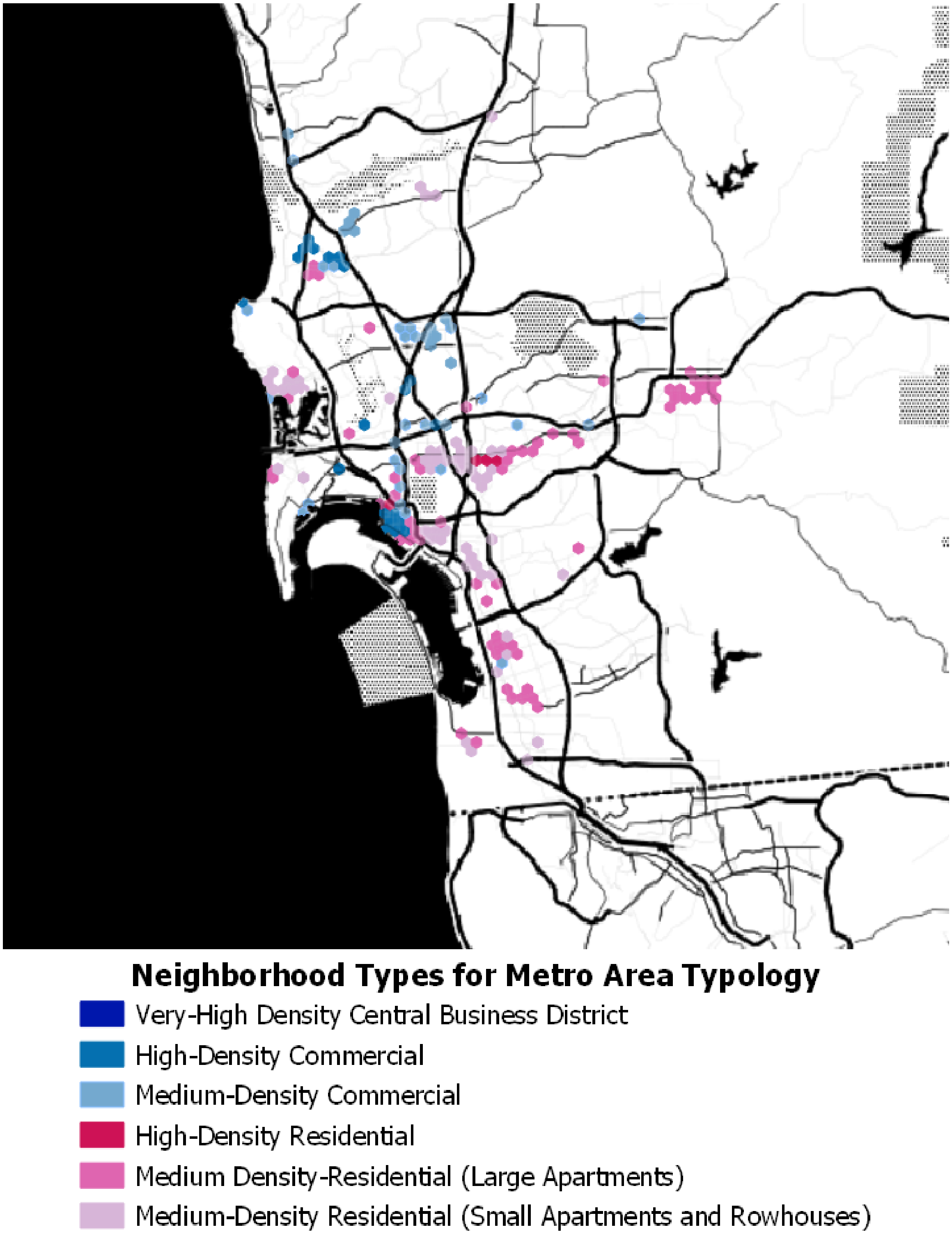

Figure J.28: San Diego-Chula Vista-Carlsbad, CA MSA map of dense neighborhoods used in my metro area typology. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table J.29: Prevalence of Dense Neighborhood Types in San Francisco

Neighborhood Type	# Hexes	Pop.	% Pop.	Jobs	% Jobs
Central Business District	9	57,000	1.2%	298,000	13.9%
High-Density Commercial	36	74,000	1.6%	221,000	10.3%
Medium-Density Commercial	74	93,000	2.0%	248,000	11.6%
High-Density Residential	59	325,000	7.0%	119,000	5.5%
Medium-Density Residential (Large Apartments)	69	169,000	3.6%	45,000	2.1%
Medium-Density Residential (Small Apartments)	228	690,000	14.8%	112,000	5.2%

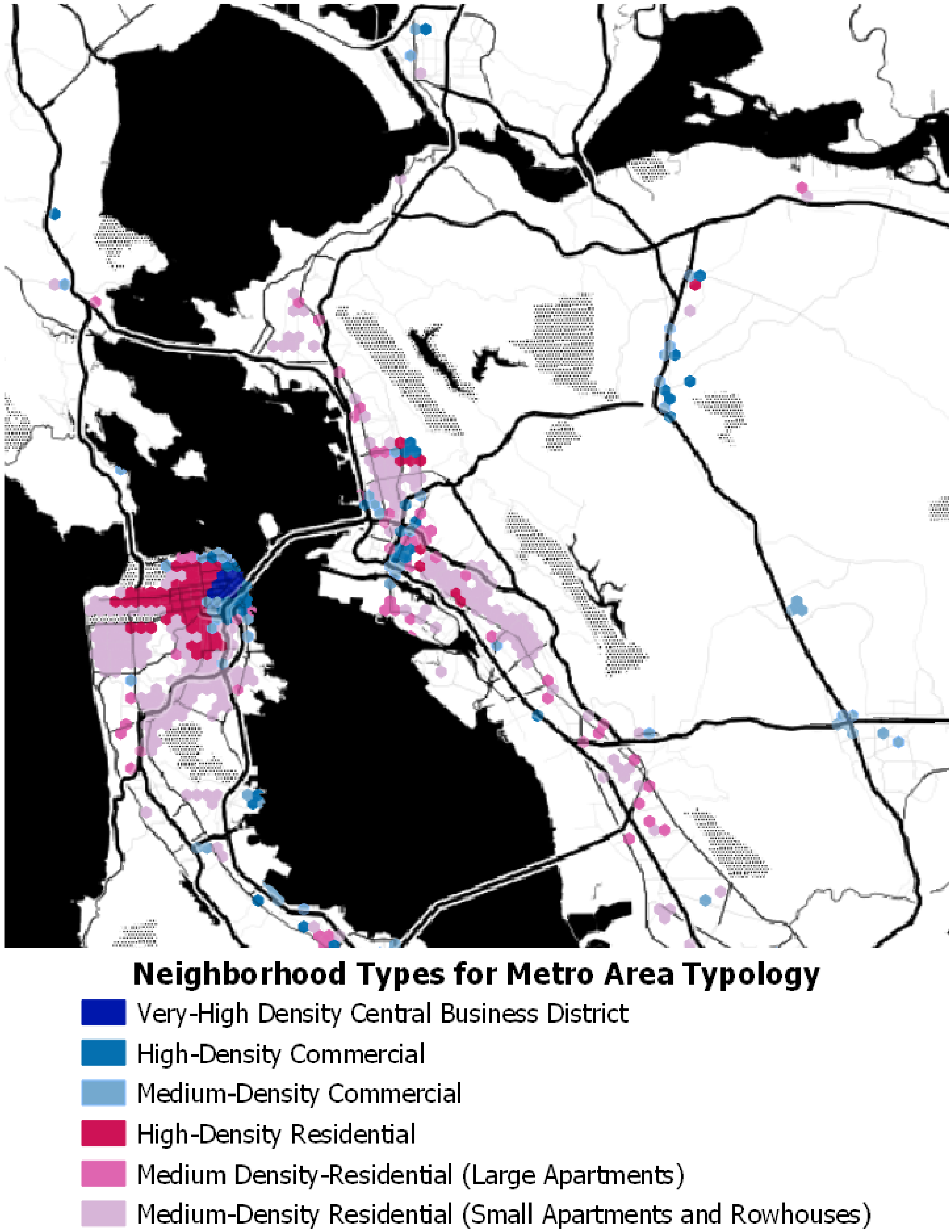

Figure J.29: San Francisco-Oakland-Berkeley, CA MSA map of dense neighborhoods used in my metro area typology. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table J.30: Prevalence of Dense Neighborhood Types in San Jose

Neighborhood Type	# Hexes	Pop.	% Pop.	Jobs	% Jobs
Central Business District	1	1,000	0.1%	25,000	2.5%
High-Density Commercial	19	15,000	0.8%	124,000	12.4%
Medium-Density Commercial	42	29,000	1.4%	150,000	15.0%
High-Density Residential	0	0	0%	0	0%
Medium-Density Residential (Large Apartments)	53	124,000	6.3%	37,000	3.7%
Medium-Density Residential (Small Apartments)	39	96,000	4.9%	18,000	1.8%

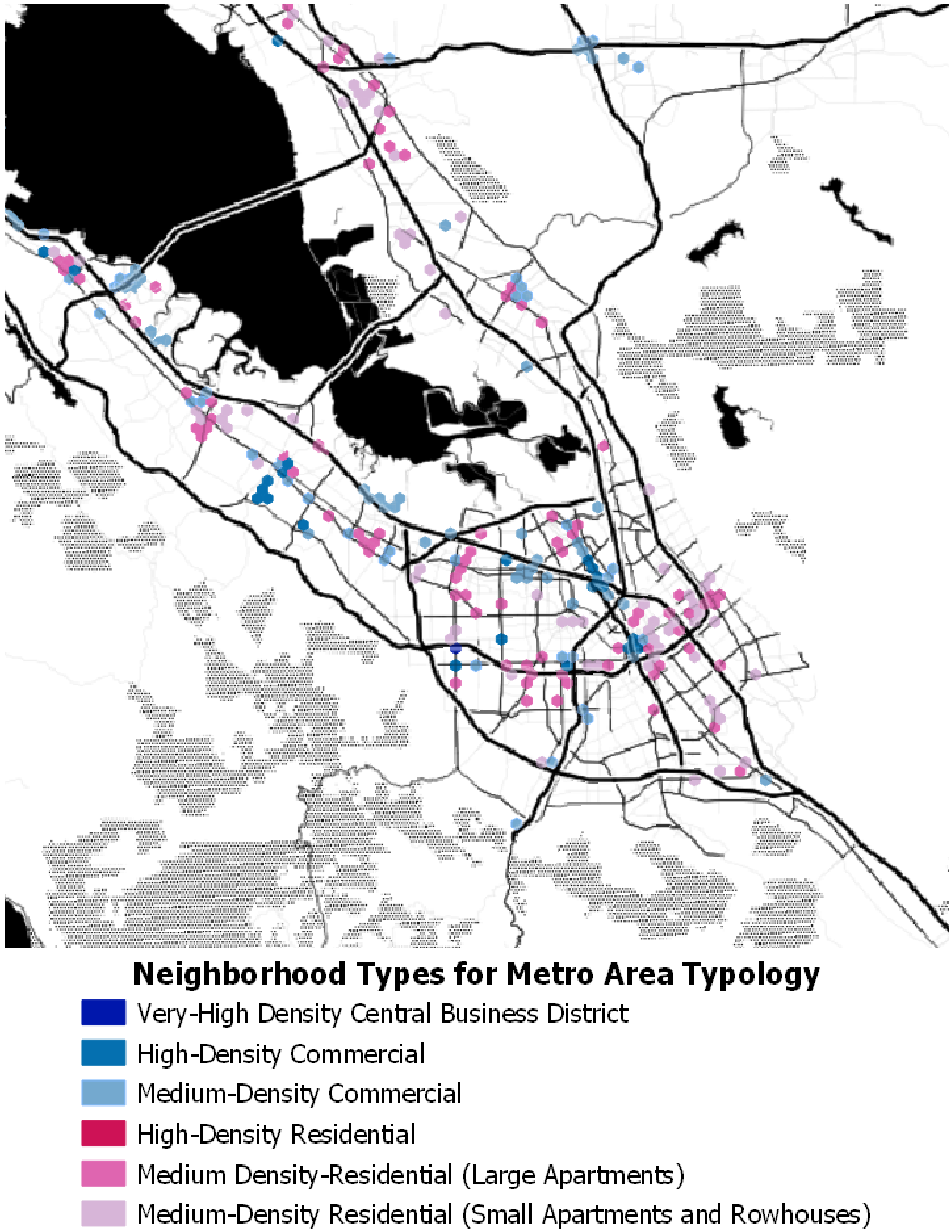

Figure J.30: San Jose-Sunnyvale-Santa Clara, CA MSA map of dense neighborhoods used in my metro area typology. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table J.31: Prevalence of Dense Neighborhood Types in Seattle

Neighborhood Type	# Hexes	Pop.	% Pop.	Jobs	% Jobs
Central Business District	3	9,000	0.2%	123,000	7.2%
High-Density Commercial	28	42,000	1.1%	186,000	11.0%
Medium-Density Commercial	48	57,000	1.5%	175,000	10.3%
High-Density Residential	10	50,000	1.3%	25,000	1.5%
Medium-Density Residential (Large Apartments)	43	101,000	2.7%	40,000	2.3%
Medium-Density Residential (Small Apartments)	18	39,000	1.0%	16,000	1.0%

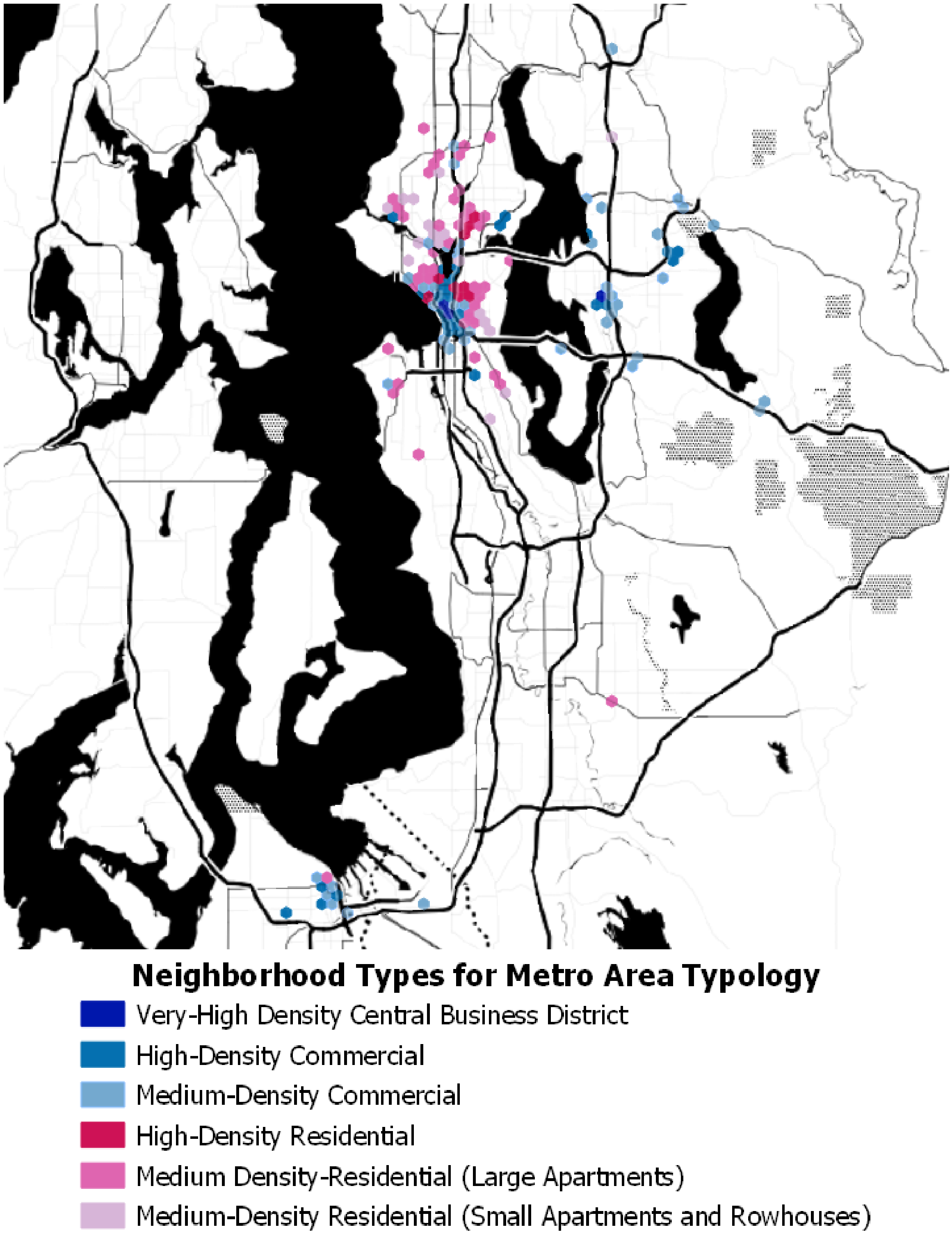

Figure J.31: Seattle-Tacoma-Bellevue, WA MSA map of dense neighborhoods used in my metro area typology. Seattle is in the upper center and Tacoma is to the lower left. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table J.32: Prevalence of Dense Neighborhood Types in St. Louis

Neighborhood Type	# Hexes	Pop.	% Pop.	Jobs	% Jobs
Central Business District	0	0	0%	0	0%
High-Density Commercial	19	17,000	0.6%	126,000	10.3%
Medium-Density Commercial	15	10,000	0.4%	47,000	3.8%
High-Density Residential	0	0	0%	0	0%
Medium-Density Residential (Large Apartments)	1	2,000	0.1%	1,000	0.1%
Medium-Density Residential (Small Apartments)	23	44,000	1.6%	8,000	0.6%

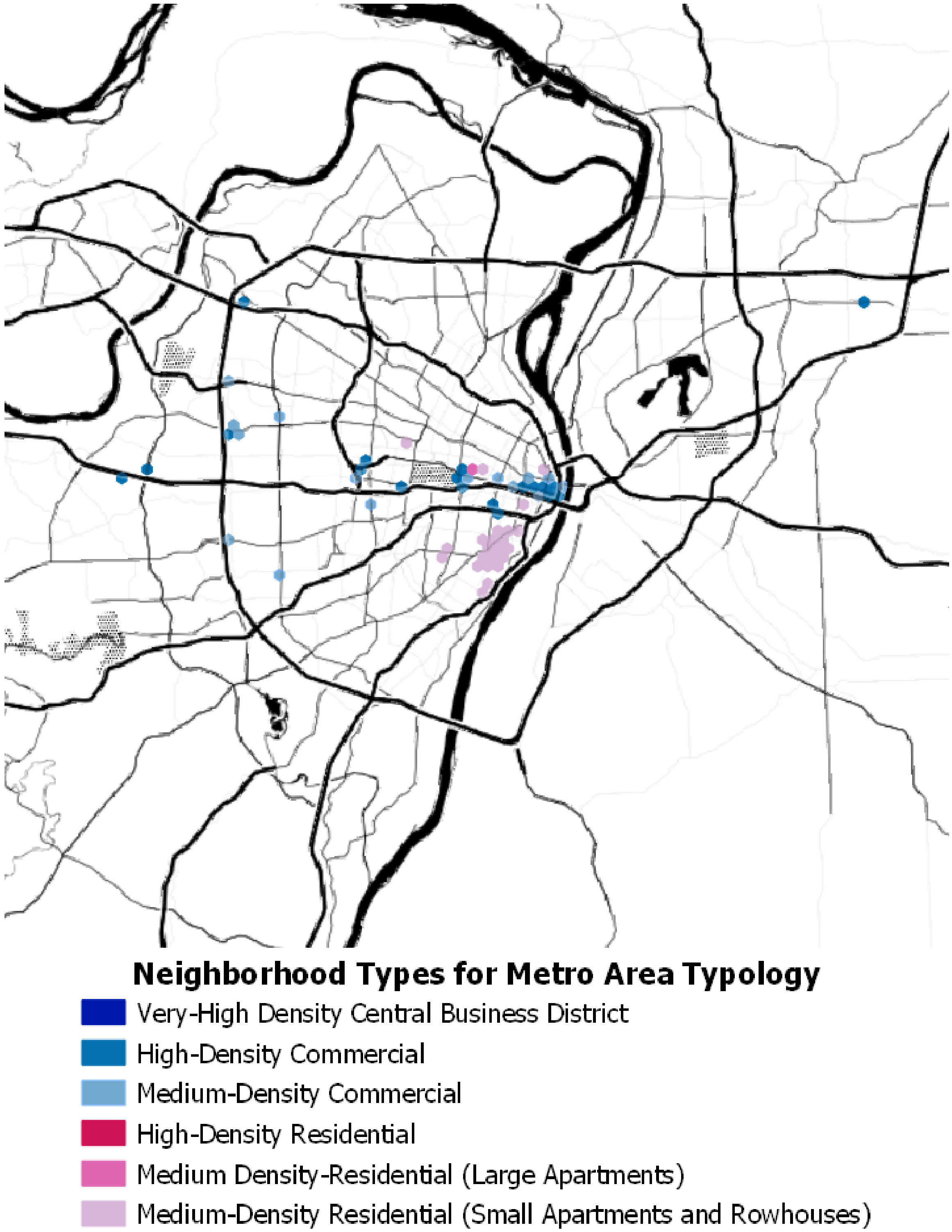

Figure J.32: St. Louis, MO-IL MSA map of dense neighborhoods used in my metro area typology. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table J.33: Prevalence of Dense Neighborhood Types in Tampa

Neighborhood Type	# Hexes	Pop.	% Pop.	Jobs	% Jobs
Central Business District	0	0	0%	0	0%
High-Density Commercial	24	13,000	0.4%	97,000	8.1%
Medium-Density Commercial	28	18,000	0.6%	76,000	6.3%
High-Density Residential	0	0	0%	0	0%
Medium-Density Residential (Large Apartments)	7	12,000	0.4%	2,000	0.2%
Medium-Density Residential (Small Apartments)	1	1,000	0.0%	1,000	0.1%

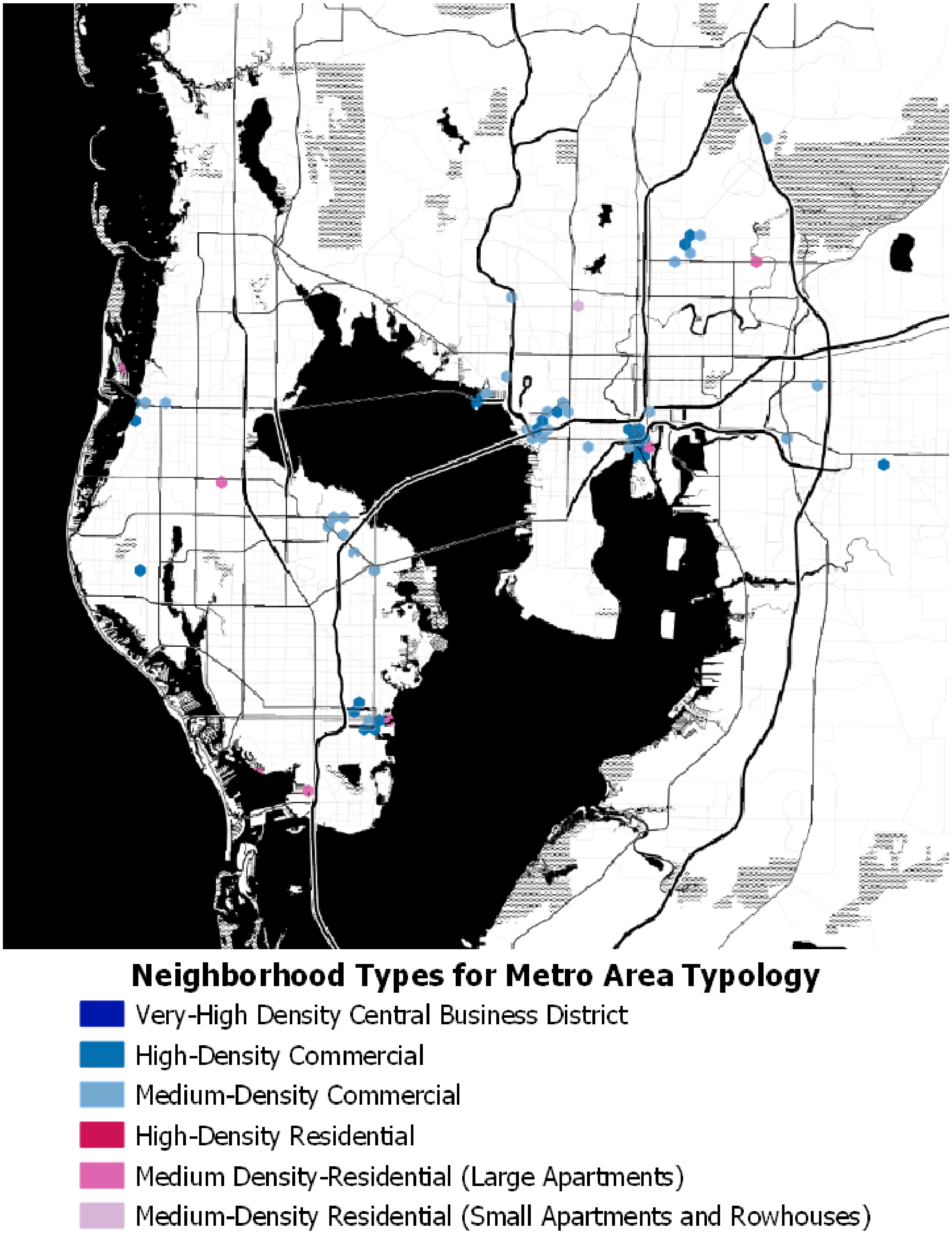

Figure J.33: Tampa-St. Petersburg-Clearwater, FL MSA map of dense neighborhoods used in my metro area typology. Tampa is to the upper right and St. Petersburg is to the lower left. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table J.34: Prevalence of Dense Neighborhood Types in Urbana-Champaign, IL

Neighborhood Type	# Hexes	Pop.	% Pop.	Jobs	% Jobs
Central Business District	0	0	0%	0	0%
High-Density Commercial	1	1,000	0.3%	7,000	9.8%
Medium-Density Commercial	1	0	0.2%	3,000	3.8%
High-Density Residential	1	7,000	3.1%	1,000	2.0%
Medium-Density Residential (Large Apartments)	4	11,000	4.8%	2,000	3.6%
Medium-Density Residential (Small Apartments)	0	0	0%	0	0%

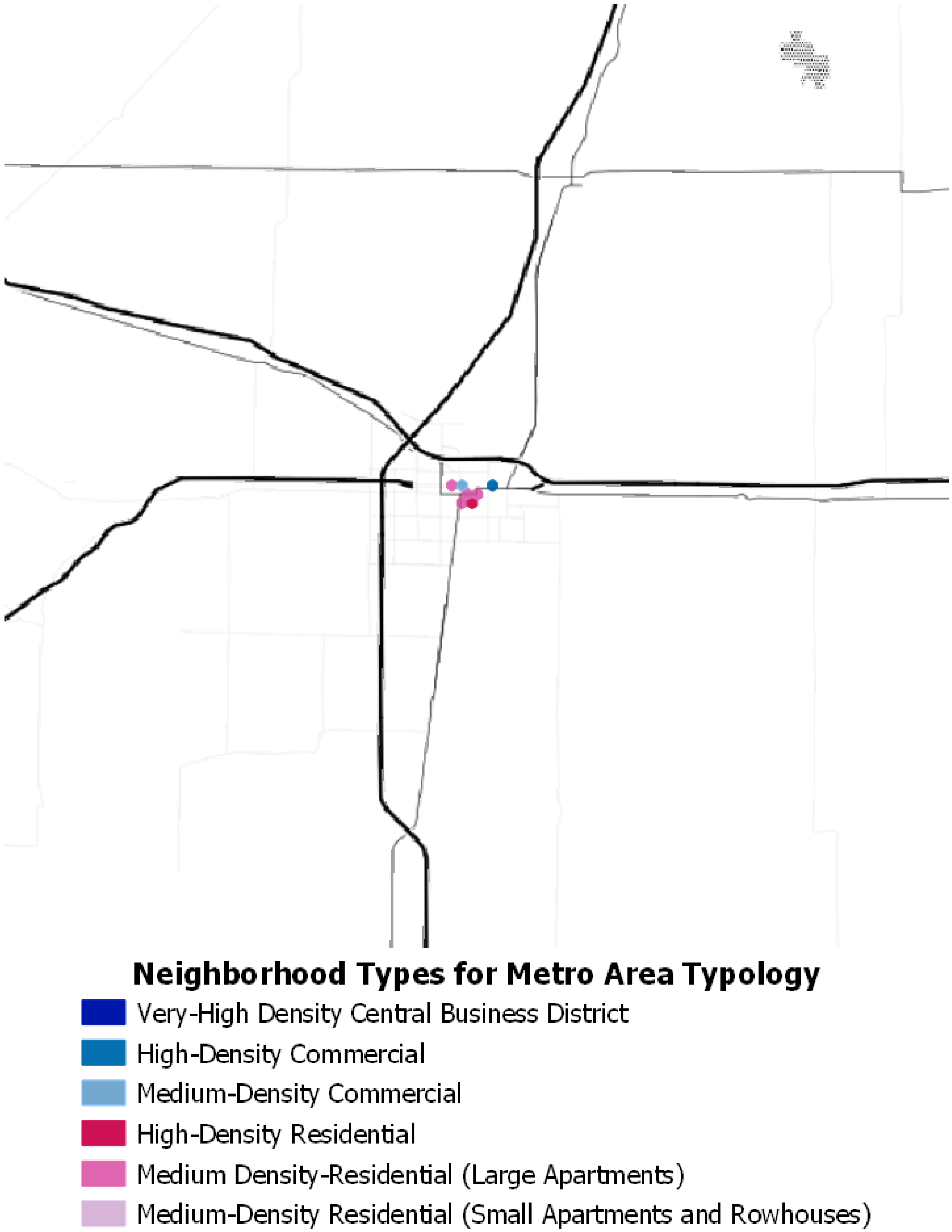

Figure J.34: Champaign-Urbana, IL MSA map of dense neighborhoods used in my metro area typology. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Table J.35: Prevalence of Dense Neighborhood Types in Washington

Neighborhood Type	# Hexes	Pop.	% Pop.	Jobs	% Jobs
Central Business District	7	18,000	0.3%	223,000	8.2%
High-Density Commercial	63	95,000	1.6%	480,000	17.6%
Medium-Density Commercial	108	136,000	2.2%	317,000	11.7%
High-Density Residential	30	163,000	2.7%	59,000	2.2%
Medium-Density Residential (Large Apartments)	60	173,000	2.8%	41,000	1.5%
Medium-Density Residential (Small Apartments)	71	188,000	3.1%	41,000	1.5%

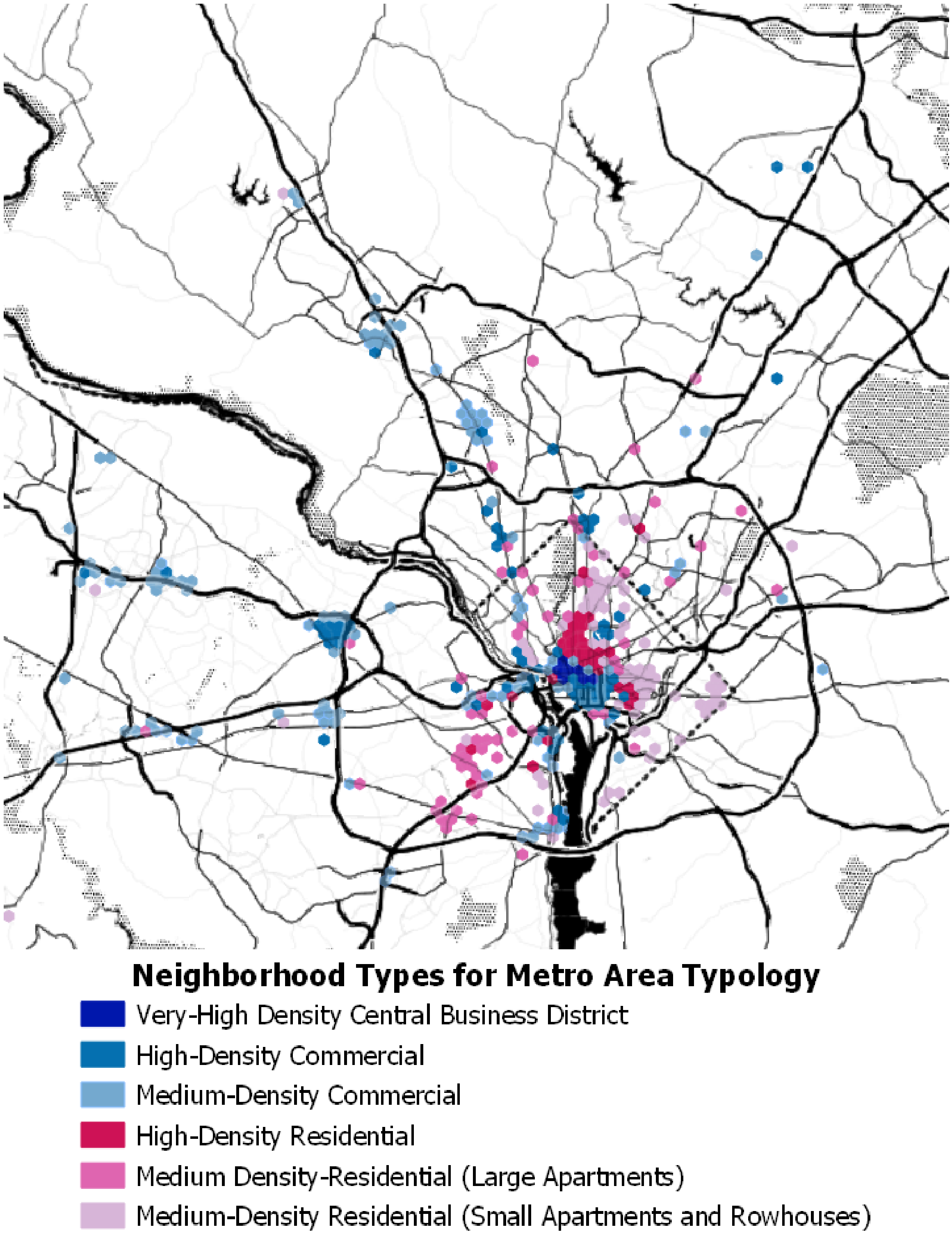

Figure J.35: Washington-Arlington-Alexandria DC-VA-MD-WV MSA map of dense neighborhoods used in my metro area typology. The area shown is a 40-mile by 40-mile square. Roads and water features by Stamen Design used under Creative Commons CC BY 3.0 license.

Appendix K: Median Job and Population Density Tables

This appendix contains four tables of the median activity densities experienced by different groups for each of the 60 largest US metro areas. These tables were were produced as part of the analyses in Sections 3.3.3 and Sections 4.4.5.

Table K.1 on page 683 shows the median activity densities of residents—in other words, the activity density of the hex where the median resident lives for each metro area—along with the ratios between the median activity densities of non-Hispanic white, non-Hispanic Black, Latin of any race, non-Hispanic Asian, and non-Hispanic of some other race residents and the median activity density of all residents for each metro area.

Table K.2 on page 686 shows the median activity densities of jobs—in other words, the activity density of the hex where the median job is located for each metro area—along with the ratios between the median activity densities of low-income (earning less than $1,250 per month), middle-income (earning $1,251–$3,333 per month), and high-income (earning more than $3,333 per month) jobs and the median activity density of all jobs for each metro area.

Table K.3 on page 689 shows the percentage of workers who commute by transit, the median activity densities of workers—in other words, the activity density of the hex where the median worker lives for each metro area—along with the median activity densities of workers who commute by transit and the ratio between the median activity densities of workers commuting by transit and the median activity density of all workers for each metro area.

Table K.3 on page 692 shows the percentage of carfree households, the median activity densities of households—in other words, the activity density of the hex where the median household is located for each metro area—along with the median activity densities of carfree households and the ratio between the median activity densities of carfree households and all households for each metro area.

Table K.1: Median Density of Residents by Race in Large Metros

Metro Area	**Median Activity Density of Residents (/ sq. mi.)**	**White Median / Overall Median**	**Black Median / Overall Median**	**Latin Median / Overall Median**	**Asian Median / Overall Median**	**Other Median / Overall Median**
Albuquerque	4,900	97%	121%	101%	107%	91%
Atlanta	2,600	78%	114%	139%	140%	107%
Austin	4,100	91%	114%	110%	112%	102%
Baltimore	5,300	74%	166%	123%	95%	102%
Birmingham	1,700	73%	151%	111%	137%	105%
Boston	5,300	68%	311%	324%	202%	144%
Bridgeport	4,500	58%	237%	235%	120%	131%
Buffalo	4,500	79%	189%	173%	150%	124%
Charlotte	2,200	78%	133%	139%	146%	114%
Chicago	6,500	76%	138%	155%	114%	104%
Cincinnati	3,000	87%	184%	136%	116%	128%
Cleveland	4,000	80%	160%	148%	110%	131%
Columbus	4,100	84%	143%	139%	133%	125%
Dallas	5,100	83%	107%	119%	111%	102%
Denver	6,300	91%	132%	122%	104%	104%

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Table K.1 – *Continued from previous page*

Metro Area	**Median Activity Density of Residents (/ sq. mi.)**	**White Median / Overall Median**	**Black Median / Overall Median**	**Latin Median / Overall Median**	**Asian Median / Overall Median**	**Other Median / Overall Median**
Detroit	4,500	86%	133%	118%	99%	110%
Fresno	5,900	91%	128%	104%	101%	97%
Grand Rapids	2,500	80%	251%	222%	140%	153%
Hartford	2,600	74%	221%	268%	115%	126%
Honolulu	9,900	81%	100%	97%	116%	89%
Houston	4,900	80%	107%	118%	106%	96%
Indianapolis	2,900	88%	150%	147%	101%	113%
Jacksonville	3,000	87%	125%	121%	120%	100%
Kansas City	3,200	91%	117%	128%	131%	104%
Las Vegas	8,000	90%	109%	115%	97%	100%
Los Angeles	13,000	77%	113%	116%	92%	89%
Louisville	3,500	85%	153%	123%	130%	114%
Memphis	3,100	73%	119%	138%	91%	92%
Miami	8,200	77%	105%	117%	88%	91%
Milwaukee	5,200	65%	177%	190%	114%	136%
Minneapolis	3,700	87%	194%	156%	143%	129%
Nashville	2,200	79%	166%	169%	143%	130%
New Orleans	5,800	84%	110%	122%	107%	94%
New York	17,700	44%	174%	186%	142%	143%
Oklahoma City	3,500	84%	117%	142%	116%	97%
Omaha	4,400	90%	117%	131%	126%	111%
Orlando	3,800	87%	129%	109%	97%	106%
Philadelphia	5,400	73%	262%	195%	114%	113%
Phoenix	5,600	87%	118%	127%	99%	104%
Pittsburgh	2,600	87%	219%	151%	198%	155%
Portland	5,900	94%	139%	122%	118%	110%
Providence	4,200	72%	259%	301%	142%	190%

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Table K.1 – *Continued from previous page*

Metro Area	Median Activity Density of Residents (/ sq. mi.)	White Median / Overall Median	Black Median / Overall Median	Latin Median / Overall Median	Asian Median / Overall Median	Other Median / Overall Median
Raleigh	2,700	89%	116%	94%	145%	104%
Richmond	2,800	84%	120%	120%	131%	103%
Riverside	5,300	74%	113%	117%	102%	94%
Rochester	2,600	81%	347%	281%	134%	144%
Sacramento	6,200	85%	130%	117%	115%	111%
Salt Lake City	6,300	95%	125%	118%	110%	112%
San Antonio	4,900	73%	104%	114%	106%	91%
San Diego	8,200	79%	121%	123%	105%	93%
San Francisco	11,100	77%	118%	115%	115%	98%
San Jose	10,800	85%	112%	112%	103%	100%
Seattle	5,500	91%	127%	115%	113%	106%
St. Louis	3,300	86%	147%	117%	133%	118%
Tampa	4,400	93%	126%	110%	102%	105%
Tucson	3,800	81%	132%	123%	115%	90%
Tulsa	2,600	87%	133%	172%	161%	71%
Virginia Beach	4,400	86%	120%	121%	119%	109%
Washington	5,900	81%	117%	141%	104%	95%
Worcester	1,900	78%	324%	347%	156%	138%

Table K.2: Median Density of Jobs by Income in Large Metros

Metro Area	**Median Activity Density of Jobs (/ sq. mi.)**	**Low-Income Median / Overall Median**	**Middle-Income Median / Overall Median**	**High-Income Median / Overall Median**
Albuquerque	7,500	100%	99%	102%
Atlanta	6,900	83%	85%	129%
Austin	8,600	93%	92%	111%
Baltimore	8,400	93%	95%	108%
Birmingham	4,600	94%	94%	115%
Boston	12,200	80%	82%	122%
Bridgeport	8,600	90%	91%	116%
Buffalo	6,500	97%	96%	106%
Charlotte	5,000	95%	90%	118%
Chicago	10,500	91%	92%	113%
Cincinnati	6,100	95%	94%	107%
Cleveland	6,200	96%	94%	106%
Columbus	7,100	99%	96%	104%
Dallas	9,000	89%	89%	121%
Denver	10,000	95%	93%	109%
Detroit	7,100	91%	94%	112%
Fresno	8,000	103%	98%	99%
Grand Rapids	6,300	108%	94%	97%
Hartford	5,400	86%	87%	116%
Honolulu	23,700	97%	97%	109%
Houston	9,000	96%	93%	109%
Indianapolis	6,600	93%	92%	111%
Jacksonville	6,200	90%	92%	115%
Kansas City	6,000	93%	93%	116%
Las Vegas	11,400	92%	102%	105%
Los Angeles	17,000	105%	92%	105%
Louisville	6,500	96%	95%	107%

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Table K.2 – *Continued from previous page*

Metro Area	Median Activity Density of Jobs (/ sq. mi.)	Low-Income Median / Overall Median	Middle-Income Median / Overall Median	High-Income Median / Overall Median
Memphis	5,700	100%	92%	107%
Miami	11,000	96%	97%	106%
Milwaukee	7,300	100%	96%	103%
Minneapolis	8,200	89%	90%	112%
Nashville	6,800	84%	87%	127%
New Orleans	8,900	100%	100%	100%
New York	25,900	79%	84%	142%
Oklahoma City	5,400	100%	98%	101%
Omaha	7,200	93%	96%	111%
Orlando	8,100	96%	93%	112%
Philadelphia	8,000	93%	94%	107%
Phoenix	9,900	90%	93%	112%
Pittsburgh	6,000	88%	92%	113%
Portland	9,800	95%	93%	111%
Providence	6,300	95%	98%	103%
Raleigh	6,000	92%	89%	114%
Richmond	6,000	92%	91%	118%
Riverside	7,100	103%	100%	99%
Rochester	6,000	97%	95%	111%
Sacramento	8,000	99%	95%	107%
Salt Lake City	8,800	99%	98%	101%
San Antonio	8,000	100%	94%	104%
San Diego	11,800	98%	95%	104%
San Francisco	19,600	85%	80%	119%
San Jose	15,700	85%	85%	113%
Seattle	12,500	81%	81%	134%
St. Louis	6,500	89%	94%	119%

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Table K.2 – *Continued from previous page*

Metro Area	**Median Activity Density of Jobs (/ sq. mi.)**	**Low-Income Median / Overall Median**	**Middle-Income Median / Overall Median**	**High-Income Median / Overall Median**
Tampa	7,500	90%	93%	119%
Tucson	6,800	98%	97%	107%
Tulsa	5,400	100%	98%	102%
Virginia Beach	7,500	93%	95%	113%
Washington	15,200	70%	73%	138%
Worcester	4,400	92%	95%	109%

Table K.3: Median Density of Transit Commuters in Large Metros

Metro Area	% of Workers Who Commute by Transit	Median Activity Density of Workers (/ sq. mi.)	Median Activity Density of Transit Commuters (/ sq. mi.)	Transit Commuter Median / Overall Median
New York	31.9%	17,000	55,200	320%
San Francisco	17.1%	11,800	20,000	170%
Washington	13.6%	6,200	11,700	190%
Boston	13.3%	5,500	18,200	330%
Chicago	12.1%	6,500	17,500	270%
Bridgeport	10.0%	4,800	5,300	110%
Seattle	9.9%	5,800	9,400	160%
Philadelphia	9.5%	5,100	16,100	320%
Honolulu	9.0%	10,400	16,100	160%
Portland	6.5%	6,100	9,200	150%
Baltimore	6.4%	5,200	10,300	200%
Pittsburgh	5.7%	2,600	6,800	260%
Los Angeles	5.1%	13,100	20,500	160%
Minneapolis	4.7%	3,700	7,400	200%
San Jose	4.2%	11,100	13,100	120%
Denver	4.2%	6,400	8,200	130%
Las Vegas	3.8%	8,000	10,600	130%
Salt Lake City	3.7%	6,400	7,800	120%
Miami	3.5%	8,300	11,100	130%
Milwaukee	3.3%	4,800	10,000	210%
Buffalo	3.3%	4,400	9,100	210%
Atlanta	3.1%	2,700	4,500	170%
Cleveland	3.0%	3,800	6,900	180%
San Diego	2.9%	8,400	12,500	150%
New Orleans	2.8%	5,900	8,300	140%
Hartford	2.8%	2,500	7,000	280%

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Table K.3 – *Continued from previous page*

Metro Area	% of Workers Who Commute by Transit	Median Activity Density of Workers (/ sq. mi.)	Median Activity Density of Transit Commuters (/ sq. mi.)	Transit Commuter Median / Overall Median
Providence	2.6%	3,800	7,000	180%
Tucson	2.5%	4,000	6,900	170%
St. Louis	2.5%	3,400	5,700	170%
Sacramento	2.4%	6,300	7,300	120%
Rochester	2.3%	2,600	9,200	360%
Austin	2.2%	4,400	7,700	170%
Houston	2.1%	5,100	7,000	140%
San Antonio	2.0%	5,000	6,800	140%
Phoenix	2.0%	5,800	8,900	150%
Louisville	1.9%	3,500	6,600	190%
Cincinnati	1.9%	3,000	6,000	200%
Orlando	1.8%	3,900	6,200	160%
Columbus	1.7%	4,200	7,100	170%
Albuquerque	1.6%	5,000	6,700	130%
Worcester	1.6%	1,700	3,300	190%
Charlotte	1.6%	2,300	4,400	190%
Richmond	1.6%	2,800	4,900	180%
Grand Rapids	1.5%	2,500	6,500	260%
Virginia Beach	1.5%	4,500	6,400	140%
Dallas	1.4%	5,200	6,900	130%
Riverside	1.4%	5,500	7,100	130%
Detroit	1.4%	4,400	5,900	140%
Tampa	1.4%	4,500	6,400	140%
Jacksonville	1.2%	3,100	4,600	150%
Fresno	1.2%	5,900	8,300	140%
Nashville	1.1%	2,300	4,200	180%
Kansas City	1.0%	3,300	4,700	140%

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Table K.3 – *Continued from previous page*

Metro Area	**% of Workers Who Commute by Transit**	**Median Activity Density of Workers (/ sq. mi.)**	**Median Activity Density of Transit Commuters (/ sq. mi.)**	**Transit Commuter Median / Overall Median**
Indianapolis	1.0%	2,900	5,200	180%
Raleigh	.9%	2,900	4,800	170%
Memphis	.9%	3,100	4,400	140%
Omaha	.9%	4,500	5,700	130%
Birmingham	.6%	1,800	3,300	180%
Tulsa	.5%	2,700	4,600	170%
Oklahoma City	.4%	3,600	4,600	130%

Table K.4: Median Density of Carfree Households in Large Metros

Metro Area	% Carfree Households	Median Activity Density of Households (/ sq. mi.)	Median Activity Density of Carfree Households (/ sq. mi.)	Carfree Household Median / Overall Median
New York	30.7%	19,200	67,800	350%
Boston	13.1%	5,600	21,500	390%
Philadelphia	13.0%	5,500	17,600	320%
Buffalo	12.6%	4,600	7,100	150%
San Francisco	12.2%	11,500	29,800	260%
Chicago	12.0%	6,700	16,000	240%
Baltimore	10.9%	5,500	11,300	210%
Pittsburgh	10.6%	2,700	5,600	200%
Cleveland	10.5%	4,200	6,400	150%
New Orleans	10.3%	5,900	7,600	130%
Rochester	10.3%	2,700	6,100	220%
Honolulu	10.2%	10,700	26,100	240%
Providence	10.0%	4,300	10,300	240%
Milwaukee	9.8%	5,100	9,000	170%
Washington	9.7%	6,400	16,200	260%
Hartford	9.1%	2,600	7,100	270%
Worcester	9.0%	1,900	6,000	320%
Detroit	8.9%	4,600	5,700	130%
Fresno	8.5%	6,100	8,000	130%
Tucson	8.4%	3,800	6,400	170%
Las Vegas	8.4%	8,000	10,300	130%
Miami	8.2%	8,300	10,700	130%
Seattle	8.1%	5,800	11,200	190%
Los Angeles	7.9%	13,000	19,400	150%
Portland	7.9%	6,100	9,200	150%
Cincinnati	7.8%	3,100	5,400	170%

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Table K.4 – *Continued from previous page*

Metro Area	% Carfree Households	Median Activity Density of Households (/ sq. mi.)	Median Activity Density of Carfree Households (/ sq. mi.)	Carfree Household Median / Overall Median
Memphis	7.8%	3,200	3,900	120%
St. Louis	7.7%	3,500	4,800	140%
Bridgeport	7.7%	4,600	11,500	250%
Louisville	7.7%	3,700	5,600	150%
Minneapolis	7.2%	3,800	8,000	210%
Richmond	7.0%	2,800	4,600	160%
Tampa	6.9%	4,500	5,900	130%
Virginia Beach	6.8%	4,400	5,700	130%
Columbus	6.5%	4,200	5,800	140%
San Antonio	6.5%	5,000	6,500	130%
Indianapolis	6.3%	3,000	4,600	150%
Sacramento	6.3%	6,200	7,900	130%
Jacksonville	6.3%	3,200	4,400	140%
Grand Rapids	6.2%	2,500	4,700	190%
Birmingham	6.1%	1,800	2,700	150%
Kansas City	6.1%	3,300	4,100	120%
Phoenix	6.0%	5,600	8,100	150%
Omaha	6.0%	4,500	5,600	120%
Atlanta	5.9%	2,700	4,000	150%
Tulsa	5.9%	2,700	3,800	140%
Albuquerque	5.8%	5,000	6,700	130%
Denver	5.7%	6,500	9,300	140%
San Diego	5.5%	8,300	12,500	150%
Orlando	5.4%	3,900	4,900	130%
Houston	5.2%	5,100	6,600	130%
Salt Lake City	5.2%	6,600	8,300	130%
San Jose	5.1%	10,800	13,200	120%

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Table K.4 – *Continued from previous page*

Metro Area	**% Carfree Households**	**Median Activity Density of Households (/ sq. mi.)**	**Median Activity Density of Carfree Households (/ sq. mi.)**	**Carfree Household Median / Overall Median**
Charlotte	5.1%	2,300	3,100	130%
Oklahoma City	5.0%	3,600	4,500	120%
Dallas	4.8%	5,200	6,300	120%
Nashville	4.7%	2,300	3,800	170%
Riverside	4.7%	5,000	5,900	120%
Austin	4.4%	4,400	6,800	160%
Raleigh	4.1%	2,900	3,700	130%

Appendix L: Transit and Dense Neighborhood Maps

This appendix contains maps of rapid transit, light rail, and some bus rapid transit lines in fourteen of the sixteen major metropolitan areas with the highest transit commute shares in the US (see Table 4.2 on page 232), as discussed in Section 4.4.1. Honolulu and Madison, Wisconsin are not shown because they currently have no rail transit, although a rapid transit line is currently under construction in Honolulu. All the maps are at the same scale, and show a 30-mile by 30-mile square, which means that outlying parts of larger metro areas may be left out.

The colored hexes represent the six high- and medium-density neighborhood types shown in the maps in J and described in Table 3.9 on page 149. In general, neighborhoods are shown if they have a density of roughly 15,000 activity units per square mile. The roads and water features shown are by Stamen Design and used under Creative Commons CC BY 3.0 license.

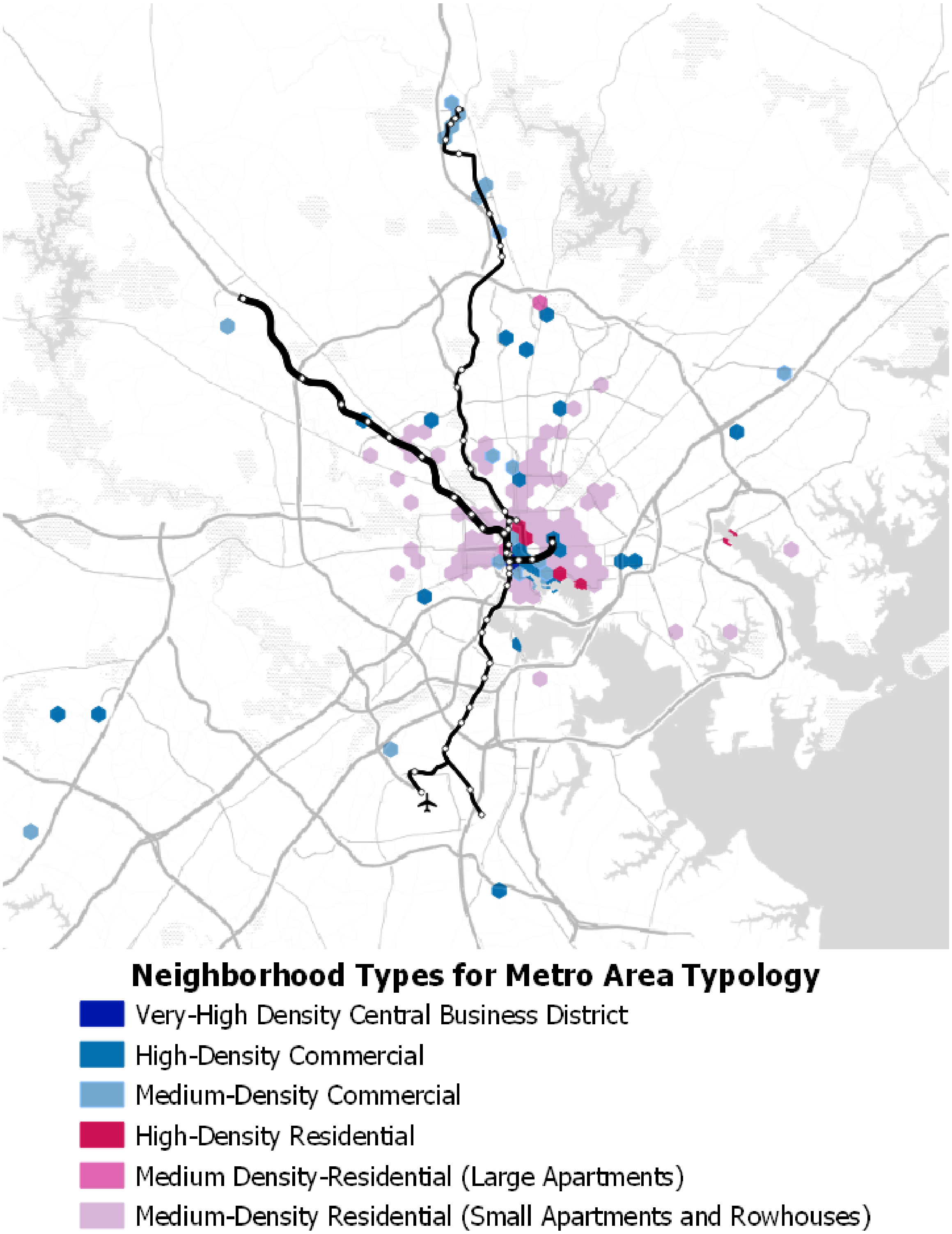

Figure L.1: Rapid transit and light rail in the Baltimore metro area. The Baltimore Metro Subway is shown with a thick line; the Baltimore Light Rail is shown with thin lines. The area shown is a 30-mile by 30-mile square.

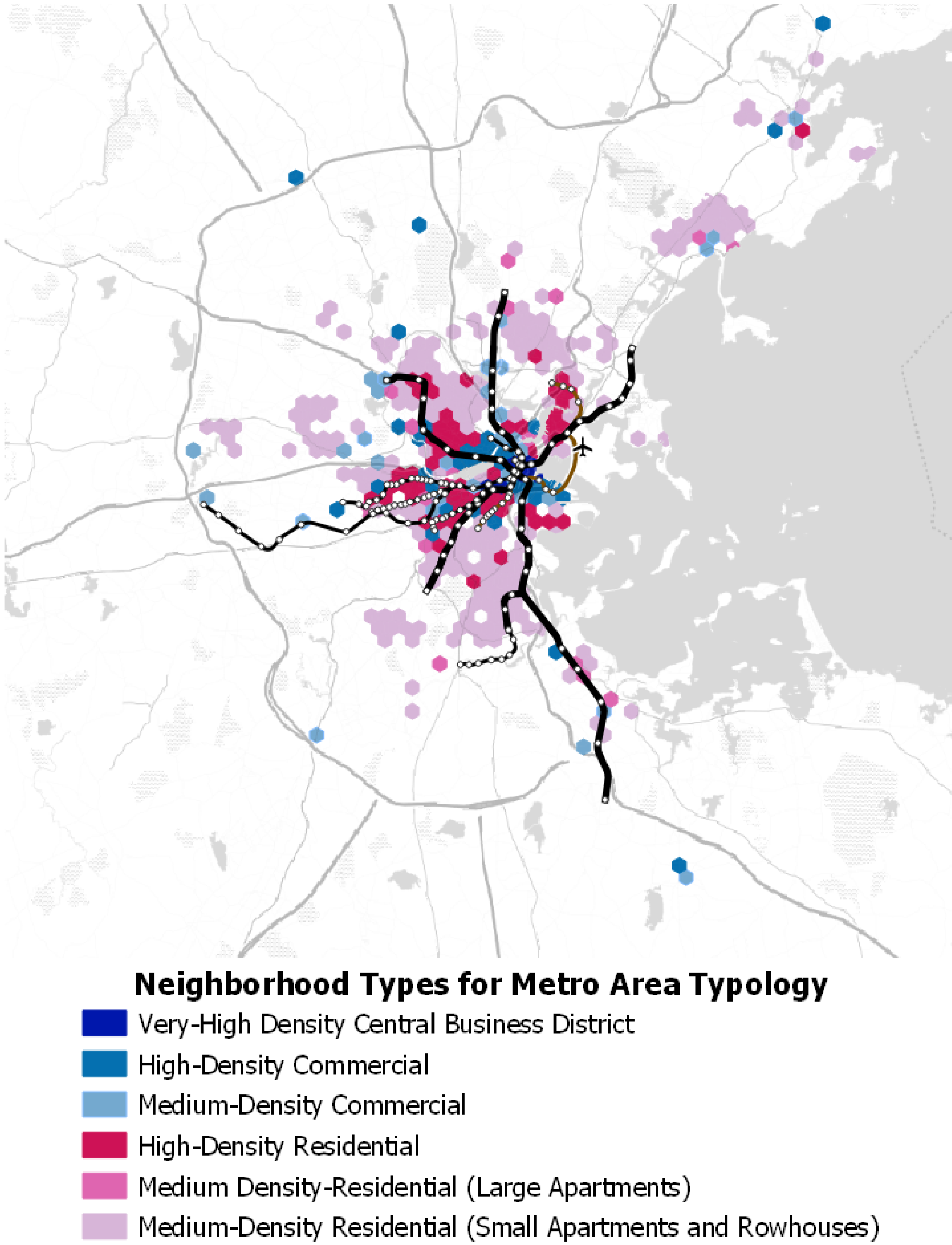

Figure L.2: Rapid transit, light rail, and bus rapid transit in the Boston metro area. The Red, Orange, and Blue Lines are shown with thick lines; the Green Line and Mattapan High-Speed Line are shown with thin lines, and the underground portion of the Silver Line are shown with thin lines. The Silver Line is shown with brown lines. The area shown is a 30-mile by 30-mile square.

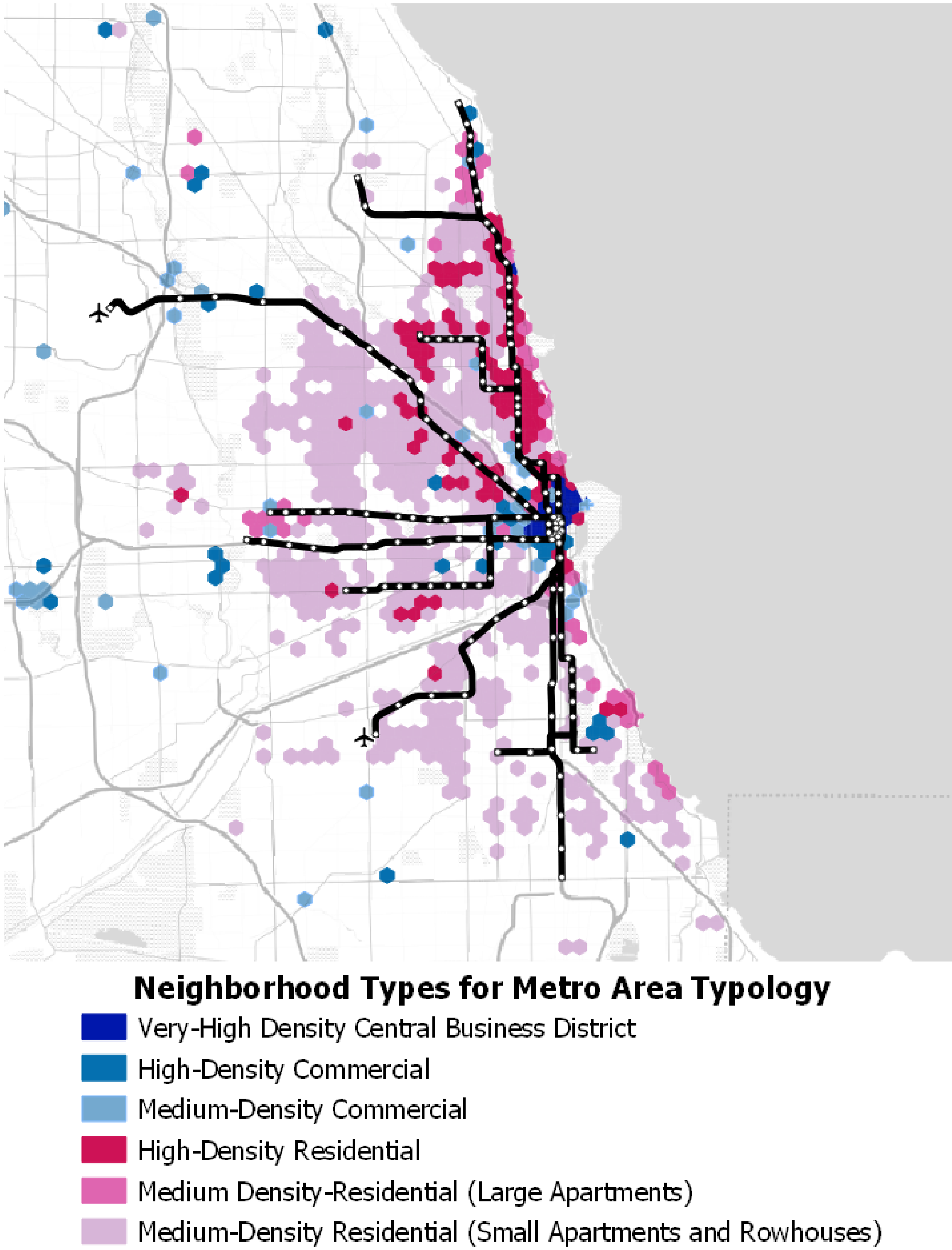

Figure L.3: Rapid transit in the Chicago metro area. The Chicago 'L' is shown with thick lines. The area shown is a 30-mile by 30-mile square.

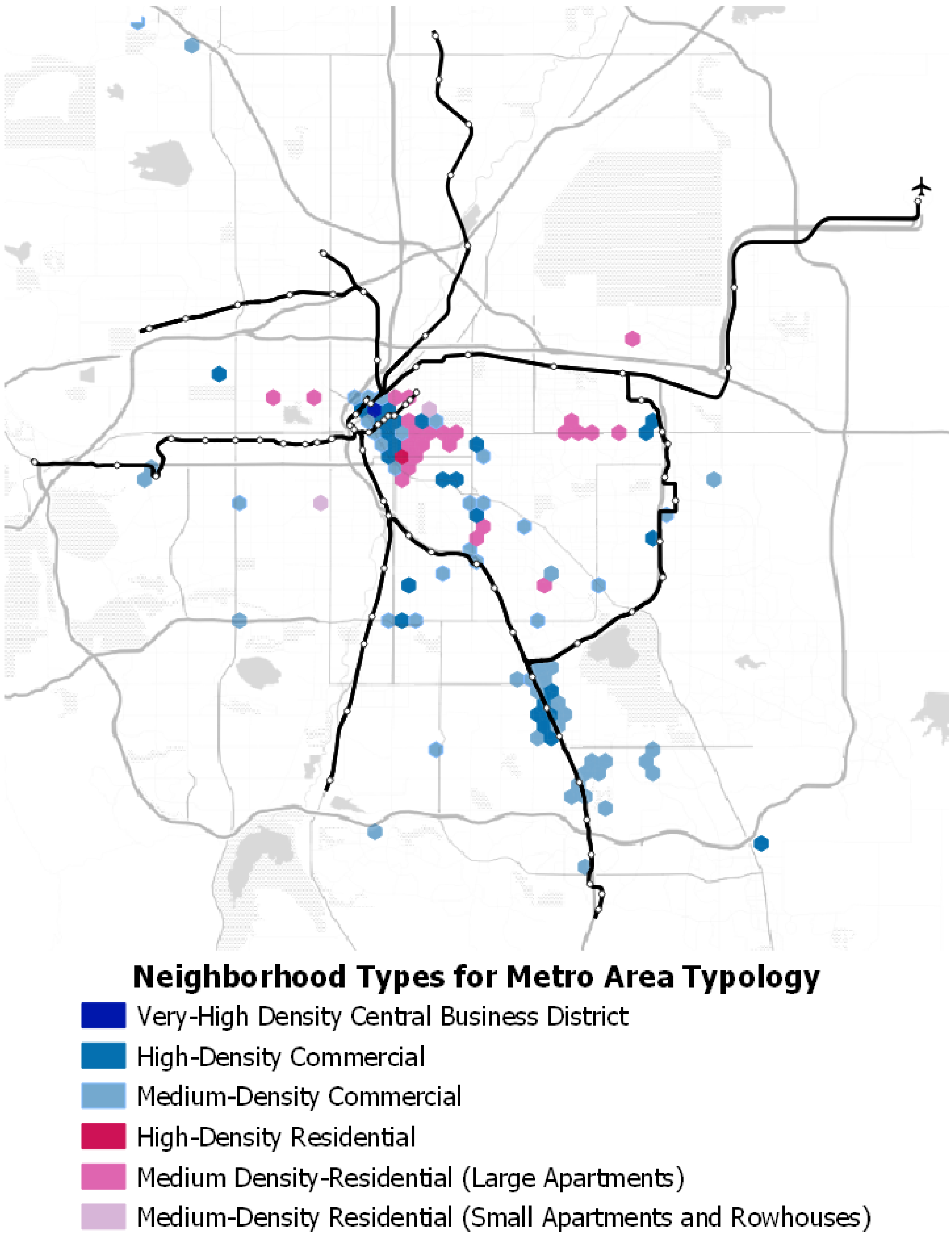

Figure L.4: Light rail and frequent commuter rail in the Denver metro area. The Denver light rail and commuter rail lines are shown with thin lines. Denver's commuter rail, uniquely in the US, operates with the same fares, headways and hours of operation as its light rail. The area shown is a 30-mile by 30-mile square.

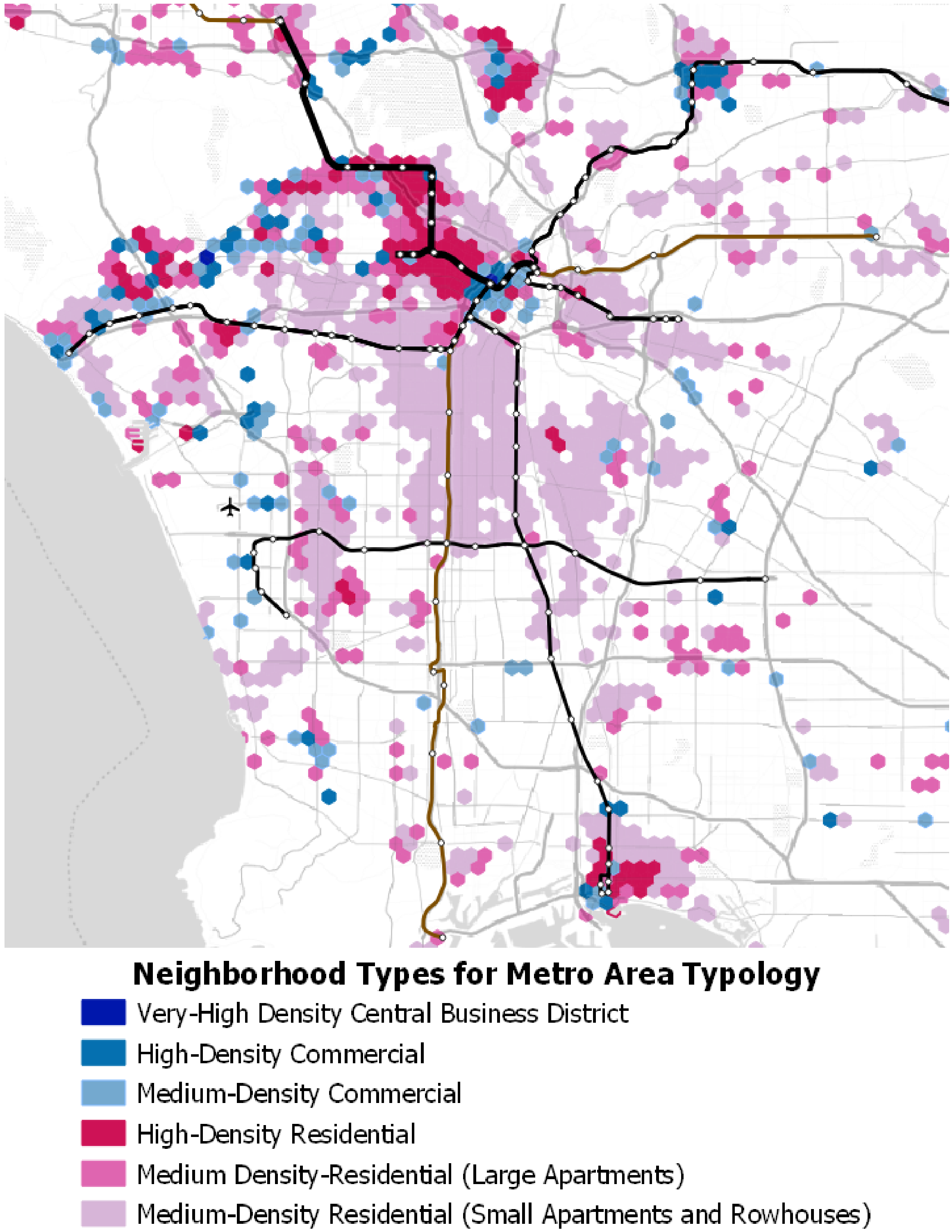

Figure L.5: Rapid transit, light rail, and bus rapid transit in the Los Angeles metro area. The Red and Purple Lines are shown with thick lines; the Blue, Expo, and Gold Lines are shown with thin lines. The Orange and Silver Lines are shown with brown lines. The area shown is a 30-mile by 30-mile square.

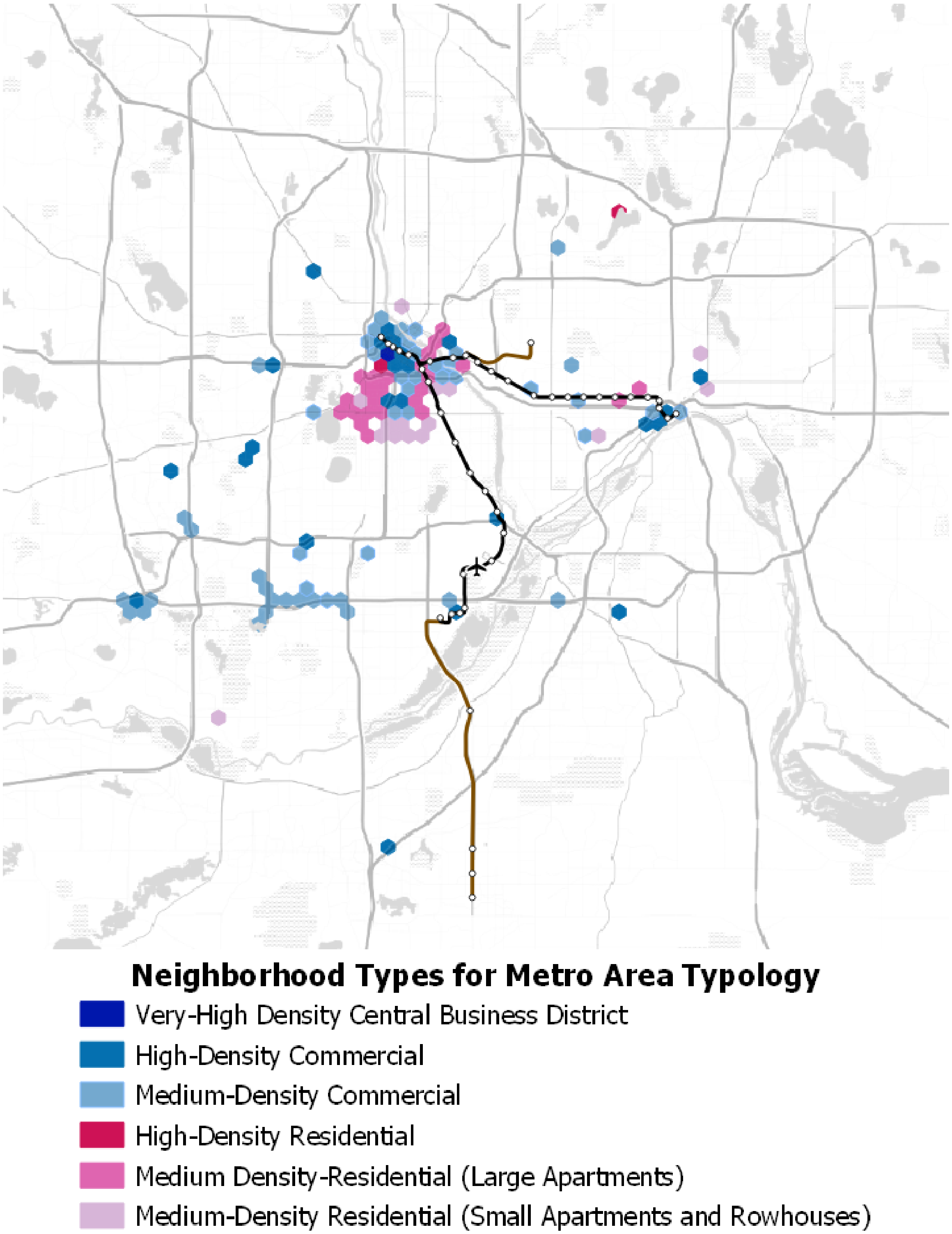

Figure L.6: Light rail and bus rapid transit in the Minneapolis metro area. The Blue and Green Lines are shown with thin lines. The Red Line and the University of Minnesota Busway are shown with brown lines. The area shown is a 30-mile by 30-mile square.

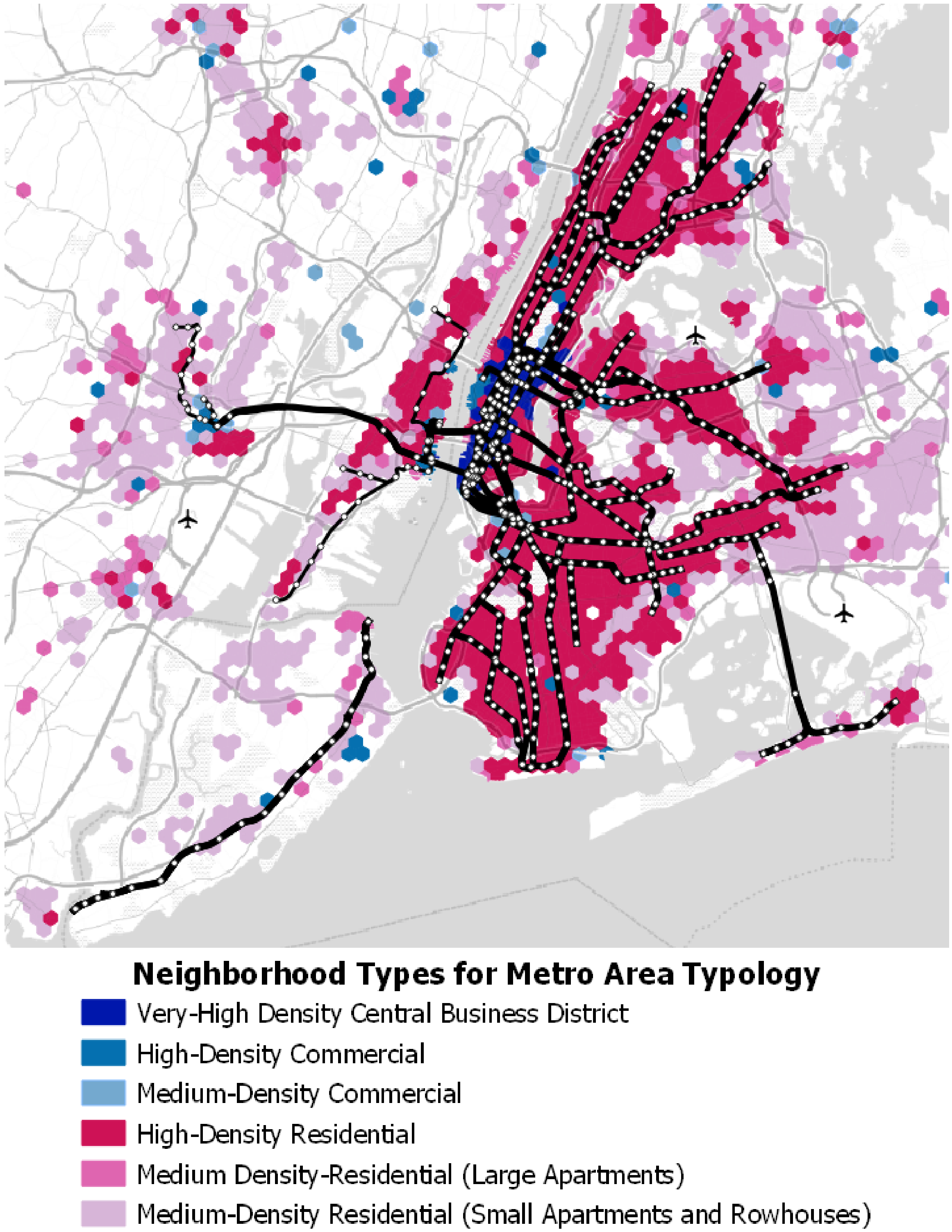

Figure L.7: Rapid transit and light rail in the New York metro area. The New York City Subway, Staten Island Rapid Transit, and PATH are shown with thick lines; the Hudson-Bergen Light Rail and Newark Light Rail are shown with thin lines. The area shown is a 30-mile by 30-mile square.

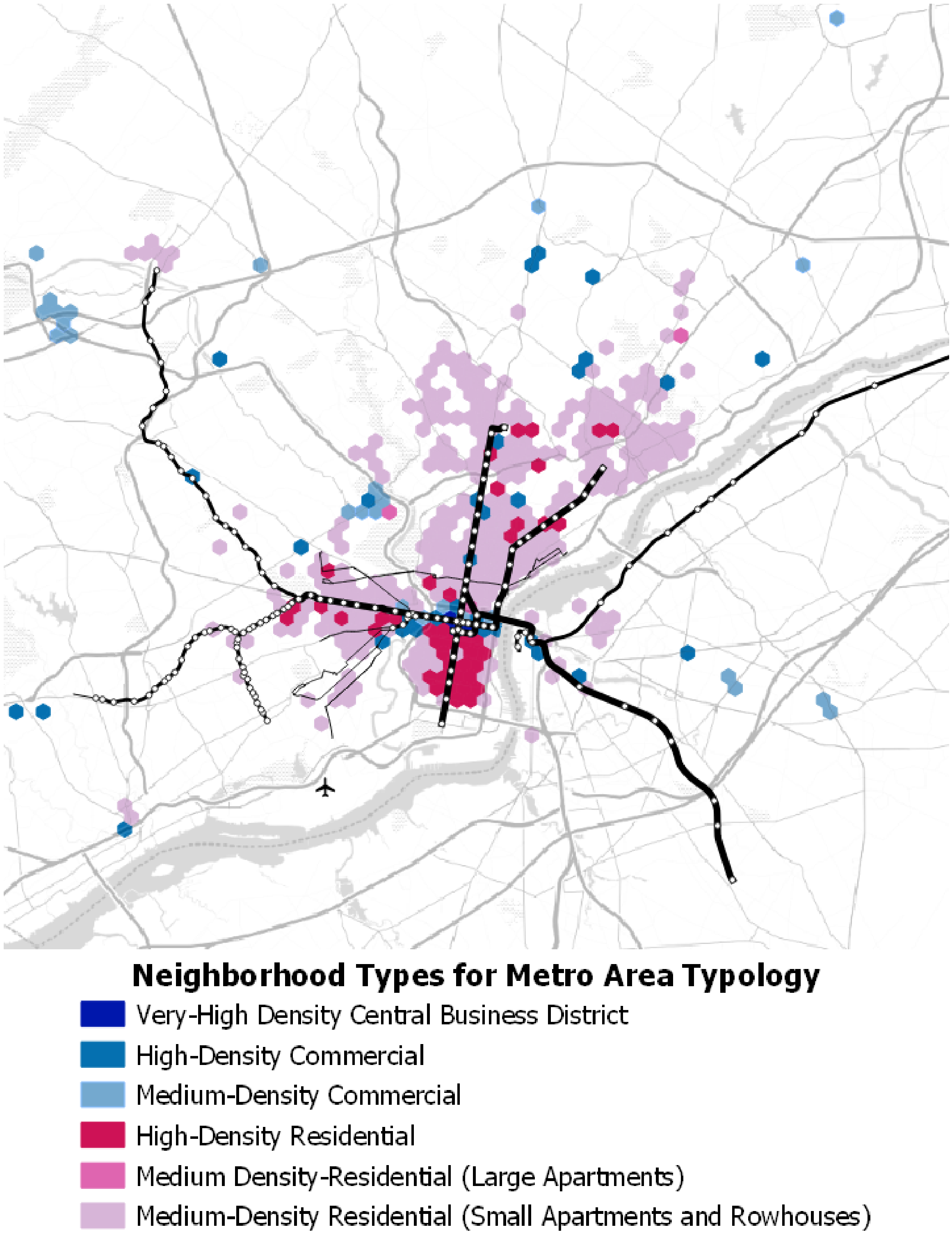

Figure L.8: Rapid transit, light rail, and streetcars in the Philadelphia metro area. The Market-Frankford Line, Broad Street Subway, PATCO Speedline, and Norristown High-Speed Line are shown with thick lines; SEPTA and New Jersey Transit light rail lines are shown with thin lines. Surface stops on SEPTA light rail lines are closely spaced and not shown. The area shown is a 30-mile by 30-mile square.

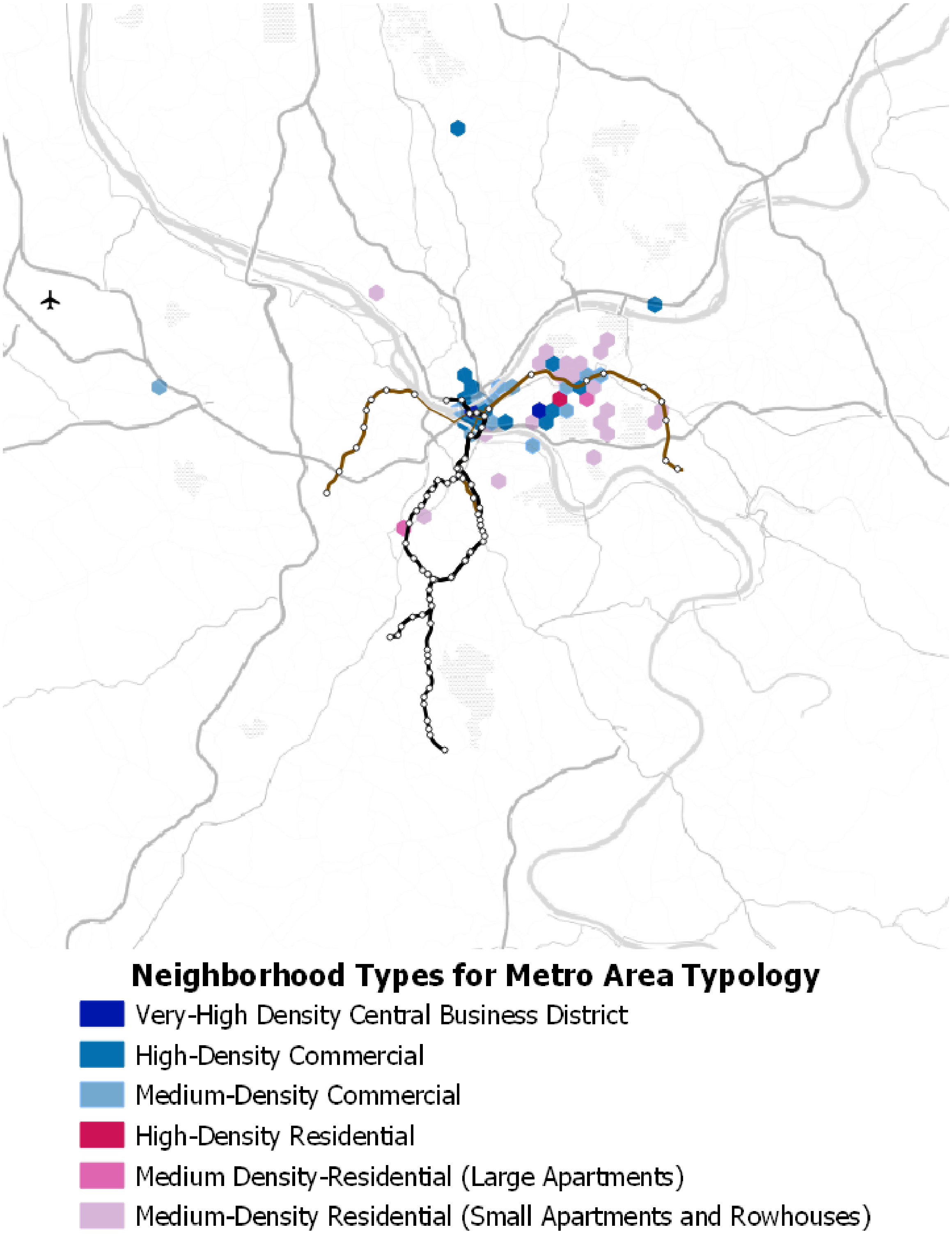

Figure L.9: Light rail and bus rapid transit in the Pittsburgh metro area. Light Rail lines are shown with thin lines; the West, South, and East Busways are shown with brown lines. Note that all busways connect downtown via street running. The area shown is a 30-mile by 30-mile square.

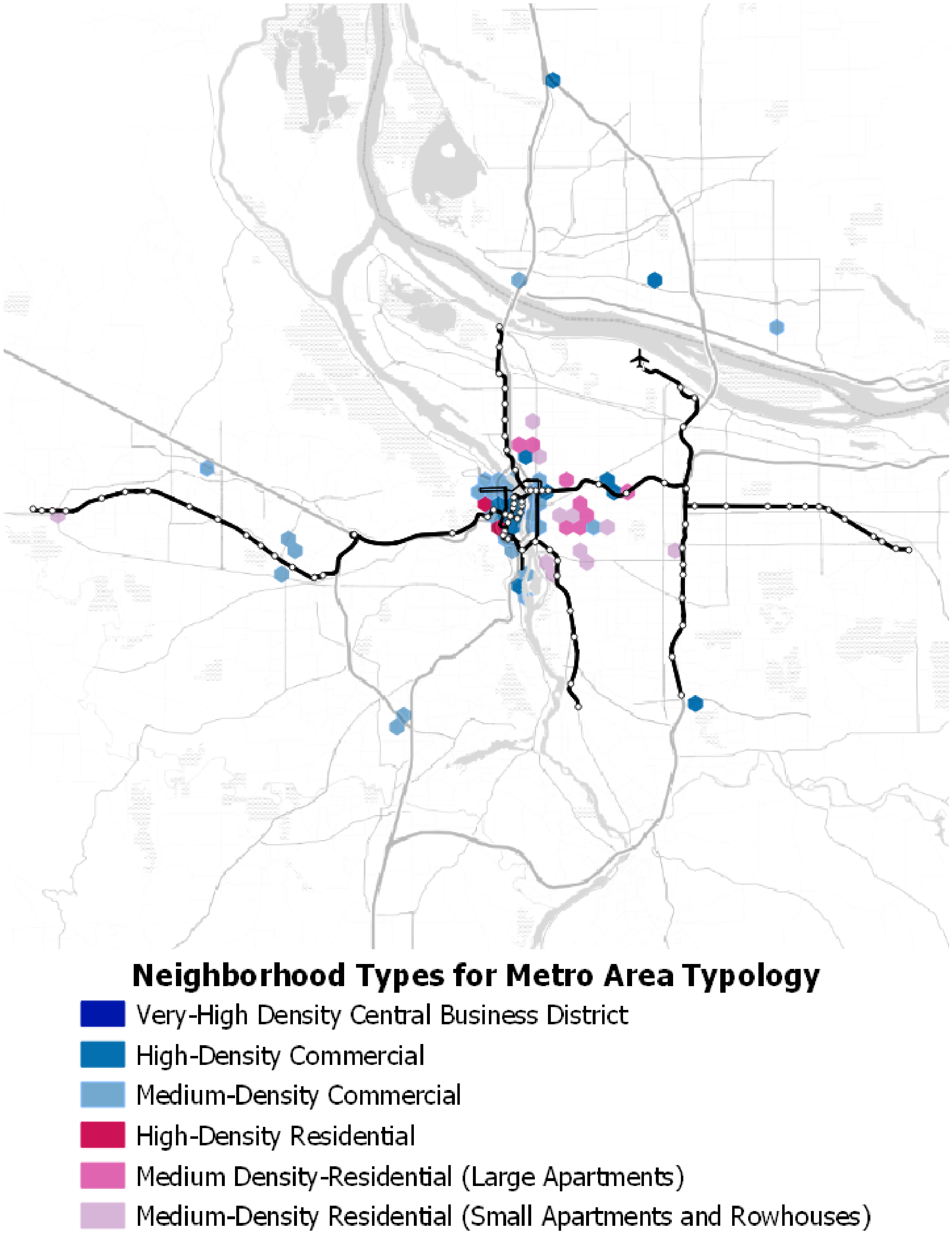

Figure L.10: Light rail and streetcars in the Portland metro area. The MAX Light Rail is shown with thick lines; the Portland Streetcar is shown with thin lines. Stops on the streetcar are closely spaced and not shown. The area shown is a 30-mile by 30-mile square.

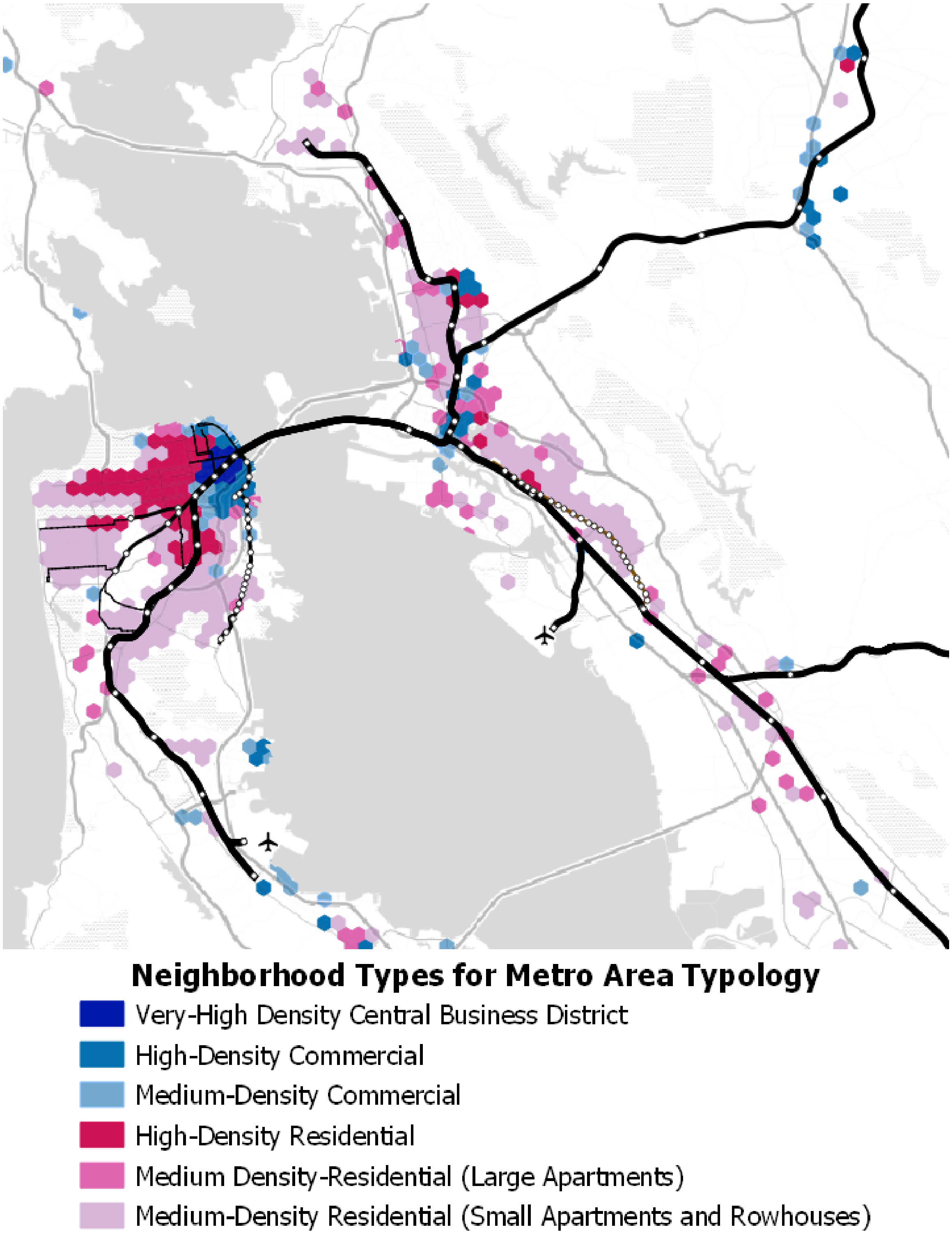

Figure L.11: Rapid transit, light rail, and bus rapid transit in the San Francisco metro area. BART is shown shown with thick lines; the San Francisco Muni Metro, streetcars, and cable cars are shown with thin lines. The Tempo BRT line is shown with a brown line. Surface stops on light rail are closely spaced and not shown. The area shown is a 30-mile by 30-mile square.

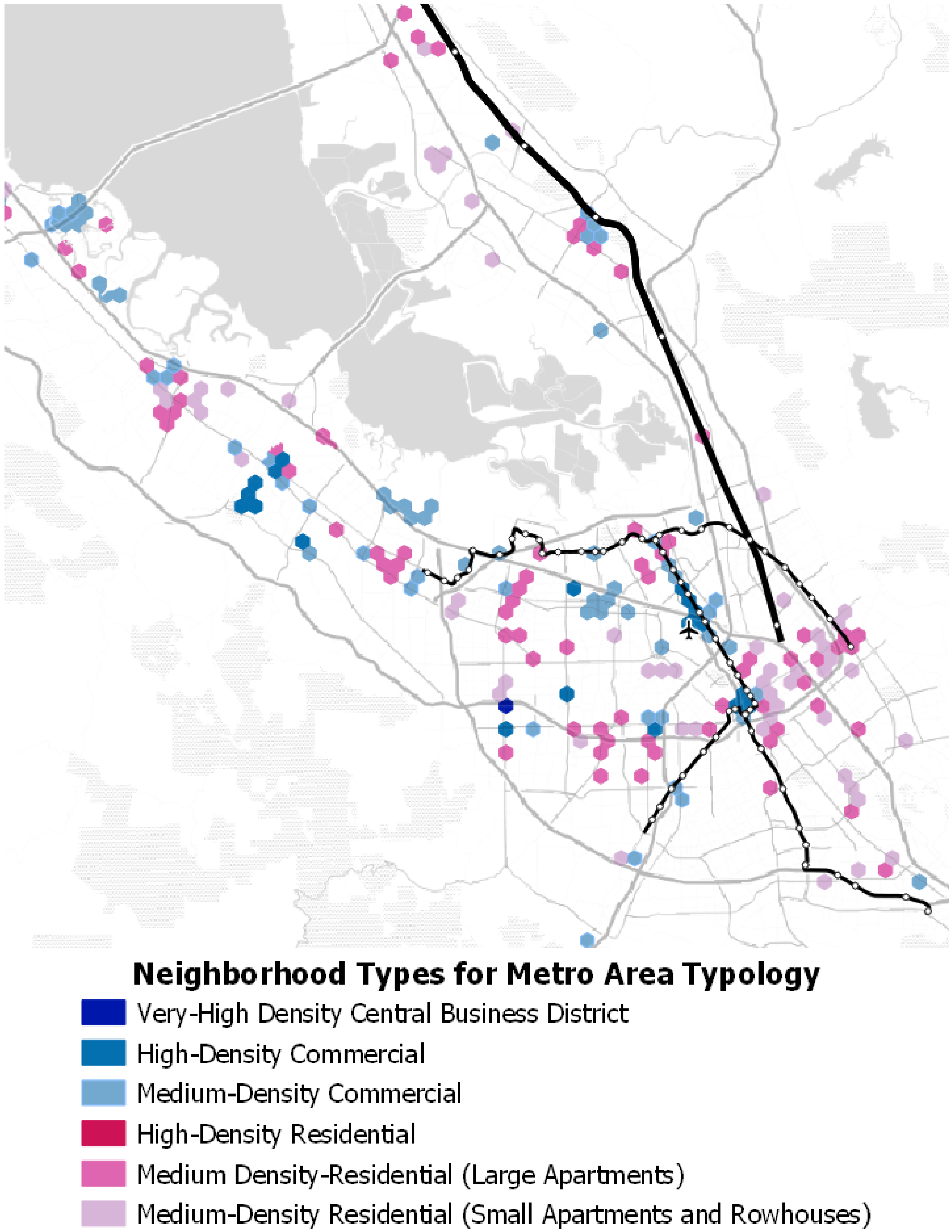

Figure L.12: Rapid transit and light rail in the San Jose metro area. BART is shown with thick lines; the VTA Light Rail is shown with thin lines. The area shown is a 30-mile by 30-mile square.

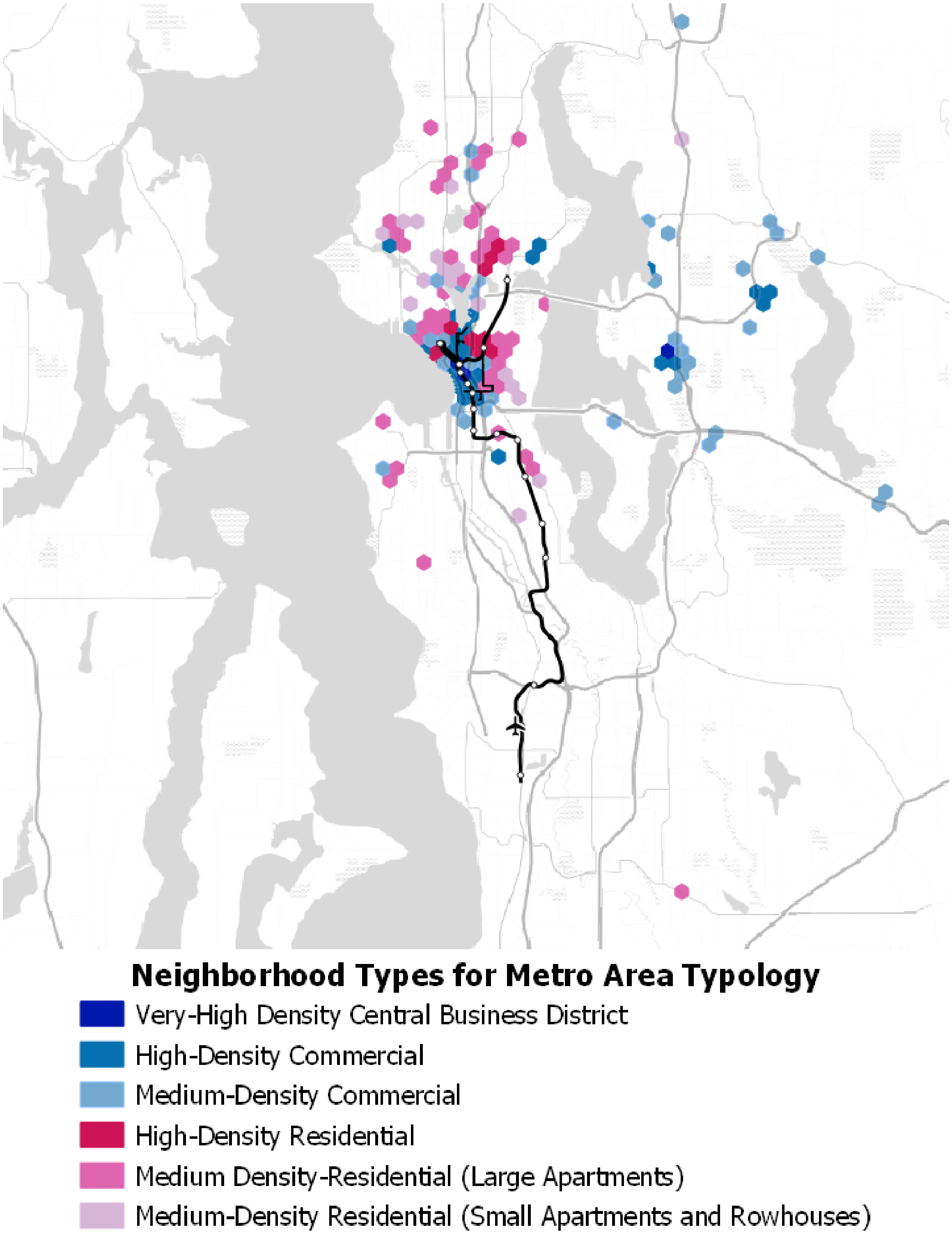

Figure L.13: Rapid transit and light rail in the Seattle metro area. The Seattle Center Monorail is shown with a thick line. Seattle Link light rail is shown with a medium line. The South Lake Union Streetcar and First Hill Streetcar are shown with thin lines. Streetcar stops are closely spaced and not shown. The area shown is a 30-mile by 30-mile square.

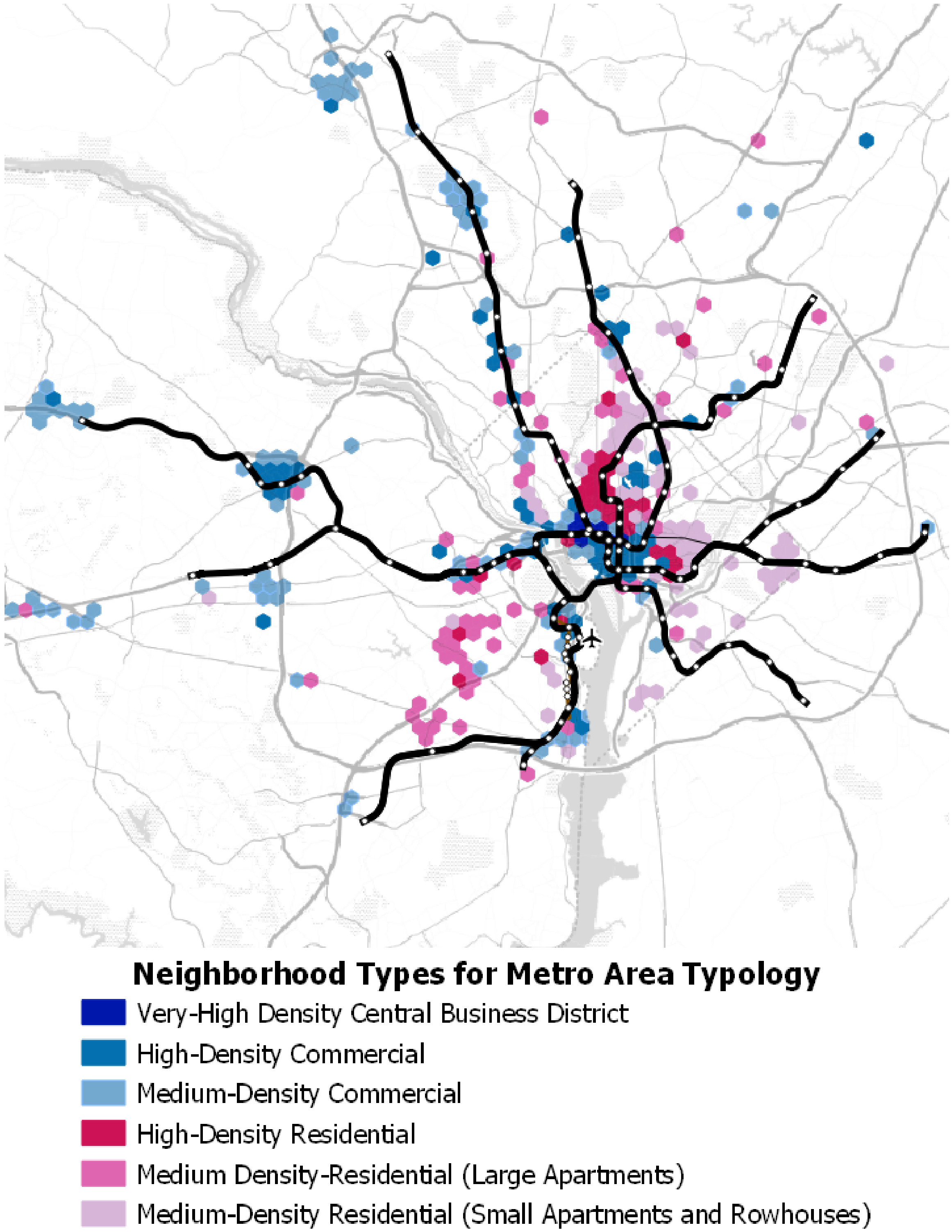

Figure L.14: Rapid transit, streetcar, and bus rapid transit in the Washington metro area. WMATA Metrorail lines are shown with thick lines; the DC Streetcar is shown with a thin line; the Metroway BRT line is shown with a brown line. Streetcar stops are closely spaced and not shown. The area shown is a 30-mile by 30-mile square.

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